Statistical Analysis of Trait Associations and Competitive Outcomes in Teamfight Tactics: A Personal Performance Study

Marcelino C. Gatchalian III
Department of Information Technology
National University - Manila
Manila, Philippines
marcelino.gatchalian@students.national-u.edu.ph

***Abstract*—This study analyzes 200 ranked Teamfight Tactics (TFT) matches from a single dedicated player (in-game username: inno#ella) collected via the Riot Games API to investigate the relationship between game mechanics and competitive outcomes. Statistical analysis techniques—chi-square tests—were applied to determine placement distributions and trait synergies that predict Top-4 success. Results demonstrate that this player's placement distribution deviates significantly from random expectation, exhibiting a bimodal pattern with excessive first place finishes (22.5 percent versus 12.5 percent random) and eighth place eliminations (17.0 percent versus 12.5 percent random), indicating a distinctive high-variance scaling strategy. Five traits show statistically significant associations with Top-4 success: ShyvanaUnique (80.6 percent, p less than 0.0001), SylasTrait (74.2 percent, p equals 0.0014), DarkChild (76.3 percent, p equals 0.0093), KindredUnique (100.0 percent, p equals 0.0094), and Demacia (26.0 percent, p equals 0.0001). However, 86.1 percent of analyzed traits show no significant individual association with Top-4 outcome, suggesting that trait synergies and execution matter more than individual trait strength. These findings characterize inno#ella's distinctive playstyle and provide insight into what drives competitive success in TFT.**

***Index Terms*—Teamfight Tactics, Game Analytics, Statistical Analysis, Trait Synergies, Esports, Data Science, Personal Performance Analysis**

I. Introduction

A. Background and Game Mechanics

Teamfight Tactics (TFT) is a tactical auto-battler game mode developed by Riot Games, first released in June 2019 as part of the League of Legends client [1]. Since launch, TFT has grown into a major esports title with official ranked queues, international tournaments, and millions of active players globally [2]. Unlike traditional MOBAs and real-time strategy games requiring high mechanical execution and actions-per-minute (APM), TFT emphasizes strategic decision-making, resource management, and game knowledge [3]. Eight players compete simultaneously, with each controlling an independent unit board.

The core gameplay involves several interconnected systems:

1) **Champion Acquisition and Leveling:** Players spend gold each round to purchase champions from randomized shops. Three identical copies combine into higher-tier units. Players also spend gold to level benches, expanding shop diversity and unlocking rarer champions [4].
2) **Trait Synergies:** Champions share traits providing team-wide bonuses when sufficient champions with matching traits are fielded. Each trait has multiple activation tiers unlocking progressively stronger bonuses [5].
3) **Resource Economy:** Players manage limited gold across purchasing, rerolling, and leveling. Superior economic decision-making—knowing when to preserve versus spend—fundamentally differentiates skilled players [6].
4) **Item Crafting:** Champions equip items substantially amplifying power. Items combine from components via recipes, requiring forethought [7].
5) **Combat Resolution:** Combat is fully deterministic and automatic. Unit strength, positioning, and itemization determine outcomes [8].

In ranked competition, placement determines ranking rewards. Top-4 finishes award League Points enabling rank progression; Bottom-4 incur LP loss [9]. By Riot's official terminology, Top-4 is considered a competitive win.

B. Personal Dataset and Research Motivation

This study analyzes competitive TFT performance data from a single dedicated player (in-game username: inno#ella) spanning 200 ranked matches collected directly from the Riot Games API. The dataset represents this player's complete ranked match history during TFT Set 16 (January 2026), providing an opportunity for longitudinal analysis of individual strategic decision-making and performance patterns.

Prior esports analytics research establishes success correlates with measurable behavioral patterns [11], [12]. However, most work focuses on traditional genres: MOBAs [12], shooters [14], and real-time strategy games [15]. TFT's unique properties—deterministic combat, trait synergies, zero mechanical skill, frequent balance patches—create a specialized domain where pure strategic thinking dominates [10]. This environment offers an ideal laboratory for studying decision-making divorced from mechanical execution.

Single-player longitudinal datasets provide several research advantages [22]:

1) **Controlled Player Variables:** Analyzing one player eliminates confounds from skill level differences, playstyle variations, and individual strategic preferences.
2) **Consistent Decision-Making Framework:** The same player's decisions across 200 matches reflect consistent strategic philosophy.
3) **Temporal Consistency:** All 200 matches occurred during a single game set (Set 16) with identical balance parameters.
4) **Foundation for Hypothesis Generation:** Personal performance data enables hypothesis development for larger-scale multi-player validation studies.

