BAYESIAN (FOOT)BALLERS

2022 SOA Student Research Case Study Challenge

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Executive Summary

The Actuarial Consulting Firm (ACF) has enjoyed the opportunity to work with the Executive Committee of Hammessi Bayes on this project beginning January 2022. ACF has successfully applied machine learning techniques to build a player selection model and construct the first ever competitive national football team for Rarita, the Bayesian (Foot)Ballers. From its pre-existing organized leagues using 995 million Doubloons (∂) of government funding, this newly branded team has an initial roster of 25 Rarita football players.

ACF is confident that by following the ten-year implementation plan and annual review process in this report in conjunction with the player selection model, the Bayesian (Foot)Ballers will be a “competitive” team and qualify for the international Football and Sporting Association (FSA) League, place in the FSA top ten within the next five years, and have high probability of winning the FSA championship within ten years. As a result of this football brand, Rarita will undergo economic growth and development, detailed by GDP and profit increases after considering fixed and variable expenses throughout the next ten years. ACF has also provided in this report risk assessment and mitigation to assure the team’s victory.

Team Selection

Player Selection Process

ACF utilized several resources to determine which player statistics are most indicative of success for each position. These resources included data-driven techniques such as decision trees and principal component analysis (PCA), along with literary sources. Notable important statistics included goals, shots, expected goals, pass completions, key passes, tackles that led to possession, successful pressures, interceptions, and save percentages.

Additionally, ACF used literary sources to determine which formation would best suit Rarita's initial team. The most optimal choices were 4-4-2, 4-5-1, or 4-3-3, with the two former options being more defensive and the latter more offensive. 4-5-1 was selected as the best fit for Rarita's scheme since it allows for the most flexibility with midfielders and has a more defensive nature, useful for newer teams.

After developing assumptions based on PCA (Appendix C Tables 16-19), ACF created a selection model to assign scores to players based on their position and statistical performance relative to other players of the same position; these scores serve as a measure of player skill for player selection. By applying the PCA's weight assumptions, scores (Equations 1-4) for player skills were generated based on 2020 and 2021 league data.

Equation 1: Score Calculation for Forwards

$$Forward\ Score = 0.60 * Shooting\ Score + 0.40 * Passing\ Score$$

Equation 2: Score Calculation for Midfielders

$$Midfielder\ Score = 0.25 * Shooting\ Score + 0.50 * Passing\ Score + 0.25 * Defense\ Score$$

Equation 3: Score Calculation for Defenders

$$Defender\ Score = 0.25 * Passing\ Score + 0.75 * Defense\ Score$$

Equation 4: Score Calculation for Goalkeepers

$$Goalkeeper\ Score = Goalkeeping\ Score$$

Final player scores for their primary position were then computed using a playing time weighted average (Equation 5).

Equation 5: Final Player Score Calculation

$$Final\ Player\ Score = \frac{(2020\ 90s * 2020\ Position\ Score + 2021\ 90s * 2021\ Position\ Score)}{(2020\ 90s + 2021\ 90s)}$$

When selecting players, ACF adopted a holistic approach using player scores as a component of the process rather than the sole factor considered. The process involved selecting a mixture of younger players to start as backups, along with experienced players to serve as starters and mentor younger players. This ideology allows younger players time to develop before taking on starting roles and provides the baseline for a sustainable cycle of players over the next several years. Additionally, ACF only considered Rarita players to increase national pride in the team amongst Rarita's citizens. The above analysis contributed to the Rarita players selected (Table 1).

Table 1: Team Selection

Player	Nation	Position	Role
U. Shoko	Rarita	FW	Starter
Z. Zziwa	Rarita	FW	Backup
I. Shoshan	Rarita	FW	Reserve
Q. Morrison	Rarita	MF	Starter
X. Leroy	Rarita	MF	Starter
P. Rabiu	Rarita	MFFW	Starter
Z. Kakai	Rarita	MFDF	Starter
J. Nurhayati	Rarita	MF	Starter
P. Villa	Rarita	MFFW	Backup
G. binti Salleh	Rarita	MFFW	Backup
L. Leibowitz	Rarita	MF	Backup
O. Wanjala	Rarita	MF	Backup
S. Barman	Rarita	MF	Backup
Y. Cheu	Rarita	MF	Reserve
Z. Rajabi	Rarita	DF	Starter
F. Acayo	Rarita	DF	Starter
K. Musah	Rarita	DF	Starter
S. Szabó	Rarita	DF	Starter
N. Terzi?	Rarita	DF	Backup
P. Murmu	Rarita	DF	Backup
X. Takagi	Rarita	DF	Backup
R. Tsao	Rarita	DF	Backup
W. Nasiru	Rarita	GK	Starter
F. Akumu	Rarita	GK	Backup
F. Ithungu	Rarita	GK	Reserve

To verify the above player selection, ACF employed another similar methodology based on selected statistics determined by decision trees (Appendix B) and literature review. The weight assumptions and player selection results are in Appendix C. Through comparison with the PCA's selected players in Table 21, 76% of players selected were consistent across both methodologies, leading to confidence in PCA player selections (Table 1).

As another way to verify the above selection result, ACF applied the PCA player selection model to 2021 tournament data and then computed team scores for comparison to tournament results. Position grouping scores were computed for each team using a playing time weighted average for players in that position, and final team scores were created using Equation 6.

Equation 6: Final Team Score Calculation

$$\begin{gathered} Final\ Team\ Score = 0.15 * Team\ Forward\ Score + \\ 0.30 * Team\ Midfielder\ Score + \\ 0.30 * Team\ Defender\ Score + \\ 0.25 * Team\ Goalkeeper\ Score \end{gathered}$$

The results for final team scores (Appendix D Table 27) were directionally consistent with tournament results, confirming PCA as a promising method to select players.

Probability of Success

Bayes stated two goals for success: finishing in the FSA top ten within five years and having a high likelihood of winning the FSA championship within ten years. The probabilities of achieving these goals were computed by comparing the position grouping scores of 2021 tournament nations with those of the Bayesian (Foot)Ballers. Upper and lower bound success probabilities for the Bayesian (Foot)Ballers were computed based on this comparison (Appendix E Tables 30-31). The analysis showed an 82.5% probability for the first goal and 62.5% for the second. More in-depth explanation is in Appendix E.

Economic Impact

Expenses

ACF considered expenses such as player and staff salaries as well as other expenses including facilities, rent, and equipment (Table 2).

Table 2: Fixed/Variable Distribution of Expense Categories

Expense Category	Expense	Variable Percentage	Fixed Percentage
Salaries	Player Salaries	100%	0%
Salaries	Management, Board, Committees	50%	50%
Other	Facilities, Rent, Equipment, etc.	80%	20%

To be consistent with practices of other national teams, player salaries for the team will be paid on a per-match basis. To estimate the cost of all player salaries in a season, the per-match salary was set at ∂3,453.03 (Appendix F). ACF assumed that teams play four "friendlies", or non-tournament matches against other teams, each season. Qualifying rounds are common in the FSA tournament. Based on the number of teams in the tournament data, ACF assumed that two zones of 28 teams each would be used for qualifying, including Rarita's Bayesian (Foot)Ballers. If the team qualifies, they can progress to the tournament.

The lower bound, average, and upper bound for number of matches per season is shown in Table 3.

Table 3: Matches Played Estimation

Match Type	Lower Bound No. Matches	Average No. Matches	Upper Bound No. Matches
Friendlies	4	4	4
Qualifiers	4	4	4
Tournament	0	2	5
Total	8	10	13

ACF calculated estimations for total player salaries using the number of players on the roster. Then, ACF estimated salaries for team staff such as management, committees, and board members, based on salaries from the United States Soccer Federation (USSF), separated into fixed and variable expenses. Other expenses were estimated using Rarita's Per Capita Other Expenses in the provided data. All variable expenses were scaled by the number of matches, since being knocked out of the tournament earlier will result in fewer expenses for training and staff.

Table 4: Annual Expenses

Per Season Expense	Lower Bound (∂)	Average (∂)	Upper Bound (∂)
Player Salaries	690,606	863,258	1,122,235
Fixed Staff Costs	16,118,713	16,118,713	16,118,713
Variable Staff Costs	3,393,413	4,241,767	5,514,297
Fixed Other Expenses	450,694,187	450,694,187	450,694,187
Variable Other Expenses	23,720,747	29,650,933	38,546,213
Total Expenses	494,617,667	501,568,858	511,995,645

Revenue and Profit

Broadcast and commercial revenue were considered as the main sources of revenue for the international team, since ACF assumed that the FSA would receive any ticket revenue from games. ACF calculated broadcast and commercial revenues using Rarita's 2016-2021 Per Capita Broadcast and Per Capita Commercial revenues (Appendix F). ACF assumed revenues as 20% fixed and 80% variable. Profit per season was calculated from the total revenue per season and total expenses per season (Table 5). This indicates that Rarita's new team is profitable.

Table 5: Seasonal Expenses, Revenues, and Profits

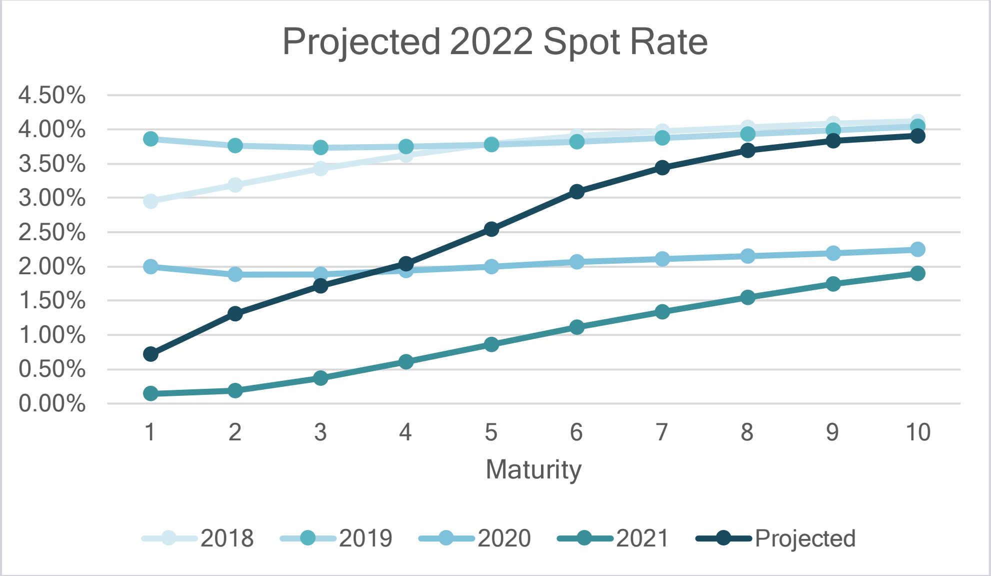
	Lower Bound (∂)	Average (∂)	Upper Bound (∂)
Total Expenses Per Season	494,617,667	501,568,85	511,995,645
Total Revenue Per Season	620,181,628	691,059,528	797,376,379
Total Profit Per Season	125,563,962	189,490,670	285,380,734

Tournament winners earn an unknown amount of prize money, so the prize was not included as potential revenue. However, if the Bayesian (Foot)Ballers win a tournament, it is recommended that half of the prize money is split among the players and the other half used to reinvest in the team or make charitable contributions to sports organizations around Rarita.

