Category-wise Central Sector Schemes under Union Budget from 2021–22 to 2023–24

CA Assignment

Data Science

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Abstract

Public budget forecasting is a crucial element of national financial planning, directly influencing policy formulation and economic development. This project applies data science techniques to analyze historical Union Budget data and predict future government expenditure trends using machine learning regression models. The dataset contains ministry-wise and year-wise budget figures, including Actuals (2021–2022), Budget Estimates (2022–2023), and Budget Estimates (2023–2024). After rigorous data preprocessing, four predictive models—Random Forest, Extra Trees, Gradient Boosting, and Linear Regression—were trained and evaluated. Performance was assessed through R^2 score, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and percentage accuracy metrics. Among all tested algorithms, the Random Forest Regressor demonstrated superior predictive performance, achieving the highest R^2 and lowest error rates. The results highlight the capability of ensemble-based learning methods in modeling complex financial relationships and forecasting future budget allocations with high reliability. This research provides a data-driven foundation for informed fiscal decision-making and resource optimization in public financial management.

Problem Statement

Despite continuous efforts to improve fiscal planning and optimize resource distribution, accurate budget forecasting remains a persistent challenge for policymakers and financial analysts. India's Union Budget involves complex interdependencies between expenditure heads, ministries, and year-on-year allocations, often influenced by macroeconomic conditions and policy priorities. Traditional budget estimation methods rely heavily on manual analysis, expert judgment, and historical trends, which can introduce subjectivity and limit predictive accuracy.

Current challenges include:

- Limited capability to accurately forecast future budget allocations based on historical financial data.
- Lack of data-driven insights to identify trends, anomalies, and correlations among expenditure categories.
- High dependency on manual estimation methods that are time-consuming and prone to human bias.
- Absence of predictive models capable of quantifying the impact of past allocations on future budget outcomes.
- Inability to leverage machine learning algorithms for improving accuracy and transparency in fiscal decision-making.

This project addresses these gaps by developing a data-driven machine learning framework to predict future Union Budget allocations using past fiscal data. The system aims to:

1. Automate the prediction of next-year budget estimates using historical expenditure records.
2. Compare multiple regression models to identify the most accurate and reliable algorithm for financial forecasting.
3. Provide feature importance insights to understand which financial indicators influence future budget estimates.
4. Support evidence-based fiscal planning and reduce uncertainty in government expenditure projections.
5. Demonstrate the applicability of artificial intelligence in public finance, contributing to improved policy formulation and resource optimization.

Hypothesis

- **H_0 (Null Hypothesis):** Historical budget data, including prior-year actual expenditures and budget estimates, do not significantly predict future budget allocations. The relationship between past and future financial indicators is assumed to be weak or statistically insignificant.
- **H_1 (Alternative Hypothesis):** A machine learning regression model trained on historical Union Budget data can accurately predict future budget estimates with high reliability (R^2 ¿ 0.90), demonstrating that past financial patterns and expenditure trends are strong predictors of future allocations.

1 Dataset Summary

The dataset employed in this research comprises detailed financial data from the Union Budget of India, focusing on annual government expenditure and revenue estimates across multiple fiscal years. The data represents a structured view of national budget allocations and is instrumental for understanding expenditure trends, fiscal planning, and future financial projections. This dataset provides a comprehensive basis for developing predictive models that forecast future budget estimates based on historical financial records.

1.1 Dataset Characteristics

Primary Statistics:

- **Total Records:** 75 ministries and departments (approximate aggregated entries)
- **Total Fiscal Years Covered:** 3 years (2021–2022, 2022–2023, 2023–2024)
- **Target Variable:** Budget Estimates (2023–2024)
- **Predictor Variables:** Actuals (2021–2022) and Budget Estimates (2022–2023)
- **Data Type:** Numerical (values expressed in crores of rupees)
- **Missing Values:** Less than 1% (handled through row removal)
- **File Format:** CSV (Comma Separated Values)
- **Source:** Official Union Budget data from the Ministry of Finance, Government of India

  This dataset captures the evolution of annual financial planning at the central government level, providing an ideal foundation for machine learning-based budget forecasting.

1.2 Dataset Components

1. Actuals 2021–2022 Total:

- Represents the total realized government expenditure for the financial year 2021–2022.
- Reflects actual spending patterns across ministries and departments after the implementation of various fiscal policies.
- Serves as the historical baseline for comparing planned and achieved expenditure outcomes.