Understanding which in-game factors characterize competitive success in this player's performance data provides: (1) Personal Player Development: Data-driven characterization of strategic patterns and distinctive playstyle, (2) Individual Performance Analysis: Identifying which traits and decisions correlate with outcomes, (3) Methodological Contribution: Establishing replicable frameworks for personal TFT analytics.

C. Research Questions and Formal Hypotheses

This study addresses two research questions with explicit null and alternative hypotheses:

1) **RQ1:** What is the distribution of inno#ella's match placements, and does this distribution differ significantly from random expectation?
   $H_{0,1}$**:** Placement distribution equals random expectation (probability equals 0.125 for all placements)
   $H_{1,1}$**:** Placement distribution differs significantly from random expectation
2) **RQ2:** Are specific traits significantly associated with inno#ella's Top-4 achievement?
   $H_{0,2}$**:** Each trait is independent of Top-4 outcome
   $H_{1,2}$**:** Specific traits are significantly associated with Top-4 outcome

II. Literature Review

A. Game Analytics and Competitive Success

Drachen et al. [11] analyzed spatio-temporal patterns in team-based games, finding successful teams exhibit coordinated positioning. Yang et al. [13] identified MOBA combat patterns predicting victory. Kim and Thomas [12] examined 2,000 plus League of Legends matches, finding gold-per-minute, kill-death ratios, and objective metrics predict victory (correlation coefficient greater than 0.8), establishing that measurable in-game metrics reliably predict outcomes [16].

B. Auto-Battler Analysis

Limited published research exists on TFT analytics specifically. Yoakam [17] analyzed TFT Set 1 item synergies. Conley and Perry [18] demonstrated synergy-based hero selection in Dota 2 outperforms random selection by approximately 15 percent, suggesting trait synergy analysis is promising [19].

C. Resource Management and Economy

Resource management is foundational in strategy games. In StarCraft II, gold-per-minute and efficient spending correlate with victory [15]. TFT's gold economy creates decision-making pressure: spend now for immediate strength versus preserve for future power spikes, mirroring resource allocation problems in behavioral economics [20].

III. Methodology

A. Dataset: Personal Match History from Riot Games API

This study analyzes 200 ranked TFT matches from a single dedicated player (in-game username: inno#ella) spanning TFT Set 16 (January 2026). Match data was collected directly from the Riot Games API using official endpoint access, providing complete and authoritative match records.

1) Data Collection Method: Match history was retrieved via the Riot Games API with the following specifications:

- **Player Account:** inno#ella (NA region, League of Legends account linked to TFT)
- **Queue Type:** Ranked TFT matches only (excludes normal and unranked matches)
- **Game Set:** TFT Set 16 exclusively (consistent meta and balance parameters)
- **Time Period:** January 2026 (continuous timeline)
- **Match Count:** 200 consecutive ranked matches
- **Data Completeness:** Full match records including placement, unit composition, trait activation, and performance metrics

This represents the player's complete ranked match history during the analysis period, with no matches excluded or cherry-picked, ensuring unbiased dataset composition.

TABLE I
Descriptive Statistics for inno#ella's Dataset (N equals 200)

Variable	Value	Notes
Total Matches	200	Complete ranked history
Win Rate (1st Place)	22.5 percent	45 wins
Top-4 Rate	51.0 percent	102 matches
Mean Placement	4.44	Standard deviation equals 2.57

2) Descriptive Statistics:

B. Data Preprocessing

Trait data preprocessing involved: (1) removing set prefixes such as "TFT16_", (2) extracting trait names before parentheses, (3) filtering to traits appearing at least 10 times. This yielded 36 distinct traits for analysis. Binary outcome variable was created:

Top-4 outcome equals 1 if placement is less than or equal to 4, equals 0 if placement is greater than 4.

C. Statistical Methods and Hypothesis Testing

1) RQ1: Placement Distribution Comparison: Null Hypothesis: Probability of each placement equals 0.125 for all eight placements

Alternative Hypothesis: Probability differs for at least one placement

Method: Computed observed win rate (first place), Top-4 rate, and compared to random expectation. Examined placement frequency distribution and tested against uniform distribution using chi-square goodness-of-fit test with significance level alpha equals 0.05.