Financial Projections

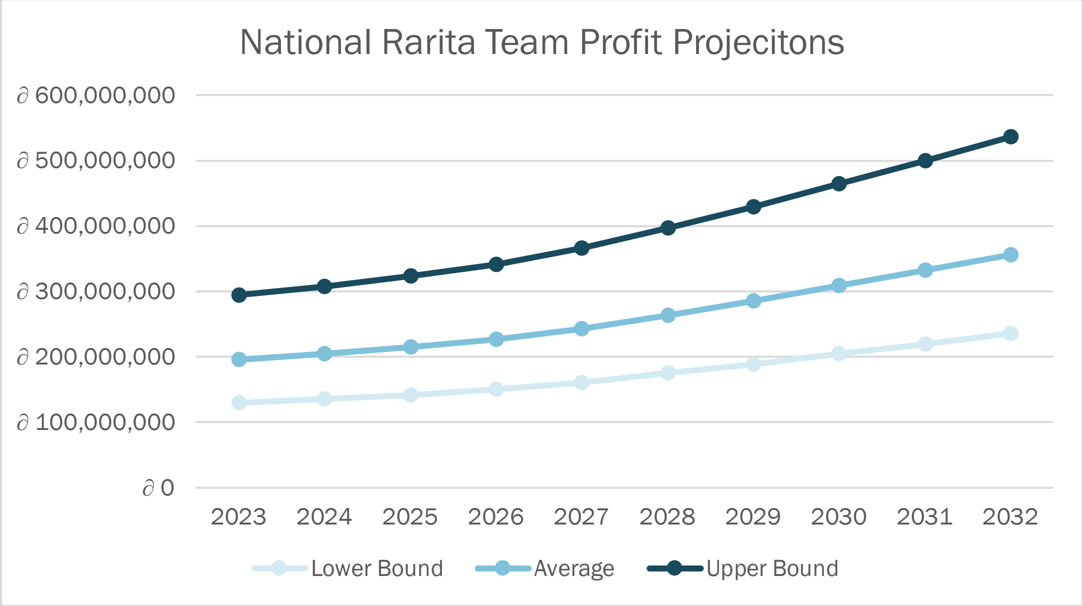
To estimate the spot rates as of January 1, 2022, ACF selected the median of the provided spot rates at each maturity (Figure 1).

Figure 1: Projected Spot Rates



ACF used the estimated spot rates to calculate future values for expenses, revenues, and profit. Figure 2 illustrates lower bound, average, and upper bound profit projections.

Figure 2: Projected Annual Profits



GDP Impact

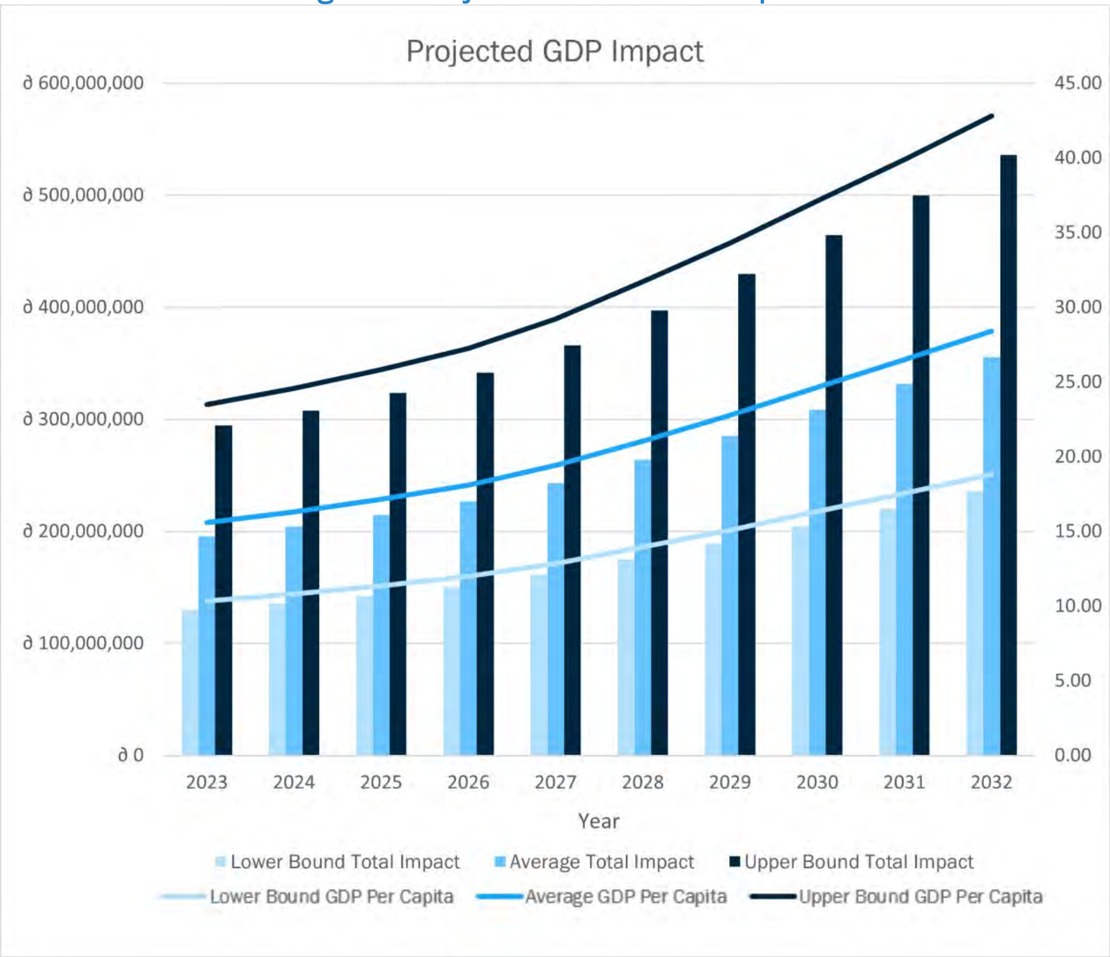
The annual GDP impact was calculated by Equation 7.

Equation 7: GDP Impact Per Capita

$$GDP\ Per\ Capita = \frac{Profit}{Population}$$

The total Rarita population data was given up to 2020; thus, the total population was projected through 2032 (Appendix H). The annual Rarita GDP can be observed in Figure 3 and Appendix H. The Bayesian (Foot)Ballers are projected to annually increase the Rarita GDP per capita regardless of number of matches played.

Figure 3: Projected Annual GDP Impact

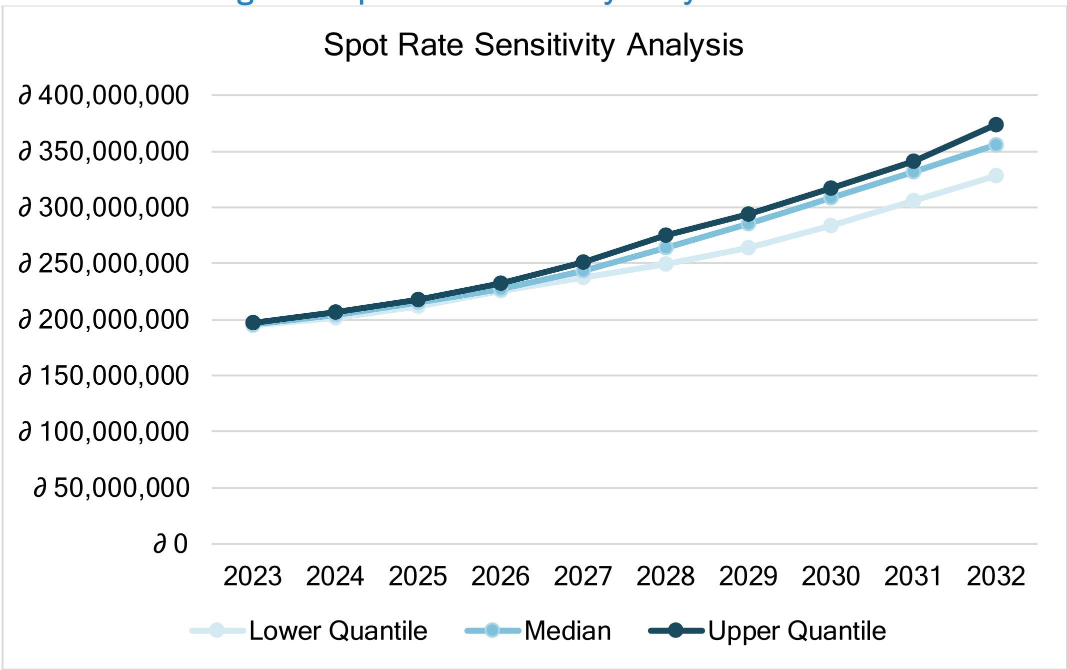


The Bayesian (Foot)Ballers will bring economic benefits to other related industries. Restaurants and bars will have more customers watching matches. Retail will also benefit from the sale of team-related merchandise. Sponsoring brands will see increased sales from the recognition. Hosting friendlies will increase tourism, bringing revenue to related transportation industries.