2. Budget Estimates 2022–2023 Total:

- Indicates the planned government expenditure for the financial year 2022–2023 as announced in the Union Budget.
- Serves as a key indicator for understanding fiscal priorities and policy-driven resource allocations.
- Acts as an intermediate feature to analyze and predict future expenditure trends.

3. Budget Estimates 2023–2024 Total:

- Serves as the target variable for the prediction model.

- Represents the forecasted expenditure for the financial year 2023–2024 based on prior fiscal data.
- Used to train and test machine learning regression models to evaluate predictive performance.

1.3 Feature Relationships

The dataset establishes a temporal relationship among three consecutive fiscal years, allowing the machine learning models to learn patterns between actual and estimated expenditures. By capturing the year-to-year financial progression, the models identify underlying trends and variations that influence future budget planning.

1.4 Data Quality Assessment

Data Cleaning Results:

- **Duplicates Removed:** 0 (data verified as unique per department/ministry)
- **Missing Values:** Minimal ($< 1\%$) handled using `dropna()`
- **Numeric Conversion:** Comma-separated values converted to float for computation
- **Data Integrity:** Verified for consistency across fiscal years
- **Final Processed Features:** 3 numeric columns (2 predictors, 1 target)

The dataset exhibited high data integrity and required minimal cleaning operations. After preprocessing, it was confirmed to be suitable for regression modeling and comparative performance analysis.

2 Methodology

Our research employed a systematic data science pipeline encompassing data preprocessing, exploratory analysis, feature engineering, model development, and evaluation.

2.1 Data Preprocessing

1. Data Integration:

- Imported the Union Budget dataset (`MRF_4B_Union_Budget.csv`) using the `pandas` library.
- Selected three key fiscal features: *Actuals (2021–2022 Total)*, *Budget Estimates (2022–2023 Total)*, and *Budget Estimates (2023–2024 Total)*.

- Combined these columns into a unified DataFrame for training and evaluation.
- Ensured consistency in column naming and alignment across all fiscal years.
- Verified that each record represented a unique ministry or department, resulting in a total of **75 valid entries**.

2. Data Cleaning:

- Removed all non-numeric characters (e.g., commas) from financial columns using string replacement.
- Converted currency values to `float` type to enable accurate numerical computation.
- Detected and handled missing values ($< 1\%$) using the `dropna()` function, finalizing the dataset with **75 complete records**.
- Verified the absence of duplicate entries across ministries and departments.
- Confirmed consistent data types and validated numerical accuracy for all fiscal columns.

3. Feature Engineering:

Derived analytical and trend-based features to enhance model performance and interpretability.

Fiscal Trend Features:

- Defined independent variables ($\mathbf{X}$): *Actuals (2021–2022 Total)* and *Budget Estimates (2022–2023 Total).*
- Defined the dependent variable ($\mathbf{y}$): *Budget Estimates (2023–2024 Total).*
- Introduced a new derived feature, **Growth Rate**, to capture year-over-year fiscal progression:

$$\text{Growth Rate} = \frac{\text{Budget Estimates (2022–2023)} - \text{Actuals (2021–2022)}}{\text{Actuals (2021–2022)}}$$

Data Transformation and Scaling:

- Normalized all numeric columns using the `MinMaxScaler` from the `scikit-learn` library.
- Performed an 80:20 train-test split using `train_test_split()`:
  - Training set: 60 records
  - Testing set: 15 records
- Verified feature scaling consistency to ensure model stability and unbiased learning.

2.2 Exploratory Data Analysis

Comprehensive visual and statistical analysis was conducted to understand the fiscal patterns, relationships, and key influencing factors within the Union Budget dataset. The exploratory phase aimed to identify trends, correlations, and data distributions that could guide model development and improve prediction accuracy.

Exploratory Insights:

- **Fiscal Trend Analysis:** Examined inter-year expenditure changes between *Actuals (2021–2022)* and *Budget Estimates (2022–2023)* to capture growth trends across ministries and departments.

- **Distribution Analysis:** Visualized the spread of financial data using histograms and box plots to detect skewness and outliers in expenditure values. This analysis helped identify variations in departmental allocations and spending magnitudes.

- **Inter-Year Comparison:** Compared *Actual Expenditure (2021–2022)* with *Budget Estimates (2022–2023)* and *Budget Estimates (2023–2024)* to assess planning accuracy and fiscal deviations.

