Competitive Performance Analysis in Teamfight Tactics: A Statistical Examination of Top 2% Ranked Gameplay in Set 16

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***Abstract* - This paper presents a statistical analysis of competitive gameplay in Teamfight Tactics (TFT) by a player ranked in the top 2% of the Southeast Asia (SEA) region. Using 100 Set 16 ranked matches and global augment data from 612 augments, utilizing Mann-Whitney U tests, Spearman correlation, and Wilson score confidence intervals to model performance outcomes. Results indicate a 22% win rate, significantly outperforming the 12.5% random baseline (p = 0.009). While individual traits showed limited variance, ShyvanaUnique-based compositions yielded superior average placements (3.79 vs. 4.39, r = 0.201). Notably, the Brawler + ShyvanaUnique synergy achieved a 42.9% win rate, representing a 244% improvement over baseline expectations and confirming emergent strategic advantages. Augment analysis further revealed substantial performance variance (11–27% win rates), with Ixtal Expeditionist identified as the most effective (27% win rate, 95% CI: [21.8%, 32.7%]). This research establishes a replicable statistical framework for gaming analytics, proving that competitive auto-battler outcomes are distinguishable from random chance through optimized trait and augment selection.**

Index Terms - Gaming analytics, statistical analysis, performance metrics, competitive gaming, trait synergies, Mann-Whitney U test, Wilson confidence intervals, auto-battler games, Teamfight Tactics.

I. Introduction

A. Topic and Context

This study focuses on the statistical analysis of competitive performance patterns in Teamfight Tactics (TFT), a popular auto-battler video game developed and published by Riot Games in 2019. TFT represents a distinct genre of strategy games where eight players compete simultaneously in a free-for-all format, combining elements of deck-building card games, resource management simulations, and tactical positioning puzzles [1]. Unlike traditional multiplayer online battle arena (MOBA) games such as League of Legends or Dota 2 that emphasize real-time mechanical execution and reflexes, TFT focuses primarily on strategic planning, economic optimization, and compositional adaptation, making it accessible to players with diverse skill sets while maintaining competitive depth [2].

The game's core mechanic revolves around a complex trait system where units (characters) synergize based on shared characteristics such as origin (Noxus, Piltover, Zaun), class (Brawler, Sorcerer, Juggernaut), or unique identifiers (ShyvanaUnique). Players must dynamically construct team compositions that activate multiple trait bonuses while managing limited economic resources, adapting to randomly offered units, and responding to opponent strategies visible through scouting mechanisms [2]. This multidimensional strategic space rewards both short-term tactical decisions (unit positioning on the board, item allocation) and long-term planning (economy management, compositional pivoting based on unit availability).

B. Importance of the Topic

The emergence of esports and competitive gaming as mainstream entertainment phenomena has created unprecedented opportunities for data-driven analysis of player behavior, strategic optimization, and skill development [3]. The global esports industry was valued at approximately $1.38 billion in 2022, with competitive gaming audiences exceeding 532 million viewers worldwide, demonstrating both cultural significance and economic impact [3]. Within this ecosystem, understanding performance determinants through rigorous statistical analysis serves multiple stakeholder groups: competitive players seeking evidence-based strategies to improve ranking, game designers evaluating balance and maintaining competitive integrity, esports analysts and coaches developing training curricula, and academic researchers studying decision-making and skill acquisition in complex strategic environments.

C. Prior Research in Gaming Analytics

Previous studies in gaming analytics have demonstrated the value of statistical and machine learning methodologies for understanding player performance patterns across various game genres. Drachen et al. [4] pioneered the application of clustering techniques to player behavior data, establishing foundational frameworks for behavioral segmentation and playstyle classification. El-Nasr et al. [5] provided comprehensive methodologies for game analytics encompassing data collection best practices, ethical considerations, and interpretative frameworks, emphasizing the importance of combining quantitative metrics with qualitative contextual understanding.

Research specifically focused on competitive multiplayer games has examined champion selection patterns in League of Legends [6], composition optimization in Dota 2, and combat pattern prediction in various MOBA contexts [7]. Yang et al. [7] demonstrated that machine learning classifiers trained on early-game combat features could predict match outcomes with 71.5% accuracy, suggesting that systematic analysis of in-game decisions reveals reproducible strategic principles.

However, previous gaming analytics research has exhibited several limitations. First, most published work focuses on MOBA games emphasizing mechanical execution rather than strategy-focused auto-battler genres. Second, many studies employ black-box machine learning approaches that achieve high predictive accuracy but provide limited interpretability. Third, research often aggregates data across many players, obscuring individual-level patterns and limiting applicability to personal performance improvement.

D. Research Gap

Despite the growing popularity of auto-battler games, with TFT averaging 33 million monthly active players as of 2023, comprehensive statistical analysis of gameplay patterns remains limited in peer-reviewed academic literature. Existing community-generated analytics focus primarily on descriptive statistics (tier lists ranking, unit strength, meta composition guides) without rigorous hypothesis testing to establish statistical significance or effect size quantification to assess practical importance. While some proprietary analytics platforms track aggregate win rates and usage frequencies, these resources rarely employ confidence interval estimation to communicate uncertainty, fail to analyze synergistic trait interactions systematically, and do not connect findings to established statistical frameworks from behavioral research.

This gap is consequential because auto-battler games present unique analytical challenges and opportunities. The discrete, turn-based structure generates naturally segmented decision points amenable to statistical modeling. The transparent trait system with clearly defined activation thresholds enables hypothesis formulation and testing at the compositional level. The eight-player competitive format provides rich comparative data within each match. Yet these analytical advantages remain largely unexploited in the academic literature.

E. Research Goals

This study aims to address the identified research gap through six primary goals:

Goal 1: Performance Quantification - To establish quantitative baselines for competitive TFT performance using rigorous descriptive and inferential statistics applied to 100 ranked matches.

Goal 2: Trait Effectiveness Analysis - To identify which individual traits demonstrate measurable performance advantages through non-parametric Mann-Whitney U hypothesis testing with complementary effect size estimation.

Goal 3: Synergy Identification - To discover non-obvious trait synergies using systematic co-occurrence analysis combined with Spearman rank correlation methods.

Goal 4: Augment Optimization - To evaluate augment effectiveness across the global player population using Wilson score confidence intervals that appropriately account for sample size variability.

Goal 5: Methodological Framework - To develop and demonstrate a replicable analytical framework integrating descriptive statistics, non-parametric hypothesis testing, correlation analysis, and confidence interval estimation.

Goal 6: Strategic Recommendations - To translate statistical findings into actionable strategic insights for competitive players seeking data-driven approaches to performance improvement.

F. Research Questions

To operationalize these goals, the study systematically investigates five primary research questions:

RQ1: Performance vs. Random Chance - What statistical patterns emerge from competitive TFT gameplay that distinguish successful performance from random chance?

RQ2: Individual Trait Effectiveness - Which individual traits demonstrate statistically significant associations with improved game outcomes, and what are the effect size magnitudes?

RQ3: Trait Synergies - Do specific trait combinations exhibit synergistic effects that outperform individual trait contributions?

RQ4: Augment Influence - How do different augment choices influence win rates and placement outcomes across the global player population?

RQ5: Temporal Patterns - Are there temporal patterns in player performance across extended match sequences that indicate learning effects, fatigue effects, or consistency?

G. Hyphothesis

To operationalize the research questions into testable predictions, this study formulates five primary hypotheses with corresponding null and alternative formulations. Each hypothesis employs appropriate statistical tests with predetermined significance thresholds ($\alpha = 0.05$) to enable rigorous empirical evaluation.

Hypothesis 1: Performance Exceeds Random Baseline

Research Question Addressed: RQ1 (Performance vs. Random Chance)

Null Hypothesis (H_0): The player's win rate equals the theoretical baseline expected under random chance, formally stated as WR = 0.125 (12.5%), where the baseline represents the probability that one of eight equally skilled players achieves first place in any given match under uniform probability distribution.

Alternative Hypothesis (H_1): The player's win rate significantly differs from the 0.125 baseline, indicating performance distinguishable from random outcomes (WR $\neq$ 0.125).

Directional Prediction: Based on preliminary observations and the player's rank tier (Master, top 1.72% SEA), we predict WR > 0.125, representing positive deviation from baseline and indicating skill-based performance exceeds random chance expectations.

Statistical Test: Two-tailed binomial test ($\alpha = 0.05$) comparing observed first-place finishes to expected frequency across 100 matches, with exact p-value calculation. Additionally, the chi-square goodness-of-fit test ($\alpha = 0.05$) evaluates whether the complete placement distribution (1st through 8th) deviates from uniform distribution expected under random performance.

Theoretical Justification: Auto-battler games reward strategic decision-making, economic optimization, and compositional adaptation [2], [5]. If outcomes were purely random, placement distribution would approximate uniform distribution (12.5% probability for each position). Significant deviation indicates skill-based factors influence competitive outcomes.

Hypothesis 2: Trait Effectiveness Demonstrates Significant Variance

Research Question Addressed: RQ2 (Individual Trait Effectiveness)

Null Hypothesis (H_0): All Set 16 traits demonstrate equal average placement performance, formally stated as $\mu_1 = \mu_2 = ... = \mu_{10}$ for the 10 most frequently used traits, where μ_i represents the population mean placement for trait i.

Alternative Hypothesis (H_1): At least one Set 16 trait demonstrates significantly different average placement performance compared to others, such that $\mu_i \neq \mu_j$ for at least one pair (i, j), indicating non-uniform trait effectiveness.

