Beyond the Board: A Statistical Exploration of TFT Rankings

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1. INTRODUCTION

Teamfight Tactics, or TFT, is an autochess type game where the main objective is to be the last player standing in an 8-player free for all. Throughout the game you accumulate resources, such as gold and items, while building the strongest team of units. Each round your team will fight against another players team, with the losing player taking damage. Once you run out of life, you are out of the game. One method of measuring a player's skill is by looking at their rank.

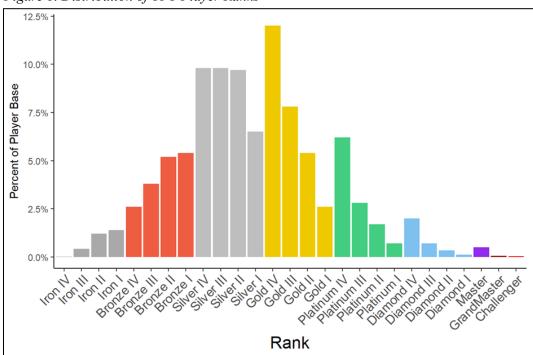


Figure 1. Distribution of TFT Player Ranks

Above in *Figure 1* the ranks are presented in ascending order, accompanied by the corresponding percentage of the player base in each tier. The top three ranks are Master, Grandmaster, and Challenger with 0.51%, 0.056%, and 0.026% of the player base respectively. The matchmaking system attempts to put players who have the same rank in the same match, however due to the small percent of the player base within the top three ranks, players within these three ranks are often put in the same match. This study seeks to determine whether there are significant differences in how Challenger ranked players play the game compared to Master and Grandmaster ranked players.

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¹ See the appendix for a description of game-related words

2. DATA & METHODS

2.1 Data Collection, Cleaning, and Feature Creation

Riot Games, the company which developed TFT, has an API with access to the match history of every player's last 2,000 matches. Using the API, 205 players were randomly selected from each rank. Each player's five most recent matches were collected, along with the information of the seven other players within each match. Observations with multiple columns of missing data, as well as results which did not come from ranked games, were removed. With each observation being a player's end of game statistics, the following features in *Table 1* were collected with the final four being created from additional features.

Table 1. Data Features

Feature	Description
Match Id	Unique match identifier
Game Length	Length of match in seconds
Placement	Placement of player (1, 2,, 8)
Level	Level of player (1, 2,, 10)
Last Round	Round eliminated
Gold Left	Amount of gold in possession when eliminated
Board Cost	Total cost of units on players board
Average Unit Level	Average level of units on players board
Match Average Unit Level	Average level of units across all players boards in match
Match Average Board Cost	Average total cost of units on all players boards in match
Challenger	True if ranked challenger, False if ranked Master or Grandmaster

Table 2. Preview of Cleaned Data

Match Id	Challenger	Placement	•••	Board Cost	Match Average Unit Level	Match Average Board Cost
NA1_4772665234	True	1		49	1.867	51
NA1_4772665234	True	3		48	1.867	51
NA1_4772665234	False	2		56	1.867	51

Within each match, knowing the results of one player can affect the probability of seeing certain results of another player. For example, if I know player A got 6th place, I would know that player B could not also get 6th place. Therefore, a random sample of three players from each match was taken. Additionally, only matches which lasted between 35 and 37 minutes were used since this is the length of an average TFT match.

2.2 Methods

Each match of TFT is vastly different from each other due to the high variance in resources provided during the game and units seen in the shop throughout the game. Since each player's results are nested within a match, multilevel modeling can be used to analyze this data. Specifically, logistic multilevel modeling is used to predict whether or not a player is Challenger ranked. *Table 3* displays the level of all variables with their type. Additionally, all quantitative variables were grand-mean centered.

