DSA 210 Project Report: The Correlation Between "Clutch" Performance and Career Success in ATP Tennis

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Abstract

This project analyzes the relationship between a professional tennis player's ability to perform under high-pressure scenarios—defined here as "Clutchness"—and their overall long-term career success. Using data from ATP Men's Singles matches (2000-2025), a custom "Clutch Index" was engineered and tested against career win rates. The study employs statistical hypothesis testing and machine learning clustering to determine if mental fortitude is a quantifiable predictor of titles and rankings.

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1 Project Proposal and Motivation

This project seeks to analyze the relationship between a professional tennis player's ability to perform successfully under high-pressure scenarios—referred to here as "Clutchness"—and their overall long-term career success.

As a long-time tennis watcher, I realized that big comebacks in games were the best to watch. A prime example is the **2025 Roland Garros Final**, where Carlos Alcaraz's comeback from 3 championship points down was unbelievable. These matches are not only long and enjoyable but also showcase the highest level of competition. Viewers can see the "blood, sweat, and tears" of the players. Therefore, I decided to build a project analyzing these moments and the effects of "Clutchness" on the career wins of tennis players.

2 Research Question and Hypotheses

2.1 Research Question

If we can quantify the "Clutchness" of a player, does it correlate with success metrics (measured by total titles, win percentage, and average ranking)?

2.2 Hypotheses

- **Null Hypothesis (H_0):** The quantified measure of the Clutchness Index does **not** show any significant correlation with the success metrics of a player.
- **Alternative Hypothesis (H_a):** The quantified measure of the Clutchness Index is **positively correlated** with the success metrics of a player.

3 Data Sources and Scope

3.1 Data Source

The dataset is primarily sourced from **Jeff Sackmann's GitHub repository** (tennis_atp) and *Tennis Abstract*. These sources provide detailed match-level information required for calculating specific metrics [1].

3.2 Data Scope

The data contains matches from **2000–2025** for **Men's Singles (ATP)** only. Women's Singles (WTA) were not included due to:

1. Lack of consistency in winners compared to ATP.
2. Complications regarding doping bans (e.g., Sharapova, Halep) affecting long-term statistics.
3. Personal familiarity with the history of ATP tennis over WTA [1].

4 Data Cleaning and Preparation

To ensure high data quality, the following steps were taken [2]:

- **Tournament Filtering:** Lower-tier events (ATP 250 and ATP 500) were excluded. The analysis focuses on **ATP Masters 1000** and **Grand Slam** tournaments to capture peak competitive performance.
- **Handling Missing Values:** Missing numerical data points (N/A) were imputed using the **mean** value of their respective features.

5 Methodology

5.1 The "Clutch Index" Measure

A custom metric was engineered to quantify mental fortitude. It is a weighted aggregate of the following components [3]:

- **Break Point Resilience (40%):** Weighted ratio of break points saved vs. faced.
- **Tie-Break Performance (20%):** Win rate in tie-breaks.
- **Deciding Set Performance (20%):** Win rate in final sets (3rd in Masters, 5th in Slams).
- **Bonuses:**
  - *Comeback Bonus:* For recovering from 0-1 or 0-2 set deficits.
  - *Dominance Bonus:* Rewards "clean" wins (straight sets) to acknowledge players like Nadal/Federer who avoid clutch moments by dominating early.
  - *Longevity Bonus:* Logarithmic scaling to reward sustained performance.

5.2 Bayesian Adjusted Win Rate

To correct for ranking anomalies (e.g., a rookie with a 2-0 record vs. a legend with 800-200), a Bayesian adjustment was applied to dampen win rates toward the global average [4].

$$\text{Adjusted Win Rate} = \frac{\text{Wins} + 25}{\text{Matches} + 50} \tag{1}$$

Note: The confidence weight C is set to 50 matches.

5.3 Statistical Hypothesis Testing

A **Pearson Correlation Test** was performed to validate the relationship between the Clutch Index and Adjusted Win Rate [4].

- **Correlation Coefficient (r):** 0.642
- **P-Value:** 1.44×10^{-43} (significantly < 0.05)

Result: We reject the Null Hypothesis (H_0). There is strong evidence that clutch performance is linked to winning more matches.

6 Exploratory Data Analysis (EDA)

6.1 Component Correlation Analysis

We analyzed how individual components correlate with success [5]:

- **Dominance is Key ($r = 0.96$):** The strongest predictor is winning easily (Dominance Ratio).
- **Deciding Set Win % ($r = 0.63$):** Winning the final set has a strong positive correlation.
- **Tie-Break Win % ($r = 0.60$):** Indicates top-tier closing ability.