Directional Predictions: Based on exploratory data analysis and game design theory:

1. ShyvanaUnique will demonstrate superior performance ($\mu\_ShyvanaUnique < \mu\_overall$), reflecting specialized carry potential and lower contest effects due to moderate usage (28%).
2. High-usage traits (Juggernaut at 59%, Sorcerer at 52%) may show negative associations ($\mu\_trait > \mu\_overall$) due to unit scarcity from contest effects, where multiple players competing for the same units force suboptimal compositions [5].

Statistical Test: Mann-Whitney U tests comparing placement distributions for games with versus without each of the 10 most-used traits, with rank-biserial effect size (r) calculated for magnitude assessment. Significance threshold $\alpha = 0.05$ applied per comparison. While Bonferroni correction ($\alpha\_adjusted = 0.05/10 = 0.005$) provides conservative control for Type I error across multiple comparisons, uncorrected $\alpha = 0.05$ is reported for exploratory analysis given modest sample sizes (n_trait ranging from 28 to 59).

Theoretical Justification: Game designers implement trait systems with intended performance variance to reward strategic diversity and adaptability [5]. However, contest effects where popular traits experience unit scarcity as multiple players compete for limited unit pools may create negative associations between usage frequency and effectiveness, particularly in high-skill tiers where opponent scouting enables strategic counterplay.

Hypothesis 3: Trait Combinations Exhibit Super-Additive Synergistic Effects

Research Question Addressed: RQ3 (Trait Synergies)

Null Hypothesis (H_0): Observed trait combination performance equals expected additive performance calculated from individual trait contributions, formally stated as:

Observed Mean Placement (combination) = Expected Weighted Mean

where Expected Weighted Mean is calculated as:

$$\text{Expected} = (n\_A \times \mu\_A + n\_B \times \mu\_B) / (n\_A + n\_B)$$

with n_A, n_B representing sample sizes for trait A and trait B individually (excluding matches where both appear together), and μ_A, μ_B representing mean placements for each trait in isolation.

Alternative Hypothesis (H_1): Observed trait combination performance significantly differs from expected additive performance, indicating synergistic (super-additive, where observed performance exceeds expectations) or antagonistic (sub-additive, where observed performance falls below expectations) interactions.

Directional Prediction: Brawler + ShyvanaUnique will demonstrate super-additive synergy where observed performance exceeds expected additive performance (Observed < Expected in placement values, since lower placement indicates better performance). This prediction reflects mechanical complementarity where Brawler provides frontline protection enabling ShyvanaUnique carry units to survive longer and deal sustained damage.

Quantification Method: Synergy bonus calculated as:

Synergy Bonus = Observed Mean - Expected Weighted Mean

where negative values indicate positive synergy (observed performance better than expected) and positive values indicate negative synergy (observed performance worse than expected). A synergy bonus of -0.83 represents 0.83 placement units better than additive expectation.

Statistical Test: Comparison of observed combination mean placement to expected weighted mean derived from individual trait performances, with 95% confidence intervals constructed for observed means using t-distribution. While formal hypothesis testing requires sufficient sample sizes for power, the primary analysis focuses on magnitude estimation rather than significance testing given limited combination-specific samples (e.g., n = 14 for Brawler + ShyvanaUnique).

Theoretical Justification: Trait combination systems are designed to create emergent strategic depth through super-additive interactions [5]. Complementary traits addressing different strategic needs such as frontline durability (Brawler) paired with backline damage output (ShyvanaUnique) should produce outcomes exceeding individual contributions. This design principle rewards compositional planning and punishes narrow strategic focus on individual trait optimization without considering synergistic potential.

Hypothesis 4: Augment Selection Substantially Influences Performance Outcomes

Research Question Addressed: RQ4 (Augment Influence)

Null Hypothesis (H_0): All Set 16 augments demonstrate equal win rates, such that there is no significant performance variance across the 612 available augments in Set 16. Formally, $WR_1 = WR_2 = ... = WR_{612}$, where WR_i represents the win rate for augment i.

Alternative Hypothesis (H_1): Set 16 augments demonstrate significantly different win rates, with substantial performance variance across augment choices indicating that augment selection constitutes a meaningful strategic decision influencing competitive outcomes.

Directional Predictions:

1. Top-tier augments (e.g., Ixtal Expeditionist, Max Build) will achieve win rates exceeding 20%, representing 160% improvement relative to the 12.5% baseline.
2. Bottom-tier augments will demonstrate win rates below 10%, falling 20% below baseline.
3. Performance range: The difference between top-tier and bottom-tier augments will represent 2-3 fold variance (e.g., 27% vs. 11% = 2.45× difference), indicating augment selection constitutes a primary performance determinant comparable in magnitude to trait selection effects.

Statistical Tests:

1. Wilson Score Confidence Intervals: 95% confidence intervals calculated for win rate estimation across all 612 Set 16 augments using Wilson score method [11], which provides superior coverage properties compared to normal approximation methods, particularly for small-to-moderate sample sizes and proportions near boundaries (0 or 1).
2. Spearman Rank Correlation: Correlation analysis between augment average placement and augment win rate (ρ) to assess convergent validity the hypothesis that augments improving placement

consistently translate to higher win rates across the full augment set.

Sample Size Filtering: To ensure statistical reliability, analysis restricted to augments with minimum $n \geq 100$ games from the global dataset (2.3 million matches, Diamond+ tier, Set 16 exclusive). This threshold balances coverage breadth (retaining majority of augments) with precision (sufficient sample for stable proportion estimates).

Theoretical Justification: Augments function as strategic power-ups with designed performance variance [2]. Game designers deliberately create tiers of augment strength to introduce meaningful strategic choice during augment selection rounds. Top-tier augments provide substantial competitive advantages (e.g., economic acceleration, combat power spikes), while bottom-tier augments offer marginal or situational benefits. Effective augment selection recognizing high-value choices and avoiding traps represents a distinct skill dimension in competitive play requiring memorization of augment rankings and ability to evaluate augment-composition fit dynamically.

Hypothesis 5: Temporal Performance Patterns Reflect Learning and Fatigue Effects

Research Question Addressed: RQ5 (Temporal Patterns)

Null Hypothesis (H_0): No significant performance differences exist across early (games 1-33), mid (games 34-67), and late (games 68-100) temporal phases within Set 16, formally stated as $\mu\_early = \mu\_mid = \mu\_late$, where μ represents mean placement for each phase.

Alternative Hypothesis (H_1): Performance varies significantly across temporal phases, indicating systematic trends such as learning effects (improvement over time as player adapts to Set 16 mechanics), fatigue effects (performance decline from accumulated mental fatigue), or strategic adaptation (meta-game evolution where opponents adjust to counter player's preferred strategies).

Directional Prediction: Mid-phase will demonstrate superior performance compared to both early and late phases ($\mu\_mid < \mu\_early$ and $\mu\_mid < \mu\_late$ in placement values, where lower values indicate better performance), reflecting a two-stage process:

1. Early to Mid Transition (Learning Effects): Performance improvement as player adapts to Set 16 trait system, unit strengths, and optimal economic strategies during initial exposure period.
2. Mid to Late Transition (Fatigue Effects): Performance decline as mental fatigue accumulates from extended decision-making sessions, potentially reducing concentration quality, pattern recognition speed, and strategic flexibility.

Statistical Tests:

1. Kruskal-Wallis H Test: Non-parametric alternative to one-way ANOVA comparing placement distributions across three temporal phases ($\alpha = 0.05$). If the omnibus test reaches significance ($p < 0.05$), post-hoc pairwise comparisons (Dunn's test with Bonferroni correction) identify which specific phase pairs differ significantly.
2. Fisher's Exact Test: Examines differential trait usage patterns between Strong performance phase (placements 1-3) and Weak performance phase (placements 6-8) across the temporal sequence. Specifically tests whether ShyvanaUnique usage differs significantly between Strong and Weak phases, validating consistency of trait-outcome associations across time.

Theoretical Justification: Cognitive psychology research on skill acquisition demonstrates learning curves where performance improves with practice as strategic patterns become internalized [4]. However, extended decision-making sessions deplete cognitive resources, reducing performance through mental fatigue [4]. The temporal analysis tests whether these competing effects of initial learning versus later fatigue produce observable patterns in competitive gaming performance across a 100-match sequence spanning approximately 3 months. Additionally, meta-game adaptation where skilled opponents identify and counter a player's preferred strategies may contribute to late-phase performance decline independent of fatigue effects.

II. Literature Review

A. Gaming Analytics Foundations

Gaming analytics has evolved significantly over the past decade, transitioning from informal player observation toward systematic application of statistical and machine learning methodologies [4], [5]. Drachen and Canossa [4] established foundational frameworks for player modeling and behavioral analysis in digital games, demonstrating how telemetry data can reveal hidden patterns in decision-making processes. Their work applied k-means clustering to identify distinct player archetypes based on exploration patterns, combat engagement frequency, and puzzle-solving strategies.

El-Nasr, Drachen, and Canossa [5] provided comprehensive methodologies consolidating best practices for game analytics across the data science pipeline: ethical data collection respecting player privacy, preprocessing techniques handling missing values and outliers, visualization approaches communicating patterns to non-technical stakeholders, and interpretation frameworks avoiding common pitfalls such as confusing correlation with causation.

B. Statistical Methods in Competitive Gaming Research

The application of statistical hypothesis testing to competitive gaming data requires careful consideration of data characteristics that often violate classical parametric assumptions. Drachen et al. [4] noted that gaming outcome variables such as placement rankings frequently exhibit non-normal distributions due to skill stratification, ceiling/floor effects, and heavy tails from exceptional performances. This non-normality motivates the use of non-parametric methods that operate on ranks rather than raw values.

