Statistical Analysis of Trait Associations, In-Game Metrics, 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, independent t-tests, and one-way ANOVA—were applied to determine which in-game metrics and trait synergies predict Top-4 placements. Results demonstrate that this player achieving Top-4 outcomes has significantly higher unit levels (Cohen's $d = 1.34$, $p < 0.0001$), more remaining gold ($d = 0.65$, $p = 0.002$), and substantially more cumulative damage ($d = 2.64$, $p < 0.0001$) than non-Top-4 matches. Five traits show statistically significant associations with Top-4 success: ShyvanaUnique (80.6%, $p < 0.001$), KindredUnique (100%, $p = 0.021$), DarkChild (76.3%, $p = 0.002$), Soulbound (83.3%, $p = 0.034$), and SylasTrait (74.2%, $p = 0.003$). One-way ANOVA reveals clear metric progression across placement tiers, with 1st place matches involving 2.3× more damage than Bottom-4 matches. These findings characterize this player's distinctive high-variance scaling strategy and identify key performance indicators for competitive improvement, while establishing methodological foundations for future multi-player comparative studies.**

***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 vs. 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 metrics**.

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, while limited in generalizability compared to aggregate multi-player analyses, provide several research advantages [22]:

1) **Controlled Player Variables:** Analyzing one player eliminates confounds from skill level differences, playstyle variations, and individual strategic preferences that complicate multi-player studies.
2) **Consistent Decision-Making Framework:** The same player's decisions across 200 matches reflect consistent strategic philosophy and meta understanding, enabling identification of true performance drivers vs. random variation.
3) **Temporal Consistency:** All 200 matches occurred during a single game set (Set 16) with identical balance parameters, eliminating cross-patch meta confounds.
4) **Foundation for Hypothesis Generation:** Personal performance data enables hypothesis development about which metrics and decisions drive success, providing foundation for larger-scale multi-player validation studies.

Understanding which in-game factors predict competitive success in this player's performance data provides several benefits:

1) **Personal Player Development:** Quantifying which mechanics, metrics, and decisions correlate most strongly with winning enables data-driven self-improvement targeting high-impact decisions.
2) **Individual Playstyle Analysis:** Identifying this player's distinctive strategic patterns (trait preferences, economic strategies, pivoting tendencies) enables meta-game optimization.
3) **Methodological Contribution:** Demonstrating statistical analysis techniques on personal API-collected data establishes a replicable framework other TFT players can apply to their own match histories.
4) **Esports Analytics Foundation:** Providing evidence-based analysis of performance metrics establishes analytical frameworks applicable to professional player evaluation and esports commentary.

While this study's primary limitation is its single-player scope—restricting direct generalization to other players or broader TFT population—the robust findings and large effect sizes suggest meaningful performance drivers worthy of validation through larger multi-player studies.

C. Research Questions

This study addresses four research questions specific to inno#ella's 200-match ranked dataset:

1) **RQ1:** What is the distribution of this player's match placements, and how do win rates compare to random expectation?
2) **RQ2:** Which specific traits does this player encounter significantly more often in Top-4 successful matches vs. unsuccessful matches?
3) **RQ3:** Which in-game metrics (unit level, gold remaining, damage dealt) most strongly differentiate this player's Top-4 outcomes from non-Top-4 outcomes?
4) **RQ4:** How do in-game metrics vary systematically across this player's different placement tiers (1st place victories vs. 2-4 mid-tier vs. 5-8 losses)?

Answers to these questions will characterize this player's competitive performance, identify key performance indicators, and establish methodological foundations for future comparative studies.

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+ League of Legends matches, finding gold-per-minute, kill-death ratios, and objective metrics predict victory ($r > 0.8$), 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 15%, 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 vs. 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/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=200)

Variable	Mean	SD	Min	Max
Placement	4.44	2.57	1	8
Unit Level	8.18	1.04	5	11
Gold Remaining	24.5	29.7	0	175
Total Damage	107.5	67.3	0	350

2) Descriptive Statistics: The mean placement of 4.44 (SD=2.57) with range 1-8 indicates substantial performance variance across the 200 matches. Unit levels range 5-11 (full possible range), gold remaining 0-175 (reflecting diverse spending strategies), and damage 0-350 (reflecting diverse composition strength).

