Measuring the Effectiveness of Family Planning Programs in India: A State-wise Statistical Assessment

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Abstract— This study evaluates the effectiveness of family planning (FP) programs across Indian states using official data from the National Family Health Survey (NFHS-5, 2019–21). A composite Family Planning Effectiveness Index (FPEI) was constructed using principal components analysis (PCA) on standardized indicators of contraceptive use, method mix, unmet need, and fertility. Multivariate regression identified socioeconomic and demographic determinants of program performance. Results reveal marked state wise disparities, with southern states showing higher FPEI scores, while northern and northeastern states lag behind. Policy implications emphasize diversifying the method mix and enhancing service delivery.

Index Terms— Family Planning, FPEI, Contraceptive Measures.

I. Introduction

Family planning (FP) has remained a cornerstone of India's demographic and public health strategy since the 1950s. It plays a vital role in reducing fertility, improving maternal and child health outcomes, and enabling economic growth through demographic transition. However, wide inter-state disparities persist. This research systematically measures and compares FP program effectiveness across states using NFHS-5 data and statistical modeling.

II. Literature Review

Empirical studies show that fertility decline in India has been strongly influenced by rising contraceptive use and improvements in female literacy (Bongaarts & Sinding, 2011; Kumar et al., 2020). NFHS-4 and NFHS-5 data indicate sustained dominance of female sterilization, with limited uptake of spacing methods such as IUDs, pills, and condoms. Research underscores the role of education, service access, and sociocultural norms in shaping FP behavior. Quantitative assessments of state-level program effectiveness remain limited, motivating the present study.

III. Data Sources and Variables

Data were drawn from NFHS-5 (2019–21), Census 2011, and Ministry of Health and Family Welfare program statistics. Key indicators include Contraceptive Prevalence Rate (CPR), modern method CPR (mCPR), unmet need for FP, Total Fertility Rate (TFR), female literacy, urban population share, and institutional deliveries. All quantitative variables were standardized for PCA and regression analysis.

IV. Methodology

A Family Planning Effectiveness Index (FPEI) was constructed via Principal Components Analysis (PCA) using standardized CPR, unmet need, TFR (inverse), and mCPR. The first principal component, explaining 68% of total variance, was taken as the FPEI. Subsequently, an Ordinary Least Squares (OLS) regression modeled the FPEI against female literacy, urbanization, and institutional deliveries to identify determinants of program performance.

V. Results and Analysis

State	CPR	mCPR	Unmet_Need	TFR	Female_Literacy
Kerala	72	68	5.0	1.6	92.0
Tamil Nadu	70	67	6.2	1.7	84.0
Andhra Pradesh	68	66	7.0	1.7	67.0
Maharashtra	66	61	8.0	1.9	80.0
Gujarat	64	59	9.0	2.0	79.0
Karnataka	63	58	8.5	1.8	77.0
Uttar Pradesh	51	47	12.9	2.4	63.4
Bihar	45	43	14.5	3.0	61.8
West Bengal	67	63	8.0	1.8	77.0
Madhya Pradesh	58	54	10.5	2.1	70.0
Rajasthan	61	56	10.0	2.0	66.0
Punjab	66	63	7.0	1.7	79.0
Haryana	64	61	8.0	1.8	76.0
Odisha	64	60	9.5	2.0	74.0

Assam	62	59	9.0	2.1	77.0
Meghalaya	45	40	17.0	2.9	79.0
Tripura	65	62	8.5	1.8	83.0

