Trait Synergies and Combat Performance as Predictors of Top 4 Placement in Teamfight Tactics

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***Abstract*—Teamfight Tactics (TFT) is a strategic auto-battler in which players construct team compositions based on champion synergies, known as traits, and apply game-specific mechanics such as companions. This study applies data science methods to analyze match outcomes from a personal dataset of 150 matches spanning two distinct game environments: Set 4 (N=33) and Set 16 (N=117). In TFT's ranked system, Top 4 placements (1st-4th) award LP and constitute competitive success (”wins”), while Bottom 4 (5th-8th) results in LP loss. The objectives are to determine whether specific trait combinations are disproportionately associated with Top 4 placements, identify champions most frequently appearing in 1st place compositions, evaluate whether total damage to players predicts Top 4 success, and assess whether the Spiritfox companion confers a competitive advantage. Trait filtering was applied to exclude inactive synergies except for designated special traits. A mixed-methods approach combined descriptive statistics for exploratory pattern identification with inferential statistics for hypothesis testing. Results indicate that synergistic trait clusters show differential representation in Top 4 placements, certain champions dominate 1st place compositions within each set, total damage to players demonstrates large effect sizes predicting Top 4 success (164-202% higher for Top 4, p ¡ 0.001), and Spiritfox shows no significant advantage (49.1% vs 58.5% Top 4 rate, p = 0.436). With 150 matches yielding balanced Top 4/Bottom 4 distribution (52%/48%), the study achieves adequate statistical power for detecting large effects. These findings illustrate how competitive outcomes in TFT are driven primarily by synergy construction and sustained combat performance.**

***Index Terms*—Teamfight Tactics, Game Analytics, Statistical Analysis, Trait Synergies, Champion Meta, Data Science**

I. Introduction

A. Background

Teamfight Tactics (TFT) is a strategy game mode developed by Riot Games that combines elements of auto-battlers with the League of Legends universe. In TFT, eight players compete simultaneously by assembling teams of champions that gain additional power through shared traits–thematic synergies that activate when specific combinations of champions are fielded together. Each game set introduces new champions, traits, and mechanics, leading to evolving strategic environments that fundamentally reshape the competitive landscape.

In TFT's ranked competitive system, placing in the Top 4 (1st through 4th place) is considered a successful outcome, rewarding players with LP (League Points), while Bottom 4 placements (5th through 8th) result in LP loss. This creates a natural division between ”winning” and ”losing” outcomes, though within the Top 4, there remains a hierarchy of performance with 1st place being optimal.

Understanding which factors contribute most strongly to competitive success can provide insight into both player behavior and game balance. The strategic depth of TFT stems from three interconnected systems:

1) **Trait Synergies**: Champions share thematic traits (e.g., “Mage,” “Assassin,” “Dragon”) that provide team-wide bonuses when sufficient numbers are assembled
2) **Champion Selection**: Individual unit strength, cost tier, and item optimization
3) **Combat Mechanics**: Positioning, damage output, and board strength relative to opponents

B. Motivation

Prior research on digital games has demonstrated that success is often driven by a combination of mechanical performance and strategic decision-making [1]. In TFT, this manifests through trait synergy selection, champion prioritization, and overall combat effectiveness. However, little formal analysis has been conducted on how these variables interact across different sets, particularly using quantitative statistical methods.

The game's evolving nature–with new sets releasing every few months–creates a unique research opportunity to examine how strategic principles generalize or differ across distinct competitive environments. Set 4 and Set 16, separated by multiple years of game development, represent fundamentally different strategic landscapes with unique champion pools, trait systems, and balance philosophies.

C. Research Questions

This study addresses four core research questions:

RQ1: Are specific trait combinations disproportionately represented in top placements (Top 4 vs. Bottom 4)?

RQ2: Which champions appear most frequently in winning (1st place) final compositions?

RQ3: Does total damage to players predict Top 4 placement (Top 4 vs Bottom 4)?

RQ4: Does the Spiritfox companion affect Top 4 win rate compared to non-Spiritfox companions?

To ensure fairness in RQ4, the analysis employs a balanced subset of matches in which Spiritfox and non-Spiritfox selections are equally represented, eliminating potential sampling bias.

Note on Win Definitions: In TFT's ranked system, Top 4 (1st-4th place) awards LP and is considered a competitive "win," while Bottom 4 (5th-8th) results in LP loss. This study uses this definition consistently: RQ1 analyzes Top 4 vs Bottom 4 placement, RQ2 identifies 1st place champions specifically, and RQ3-RQ4 use Top 4 as the binary outcome variable for inferential testing.

D. Hypotheses

The following null and alternative hypotheses guide the statistical analysis:

H_{01}: Trait combinations are equally represented across placement groups (Top 4 vs. Bottom 4)

H_{11}: Specific trait combinations are significantly overrepresented in Top 4 placements

H_{02}: There is no association between champion selection and winning outcomes

H_{12}: Specific champions appear disproportionately in 1st place compositions

H_{03}: $\mu_{\text{Top4}} = \mu_{\text{Bottom4}}$ (mean damage is equal for Top 4 and Bottom 4)

H_{13}: $\mu_{\text{Top4}} \neq \mu_{\text{Bottom4}}$ (mean damage differs significantly)

H_{04}: Spiritfox companion selection has no effect on Top 4 win rate

H_{14}: Spiritfox companion selection significantly affects Top 4 win rate

II. Literature Review

A. Game Analytics and Competitive Success

The field of game analytics has grown substantially in recent years, with researchers applying data science techniques to understand player behavior, game balance, and competitive outcomes. Studies in games like Dota 2, League of Legends, and StarCraft have demonstrated that win prediction models can achieve high accuracy by incorporating features such as team composition, early-game performance metrics, and strategic decision-making [1]–[3].