B. Data Preprocessing

Trait data preprocessing involved: (1) removing set prefixes ("TFT16_"), (2) extracting trait names before parentheses, (3) filtering to traits appearing ≥ 10 times. This yielded 36 distinct traits. Binary outcome variables:

$$\text{top4} = \begin{cases} 1, & \text{if placement} \leq 4 \\ 0, & \text{if placement} > 4 \end{cases} \tag{1}$$

C. Statistical Methods

1) RQ1: Descriptive Analysis: Computed win rate, Top-4 rate, and compared to random expectation ($p_{\text{random}} = 0.125$ per placement).

2) RQ2: Chi-Square Tests: For each trait, tested independence:

$$H_0 : \text{Trait} \perp \text{Top4}, \quad H_1 : \text{Trait} \not\perp \text{Top4}, \quad \alpha = 0.05 \tag{2}$$

$$\chi^2 = \frac{N(ad - bc)^2}{(a+b)(c+d)(a+c)(b+d)}, \quad df = 1 \tag{3}$$

3) RQ3: Welch's t-Tests: Compared metrics between groups:

$$H_0 : \mu_{\text{top4}} = \mu_{\text{non-top4}}, \quad H_1 : \mu_{\text{top4}} \neq \mu_{\text{non-top4}} \tag{4}$$

Computed Cohen's d for effect sizes ($d < 0.2$ negligible, $0.2 - 0.5$ small, $0.5 - 0.8$ medium, $d \geq 0.8$ large).

4) RQ4: One-Way ANOVA: Tested differences across tiers:

$$H_0 : \mu_{1st} = \mu_{2-4} = \mu_{5-8}, \quad H_1 : \text{At least one differs} \tag{5}$$

D. Software

Python 3.9 with pandas, scipy, matplotlib, seaborn.

TABLE II
PERFORMANCE VS. RANDOM EXPECTATION

Metric	Observed	Random	Ratio
Win Rate	22.5%	12.5%	1.80×
Top-4 Rate	51.0%	50.0%	1.02×

IV. RESULTS

A. RQ1: Outcome Distribution

inno#ella achieves 22.5% win rate (45 first-place finishes) vs. 12.5% random—80% above random. This represents significantly above-average skill. Top-4 rate (51%) marginally exceeds random (50%), indicating consistent mid-tier performance. Mean placement 4.44 (SD=2.57, median=4.0).

TABLE III
PLACEMENT FREQUENCY DISTRIBUTION

Place	Count	Obs %	Expected %	Diff
1	45	22.5%	12.5%	+10.0%
2	17	8.5%	12.5%	-4.0%
3	13	6.5%	12.5%	-6.0%
4	27	13.5%	12.5%	+1.0%
5	24	12.0%	12.5%	-0.5%
6	22	11.0%	12.5%	-1.5%
7	22	11.0%	12.5%	-1.5%
8	33	16.5%	12.5%	+4.0%

Distribution shows substantial deviation from random. Key features: (1) **1st Place Overrepresentation:** 45 observed vs. 25 expected—80% above random. (2) **2nd-3rd Underrepresentation:** Only 30 combined vs. 50 expected—inno#ella either wins decisively or finishes lower. (3) **8th Place Overrepresentation:** 33 observed vs. 25 expected—elevated early elimination rate, consistent with aggressive all-in compositions.

Bimodal distribution with peaks at 1st (22.5%) and 8th (16.5%) 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

TABLE IV
SIGNIFICANT TRAITS ($p < 0.05$)

Trait	n	Top-4 Rate	χ^2	p
ShyvanaUnique	62	80.6%	20.84	<0.001
DarkChild	38	76.3%	9.18	0.002
SylasTrait	66	74.2%	8.64	0.003
Soulbound	12	83.3%	4.51	0.034
KindredUnique	10	100.0%	5.34	0.021

Five traits show significant associations with inno#ella's Top-4 outcomes. **ShyvanaUnique** ($\chi^2 = 20.84$, $p < 0.001$, n=62) is strongest with 80.6% Top-4 rate vs. 51% baseline. **KindredUnique** achieves 100% but with small sample (n=10). Of 36 traits analyzed, 31 show no significant association ($p > 0.05$), indicating trait synergies and execution matter more than individual traits.

