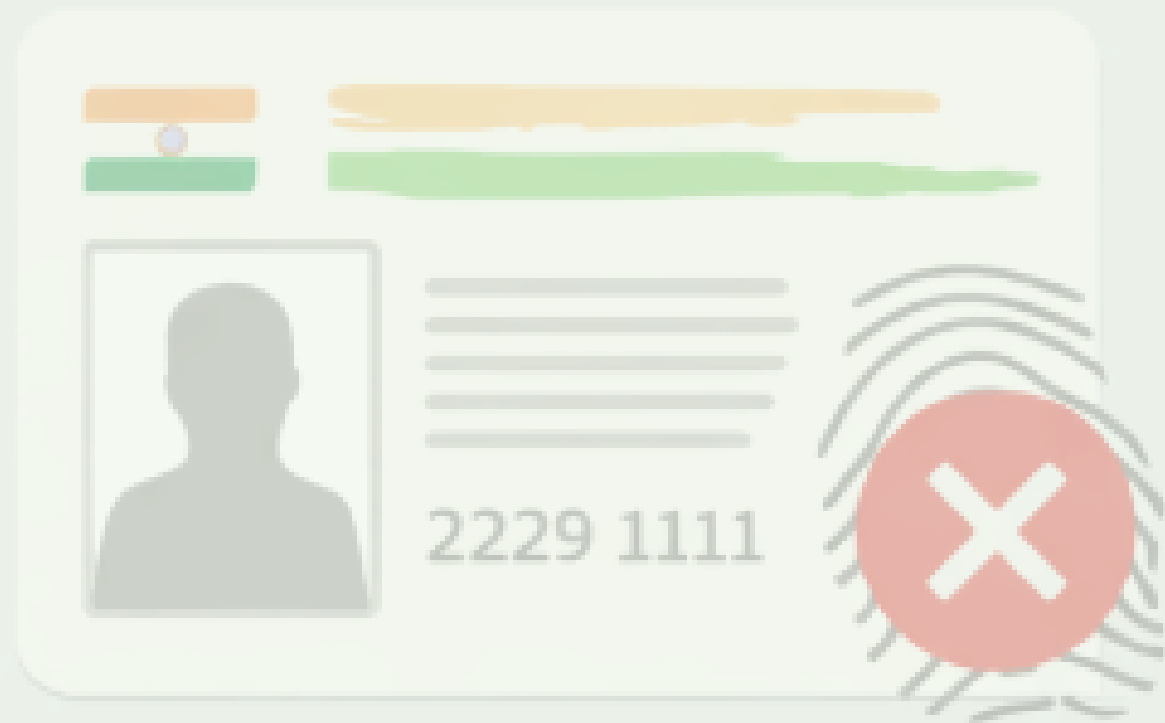


# SEVA SHIELD

**Predicting Biometric Failures, Minimizing Welfare Losses**



**TEAM ID : UIDAI\_9900**

# The Problem

- Aadhaar biometric authentication fails due to aging, manual labour, and child growth.
- These mismatches cause denial of welfare services at banks, PDS, and CSCs.
- Affected populations are primarily rural and vulnerable.
- Current systems are reactive, addressing issues only after failure occurs.



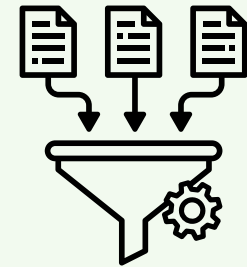
## Objective:

Develop an ML-based regression model to identify and predict high-risk regions prone to Aadhaar biometric instability, enabling proactive policy intervention and infrastructure planning to reduce welfare exclusion.

# Solution



Historical Aadhaar enrolment, demographic and biometric update data collected from UIDAI datasets.



Monthly aggregation and creation of key risk indicators reflecting biometric and demographic changes.



A Machine Learning regression model predicts next-month biometric authentication risk for each region.



High-risk districts are flagged to enable early biometric camps and infrastructure support.