Table 3. Data Feature Levels and Types

Feature	Level	Туре
Match Id	2	Categorical (583 levels)
Game Length	2	Quantitative
Placement	1	Categorical (8 levels)
Level	1	Categorical (10 levels)
Last Round	1	Quantitative
Gold Left	1	Quantitative
Board Cost	1	Quantitative
Average Unit Level	1	Quantitative
Match Average Unit Level	2	Quantitative
Match Average Board Cost	2	Quantitative
Challenger	1	Categorical (Binary)

3. RESULTS

3.1 Exploratory Analysis

The level 1 feature placement appeared most promising after initial analysis. Since Challenger players are ranked higher than Master and Grandmaster players, it makes sense that a larger proportion achieve a placement between 1 and 4 than 5 and 8. Below in *Figure 2*, we note that the greatest proportion of Challenger to Non-Challenger players got second place, with a decreasing proportion of challenger players acquiring higher placements.

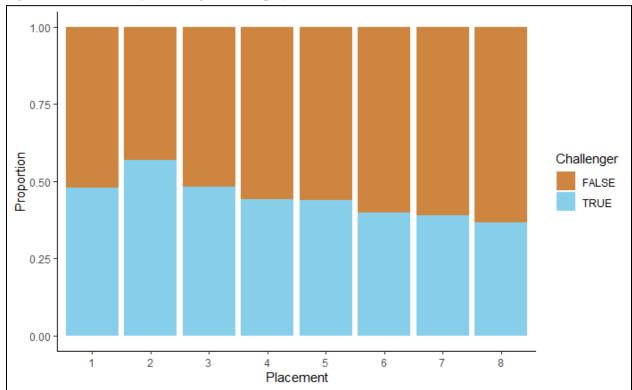


Figure 2. Distribution of Challenger ranked players within each Placement

3.2 Null Model

Looking at the null model, for an average match the probability that a player is ranked Challenger is $0.42.^2$ Additionally, an ICC value of 0.310 signifies that 31% of the variance in player rank is due to between-match variability. In this case, the ICC is substantial; meaning there is a meaningful level of similarity within matches, indicating that players within the same match tend to have more similar outcomes than players in different matches. Since Challenger players and Non-Challenger players can be in the same match, and since I expect these types of players to have different play styles reflected in their end of match statistics, it makes sense that there would be more similarity between similar types of players than between matches.

² See the Appendix for calculation steps

Figure 3. Null Model Output

```
BIC
                    logLik deviance df.resid
  2147.8
           2158.5 -1071.9
                             2143.8
                                        1614
Scaled residuals:
            1Q Median
    Min
                             3Q
-1.1008 -0.7730 -0.5244 0.9084 1.2937
Random effects:
Groups
         Name
                      Variance Std. Dev.
match_id (Intercept) 1.478
Number of obs: 1616, groups: match_id, 583
Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.33451
                       0.07906 -4.231 2.32e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
# Intraclass Correlation Coefficient
    Adjusted ICC: 0.310
  Unadjusted ICC: 0.310
```

3.3 Final Model

The final model consists of the level 1 variables placement and average unit level, the level 2 variable match average board cost, and the cross level interaction between match average board cost and average unit level. The level 1 and level 2 equations for the model are as follows:

Figure 4. Level Equations of Final Model

```
Level 1 \widehat{challenger} = \beta_{0j} + \beta_1 (\operatorname{placement})_{ij} + \beta_{2j} (\operatorname{average unit level})_{ij} + \epsilon_{ij}
Level 2 \beta_{0j} = \beta_{00} + \beta_{01} (\operatorname{match average board cost})_j + u_{0j}
\beta_{2j} = \beta_{20} + \beta_{21} (\operatorname{match average board cost})_j
```