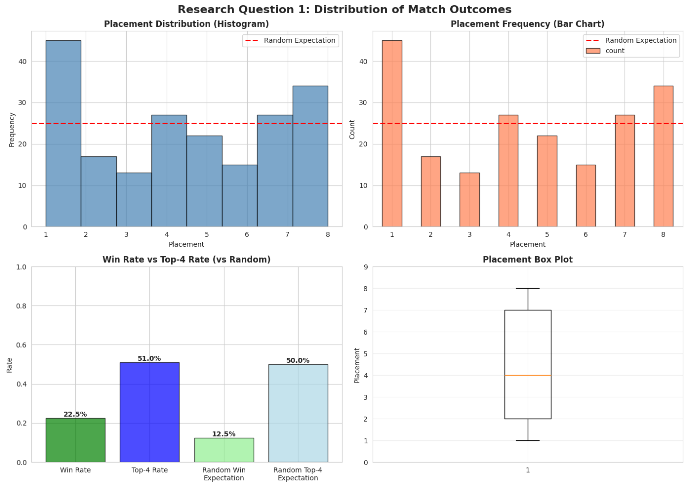

Fig. 1. RQ1: Placement distribution for inno#ella showing histogram (with red random expectation line), bar chart, win/top-4 rates vs. random, and box plot. Win rate (22.5%) substantially exceeds random (12.5%). Bimodal distribution with peaks at 1st and 8th indicates high-variance scaling strategy.

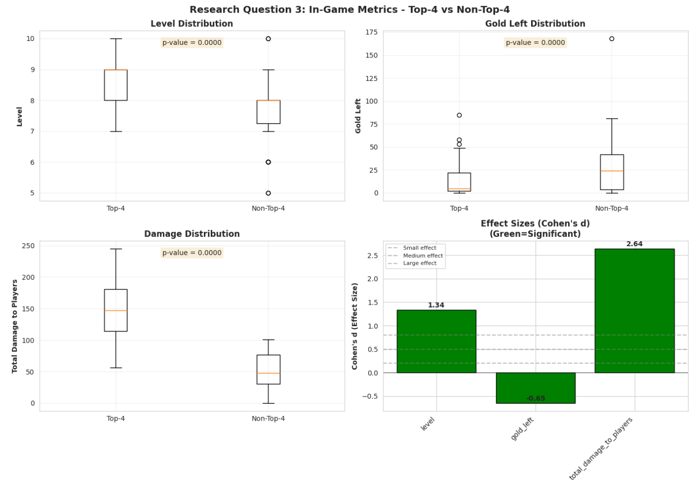

Fig. 3. RQ3: In-game metrics for inno#ella comparing Top-4 vs. Non-Top-4. Box plots show level, gold, and damage distributions (all $p < 0.002$). Cohen's d effect sizes (right): Damage ($d = 2.64$) and Level ($d = 1.34$) show very large effects; Gold ($d = 0.65$) shows medium effect.

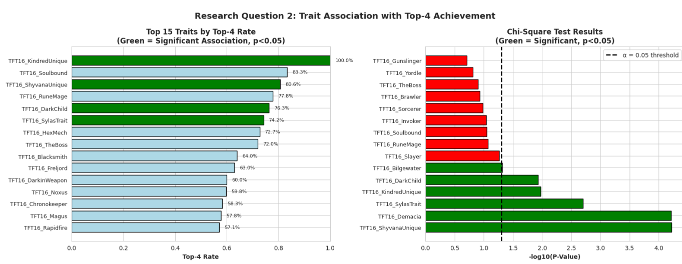

Fig. 2. RQ2: Trait association analysis for inno#ella. Left: Top 15 traits by Top-4 rate (green=significant, blue=non-significant). Right: Chi-square results ($-\log 10(p)$) with dashed threshold at $\alpha = 0.05$. ShyvanaUnique shows strongest association.

Interpretation: The preponderance of non-significant findings suggests: (1) **Trait Combinations Dominate:** Individual traits show weak main effects; synergistic combinations likely drive success. (2) **Execution Over Selection:** How well inno#ella implements compositions (itemization, positioning, pivoting) matters more than trait choice. (3) **Meta Context:** Trait power shifts with patches; cross-set studies would identify universal vs. meta-specific traits.