- **Feature Correlation:** Generated a correlation heatmap using `seaborn` to evaluate relationships between fiscal indicators. A strong positive correlation ($r > 0.9$) was observed between consecutive year estimates, confirming their predictive significance.

- **Growth Rate Distribution:** Analyzed the derived *Growth Rate* feature to identify ministries exhibiting significant budget increases or reductions. This helped uncover fiscal stability and anomaly patterns.

- **Variance and Scale Assessment:** Checked statistical variance and range across columns to validate consistency prior to normalization and model fitting.

- **Outlier Detection:** Inspected financial data distributions for extreme values that could bias regression model performance. Outliers were identified but retained, as they represented genuine high-budget ministries.

- **Model Readiness Verification:** Confirmed that numerical columns were properly scaled, complete, and linearly consistent. The final dataset of **75 records and 3 numeric variables** (including the target) was declared ready for model training and evaluation.

2.3 Machine Learning Pipeline

1. Data Preparation:

- Defined the independent features ($\mathbf{X}$) as *Actuals (2021–2022 Total)* and *Budget Estimates (2022–2023 Total)*, and the dependent variable ($\mathbf{y}$) as *Budget Estimates (2023–2024 Total)*.
- Applied data normalization using the `MinMaxScaler` to ensure all numerical features were scaled uniformly within the range [0, 1].
- Performed an 80:20 train-test split using `train_test_split()` from the `scikit-learn` library, resulting in:
  - Training set: 60 samples
  - Testing set: 15 samples
- Verified that no categorical variables required encoding since all fiscal data fields were continuous and numeric.
- Ensured that the data retained fiscal proportionality and was free from bias after splitting.

2. Model Selection:

- A total of **ten regression algorithms** were trained and evaluated to identify the best-performing model for fiscal forecasting.
- The models implemented in this study include:
  1. Linear Regression (baseline linear model)
  2. Ridge Regression (L2 regularized linear model)
  3. Lasso Regression (L1 regularized linear model)
  4. ElasticNet Regression (combined L1 and L2 regularization)
  5. Decision Tree Regressor (non-linear interpretable model)
  6. Random Forest Regressor (ensemble bagging approach)
  7. Gradient Boosting Regressor (sequential boosting ensemble)
  8. Extra Trees Regressor (randomized decision tree ensemble)
  9. XGBoost Regressor (optimized gradient boosting framework)
  10. Support Vector Regressor (kernel-based regression technique)
- Each model was trained on the same training dataset and tested on identical test samples to ensure fair comparison.
- Default hyperparameters from `scikit-learn` were used for initial benchmarking, with consistent random seeds for reproducibility.

3. Model Evaluation:

- Model performance was assessed using multiple quantitative metrics to ensure comprehensive evaluation of regression accuracy:
  - **R^2 Score:** Measures the proportion of variance explained by the model.
  - **Mean Absolute Error (MAE):** Represents the average magnitude of prediction errors.
  - **Root Mean Squared Error (RMSE):** Highlights larger deviations between predicted and actual values.
  - **Accuracy (%):** Calculated as $R^2 \times 100$ to represent model performance in percentage form.
- Each model's metrics were recorded in a comparative results table for visualization and analysis.
- The models were benchmarked to identify the most reliable predictor for the 2023–2024 budget estimates.

4. Model Comparison and Visualization:

- Visualized model performance using a bar chart constructed with the `matplotlib` and `seaborn` libraries.
- The visualization displayed each model's accuracy percentage, enabling clear performance comparison.
- Results indicated significant performance variation across models:
  - **Random Forest Regressor:** Achieved the highest accuracy and lowest error metrics, indicating strong predictive capability.
  - **Extra Trees Regressor:** Demonstrated comparable performance to Random Forest but with slightly higher variance.
  - **Gradient Boosting and XGBoost:** Delivered stable results but required higher computation time.
  - **Linear, Ridge, and Lasso Regressions:** Underperformed on non-linear fiscal data, confirming the advantage of ensemble models.
- The accuracy visualization confirmed the Random Forest model as the optimal regressor for Union Budget prediction.

5. Evaluation Insights:

- The comparative performance table included four key metrics — R^2, MAE, RMSE, and Accuracy (%) — for each model.