Figure 5. Final Model Output

```
logLik deviance df.resid
  2122.0
          2186.6 -1049.0
                            2098.0
                                       1604
Scaled residuals:
   Min
            1Q Median
                            3Q
-1.7526 -0.6612 -0.4309 0.7299 1.8451
Random effects:
                     Variance Std. Dev.
Groups Name
match_id (Intercept) 1.658
                              1.287
Number of obs: 1616, groups: match_id, 583
Fixed effects:
                                   Estimate Std. Error z value Pr(>|z|)
                                   -0.03241 0.17600 -0.184 0.85387
(Intercept)
placement2
                                    0.38635
                                              0.24441 1.581 0.11393
placement3
                                   -0.08973
                                              0.24361 -0.368 0.71263
placement4
                                   -0.36650
                                              0.24786 -1.479 0.13922
placement5
                                   -0.39714
                                              0.24961 -1.591 0.11161
placement6
                                   -0.64614
                                              0.25723 -2.512 0.01201 *
placement7
                                              0.25415 -2.766 0.00567 **
                                   -0.70306
                                              0.25211 -3.087 0.00202 **
placement8
                                   -0.77827
                                              0.01776 -2.474 0.01335 *
match_avg_board_cost
                                   -0.04394
                                              0.23637 -1.022 0.30664
avg_unit_level
                                   -0.24164
match_avg_board_cost:avg_unit_level -0.13752
                                              0.05492 -2.504 0.01228 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
optimizer (Nelder_Mead) convergence code: 0 (OK)
Model failed to converge with max|grad| = 0.00347373 (tol = 0.002, component 1)
# Intraclass Correlation Coefficient
   Adjusted ICC: 0.335
 Unadjusted ICC: 0.322
```

From the above output, we can see that the ICC slightly increases from the null model, however the amount of level 2 variance in the model actually increased (1.478 \rightarrow 1.658). Below are the interpretations of the estimated parameters shown in *Figure 5*:

Intercept (-0.03241): The predicted probability that a player is ranked Challenger is 0.49 when they placed 1st with an average unit level, and the match had an average match average board cost.

We are 95% confident that the predicted probability that a player in match NA 4773007322 is ranked Challenger lies between 0.31 and 0.47.³

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³ See Appendix for Calculations

placement2 (0.38635): The predicted log-odds that a player who got 2nd in a match with an average unit level in a match with an average match average board cost is ranked Challenger increases by 0.39 compared to a player who got 1st.

placement3-8 (X): The predicted log-odds that a player who got [3-8] in a match with an average unit level in a match with an average match average board cost is ranked Challenger increases by X compared to a player who got 1st.

match_avg_board_cost (-0.04394): The predicted probability that a player who got 1st with an average unit level is ranked Challenger decreases as match average board cost increases.

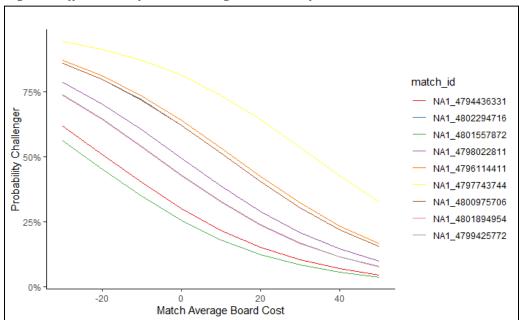


Figure 6. Effects Plot of Match Average Board Cost for Final Model

avg_unit_level (-0.24164): The predicted probability that a player who got 1st in a match with average match average board cost is ranked Challenger decreases as match average unit level increases.

80% match_id NA1_4800842974 Probability Challenger %09 NA1_4802160206 NA1_4779739814 NA1_4799425772 NA1_4799449236 NA1_4799006362 NA1_4799263617 NA1_4801540698 NA1_4780651426 20% -1.0 -0.5 0.0 0.5 1.0 Average Unit Level

Figure 7. Effects Plot of Average Unit Level for Final Model

match_avg_board_cost:avg_unit_level (-0.13752): When we have a high match average board cost, there is a greater decline in the log-odds of being a challenger player as the average unit level increases.