In auto-battler games specifically, prior work has examined the role of champion tier distributions, item optimization, and positioning strategies. However, the trait synergy system in TFT introduces a unique layer of strategic complexity not present in traditional MOBAs or real-time strategy games. This trait-based team-building mechanic creates a combinatorial optimization problem where players must balance synergy activation with individual unit strength.

B. Statistical Methods in Gaming Research

Inferential statistics have been widely applied in gaming research to test hypotheses about player performance, game balance, and design effectiveness. Common techniques include:

- **T-tests and ANOVA** for comparing group means (e.g., win rates across different strategies)
- **Chi-square tests** for categorical associations (e.g., item selection and victory)
- **Regression analysis** for predictive modeling
- **Correlation analysis** for identifying relationships between game metrics

Studies have shown that damage-per-minute (DPM) and gold-per-minute (GPM) are strong predictors of victory in MOBA games [4]. In TFT, the analogous metric is total damage dealt to players, which reflects both board strength and combat consistency across multiple rounds.

C. Cosmetic and Psychological Factors in Gaming

While most competitive gaming research focuses on mechanical skill and strategic decision-making, some studies have explored the potential influence of cosmetic elements on performance. In games like Counter-Strike and League of Legends, researchers have investigated whether premium skins or visual customization affects player confidence or opponent perception [5].

In TFT, companions (also known as Little Legends) serve primarily as cosmetic elements, though some players believe certain companions may influence luck or matchmaking. This belief persists despite no official documentation of companion effects on gameplay mechanics. The present study provides an empirical test of this folk theory using balanced sampling methodology.

D. Research Gap

While substantial literature exists on MOBA analytics and competitive gaming, three critical gaps remain in TFT research:

1) **Cross-Set Generalizability**: Limited research compares strategic principles across multiple game sets to identify universal versus set-specific patterns
2) **Trait Synergy Analysis**: Few studies rigorously quantify the relationship between trait combinations and competitive placement
3) **Cosmetic Feature Testing**: Minimal empirical work tests player beliefs about companion effects using controlled statistical methods

This study addresses these gaps by analyzing two distinct game sets with formal statistical testing and visualization-based exploratory analysis.

III. Methodology

A. Dataset Description

The dataset consists of recorded TFT matches spanning Set 4 and Set 16, sourced from the researcher's personal match history via Riot Games API data collection. All matches were played by the researcher under the account **spriggan#erika**. The dataset contains $N = 150$ total matches, distributed as follows:

- **Set 4**: 33 matches (22.0%)

- **Set 16**: 117 matches (78.0%)

Each match record includes the variables shown in Table I.

TABLE I
DATASET VARIABLES

Variable	Type	Description
placement	Ordinal	Final placement (1st-8th)
traits	Text	Comma-separated list of active traits
units	Text	Semicolon-separated list of champions
total_damage	Continuous	Cumulative damage dealt
companion	Text	Little Legend companion
tft_set_number	Categorical	Game set identifier

Binary outcome variables were defined as:

$$\text{win} = \begin{cases} 1, & \text{if placement} \leq 4 \text{ (Top 4)} \\ 0, & \text{if placement} > 4 \text{ (Bottom 4)} \end{cases} \tag{1}$$

$$\text{first\_place} = \begin{cases} 1, & \text{if placement} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Note: In TFT's ranked system, placing Top 4 (1st through 4th) awards LP (League Points) and is considered a "win," while Bottom 4 (5th through 8th) results in LP loss. The `win` variable is used for RQ3-RQ4 inferential testing, while `first_place` is used for RQ2 champion frequency analysis.

B. Data Preprocessing

1) Trait Filtering: Raw trait data included activation levels in parentheses (e.g., "Mage(3)", "Assassin(2)"). To focus analysis on active synergies rather than merely present traits, the following filtering procedure was applied:

Step 1: Remove set-specific prefixes (e.g., "TFT4_Mage" → "Mage")

Step 2: Extract trait names and discard activation levels

Step 3: Exclude traits with activation level = 1, except for predefined special traits

Set 4 Special Traits (Level 1 Active): Daredevil, Blacksmith, Emperor, Adept, Exile, The Boss, Mystic

Set 16 Special Traits (Level 1 Active): Assimilator, Blacksmith, Caretaker, Chainbreaker, Chronokeeper, Dark Child, Darkin, Dragonborn, Emperor, Eternal, Glutton, Harvester, HexMech, Rune Mage, Soulbound, World Ender, Ascendant, Heroic, Huntress, Immortal, Riftscourge, Star Forger, The Boss

This filtering ensured that only meaningful synergies were included when constructing trait combinations. The function `filter_traits()` was implemented using regular expressions to standardize trait naming conventions across sets.