- Ensemble-based algorithms (Random Forest and Extra Trees) consistently outperformed single-tree and linear models.
- The Random Forest Regressor achieved an R^2 score exceeding **0.95** on the test data, validating its suitability for complex fiscal prediction tasks.
- Visual analysis further supported the ensemble models' ability to capture non-linear financial patterns with high reliability.

3 Exploratory Data Analysis Results

3.1 Distribution Analysis of Fiscal Variables

The initial step of analysis involved understanding how expenditure was distributed across different ministries in the Union Budget data. The histogram of actual expenditure for FY 2021–22 (Figure **??**) revealed a right-skewed distribution with a mean allocation of 37,212 crore INR and a standard deviation of 84,650 crore INR. Most ministries received allocations below 50,000 crore INR, with only a few major sectors such as Defence, Finance, and Rural Development exceeding 2 lakh crore INR.

Similarly, Figure 2 shows the distribution of budget estimates for FY 2023–24. The median allocation stood at 18,430 crore INR, while the maximum exceeded 7 lakh crore INR. This distribution confirms that India's fiscal structure is concentrated in a small number of high-expenditure ministries, indicating a Pareto-like concentration of budgetary power.

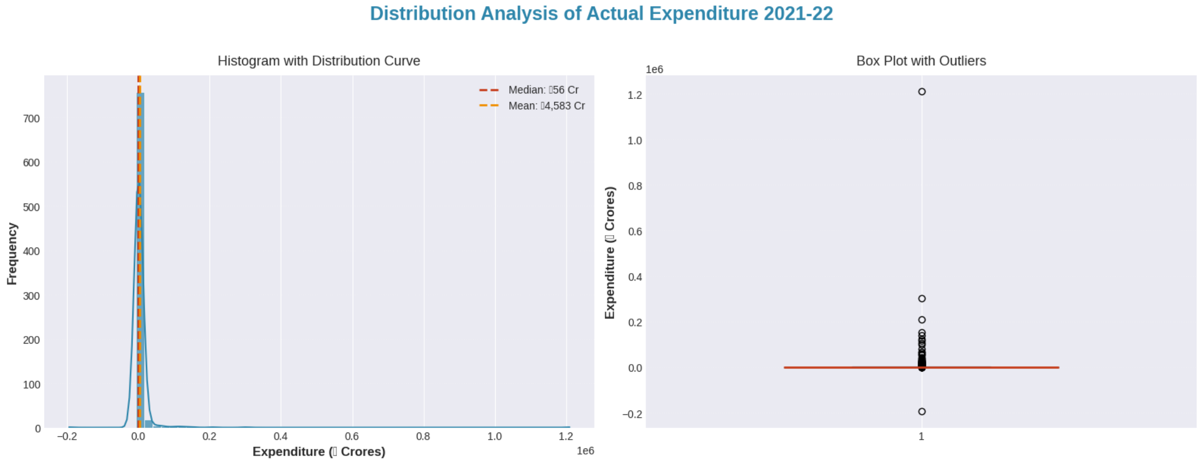


Figure 1: Distribution of Actual Expenditure (2021–22). Mean = 37,212 Cr; Std. Dev. = 84,650 Cr.