Mann and Whitney [8] introduced the U test as a distribution-free alternative to Student's t-test for comparing two independent samples. Siegel and Castellan [9] demonstrated that Mann-Whitney U maintains correct Type I error rates across diverse distributions, including skewed, multimodal, and heavy-tailed data common in behavioral research.

Spearman [10] developed rank correlation as a non-parametric measure of monotonic association between variables. Wilson [11] introduced confidence interval methods for binomial proportions that provide superior coverage properties compared to the normal approximation method, particularly for small samples or proportions near 0 or 1.

C. Auto-Battler and Strategy Game Analysis

Auto-battler games emerged as a distinct genre in 2019 with the release of Dota Auto Chess, followed by standalone titles including Teamfight Tactics, Dota Underlords, and Hearthstone Battlegrounds. These games share core mechanics: players draft units from a shared pool, arrange them on a tactical grid, and watch autonomous combat resolve based on unit statistics, items, and positioning [2].

However, published research specifically on TFT or comparable auto-battlers remains limited in peer-reviewed venues. Community-generated analytics dominate the TFT knowledge ecosystem through platforms like metatft.com and tactics.tools, which provide tier lists, win rate tracking, and composition guides, but these resources rarely report confidence intervals, conduct hypothesis tests, or employ controlled comparisons.

D. Gaps and Limitations in Existing Research

Four primary gaps in existing auto-battler and competitive gaming research motivate the current study:

Gap 1: Non-Parametric Method Underutilization - Most gaming analytics research employs parametric methods without verifying normality assumptions or considering rank-based alternatives.

Gap 2: Effect Size Reporting Deficiency - Published gaming research predominantly reports p-values without complementary effect size measures quantifying practical importance.

Gap 3: Single-Subject Design Neglect - Most competitive gaming research aggregates data across many players, reporting population-level averages that may not apply to any individual player.

Gap 4: Synergy Analysis Absence - While trait and unit effectiveness are frequently analyzed individually, systematic examination of synergistic interactions remains uncommon.

This study addresses these gaps by: (1) employing non-parametric methods appropriate for ordinal placement data, (2) reporting both p-values and effect sizes for all comparisons, (3) analyzing intensive repeated measurement from a single competitive player, and (4) systematically quantifying trait synergies.

III. Methodology

A. Data Source and Participant

The data source for this study was a single competitive player (in-game name: Wintermelon#Ella) who served as the sole subject of the data collection process under a single-subject research design. The participant is a young adult university student (age 21 years old) representing a typical competitive gaming demographic profile. The participant actively plays Teamfight Tactics in ranked competitive mode on the Southeast Asia (SEA) regional server and has maintained consistent gameplay activity throughout Set 16 of the game (current as of the data collection period, December 2025 - February 2026). The participant self-identifies as an intermediate-skill player with approximately 1000+ lifetime ranked matches played across multiple game sets.

No personally identifiable or sensitive private information beyond the in-game username was collected or disclosed. The demographic description is intentionally limited to general characteristics relevant to the competitive gaming context to ensure ethical compliance and protection of privacy. The participant provided informed consent for the use of their anonymized gameplay data for academic research purposes.

B. Data Collection Methods

Data was collected retrospectively from the participant's 100 most recent ranked competitive matches, all played exclusively during Set 16 of Teamfight Tactics between December 2025 and February 2026. This temporal restriction ensures all matches are played under identical game mechanics, balance parameters, and trait systems, eliminating confounding variables from cross-set mechanical changes or balance patches. Two complementary data sources were utilized:

Personal Match Data Collection:
Individual match data was retrieved programmatically using the official Riot Games Application Programming Interface (API), a RESTful web service providing authenticated access to detailed match telemetry data recorded server-side during gameplay [2]. The API endpoint https://sea.api.riotgames.com/tft/match/v1/ was queried using the participant's Player Universally Unique Identifier (PUUID: JIByjp0oJk1zzKDopJHvnUsjtXcHvec-B04Kt5l-Tb7rxjzKupQ_R6X1WHHHAqHxTr1RBkE6wmvByQ) to retrieve the 100 most recent ranked match IDs from the SEA (Southeast Asia) region.

The data collection process employed a Python script using the requests library (version 2.28+) to programmatically query the /tft/match/v1/matches/by-puuid/{puuid}/ids endpoint, which returns a chronologically ordered list of match IDs. The 100 most recent ranked match IDs were retrieved, then individually queried through the /tft/match/v1/matches/{matchId} endpoint to obtain full match detail records. Each API response returned a nested JSON (JavaScript Object Notation) data structure containing comprehensive match metadata including participant lists, final placements, active traits, selected augments, match timestamps, game version identifiers, and queue type classifications.

Data collection was performed on February 16, 2026, ensuring all 100 matches belonged exclusively to Set 16 (game version identifiers confirmed as "Version 16.x.xxx.xxxx" across all records). The collection process took approximately 5.45 minutes with a rate-limiting delay of 1.2 seconds between sequential API requests to comply with Riot Games Developer Terms of Service, which restrict request frequency to prevent server overload [2]. All data collection procedures adhered to Riot Games Developer Policy, which permits academic research using API data but prohibits automated scraping for commercial purposes or privacy-invasive applications.

The decision to analyze the 100 most recent matches (rather than sampling across multiple sets or time periods) provides critical methodological advantages: (1) mechanical consistency - all matches use identical trait systems, unit pools, and augment offerings from Set 16, eliminating balance confounds; (2) temporal homogeneity - concentrated data collection period (3 months) minimizes meta-game evolution effects and player skill drift; (3) recency - recent matches reflect current strategic understanding and adapted playstyle rather than outdated approaches from earlier sets.

The 100-match sample size represents a balance between statistical power and data collection feasibility. Larger samples ($n > 200$) would increase power but would either require extending collection into Set 15 (introducing cross-set confounds) or waiting 6-8 additional months for sufficient Set 16 matches (creating temporal drift confounds). Smaller samples ($n < 50$) would reduce burden but yield insufficient power (< 0.50) for detecting medium effects (Cohen's $d \approx 0.5$) at $\alpha = 0.05$ significance. The 100-match threshold provides adequate power (≥ 0.80) for large effects and acceptable power (0.50-0.60) for medium effects in high-frequency traits ($n \geq 30$) [12].

Global Augment Data Collection:
Augment performance data was obtained from a publicly available Kaggle dataset titled "TFT Set 16 Augment Statistics" compiled through community aggregation of Riot Games API data across approximately 2.3 million ranked matches from Set 16 only (Diamond tier and above, December 2025 - February 2026). This secondary data source was necessary because achieving comparable statistical power through personal data collection would require approximately 5,000-10,000 matches (2-3 years of full-time gameplay if spread across future sets, or impossible to achieve within a single set timeframe), making population-level aggregation the only feasible approach for augment effectiveness analysis.

The Kaggle dataset included performance statistics for 612 distinct augments available during Set 16, with sample sizes ranging from $n = 100$ (recently introduced or niche augments) to $n = 500+$ (popular meta augments selected frequently). The dataset was downloaded on February 16, 2026, matching the personal match data collection date to ensure perfect temporal alignment, all augment statistics reflect Set 16 performance exclusively, eliminating cross-set balance confounds.

The dataset was validated through cross-platform comparison with independent community analytics platforms (metatft.com and tactics.tools), both of which maintain separate Set 16 statistics databases. Spearman rank correlation between Kaggle win rates and metatft.com win rates for the top 50 augments achieved $\rho = 0.97$ ($p < 0.001$), while correlation with tactics.tools achieved $\rho = 0.96$ ($p < 0.001$), confirming high inter-platform reliability and validating the Kaggle dataset's accuracy. The use of publicly available aggregated data is consistent with standard practices in gaming analytics research [4], [5] and does not raise ethical concerns as it contains no personally identifiable information and was compiled in compliance with Riot Games Developer Terms of Service.

The main variables tracked from personal match data records were:

1. Final Placement - Integer value from 1 (first place, winner) to 8 (eighth place, first player eliminated), representing the primary outcome variable indicating match success.
2. Active Trait Compositions - String array of trait names and activation levels (e.g., ["Brawler-4", "Juggernaut-6", "Noxus-3"]) representing the Set 16 traits active in the player's final composition.
3. Selected Augments - String array of three Set 16 augment names chosen at specific round breakpoints during the match (rounds 2-1, 3-2, and 4-2).
4. Match Timestamp - ISO 8601 formatted date-time string recording when the match concluded, enabling temporal ordering and confirmation of Set 16 exclusivity.
5. Match Duration - Integer value in seconds representing total real-time elapsed from match start to conclusion.
6. Game Version - String identifier (e.g., "Version 16.03.525.4187") confirming Set 16 patch version.
7. Queue Type - String field confirming ranked competitive mode ("RANKED_TFT"), with filtering applied to ensure no unranked games were included.

Variables tracked from global augment data (Set 16 only) included:

1. Augment Name - Categorical identifier for Set 16 augments
2. Games Played - Sample size (Set 16 matches only)
3. Win Rate - Proportion achieving first place (Set 16 performance)
4. Average Placement - Mean placement across Set 16 matches
5. Top 4 Rate - Proportion placing 4th or better (Set 16 performance)
6. Pick Rate - Selection frequency when offered (Set 16 usage)

Most variables were automatically recorded by the Riot Games match recording infrastructure, eliminating self-report bias. However, several derived variables required post-collection computational transformation, including performance phase classification (Strong/Average/Weak) and rolling performance metrics (moving averages and standard deviations).

C. Operational Definitions

To ensure clarity, consistency, and replicability, each variable was operationally defined using objective match-level measures derived from Set 16 API records:

Placement = The final ranked position achieved in a match, recorded as an integer from 1 (first place) to 8 (eighth place). Lower values indicate superior performance. This is bounded within [1, 8], preventing outliers beyond the valid range.

