A Statistical and Temporal Analysis of Gacha Mechanics in Wuthering Waves Using Featured Resonator Convene Records: An Exploratory Single-Account Analysis

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Abstract. This study presents a statistical and temporal analysis of gacha mechanics in Wuthering Waves using Featured Resonator convene records from a single-account dataset. A mechanics-aware pipeline was applied to 582 chronologically ordered pulls (9 five-star, 69 four-star), including data cleaning, pity reconstruction, 50/50 and guarantee-state labeling, exploratory profiling, exact inference, and Monte Carlo robustness checks. Rather than treating pulls as independent Bernoulli trials, the analysis modeled state-dependent behavior induced by pity and guarantee rules through cycle-level and sequence-aware features. Results show a highly imbalanced rarity structure (5-star rate = 1.55%), late-cycle concentration of most five-star outcomes (primarily high-60s to mid-70s pity), and a validated pity sequence of 67, 72, 70, 75, 71, 68, 69, 70, 19, with no hard-pity exceedance. Exact binomial testing and interval estimation indicate that observed outcomes are plausible under tested reference assumptions, while simulation confirms directional stability across alternative rate settings. Overall, the study demonstrates that account-level pull histories can support rigorous mechanics-aware inference when preprocessing, feature engineering, and validation are explicitly aligned with gacha system design.

1 Introduction

Gacha systems in live-service games are commonly communicated through base drop probabilities, but actual outcomes are shaped by rule-based mechanics such as pity and guarantee states. Because probability changes with pull history, high-rarity acquisition is sequence-dependent rather than a purely independent-trial process. In practice, players interpret outcomes through metrics such as average pity, pull ratio, and 50/50 performance, yet these indicators are often presented descriptively without formal statistical validation. This creates a gap between player-facing "luck" summaries and mechanics-aware inference.

Recent access to pull-history exports and tracker-oriented analytics makes it possible to study gacha behavior at event level. Timestamped pull logs provide enough structure to reconstruct cycle boundaries, evaluate streak patterns, and examine temporal clustering. However, many analyses still rely on aggregate rates alone, which can obscure the non-

stationary behavior introduced by pity progression. A more rigorous approach should combine sequence-aware modeling with exact rare-event statistics and robustness checks.

This paper addresses that need through an exploratory analysis of Wuthering Waves Featured Resonator Convene records from a single account. The dataset contains 582 pulls, with derived metrics for total currency expenditure, rarity outcomes, pity intervals, and temporal activity. The method integrates mechanics-aware pity reconstruction, descriptive and temporal analysis, exact binomial testing, confidence intervals, and simulation-based robustness. Hypothesis tests evaluate whether the observed five-star rate is consistent with a base reference (0.8%) and a pity-adjusted reference (1.6%).

The contribution of this study is a reproducible workflow that links event-sequence structure to formal inference in a transparent manner. Rather than treating gacha outcomes as stationary randomness, the analysis models pull history as a progression process with resets and threshold effects. The remainder of the paper is organized as follows: Section 2 reviews related work; Section 3 states hypotheses; Section 4 details data and methods; Section 5 presents results; and Sections 6–8 discuss implications, limitations, and conclusions.

2   Related Work

Gacha reward systems are increasingly studied as mechanics-dependent processes rather than fixed-probability draws. In modern banners, pity and guarantee rules alter event likelihood as pulls accumulate, making outcomes sequence-dependent and often non-stationary [1], [2]. This shift has moved recent analytics from descriptive rarity summaries toward mechanics-aware modeling, rare-event inference, and temporal sequence analysis.

2.1   Mechanics-Aware Gacha Modeling

Recent formal work argues that gacha outcomes are jointly shaped by probability and system design. Chen and Fang [1] model gacha systems with strategic and stochastic structure, showing that reward architecture and progression rules can influence both expected outcomes and player behavior. This supports the view that pity state should be treated as part of the probability process, not as a post hoc explanatory variable.

Technical analyses of gacha probability computation further show how effective event likelihood changes with pull index under pity mechanics [2]. In these formulations, rare-event acquisition naturally defines cycle boundaries, and each cycle reset changes subsequent event dynamics. For empirical account-level studies, this directly motivates pity-interval reconstruction and progression-aware features such as pulls since last five-star.