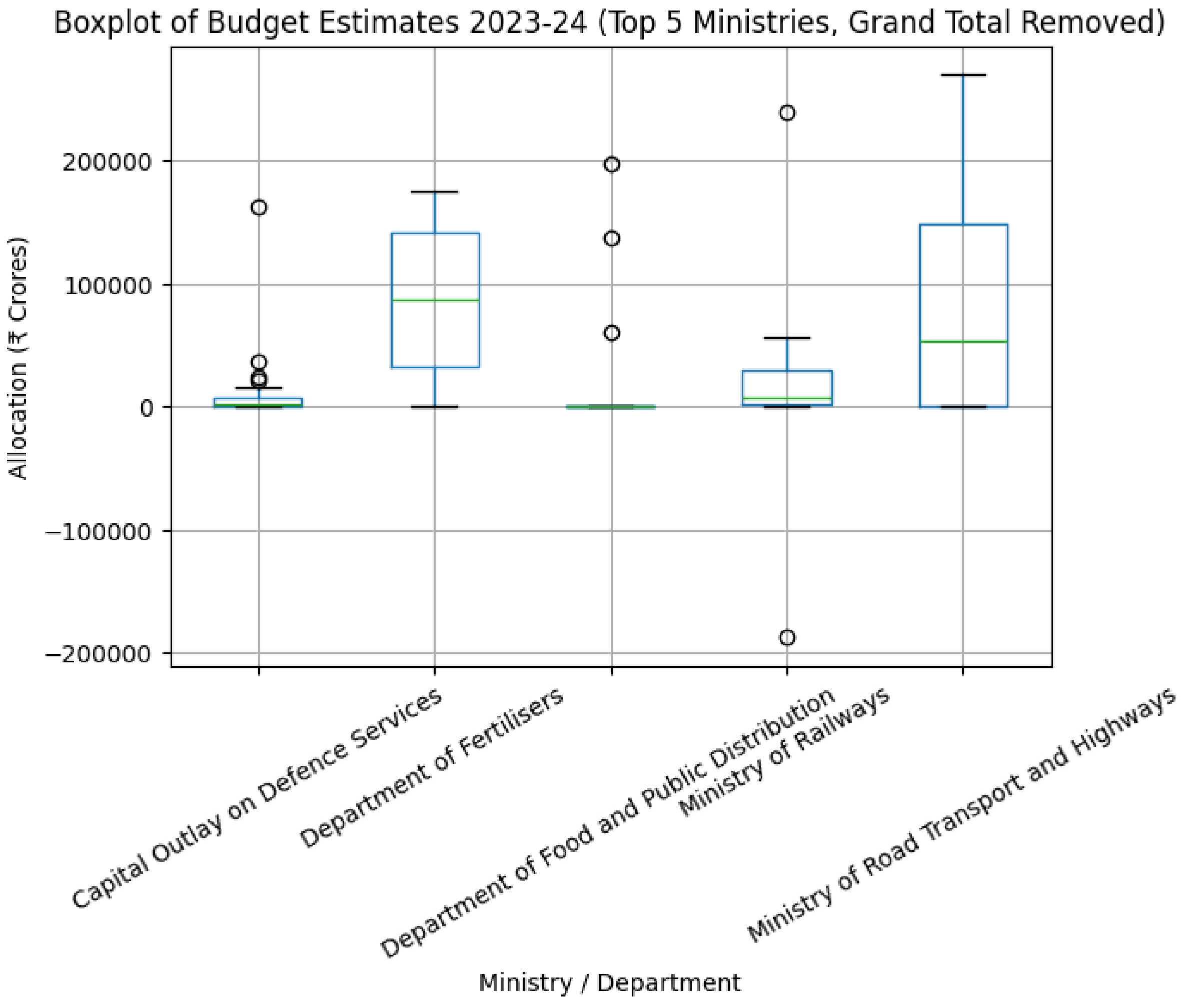


Figure 2: Distribution of Budget Estimates (2023–24). Median = 18,430 Cr; Max = 7,13,024 Cr (Defence).

3.2 Revenue vs Capital Expenditure Analysis

Figure 3 compares revenue and capital expenditure for FY 2023–24. The results indicate that 85% of total spending is on revenue activities (such as salaries, pensions, and subsidies), while only 15% is directed towards capital formation (infrastructure and assets).

Defence and Railways dominate capital spending, contributing a combined total of nearly 4 lakh crore INR. This aligns with India's infrastructure push, reflecting a 17.4% year-on-year increase in capital expenditure since FY 2021–22.