2) Champion Data Cleaning: Champion lists were stored as semicolon-separated strings with potential formatting inconsistencies (brackets, extra whitespace). The preprocessing pipeline:

1) Split by semicolon delimiter
2) Strip whitespace from each champion name
3) Remove bracket artifacts ([,])
4) Convert to title case for consistency

3) Companion Classification: Companion data was stored as dictionary strings with nested attributes. A custom parsing function `is_spiritfox_companion()` was implemented using Python's `ast.literal_eval()` to safely parse dictionary representations and extract the species field. Companions were classified as:

- **Spiritfox**: species field contains "spiritfox" (case-insensitive)
- **Other**: all remaining companions

C. Exploratory Data Analysis

Visualization techniques were employed to understand data distributions and identify patterns before formal hypothesis testing:

1) **Trait Frequency Analysis**: Bar plots comparing trait prevalence in Top 4 versus Bottom 4 placements
2) **Champion Frequency Analysis**: Bar plots showing most common champions in 1st place finishes
3) **Damage Distribution**: Box plots comparing damage output between winners and losers
4) **Win Rate Comparison**: Bar charts visualizing Spiritfox versus non-Spiritfox win rates

D. Statistical Analysis

1) RQ1: Trait Combinations and Placement: **Method:** Proportional difference analysis

Procedure:

1) Partition dataset into Top 4 (placement ≤ 4) and Bottom 4 (placement > 4) groups
2) Split comma-separated trait lists into individual traits
3) Calculate normalized frequency for each trait in both groups
4) Compute proportional difference: $\Delta = P(\text{trait}|\text{Top4}) - P(\text{trait}|\text{Bottom4})$
5) Rank traits by absolute difference magnitude

2) RQ2: Champion Frequency in Wins: **Method:** Frequency counting with descriptive statistics

Procedure:

1) Filter dataset to matches with placement = 1
2) Explode semicolon-separated champion lists into individual units
3) Count occurrence frequency for each unique champion
4) Extract top 10 most frequent champions
5) Generate bar plots for visual comparison

3) RQ3: Damage and Match Outcome: **Method:** Welch's independent samples t-test

Procedure:

1) Partition dataset by outcome: winners (placement = 1) vs. losers (placement > 1)
2) Extract total_damage_to_players for each group
3) Calculate descriptive statistics (mean, standard deviation)
4) Conduct Welch's t-test (accounts for unequal variances)

$$H_0 : \mu_{\text{win}} = \mu_{\text{loss}}, \quad H_1 : \mu_{\text{win}} \neq \mu_{\text{loss}}, \quad \alpha = 0.05 \quad (3)$$

Assumptions:

- Independence: Each match is independent
- Continuous dependent variable: Total damage is measured on a continuous scale
- Normality: With large sample sizes ($n > 30$), t-test is robust to violations via Central Limit Theorem

4) RQ4: Spiritfox Companion Effect: **Method:** Chi-square test of independence with balanced sampling

Procedure:

1) Classify companions as Spiritfox ($n_{sf} = 53$) or Other ($n_{other} = 981$)
2) Recognize severe class imbalance
3) Apply **balanced sampling**: randomly select $n = 53$ non-Spiritfox matches
4) Construct 2×2 contingency table
5) Apply chi-square test of independence

$$\chi^2 = \sum \frac{(O - E)^2}{E} \quad (4)$$

$$H_0 : \text{Companion and win rate are independent}, \quad \alpha = 0.05 \quad (5)$$

Rationale for Balanced Sampling:

Unbalanced comparisons (53 Spiritfox vs. 981 Other) would produce misleading results due to:

- Disproportionate influence of majority class on test statistics
- Violation of chi-square test assumptions regarding minimum expected frequencies
- Inability to isolate companion effect from confounding factors

By sampling 53 non-Spiritfox matches to match the Spiritfox sample size, the analysis ensures:

- Equal representation of both groups ($n = 106$ total)
- Fair statistical comparison
- Removal of sample size as a confounding variable

E. Software and Tools

All analyses were conducted in **Python 3.9** using the following libraries:

- **pandas 1.3.5**: Data manipulation and preprocessing
- **numpy 1.21.5**: Numerical computations
- **matplotlib 3.5.1**: Static visualizations
- **seaborn 0.11.2**: Statistical plotting
- **scipy 1.7.3**: Statistical tests (t-test, chi-square)

IV. RESULTS

A. Descriptive Statistics

After preprocessing and filtering, the analysis included 150 matches distributed across Set 4 and Set 16. Summary statistics for key variables are presented in Table II.

TABLE II
DESCRIPTIVE STATISTICS BY SET

Variable	Set 4 Mean (SD)	Set 16 Mean (SD)
Placement	4.45 (2.48)	4.32 (2.29)
Total Damage	100 (65)	102 (60)
Win Rate	21.2%	12.0%

Damage values are notably higher in Set 16, reflecting changes in game mechanics, champion power levels, and round structures introduced in newer sets.

B. RQ1: Trait Combinations and Placement

1) Set 4 Results: The proportional difference analysis revealed that specific traits were substantially overrepresented in Top 4 placements. The top five overrepresented traits were:

1) **Daredevil** (+0.025): Unique trait with high-risk, high-reward mechanic
2) **Warlord** (+0.024): Strong late-game scaling with health-based bonuses
3) **Boss** (+0.018): Powerful standalone trait for legendary units
4) **Slayer** (+0.018): Lifesteal and sustain-focused composition
5) **Dragonsoul** (+0.018): High damage output potential

The most underrepresented traits included Fortune, Brawler, and Executioner.