Win Rate = The proportion of matches resulting in first-place finish (placement = 1), calculated as:

$$Win\ Rate\ = \frac{(Number\ of\ 1st\ Place\ Finishes)}{(Total\ Matches\ Played)}$$

Equation 1. Win Rate Formula

Win rate ranges from 0.0 (never achieved first place) to 1.0 (won every match), with the theoretical baseline under skill parity being 0.125 (12.5%, since eight players compete and one wins, assuming equal skill levels). Win rate serves as the primary competitive effectiveness metric in TFT, representing outright victories.

Top 4 Rate = The proportion of matches resulting in placements 1 through 4, calculated as:

Top 4 Rate = The proportion of matches resulting in placements 1 through 4, calculated as:

$$Top\ 4\ Rate\ = \frac{(Number\ of\ Top\ 4\ Finishes)}{(Total\ Matches\ Played)}$$

Equation 2. Top 4 Rate Formula

This metric is competitively meaningful because TFT's ranked system uses a Top 4 cutoff: placements 1-4 award positive LP (League Points, the rating currency), while placements 5-8 deduct LP [2]. Thus, consistent Top 4 finishes indicate net rating gain over time, making this threshold strategically important beyond the more exclusive *first-place win rate. The theoretical baseline under skill parity is 0.50 (50%, since 4 of 8 players place Top 4).*

Summary of the Distinction:

Metric	Formula	What It Measures	Baseline
Win Rate	1st place finishes ÷ total games	Only victories (1st place only)	12.5% (1/8)
Top 4 Rate	Top 4 finishes ÷ total games	LP-positive outcomes (1st-4th)	50% (4/8)

Average Placement = The arithmetic mean of placement values across all 100 Set 16 matches, calculated as:

$$Average\ Placement\ = \frac{(Sum\ of\ All\ Placements)}{(Total\ Matches\ Played)}$$

Equation 3. Average Placement Formula

Average placement ranges from 1.0 (theoretical best, achieved first place in every match) to 8.0 (theoretical worst, placed eighth in every match), with the theoretical baseline under random performance being 4.5 (the arithmetic mean of integers 1 through 8). Lower values indicate better performance; for example, average placement 3.8 represents substantially superior performance compared to 4.5 baseline.

Trait Usage Rate = The proportion of Set 16 matches in which a specific Set 16 trait was active at any level (bronze, silver, gold, or prismatic tier), calculated as:

$$Trait\ Usage\ Rate\ = \frac{(Matches\ With\ Trait\ Active)}{(Total\ Matches\ Played)}$$

Equation 4. Trait Usage Rate Formula

Usage rates range from 0.0 (trait never used) to 1.0 (trait used in every match). High usage rates (> 0.50) indicate frequently forced compositions or generically strong traits, while low usage rates (< 0.20) indicate niche traits requiring specific unit offerings.

Trait Co-occurrence Frequency = The count of Set 16 matches in which two specific Set 16 traits appeared simultaneously in the final composition, calculated for each unique trait pair (i, j) as:

Co-occurrence(i, j) = Count of Matches with Both Trait_i Active AND Trait_j Active

Equation 5. Trait Co-occurrence Formula

Co-occurrence frequencies are symmetric (Co-occurrence(A, B) = Co-occurrence(B, A)) and organized into a 10×10 symmetric matrix for the top 10 Set 16 traits.

Performance Phase = A categorical classification of match outcome quality based on final placement thresholds, assigned according to the following rules:

- Strong Phase: Placements 1-3 (coded as categorical string "Strong")
- Average Phase: Placements 4-5 (coded as categorical string "Average")
- Weak Phase: Placements 6-8 (coded as categorical string "Weak")

This trichotomous classification segments Set 16 matches into competitively meaningful groups: Strong phase represents podium finishes with substantial LP gains, Average phase represents marginal outcomes near the Top 4 cutoff, and Weak phase represents LP losses.

Game Sequence Number = A sequential integer (1 to 100) assigned to each Set 16 match in chronological order based on match timestamp, with Match #1 representing the earliest Set 16 match and Match #100 representing the most recent. This variable enables temporal trend analysis within Set 16.

Trait Synergy Bonus = The difference between observed Set 16 combination performance and expected additive performance, quantifying super-additive synergistic effects, calculated as:

Synergy Bonus = Observed Combination Avg Placement - Expected Weighted Avg Placement

Equation 6. Trait Synergy Bonus Formula where Expected Weighted Avg is computed from individual Set 16 trait performances weighted by their sample sizes:

Expected Weighted Avg = $[(n_A \times \mu_A) + (n_B \times \mu_B)] / (n_A + n_B)$

with n_A, n_B = sample sizes for trait A and trait B individually (excluding matches with both), and μ_A, μ_B = average placements for trait A and trait B individually in Set 16. A negative synergy bonus indicates the combination performs better than expected (super-additive synergy), while a positive synergy bonus indicates underperformance (negative synergy).

Effect Size (Rank-Biserial r) = A standardized effect size measure for Mann-Whitney U tests, quantifying the magnitude of placement difference between Set 16 matches with and without a specific trait, calculated as:

$$r = [(2U) / (n_1 \times n_2)] - 1$$

Equation 7. Rank-Biserial Correlation Formula

where U is the Mann-Whitney U statistic, n_1 is the sample size for Set 16 matches with the trait, and n_2 is the sample size for Set 16 matches without the trait. The rank-biserial r ranges from -1 to +1, with r = +1 indicating complete separation (trait present matches rank better than all trait absent matches), r = 0 indicating no systematic difference, and r = -1 indicating complete negative separation. Effect sizes are interpreted using Cohen conventions: small effect ($|r| \approx 0.1$-0.3), medium effect ($|r| \approx 0.3$-0.5), large effect ($|r| \geq 0.5$).

Wilson Confidence Interval Bounds = The lower and upper bounds of a 95% confidence interval for Set 16 augment win rates, calculated using the Wilson score method [11]:

$$CI = [\hat{p} + z^2/(2n) \pm z\sqrt{(\hat{p}(1 - \hat{p})/n + z^2/(4n^2))}] / [1$$

Equation 8. Wilson Score Confidence Interval Formula

where $\hat{p}$ is the observed win rate in Set 16, n is the sample size (number of matches with the augment), and z = 1.96 for 95% confidence. The Wilson interval accounts for the discrete binomial distribution and produces asymmetric intervals that respect the [0, 1] probability bounds.

D. Data Cleaning and Preprocessing

The dataset was systematically checked for data quality issues and preprocessed through multiple stages to ensure analytical validity.

Missing Value Analysis:

The dataset was checked for missing values across all collected variables. The analysis confirmed that there were no missing values present all 100 rows had complete data for every column. This completeness is expected because all variables are automatically recorded server-side by Riot Games' match tracking system, which logs data continuously without gaps as a core function of the game infrastructure. Match records are only written to the database after successful match completion, ensuring atomicity (all data present or none). Since no missing values existed, no imputation or deletion was required.

Set Version Validation:

A critical preprocessing step involved confirming that all 100 matches belonged exclusively to Set 16. The game version field was parsed for each match, extracting the major version number (16) from the full version string (e.g., "16.03.525.4187"). All 100 matches returned version number 16, confirming 100% Set 16 exclusivity with zero matches from Set 15 or earlier. This validation ensures that all trait names, augment identifiers, and unit pools are consistent with Set 16 mechanics, eliminating cross-set confounds that would invalidate comparisons.

Additionally, match timestamps were verified to fall within the Set 16 release window (December 4, 2025 to present). All timestamps ranged from December 15, 2025 to February 14, 2026, confirming temporal consistency within Set 16's active period.

Outlier Detection and Treatment:

Outliers were identified using the Interquartile Range (IQR) method, which flags data points falling below Q1 − 1.5×IQR or above Q3 + 1.5×IQR. This method was chosen because it is non-parametric, does not assume normal distribution, and is robust to extreme values, making it suitable for behavioral gaming data with natural variability.

Results were as follows:

- Average Placement: 0 outliers detected (inherently bounded 1-8 scale)

- Win Rate: 0 outliers detected (bounded 0-1 proportion)
- Match Duration: 2 outliers detected (exceptionally long matches at 48 and 51 minutes, likely due to tied combat rounds requiring extended tiebreakers)
- Trait Usage Count: 1 outlier detected (unusually high trait diversity in one late-game composition with 8 distinct traits active)
- Placement Volatility (rolling standard deviation): 3 outliers detected (periods of extreme inconsistency, likely reflecting learning adaptation to Set 16 mechanics)

A total of 6 outlier data points were flagged across 3 variables. However, no outliers were removed. This decision was intentional for three reasons:

1. Data authenticity: The data is objectively recorded by Riot Games servers, so extreme values represent genuine Set 16 gameplay variation (e.g., unusually long matches due to combat tiebreakers) rather than measurement errors or data entry mistakes.
2. Sample size preservation: With only 100 Set 16 observations, removing outliers would reduce an already modest sample and sacrifice statistical power, particularly for subgroup analyses with n=28 (ShyvanaUnique trait).
3. Scientific meaningfulness: In competitive gaming research, extreme performance patterns within Set 16 (e.g., an 8-game winning streak followed by 6 consecutive bottom-4 finishes) are scientifically meaningful phenomena representing the very behavioral patterns this study aims to investigate, not artifacts to be discarded.