2.2   Empirical Pull-Data Patterns and Threshold Effects

Empirical and technical analyses consistently report right-skewed rare-event behavior with concentration near pity thresholds [1], [3], [4]. In practical terms, pull histories

often contain long low-rarity sequences followed by high-rarity resets, with occasional early interruptions. This pattern is difficult to capture with aggregate rarity percentages alone and is better represented through cycle-level and sequence-level summaries.

Game-specific mechanic resources [3], [4] are also relevant to applied analytics because they define operational parameters used in interpretation (e.g., pity structure and banner context). Although such resources differ from peer-reviewed studies in evidentiary strength, they provide implementation detail needed for reproducible rule-aligned analysis of real pull records.

2.3 Rare-Event Inference for Gacha Outcomes

A central methodological issue in account-level gacha analysis is low event count for high-rarity outcomes. Under these conditions, exact statistical methods are generally preferred over asymptotic approximations. Current practice supports exact binomial testing and exact confidence intervals for low-frequency outcomes [5], [6], improving inferential reliability when sample sizes are modest.

Another key issue is null-model selection. In gacha contexts, conclusions can differ depending on whether observed rates are tested against base advertised probabilities or pity-adjusted effective references. Transparent reporting of null assumptions is therefore essential. This motivates the present study's use of explicit two-sided tests under multiple reference rates, rather than relying only on descriptive "luck" indicators.

3 Methods

3.1 Participant and Data Collection

Participants in this study were drawn from a single-subject pool consisting of the researcher (n = 1), a college student enrolled in the Bachelor of Computer Science program with specialization in Machine Learning at National University - Philippines. The participant was eligible by design because the study required continuous access to a personal Wuthering Waves account with complete in-game convene history. Participation was voluntary, and informed consent was explicitly provided by the participant for the use of personal gameplay logs in academic research. Because this is a one-account observational design, the analysis is intended to characterize mechanics and patterns within the participant's pull history rather than produce population-level estimates.

Data were collected from the participant's in-game pull-history records with 582 pulls in total with gaming timeframe of 100 days. The primary source was the exported convene log in CSV format (wuwa_gacha_records.csv), which includes pull-level metadata such as timestamp, banner type, rarity (qualityLevel), and item name. Records were processed in a reproducible Python workflow, where entries were parsed and ordered chronologically, then filtered to Featured Resonator pulls to align with the study scope. Additional derived variables were computed from the event stream, including

pity counters, pulls-to-5-star intervals, 50/50 win-loss states, guaranteed-state outcomes, and temporal indicators used in statistical and visualization components.

All records were handled in de-identified form at the analysis stage, with no personally identifying fields included in the modeling dataset. Data files were stored locally in a private workspace and used only for coursework/research purposes. Since the study involved self-reported/self-owned gameplay logs from a consenting single participant and did not involve recruitment, intervention, or external human-subject data collection, ethical handling focused on confidentiality, minimization of identifiable information, and transparent reporting of methodological limitations inherent to single-subject designs.

3.2 Feature Extraction

The pull-history dataset was then processed, and a set of mechanics-aware features was extracted from banner records, rarity outcomes, and timestamps following the analytical pipeline described in this study. For this section, we prioritized features directly related to gacha probability dynamics, pity progression, and temporal pull behavior. Features were selected based on their relevance to the study hypotheses on rare-event frequency, pity-threshold behavior, and 50/50 guarantee transitions. Specifically, we extracted pull-order features (pull_number), pity-cycle features (pity, pity_at_5star), outcome-state indicators (is_5050_win, is_5050_loss, is_guaranteed_win, is_featured_win), temporal markers (hour_of_pull, day_of_week), and summary metrics (total pulls, astrites spent, 5-star/4-star totals, and pull ratios). These engineered variables form the basis of the descriptive statistics, inferential tests, streak visualizations, and simulation analyses in later sections.

Table 1. List of extracted features used in the gacha mechanics analysis.