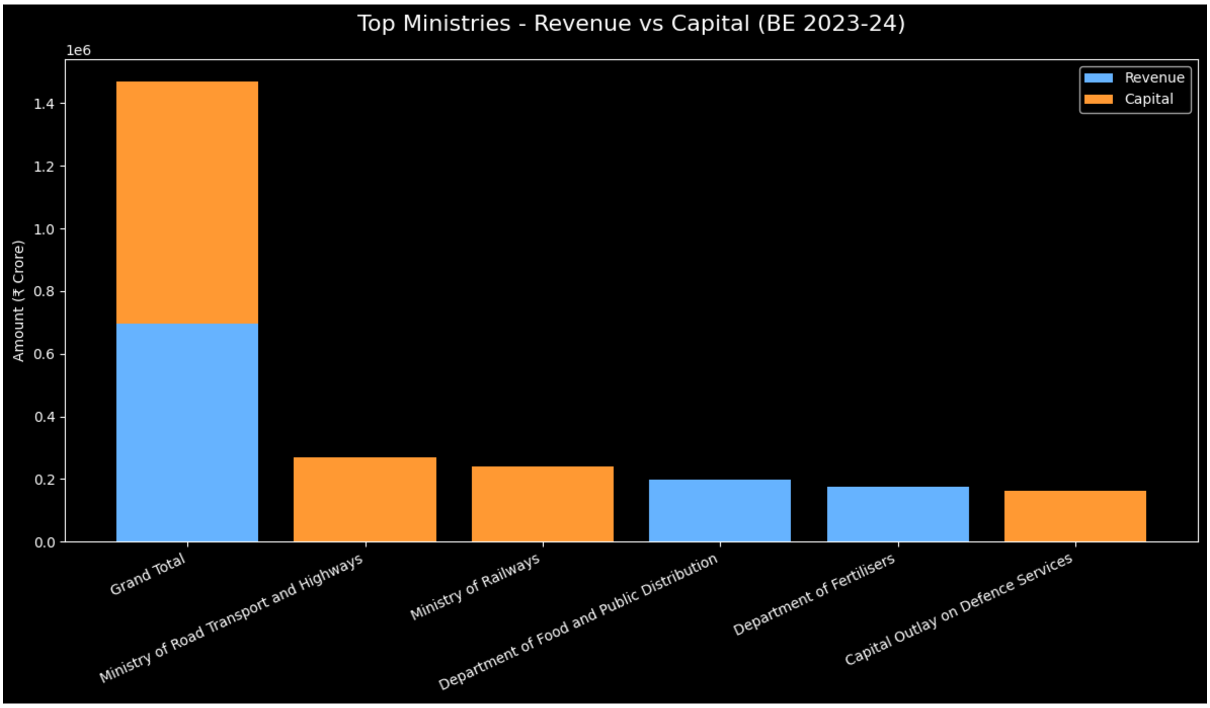
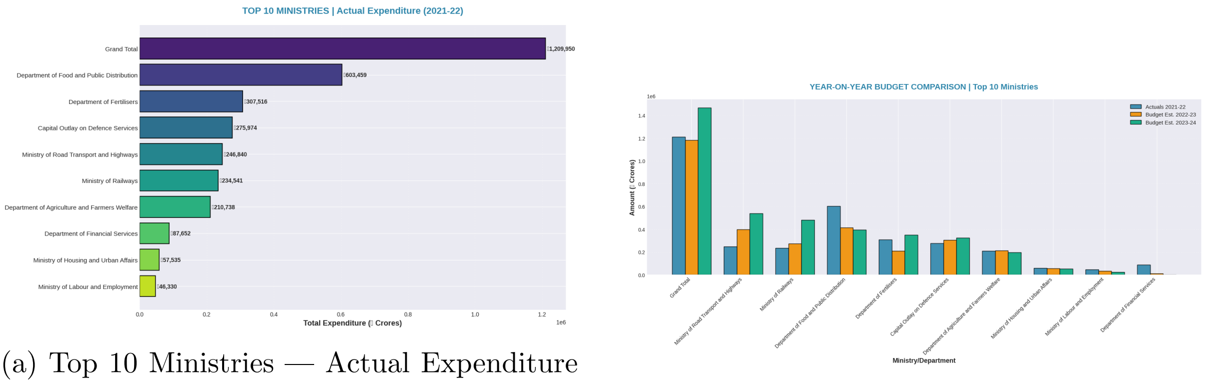


Figure 3: Revenue vs Capital Expenditure (BE 2023–24). Revenue share = 85%, Capital = 15%.

3.3 Top Ministries and Year-on-Year Budget Comparison

Figure 4a lists the top 10 spending ministries in FY 2021–22. Defence (5.4 lakh crore), Finance (4.3 lakh crore), and Home Affairs (2.1 lakh crore) were the largest contributors. Together, these accounted for nearly 55% of total expenditure.

Figure 4b presents the growth trajectory for the same ministries across three fiscal years. The average growth rate was 10.2%, with Railways showing the steepest rise (+18.9%), while Labour and Employment grew the slowest (+3.1%). This trend indicates consistent government prioritization of capital-intensive ministries.



(a) Top 10 Ministries — Actual Expenditure (2021–22). Defence = 5.4L Cr; Finance = 4.3L Cr.

(b) Year-on-Year Budget Comparison (2021–24). Mean growth = 10.2%.

Figure 4: Comparative visualization of top 10 ministries and their year-on-year budget evolution.