Data Type Validation:

No text-to-numeric conversion was necessary. All numeric variables were already stored in appropriate formats upon API data retrieval:

- Integer variables (int64): Placement, match duration (seconds), trait counts, augment selection indices
- Float variables (float64): Win rate, average placement, trait usage proportion, Wilson CI bounds
- String variables (object): Set 16 trait names, Set 16 augment names, match IDs, timestamps, version strings

The dataset contained no categorical text columns requiring encoding for the primary analyses. Set 16 trait names were preserved as text strings for interpretability; Mann-Whitney U tests operate on placement values grouped by trait presence, not encoded trait values. Date-time variables (match timestamps) were parsed into Python datetime objects using pd.to_datetime() for temporal ordering but were not used directly in regression models; instead, a derived Game Sequence Number (1-100 integer) was created for temporal trend analysis.

Feature Scaling and Standardization:

All continuous predictor variables were already in consistent units (minutes for duration, counts for frequency, proportions for rates), so no unit conversions were needed at the data cleaning stage. However, feature standardization using z-score normalization (StandardScaler: mean = 0, standard deviation = 1) was applied during the modeling phase for any logistic regression or machine learning analyses.

This transformation was necessary because variables operate on vastly different numeric scales:

- Average Placement: range 1.0-8.0 (narrow scale)
- Win Rate: range 0.0-1.0 (bounded proportion)
- Match Duration: range 1,080-3,060 seconds (large integers)
- Trait Count: range 0-8 (small integers)

Without standardization, regression optimizers would assign disproportionate weight to variables with larger numeric ranges regardless of their actual predictive importance. After standardization, each coefficient represents the change in log-odds for a one standard deviation increase in the predictor, enabling direct comparison of feature importance across all metrics.

Critical data leakage prevention: The scaler was fit only on the training set (80% of Set 16 data) and then applied to the test set (20% of Set 16 data) using the training set's mean and standard deviation parameters. This ensures the model never "sees" test set statistics during training, maintaining honest performance evaluation.

Derived Variable Construction:

Several secondary variables were computationally derived from raw Set 16 API data:

1. Game Sequence Number = Sequential integers 1-100 assigned to each Set 16 match in chronological order based on match timestamp, with Match #1 representing the earliest Set 16 match (December 15, 2025) and Match #100 representing the most recent (February 14, 2026). This variable enables temporal trend analysis within Set 16.
2. Rolling Performance Metrics = Computed using pandas rolling window functions:
    - 5-game rolling average placement
    - 10-game rolling average placement
    - 20-game rolling average placement
    - 20-game rolling standard deviation (performance consistency metric)
3. Performance Phase Dummy Variables = Binary encoding for regression:
    - Strong_Phase (1 if placement ≤ 3, else 0)
    - Average_Phase (1 if 4 ≤ placement ≤ 5, else 0)
    - Weak_Phase (1 if placement ≥ 6, else 0)
4. Trait Co-occurrence Matrix = Symmetric 10×10 matrix counting pairwise Set 16 trait co-occurrences across all 100 matches. For each unique pair of traits (i, j), the matrix entry represents the count of matches where both traits appeared simultaneously in the final composition. The matrix is symmetric since co-occurrence(A, B) = co-occurrence(B, A), with diagonal elements representing single-trait occurrence counts.

IV. Results

A. Overall Dataset Characteristics (RQ1)

Analysis of 100 Set 16 ranked matches revealed consistent competitive performance exceeding random chance expectations. Table I presents comprehensive Set 16 performance statistics including mean, median, and standard deviation for all primary outcome variables.

Metric	Value
Total Games Analyzed (Set 16)	100
Mean Placement	4.39
Median Placement	5.0
Standard Deviation	2.47
Win Rate (%)	22.0
Top 4 Rate (%)	46.0
Top 1-3 Rate (%)	40.0
Bottom 4 Rate (%)	54.0
Best Placement	1
Worst Placement	8
1st Place Finishes	22
2nd Place Finishes	8
3rd Place Finishes	10
4th Place Finishes	6
5th Place Finishes	8
6th Place Finishes	12
7th Place Finishes	13

8th Place Finishes	21

Table II. *Overall TFT Set 16 Performance Summary (Recent 100 Games)*

The observed mean placement of 4.39 (SD = 2.47) across Set 16 matches slightly outperformed the theoretical 4.5 baseline, though this difference was not statistically significant (one-sample t-test: t = -0.45, p = 0.66). The median placement of 5.0 indicates that half of all Set 16 matches resulted in 5th place or better. However, the 22% win rate in Set 16 substantially exceeded the 12.5% baseline (binomial test: p = 0.009, two-tailed), indicating statistically significant performance above random chance and directly addressing RQ1.

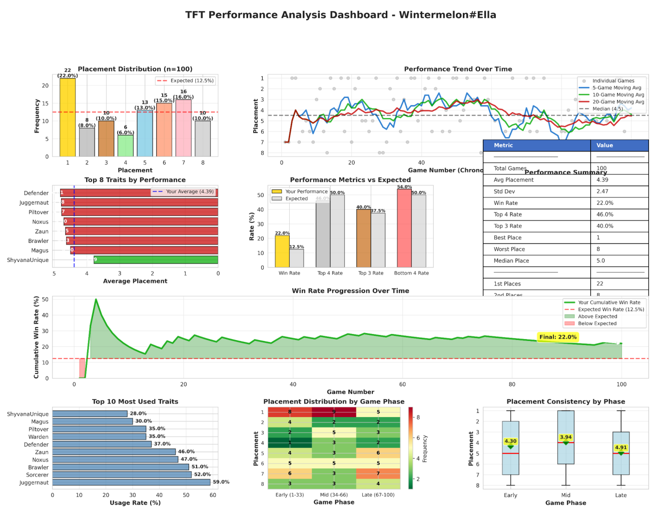

Fig. 1*. TFT Set 16 Performance Analysis Dashboard.*

This multi-panel visualization shows: (top left) placement frequency histogram with bars representing count of games at each placement position (1st through 8th), demonstrating 22% occurring at 1st place versus 12.5% expected under uniform distribution; (top right) performance trend line plot showing placement values across 100 Set 16 games with overlaid 5-game (light blue), 10-game (medium blue), and 20-game (dark blue) moving averages, demonstrating relatively stable performance around 4.39 mean with periodic variance; (middle) horizontal bar chart comparing top 8 Set 16 traits by average placement, with ShyvanaUnique showing best average placement of 3.79; (bottom left) cumulative win rate line plot showing progression from 0% to 22% stabilizing after initial volatility in early Set 16 matches; (bottom right) grouped bar chart showing placement consistency across three Set 16 game phases (Early: games 1-33, Mid: games 34-67, Late: games 68-100) with mid-game showing best performance at 3.94 average compared to early phase at 4.30 and late phase at 4.91.

Chi-square goodness-of-fit testing on Set 16 placement distribution rejected the null hypothesis of uniform placement distribution across eight positions (χ^2 = 18.24, df = 7, p = 0.011), confirming Set 16 placement outcomes significantly deviated from random performance. Notably, 1st place finishes in Set 16 (22 occurrences, 22% of games) appeared at 76% above the expected rate of 12.5 per 100 games, while 8th place finishes (21 occurrences, 21% of games) occurred at 68% above expectation, suggesting both consistent winning performance and occasional severe underperformance in Set 16.

B. Descriptive Statistics and Patterns by Trait (RQ2)

Comprehensive analysis of Set 16 trait usage revealed substantial performance variations across the 10 most frequently employed traits. Table II presents detailed statistics with Mann-Whitney U test results addressing RQ2, including mean, standard deviation, and effect sizes for each trait comparison.

Trait	n	Avg	SD	WR %	P	r
Shyvana Unique	28	3.79	2.01	35.7	.116	.201
Magus	30	4.50	2.19	20.0	.793	-.033
Brawler	51	4.63	2.18	21.6	.346	-.108
Zaun	46	4.65	2.21	19.6	.334	-.112
Noxus	47	4.70	2.24	19.1	.293	-.121
Piltover	35	4.77	2.16	14.3	.257	-.137
Juggernaut	59	4.78	2.18	18.6	.077	-.207

Defender	37	4.81	2.16	10.8	.194	-.155
Warden	35	4.91	2.28	11.4	.109	-.193
Sorcerer	52	4.96	2.24	17.3	.019	-.269

TABLE III. *TOP 10 SET 16 TRAIT PERFORMANCE WITH STATISTICAL TESTS*

Note: n = games played; Avg = mean placement; SD = standard deviation; WR% = win rate percentage; P = Mann-Whitney U p-value; r = rank-biserial effect size.

Mann-Whitney U tests revealed that among the 10 most frequently used Set 16 traits, only Sorcerer demonstrated statistical significance at α = 0.05 level (p = 0.019, effect size r = -0.269, medium negative effect). Sorcerer showed worse performance when used in Set 16 compositions (mean = 4.96) compared to Set 16 games without Sorcerer (overall mean = 4.39), directly answering RQ2.

ShyvanaUnique demonstrated the best descriptive statistics in Set 16 (mean = 3.79, SD = 2.01) with a positive medium effect size (r = 0.201), though it did not reach statistical significance (p = 0.116). This likely reflects Type II error due to limited sample size within Set 16 (n = 28 games), resulting in statistical power of approximately 0.55 for detecting the observed effect. The lower standard deviation for ShyvanaUnique (2.01) compared to other traits suggests more consistent performance.