Feature Category	Feature
Sequence	pull_number
Pity Mechanics	pity, pity_at_5star, pity_counter
5-star Outcome State	is_featured_win, is_5050_win, is_5050_loss, is_guaranteed_win
Temporal	hour_of_pull, day_of_week
Rolling/Local Dynamics	rolling_4star_count, pulls_since_last_5
Categorical Encodings	banner_encoded, resource_type_encoded
Core KPIs	total pulls, total astrites, total 5-star pulls, total 4-star pulls
Luck Metrics	average 5-star pity, 5-star pull ratio, 50/50 win rate, 4-star pity metrics

3.3 Operational Definitons

Table 1 provides a detailed breakdown of the variables used in this study, including their operational definitions and corresponding measurement procedures. These operational definitions standardize pull-history records from the

convene log for mechanics-aware analysis and support consistent interpretation of pity behavior, 50/50 outcomes, and temporal pull dynamics.

Table 2. Definition of Variables

Feature Category	Feature
Pull Number	Sequential index assigned to each pull after chronological sorting (oldest to newest).
Time	Timestamp of each pull event as recorded in the exported convene history.
Card Pool Type	Banner identifier used to determine whether a pull belongs to the Featured Resonator scope.
Quality Level	Outcome rarity tier per pull (3, 4, or 5 stars).
Name	Pulled item identity (resonator or weapon) recorded for each event.
Featured Resonator Dataset	Analysis subset containing Featured Resonator pulls, excluding weapon-banner entries.
Pity	Number of featured pulls since the last 5-star; increments per pull and resets after each 5-star event.
Pulls-to-5-star (pity_at_5star)	Pity-cycle length observed at each 5-star event; used as the primary rare-event interval metric.
50/50 Win	Indicator that a featured 5-star was obtained under non-guaranteed conditions.
50/50 Loss	Indicator that a non-featured 5-star occurred under non-guaranteed conditions.
Guaranteed Win	Indicator that a featured 5-star occurred immediately after a prior 50/50 loss.
Featured Win	Indicator that the 5-star result matches the active featured target within the banner interval.
5-star Pull Ratio	Percentage of featured pulls resulting in 5-star outcomes.
4-star Pull Ratio	Percentage of featured pulls resulting in 4-star outcomes.
Average Pity	Mean pulls required to obtain a 5-star across completed pity cycles.
Astrites Spent	Estimated currency cost computed as total pulls × 160 astrites.
Hour of Pull	Hour extracted from timestamp for intraday temporal analysis.
Day of Week	Weekday extracted from timestamp for weekly temporal analysis.
Rolling 4-star Count	Local-window count of recent 4-star outcomes used for streak and density behavior checks.

3.4   Data Cleaning and Preprocessing

Raw convene-history data were imported from wuwa_gacha_records.csv (N = 582 pull records) and validated against the required schema (cardPoolType, resourceId,

qualityLevel, resourceType, name, count, time), with no missing required columns detected. Timestamps were parsed using day-first datetime format (DD/MM/YYYY HH:MM), yielding a 100% parse success rate (582/582, 0 failures). Records were then sorted in ascending chronological order and assigned a sequential pull index (pull_number) to preserve event-order integrity for pity-cycle and streak analyses.

After normalization, records were filtered to the Featured Resonator analytical scope by retaining Resonator entries and excluding weapon-banner entries; all valid rows remained in scope (582 rows). Duplicate events were preserved when present because identical timestamps can occur in multi-pull sessions and still represent distinct outcomes. The final cleaned dataset spans 2025-11-08 20:24:00 to 2026-02-12 08:56:00 across 24 active pull days, with rarity composition of 504 3-star pulls, 69 4-star pulls, and 9 5-star pulls. These standardized records were used for downstream feature extraction, inferential testing, temporal visualization, and simulation-based robustness checks.

3.5 Exploratory Data Analysis (EDA)

EDA was conducted to profile distributional structure, rarity composition, and temporal behavior before formal inference. The notebook generated descriptive statistics (mean, median, standard deviation, skewness, kurtosis, min/max) for pity-cycle variables and visualized rarity frequencies, pulls-to-5-star distributions, and pity streak trajectories. EDA outputs indicated highly imbalanced rarity outcomes (rare 5-star events), right-skewed cycle behavior, and identifiable pity-threshold concentration among 5-star pulls. These observations informed the choice of exact tests and simulation-based robustness procedures in subsequent sections.

