

Analyzing the Relationship Between Player Level, Remaining Gold, and Final Placement in Teamfight Tactics

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Abstract—This study investigates the relationship between player level, remaining gold, and final placement in Teamfight Tactics (TFT) using match-level gameplay data from 200 matches. Gold is the core economic resource in TFT and is primarily used to increase player level and strengthen board composition. In this study, remaining gold is treated as a proxy for spending efficiency, while player level represents the outcome of gold investment. Descriptive statistics, data visualizations, and Pearson correlation analysis were applied to examine the relationships among the variables. The results indicate that player level has a stronger association with final placement ($r = -0.455, p < 0.001$) than remaining gold ($r = 0.193, p = 0.006$), suggesting that successful players are characterized by effective conversion of gold into levels rather than by gold accumulation. This research demonstrates how data science techniques can be applied to analyze economic decision-making in competitive strategy games.

Index Terms—Teamfight Tactics, Game Analytics, Player Level, Gold Management, Pearson Correlation, Data Science

I. INTRODUCTION

Teamfight Tactics (TFT) is an auto-battler strategy game where players compete by managing resources, positioning units, and adapting to probabilistic outcomes. Unlike mechanically intensive esports titles, TFT emphasizes economic decision-making, long-term planning, and risk management. Players must decide when to spend gold to increase power and when to save gold to preserve their economy.

Gold serves as the primary resource in TFT. It is used to purchase champions, reroll the shop, and gain experience to increase player level. Player level determines the maximum number of units that can be placed on the board and influences the probability of acquiring higher-cost champions. Consequently, leveling decisions have a direct impact on combat strength and survivability.

Game analytics research has shown that resource management and strategic decision-making are key factors in determining performance in competitive games [1], [2]. Prior studies have demonstrated that economic efficiency specifically, the ability to convert resources into strategic advantages often differentiates high-performing players from low-performing

ones [3]. In strategy-based environments, players who fail to allocate resources effectively typically experience weaker performance outcomes.

Despite the central role of gold and leveling in TFT, there is limited academic work that quantitatively examines how these variables relate to match outcomes. This study addresses that gap by analyzing the relationship between player level, remaining gold, and final placement using match-level data from 200 personal gameplay sessions. By applying statistical analysis, the study aims to provide empirical evidence on whether successful players are characterized by more effective resource utilization.

A. Research Questions

- 1) Is there a relationship between player level, remaining gold, and final placement in Teamfight Tactics?
- 2) Is there a relationship between player level and remaining gold at the end of the match?
- 3) Do players who achieve better placements tend to have lower remaining gold at the end of the match?

B. Hypotheses

Player Level and Placement

- H_{01} : Player level has no significant relationship with final placement.
- H_{11} : Higher player levels are associated with better final placements.

Remaining Gold and Placement

- H_{02} : Remaining gold has no significant relationship with final placement.
- H_{12} : Lower remaining gold is associated with better final placements.

Player Level and Remaining Gold

- H_{03} : Player level has no significant relationship with remaining gold.

- H₁₃: Higher player levels are associated with lower remaining gold.

II. LITERATURE REVIEW

A. Game Analytics and Performance Measurement

Game analytics focuses on the systematic analysis of gameplay data to understand player behavior and performance. El-Nasr et al. [1] emphasized that performance metrics derived from gameplay telemetry can reveal patterns not easily observed through qualitative analysis. These metrics are particularly valuable in competitive games where decision-making plays a major role.

B. Resource Management in Strategy Games

Resource management is a foundational element of strategy games. Research has shown that efficient allocation of limited resources is strongly associated with competitive success [3]. Players who fail to convert resources into strategic advantages often experience weaker performance outcomes.

C. Data-Driven Analysis in Competitive Games

Drachen et al. [2] demonstrated that player behavior data can be used to identify performance clusters and strategic tendencies. Statistical methods such as correlation analysis are frequently used to examine relationships between in-game variables and outcomes.

D. Progression Systems and Competitive Advantage

Progression systems, such as leveling, are designed to regulate power growth and strategic pacing. Adams [4] explains that progression mechanics reward effective decision-making while penalizing inefficiency. In TFT, higher levels unlock additional unit slots and stronger champions, making level progression a critical determinant of success.

III. METHODOLOGY

A. Research Design

This study follows a quantitative, correlational research design. The goal is to measure the strength and direction of relationships among player level, remaining gold, and final placement using statistical analysis. The dataset consists of 200 matches collected from personal gameplay sessions.

B. Participants

The participant in this study was the student researcher. All data were collected from personal gameplay sessions. No personal or sensitive data beyond game performance metrics were included.