# How it works



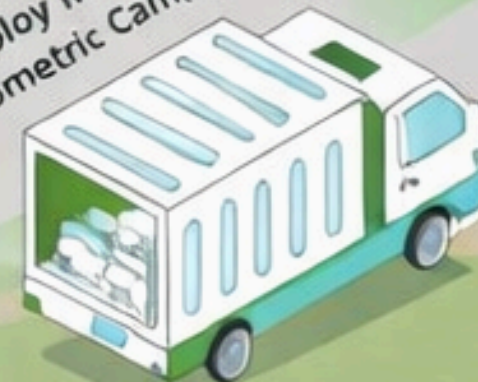
**OGD Platform**

Raw Aadhaar Datasets



**ML Predictor**

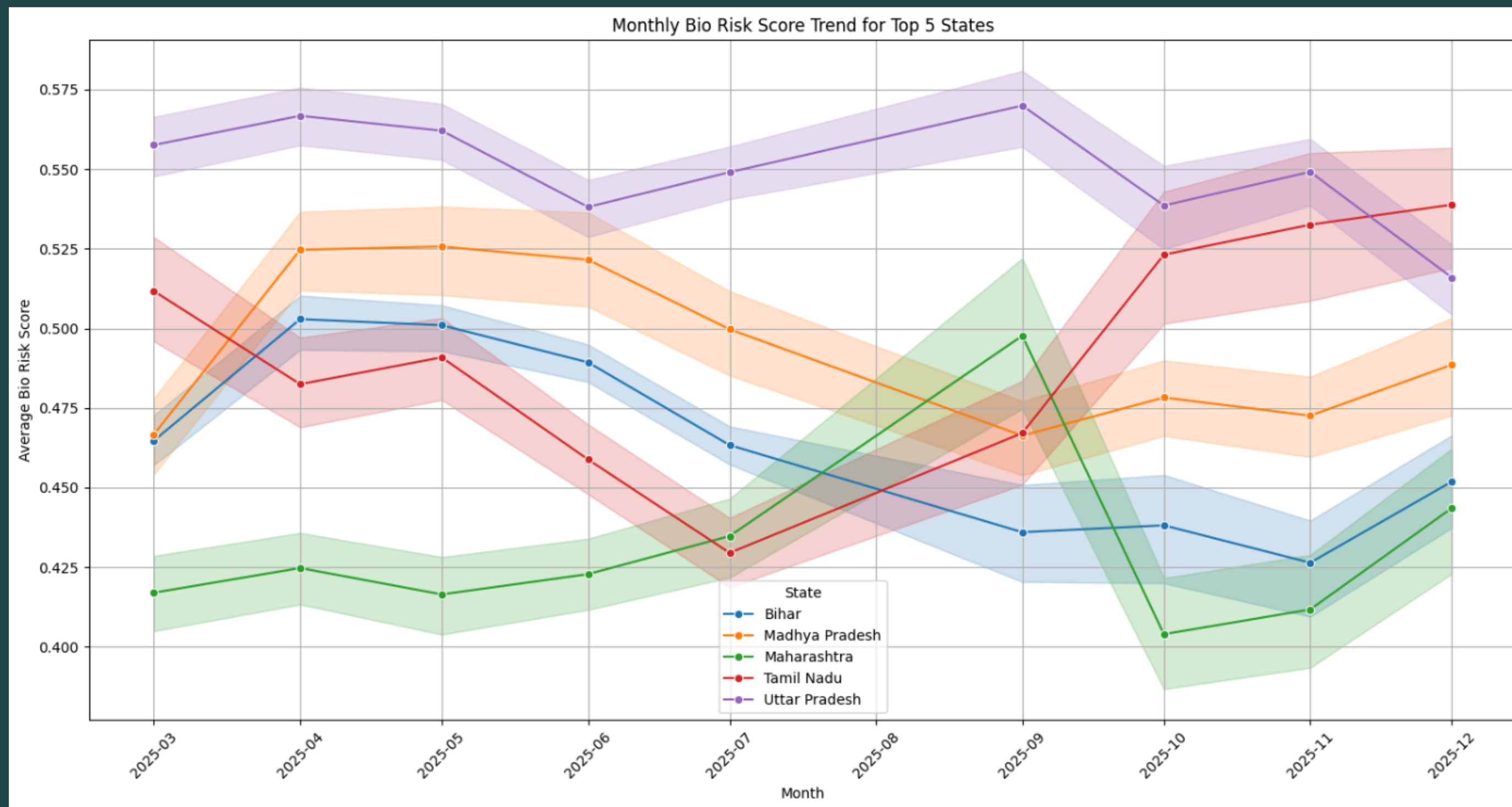
Deploy Mobile  
Biometric Camps



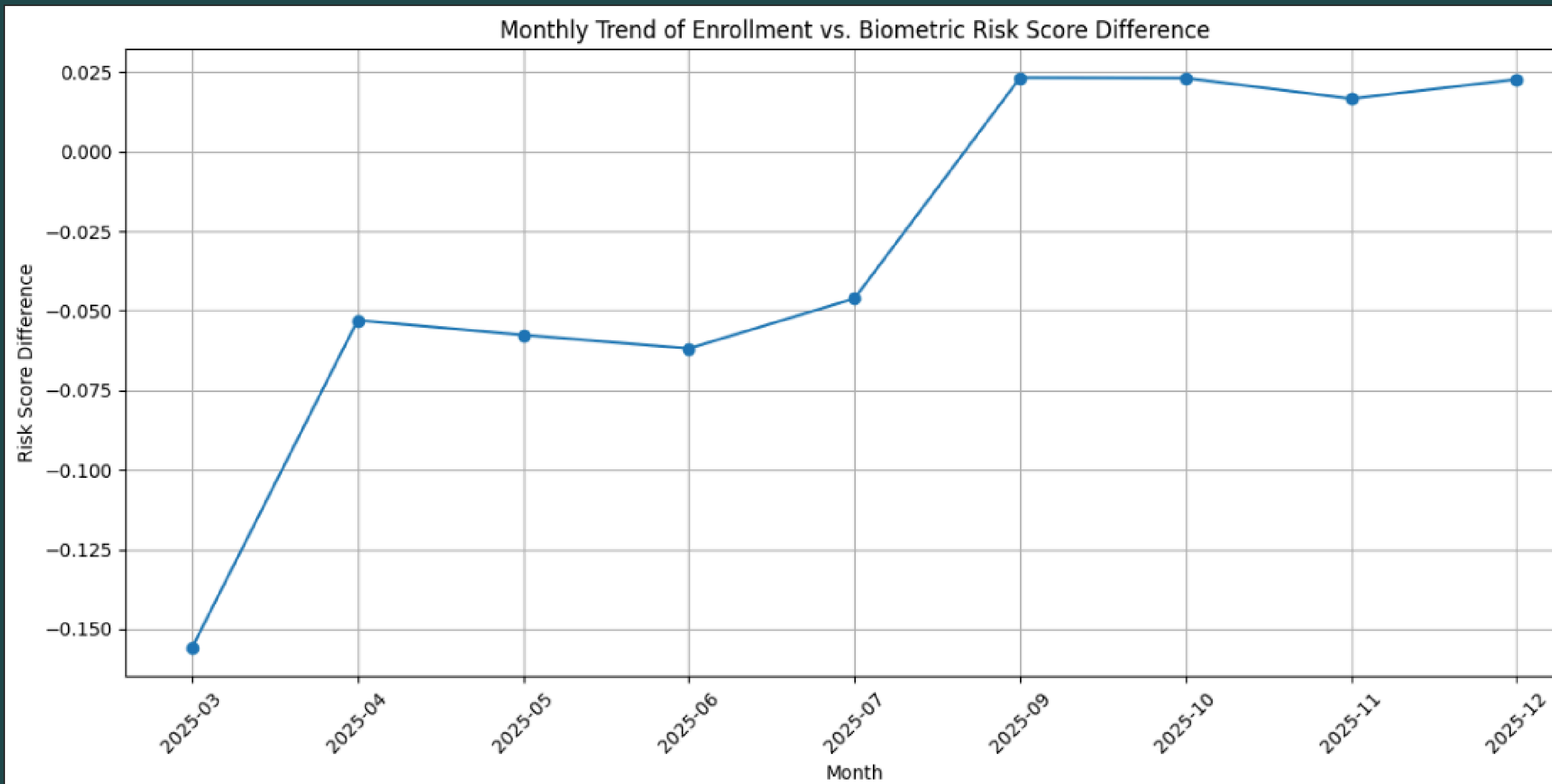
**High-Risk Districts**



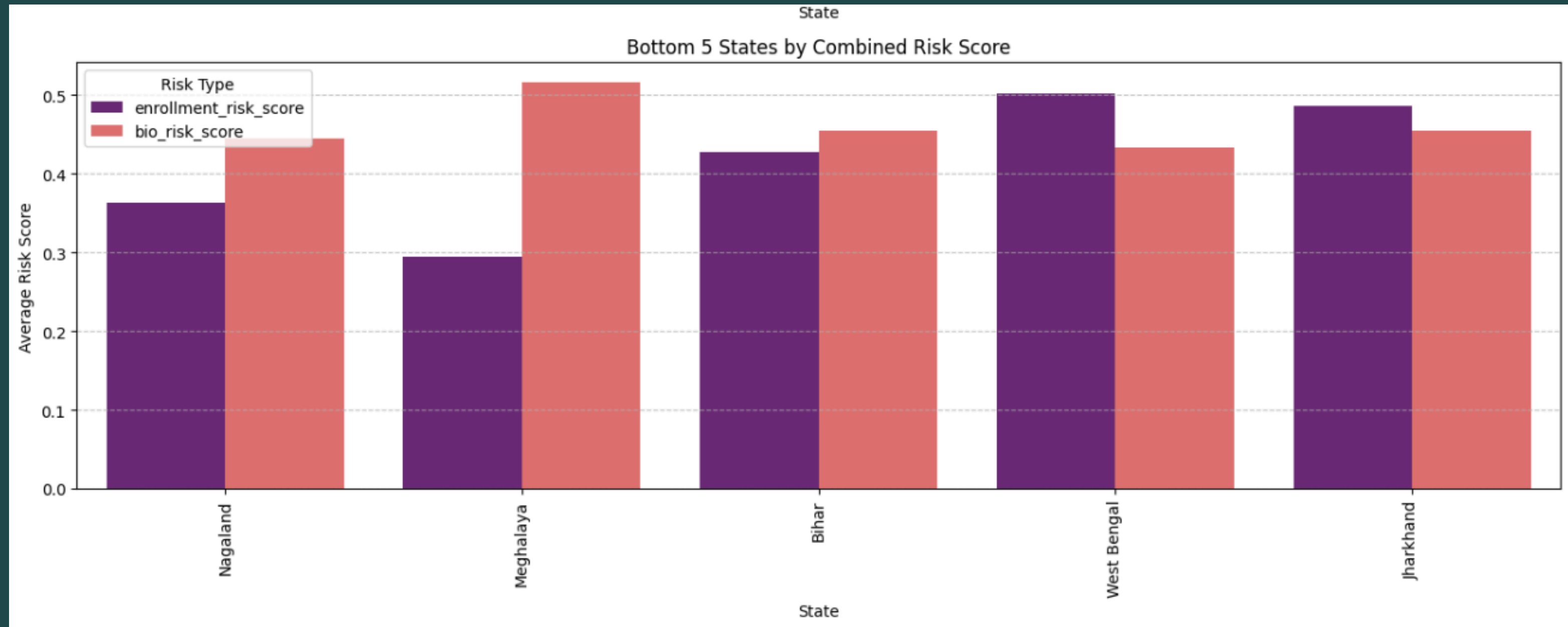




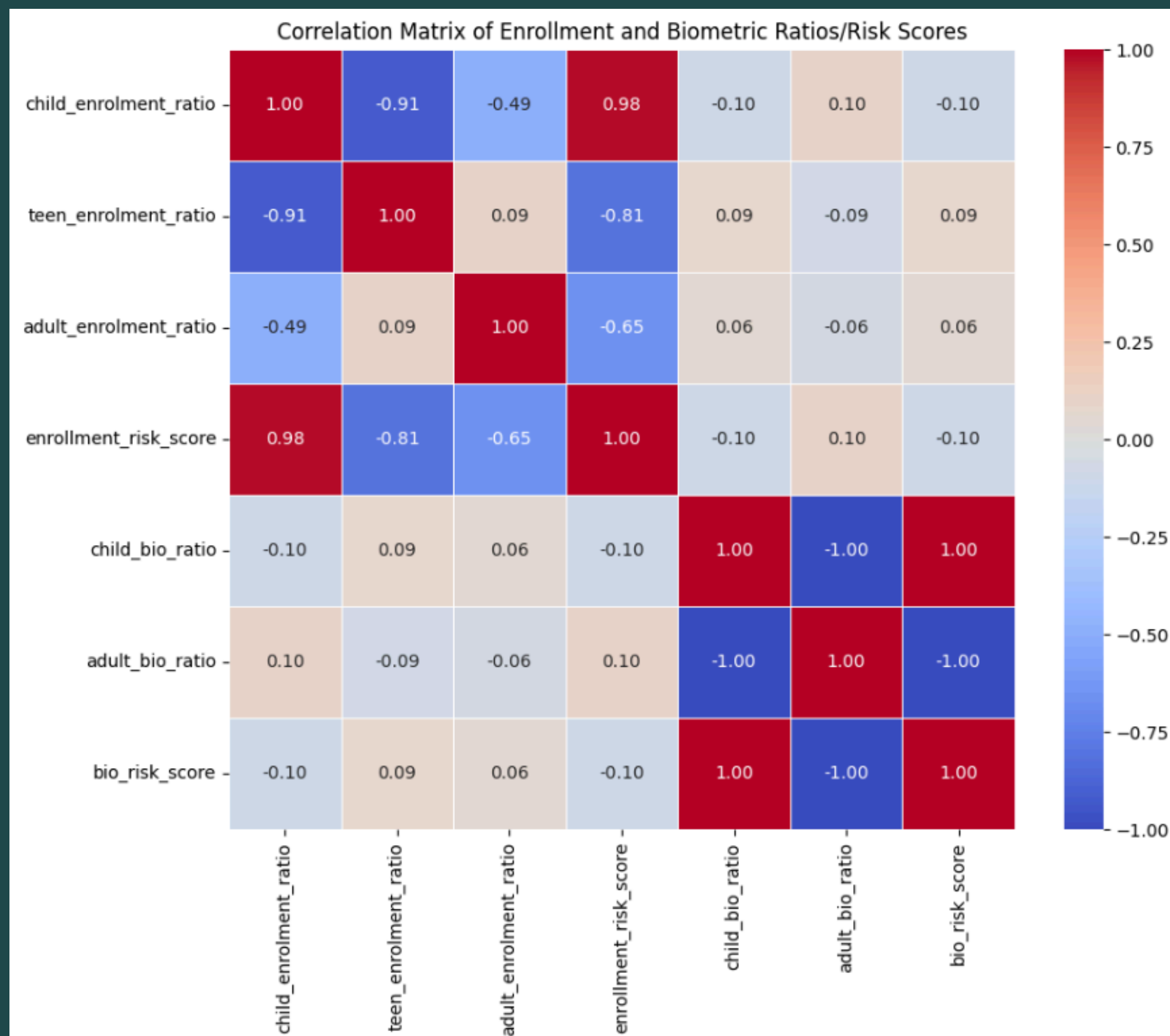
**Biometric risk varies significantly across states and months, showing clear regional and seasonal patterns. States like Uttar Pradesh and Tamil Nadu consistently exhibit higher risk levels, indicating persistent authentication challenges.