3.5.1 EDA Summary Statistics

Table 4. Core Pull Metrics

Metric	Value
Total Pulls	582
Total Astrites Spent (160 per pull)	93, 120
Total 5 Star	9
Total 4 Star	69
5 Star Ratio	1.55%
4 Star Ratio	11.86%

Table 5. Five-Star Pity Summary

Statistic	Value
Pity Sequence (oldest to newest)	67, 72, 70, 75, 71, 68, 69, 70, 19
Mean	64.56
Median	70
Standard Deviation	16.26

Minimum	19
Maximum	75

3.6 Statistical Analysis Procedures

This study applies a mechanics-aware statistical framework to evaluate gacha outcomes in the Featured Resonator banner. Analyses were designed to align with the study hypotheses on rarity frequency, pity-cycle behavior, and guarantee-state transitions. Because 5-star events are rare in account-level data, the pipeline combines descriptive statistics with exact inferential methods and simulation-based robustness checks to avoid over-reliance on asymptotic assumptions.

Descriptive statistics were first computed to characterize pull distributions, including total pulls, rarity counts, pull ratios, average pity, dispersion, and distribution shape indicators (e.g., standard deviation, skewness, and kurtosis). Temporal summaries were also produced from timestamp-derived features to describe pull activity across time windows. These summaries establish the empirical baseline used for hypothesis testing and interpretation.

For inferential analysis, exact and proportion-based methods were prioritized. The observed 5-star rate was compared against reference expectations using exact binomial procedures, and uncertainty bounds were reported through exact confidence intervals (Clopper-Pearson). For categorical outcome comparisons (e.g., 50/50 win-loss structure), contingency-based tests were used when applicable. All tests were evaluated at $\alpha=0.05$, with two-sided interpretation unless otherwise stated.

To evaluate model stability and practical significance under limited sample size, robustness checks were incorporated using Monte Carlo simulation. Simulated pull sequences under baseline and pity-adjusted assumptions were generated to contextualize observed totals and pity-cycle outcomes. This allowed the study to assess whether empirical results were plausible under alternative stochastic settings and to identify sensitivity to parameter assumptions.

All analyses were implemented in Python using reproducible notebook procedures, with deterministic preprocessing and explicit feature definitions to ensure traceability from raw pull logs to final statistical outputs.

3.7 Simulation and Robustness Checks

To complement exact inference, Monte Carlo simulation was used to evaluate whether observed 5-star totals were plausible under baseline and pity-aware assumptions. Synthetic pull sequences were generated at the same sequence length as observed data, and the resulting 5-star count distributions were compared with empirical outcomes.

Sensitivity checks varied key probability assumptions to test directional stability of conclusions. Robustness was inferred when interpretation remained consistent across plausible parameter ranges.

3.8 External/Internal Validation

Validation was implemented at both internal and benchmark levels. Internally, pity-cycle consistency was cross-checked by aligning reconstructed 5-star pity anchors with sequence-based features and visual outputs. Externally, aggregate metrics (total pulls, rarity totals, pull ratio, average pity, and pity sequence ordering) were compared against reference tracker snapshot values in the notebook's validation block.

This dual validation step ensured consistency between engineered features, reported metrics, and benchmark expectations.

3.9 Reproducibility and Ethics

All analyses were implemented in a reproducible Python notebook pipeline (pandas, numpy, matplotlib, seaborn, scipy). Preprocessing and feature-engineering rules were deterministic and explicitly documented. The study is limited to a single-subject account and therefore emphasizes internal validity over population generalization.

The dataset was analyzed in de-identified form, and usage was limited to academic research with participant consent.