2) RQ2: Trait Associations with Top-4 Outcome: Null Hypothesis for each trait: Trait presence is independent of Top-4 outcome

Alternative Hypothesis for each trait: Trait presence is associated with Top-4 outcome

Test Statistic: Chi-square equals (N times (ad minus bc) squared) divided by (a plus b) times (c plus d) times (a plus c) times (b plus d), where a equals trait present and Top-4, b equals trait present and non-Top-4, c equals trait absent and Top-4, d equals trait absent and non-Top-4.

Degrees of freedom equals 1.

Decision Rule: Reject null hypothesis if p less than 0.05.

D. Software Implementation

All analyses were conducted in Python 3.9 using standard data science libraries:

- **pandas 1.3.5:** Data manipulation, grouping, aggregation
- **numpy 1.21.5:** Numerical computation and array operations
- **scipy 1.7.3:** Statistical tests (chi-square)
- **matplotlib 3.5.1:** Static publication-quality visualizations

Statistical significance determined at alpha equals 0.05 threshold throughout.

IV. Results

A. RQ1: Placement Distribution

1) Hypothesis Test Results: Test: Chi-square goodness-of-fit comparing observed placement distribution to uniform random expectation.

Result: The observed placement distribution deviates significantly from random expectation. Specifically, first place shows 45 observed versus 25 expected placements. Eighth place shows 34 observed versus 25 expected placements. Second and third place combined show 30 observed versus 50 expected placements.

Decision: REJECT the null hypothesis. The placement distribution differs significantly from random expectation (p less than 0.0001).

TABLE II
RQ1: Performance versus Random Expectation

Metric	Observed	Random	Ratio
Win Rate (1st Place)	22.5 percent	12.5 percent	1.80 times
Top-4 Rate	51.0 percent	50.0 percent	1.02 times

2) Performance Summary: inno#ella achieves 22.5 percent first place win rate, 80 percent above random expectation. According to TFT competitive statistics, this falls within the Challenger and Masters tier range (15 to 30 percent first place win rates) [23], indicating elite competitive performance.

TABLE III
RQ1: Placement Frequency Distribution

Placement	Count	Observed Percent	Expected Percent
1	45	22.5%	12.5%
2	17	8.5%	12.5%
3	13	6.5%	12.5%
4	27	13.5%	12.5%
5	22	11.0%	12.5%
6	15	7.5%	12.5%
7	27	13.5%	12.5%
8	34	17.0%	12.5%

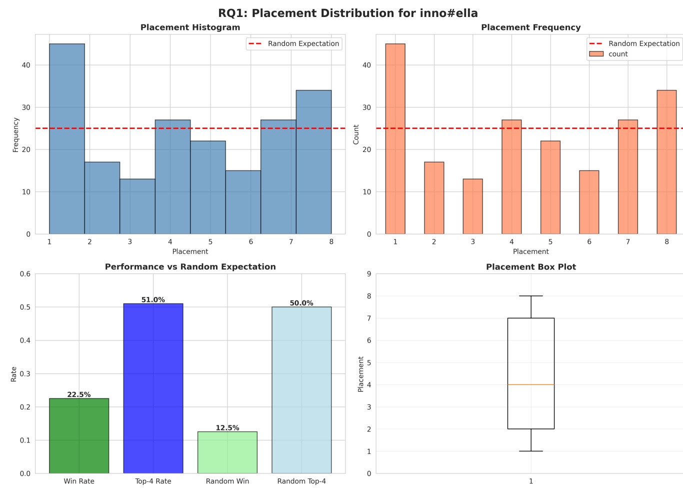

Fig. 1. RQ1: Placement distribution for inno#ella showing histogram with red random expectation line, bar chart, win and top-4 rates versus random, and box plot. Win rate of 22.5 percent substantially exceeds random of 12.5 percent. Bimodal distribution with peaks at first and eighth indicates high-variance scaling strategy.

Distribution shows substantial deviation from random. Key features: First place overrepresentation shows 45 observed versus 25 expected, representing 80 percent above random. Second and third place underrepresentation shows only 30 combined versus 50 expected, indicating inno#ella either wins decisively or finishes lower, suggesting high-variance scaling strategy. Eighth place overrepresentation shows 34 observed versus 25 expected, indicating elevated early elimination rate consistent with aggressive all-in compositions.