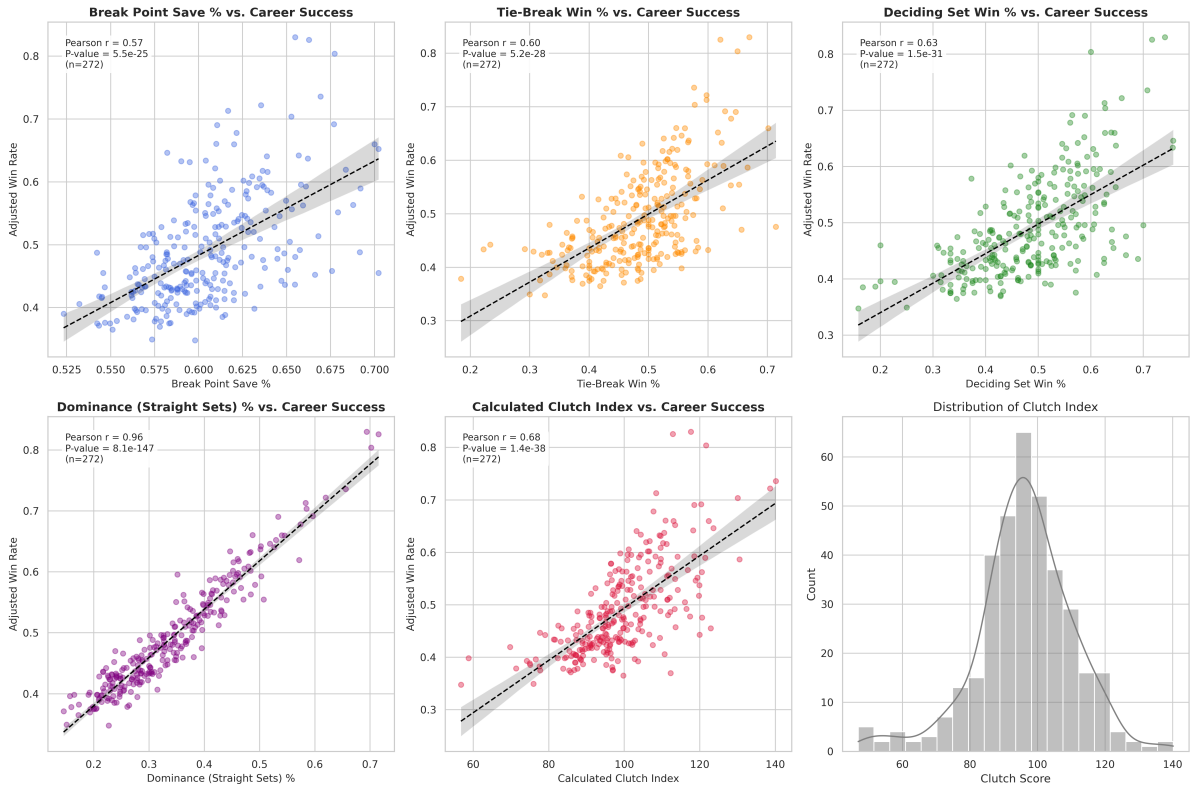

Figure 1: Component Analysis: Individual Metrics vs. Career Success [6]

6.2 Feature Correlation and Distribution

The **Clutch Index** follows a near-normal distribution centered around 100. "Extreme clutch" scores (> 120) are rare and observed mostly in elite players (The Big Three). The Clutch Index has a correlation of **0.64** with the Adjusted Win Rate, confirming it captures unique signals beyond just dominance [7].