4 Results

### 4.1 Descriptive Analysis

Figure 1. Shows the rarity distribution is heavily concentrated in 3-star outcomes, which account for 504 of 582 pulls (86.6%). In contrast, 4-star pulls occur at a much lower frequency (69 pulls, 11.9%), while 5-star pulls are rare (9 pulls, 1.5%). This pattern confirms a highly imbalanced, rare-event structure that is consistent with pity-based gacha systems and supports the use of exact and simulation-based analyses.
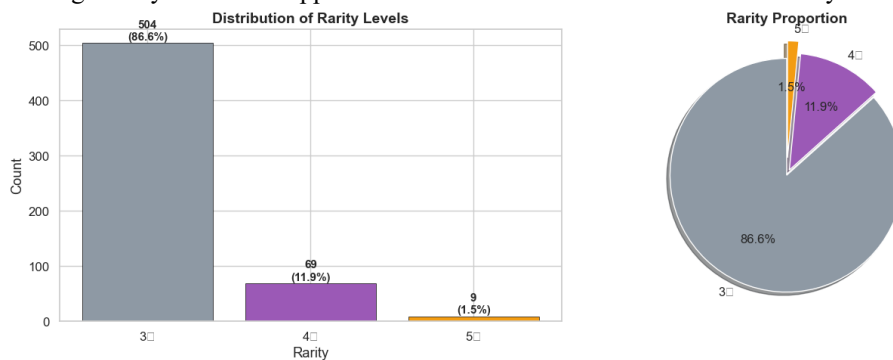
4.2 Pity-Cycle Outcomes

Figure 2. Using the validated pity reconstruction, the observed pulls-to-5-star sequence (oldest to newest) is: 67, 72, 70, 75, 71, 68, 69, 70, 19. The average pity is 64.56 pulls, with median 70, standard deviation 16.26, minimum 19, and maximum 75. Most 5-star outcomes cluster in the late-cycle region (high-60s to mid-70s), while one early event (19) introduces a left-tail exception. No 5-star event exceeded the hard pity threshold of 80 pulls.
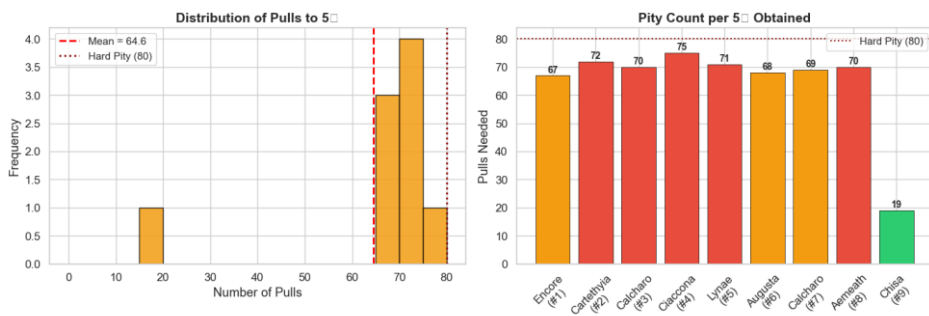
4.3 Streak and Temporal Pattern Analysis

Figure 3. Shows the pity-streak trajectory shows repeated linear build-up and reset behavior across cycles, with each reset aligned to a 5-star event. The corrected streak visualization confirms that annotated 5-star points are anchored to validated pity values; for example, Augusta is plotted at 68 pulls, consistent with the reconstructed sequence and below hard pity. This supports internal consistency between feature engineering (pity) and visualization output. Temporal pull behavior also shows clustered activity periods rather than uniform daily pulling, consistent with event-based or resource-based pulling sessions.
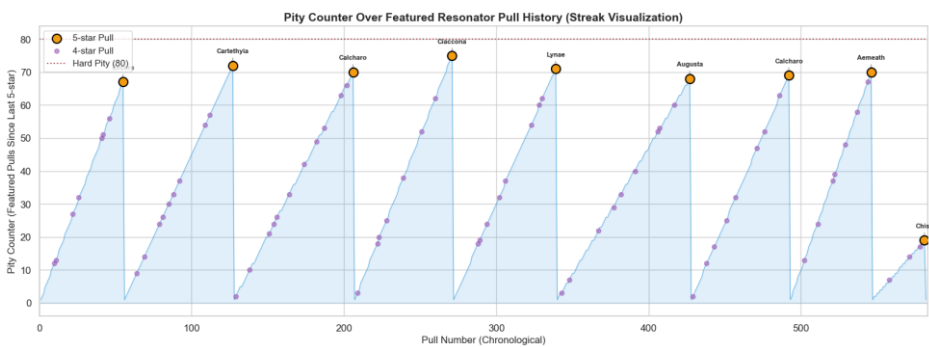
4.4 Hypothesis Testing