Sensitivity Analysis

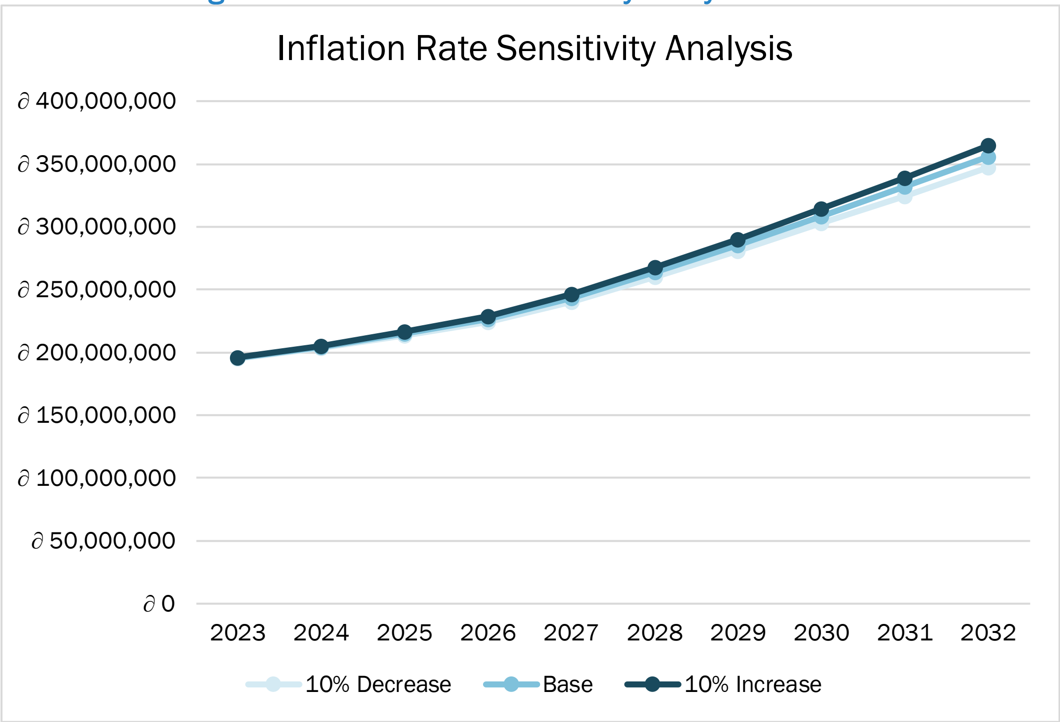
ACF tested the spot and inflation rate sensitivities. To test the spot rate sensitivity, ACF applied the lower quartile and upper quartile of spot rates (Table 33) to the average profit scenario.

Figure 4: Spot Rate Sensitivity Analysis for Profit



Similarly, the inflation rate's sensitivity was tested by increasing and decreasing the base inflation rate (2.5%) by 10%.

Figure 5: Inflation Rate Sensitivity Analysis for Profit



The sensitivity to the change in spot rate and inflation rate increases as time increases. However, it appears that the profit projections under the average scenario are more sensitive to a change in spot rate than a change in inflation rate.

Data, Data Limitations, and Assumptions

Data and Data Limitations

ACF received player statistics from the 2020 and 2021 league and tournament seasons. However, only the tournament results were provided. Similarly, some players did not have populated statistics or were only documented within the league or tournament datasets. Financial information was provided for Rarita and other nation's football teams at a total level that included the national teams and league teams. Therefore, ACF was unable to directly allocate expenses that would be applicable to the Rarita National Team.

ACF came up with solutions or assumptions for the following data limitations (Table 6).

Table 6: Data Limitations and Solutions

Limitation	Solution or Assumption
No league results data for 2020 and 2021	Used the tournament data and tournament results for creating player selection criteria
No passing or defense tournament data for 2020	Used the 2021 tournament data and tournament results for creating player selection criteria
Some players are assigned a combination of positions (i.e. DFFW)	Assumed the first position listed was their "primary" position
Some players in the league data are not included in the tournament data	Assumed that player statistics would be consistent within a league and tournament setting
Nation Dosqaly does not have 2021 tournament goalkeeping data	Nation Dosqaly was excluded from analysis
No player injury or penalty data	Advised to collect player injury and penalty data in the future as data to monitor

Data used for expenses included the USSF's 2021 Audited Financial Statement, and for player salaries, ACF used data from England's Football Association, the United States Women's National Team, and the United States Men's National Team.

Assumptions

Table 7: Assumptions

Variable	Assumption
Number of Matches	Bayesian (Foot)Ballers play four friendlies, play in a 28-team qualifying round, and may play in a 24-team FSA tournament, resulting in an estimated 8 to 13 matches.
Expenses, Revenues, and Profit	These variables are consistent for each year.
Annual Inflation Rate	2.50%
Currency Exchange Rates	The Dollar To Euro 5-year Average is 0.870. The Euro to Doubloon 5-year Average is 1.134.
Player Position	For players with multiple positions listed, the first position is their primary position and serves as the basis for their positional score.
Tournament/League Data	Tournament and league data are collected in a comparable manner.
Player Salary	The per-match player salary is ∂3,453.03 (Appendix F).

Implementation Plan

ACF developed an annual plan for the Bayesian (Foot)Ballers for repeated tasks (Figure 6) as well as a full ten-year timeline (Table 8).

Figure 6: Annual Plan

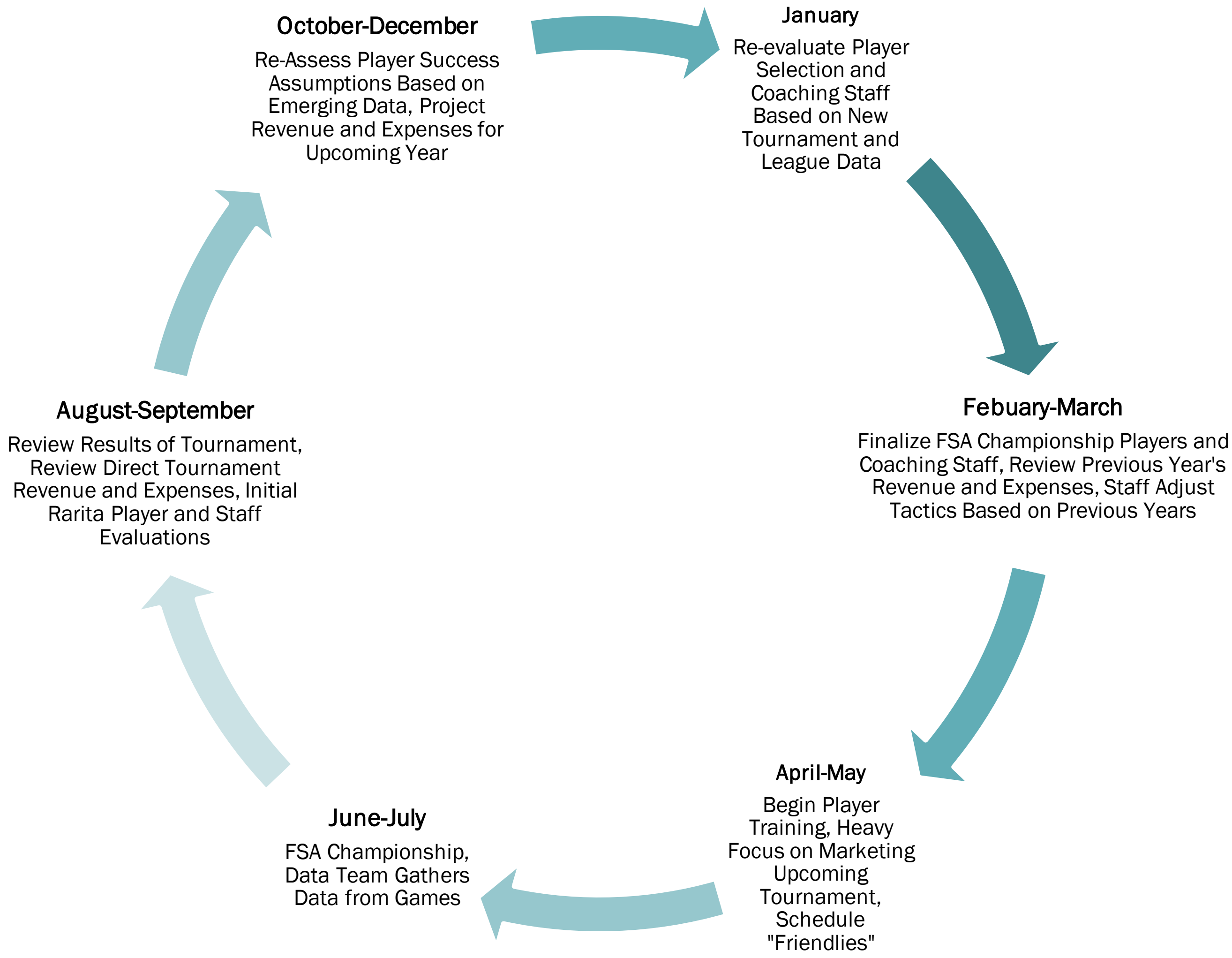


Table 8: Ten Year Implementation Plan

Years 1-3	• Heavy emphasis on marketing the new team to Rarita citizens • Qualify for the international FSA • Veteran players mentor younger players • Re-evaluate player success assumptions with new data • Finish in the top ten by year 3
Years 4-6	• Expand marketing internationally to increase tourism • Younger players begin taking on starting roles • Veterans relegate to backup or mentor roles • New set of young players join as backups • Finish in top ten at least twice
Years 7-10	• Continue cycling players; backups from years 1-3 are now leading as veterans • Evaluate additional goals for the next decade • Win an FSA championship

Data to Monitor

To improve future player selection and to conduct player performance reviews, the following data should be collected on an annual basis (Table 9).

Table 9: Data to Monitor

Annual Report Metric	**Source**
Tournament Rankings	Tournament player and team scores based on current assumptions
Annual Revenue	Both direct revenue from tournaments and indirect revenue
Annual Expenses	Both direct expenses from tournaments and indirect expenses
Detailed Tournament Player and Rarita League Player Statistics	Continue collection of player statistics; collect injury and penalty data

Risk and Risk Mitigation Considerations

Injury Risk

- Intrinsic risk factors include age and muscle strength, while extrinsic factors include equipment and rules of play.
- Repeated injury can cause chronic conditions, impact team performance, and have negative financial impact.
    - The 2014 FIFA World Cup had 1.7 injuries per match and 1.0 injuries per match expected to result in time loss.