C. Data Collection Methods

Match-level data were collected using the Riot Games API, which provides official match history and statistics for personal gameplay. The dataset consists of 200 ranked matches from the researcher's match history spanning approximately one year of gameplay. Each match represents one observation. The following variables were collected:

- **Placement:** Final rank in the match (1–8)
- **Level:** Player level at the end of the match
- **Gold_Left:** Remaining gold at the end of the match

Table I illustrates the structure of the dataset and shows how each variable was recorded across five sample matches.

TABLE I
SAMPLE OF COLLECTED MATCH DATA

Match	Placement	Level	Gold_Left
1	6	7	0
2	7	7	9
3	7	7	11
4	2	9	1
5	7	7	21

D. Operational Definitions

- **Placement:** Numerical indicator of match outcome, where lower values represent better performance (1 = 1st place, 8 = 8th place).
- **Level:** Numerical indicator of player progression resulting from gold investment. Higher levels unlock additional unit slots.
- **Gold_Left:** Amount of unused gold at match end, interpreted as a proxy for spending efficiency. Lower values suggest more complete resource conversion.

E. Data Cleaning and Preprocessing

The raw dataset obtained from the Riot Games API contained 25 variables per match. Data preprocessing involved selecting the three relevant variables (placement, level, gold_left) and verifying data completeness. No missing values were detected in the dataset. Outlier detection was performed by examining the distribution of each variable; no extreme outliers requiring removal were identified. All 200 matches were retained for analysis.

F. Statistical Analysis

To satisfy the IEEE data science methodology guidelines, the statistical method was selected based on the nature of the variables and research questions. Pearson correlation analysis was chosen because:

- 1) All variables are numerical and continuous.
- 2) The study aims to measure linear relationships, not causation.

- 3) Pearson correlation is appropriate for exploratory analysis of performance metrics.

Pearson correlation coefficients were computed to evaluate: (a) the relationship between player level and placement, (b) the relationship between remaining gold and placement, and (c) the relationship between player level and remaining gold. A significance level of $\alpha = 0.05$ was used to assess statistical relevance. This method directly addresses the research questions by quantifying the strength and direction of relationships between the variables.

G. Bias and Measurement Error Considerations

Several potential sources of bias were considered in this study. First, data collection was limited to personal gameplay from a single player, which may introduce selection bias and limit generalizability to the broader TFT player population. Second, the dataset represents matches from multiple game patches and balance updates over approximately one year, meaning the game mechanics and meta conditions may have varied across the sample period. This temporal variation could affect the consistency of relationships between variables. Third, while the Riot Games API provides reliable official match data, measurement errors were minimized by using the API's validated statistics rather than manual recording. The dataset does not account for external factors such as internet connection quality or player fatigue, which may have influenced performance. These limitations are addressed further in Section V.

IV. RESULTS

A. Descriptive Statistics

The descriptive statistics show variability in player level, remaining gold, and final placement across the 200 matches analyzed. The dataset reveals an average placement of 4.79 ($SD = 2.17$), indicating a relatively balanced distribution of match outcomes. Player level averaged 7.59 ($SD = 0.91$), with a minimum of 4 and maximum of 10. Remaining gold averaged 10.59 ($SD = 14.99$), ranging from 0 to 61, suggesting high variability in resource spending patterns. The median remaining gold was 3, indicating that most players spent the majority of their gold before match elimination.

Table II presents the mean, standard deviation, minimum, and maximum values for each variable across all 200 matches.

TABLE II
DESCRIPTIVE STATISTICS OF VARIABLES (N=200)

Variable	Mean	SD	Min	Max
Placement	4.79	2.17	1	8
Level	7.59	0.91	4	10
Gold_Left	10.59	14.99	0	61

B. Correlation Analysis

Figure 1 presents a visual heatmap representation of the Pearson correlation matrix among placement, level, and gold_left. The heatmap uses color intensity to represent correlation strength, with blue indicating negative correlations and red indicating positive correlations.