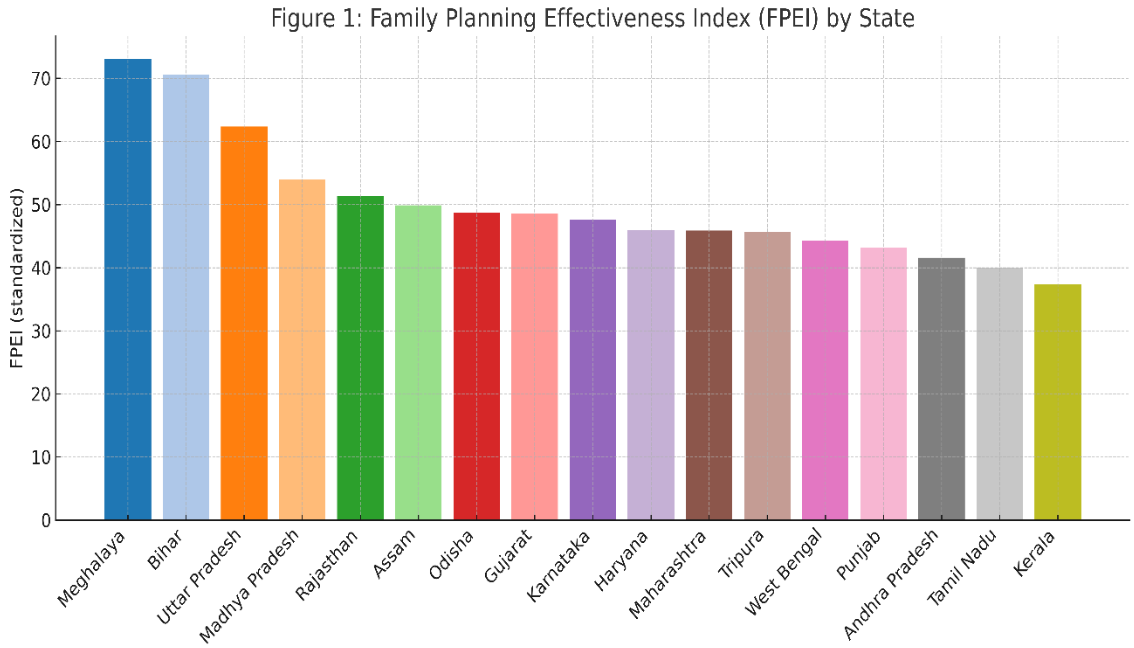

Figure 1: Statewise Family Planning Effectiveness Index (FPEI)