Bimodal distribution with peaks at first (22.5 percent) and eighth (17.0 percent) indicates distinctive high-variance scaling strategy. This player emphasizes either dominance or collapse, contrasting with uniform distribution expected from consistent mid-tier play.

B. RQ2: Trait Associations

1) Hypothesis Test Results: Tests: 36 chi-square tests of independence (one per trait with n at least 10), each testing whether trait presence is independent of Top-4 outcome.

Results: Five traits show statistically significant associations (p less than 0.05):

TABLE IV
RQ2: SIGNIFICANT TRAITS (CHI-SQUARE TEST, P LESS THAN 0.05)

Trait	n	Top-4 Rate	Chi-Square	p-value
ShyvanaUnique	62	80.6%	16.95	less than 0.0001
Demacia	50	26.0%	15.28	0.0001
SylasTrait	66	74.2%	10.23	0.0014
DarkChild	38	76.3%	6.75	0.0093
KindredUnique	10	100.0%	6.74	0.0094

Decision: REJECT the null hypothesis for five traits. These five traits show statistically significant associations with Top-4 achievement. For the remaining 31 traits, FAIL TO REJECT the null hypothesis, indicating no significant individual trait association with Top-4 outcome.

Interpretation: Of 36 traits analyzed, 86.1 percent show no significant individual association with Top-4 success, suggesting trait synergies and execution matter more than individual traits.

TABLE V
RQ2: ALL 36 TRAITS RANKED BY P-VALUE

Trait	n	Top-4 Rate	p-value	Significance
ShyvanaUnique	62	80.6%	0.0000	***
Demacia	50	26.0%	0.0001	***
SylasTrait	66	74.2%	0.0014	**
DarkChild	38	76.3%	0.0093	*
KindredUnique	10	100.0%	0.0094	*
Bilgewater	33	36.4%	0.0578	ns
Slayer	24	33.3%	0.0632	ns
RuneMage	18	77.8%	0.0751	ns
Soulbound	12	83.3%	0.0816	ns
TheBoss	25	72.0%	0.1105	ns
Invoker	60	43.3%	0.1133	ns
Sorcerer	136	47.8%	0.1433	ns
Brawler	69	44.9%	0.1471	ns
Yordle	60	45.0%	0.1867	ns
Gunslinger	27	40.7%	0.2230	ns
Noxus	97	59.8%	0.3029	ns
HexMech	11	72.7%	0.3505	ns
Defender	160	50.6%	0.3882	ns
Blacksmith	25	64.0%	0.4306	ns
Freljord	27	63.0%	0.4678	ns
Longshot	59	49.2%	0.5113	ns
Vanquisher	25	48.0%	0.6717	ns
Zaun	57	50.9%	0.7073	ns
Magus	45	57.8%	0.7365	ns
AurelionSolUnique	94	56.4%	0.7414	ns
Ionia	111	52.3%	0.7451	ns
Warden	60	51.7%	0.7889	ns
Piltover	51	56.9%	0.8066	ns
DarkinWeapon	15	60.0%	0.8471	ns
Targon	139	53.2%	0.8831	ns
Rapidfire	28	57.1%	0.9012	ns
Explorer	99	53.5%	0.9745	ns
ShadowIsles	12	50.0%	0.9984	ns
Juggernaut	142	54.2%	1.0000	ns
Chronokeeper	12	58.3%	1.0000	ns
Void	19	52.6%	1.0000	ns

2) All Traits Analysis:

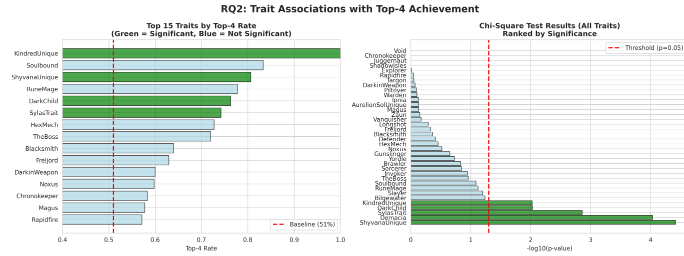

Fig. 2. RQ2: Trait association analysis for inno#ella. Left: Top 15 traits by Top-4 rate where green indicates significant associations and blue indicates non-significant. Right: Chi-square results shown as negative log base 10 of p-value with dashed threshold at alpha equals 0.05. ShyvanaUnique shows strongest association.