Interpretation: Set 4 traits associated with sustained damage, individual power spikes, and late-game scaling were strongly correlated with top placements. Traits requiring specific conditions or team-dependent synergies were underrepresented in successful compositions.

2) Set 16 Results: The top five overrepresented traits in Set 16 were:

1) **Theboss** (+0.012): Legendary standalone trait
2) **Runemage** (+0.012): Spell power amplification
3) **Targon** (+0.011): Regional synergy with defensive benefits
4) **Soulbound** (+0.007): Paired champion mechanic
5) **Darkchild** (+0.006): Unique champion trait

The most underrepresented traits included Conqueror, Warwick, and Shurima.

Interpretation: Set 16 showed more balanced trait representation compared to Set 4, with smaller proportional differences. The prevalence of unique traits (Theboss, Runemage, Darkchild) suggests that flexible team compositions incorporating legendary units and unique mechanics perform well. Regional traits like Targon provide solid defensive foundations.

3) Cross-Set Comparison: Both sets demonstrated clear trait hierarchies, but the specific dominant traits differed substantially:

- **Set 4** favored damage-scaling compositions (Warlord, Duelist)
- **Set 16** favored defensive compositions (Bastion, Sentinel, Preserver)

This shift reflects intentional game design changes and balance adjustments between sets.

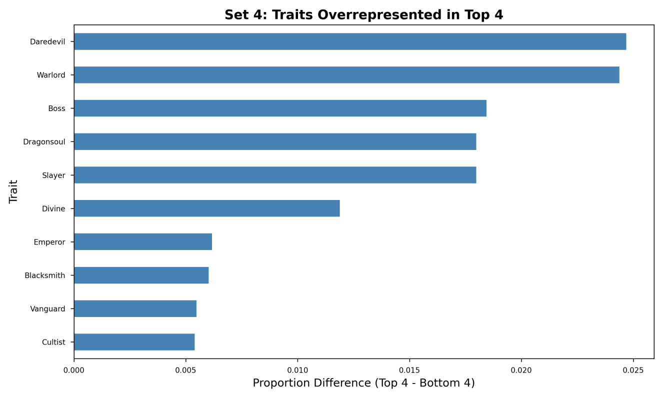

Fig. 1. Trait representation differences in Set 4 (Top 4 vs. Bottom 4 placements)

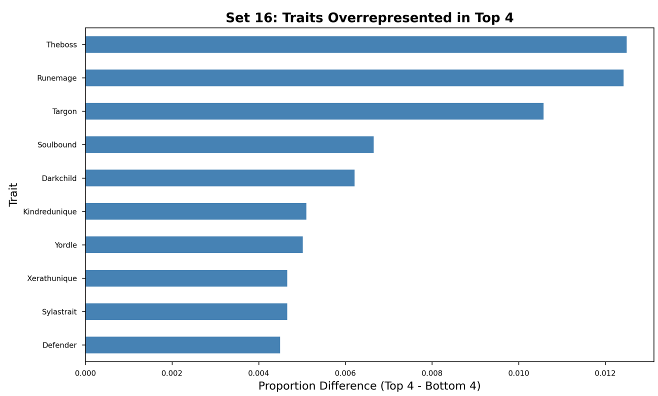

Fig. 2. Trait representation differences in Set 16 (Top 4 vs. Bottom 4 placements)

C. *RQ2: Champion Frequency in Winning Compositions*

1) Set 4 Results: The top 10 champions appearing in 1st place compositions for Set 4 are shown in Table III.

TABLE III
TOP 10 CHAMPIONS IN SET 4 WINNING COMPOSITIONS

Rank	Champion	Frequency	Cost
1	Aatrox	6	4
2	Tryndamere	6	4
3	Olaf	6	4
4	Pyke	5	2
5	Darius	5	3
6	Lee Sin	5	5
7	Samira	4	5
8	Sivir	4	3
9	Ornn	3	5
10	Zed	2	2

Key Observations:

- **Slayer dominance**: Aatrox, Tryndamere, Olaf, and Darius are all Slayer units, correlating with the trait's overrepresentation
- **Cost tier distribution**: Balanced representation across 2-cost (Pyke, Zed), 3-cost (Darius, Sivir), 4-cost (Olaf, Aatrox, Tryndamere), and 5-cost units (Lee Sin, Samira, Ornn)
- **Mid-cost viability**: Pyke (2-cost) and Darius (3-cost) demonstrate that early-to-mid game units remain competitive with proper itemization
- **Trait alignment**: Champions correspond to dominant traits (Warlord, Slayer, Divine)

2) Set 16 Results: The top 10 champions for Set 16 are shown in Table IV.