Injury Risk Mitigation

- Employ thorough training programs and invest in player injury and health insurance.
    - The FIFA 11+ Training Program reduced injuries by 30% for teams who participated at least twice per week.

Reputation Risk

- “Football hooliganism” refers to violent and abusive fans or players, which has resulted in injuries, deaths, and damaged reputations.
- Although rare, it is an imperative risk to mitigate due to the potential dire impact to Rarita’s reputation.

Reputation Risk Mitigation

- Separate fans by nation, have video surveillance for security, and impose punishments for rowdy behavior.
- Hire a sports psychologist and a coach who also emphasizes sportsmanship.

Economic risk due to changing spot and inflation rates is not a concern based on our sensitivity analysis. Other broader risks such terrorism, political, and pandemic risks can be mitigated by hiring a risk management officer, ensuring a governing body in the Rarita league, and seeking general liability insurance.

Conclusion

ACF strongly advises the Executive Committee of Hammessi Bayes to utilize the player selection framework based on a 4-5-1 formation and implementation plan in this report to launch the Bayesian (Foot)Ballers by 2023. The team is predicted with high probability to place in the FSA top ten within five years and to win the FSA championship within ten years. ACF's supporting analysis and financial projections have revealed that Rarita can launch a future top team in the FSA that subsequently brings an economic boom and increase in tourism from broadcast and commercial revenue and a reputable football brand.

Appendix A – PCA

Due to the large number of player statistics, ACF used PCA to reduce the dimensionality while continuing to encapsulate the data's information. PCA was performed on the 2021 shooting, passing, defense, and goalkeeping player statistics separately. Principal components were chosen until approximately 60% of the total variation was explained (Table 10). Similarly, the principal components are listed in the appendix in Tables 11-14.

Weights for player scoring were then found by computing a weighted average of the principal components selected using the proportion of variance explained as weights. These weighted average components were then scaled so the sum of the components was equal to one. Finally, these scaled weighted average values were multiplied by the weights found in Table 20 to arrive at the final weights for player scoring (Tables 16-19).

Table 10: Principal Component Selections by Statistical Category

Player Statistic Data	Number of Principal Components Selected	Cumulative Proportion of Variance Explained
Shooting	2	59.6%
Passing	2	60.1%
Defense	4	61.0%
Goalkeeping	2	61.4%

Table 11: Principal Components for Shooting Statistics

Shooting Principal Component		
Statistic	**PC1**	**PC2**
Gls	0.303	0.435
Standard Sh	0.369	-0.205
Standard SoT	0.380	0.052
Standard FK	0.080	-0.024
Performance PK	0.081	-0.052
Standard Sh/90	0.366	-0.206
Standard SoT/90	0.373	0.039
Performance PKatt	0.078	-0.017
Expected xG	0.411	0.019
Expected npxG	0.406	0.035
Expected G-xG	-0.024	0.599
Expected np:G-xG	-0.026	0.598
Proportion of Variance Explained	**38.37%**	**21.20%**

Table 12: Principal Components for Passing Statistics

Passing Principal Component		
Statistic	**PC1**	**PC2**
Total Cmp	0.344	-0.022
Total Att	0.342	0.008
Total TotDist	0.340	-0.117
Total PrgDist	0.271	-0.115
Short Att	0.239	0.196
Short Cmp	0.256	0.179
Medium Cmp	0.309	-0.129
Medium Att	0.314	-0.100
Long Cmp	0.253	-0.182
Long Att	0.232	-0.151
Ast	0.017	0.393
xA	0.018	0.423
A-xA	0.008	0.213
KP	0.046	0.392
1/3	0.266	-0.007
PPA	0.095	0.396
CrsPA	0.050	0.293
Prog	0.238	0.213
Proportion of Variance Explained	**44.15%**	**15.99%**

Table 13: Principal Components for Defense Statistics

Defense Principal Component				
Statistic	**PC1**	**PC2**	**PC3**	**PC4**
Tackles Tkl	0.359	-0.233	0.052	-0.141
Tackles TklW	0.313	-0.205	0.018	-0.261
Tackles Def 3rd	0.313	-0.203	0.042	0.177
Tackles Mid 3rd	0.250	-0.220	0.103	-0.224
Tackles Att 3rd	0.108	0.036	-0.098	-0.417
Tkl+Int	0.316	-0.250	-0.098	-0.083
Pressures Press	0.269	0.401	0.014	-0.081
Pressures Succ	0.254	0.303	0.025	-0.053
Pressures Def 3rd	0.262	0.118	-0.271	0.088
Pressures Mid 3rd	0.205	0.333	0.111	-0.144
Pressures Att 3rd	0.103	0.393	0.169	-0.099
Blocks Blocks	0.074	0.151	-0.553	0.005
Blocks Sh	-0.006	-0.014	-0.379	0.216
Blocks ShSv	0.000	-0.027	-0.027	0.211
Blocks Pass	0.095	0.195	-0.464	-0.114
Vs Dribbles Tkl	0.305	-0.192	0.113	0.178
Vs Dribbles Att	0.295	0.078	0.169	0.426

Vs Dribbles Past	0.183	0.238	0.151	0.450
Int	0.121	-0.147	-0.198	0.013
Clr	0.029	-0.172	-0.274	0.267
Err	-0.030	-0.077	-0.079	0.107
Proportion of Variance Explained	**27.39%**	**13.96%**	**11.81%**	**7.88%**

Table 14: Principal Components for Goalkeeping Statistics

Goalkeeping Principal Component		
Statistic	**PC1**	**PC2**
Playing Time MP	0.376	0.233
Playing Time Starts	0.359	0.279
Playing Time Min	0.367	0.258
Playing Time 90s	0.369	0.251
Performance GA	-0.321	0.245
Performance Saves	-0.165	0.334
W	0.307	-0.022
D	0.108	0.037
L	-0.326	0.229
Performance CS	0.177	-0.448
Performance PKatt	-0.160	0.387
Penalty Kicks PKA	0.044	0.182
Penalty Kicks PKsv	-0.044	0.353
Penalty Kicks PKm	-0.236	0.065
Proportion of Variance Explained	**41.10%**	**20.34%**

Appendix B – Decision Trees

Regression trees for each position (goalkeeper, defender, midfielder, and forward) were used to predict 2021 tournament places based on 2021 tournament player statistics. Calculated player statistics such as goals minus expected goals were not included in the trees. Variables that resulted in predicted tournament place closest to 1 were considered further for inclusion in the final player selection model. The selected variables for further consideration by position are shown in Table 15.

Table 15: Decision Tree Variables

Position	Regression Tree Variables
Goalkeeper	L
Defender	Tackles Att 3rd, 1/3, Tackles Def 3rd, Pressures Def 3rd, Total Cmp
Midfielder	Medium Att, Tackles Att 3rd, Pressures Def 3rd, KP, Short Cmp
Forward	Performance PK, Performance PKatt, Total Cmp, Standard SoT

Appendix C – Player Score Weights

Principal Component Approach

Table 16: PCA Shooting Statistical Weights by Position

	Weight for Position	
Statistic	FW	MF
Gls	0.093	0.039
Standard Sh	0.044	0.018
Standard SoT	0.070	0.029
Standard Sh/90	0.043	0.018
Standard SoT/90	0.068	0.028
Standard FK	0.011	0.005
Performance PK	0.009	0.004
Performance PKatt	0.012	0.005
Expected xG	0.072	0.030
Expected npxG	0.073	0.030
Expected G-xG	0.053	0.022
Expected np:G-xG	0.052	0.022

Table 17: PCA Passing Statistical Weights by Position

	Weight for Position		
Statistic	FW	MF	DF
Total Cmp	0.031	0.039	0.019
Total Att	0.032	0.040	0.020
Total TotDist	0.028	0.034	0.017
Total PrgDist	0.021	0.027	0.013
Short Cmp	0.030	0.037	0.019
Short Att	0.029	0.036	0.018
Medium Cmp	0.024	0.030	0.015
Medium Att	0.026	0.032	0.016
Long Cmp	0.017	0.022	0.011
Long Att	0.016	0.021	0.010
Ast	0.015	0.018	0.009
xA	0.016	0.020	0.010
A-xA	0.008	0.010	0.005
KP	0.017	0.022	0.011
1/3	0.024	0.031	0.015
PPA	0.022	0.028	0.014
CrsPA	0.014	0.018	0.009
Prog	0.029	0.036	0.018

Table 18: PCA Defense Statistical Weights by Position

	Weight for Position	
Statistic	MF	DF
Tackles Tkl	0.015	0.046
Tackles TklW	0.010	0.029
Tackles Def 3rd	0.019	0.058
Tackles Mid 3rd	0.008	0.025
Tackles Att 3rd	-0.002	-0.007
Vs Dribbles Tkl	0.021	0.064
Vs Dribbles Att	0.037	0.111
Vs Dribbles Past	0.035	0.104
Pressures Press	0.032	0.095
Pressures Succ	0.028	0.084
Pressures Def 3rd	0.016	0.048
Pressures Mid 3rd	0.027	0.080
Pressures Att 3rd	0.024	0.073
Blocks Blocks	-0.006	-0.018
Blocks Sh	-0.008	-0.024
Blocks ShSv	0.002	0.007
Blocks Pass	-0.003	-0.008
Int	-0.003	-0.008
Tkl+Int	0.008	0.025
Clr	-0.007	-0.021
Err	-0.005	-0.015

Table 19: PCA Goalkeeping Statistical Weights by Position

	Weight for Position
Statistic	GK
Playing Time MP	0.242
Playing Time Starts	0.244
Playing Time Min	0.243
Playing Time 90s	0.242
Performance GA	-0.098
Performance Saves	0.000
W	0.145
D	0.062
L	-0.104
Performance CS	-0.022
Performance PKatt	0.015
Penalty Kicks PKA	0.066
Penalty Kicks PKsv	0.064
Penalty Kicks PKm	-0.100

Table 20: Statistical Weights for Computing Player Scores

Weights for Position	Shooting	Passing	Defense	Goalkeeping
FW	**60%**	**40%**	0%	0%
MF	**25%**	**50%**	**25%**	0%
DF	0%	**25%**	**75%**	0%
GK	0%	0%	0%	**100%**