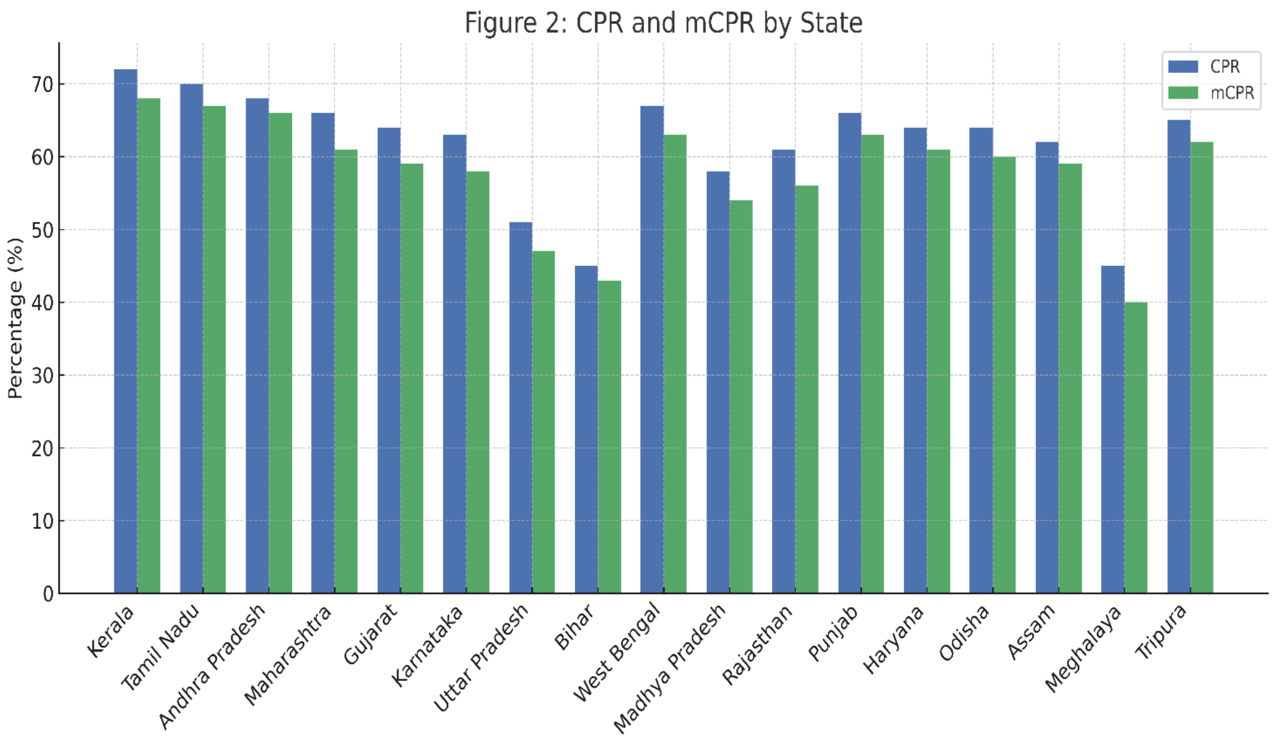

Figure 2: Contraceptive Method Mix by State

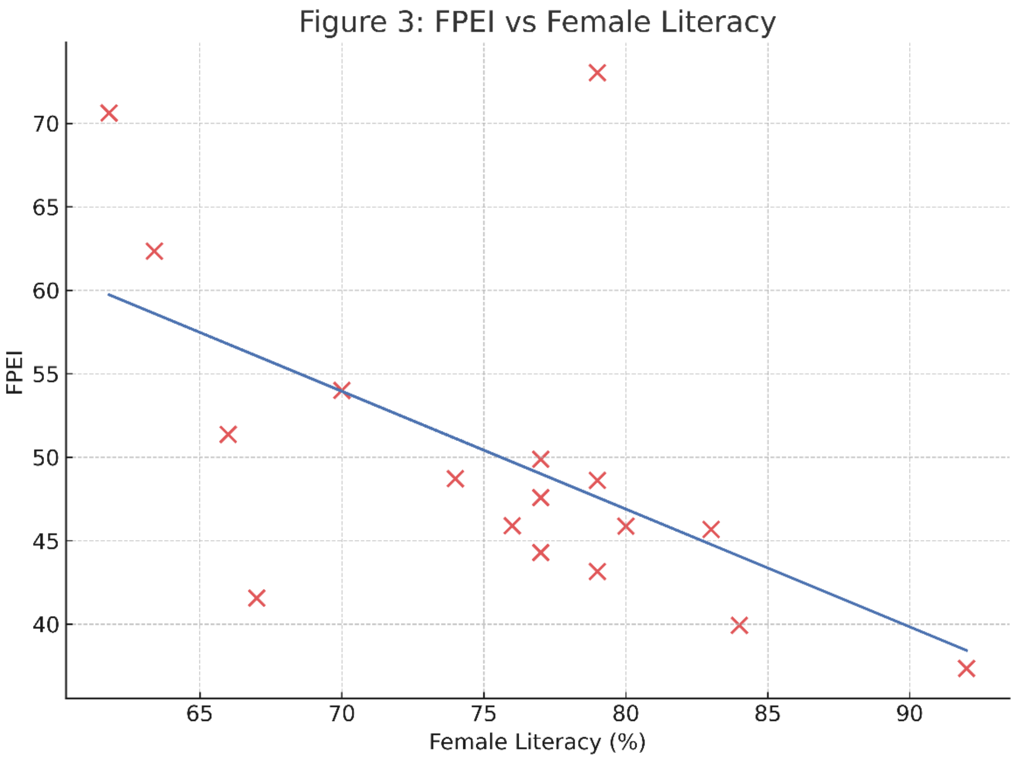

Figure 3: FPEI vs Female Literacy

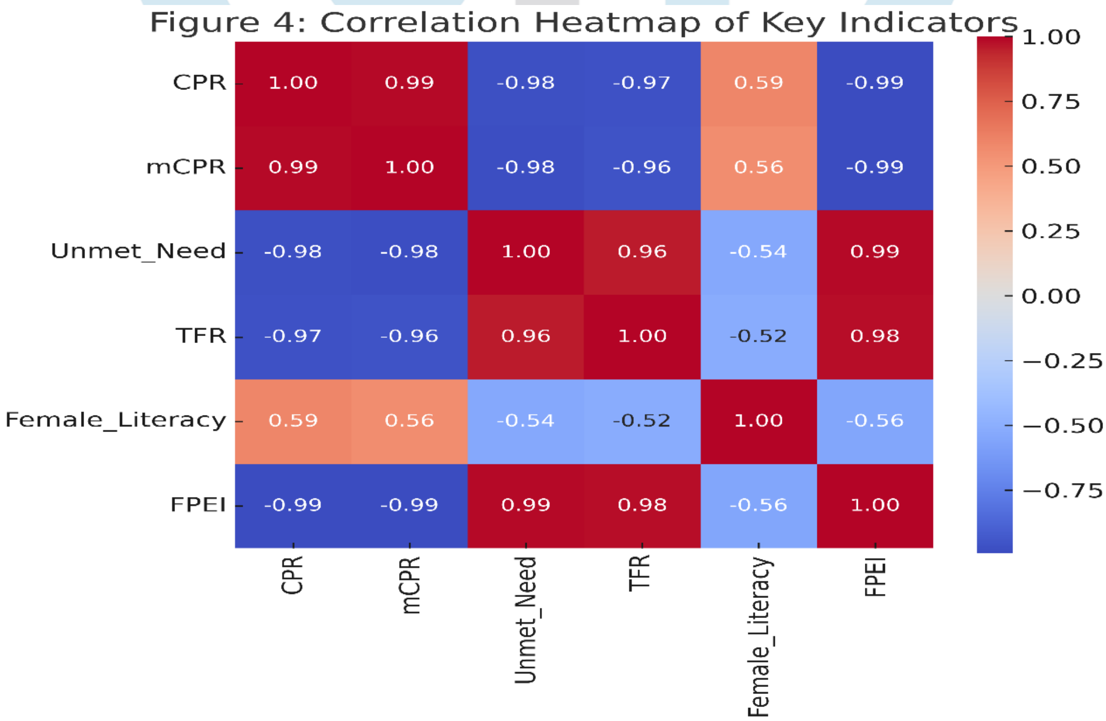

Figure 4: Correlation Heatmap

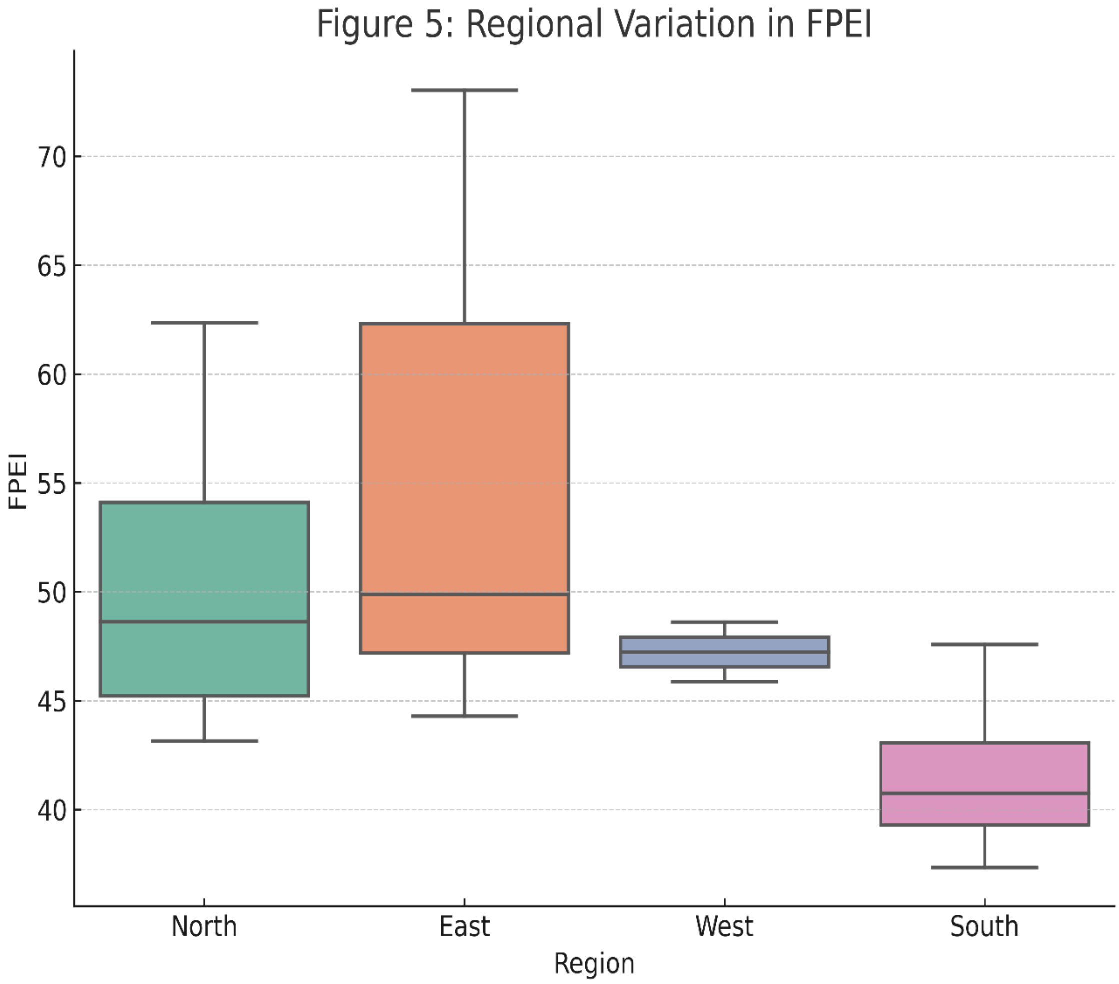