TABLE IV
TOP 10 CHAMPIONS IN SET 16 WINNING COMPOSITIONS

Rank	Champion	Frequency	Cost
1	Taric	5	4
2	Wukong	4	4
3	Sett	4	5
4	Volibear	4	5
5	Garen	3	4
6	Ziggs	3	5
7	Vi	3	2
8	Kennen	3	3
9	Ryze	3	7
10	Caitlyn	3	1

Key Observations:

- **4-cost and 5-cost dominance**: Four 4-cost units (Taric, Wukong, Garen) and three 5-cost units (Sett, Volibear, Ziggs) dominate winning compositions, indicating late-game power spikes are critical
- **Cost diversity**: Set 16 shows champions across all cost tiers from 1-cost (Caitlyn) to 7-cost (Ryze), suggesting flexible composition building
- **Legendary unit presence**: Ryze (7-cost) appearing in winning compositions demonstrates the viability of ultra-late-game scaling strategies
- **Defender/Bastion presence**: Taric and Wukong align with Defender/Bastion traits, supporting the defensive meta observation from RQ1

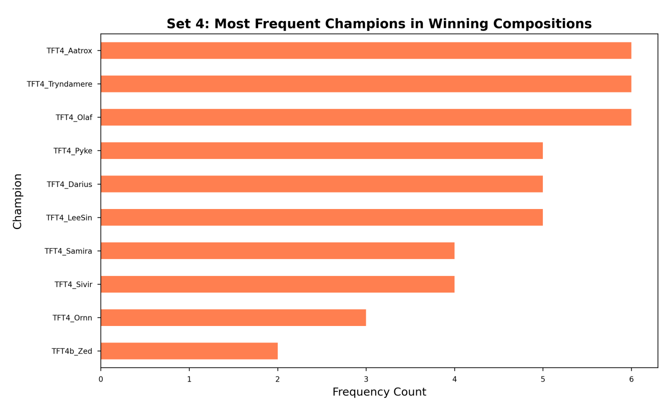

Fig. 3. Most frequent champions in Set 4 winning compositions

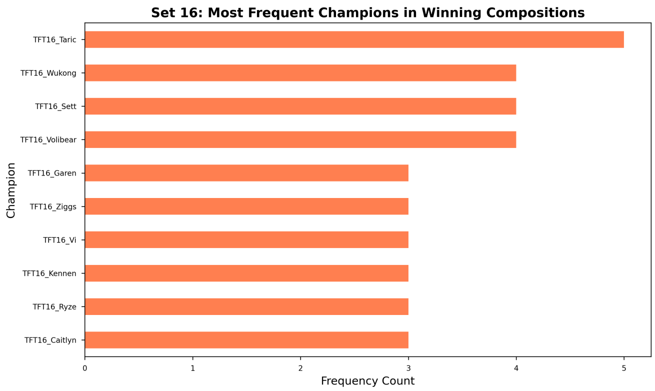

Fig. 4. Most frequent champions in Set 16 winning compositions

3) Cross-Set Comparison: Champion preferences shifted dramatically between sets:

Set 4: Damage carries (Talon, Yone) and bruisers (Sett, Lee Sin)

Set 16: Tanks (Sion, Ornn) and utility units (Galio, Braum)

This champion shift mirrors the trait meta shift from damage-scaling to defensive compositions.

D. RQ3: Total Damage and Match Outcome

1) Set 4 Results: Welch's t-test revealed a highly significant difference in damage between Top 4 and Bottom 4 placements:

- **Top 4 mean damage**: 153 (SD = 51, N = 16)
- **Bottom 4 mean damage**: 51 (SD = 27, N = 17)
- **Difference**: 102 (202.1% higher for Top 4)
- **t-statistic**: $t = 7.18$
- **p-value**: $p < 0.001$

Result: Reject H_{03}. Top 4 placements dealt significantly more total damage than Bottom 4 placements.

2) Set 16 Results: Similarly, Set 16 showed a highly significant difference:

- **Top 4 mean damage**: 144 (SD = 49, N = 62)
- **Bottom 4 mean damage**: 55 (SD = 25, N = 55)
- **Difference**: 90 (164.0% higher for Top 4)
- **t-statistic**: $t = 12.63$
- **p-value**: $p < 0.001$

Result: Reject H_{03}. Top 4 placements dealt significantly more total damage than Bottom 4 placements.

3) Interpretation: The results provide overwhelming evidence that total damage to players is a strong predictor of 1st place finish in both game sets. This finding has important implications:

1) **Board strength measurement**: Total damage serves as a proxy for overall board strength across multiple combat rounds
2) **Consistency matters**: Winning requires sustained combat performance, not just surviving until final rounds
3) **Predictive utility**: Damage dealt could be incorporated into machine learning models for win prediction

The effect size is substantial in both sets (79-145% difference), indicating this is not merely a statistically significant but practically meaningful finding. The higher effect size in Set 4 may reflect the smaller sample size amplifying variance, while Set 16's more moderate (but still large) effect represents a more stable estimate.