Table 21: Player Selections from Principal Component Analysis

Player	Nation	Position	Age	Final Score	Role
U. Shoko	Rarita	FW	24	1.16	Starter
Z. Zziwa	Rarita	FW	23	1.26	Backup
I. Shoshan	Rarita	FW	30	1.27	Reserve
Q. Morrison	Rarita	MF	33	1.36	Starter
X. Leroy	Rarita	MF	26	1.60	Starter
P. Rabiu	Rarita	MFFW	27	1.12	Starter
Z. Kakai	Rarita	MFDF	26	1.06	Starter
J. Nurhayati	Rarita	MF	33	0.88	Starter
P. Villa	Rarita	MFFW	20	0.65	Backup
G. binti Salleh	Rarita	MFFW	26	1.16	Backup
L. Leibowitz	Rarita	MF	22	0.56	Backup
O. Wanjala	Rarita	MF	23	0.96	Backup
S. Barman	Rarita	MF	24	0.89	Backup
Y. Cheu	Rarita	MF	18	0.34	Reserve
Z. Rajabi	Rarita	DF	30	1.35	Starter
F. Acayo	Rarita	DF	24	1.18	Starter
K. Musah	Rarita	DF	30	0.90	Starter
S. Szabó	Rarita	DF	29	0.88	Starter
N. Terzi?	Rarita	DF	22	1.02	Backup
P. Murmu	Rarita	DF	22	1.00	Backup
X. Takagi	Rarita	DF	23	1.14	Backup
R. Tsao	Rarita	DF	26	1.11	Backup
W. Nasiru	Rarita	GK	33	0.41	Starter
F. Akumu	Rarita	GK	20	0.37	Backup
F. Ithungu	Rarita	GK	28	0.33	Reserve

Principal Component Verification: Decision Trees and Literature Review Approach

Table 22: Decision Tree/Literature Review Shooting Statistical Weights by Position

	Weight for Position	
Statistic	FW	MF
Gls	0.00	**0.05**
Standard SoT	**0.20**	**0.10**
Performance PK	**0.10**	0.00

Expected npxG	**0.25**	0.00

Table 23: Decision Tree/Literature Review Passing Statistical Weights by Position

	Weight for Position		
Statistic	FW	MF	DF
Total Cmp%	**0.10**	0.00	0.00
Total PrgDist	**0.15**	**0.20**	**0.25**
Short Cmp%	0.00	**0.10**	0.00
Medium Cmp%	0.00	**0.10**	0.00
KP	**0.20**	**0.15**	0.00

Table 24: Decision Tree/Literature Review Defense Statistical Weights by Position

	Weight for Position	
Statistic	MF	DF
Tackles Def 3rd	**0.15**	**0.20**
Pressures %	0.00	**0.25**
Int	**0.05**	**0.15**
Err	**0.10**	**0.15**

Table 25: Decision Tree/Literature Review Goalkeeping Statistical Weights by Position

	Weight for Position
Statistic	GK
Performance GA90	**0.15**
Performance Save%	**0.55**
L	**0.15**
Performance CS%	**0.15**

Table 26: Decision Tree/Literature Review Player Selection

Player	Nation	Position	Age	Final Score	Role
I. Saha	Rarita	FW	26	1.36	Starter
U. Shoko	Rarita	FW	24	1.24	Backup
Z. Zziwa	Rarita	FW	23	1.00	Reserve
X. Leroy	Rarita	MF	26	2.70	Starter
Q. Morrison	Rarita	MF	33	2.08	Starter
O. Wanjala	Rarita	MF	23	1.68	Starter
Z. Kakai	Rarita	MFDF	26	1.52	Starter
J. Nurhayati	Rarita	MF	33	1.45	Starter
S. Barman	Rarita	MF	24	1.45	Backup
L. Leibowitz	Rarita	MF	22	1.24	Backup
G. binti Salleh	Rarita	MFFW	26	1.18	Backup
P. Rabiu	Rarita	MFFW	27	1.13	Backup
P. Villa	Rarita	MFFW	20	0.95	Backup
G. Jankowski	Rarita	MF	21	0.70	Reserve
X. Takagi	Rarita	DF	23	1.39	Starter

Z. Rajabi	Rarita	DF	30	0.47	Starter
K. Musah	Rarita	DF	30	0.77	Starter
F. Acayo	Rarita	DF	24	0.62	Starter
P. Murmu	Rarita	DF	22	0.59	Backup
N. Terzi?	Rarita	DF	22	0.49	Backup
K. Nalwanga	Rarita	DF	21	0.80	Backup
R. Tsao	Rarita	DF	26	0.42	Backup
W. Nasiru	Rarita	GK	33	1.23	Starter
F. Akumu	Rarita	GK	20	1.43	Backup
F. Ithungu	Rarita	GK	28	1.24	Reserve

Appendix D – Team Score and 2021 Tournament Result

PCA Team Score Rank is closer to the 2021 Tournament results.

Table 27: PCA Team Score Rank and Tournament Rank Comparison

Nation	Team Score	Team Score Rank	2021 Tournament Rank
Sobianitedrucy	0.74	1	1
People's Land of Maneau	0.58	3	2
Nganion	0.68	2	3
Mico	0.45	4	4
Quewenia	0.28	6	5
Southern Ristan	0.35	5	6
Galamily	0.16	11	7
Bernepamar	0.21	8	8
Giumle Lizeibon	0.16	10	10
Greri Landmoslands	0.18	9	11
Xikong	-0.17	14	12
Manlisgamncent	0.07	13	13
Esia	0.15	12	14
Byasier Pujan	0.27	7	15
Djipines	-0.19	17	16
Leoneku Guidisia	-0.18	16	17
Ledian	-0.22	19	18
Eastern Sleboube	-0.39	23	19
New Uwi	-0.19	18	20
Ngoque Blicri	-0.25	20	21
Nkasland Cronestan	-0.17	15	22
Eastern Niasland	-0.28	21	23
Varijitri Isles	-0.34	22	24

Table 28: Decision Tree/Literature Review Team Score Rank and Tournament Rank Comparison

Nation	Team Score	Team Score Rank	2021 Tournament Rank
Sobianitedrucy	0.36	2	1
People's Land of Maneau	0.41	1	2
Nganion	0.33	4	3
Mico	0.23	7	4
Quewenia	0.18	8	5
Southern Ristan	0.35	3	6
Galamily	0.14	12	7
Bernepamar	0.08	14	8
Giumle Lizeibon	0.17	10	10

Greri Landmoslands	0.29	5	11
Xikong	0.03	16	12
Manlisgamncent	0.00	17	13
Esia	-0.15	22	14
Byasier Pujan	0.28	6	15
Djipines	-0.02	18	16
Leoneku Guidisia	0.18	9	17
Ledian	-0.11	21	18
Eastern Sleboube	-0.11	20	19
New Uwi	0.07	15	20
Ngoque Blicri	0.08	13	21
Nkasland Cronestan	-0.15	23	22
Eastern Niasland	-0.03	19	23
Varijitri Isles	0.17	11	24

Appendix E – Success Probabilities

ACF computed success probabilities by comparing the team scores for tournament teams by position with Rarita team positional scores. Tournament team positional scores were taken from the previous analysis found in the *Player Selection Process* section and aggregated into final team scores using Equation 6. Since Rarita players did not have tournament playing time, Rarita positional scores were computed using Equation 8 for positions with starters, backups, and reserves or Equation 9 for positions with only starters and backups.

Equation 8: Rarita Positional Score Calculation with Reserves

$$Position\ Score = 0.75 * Average\ Starter\ Score + 0.20 * Average\ Backup\ Score + 0.05 * Average\ Reserve\ Score$$

Equation 9: Rarita Positional Score Calculation without Reserves

$$Position\ Score = 0.75 * Average\ Starter\ Score + 0.25 * Average\ Backup\ Score$$

Rarita's positional scores were then compared to the distribution of tournament team positional scores, and Rarita was assigned a theoretical rank based on this comparison (Table 29).

Table 29: Average Positional Scores

Position	Rarita Score	Average Score	Rarita Rank
FW	1.32	0.08	1
MF	1.69	0.15	1
DF	0.75	-0.05	1
GK	1.27	0.18	5
Total	**1.25**	**0.09**	**1**

ACF assigned probabilities of success to each position based on the comparison. Finally, the probability of overall team success was computed (Equation 10).

Equation 10: Rarita Team Probability of Success

$$Team\ Success\ Probability = 0.15 * FW\ Success\ Probability + 0.30 * Midfielder\ Success\ Probability + 0.30 * DF\ Success\ Probability + 0.25 * GK\ Success\ Probability$$

Probability of success ranges are in Tables 30-31.

Table 30: Probability Ranges of Finishing in the Top Ten within Five Years

	Probability of Success	
Position	Lower Bound	Upper Bound
FW	75.0%	95.0%
MF	75.0%	95.0%
DF	75.0%	95.0%
GK	65.0%	85.0%

Total	**72.5%**	**92.5%**

Table 31: Probability Ranges of Winning the FSA Championship within Ten Years

	Probability of Success	
Position	**Lower Bound**	**Upper Bound**
FW	55.0%	75.0%
MF	55.0%	75.0%
DF	55.0%	75.0%
GK	45.0%	65.0%
Total	**52.5%**	**72.5%**

Appendix F – Expenses, Revenues, and Profit

ACF estimated player salaries using other national team salaries. The England Football Association pays players £2,000, or approximately $2,650. The United States Men's National Team pays players $5,000 per match, and players on the United States Women's National Team are paid between $3,250 and $4,500 per match. Based on this data, a per-match salary of $3,500 was assumed to be reasonable. This $3,500 per-match salary was exchanged to Doubloons using the Dollar to Euro 5-year average and the Euro to Doubloon 5-year average, resulting in the basic per-match salary of ∂3,453.03.

With a 28-team bracket, a team will play four games, progressing to the tournament if they win three or four of the games. It was also assumed that the FSA will continue to include 24 teams in the tournament for the next ten years, so a team must win either four or five games to win the tournament based on what position they start in the beginning tournament bracket. The lower bound for matches per season was set at eight, since the team would play four friendlies and four matches in the qualifiers, but not progress to the tournament. The average number of matches was set at ten, since a team will play four friendlies, four qualifiers, and on average two tournament matches. The upper bound for matches was set at 13 since a winning team would play four friendlies, four qualifying matches, and up to five tournament matches.