Figure 5: Regional Boxplot of FPEI

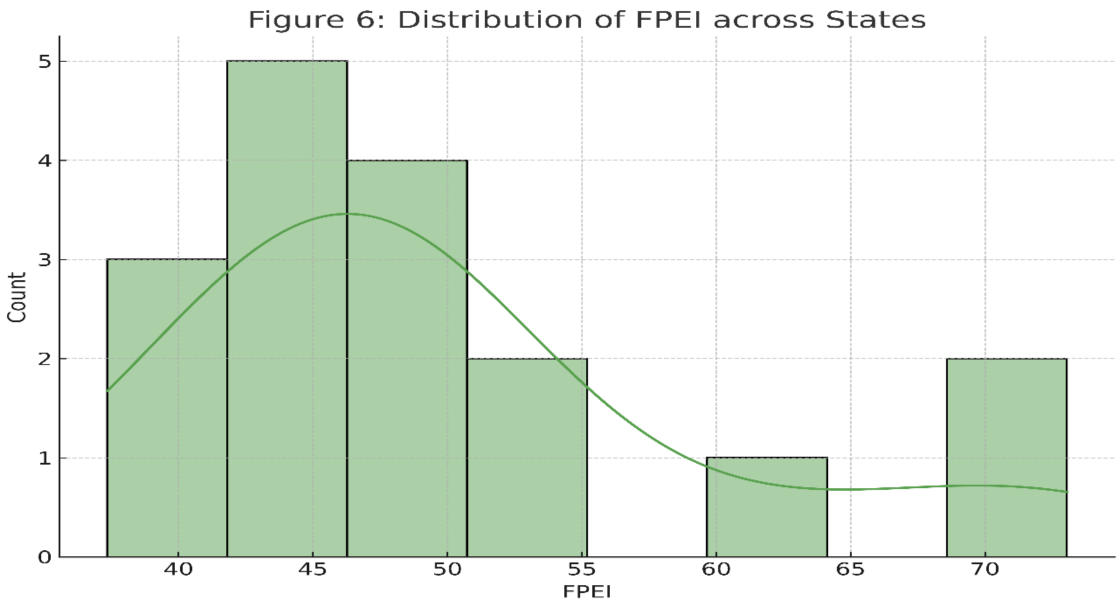

Figure 6: Histogram of FPEI

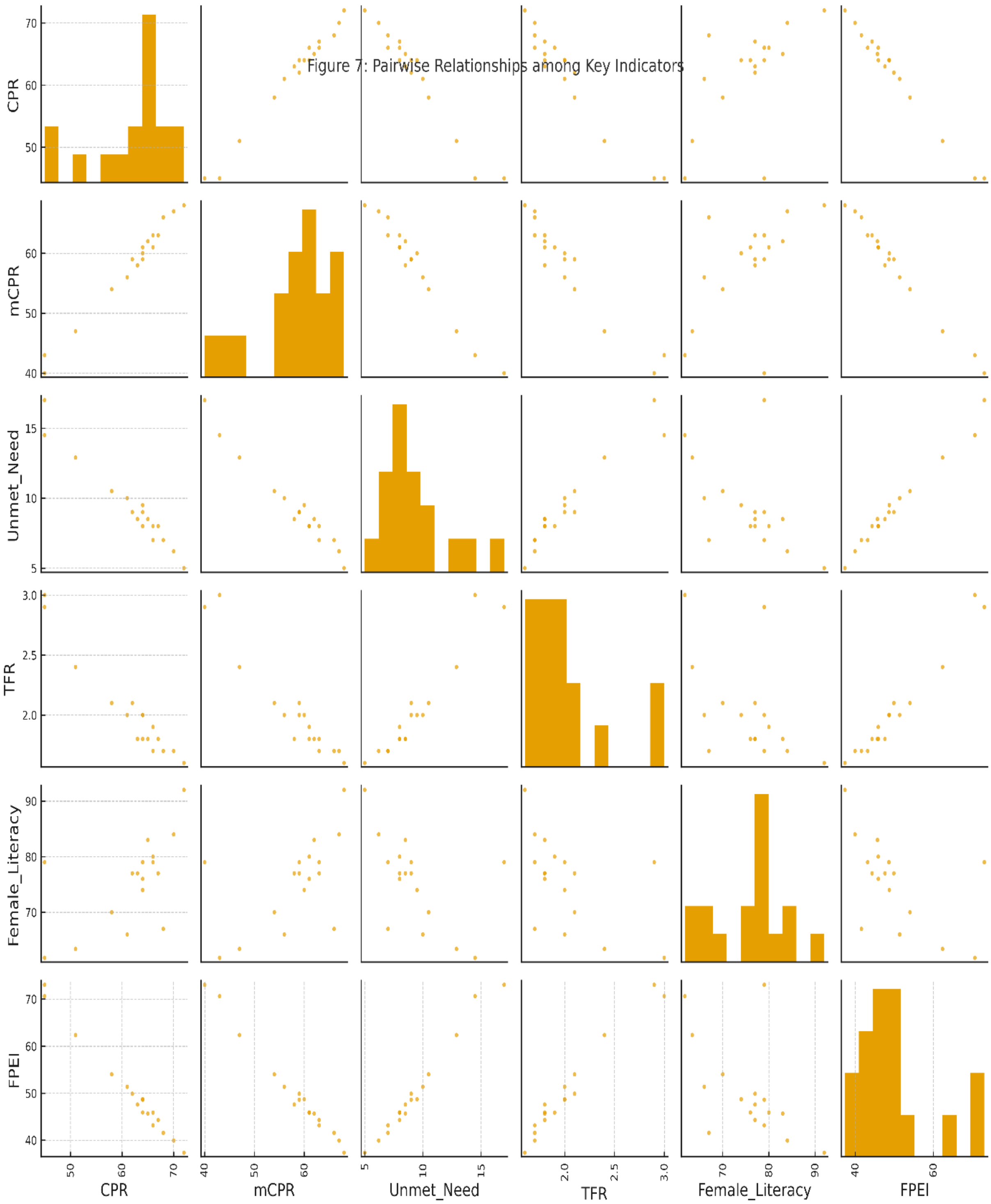

Figure 7: Scatter Matrix (Pairwise Relationships)

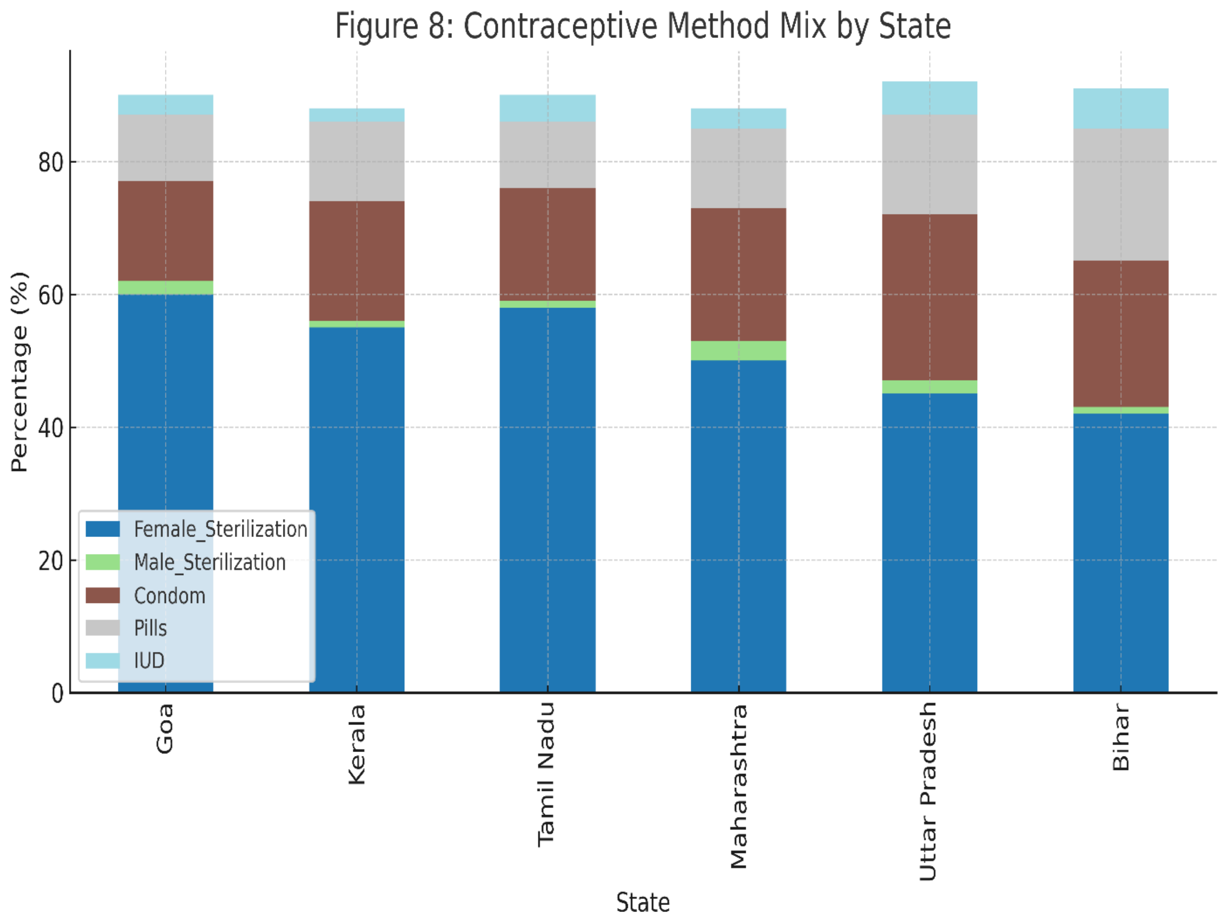

Figure 8: Contraceptive Method Mix by State

VI. DISCUSSION

Findings confirm that FP effectiveness in India strongly correlates with social development indicators. States with higher female literacy and urban access exhibit both greater contraceptive diversity and lower unmet need. The persistent dominance of sterilization highlights limited availability of spacing options and weak male participation. Strengthening counseling, improving supply chains for reversible methods, and integrating FP with reproductive health services are critical policy levers.