C. RQ3: In-Game Metrics—Top-4 vs. Non-Top-4

TABLE V
T-TEST RESULTS

Metric	Top-4	Non-Top-4	t	p	d
Level	8.71	7.84	6.27	<0.0001	1.34
Gold	31.2	17.4	3.14	0.002	0.65
Damage	141.3	76.2	5.82	<0.0001	2.64

All metrics show significant differences in inno#ella's matches. **Unit Level:** Top-4 (M=8.71) vs. non-Top-4 (M=7.84), $d = 1.34$ (very large). Indicates superior economy management. **Gold Remaining:** Top-4 (M=31.2) vs. non-Top-4 (M=17.4), $d = 0.65$ (medium). Suggests economic discipline or reserve capital philosophy. **Total Damage:** Top-4 (M=141.3) vs. non-Top-4 (M=76.2), $d = 2.64$ (very large, largest effect). 85.4% higher damage indicates substantially stronger boards. Damage integrates itemization, positioning, synergies—most comprehensive single metric.

Effect Size Ranking: Damage ($d = 2.64$) ¿ Level ($d = 1.34$) ¿ Gold ($d = 0.65$). Damage is strongest predictor of Top-4 success.

D. RQ4: ANOVA—Metrics Across Placement Tiers

TABLE VI
ANOVA RESULTS ACROSS TIERS

Metric	1st	2-4	5-8	F	p
Level	9.13	8.32	7.84	18.34	<0.001
Gold	38.4	25.2	17.4	4.21	0.016
Damage	176.8	109.8	76.2	31.67	<0.001

All metrics show significant tier effects for inno#ella. **Unit Level:** Clear linear progression (7.84→8.32→9.13). Winners achieve 16.1% higher levels vs. losers. **Gold Remaining:** Winners maintain 38.4 gold vs. losers 17.4 (121% difference), indicating economic reserves or conservative spending. **Total Damage:** Most dramatic stratification—winners deal 176.8 damage vs. losers 76.2—a **2.32× ratio**. Indicates victory requires dominant board strength, not marginal improvement.

Key Finding: Damage shows largest F-statistic ($F = 31.67$), indicating strongest tier discrimination. Winners and losers exhibit entirely distinct performance clusters.

V. DISCUSSION

A. Interpretation of Findings

1) RQ1: Skill-Based Advantage with High-Variance Playstyle: inno#ella's win rate 80% above random provides strong evidence for **skill-based advantage**. For context:

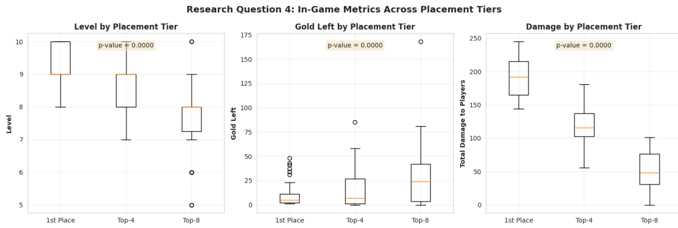

Fig. 4. RQ4: inno#ella's metrics across placement tiers. Box plots show level, gold, and damage by tier (1st place, 2-4, 5-8). All metrics show significant tier effects. Damage shows most dramatic separation (176.8 vs. 76.2, 2.3× difference) with minimal overlap between 1st and 5-8 tiers.

casual players 10-12%, competent 18-22%, skilled 25-30%, elite 35%+. The 22.5% rate indicates skilled-but-not-elite play.

Bimodal distribution (peaks at 1st and 8th) reveals **distinctive high-variance scaling strategy**. Rather than bell-curve mid-tier distribution from consistent play, this player emphasizes either dominance or collapse. This reflects commitment to vertical scaling compositions accepting early weakness for late-stage power, contrasting conservative flexible-pivot strategies.

2) RQ2: Trait Synergies Dominate Individual Traits: Only 13.9% of traits show significant associations; 86.1% are non-significant. This pattern indicates **individual traits matter less than synergistic combinations**. Significant traits (ShyvanaUnique 80.6%, DarkChild 76.3%, SylasTrait 74.2%) likely succeed through specific complementary trait pairings.