To scale variable expenses, it was assumed that leagues play 38 games per season. This scaling allows for the estimation of how expenses and revenues may change based on how well the team is performing. For example, a team which does not qualify for the tournament will only play eight games and perhaps not make as much revenue from merchandise sales; however, they may also not need to pay for training expenses since they are not moving forward in the tournament.

Equation 11: Player Salaries Calculation

$$Per\ Match\ Salary\ *\ No.Players\ on\ Roster\ *\ Dollar\ to\ Euro\ 5\ year\ Avg\ *\ Dollar\ to\ Doubloon\ 5\ year\ Avg\ *\ No.Matches\ (LB, Avg, or\ UB)\ /\ 38$$

To calculate the total Per Capita Other Expenses, ACF multiplied the 2016-2021 Per Capita Other Expenses by Rarita's total population for each year. The average of these total other costs was then taken as the Total Other Costs.

Equation 12: Fixed Other Expenses Calculation

$$Total\ Other\ Costs\ *\ 0.80$$

Equation 13: Variable Other Expenses Calculation

$$Total\ Other\ Costs\ *\ 0.20\ *\ No.Matches\ (LB, Avg, or\ UB)\ /\ 38$$

ACF found data on the USSF's expenses, which indicated that management expenses are $32,217,650 per year and the board of directors' and committees' expenses are $458,288 per year.

Equation 14: Staff Costs

$$USSF\ Management\ Expenses\ +\ USSF\ Board\ and\ Committee\ Expenses$$

Equation 15: Fixed Staff Costs

$$Staff\ Costs\ *\ Dollar\ to\ Euro\ 5\ year\ Avg\ *\ Dollar\ to\ Doubloon\ 5\ year\ Avg\ *\ 0.50$$

Equation 16: Variable Staff Costs

$$Staff\ Costs\ *\ Dollar\ to\ Euro\ 5\ year\ Avg\ *\ Dollar\ to\ Doubloon\ 5\ year\ Avg\ *\ 0.50\ *\ No.\ Matches\ (LB, Avg, or\ UB)\ /\ 38$$

The Per Capita Total Revenue from 2016-2021 was multiplied by each year's population for a yearly total revenue. These yearly total revenues were averaged, resulting in the Average Total Revenue. Broadcast and commercial revenues were found to be on average 83% of each year's total revenue.

Equation 17: Fixed Revenues

$$Average\ Total\ Revenue\ *\ 0.83\ *\ 0.20$$

Equation 18: Variable Revenues

$$Average\ Total\ Revenue\ *\ 0.83\ *\ 0.80\ *\ No.\ Matches\ (LB, Avg, or\ UB)\ /\ 38$$

Table 32: Expected Seasonal Expenses and Revenues by Category

Per Season Expenses	Lower Bound	Average	Upper Bound
Player Salaries	690,606	863,258	1,122,235
Fixed Staff Costs	16,118,713	16,118,713	16,118,713
Variable Staff Costs	3,393,413	4,241,767	5,514,297
Fixed Other Expenses	450,694,187	450,694,187	450,694,187
Variable Other Expenses	23,720,747	29,650,933	38,546,213
Total Expenses	**494,617,667**	**501,568,858**	**511,995,645**
Fixed Revenues	336,670,026	336,670,026	336,670,026
Variable Revenues	283,511,601	354,389,502	460,706,352
Total Revenues	**620,181,628**	**691,059,528**	**797,376,379**
Per Season Profit	**125,563,962**	**189,490,670**	**285,380,734**

Appendix G– Financial Projections

Table 33: Projected Spot Rates

	Spot Rates		
Maturity	Lower Quartile	Projected 1/1/2022	Upper Quartile
1	0.33%	0.72%	1.40%
2	0.68%	1.31%	1.85%
3	1.25%	1.71%	2.18%
4	1.85%	2.04%	2.68%
5	2.05%	2.55%	3.19%
6	2.15%	3.09%	3.82%
7	2.27%	3.43%	3.88%
8	2.60%	3.69%	4.03%
9	2.91%	3.83%	4.15%
10	3.07%	3.91%	4.42%

Appendix H– GDP

The total population was projected for 2021-2032 by applying a five-year moving average (Figure 7 and Table 34).

Figure 7: Rarita Population Projection

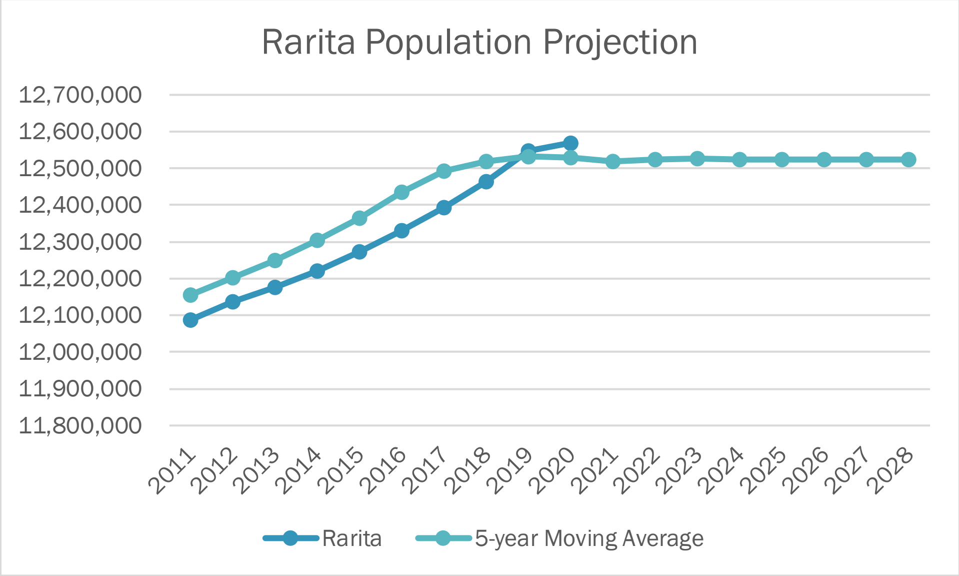


Table 34: Rarita Regional Population Estimates

Population Estimate				
Year	East Rarita	Central Rarita	West Rarita	Rarita
2021	1,926,336	3,024,192	7,543,127	12,493,655
2022	1,931,678	3,027,403	7,559,736	12,518,817
2023	1,934,416	3,028,755	7,569,513	12,532,683
2024	1,933,911	3,025,135	7,569,611	12,528,657
2025	1,931,585	3,026,371	7,560,497	12,518,453
2026	1,932,898	3,026,916	7,564,839	12,524,652
2027	1,933,202	3,026,794	7,566,115	12,526,111
2028	1,932,899	3,026,304	7,565,265	12,524,468
2029	1,932,646	3,026,596	7,564,179	12,523,421
2030	1,932,911	3,026,653	7,565,099	12,524,663
2031	1,932,915	3,026,587	7,565,165	12,524,666
2032	1,932,843	3,026,535	7,564,927	12,524,305

Table 35: Rarita GDP per capita Impact

GDP Impact			
Year	Lower Bound	Average	Upper Bound
2023	10.34	15.61	23.51
2024	10.81	16.31	24.56

2025	11.37	17.15	25.83
2026	12.00	18.10	27.26
2027	12.86	19.41	29.23
2028	13.95	21.06	31.71
2029	15.10	22.78	34.31
2030	16.33	24.64	37.11
2031	17.56	26.49	39.90
2032	18.83	28.42	42.80