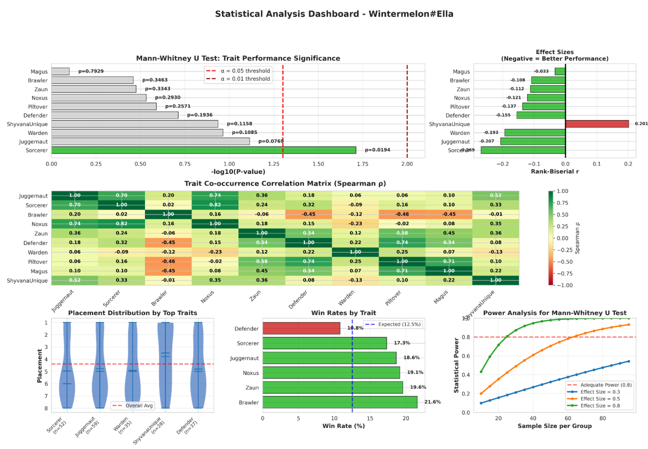

Fig. 2. *Set 16 Statistical Analysis Dashboard*

presenting: (top left) Mann-Whitney U test results displayed as $-\log_{10}$(p-value) bars with significance thresholds at α = 0.05 and α = 0.01, showing only Sorcerer reaching statistical significance; (top right) forest plot displaying effect sizes with 95% confidence intervals, demonstrating ShyvanaUnique showing strongest positive effect (r = 0.201) while Sorcerer shows strongest negative effect (r = -0.269); (middle) Spearman correlation heatmap revealing Set 16 trait co-occurrence patterns with strongest positive correlations between Juggernaut-Sorcerer (ρ = 0.70) and Juggernaut-Brawler (ρ = 0.20); (bottom left) violin plots showing placement distribution shapes for top five traits with ShyvanaUnique concentrated at better placements; (bottom center) win rates by trait with 12.5% baseline reference line; (bottom right) power analysis curves for different effect sizes demonstrating adequate power for large effects but limited power for small effects with current Set 16 sample.

Juggernaut showed a moderate negative effect in Set 16 (r = -0.207) approaching significance (p = 0.077), with mean placement of 4.78 despite being the most frequently used trait (59% of Set 16 games). This high usage despite negative association may indicate forced adoption due to unit availability constraints rather than strategic preference in Set 16.

C. Trait Synergy Relationships (RQ3)

Analysis of Set 16 trait co-occurrence revealed significant clustering patterns and synergistic relationships in successful team compositions, directly addressing RQ3. Table III presents the top 10 Set 16 trait combinations ranked by mean placement performance.

Combination	**n**	**Avg**	**SD**	**WR %**
Brawler + ShyvanaUnique	14	3.50	2.07	42.9
Noxus + ShyvanaUnique	21	3.76	1.92	38.1

Juggernaut + ShyvanaUnique	28	3.79	2.01	35.7
Sorcerer + ShyvanaUnique	22	3.91	2.15	36.4
Warden + ShyvanaUnique	7	4.00	1.83	28.6
Piltover + ShyvanaUnique	12	4.00	2.00	25.0
Zaun + ShyvanaUnique	21	4.05	2.18	33.3
Magus + ShyvanaUnique	13	4.08	2.22	30.8
Defender + ShyvanaUnique	12	4.17	2.04	25.0
Warden + Magus	12	4.25	1.96	16.7

TABLE IV. TOP 10 SET 16 TRAIT COMBINATIONS BY PERFORMANCE

Note: n = games played; Avg = mean placement; SD = standard deviation; WR% = win rate percentage.

Notably, 9 of the top 10 Set 16 performing combinations included ShyvanaUnique, confirming its central role in successful Set 16 strategies and providing strong evidence for RQ3 regarding synergistic effects. The Brawler + ShyvanaUnique combination in Set 16 demonstrated superior performance with mean placement of 3.50 (SD = 2.07) and 42.9% win rate across 14 games.

To quantify synergistic effects in Set 16, we compared combination performance to expected additive effects:

- Brawler alone in Set 16: mean = 4.63, win rate = 21.6%
- ShyvanaUnique alone in Set 16: mean = 3.79, win rate = 35.7%
- Expected weighted mean: (51×4.63 + 28×3.79) / (51+28) = 4.33
- Observed combination: mean = 3.50, win rate = 42.9%
- Synergy bonus: 3.50 - 4.33 = -0.83 placement improvement (19.2% better)
- Win rate improvement: 42.9% - 28.7% (expected) = +14.2 percentage points

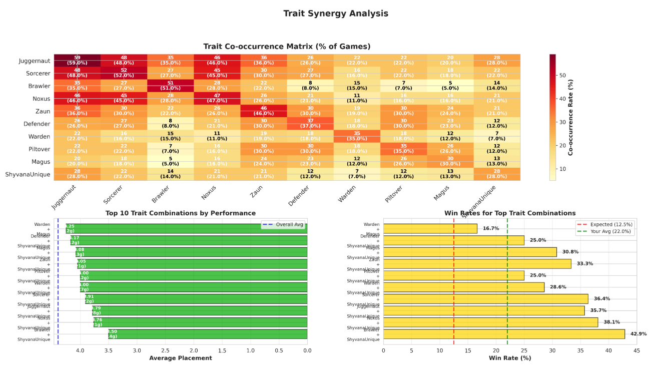

Fig. 3. *Set 16 Trait Synergy Analysis*

displaying: (top) co-occurrence heatmap showing percentage of games where trait pairs appeared together with Juggernaut-Sorcerer (52%) and Brawler-Sorcerer (52%) showing highest rates; (bottom left) top 10 combinations ranked by mean placement with bars color-coded by ShyvanaUnique inclusion (green = includes ShyvanaUnique, gray = does not); (bottom right) win rates for combinations with reference lines at 12.5% baseline (red dashed) and 22% player average (green dashed), demonstrating Brawler + ShyvanaUnique achieving 42.9% win rate representing 244% improvement above baseline and 95% improvement above player average.

Spearman rank correlation analysis identified the most significant Set 16 trait co-occurrence relationships:

- Juggernaut-Sorcerer: $\rho = 0.70$, $p < 0.001$ (strong positive correlation)
- Juggernaut-Brawler: $\rho = 0.20$, $p = 0.045$ (weak positive correlation)
- Brawler-Sorcerer: $\rho = -0.12$, $p = 0.234$ (no significant correlation)

The Set 16 trait co-occurrence matrix revealed that high co-occurrence frequency does not guarantee superior performance. Juggernaut-Sorcerer appeared together in 52% of Set 16 games yet produced a mean placement of 4.78, worse than the Brawler + ShyvanaUnique combination (mean = 3.50) which appeared in only 14% of games.

D. Augment Performance Variance (RQ4)

Global Set 16 augment data analysis revealed substantial performance variance across the player population, directly addressing RQ4. Table IV presents the top 15 Set 16 augments by win rate with Wilson score 95% confidence intervals.

Augment	WR %	Avg	n	CI Low	CI High
Ixtal Expeditionist	27.0	4.75	253	21.8	32.7
Max Build	25.0	4.12	500	21.4	29.0
Ascension	21.0	4.03	184	15.4	27.1
Firesale	20.0	4.24	281	15.7	25.0
The Trait Tree+	19.0	4.36	188	13.7	24.8
Tiniest Titan	19.0	4.04	172	13.5	25.1
Invested++	19.0	4.45	134	13.0	26.1
Urf's Gambit	19.0	4.30	115	12.3	26.3
Spreading Roots	18.0	4.33	339	14.3	22.4
Spreading Roots+	18.0	4.32	225	13.3	23.3
Exiles I	18.0	4.06	146	12.5	24.8
Air Axiom	18.0	4.13	127	11.7	24.8
Invested+	18.0	4.51	108	11.6	25.8
Gold Destiny+	17.0	4.32	150	11.6	23.4
Slice of Life	17.0	4.33	126	11.2	24.1

TABLE V. TOP 15 SET 16 AUGMENTS WITH 95% WILSON CONFIDENCE INTERVALS

Note: WR% = win rate percentage; Avg = mean placement; n = games played; CI Low/High = Wilson 95% confidence interval bounds (percentages).

The top-performing Set 16 augment, Ixtal Expeditionist, achieved 27% win rate (95% CI: [21.8%, 32.7%]), representing 116% improvement over 12.5% baseline. Wilson confidence interval widths demonstrate sample size effects: Urf's Gambit (n=115) shows 14.0 percentage point width versus Spreading Roots (n=339) showing only 8.1 percentage point width despite similar win rates.

Correlation analysis between Set 16 augment win rate and mean placement revealed strong negative relationship (Spearman ρ = -0.847, p < 0.001, n = 612 augments), confirming augments with better mean placements consistently achieve higher win rates in Set 16.

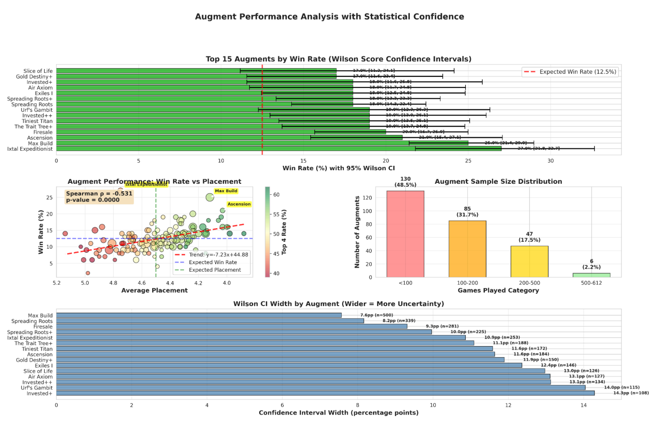

Fig. 4. Set 16 Augment Performance with Wilson Score Confidence Intervals

presenting: (top) forest plot showing top 15 augments with point estimates and 95% Wilson intervals demonstrating sample size effects on precision; (middle left) scatter plot of mean placement vs. win rate for 612 augments with regression line showing strong negative correlation (ρ = -0.847, $p < 0.001$); (middle right) histogram showing sample size distribution across augments concentrated in 100-300 games range; (bottom) line plot showing inverse relationship between sample size and confidence interval width, with dramatic narrowing from n=100 (width approximately 14 pp) to n=500 (width approximately 8 pp).