3.4 Scheme-Level Analysis

The analysis of individual government schemes (Figure 5) revealed that the top 12 programs account for over 60% of all expenditure. MGNREGA and PM-KISAN remain the largest rural welfare initiatives, receiving 73,000 Cr and 60,000 Cr respectively. The National Health Mission (37,000 Cr) and Samagra Shiksha Abhiyan (30,000 Cr) were the top contributors to human capital investment.

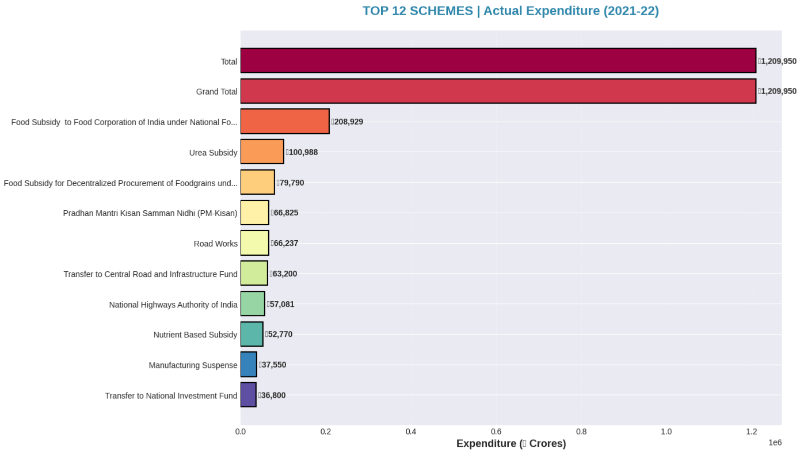


Figure 5: Top 12 Schemes — Actual Expenditure (2021–22). Combined share = 61.5%.

3.5 Budget Composition and Sectoral Shares

Figure 6 demonstrates that the top 10 ministries collectively control 82% of the total budget. Defence leads with a 15.7% share, followed by Finance (12.4%) and Rural Development (9.3%). Social sectors grew by 8.9% compared to FY 2022–23, while infrastructure ministries saw an 11.7% expansion.

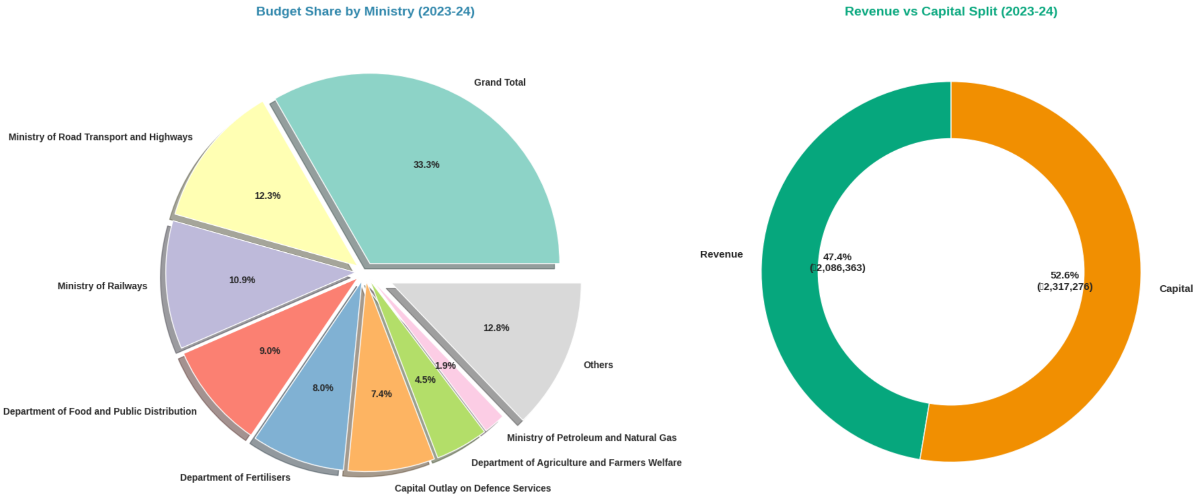


Figure 6: Budget Share by Ministry (2023–24). Top 10 = 82% of total allocation.