Appendix I– R code: PCA

```
#Required Packages
require(readxl)
require(tidyverse)
require(corrplot)
require(analogue)

#Import Data
path = "C:/Users/lilyg/OneDrive/Spring 2022/SOA Case Study/"

shooting <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament Shooting",
guess_max = 1000000)
passing <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament Passing",
guess_max = 1000000)
defense <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament Defense",
guess_max = 1000000)
goalkeep <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament Goalkeeping",
guess_max = 1000000)
results <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament Results",
guess_max = 1000000)

shooting.l <- read_excel(path = paste0(path,"/Data/League.xlsx"), sheet = "shooting", guess_max =
1000000)
passing.l <- read_excel(path = paste0(path,"/Data/League.xlsx"), sheet = "passing", guess_max =
1000000)
defense.l <- read_excel(path = paste0(path,"/Data/League.xlsx"), sheet = "defense", guess_max =
1000000)
goalkeep.l <- read_excel(path = paste0(path,"/Data/League.xlsx"), sheet = "goalkeeping", guess_max =
1000000)

salary.2020 <- read_excel(path = paste0(path,"/Data/salary.xlsx"), sheet = "2020 Salaries", guess_max =
1000000, skip = 11)
salary.2021 <- read_excel(path = paste0(path,"/Data/salary.xlsx"), sheet = "2021 Salaries", guess_max =
1000000, skip = 11)

#Summarized Data
summary(shooting)
summary(passing)
summary(goalkeep)
summary(defense)

#Data Manipulation
shooting <- shooting %>% mutate(Nation = as.factor(Nation),
                    Pos = as.factor(Pos),
                    Age = as.factor(Age),
                    Born = as.factor(Born),
                    Year = as.factor(Year),
                    `Standard Dist` = as.numeric(`Standard Dist`),
                    `Standard FK` = as.numeric(`Standard FK`),
```

```
                  `Expected xG`= as.numeric(`Expected xG`),
                  `Expected npxG` = as.numeric(`Expected npxG`),
                  `Expected npxG/Sh` = as.numeric(`Expected npxG/Sh`),
                  `Expected G-xG` = as.numeric(`Expected G-xG`),
                  `Expected np:G-xG` = as.numeric(`Expected np:G-xG`))

passing <- passing %>% mutate(Nation = as.factor(Nation),
                 Pos = as.factor(Pos),
                 Age = as.factor(Age),
                 Year = as.factor(Year))

defense <- defense %>% mutate(Nation = as.factor(Nation),
                 Pos = as.factor(Pos),
                 Age = as.factor(Age),
                 Year = as.factor(Year))

goalkeep <- goalkeep %>% mutate(Nation = as.factor(Nation),
                  Pos = as.factor(Pos),
                  Age = as.factor(Age),
                  Year = as.factor(Year))

results <- results %>% mutate(Year = as.factor(Year),
                 Place = as.factor(Place),
                 Country = as.factor(Country))

shooting.l <- shooting.l %>% mutate(Nation = as.factor(Nation),
                  Pos = as.factor(Pos),
                  Age = as.factor(Age),
                  Born = as.factor(Born),
                  Year = as.factor(Year),
                  `Standard Dist` = as.numeric(`Standard Dist`),
                  `Standard FK` = as.numeric(`Standard FK`),
                  `Expected xG`= as.numeric(`Expected xG`),
                  `Expected npxG` = as.numeric(`Expected npxG`),
                  `Expected npxG/Sh` = as.numeric(`Expected npxG/Sh`),
                  `Expected G-xG` = as.numeric(`Expected G-xG`),
                  `Expected np:G-xG` = as.numeric(`Expected np:G-xG`))

passing.l <- passing.l %>% mutate(Nation = as.factor(Nation),
                 Pos = as.factor(Pos),
                 Age = as.factor(Age),
                 Year = as.factor(Year))

defense.l <- defense.l %>% mutate(Nation = as.factor(Nation),
                 Pos = as.factor(Pos),
                 Age = as.factor(Age),
                 Year = as.factor(Year))

goalkeep.l <- goalkeep.l %>% mutate(Nation = as.factor(Nation),
                  Pos = as.factor(Pos),
                  Age = as.factor(Age),
                  Year = as.factor(Year))
```

```
salary.2020 <- salary.2020 %>% mutate(Player = as.factor(`Player Name`),
                                      Squad = as.factor(Squad),
                                      League = as.factor(League),
                                      Country = as.factor(Country),
                                      Position = as.factor(Position))

salary.2021 <- salary.2021 %>% mutate(Player = as.factor(`Player Name`),
                                      Squad = as.factor(Squad),
                                      League = as.factor(League),
                                      Country = as.factor(Country),
                                      Position = as.factor(Position))

results <- results %>% rename(Nation = Country)
results.2020 <- results %>% filter(Year == 2020)
results.2021 <- results %>% filter(Year == 2021)

shooting.2020 <- shooting %>% filter(Year == 2020)
shooting.2021 <- shooting %>% filter(Year == 2021)

goalkeep.2020 <- goalkeep %>% filter(Year == 2020)
goalkeep.2021 <- goalkeep %>% filter(Year == 2021)


shooting.l.2020 <- shooting.l %>% filter(Year == 2020)
shooting.l.2021 <- shooting.l %>% filter(Year == 2021)

defense.l.2020 <- defense.l %>% filter(Year == 2020)
defense.l.2021 <- defense.l %>% filter(Year == 2021)

passing.l.2020 <- passing.l %>% filter(Year == 2020)
passing.l.2021 <- passing.l %>% filter(Year == 2021)

goalkeep.l.2020 <- goalkeep.l %>% filter(Year == 2020)
goalkeep.l.2021<- goalkeep.l %>% filter(Year == 2021)


#Data Joins
defense.2021.r <- full_join(defense, results.2021, by = "Nation")

shooting.2021.r <- full_join(shooting.2021, results.2021, by = "Nation")
shooting.2021.r$Place <- addNA(shooting.2021.r$Place)

passing.2021.r <- full_join(passing, results.2021, by = "Nation")

goalkeep.2020.r <- left_join(goalkeep.2020, results.2020, by = "Nation") #no goal keep data for a nation
goalkeep.2021.r <- left_join(goalkeep.2021, results.2021, by = "Nation") #same thing here

#Shooting PCA
shoot.pca <- shooting.2021.r %>% select(Gls, `Standard Sh`, `Standard SoT`,
                                        `Standard FK`, `Performance PK`,
                                        `Standard Sh/90`, `Standard SoT/90`,
```

```
                    `Performance PKatt`,
                    `Expected xG`, `Expected npxG`,
                    `Expected G-xG`, `Expected np:G-xG`)
shoot.pca.r <- as.numeric(shooting.2021.r$Place)


pr.shoot <- prcomp(shoot.pca, scale=TRUE) # will scale automatically
pr.shoot$rotation

pr.var.exp.shoot <- pr.shoot$sdev^2 # variance of each principal component.
pve.exp.shoot <- pr.var.exp.shoot/sum(pr.var.exp.shoot) #Compute the PVE (proportion of variance
explained)

plot(pve.exp.shoot, xlab="Principal Component", ylab="Proportion of Variance Explained ", ylim=c(0,1),
type="b")
plot(cumsum(pve.exp.shoot), xlab="Principal Component ", ylab=" Cumulative Proportion of Variance
Explained ", ylim=c(0,1), type="b")

biplot(pr.shoot, scale=0)

shoot.pcs <- as.data.frame(pr.shoot$x)
plot(shoot.pca.r, shoot.pcs$PC1)
plot(shoot.pca.r, shoot.pcs$PC2)
plot(shoot.pca.r, shoot.pcs$PC3)

cumsum(pve.exp.shoot[1:2])


#Passing PCA
pass <- passing.2021.r %>% select(`Total Cmp`, `Total Att`,
               `Total TotDist`, `Total PrgDist`,
               `Short Att`, `Short Cmp`,
               `Medium Cmp`, `Medium Att`,
               `Long Cmp`, `Long Att`,
               Ast, xA,
               `A-xA`, KP,
               `1/3`, PPA,
               CrsPA, Prog)
pass.pca.r <- as.numeric(passing.2021.r$Place)

pr.pass <- prcomp(pass, scale. = TRUE)
pr.pass$rotation

pr.var.pass <- pr.pass$sdev^2 # variance of each principal component.
pve.exp.pass <- pr.var.pass/sum(pr.var.pass) #Compute the PVE (proportion of variance explained)

plot(pve.exp.pass, xlab="Principal Component", ylab="Proportion of Variance Explained ", ylim=c(0,1),
type="b")
plot(cumsum(pve.exp.pass), xlab="Principal Component ", ylab=" Cumulative Proportion of Variance
Explained ", ylim=c(0,1), type="b")

biplot(pr.pass, scale=0) # Visualize the dataset using the first two principal components
```

```
pass.pcs <- as.data.frame(pr.pass$x)
plot(pass.pca.r, pass.pcs$PC1)
plot(pass.pca.r, pass.pcs$PC2)
plot(pass.pca.r, pass.pcs$PC3)


cumsum(pve.exp.pass[1:2])


#Defense PCA
def <- defense.2021.r %>% select(`Tackles Tkl`, `Tackles TklW`,
                         `Tackles Def 3rd`, `Tackles Mid 3rd`,
                         `Tackles Att 3rd`, `Tkl+Int`,
                         `Pressures Press`, `Pressures Succ`,
                          `Pressures Def 3rd`, `Pressures Mid 3rd`,
                          `Pressures Att 3rd`,
                         `Blocks Blocks`, `Blocks Sh`,
                          `Blocks ShSv`, `Blocks Pass`,
                         `Vs Dribbles Tkl`, `Vs Dribbles Att`,
                          `Vs Dribbles Past`, `Int`, `Clr`, `Err`)
def.pca.r <- as.numeric(defense.2021.r$Place)

pr.def <- prcomp(def, scale. = TRUE)
pr.def$rotation

pr.var.def <- pr.def$sdev^2 # variance of each principal component.
pve.exp.def <- pr.var.def/sum(pr.var.def) #Compute the PVE (proportion of variance explained)

plot(pve.exp.def, xlab="Principal Component", ylab="Proportion of Variance Explained ", ylim=c(0,1),
type="b")
plot(cumsum(pve.exp.def), xlab="Principal Component ", ylab=" Cumulative Proportion of Variance
Explained ", ylim=c(0,1), type="b")

biplot(pr.def, scale=0) # Visualize the dataset using the first two principal components
def.pcs <- as.data.frame(pr.def$x)
plot(def.pca.r, def.pcs$PC1)
plot(def.pca.r, def.pcs$PC2)
plot(def.pca.r, def.pcs$PC3)

cumsum(pve.exp.def[1:4])


#Goalkeeping PCA
gk <- goalkeep.2021.r %>% select(`Playing Time MP`, `Playing Time Starts`,
                          `Playing Time Min`, `Playing Time 90s`, `Performance GA`, `Performance Saves`, W, D,
L, `Performance CS`, `Performance PKatt`,
                              `Penalty Kicks PKA`, `Penalty Kicks PKsv`, `Penalty Kicks PKm`)

gk.pca.r <- as.numeric(goalkeep.2021.r$Place)

pr.gk <- prcomp(gk, scale. = TRUE)
pr.gk$rotation
```

```
pr.var.gk <- pr.gk$sdev^2 # variance of each principal component.
pve.exp.gk <- pr.var.gk/sum(pr.var.gk) #Compute the PVE (proportion of variance explained)

plot(pve.exp.gk, xlab="Principal Component", ylab="Proportion of Variance Explained ", ylim=c(0,1),
type="b")
plot(cumsum(pve.exp.gk), xlab="Principal Component ", ylab=" Cumulative Proportion of Variance Explained
", ylim=c(0,1), type="b")

biplot(pr.gk, scale=0) # Visualize the dataset using the first two principal components
gk.pcs <- as.data.frame(pr.gk$x)
plot(gk.pca.r, gk.pcs$PC1) #this might be promising
plot(gk.pca.r, gk.pcs$PC2)
plot(gk.pca.r, gk.pcs$PC3)

cumsum(pve.exp.gk[1:2])
```