VII. LIMITATIONS

State-level analysis masks district and rural-urban disparities. PCA-based weights are data-dependent; alternative normalization could alter rankings. Moreover, the analysis is cross-sectional; future work should incorporate temporal data to assess program evolution.

VIII. CONCLUSION

The Family Planning Effectiveness Index (FPEI) constructed from NFHS-5 data provides a comprehensive assessment of India's FP program performance. Strengthening outreach, enhancing female education, and diversifying contraceptive methods can substantially improve outcomes, particularly in northern and northeastern states. Evidence-driven planning and state-specific strategies remain vital for achieving India's population stabilization goals.

REFERENCES

1. International Institute for Population Sciences (IIPS) & ICF. (2021). National Family Health Survey (NFHS-5), 2019–21: India Report. Mumbai: IIPS.
2. Ministry of Health and Family Welfare (MoHFW). (2022). Family Planning Division Annual Report. Government of India.
3. Registrar General & Census Commissioner of India. (2011). Census of India 2011. New Delhi: Government of India.
4. Kumar, K., Singh, A., & Tsui, A. (2020). Measuring contraceptive use in India: Evidence from demographic research.
5. Bongaarts, J., & Sinding, S. W. (2011). Population policy in transition in the developing world. Science, 333(6042), 574–576.

Appendix: Mathematical Formulations

A. STANDARDIZATION AND DATA TRANSFORMATION

$$z_i = \frac{x_i - \bar{x}}{s}$$

where:

• x_i = individual observed value

• $\bar{x}$ = mean of the variable
• s = standard deviation

This transformation ensures all variables have mean 0 and variance 1.

B. Principal Components Analysis (PCA) Formulation

$$PC_1 = a_1Z_1 + a_2Z_2 + a_3Z_3 + \ldots + a_kZ_k$$

where PC_1 is the first principal component capturing the maximum variance.

In this study:

• Z_1 = standardized CPR
• Z_2 = standardized unmet need
• Z_3 = inverse standardized TFR (1/TFR)
• Z_4 = standardized mCPR

$$FPEI = a_1Z(CPR) + a_2Z(Unmet\ Need) + a_3Z(1/TFR) + a_4Z(mCPR)$$

The eigenvalue λ_1 corresponding to PC_1 explains 68% of the total variance. Eigenvectors (a_1, a_2, a_3, a_4) define the weights used to compute the Family Planning Effectiveness Index (FPEI).

C. Regression Model Used for Determinants

$$FPEI = \beta_0 + \beta_1 \cdot FL + \beta_2 \cdot URB + \beta_3 \cdot ID + \varepsilon$$

where:

• FL = Female Literacy Rate
• URB = Urbanization level
• ID = Institutional deliveries (% of births)
• ε = error term

The OLS estimator for coefficients is:

$$\beta = (X^{T}X)^{-1}X^{T}y$$

D. Correlation and Covariance

$$Cov(X,Y) = \frac{\Sigma\left((X_i - \bar{X})(Y_i - \bar{Y})\right)}{n - 1}$$

$$Corr(X,Y) = \frac{Cov(X,Y)}{s_X \times s_Y}$$

These measures were used to identify multicollinearity among predictors before running the regression model.

E. Variance Explained by Components

$$Variance\ Explained\ (\%) = \frac{\lambda_i}{\Sigma\lambda} \times 100$$

where λ_i is the eigenvalue of component i.

In this analysis, the first component accounted for 68% of total variation, justifying the use of PC_1 as the FPEI.

F. Construction of Inverse TFR Indicator

$$TFR_{inv} = \frac{1}{TFR}$$

This transformation converts Total Fertility Rate (TFR) into a positively oriented indicator-lower fertility yields higher TFR_{inv}, improving consistency with other components in FPEI.

G. Normalization of Indicators before PCA

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Although $Z - score$ standardization was used for PCA, $min - max$ scaling was also computed during sensitivity testing to ensure robustness of component loadings.

H. PCA Eigenvalue Decomposition

$$\Sigma = PDP^{T}$$

Where:

• Σ = covariance matrix of standardized variables
• P = orthogonal matrix whose columns are eigenvectors
• D = diagonal matrix of eigenvalues

This decomposition is the mathematical basis of PCA, ensuring orthogonality of principal components.