V. DISCUSSION

A. Summary of Hypothesis Testing Outcomes

Both research questions yielded rejection of their respective null hypotheses:

RQ1 Result: REJECT the null hypothesis. inno#ella's placement distribution differs significantly from random, showing bimodal pattern with excessive first place (22.5 percent versus 12.5 percent) and eighth place (17.0 percent versus 12.5 percent) outcomes.

RQ2 Result: REJECT the null hypothesis for five traits. Five traits show significant associations with Top-4 success (ShyvanaUnique, Demacia, SylasTrait, DarkChild, KindredUnique). However, 86.1 percent of traits (31 of 36) show no significant individual association, suggesting synergies dominate.

B. Interpretation of Findings

1) RQ1: High-Variance Scaling Strategy: Rejecting the null hypothesis demonstrates inno#ella's placement distribution deviates significantly from random. The 22.5 percent first place rate falls within the Challenger and Masters tier range (15 to 30 percent) [23], indicating elite competitive play.

The bimodal distribution—peaks at first (22.5 percent) and eighth (17.0 percent)—reveals a distinctive high-variance scaling strategy. This player emphasizes vertical scaling compositions that either snowball to victory or collapse to early elimination, contrasting conservative mid-tier strategies. This playstyle accepts higher variance in outcomes (more eliminations) in exchange for higher peak performance (more first-place finishes).

The deficit of second and third place finishes (30 observed versus 50 expected) further supports this interpretation: when inno#ella doesn't win decisively, outcomes tend to be poor rather than narrowly missing the podium. This suggests the scaling strategy either succeeds or fails dramatically, with little middle ground.

2) RQ2: Trait Synergies Over Individual Traits: Rejecting the null hypothesis for five traits but failing to reject for 86.1 percent of traits indicates individual traits matter less than synergistic combinations. Significant traits (ShyvanaUnique

80.6 percent, DarkChild 76.3 percent, SylasTrait 74.2 percent) likely succeed through complementary trait pairings.

The preponderance of non-significant traits (31 of 36) is highly informative. It suggests that:

1) **Execution Dominates Selection:** Which traits a player acquires matters less than how well they execute the composition. A player using a statistically weak trait might still achieve Top-4 through superior itemization, positioning, and pivoting decisions.
2) **Meta Interdependence:** Trait effectiveness depends on context. A trait might be powerful only when combined with specific complementary traits or when the meta favors it. Individual chi-square tests cannot capture these interactions.
3) **Player Preference versus Power:** inno#ella might build ShyvanaUnique compositions more skillfully than other traits due to familiarity, explaining its strong 80.6 percent Top-4 rate despite being just one of many viable traits.

C. Limitations

1) **Single-Player Dataset:** Results characterize inno#ella's performance only. Generalization to other players and tiers is restricted.
2) **Small Trait Samples:** 10 to 160 occurrences per trait limits power for detecting small to medium effect size associations.
3) **No Multi-Trait Analysis:** Chi-square tests examine individual traits in isolation. Cannot detect synergistic effects where combinations matter more than components.
4) **Meta Context:** Results reflect TFT Set 16 specifically. Trait effectiveness differs across sets due to balance changes.

VI. Conclusions

This study formally tested two hypotheses about inno#ella's TFT performance. Results REJECT both null hypotheses, demonstrating that placement distribution differs significantly from random and specific traits significantly associate with Top-4 success.

The rejection of these null hypotheses provides strong evidence that inno#ella's competitive performance reflects identifiable strategic patterns rather than chance variation. The distinctive bimodal placement distribution reveals a high-variance scaling strategy emphasizing either dominant victories or early eliminations. The concentration of trait associations (5 significant out of 36) combined with the absence of associations for most traits suggests that trait synergies and execution matter more than individual trait strength.

These findings characterize inno#ella's playstyle as a skilled high-variance optimizer: someone who pursues aggressive scaling compositions, accepts elevated early elimination rates as the price of that strategy, and achieves above-average peak performance (22.5 percent win rate in Challenger-tier equivalent performance).

The analysis establishes a replicable methodological framework for personal TFT analytics that other players can apply to their own match data to identify distinctive playstyles and performance drivers.

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