Appendix J – R code: Decision Trees

```
# Required Packages
require(readxl)
require(tidyverse)
require(ggplot2)
require(tree)


# Import Data
path = "C:/Users/h1562/Documents/spring 2022/ACT 551/soa case study"

shooting <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament
Shooting",guess_max = 10000000)
passing <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament
Passing",guess_max = 10000000)
defense <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament
Defense",guess_max = 10000000)
goalkeep <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament
Goalkeeping",guess_max = 10000000)
results <- read_excel(path = paste0(path,"/Data/Tournament.xlsx"), sheet = "Tournament
Results",guess_max = 10000000)


# Data Manipulation
shooting <- shooting %>% mutate(Nation = as.factor(Nation),
                         Pos = as.factor(Pos),
                         Age = as.numeric(Age),
                         Born = as.factor(Born),
                         Year = as.factor(Year),
                         `Standard Dist` = as.numeric(`Standard Dist`),
                         `Standard FK` = as.numeric(`Standard FK`),
                         `Expected xG`= as.numeric(`Expected xG`),
                         `Expected npxG` = as.numeric(`Expected npxG`),
                         `Expected npxG/Sh` = as.numeric(`Expected npxG/Sh`),
                         `Expected G-xG` = as.numeric(`Expected G-xG`),
                         `Expected np:G-xG` = as.numeric(`Expected np:G-xG`))

passing <- passing %>% mutate(Nation = as.factor(Nation),
                       Pos = as.factor(Pos),
                       Age = as.numeric(Age),
                       Year = as.factor(Year))

defense <- defense %>% mutate(Nation = as.factor(Nation),
                       Pos = as.factor(Pos),
                       Age = as.numeric(Age),
                       Year = as.factor(Year))

goalkeep <- goalkeep %>% mutate(Nation = as.factor(Nation),
                         Pos = as.factor(Pos),
```

```
                     Age = as.numeric(Age),
                     Year = as.factor(Year))

results <- results %>% mutate(Year = as.factor(Year),
                    Place = as.numeric(Place),
                    Country = as.factor(Country))%>% rename(Nation = Country)

#Joining Tournament Results
shooting <- merge(shooting, results, by = c("Nation", "Year"), all.x = TRUE)

passing <- merge(passing, results, by = c("Nation", "Year"), all.x = TRUE)

defense <- merge(defense, results, by = c("Nation", "Year"), all.x = TRUE)

goalkeep <- merge(goalkeep, results, by = c("Nation", "Year"), all.x = TRUE)


#Selecting Player Statistics fields
shooting_s <- shooting %>% filter(Year==2021) %>% select(Place,Player, Pos, Age, '90s', Gls, 'Standard
Sh', 'Standard SoT', 'Standard G/Sh', 'Standard G/SoT', 'Standard Dist', 'Standard FK', 'Performance PK',
'Performance PKatt', 'Expected xG', 'Expected npxG', 'Expected npxG/Sh') %>%
rename(x90s='90s',Standard_Sh='Standard Sh',Standard_SoT = 'Standard
SoT',Standard_GpSH='Standard G/Sh',Standard_GpSoT='Standard G/SoT',Standard_Dist='Standard
Dist',Standard_FK= 'Standard FK',Performance_PK= 'Performance PK', Performance_PKatt='Performance
PKatt', Expected_xG='Expected xG', Expected_npxG= 'Expected npxG', Expected_npxGpSh='Expected
npxG/Sh')

passing_s <- passing %>% filter(Year==2021) %>% select(Place, Player, Pos, Age, '90s', 'Total Cmp', 'Total
Att', 'Total TotDist', 'Total PrgDist', 'Short Cmp', 'Short Att', 'Medium Cmp', 'Medium Att', 'Long Cmp', 'Long
Att', Ast, xA, KP, '1/3', PPA, CrsPA, Prog) %>% rename(x90s='90s', Total_cmp='Total Cmp',total_att= 'Total
Att', total_totdist='Total TotDist', total_prgdist='Total PrgDist', short_cmp='Short Cmp',short_att= 'Short
Att',medium_cmp= 'Medium Cmp',medium_att= 'Medium Att', long_cmp='Long Cmp',long_att= 'Long Att',
onethird='1/3')

defense_s <- defense %>% filter(Year==2021) %>% select(Place, Player, Pos, Age,'90s','Tackles
Tkl','Tackles TklW','Tackles Def 3rd','Tackles Mid 3rd','Tackles Att 3rd','Vs Dribbles Tkl','Vs Dribbles Att','Vs
Dribbles Past','Pressures Press','Pressures Succ','Pressures Def 3rd','Pressures Mid 3rd','Pressures Att
3rd','Blocks Blocks','Blocks Sh','Blocks ShSv','Blocks Pass',Int,'Tkl+Int',Clr,Err) %>%
rename(x90s='90s',tackles_tkl='Tackles Tkl',tackles_tklw='Tackles TklW',tackles_def_3rd='Tackles Def
3rd',takles_mid_3rd='Tackles Mid 3rd',tackles_att_3rd='Tackles Att 3rd',vs_dribbles_tkl='Vs Dribbles
Tkl',vs_dribbles_att='Vs Dribbles Att',vs_dribbles_past='Vs Dribbles Past',pressures_press='Pressures
Press',pressures_succ='Pressures Succ',pressures_def_3rd='Pressures Def
3rd',pressures_mid_3rd='Pressures Mid 3rd',pressures_att_3rd='Pressures Att 3rd',blocks_blocks='Blocks
Blocks',blocks_sh='Blocks Sh',blocks_shsv='Blocks ShSv',blocks_pass='Blocks Pass',tkl_int='Tkl+Int')

goalkeep_s <- goalkeep %>% filter(Year==2021) %>% select(Place, Player, Pos, Age,'Playing Time
MP','Playing Time Starts','Playing Time Min','Playing Time 90s','Performance GA','Performance
GA90','Performance SoTA','Performance Saves',W,D,L,'Performance CS','Performance PKatt','Penalty Kicks
PKA','Penalty Kicks PKsv','Penalty Kicks PKm') %>% rename(playing_time_mp='Playing Time
MP',playing_time_starts='Playing Time Starts',playing_time_min='Playing Time
Min',playing_time_90s='Playing Time 90s',performance_ga='Performance
GA',performance_ga90='Performance GA90',performance_sota='Performance
```

```
SoTA',performanec_saves='Performance Saves',performance_cs='Performance
CS',performance_pkatt='Performance PKatt',penalty_kicks_pka='Penalty Kicks
PKA',penalty_kicks_pksv='Penalty Kicks PKsv',penalty_kicks_pkm='Penalty Kicks PKm')


# Goalkeepers, considering goalkeeping and passing skills
set.seed(551)
passing_s_gk <- passing_s %>% filter(Pos=="GK")

gk <- merge(passing_s_gk,goalkeep_s,by="Player", all=TRUE)
gk <- gk %>% select(., -Age.y,-Pos.y,-Place.y,-Player,-Pos.x) %>% rename(Age = Age.x, Place = Place.x)

train.gk <- sample (1: nrow (gk), nrow (gk)*7/10)
gk.tree <- tree(Place ~.,data=gk,subset=train.gk)
plot(gk.tree)
text(gk.tree)

gk.pred <- predict(gk.tree,newdata=gk[-train.gk,])
gk.test <- gk[-train.gk,"medv"]
plot(gk.pred,gk.test)
abline(0,1)
mean((gk.pred-gk.test)^2)


# Defenders, considering defense and passing skills
set.seed(551)
defense_s_def <- defense_s %>% filter(Pos %in% c("DF","DFFW","DFMF","FWDF","MFDF"))
passing_s_def <- passing_s %>% filter(Pos %in% c("DF","DFFW","DFMF","FWDF","MFDF"))

def <- merge(defense_s_def,passing_s_def,by="Player", all=TRUE)
def <- def %>% select(., -Age.y,-Pos.y,-Place.y,-Player,-Pos.x,-'x90s.y',-'x90s.x') %>% rename(Age = Age.x,
Place = Place.x)

train.def <- sample (1: nrow (def), nrow (def) *7/10)
def.tree <- tree(Place~.,def,subset = train.def)
plot(def.tree)
text(def.tree)

cv.def <- cv.tree(def.tree)
plot(cv.def$dev) ##11

prune.def <- prune.tree(def.tree,best=13)
plot(prune.def)
text(prune.def)

def.pred <- predict(def.tree,newdata=def[-train.def,])
def.test <- def[-train.def,"medv"]
plot(def.pred,def.test)
abline(0,1)
mean((def.pred-def.test)^2)
```

```
#Midfielders, considering passing and defense since most midfielders are missing shooting data
set.seed(551)
defense_s_mid <- defense_s %>% filter(Pos %in% c("MF","MFDF","MFFW","FWMF","DFMF"))
passing_s_mid <- passing_s %>% filter(Pos %in% c("MF","MFDF","MFFW","FWMF","DFMF"))

mid <- merge(defense_s_mid,passing_s_mid,by="Player", all=TRUE)
mid <- mid %>% select(., -Age.y,-Pos.y,-Place.y,-Player,-Pos.x,-'x90s.y',-'x90s.x') %>% rename(Age = Age.x,
Place = Place.x)

train.mid <- sample (1: nrow (mid), nrow (mid) *7/10)
mid.tree <- tree(Place~.,mid,subset=train.mid)
plot(mid.tree)
text(mid.tree)

cv.mid <- cv.tree(mid.tree)
plot(cv.mid$dev) ## 12

prune.mid <- prune.tree(mid.tree,best=12)
plot(prune.mid)
text(prune.mid)

mid.pred <- predict(mid.tree,newdata=mid[-train.mid,])
mid.test <- mid[-train.mid,"medv"]
plot(mid.pred,mid.test)
abline(0,1)
mean((mid.pred-mid.test)^2)


# Attackers, considering shooting and passing
set.seed(551)
shooting_s_att <- shooting_s %>% filter(Pos %in% c("FW","FWDF","FWMF","MFFW","DFFW"))
passing_s_att <- passing_s %>% filter(Pos %in% c("FW","FWDF","FWMF","MFFW","DFFW"))

att <- merge(shooting_s_att,passing_s_att,by="Player",all=TRUE)
att <- att %>% select(., -Age.y,-Pos.y,-Place.y,-Player,-Pos.x,-'x90s.y',-'x90s.x') %>% rename(Age = Age.x,
Place = Place.x)

train.att <- sample (1: nrow (att), nrow (att) / 2)
att.tree <- tree(Place~.,att)
plot(att.tree)
text(att.tree)

cv.att <- cv.tree(att.tree)
plot(cv.att$dev) ##10

prune.att <- prune.tree(att.tree,best=10)
plot(prune.att)
text(prune.att)

att.pred <- predict(att.tree,newdata=att[-train.att,])
att.test <- att[-train.att,"medv"]
plot(att.pred,att.test)
```

```
abline(0,1)
mean((att.pred-att.test)^2)
```

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