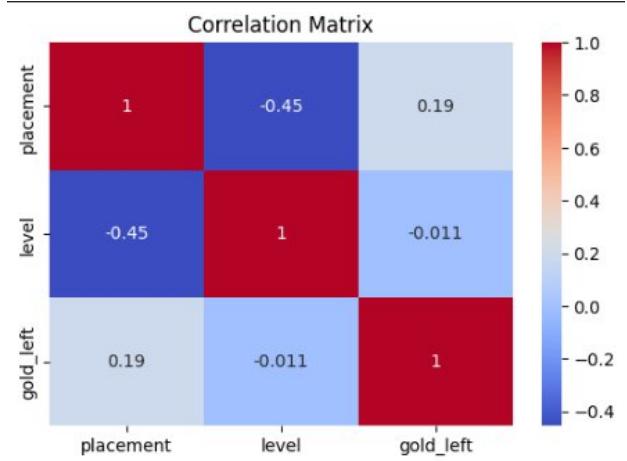


Fig. 1. Correlation heatmap visualizing the strength and direction of relationships between placement, level, and gold_left. Darker blue indicates stronger negative correlation, while darker red indicates stronger positive correlation.

Table III presents the numerical Pearson correlation coefficients corresponding to the heatmap visualization.

TABLE III
PEARSON CORRELATION MATRIX

Variable	Placement	Level	Gold_Left
Placement	1.000	-0.455	0.193
Level	-0.455	1.000	-0.011
Gold_Left	0.193	-0.011	1.000

The correlation matrix shows that Level has a moderate negative correlation with Placement (-0.455), Gold_Left has a weak positive correlation with Placement (0.193), and Level and Gold_Left show virtually no linear relationship (-0.011).

C. Statistical Significance Testing

Pearson correlation analysis with significance testing was conducted to determine whether the observed correlations are statistically meaningful. The results are presented below:

Level vs. Placement: A moderate negative correlation was found ($r = -0.455$, $p < 0.001$), indicating that higher player levels are significantly associated with better placements. This relationship is statistically significant at the $\alpha = 0.05$ level.

Gold_Left vs. Placement: A weak positive correlation was found ($r = 0.193$, $p = 0.006$), suggesting that players with more remaining gold tend to have slightly worse placements. This relationship is statistically significant but weak in magnitude.

Level vs. Gold_Left: A negligible negative correlation was found ($r = -0.011$, $p = 0.880$), indicating no meaningful linear relationship between player level and remaining gold. This suggests that achieving higher levels does not necessarily deplete gold reserves in a predictable manner.

D. Relationship Between Player Level and Placement

Figure 2 illustrates the average placement achieved at each player level. The bar chart demonstrates a clear downward trend, showing that higher player levels are consistently associated with better (lower) average placements.

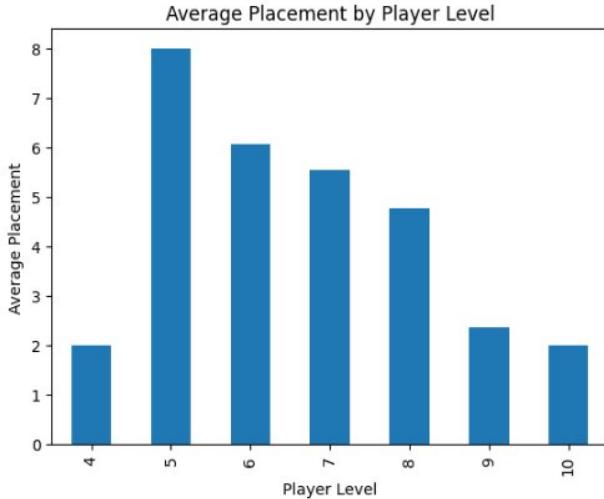


Fig. 2. Average placement by player level. The chart shows that higher levels (9-10) correspond to better average placements (closer to 2.0), while lower levels (4-5) correspond to worse average placements (above 6.0).

E. Relationship Between Gold Management and Placement

Figure 3 examines the relationship between remaining gold at match end and average placement. The data was grouped into gold ranges to identify spending patterns.

F. Top-4 Placement Rate Analysis

Figure 4 presents the top-4 placement rate (defined as finishing in 4th place or better) across different player levels. This metric provides a practical measure of competitive success.

V. DISCUSSION

A. Interpretation of Results

The results indicate that player level has the strongest relationship with final placement among the variables examined. The moderate negative correlation ($r = -0.455$) suggests that higher levels are associated with better placements, which aligns with TFT game mechanics. As shown in Figure 2, the relationship between level and average placement is remarkably consistent, with level 10 players averaging 2nd place while level 5 players averaged 8th place. Higher levels