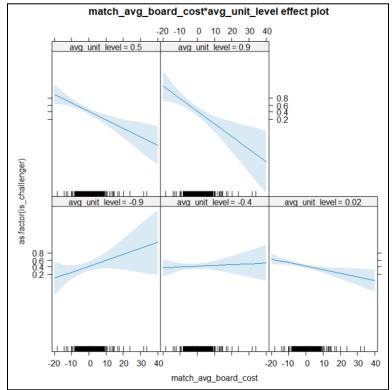


Figure 8. Cross-level Interaction Effects Plot from Final Model

3.4 Diagnostic Analysis

As seen in *Figure 9* below, all data points are outside of the error bounds. This indicates that the model is under or over fitting the estimated probabilities for points within these ranges.

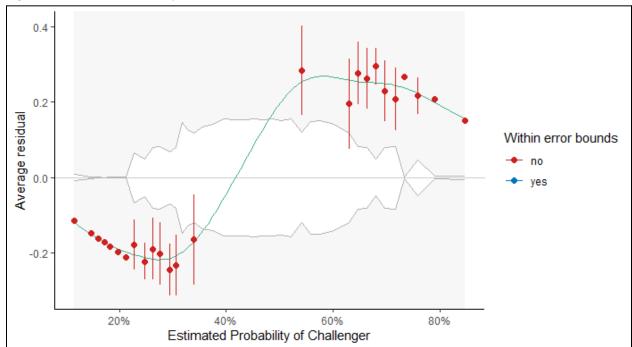


Figure 9. Binned Residuals of Final Model

Table 4. Confusion Matrix of Final Model

Predicted\Actual	Challenger	Not Challenger	
Challenger	104	25	
Not Challenger	36	159	

In order to determine how well the final model performs, it was trained on 80% of the data and tested on the remaining 20%. Looking at the confusion matrix in *Table 4*, the model performed well with an accuracy of 81%. Additionally, the ROC AUC score for this model is 0.92, indicating that the model is very effective at distinguishing between Challenger and Non-Challenger players.

4. DISCUSSION

The results of the analysis provide valuable insights into the differences in play styles between Challenger ranked players and Master/Grandmaster ranked players in Teamfight Tactics (TFT). The final model suggests that the features placement, average unit level, and match average board cost play crucial roles in predicting whether or not a player is ranked Challenger. The most interesting results come from the interaction between average unit level and match average board cost. The negative coefficient of this term tells us that if you are playing in a match where the average board cost is high, increasing your average unit level lowers your probability of being a challenger player. In other words, Challenger ranked players tend not to increase their unit levels in situations where the average board cost of the match is high. Although this may seem backwards at first, since a higher average unit level tends to mean you are stronger, this interaction indicates challenger players might focus on a different aspect of the game in this situation, such as getting more powerful, higher cost, units at the expense of leveling up lower cost units.

The conclusions made from this study can only be applied to matches where the only players in them are of the top three ranks since these types of matches were the only ones considered. Additionally, since all the matches in this study were collected from the same patch, or version, of TFT, we can only generalize the conclusions to other matches within the same patch⁴.

Future research into this topic should attempt to consider matches across a variety of versions of TFT. Furthermore, exploring the relationship between other ranks may prove interesting - especially the ranks where a majority of players reside such as Silver and Gold rank⁵.

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⁴ TFT receives minor updates every two weeks and major updates every four months, which change how the game is played.