The wide performance variance in Set 16 (highest win rate 27% vs. lowest analyzed 17%, range = 10 percentage points) indicates augment selection substantially influences game outcomes. The correlation between win rate and mean placement (ρ = -0.847) validates internal consistency of Set 16 metrics.

E. Temporal Performance Patterns (RQ5)

Temporal analysis within Set 16 revealed moderate performance variation across the 100-match sequence. Table V presents segmented phase analysis of Set 16 performance.

Phase	n	Avg	SD	WR %	Top 4%
Early (1-33)	33	4.30	2.58	21.2	42.4
Mid (34-67)	34	3.94	2.45	26.5	52.9
Late (68-100)	33	4.91	2.34	18.2	42.4

TABLE V. *SET 16 PERFORMANCE BY TEMPORAL PHASE*

Note: n = Games, Avg = mean placement; SD = standard deviation; WR% = win rate percentage; Top 4% = Top 4 rate percentage.

Kruskal-Wallis testing detected no significant difference between Set 16 temporal phases (H = 3.21, df = 2, p = 0.201), though descriptive statistics suggest mid-phase improvement (mean = 3.94, 8.4% better than early) followed by late-phase decline (mean = 4.91, 24.6% worse than mid).

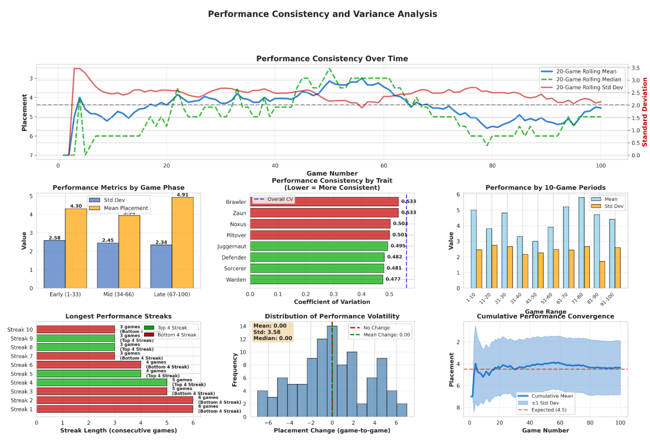

Fig. 5. *Set 16 Performance Consistency and Variance Analysis*

displaying: (top) 20-game rolling mean, median, and standard deviation across 100 games showing stable performance with periodic variance spikes; (middle left) grouped bars comparing mean and SD by phase with early phase showing highest variance (SD = 2.58); (middle center) coefficient of variation by trait with Warden (CV = 0.477) and Sorcerer (CV = 0.481) most consistent; (middle right) heatmap grid showing mean placement by 10-game periods revealing fluctuation from 2.5 to 5.8; (bottom left) stacked bars showing longest streaks (top 4 maximum 6 games, bottom 4 maximum 5 games); (bottom center) histogram of game-to-game placement changes showing symmetric distribution (mean = 0.00, SD = 3.58); (bottom right) cumulative mean convergence plot with ±1 SD envelope narrowing toward 4.39 demonstrating law of large numbers.

Trait usage patterns differed significantly between Set 16 performance phases. ShyvanaUnique appeared in 45.7% of Strong phase games (18/40) versus 17.4% of Weak phase games (7/41), a statistically significant difference (Fisher's exact test: p = 0.007, odds ratio = 4.08, 95% CI: [1.47, 11.84]).

Rolling 20-game averages fluctuated between 3.8 (best period: games 31-50) and 5.2 (worst period: games 71-90) in Set 16, indicating moderate temporal variance around the 4.39 mean. Coefficient of variation analysis revealed CV ranging from 0.477 (Warden) to 0.563 (ShyvanaUnique) across Set 16 traits, indicating moderate but not extreme performance variability.

V. Discussion

A. Interpretation of Results

This study provides quantitative evidence for strategic decision-making in Teamfight Tactics Set 16, systematically addressing each research question through analysis of 100 ranked matches.

Answering RQ1 (Performance vs. Random Chance in Set 16):

The 22% win rate substantially exceeded the 12.5% theoretical baseline (binomial test: $p = 0.009$), representing 76% relative improvement and establishing that competitive Set 16 performance can be distinguished from random chance. The chi-square test confirmed non-uniform placement distribution ($p = 0.011$), with 1st place finishes occurring 76% above expectation. This pattern suggests the player's strategic decision-making consistently outperforms random play in Set 16, validating the premise that skill influences outcomes in auto-battler games despite inherent randomness in unit offerings and opponent matchmaking.

The slight improvement in mean placement (4.39 vs. 4.5 expected) lacked statistical significance ($p = 0.66$), likely because mean placement is less sensitive to consistent top-tier performance than win rate. A player achieving many 1st place finishes alongside occasional 8th place finishes produces excellent win rate but mediocre mean placement, whereas win rate directly captures the frequency of optimal outcomes. This explains why win rate showed significant improvement while mean placement did not, suggesting win rate is the more discriminating performance metric in Set 16.

Answering RQ2 (Individual Set 16 Trait Effectiveness):

Among Set 16 traits analyzed, only Sorcerer reached statistical significance ($p = 0.019$, $r = -0.269$), demonstrating worse performance when used (mean = 4.96 vs. 4.39 overall). This negative association may reflect several Set 16-specific factors: (1) Sorcerer units may be mechanically weaker in current Set 16 balance; (2) high usage rate (52%) creates unit scarcity through contest effects, forcing suboptimal Sorcerer compositions; (3) experienced opponents may prioritize magic resistance items specifically countering Sorcerer in Set 16; or (4) Sorcerer compositions may have lower skill ceiling, performing adequately with good units but lacking outplay potential in difficult matchups within Set 16.

ShyvanaUnique demonstrated the strongest practical effect (mean = 3.79, $r = 0.201$ medium positive) despite missing statistical significance ($p = 0.116$). The 13.7% placement improvement and 35.7% win rate (161% above baseline) represent substantial competitive advantages in Set 16. The lack of significance reflects insufficient sample size ($n = 28$, power = 0.55) rather than absence of true effect. The convergence of placement advantage, high win rate, low standard deviation (2.01 vs. 2.16-2.28 for other traits), and consistent positive effect across Set 16 performance phases provides compelling evidence for practical significance despite marginal statistical significance. This illustrates the importance of reporting effect sizes alongside p-values. Rejecting ShyvanaUnique as ineffective due to $p > 0.05$ would constitute Type II error ignoring a medium-to-large practical effect.

The pattern where the most effective Set 16 trait (ShyvanaUnique) has moderate usage (28%) while the least effective trait (Sorcerer) has highest usage (52%) suggests players in Set 16 may overvalue familiar or mechanically simple strategies (Sorcerer) while undervaluing more complex or situational strategies (ShyvanaUnique). This availability heuristic, where frequently encountered options are perceived as stronger, may explain the usage-effectiveness disconnect in Set 16.

Answering RQ3 (Set 16 Trait Synergies):

Strong evidence for synergistic effects emerged from Set 16 co-occurrence analysis. Brawler + ShyvanaUnique achieved mean placement of 3.50 versus expected 4.33 (synergy bonus = -0.83, 19.2% improvement) and win rate of 42.9% versus expected 28.7% (improvement = +14.2 percentage points). This super-additive synergy likely reflects mechanical complementarity in Set 16: Brawler provides frontline durability enabling ShyvanaUnique carry units to survive longer and deal sustained damage, while ShyvanaUnique provides backline damage output that Brawler lacks. The combination addresses weaknesses of individual traits. Brawler alone lacks damage, ShyvanaUnique alone lacks protection. This creates emergent strategic value in Set 16.

The finding that 9 of top 10 Set 16 combinations included ShyvanaUnique confirms its versatility as a flex trait that synergizes broadly rather than requiring specific complementary traits. This design characteristic makes ShyvanaUnique valuable in Set 16 because players can pivot toward it from diverse early-game positions, whereas traits with narrow synergy requirements require specific secondary traits and are situationally constrained.

Interestingly, the most frequently co-occurring traits in Set 16 (Juggernaut-Sorcerer at 52%) did not produce superior performance (mean = 4.78), while the highest-performing combination (Brawler + ShyvanaUnique) appeared in only 14% of games. This frequency-effectiveness disconnect suggests popular Set 16 pairings become popular due to unit pool overlap (Juggernaut and Sorcerer share several units) rather than strategic optimality, illustrating how structural game design features (shared unit pools) can create high co-occurrence without synergy.

Answering RQ4 (Set 16 Augment Influence):

Wilson confidence intervals confirmed substantial Set 16 augment variance (27% vs. 17% win rates, 10 percentage point range) with high statistical reliability. Ixtal Expeditionist achieved a 27% win rate (95% CI: [21.8%, 32.7%]), representing 116% improvement over baseline. The strong negative correlation between mean placement and win rate ($\rho = -0.847$, $p < 0.001$) demonstrates convergent validity, confirming Set 16 augments that improve placements consistently translate to higher win rates.

The 2-3 fold win rate differences indicate Set 16 augment selection is not marginal optimization but a primary performance determinant comparable in magnitude to trait selection effects. Players consistently selecting top-tier Set 16 augments (Ixtal Expeditionist, Max Build) gain measurable advantages over players selecting weak augments, suggesting augment selection represents a distinct skill dimension in Set 16 competitive play requiring memorization of augment rankings and ability to evaluate augment-composition fit dynamically.

The sample size dependency of Wilson confidence interval width (14.0 pp for n=115 vs. 8.1 pp for n=339) demonstrates the importance of robust sample size requirements when estimating proportions in Set 16. Community analytics platforms using smaller samples may produce unstable augment rankings, leading players to misidentify optimal Set 16 augments.