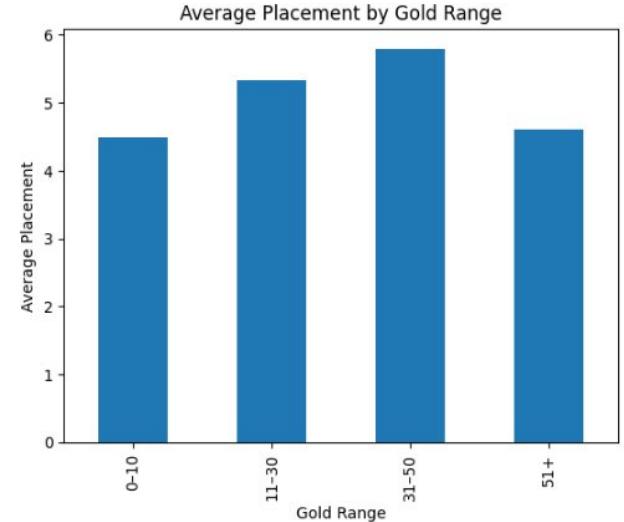


Fig. 3. Average placement by gold range. Players who finished with 31-50+ gold had the worst average placements (approximately 5.7), while those with 0-10 gold or 51+ gold showed better performance. This suggests that moderate gold retention without strategic purpose may indicate inefficient resource management.

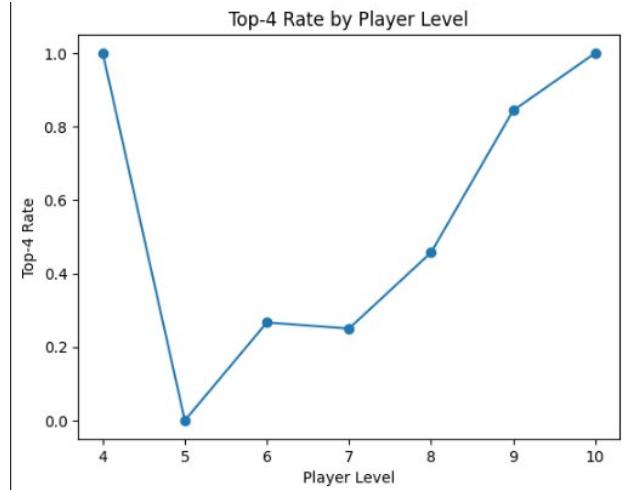


Fig. 4. Top-4 placement rate by player level. The chart reveals a strong positive relationship between level and top-4 success rate. Players at level 4 and 10 achieved 100% top-4 rates, while level 5 players had only 2% success. Levels 8-10 consistently showed high top-4 rates (45-100%), demonstrating the competitive advantage of higher levels.

provide additional unit slots and access to stronger champions, directly increasing combat strength and survivability. This finding supports the hypothesis that effective conversion of gold into levels is a critical factor in match success.

The visualization in Figure 3 reveals an interesting pattern regarding gold management. Players who finished with moderate amounts of remaining gold (31-50 range) had the worst average placements, suggesting that hoarding gold without converting it into board power may be ineffective. The weak positive correlation ($r = 0.193$) between remaining gold and

placement supports this interpretation. Players eliminated early in matches may still have substantial gold remaining, which does not contribute to performance once they are eliminated. This finding reinforces the importance of timely resource expenditure rather than mere accumulation.

The top-4 rate analysis in Figure 4 provides additional evidence for the importance of leveling. The dramatic increase in success rates from level 5 (2%) to levels 9-10 (85-100%) demonstrates that reaching higher levels creates a substantial competitive advantage. The negligible relationship between level and remaining gold ($r = -0.011$) is initially surprising, as one might expect that higher levels would require more gold expenditure and thus correlate with lower remaining gold. However, this weak correlation can be explained by the dynamic nature of TFT gameplay. Gold accumulation and spending occur continuously throughout a match, and the final snapshot may not reflect the full economic trajectory. Additionally, players who reach higher levels often survive longer in matches, potentially giving them more opportunities to regenerate gold through passive income, which could offset their earlier spending.

B. Comparison to Related Work

These findings align with broader research on resource management in strategy games. Prior studies have emphasized that efficient resource conversion rather than resource accumulation distinguishes successful players [3]. The current study extends this principle to TFT by demonstrating that converting gold into levels is more predictive of success than simply retaining gold. The visualization evidence from Figures 2 and 4 provides clear quantitative support for this relationship, showing consistent performance improvements across the level spectrum. This is consistent with the literature on progression systems, which argues that effective utilization of progression mechanics creates competitive advantages [4].

The results also support findings from game analytics research showing that quantitative analysis of gameplay telemetry can reveal meaningful patterns in player behavior [1], [2]. By applying correlation analysis and data visualization to match-level data, this study demonstrates that statistical methods can uncover relationships between economic variables and performance outcomes in competitive games. The inclusion of multiple visualization approaches (heatmap, bar charts, line plots) provides complementary perspectives on the data that strengthen the interpretation of results.