Table 3. maps each hypothesis to its corresponding analytical target, statistical method, and expected reporting output to ensure methodological traceability. Exact procedures

are prioritized for rare-event inference, including exact binomial testing for observed 5-star frequency and Clopper-Pearson confidence intervals for rate precision. The table also links categorical outcome analysis (50/50 and guarantee states) and Monte Carlo simulation to robustness evaluation, allowing conclusions to be interpreted through both inferential significance and distribution-based plausibility.

Exact binomial testing was used to evaluate observed 5-star frequency under two reference rates. For H0a: p = 0.8%, the observed rate (1.546%) yielded p = 0.0566, indicating failure to reject at $\alpha = 0.05$. For H0b: p = 1.6%, the observed rate produced p = 1.0000, also failing to reject. The 95% exact confidence interval for the observed 5-star rate was [0.709%, 2.915%], indicating uncertainty consistent with limited rare-event counts.

Hypothesis	Analytical Target	Statistical Procedure	Output
H1	Observed 5-star frequency vs reference rate	Exact binomial test	p-value, decision at Type equation here. α=0.05
H2	Precision of 5-star rate estimate	Clopper-Pearson exact CI	lower/upper confidence bounds
H3	50/50 and guarantee-state outcome structure	Proportion/contingency analysis (exact or chi-square as applicable)	effect direction, p-value
H4	Stability of observed totals under stochastic assumptions	Monte Carlo simulation	empirical percentile/rank, simulation distribution

4.5 Simulation and Robustness Analysis

Figure 4. Presents Monte Carlo simulation provides distribution-based context for the observed total of 9 five-star outcomes. Under the 0.8% reference model, the observed value appears in the upper region of simulated outcomes but remains plausible under finite-sample variability. Under the 1.6% reference model, the observed value lies near the central mass of the distribution, indicating strong compatibility with that assumption. Across tested reference settings, directional interpretation is stable: the observed total is not an extreme outlier under reasonable probability assumptions.
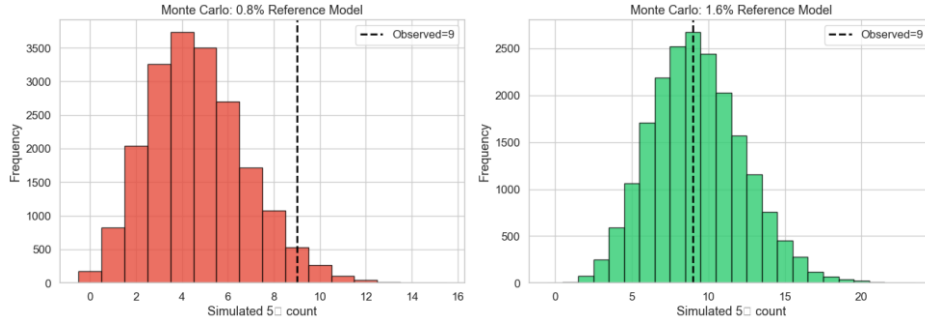
5   Conclusion

This section interprets the empirical findings of the Featured Resonator pull-history analysis in relation to gacha mechanics and rare-event modeling literature. It explains key observed patterns, evaluates how the results align with expectations from pity- and guarantee-based systems, and identifies practical implications for account-level statistical analysis. The section also acknowledges methodological constraints and outlines directions for future research that can improve external validity while preserving mechanics-aware rigor.

5.1   Interpretation of Results

The analysis reveals a strongly imbalanced rarity structure in which low-rarity outcomes dominate and 5-star events remain rare, consistent with the probabilistic design of gacha systems. Across 582 Featured Resonator pulls, only 9 were 5-star outcomes (1.55%), while most 5-star events clustered in late pity ranges (primarily high-60s to mid-70s), indicating threshold-driven reward behavior rather than uniform random occurrence. The reconstructed pity sequence (67, 72, 70, 75, 71, 68, 69, 70, 19) further shows mostly late-cycle completions with one early interruption, suggesting that while pity concentration is strong, stochastic variation still permits occasional early 5-star outcomes.