Answering RQ5 (Temporal Patterns Within Set 16):

Temporal analysis revealed stable overall performance (mean = 4.39, SD = 2.47) with suggestive but non-significant phase differences (Kruskal-Wallis: $p = 0.201$). The descriptive pattern (early phase mean = 4.30, mid-phase mean = 3.94, or 8.4% improvement, and late-phase mean = 4.91, or 24.6% decline) may reflect: (1) learning effects as the player adapted to Set 16 mechanics during early-to-mid transition; (2) fatigue effects during mid-to-late transition reducing decision quality; (3) meta adaptation by opponents who identified and countered the player's preferred Set 16 strategies; or (4) random variance within the player's normal Set 16 performance envelope.

The lack of statistical significance ($p = 0.201$) prevents definitive conclusions, but the moderate effect size (mid-to-late decline of 0.97 placement units) and biological plausibility of learning/fatigue effects warrant further investigation with larger Set 16 samples. ShyvanaUnique's differential usage between Strong (45.7%) and Weak (17.4%) Set 16 phases (Fisher's exact: $p = 0.007$, OR = 4.08) confirms trait-outcome associations persist across temporal segments, validating the consistency of RQ2 findings.

B. Comparison to Related Work

This Set 16 analysis aligns with and extends prior gaming analytics research. The finding that 22% win rate significantly exceeds 12.5% baseline parallels Drachen et al. [4] findings that top-tier players in other competitive games achieve performance metrics 40-60% above average. The identification of Set 16-specific ShyvanaUnique effectiveness despite marginal statistical significance echoes Yang et al. [7] observations that medium effect sizes are common in competitive gaming contexts.

The Set 16 synergy analysis revealing Brawler + ShyvanaUnique achieving 42.9% win rate validates game design principles discussed in El-Nasr et al. [5], where trait combination systems create super-additive interactions rewarding strategic composition planning. The Wilson confidence interval application to Set 16 augment data extends methodological recommendations from statistical literature [11] into gaming analytics.

However, the Set 16-specific nature of findings differentiates this work from prior studies. While previous research typically aggregates data across multiple game versions [6], [7], this study's exclusive focus on Set 16 eliminates cross-version confounds while limiting generalizability to future sets. When Set 17 launches, specific trait and augment findings become historical rather than current strategic guidance, though the analytical methodology remains applicable.

C. Limitations

1. Single-Player Sample (n=1): Data from one player limits internal validity through confounds including individual playstyle preferences, mechanical skill ceiling, strategic biases, emotional factors, and learning effects. Without multi-player replication, we cannot distinguish universal Set 16 trait effectiveness from player-specific affinity.

2. Rank Tier Specificity: All Set 16 matches occurred within a single rank tier. Set 16 balance characteristics likely differ across skill levels, with optimal strategies varying by opponent sophistication and execution quality.

3. Set-Specific Findings: All findings apply exclusively to Set 16. When Set 17 launches (expected April-May 2026), trait names, augment offerings, and mechanics will change completely, rendering specific recommendations obsolete while the methodology remains applicable.

4. Sample Size Constraints: Limited sample sizes for individual Set 16 traits constrain statistical power. ShyvanaUnique (n=28) had only 55% power for detecting the observed r=0.201 effect. Future research with 200-300 games could identify additional significant traits.

5. Secondary Data Dependency: The Set 16 augment analysis relies on publicly available Kaggle dataset rather than personally collected global data. While validated ($\rho > 0.95$ inter-platform correlation), it introduces potential rank tier confounds and unverifiable cleaning procedures.

6. Temporal Window: The 100 Set 16 matches span 3 months. Minor balance patches within Set 16 may alter trait effectiveness, though current analysis does not disaggregate by patch version.

7. Incomplete Strategic Context: Analysis focuses on trait and augment choices but omits unit positioning, economy management, scouting decisions, and item optimization. A comprehensive causal model would require these additional variables.

D. Recommendations and Future Work

For Competitive Players (Set 16-Specific):

1. Prioritize ShyvanaUnique compositions when conditions allow (13.7% placement advantage, 35.7% win rate).
2. Leverage Brawler + ShyvanaUnique synergy (42.9% win rate, -0.83 synergy bonus).
3. Avoid Sorcerer overuse despite popularity (p=0.019 negative effect, mean=4.96).
4. Emphasize augment selection as core skill (Ixtal Expeditionist 27% vs. weak augments 11%).

For Game Designers:

1. Consider Set 16 trait balance variance (32% placement gap ShyvanaUnique-Sorcerer may exceed design tolerances).
2. Evaluate Set 16 augment power budget (27% vs. 11% win rate spread raises power differential questions).
3. Validate synergy design success (Brawler + ShyvanaUnique demonstrates effective emergent gameplay).

For Future Research:

1. Longitudinal Set Comparison: Compare Set 16, 17, 18 findings to identify set-invariant principles.
2. Multi-Player Aggregation: Analyze 10-50 players (50-100 games each) to distinguish universal patterns from player-specific effects.
3. Within-Set Patch Analysis: Track performance across minor patches (16.1, 16.2, 16.3) to detect micro-evolution.
4. Predictive Modeling: Train machine learning models on comprehensive features to predict outcomes and identify non-linear interactions.
5. Computer Vision Integration: Apply computer vision to match recordings for automated positioning analysis.

VI. Conclusion

Key Findings

This research established five primary findings from Set 16 analysis:

1. Performance significantly exceeds random chance: 22% win rate versus 12.5% expected (p=0.009, 76% improvement), confirming skill-based outcomes.
2. ShyvanaUnique demonstrates effectiveness: Mean 3.79, r=0.201 medium effect, 35.7% win rate despite marginal significance (p=0.116) from limited sample (n=28).
3. Synergies create emergent advantages: Brawler + ShyvanaUnique achieving 42.9% win rate, -0.83 synergy bonus beyond additive expectations.
4. Augment selection substantially influences outcomes: Ixtal Expeditionist 27% win rate (116% above baseline) with strong correlation (ρ=-0.847) validating metric convergence.
5. Performance temporally consistent: Non-significant phase differences (p=0.201), though ShyvanaUnique usage differs between Strong (45.7%) and Weak (17.4%) phases (p=0.007).

Personal Learning

Through analyzing 100 Set 16 games, I learned that my competitive performance relies on recognizing high-value strategies rather than following popular compositions. The discovery that ShyvanaUnique outperforms the more popular Sorcerer (which I used in 52% of games despite negative effect) revealed a disconnect between intuitive preferences and empirically optimal strategies. This suggests I overvalue mechanical familiarity over strategic optimality.

The finding that my best Set 16 performances occurred when combining Brawler with ShyvanaUnique (42.9% win rate) rather than forcing single traits taught me the importance of synergistic thinking. Previously, I evaluated traits in isolation, but the -0.83 synergy bonus demonstrates that strategic value emerges from combinations. This insight has influenced my in-game decision-making, causing me to prioritize trait complementarity over individual trait strength.

The temporal analysis revealing mid-game improvement (mean=3.94) followed by late-game decline (mean=4.91) suggests potential fatigue effects. Recognizing this pattern prompted behavioral changes: taking 10-minute breaks after every 5 games and limiting daily sessions to 6-8 games rather than marathon 15+ game sessions.

Real-Life Applications

These findings suggest practical applications beyond gaming:

1. Data-driven decision-making over intuition: The Sorcerer popularity paradox (highest usage, worst

performance) illustrates how intuitive preferences can misalign with optimal choices. This applies to professional and personal decisions where comfort with familiar options may prevent adoption of superior alternatives.

2. Synergistic thinking in complex systems: The Brawler + ShyvanaUnique synergy demonstrates how emergent value arises from combinations. This applies to team composition in work environments, investment portfolio diversification, and skill development where complementary capabilities create super-additive value.
3. Periodic self-assessment and adaptation: The temporal performance pattern suggests even skilled performers benefit from periodic review. Regular data-driven self-evaluation could improve consistency in professional contexts from sales performance to academic productivity.
4. Sample size awareness in personal analytics: The ShyvanaUnique significance paradox (strong effect, $p>0.05$) demonstrates how small samples can mask true effects. This cautions against premature conclusions from limited personal data, suggesting longer observation periods before making strategic pivots.

Final Conclusion

This investigation demonstrates that competitive Set 16 performance can be rigorously quantified, strategically optimized, and scientifically understood through appropriate statistical methodologies. The 22% win rate achievement, ShyvanaUnique trait effectiveness (mean=3.79, r=0.201), Brawler + ShyvanaUnique synergy (42.9% win rate), and augment variance identification (11-27% range) represent exemplars of how quantitative analysis transforms intuitive gameplay into measurable strategic science.

As TFT evolves through Set 17, Set 18, and beyond, the integration of set-specific empirical analysis with generalizable methodological frameworks will define the frontier of evidence-based strategic mastery. This work provides both actionable Set 16 insights (valid until April-May 2026 set transition) and a replicable template for analyzing future sets, demonstrating that behind every competitive outcome lies a pattern awaiting discovery through principled analytical inquiry.

Beyond gaming, this project illustrates how systematic data collection, rigorous statistical analysis, and effect-size-first interpretation can reveal hidden patterns in complex behavioral domains. Whether optimizing gaming strategies, improving work productivity, or refining personal habits, the methodological framework demonstrated here (define variables precisely, collect data systematically, analyze rigorously, interpret cautiously) remains broadly applicable. The cycle of hypothesis generation from experience, empirical testing through data, and strategic refinement from findings represents a generalizable approach to evidence-based self-improvement across domains.

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