C. Limitations

This study has several limitations that should be acknowledged. First, the dataset consists of only 200 matches from a single player, which limits the generalizability of the findings to the broader TFT player population. Different players may exhibit different spending patterns and strategic preferences. The extreme values observed at certain levels (e.g., 100% top-

4 rate at level 4) may be artifacts of small sample sizes at those levels rather than true population characteristics.

Second, the analysis focused exclusively on three variables placement, level, and remaining gold while excluding other potentially relevant factors such as items, augments, team composition, and opponent strength. These omitted variables may confound or mediate the observed relationships. For example, a player at level 8 with strong items and augments may perform better than a player at level 9 with weaker items, which is not captured in the current analysis.

Third, the study examines only end-of-match data, which represents a single snapshot in time. TFT is a dynamic game where gold and level change continuously throughout each match. Analyzing only the final state may miss important patterns in resource management timing and decision-making processes. The correlation heatmap and other visualizations provide insights into final outcomes but do not capture the strategic decision sequences that led to those outcomes. Additionally, the dataset includes matches from multiple game patches over approximately one year, during which balance changes and meta shifts may have altered the relationships between variables.

Fourth, the correlational design does not establish causation; while higher levels are associated with better placements, this does not prove that leveling up causes improved performance. Other factors such as overall strategic skill or itemization may drive both variables. Finally, the dataset spans multiple game patches and balance updates, which introduces temporal heterogeneity. While this provides a more comprehensive view of gameplay across different meta conditions, it also means that the specific numerical relationships observed may not be stable across individual patches.

D. Recommendations and Future Work

Future research should expand the dataset to include multiple players across different skill levels to improve generalizability and validate whether the patterns observed in Figures 2–4 hold across diverse player populations. Incorporating additional variables such as items, augments, and team composition would provide a more comprehensive understanding of the factors influencing match outcomes. Special attention should be paid to levels with small sample sizes (e.g., level 4 and level 10) to determine whether the extreme success rates observed are representative or anomalous.

Longitudinal analysis tracking gold and level changes throughout matches, rather than only at match end, could reveal important patterns in resource management timing. This would allow researchers to identify critical decision points where gold-to-level conversion has the greatest impact on match outcomes. Time-series visualizations could complement the static charts presented in this study.

Applying predictive modeling techniques such as multiple regression or machine learning algorithms could estimate

placement outcomes based on combinations of variables and identify the relative importance of each factor. The current visualizations suggest non-linear relationships (e.g., the U-shaped pattern in Figure 3) that could be better captured with more sophisticated modeling approaches. Additionally, comparative analysis across different game patches would help determine whether the observed relationships remain stable over time or vary with meta shifts.

For players seeking to improve their performance, these findings suggest that prioritizing efficient gold-to-level conversion may be more effective than accumulating large gold reserves. The dramatic difference in top-4 rates between levels 8-10 (45-100%) and levels 5-7 (2-27%) indicates that reaching higher levels should be a strategic priority. Understanding the optimal timing for leveling decisions could provide a strategic advantage in competitive play.

VI. CONCLUSION

This study examined the relationship between player level, remaining gold, and final placement in Teamfight Tactics using Pearson correlation analysis and data visualization on a dataset of 200 matches. The findings show that player level is more strongly associated with placement ($r = -0.455, p < 0.001$) than remaining gold ($r = 0.193, p = 0.006$), indicating that effective conversion of gold into levels plays a critical role in success. The visualization analyses revealed consistent performance improvements across the level spectrum, with top-4 rates ranging from 2% at level 5 to 100% at level 10. The negligible correlation between level and remaining gold ($r = -0.011, p = 0.880$) suggests that the relationship between resource spending and progression is more complex than a simple trade-off.

The results contribute to a data-driven understanding of economic decision-making in competitive games and demonstrate the applicability of data science methods to gameplay analysis. By quantifying the relationships among key performance variables through both statistical testing and visualization, this research provides empirical evidence that strategic resource utilization rather than mere resource accumulation is associated with better match outcomes. The inclusion of multiple analytical approaches (correlation matrices, bar charts, line plots) provided complementary insights that strengthened the interpretation of results.

While this study focused on a limited set of variables from personal gameplay data, it establishes a foundation for more comprehensive future research. Expanding the analysis to include additional players, variables, and longitudinal data would provide deeper insights into the factors that determine success in Teamfight Tactics and similar strategy games. The clear visual evidence of level-placement relationships suggests that game developers and players alike can benefit from quantitative analysis of gameplay mechanics.

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