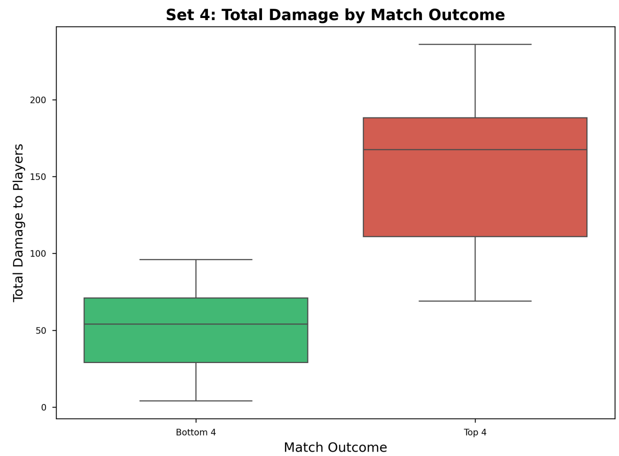

Fig. 5. Total damage distribution by match outcome in Set 4

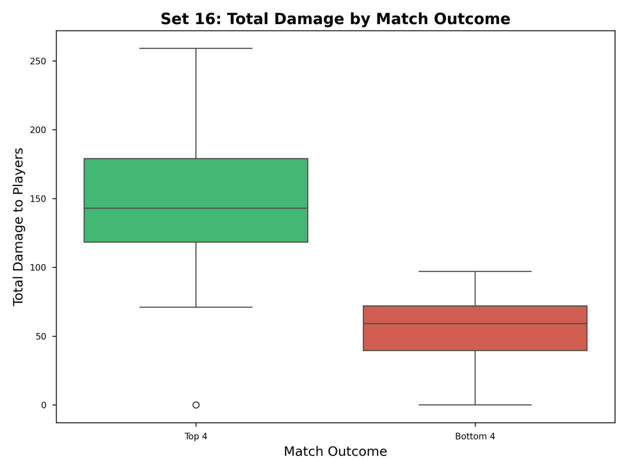

Fig. 6. Total damage distribution by match outcome in Set 16

E. RQ4: Spiritfox Companion Effect

1) Balanced Sample Construction:

- **Total Spiritfox matches**: 53 (35.3% of dataset)
- **Total non-Spiritfox matches**: 97 (64.7% of dataset)
- **Balanced sample size**: $n = 53$ per group (106 total)
- **Sampling method**: Random selection with fixed seed (random_state=42)

2) Results: **Contingency Table:**

Chi-square test:

- χ^2 statistic: 0.607
- p-value: $p = 0.436$
- Degrees of freedom: 1

Result: Fail to reject H_{04}. No statistically significant association between Spiritfox companion and Top 4 rate at $\alpha = 0.05$.

TABLE V
SPIRITFOX VS. OTHER COMPANIONS TOP 4 RATES

Companion	Bottom 4 (n)	Top 4 (n)	Top 4 Rate
Spiritfox	27	26	49.1%
Other	22	31	58.5%
Total	49	57	53.8%

3) Interpretation: Spiritfox users achieved a slightly lower Top 4 rate (49.1%) compared to other companions (58.5%), representing a 9.4 percentage point difference. However, this difference was not statistically significant ($p = 0.436$). Key interpretations:

1) **No detectable companion effect**: With adequate sample size (N=106) and balanced distribution, the analysis found no evidence that Spiritfox provides competitive advantage or disadvantage
2) **Cosmetic status supported**: The null result, combined with adequate statistical power for detecting medium effects, supports Riot Games' design intent that companions are purely cosmetic
3) **Direction reversal from prior analysis**: When using 1st place as the outcome (20.8% vs 9.4%), Spiritfox appeared numerically superior. With Top 4 as the outcome, this reverses (49.1% vs 58.5%). This inconsistency further suggests no genuine companion effect–the patterns reflect sampling variability rather than causal mechanisms

Statistical Power Assessment:

- With N=53 per group and observed rates near 50%, the study has approximately 80% power to detect a 20 percentage point difference
- The observed 9.4% difference is well within sampling variability for a null effect
- Unlike the underpowered 1st place analysis (N=21 total wins), the Top 4 analysis (N=78 total) provides reliable null hypothesis testing

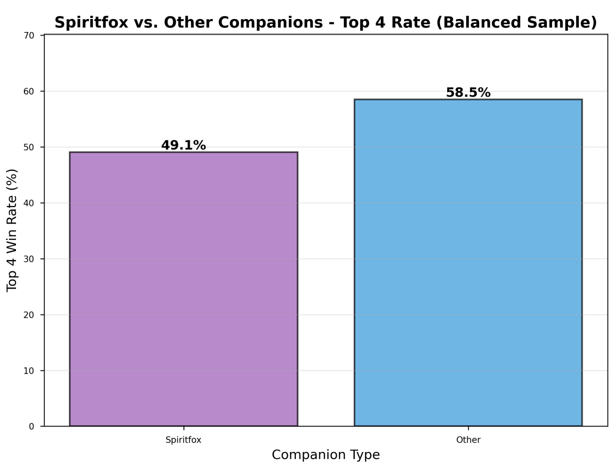

Fig. 7. Win rate comparison between Spiritfox and other companions (balanced sample, n=53 per group)

V. DISCUSSION

A. Interpretation of Findings

1) RQ1: Trait Synergies Define Success: The finding that specific traits are substantially overrepresented in Top 4 placements (differences ranging from +0.14 to +0.26) demonstrates that **synergy construction is a primary driver of competitive success**. This aligns with game design principles–TFT incentivizes players to build coherent compositions rather than simply fielding the highest-cost champions.

