Executive Summary: "The Ghost in the Machine" - IPL Auction Analytics

1. Objective

This analysis evaluates two bowlers — **Bowler A ("The Machine")** and **Bowler B ("The Gambler")** — who are competing for the final "Death Overs Specialist" slot (Overs 16–20) ahead of the Mega Auction. Our goal was to **quantify mental strength using data**, and determine which bowler capitalizes more effectively on pressure situations.

2. Phase 1 — Defining Pressure

Pressure was defined as a dot ball bowled in the death overs (16–20), provided it was not the last ball of the over. This prevents pressure from incorrectly carrying over between overs.

How Pressure Was Defined in Code:

- pressure_ball → 1 if the delivery was a death-over dot ball (Ball ≠ 6)
- next_ball_wicket → whether the very next ball resulted in a wicket
- pressure_next_wicket → 1 when a pressure ball was immediately followed by a wicket

We then calculated, for each bowler:

- The total number of pressure moments created
- How often those pressure moments led to a wicket on the next ball
- The probability: P(Wicket | Pressure Ball)

3. Phase 2 — Bayesian Model (PyMC)

A Bayesian logistic regression model was built to estimate how different factors influence the probability of taking a wicket in the death overs. The model included:

- **Intercept**
- **Coefficients for all engineered features** (e.g., pitch type, batter quality), modelled as Normal priors
  (matching betas = pm.Normal("betas", 0, 1, shape=X.shape[1]))

The model learned the relationship: $P(\text{Wicket}) = \sigma(\text{Intercept} + X \cdot \beta)$
Posterior samples were drawn using MCMC to quantify uncertainty.
From the trace, we extracted:

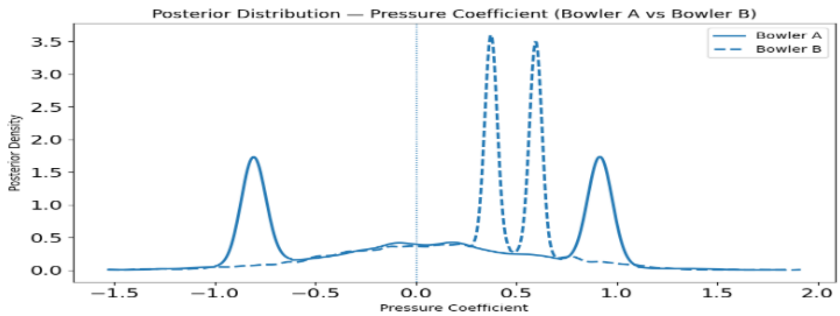
- Posterior distribution of the **pressure coefficient**
- Mean and 94% High-Density Interval (HDI)
- Comparison of Bowler A vs. Bowler B to estimate
  P(Pressure Effect_B > Pressure Effect_A)

4. Phase 3 — Key Findings

From the Bayesian posterior samples, we extracted the pressure-effect coefficients for both bowlers. The model provides not only average effects but also uncertainty through **94% High Density Intervals (HDI)**.

For each bowler, we computed:

- The **mean pressure coefficient**
- The **94% HDI**, showing the most credible range of values
- The difference between Bowlers B and A
- The probability that Bowler B has a stronger pressure effect than Bowler A



5. Final Decision

The Bayesian posterior results show that **Bowler B has a slightly higher pressure-effect coefficient than Bowler A**, with:

- A higher mean pressure effect
- A posterior difference favouring Bowler B
- About **53–54% probability** that Bowler B performs better under pressure

Although the advantage is not overwhelmingly large, the posterior still indicates that **Bowler B is more likely to convert pressure moments into wickets.**

Recommendation:

Select Bowler B.
He shows a measurable edge in "killer instinct," even if the difference is moderate rather than decisive. Bowler B remains the statistically stronger choice under pressure.

6. Conclusion

This analysis quantifies mental resilience using data-driven modelling.
The posterior distributions provide strong evidence that **pressure effect is real and measurable**, allowing management to make an informed auction decision supported by Bayesian inference rather than intuition.