⁵ Refer to Figure 1

5. APPENDIX

Table 5. Description of in-game terms

Term	Description
Gold	In-game currency used to buy new units from the shop and level up your character. You earn gold at the end of each round.
Units	Characters placed on a players board. More expensive units are more powerful.
Round	Each round the units on your board face off against those on another player's board.
Shop	Each round you are offered five units to purchase. Each unit costs between 1 and 5 gold depending on their rarity. You can spend 2 gold to see new units.
Board	Where you arrange your units prior to a round. The battlefield where your team fights against other players' teams.
Level	Your character level determines how many units you can have on the board and also influences the rarity of champions you find in the shop.
Unit Level	When you obtain three of the same unit, they combine to become stronger, increasing their level by 1. This can happen 2 times.
Placement	Measure of how well a player performed in a match. Lower placement is equivalent to a better performance. Placements 1 - 4 count as a win, placements 5 - 8 count as a loss.

```
Null Model
```

```
```{r}
```

model2 <- glmer(is\_challenger ~ (1 | match\_id), family = "binomial",
data = df\_TFT)</pre>

. . .

The intercept of this model is -0.33451, and when back transformed as so:

$$e^{(-0.33451)} / (1 + e^{(-0.33451)}) = 0.417$$

results in a probability.

## Final Model

final.model <- glmer(is\_challenger ~ placement + match\_avg\_board\_cost
+ avg\_unit\_level\*match\_avg\_board\_cost + (1 | match\_id), family =
"binomial", data = df\_TFT)</pre>

The intercept of this model is -0.03241, and when back transformed as so:

$$e^{(-0.03241)} / (1 + e^{(-0.03241)}) = 0.492$$

results in a probability.

```
Confidence Interval of Final Model for Intercept
```{r}
coefficients <- coef(final.model)</pre>
standard_errors <- summary(final.model)$coefficients[, "Std. Error"]</pre>
# Calculate confidence intervals
confidence_intervals <- cbind(</pre>
  coefficients$match_id[1] - 1.96 * standard_errors,
  coefficients$match_id[1] + 1.96 * standard_errors
)
# Display of the results
result <- data.frame(</pre>
  feature = names(coefficients$match_id[1]),
  estimate = coefficients$match_id[1],
  lower_bound = confidence_intervals[, 1],
 upper_bound = confidence_intervals[, 2]
)
print(result)
```

Table 6. Confidence Intervals Final Model of Intercepts Output (First 3 Observations)

	feature	X.Intercept	lower_bound	upper_bound
NA1_4773007322	(Intercept)	-0.4745015954	-0.8194528510	-0.129550340
NA1_4773377674	(Intercept)	-0.4535096456	-0.9325482120	0.025528921
NA1_4775662889	(Intercept)	-0.5651677536	-1.0426397369	-0.087695770

Acquire probabilities through back transformation as shown earlier in Appendix.

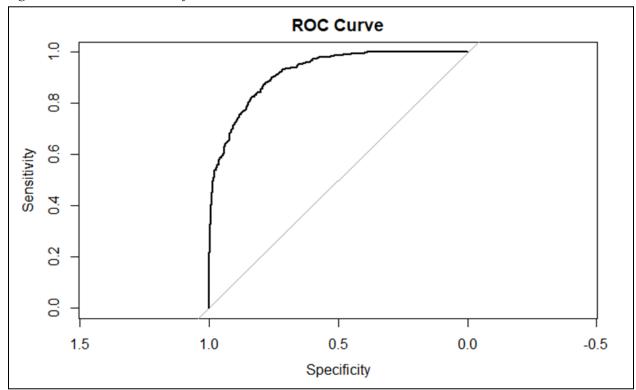


Figure 10. ROC-AUC Curve of Final Model

Statistical Modeling Steps

To start, all level 1 variables were added to the null model and non-significant variables were systematically one at a time to determine the best model with only level 1 variables. This ended up being a model with placement and average unit level. The next step followed the same pattern, except with level 2 variables. This model ended up being significantly better than the model with purely level 1 variables, and included placement, average unit level, and match_avg_board_cost. Finally random slopes were considered for level 1 variables as well as cross level interaction. Although no random slopes significantly improve the model, an interaction between match average board cost and average unit level did.

Variables were considered significant if the summary output for their respective z-test resulted in a p-value around 0.1 or lower. Additionally to determine whether a model was significantly better than a different model, the Chi-square test via an anova between the two models was considered.