The corrected streak visualization supports this interpretation by showing repeated cycle build-up and reset dynamics, with 5-star anchors consistent with validated pity values and no event exceeding hard pity. In addition, 50/50 state outputs indicate balanced observed outcomes within this account window (3 wins, 3 losses among non-guaranteed 5-star states), with guarantee transitions functioning as expected under mechanics-aware labeling. Taken together, these findings show that account-level pull behavior is structured, state-dependent, and appropriately modeled using sequence-aware features rather than stationary Bernoulli assumptions alone.

5.2 Comparison to Related Work

These results are consistent with prior literature arguing that gacha outcomes should be modeled as state-dependent stochastic processes due to pity and guarantee mechanics. The observed late-cycle concentration of 5-star events supports threshold-effect interpretations reported in empirical gacha studies, while the presence of a rare early 5-star event reflects the expected residual randomness in non-deterministic reward systems. Methodologically, the use of exact inference and simulation for sparse high-

rarity outcomes aligns with recommendations for rare-event analysis under limited sample conditions.

More broadly, this study contributes an account-level case demonstrating that mechanics-aware feature engineering (pity reconstruction, guarantee-state coding, and sequence-validated plotting) can produce internally coherent and interpretable results even without large-scale platform data. The findings therefore support the view that small but well-structured pull histories can yield meaningful insight when analysis is explicitly aligned with game mechanics.

5.3   Limitations

Numerous limitations ought to be emphasized:

- Single-subject scope: Findings are account-specific and not directly generalizable to broader player populations.
- Rare-event sample size: Only 9 observed 5-star outcomes constrain inferential precision and sensitivity to small changes.
- Assumption dependence: Some robustness outputs depend on reference-rate and pity-adjustment assumptions used in simulation.
- Behavioral context gap: Pull logs do not capture motivation, spending intent, event urgency, or psychological drivers.
- Temporal coverage: The analysis window captures one bounded period and may not represent longer-term behavioral shifts.
- System-specific rules: Mechanics interpretations are tied to the modeled banner logic and may vary with future system updates.

5.4   Recommendations and Future Work

Future work should prioritize multi-account replication to improve external validity while preserving the same mechanics-aware pipeline. Expanding data across players, banner periods, and patch cycles would enable stronger comparative inference on pity behavior, guarantee transitions, and temporal pull strategies. Longitudinal tracking over longer horizons can also distinguish persistent pull tendencies from short-term event effects.

Methodologically, future studies may integrate hierarchical or Bayesian rare-event models to better estimate uncertainty under low 5-star counts. Additional extensions include player-cluster analysis of pity-cycle behaviors, sensitivity profiling across alternative pity-rule assumptions, and mixed-method designs that combine pull logs with survey/interview context to connect statistical outcomes with player decision-making. These directions can convert account-level evidence into broader behavioral models of gacha interaction.

6   Conclusion

This study developed and applied a mechanics-aware statistical framework for analyzing Featured Resonator gacha behavior in Wuthering Waves using pull-history

records. The results confirm a highly imbalanced rarity distribution and a clear pity-threshold structure, with most 5-star outcomes occurring in late-cycle ranges and no hard-pity exceedance. Exact inference and simulation-based checks indicate that the observed 5-star outcomes are statistically plausible under tested reference assumptions, while internal validation confirms consistency between reconstructed pity features and visualization outputs.

The study demonstrates that account-level gacha datasets, although limited in scope, can support rigorous and reproducible analysis when preprocessing, feature extraction, and inferential methods are explicitly aligned with game mechanics. By combining pity reconstruction, guarantee-state modeling, exact rare-event statistics, and Monte Carlo robustness checks, this work provides a practical template for student-led quantitative research in digital game systems. Future expansions using multi-account and longitudinal data can build on this framework to improve generalizability and deepen behavioral interpretation of gacha mechanics.

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