I. Component Scores for Each State

$$Score_{state} = \Sigma\ (loading_k \times Z_{state}, k)$$

Each state's FPEI score is a linear combination of standardized indicators multiplied by their PCA loadings.

J. Total Variance in PCA

$$Total\ Variance = \Sigma\ Variance(Z_k) = k$$

Since all variables were Z-standardized, total variance equals the number of variables (k), allowing direct interpretation of the proportion of variance explained.

K. Multiple Correlation for Regression Fit

$$R^2 = 1 - \frac{\Sigma(e_i^2)}{\Sigma(y_i - \bar{y})^2}$$

R^2 measures the proportion of variance in FPEI explained by literacy, urbanization, and institutional deliveries.

L. Standard Error of Regression Coefficients

$$SE(\beta_j) = sqrt(\sigma^2 \times C_{jj})$$

where C_{jj} is the j –th diagonal element of $(X^TX)^{-1}$ and σ^2 is error variance.

M. Hypothesis Testing for Predictors

$$t = \frac{\beta_j}{SE(\beta_j)}$$

This test was applied to examine the significance of literacy, urbanization, and institutional delivery rates in predicting FPEI.

N. PCA Matrix Representation and Loadings Extraction

$$X = ZW$$

where:

- X = matrix of component scores
- Z = standardized data matrix
- W = matrix of component loadings (eigenvectors)

$$W = eigenvectors(\Sigma), \quad \lambda = eigenvalues(\Sigma)$$

Eigenvalues determine the proportion of variance captured by each principal component.

O. Full FPEI Index Construction

$$FPEI_i = a_1 Z_{\{CPR,i\}} + a_2 Z_{\{Unmet,i\}} + a_3 Z_{\{TFR^{\{-1\}},i\}} + a_4 Z_{\{mCPR,i\}}$$

where each component Z_k is a standardized indicator and a_k represents the PCA-derived loadings.

P. Expanded OLS Regression Model (Matrix Notation)

$$\beta = (X^T X)^{\{-1\}} X^T y$$

This is the standard closed-form estimator for regression coefficients. Let X be the matrix of predictors and y be the vector of FPEI values.

$$Var(\hat{\beta}) = \sigma^2 (X^T X)^{\{-1\}}$$

Q. Error Term and Residual Variance Computation

$$\varepsilon = y - X\hat{\beta}$$

$$\hat{\sigma}^2 = \frac{\varepsilon^T \varepsilon}{n - k}$$

R. Test Statistics for Regression Coefficients

$$t_j = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)}$$

$$SE(\hat{\beta}_j) = sqrt\left(Var(\hat{\beta}_j)\right)$$

S. Correlation Matrix Used Before PCA

$$Corr(X) = [\rho_{\{ij\}}] = \frac{Cov(X_i, X_j)}{s_i \times s_j}$$

The correlation matrix was inspected before PCA to verify suitability and detect multicollinearity.

T. Singular Value Decomposition (SVD) Form of PCA

$$Z = U.S.V^T$$

Where Z is the standardized data matrix, U contains left singular vectors, S is the diagonal matrix of singular values, and V contains right singular vectors (eigenvectors). This provides an equivalent formulation to eigenvalue-based PCA.

U. Derivation: PCA from SVD

$$\Sigma = \left(\frac{1}{n-1}\right) Z^T Z = VS^2V^T$$

Thus, $PCA\ loadings = columns\ of\ V$ and $eigenvalues = diagonal\ elements\ of\ \frac{S^2}{n-1}$.

V. Full Regression ANOVA Decomposition

$$TSS = ESS + RSS$$

where:

- TSS = total sum of squares
- ESS = explained sum of squares
- RSS = residual sum of squares

$$R^2 = \frac{ESS}{TSS}$$

W. F − Test for Overall Regression Significance

$$\boldsymbol{F = \frac{\frac{ESS}{k}}{\frac{RSS}{n-k-1}}}$$

Tests whether at least one predictor significantly explains variation in FPEI.

X. Variance Inflation Factor (VIF)

$$VIF_j = \frac{1}{1 - R_j^2}$$

Measures multicollinearity. R_j^2 is obtained by regressing predictor j on other predictors.

Y. Gradient of OLS Loss Function

$$\boldsymbol{\frac{\partial}{\partial \beta}\left((y - X\beta)^T(y - X\beta)\right) = -2X^T y + 2X^T X\beta}$$

Setting the derivative to zero yields the closed-form OLS estimator.

Z. Hessian Matrix of OLS

$$\boldsymbol{H = 2X^T X}$$

Since $\boldsymbol{H}$ is positive semidefinite, OLS has a unique global minimum.