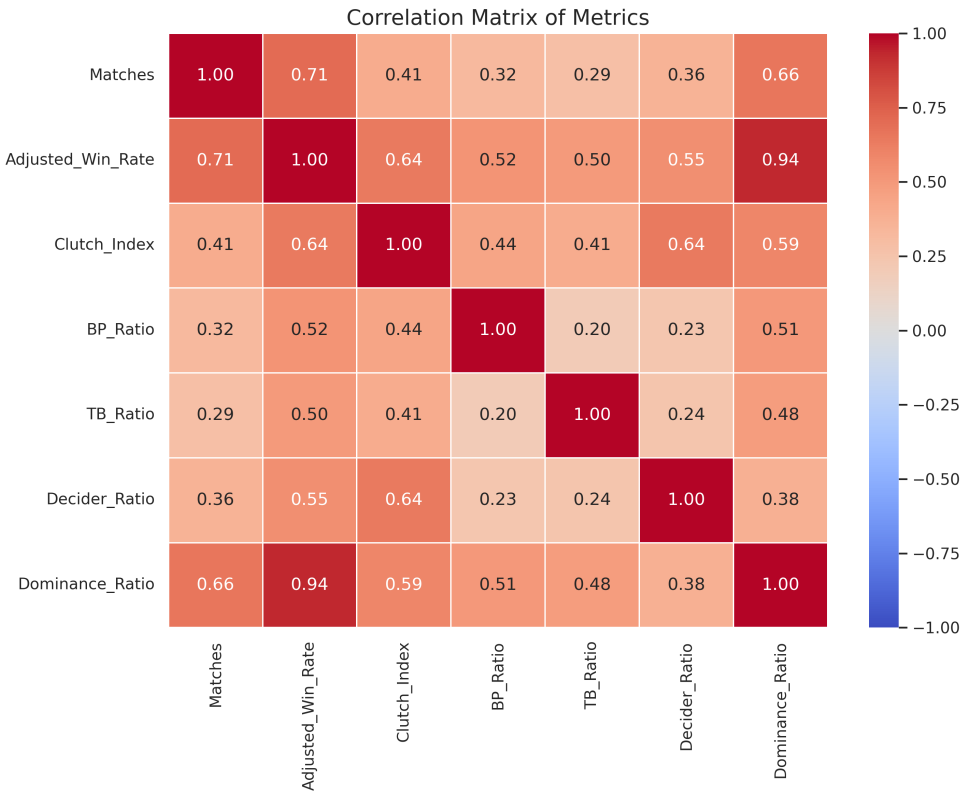

Figure 2: Correlation Matrix of Metrics [8]

7 Machine Learning Application

K-Means clustering ($k = 3$) was applied to segment players into profiles based on clutch performance [9]:

1. **Elite Clutch:** Highest mean win rate.
2. **Moderate Clutch:** Intermediate performance.
3. **Low Clutch:** Lowest performing group.

A composite Clutch Score (mean of offensive/defensive rates) was also evaluated using linear regression.

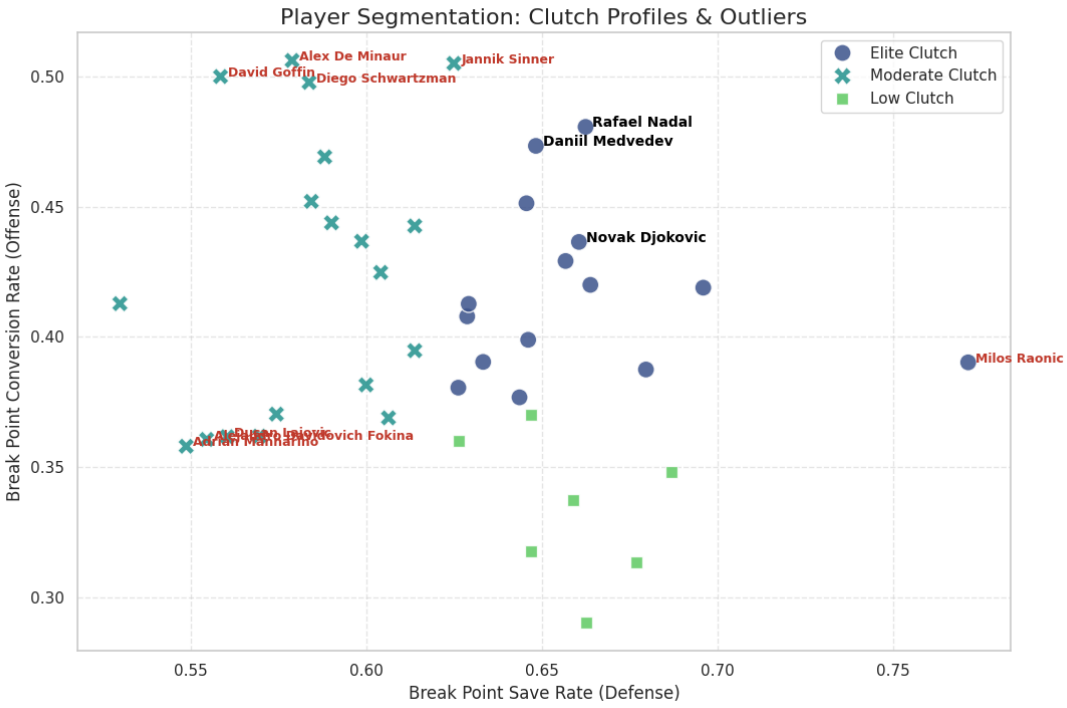

Figure 3: Player Segmentation: Clutch Profiles (Defense vs. Offense) [10]

8 Findings

The results align with expectations. Being a "Clutch" player is a statistically significant factor in winning titles; however, it is not sufficient on its own. Talent and dominance are prerequisites. Clutch performance can be further segmented into defensive (saving break points) and offensive (converting match points) capabilities [11].

9 Limitations and Future Work

9.1 Limitations

- **Data Depth:** The analysis utilized match-level data. Shot-level data (e.g., shot direction, serve placement) could provide deeper insights [12].
- **Scope:** The exclusion of WTA (Women's Tennis) limits the generalizability of the findings to the entire sport.

9.2 Future Work

Future iterations of this project could include [13]:

- Integrating WTA data from Tennis Abstract.
- Experimenting with player positioning data and changes in shot direction.
- Testing advanced Machine Learning models beyond K-Means and Linear Regression.

10 AI Usage Declaration

In this project, **Gemini** was used for assistance with coding and structuring the README file. Specifically, the concept of "Bayesian Adjustment" to correct rookie ranking anomalies was suggested by Gemini. The remaining metrics, weights, and the Clutch Index formula were engineered independently by the author [13].