**



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**These states show relatively lower combined risk due to manageable enrollment volumes. However, moderate biometric risk still exists, indicating that low scale does not eliminate mismatch issues.**



Strong correlations show that child enrollment and biometric update ratios are key drivers of risk. This statistically validates demographic change as a major cause of biometric authentication failure.



# Key Data Insights

Child (0–5) enrolments dominate in many regions, leading to frequent biometric changes due to natural growth.

Biometric updates vary widely across districts, indicating unequal access to update facilities.

High enrolment but low biometric updates highlight potential welfare-exclusion zones.

Higher adult enrolment ratios show more stable biometrics, resulting in lower authentication risk.

Enrolment spikes are often followed by biometric update pressure, making future risk prediction feasible.

# Conclusion

- Aadhaar biometric mismatches are a predictable risk, not just a random failure.
- By leveraging Aadhaar enrollment, update our ML model identifies high-risk regions in advance.
- This enables proactive policy action such as biometric update camps, infrastructure support, and alternate authentication methods.
- The solution helps reduce welfare exclusion, improve service reliability, and ensure last-mile inclusion.

**Github Link:** [https://github.com/vinayR-cmd/Seva\\_Shield.git](https://github.com/vinayR-cmd/Seva_Shield.git)

**Website Link:** [https://huggingface.co/spaces/vinay7410/Aadhaar\\_risk\\_2](https://huggingface.co/spaces/vinay7410/Aadhaar_risk_2)

**From reactive authentication failures to proactive welfare inclusion.**