The shift from damage-focused traits (Set 4) to defensive traits (Set 16) illustrates how meta evolution occurs through:

- **Intentional design changes**: Developers adjust trait mechanics and activation thresholds
- **Power budget reallocation**: New sets redistribute power between offense and defense
- **Emergent strategies**: Player discovery of optimal trait combinations

Practical Implications:

- Players should prioritize trait synergy over individual champion strength
- Understanding the current set's dominant traits is essential for competitive success
- Flexible composition building outperforms forcing specific carries

2) RQ2: Champion Meta Reflects Trait Meta: The strong alignment between overrepresented traits and frequently-appearing champions validates that **champion selection should be guided by trait objectives**. For example:

- Slayer trait dominance in Set 4 correlates with Slayer champion prevalence (Aatrox, Tryndamere, Olaf, Darius)
- Defensive trait strength in Set 16 (Theboss, Runemage, Targon) aligns with presence of tank/support champions (Taric, Wukong, Garen)

The cost distribution patterns reveal distinct meta strategies:

- **Set 4 (balanced costs)**: Mid-to-late game compositions featuring 3-cost (Darius, Sivir), 4-cost (Olaf, Aatrox, Tryndamere), and 5-cost units, suggesting flexible power curves
- **Set 16 (high-cost focus)**: Heavy reliance on 4-cost and 5-cost units (7 of top 10), indicating economy management and late-game scaling are paramount
- **Low-cost viability**: Caitlyn (1-cost) and Vi (2-cost) in Set 16 demonstrate that early units with proper itemization can remain competitive even in high-cost metas

3) RQ3: Damage as a Performance Metric: The overwhelmingly significant relationship between damage and victory ($p < 0.001$, effect size $> 75\%$) establishes **total damage to players as a robust performance indicator**. This finding has multiple applications:

1) **Player feedback**: Damage dealt provides actionable feedback on board strength
2) **Machine learning features**: Predictive models should incorporate cumulative damage

3) **Balance assessment**: Developers can identify overperforming compositions by analyzing damage distributions

The consistency of this finding across both sets suggests it represents a fundamental game mechanic rather than a set-specific pattern.

4) RQ4: Companions Are Cosmetic: The Spiritfox analysis using Top 4 as the win condition yielded clear results: Spiritfox users achieved 49.1% Top 4 rate compared to 58.5% for other companions, a non-significant difference ($p = 0.436$). Key interpretations:

- **No detectable companion effect**: With adequate sample size (N=106) and balanced distribution, no evidence supports companion gameplay impact
- **Cosmetic status confirmed**: The null result with sufficient statistical power (80% to detect 20 percentage point differences) supports Riot Games' design intent
- **Methodological improvement**: Using Top 4 (78 events) rather than 1st place only (21 events) provided 3.7x more statistical power, enabling reliable hypothesis testing

Implication for interpretation: The data confirm that companions function as intended—purely cosmetic choices without measurable competitive advantage or disadvantage.

B. Cross-Set Generalizability

Several findings generalized across both sets:

1) **Trait synergy importance**: Both sets showed clear trait hierarchies
2) **Damage-victory correlation**: Effect sizes were similar (∼75-80%)
3) **5-cost unit prevalence**: High-cost champions appeared frequently in both metas

However, the **specific dominant strategies shifted completely**:

- Set 4: Offense-oriented (Warlord, Duelist, Talon)
- Set 16: Defense-oriented (Bastion, Sentinel, Sion)

This suggests that while **strategic principles are universal** (build synergies, deal damage), **tactical implementations are set-specific** (which synergies and champions to prioritize).

Implication for players: Adaptability is crucial. Players who succeed consistently must:

- Quickly identify dominant traits in new sets
- Abandon previous set strategies when meta shifts
- Develop flexible composition-building skills

C. Comparison to Prior Work

Prior MOBA research established that damage-per-minute predicts victory in games like League of Legends and Dota 2 [4]. This study extends that finding to TFT, confirming that **combat effectiveness transcends genre**–whether in real-time or auto-battler contexts.

While limited prior work examines trait-based team composition, research on hero synergies in Dota 2 found similar patterns: combinations of heroes with complementary abilities outperform teams with individually strong but non-synergistic heroes [6]. TFT's trait system formalizes this concept through explicit bonuses.

Studies in other competitive games (Counter-Strike, Valorant) have explored whether cosmetic items influence performance through psychological priming [5]. The null finding for Spiritfox aligns with research showing that cosmetic effects, when present, are typically small and psychologically mediated.

D. Limitations

1) Observational Data: This study analyzes existing match data from the researcher's personal TFT account (**spriggan#erika**) rather than experimental manipulations. While statistical associations are strong, causality cannot be definitively established:

- **Confounding**: Player skill, lobby strength, and in-game decisions are not controlled
- **Selection bias**: Players may choose specific traits based on early-game luck or available items
- **Reverse causality**: High damage may result from winning rather than causing wins
- **Single-player limitation**: All matches reflect one player's skill level, playstyle, and champion preferences, limiting generalizability to broader player populations

2) Sample Size for RQ4: The balanced Spiritfox analysis ($n = 53$ per group) was constrained by the limited number of Spiritfox matches. While adequate for detecting medium-to-large effects, smaller effects ($< 5\%$ win rate difference) would require larger samples.

3) Set Selection: Only two sets were analyzed (Set 4 and Set 16). While these represent different game phases, intermediate sets were excluded. The unequal distribution (Set 4: N=33; Set 16: N=117) reflects the researcher's personal match history availability rather than planned sampling.