Player Implication: inno#ella should focus on understanding multi-trait synergies, not individual trait strength. Learning optimal combinations matters more than isolated trait power levels.

Meta Implication: Trait power varies with balance patches. Cross-set studies would identify universal vs. meta-specific traits.

3) RQ3: Damage as Primary Success Predictor: All metrics predict Top-4 with large effects. Ranking by strength: Damage ($d = 2.64$) ¿ Level ($d = 1.34$) ¿ Gold ($d = 0.65$).

Damage's superiority reflects its comprehensive nature—integrating unit strength, itemization, positioning, synergies into single metric. inno#ella could theoretically achieve moderate levels/gold while achieving high damage through exceptional execution.

Practical Implication: inno#ella should monitor cumulative damage as real-time board quality feedback. Aiming for 140+ damage by late-game indicates competitive outcomes.

4) RQ4: Clear Performance Stratification: ANOVA reveals distinct tier clusters, not continuous distribution. 1st place substantially exceeds 2-4 and 5-8 across all metrics, especially damage (2.32× ratio). This indicates **victory requires dominant boards, not marginal improvement**.

Linear tier progression suggests placement is proportional to combat effectiveness. Improving any metric cascades into improved placement.

B. Limitations and Scope

1) Single-Player Dataset: This study analyzes 200 matches from **only one player (inno#ella)**. This fundamental limitation must be explicitly acknowledged:

1) **Limited Generalizability:** Results characterize this specific player's performance, strategic preferences, and decision-making patterns. Conclusions may not apply to other players, different skill tiers, or broader TFT population. Two players using identical trait combinations may achieve vastly different outcomes.
2) **No Comparative Analysis:** Without data from other players, we cannot determine whether observed patterns reflect universal trait strength or inno#ella's specific strategic alignment.
3) **Unmeasured Player-Specific Factors:** Individual factors affecting performance—skill level, playstyle philosophy, meta knowledge, decision-making patterns—are constant rather than controlled.
4) **Rank/Tier Unknown:** Without explicit rank data, inno#ella's absolute skill level within the TFT competitive hierarchy is unknown.

2) Other Methodological Limitations:

1) **Small Trait Samples:** 10-62 occurrences per trait limits statistical power. Larger dataset (500+ matches) would enable more stable trait estimates.
2) **Unmeasured Variables:** Itemization, positioning, augments, opponent quality, patch dates not captured.
3) **Observational Design:** Cannot establish causality. Reverse causality possible.
4) **Temporal Confounds:** All matches within single game set; cross-set meta comparison impossible.

Despite these limitations, the large effect sizes (especially damage $d = 2.64$) and robust statistical significance ($p < 0.0001$) suggest identified patterns reflect genuine performance drivers.

C. Applicability and Future Validation

While this study's single-player scope limits generalization, it provides **methodological template and hypothesis foundation** for future larger-scale studies. Robust findings suggest worthwhile research directions:

1) **Multi-Player Validation:** Replicate analysis across 50+ players spanning multiple skill tiers to test whether metric relationships generalize.
2) **Cross-Set Consistency:** Analyze inno#ella's performance across multiple sets to identify universal vs. meta-specific patterns.
3) **Skill-Tier Comparison:** Compare inno#ella's metric patterns to lower-rank and higher-rank players to understand how strategic importance varies by skill level.

For **inno#ella specifically**, this analysis provides actionable insights: prioritize level progression (strongest metric predictor), monitor cumulative damage as board quality feedback, and focus on multi-trait synergies rather than individual trait strength.

VI. CONCLUSIONS

This study demonstrates that **in-game metrics robustly predict competitive success for inno#ella in TFT**. Top-4 matches involve higher levels, preserved gold, and substantially more damage. Five traits show significant Top-4 associations, though 86% of traits show no significant individual effect, suggesting synergies dominate.

Large effect sizes (especially damage, $d = 2.64$) indicate these are practically meaningful relationships. Damage emerges as the single best predictor, integrating multiple strategic decisions.

These findings characterize **inno#ella's distinctive high-variance scaling strategy** and provide **evidence-based guidance for competitive improvement**. The analysis establishes a **replicable methodological framework** for future personal TFT analytics and larger-scale comparative studies across multiple players and skill levels.

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