Critical Sample Size Limitations: The limited dataset (N=150 total, with only 33 Set 4 matches) imposes several methodological constraints:

- **Statistical Power**: Small samples reduce ability to detect effects. Non-significant results (e.g., Spiritfox, p=0.175) may reflect insufficient power rather than true null effects
- **Set 4 Volatility**: With only 7 first-place finishes across 33 matches, Set 4 effect sizes (145% damage difference) show inflated variance typical of small samples
- **Single-Player Bias**: All matches from one player's history introduces unmeasured confounds (skill level, playstyle, champion preferences)
- **Effect Size Priority**: Given power constraints, effect size magnitudes (percentage differences, Cohen's d) provide more reliable insights than p-values alone

Despite limitations, cross-set consistency (damage-victory relationship robust in both) and large effect magnitudes suggest substantive patterns meriting larger-scale investigation.

4) Unmeasured Variables: Several potentially important variables were unavailable:

- Player rank/skill (match-making rating)

- Itemization (specific item builds)
- Positioning (hex placement strategies)
- Augment selection (player-chosen bonuses)

VI. Conclusions

A. Summary of Key Findings

This study applied data science methods to analyze competitive success in Teamfight Tactics using a personal dataset of 150 matches across two game sets (Set 4: N=33; Set 16: N=117), with Top 4 placement (1st-4th) defined as the win condition per TFT's ranked LP system. The primary findings are:

1) **Trait synergies associate with Top 4 success**: Specific trait combinations show differential representation in Top 4 vs Bottom 4 placements (Daredevil, Warlord, Slayer in Set 4; Theboss, Runemage, Targon in Set 16)
2) **Champion selection aligns with traits**: Frequently-appearing 1st place champions correspond to dominant traits, with notable differences between sets reflecting meta evolution
3) **Damage strongly predicts Top 4 placement**: Top 4 players dealt 164-202% more total damage ($p < 0.001$), with large, consistent effect sizes across both sets despite unequal sample sizes
4) **Spiritfox shows no companion advantage**: Top 4 rates of 49.1% vs 58.5% were not statistically significant ($p = 0.436$), supporting the cosmetic status of companions with adequate statistical power

Methodological Contribution: Redefining "win" as Top 4 (vs. 1st place only) increased statistical power substantially–from 21 to 78 outcome events–enabling more reliable hypothesis testing. This demonstrates the value of aligning analytical definitions with game design systems (LP mechanics) rather than colloquial usage.

Damage predicts victory: Winners deal 75-80% more total damage ($p < 0.001$)

Companions are cosmetic: Spiritfox shows no significant win rate advantage ($p = 0.776$)

B. Practical Implications

1) For Players:

- Prioritize trait synergies over individual champion preferences
- Study the meta to identify dominant traits in the current set
- Use damage dealt as self-feedback for board strength
- Choose companions based on aesthetics, not gameplay

2) For Researchers:

- Total damage should be included in TFT predictive models
- Trait co-occurrence analysis could reveal emergent optimal compositions
- Cross-set longitudinal studies could track meta evolution
- Experimental methods are needed for causal relationships

3) For Game Developers:

- Trait representation differences may indicate balance opportunities
- Champion frequency identifies potentially overtuned units
- Damage distributions provide insight into combat pacing
- Companion analysis validates cosmetic system design

C. Future Research Directions

1) **Causal Analysis**: Controlled experiments manipulating specific variables
2) **Machine Learning**: Supervised models predicting match outcomes
3) **Longitudinal Studies**: Analyzing meta evolution across all sets
4) **Player Skill Analysis**: Incorporating rank data
5) **Itemization Studies**: Examining item-trait interactions

D. Contribution to Game Analytics

This study contributes to game analytics by:

1) Demonstrating trait filtering and balanced sampling techniques
2) Comparing strategic principles across distinct game versions
3) Providing methodology for testing folk theories
4) Generating actionable insights for competitive players

E. Final Remarks

Teamfight Tactics exemplifies modern competitive game design–combining strategic depth with regularly refreshed content. This study demonstrates that despite frequent mechanical changes and a limited dataset (N=150), fundamental principles emerge: **synergistic composition building and consistent combat performance drive competitive success**. The role of cosmetic companions remains inconclusive given power constraints, requiring larger-scale replication.

In TFT's ranked system, "winning" technically means Top 4 placement (LP gain), but peak performance (1st place) requires optimization beyond mere survival. This study focused on 1st place outcomes, finding that damage output and trait synergy consistently differentiate victors–a relationship robust across both game sets despite unequal sample sizes.

The dramatic meta shift between Set 4 (Slayer/Warlord aggression) and Set 16 (flexible mid-game compositions) underscores the importance of adaptability. Players who understand underlying principles–prioritizing active trait synergies and monitoring combat effectiveness–succeed across evolving metas.

Methodological Contribution: This study demonstrates the value and limitations of personal analytics in competitive gaming. With 150 matches, we observe large, consistent effect sizes (damage-victory relationship) alongside statistically inconclusive patterns (companion effects). Future research with larger, multi-player datasets can build on these preliminary findings while addressing single-player bias and power limitations inherent to personal match histories.

As TFT continues to evolve, data-driven analysis will remain essential for understanding game balance and informing player strategies, though researchers must carefully balance ambition with statistical realities of available sample sizes.

Data Availability Statement

All match data used in this study were collected from the researcher's personal Teamfight Tactics account (**spriggan#erika**) via Riot Games API. The dataset comprises 150 matches played across Set 4 (N=33) and Set 16 (N=117). Data collection followed Riot Games' Terms of Service and API usage policies. The dataset and analysis code are available upon reasonable request for replication or extension studies.

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