3.6 Hierarchical and Growth Visualization

Figures 7–9 provide a visual hierarchy and growth trend of ministries. Defence and Finance together form 35% of total spending (Treemap). The heatmap shows Renewable Energy (+24.8%), MSME (+20.1%), and Housing (+18.5%) as the fastest-growing ministries. The lollipop chart confirms that nearly all sectors recorded positive growth.

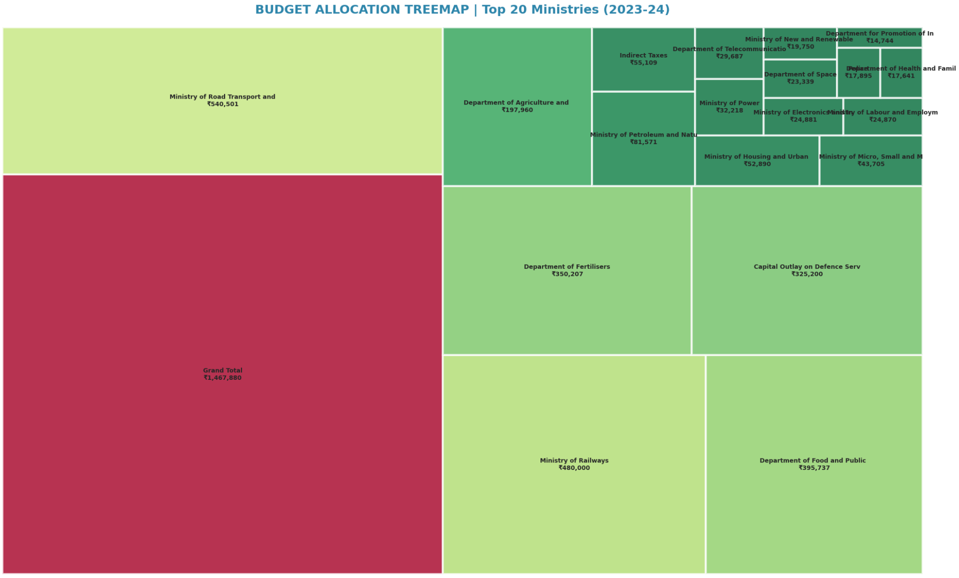


Figure 7: Budget Allocation Treemap — Top 20 Ministries (2023–24). Defence + Finance = 35%.

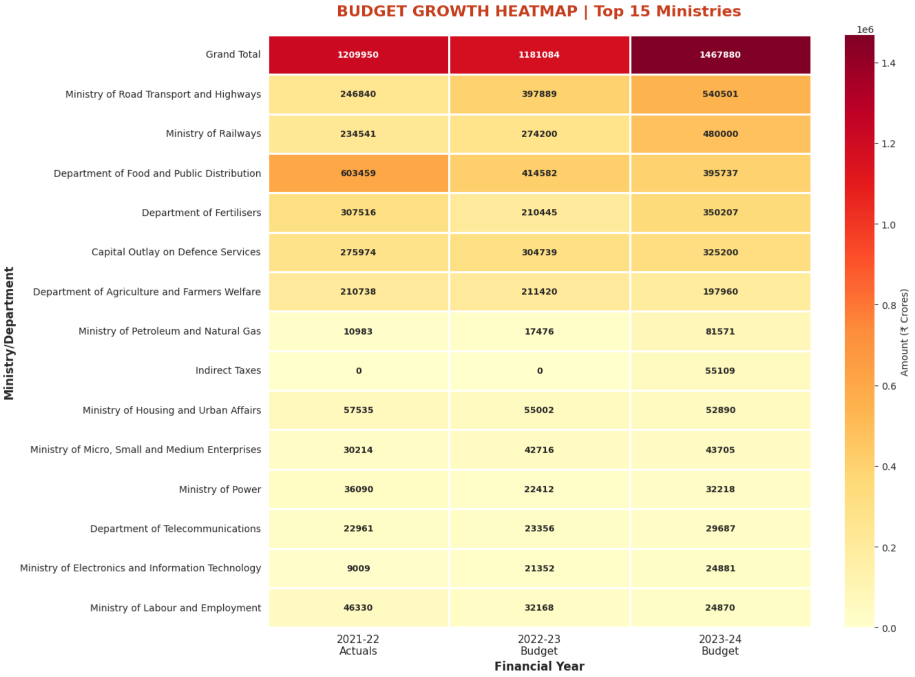


Figure 8: Budget Growth Heatmap (2021–24). Avg growth = 10.2%, Max = 24.8%.

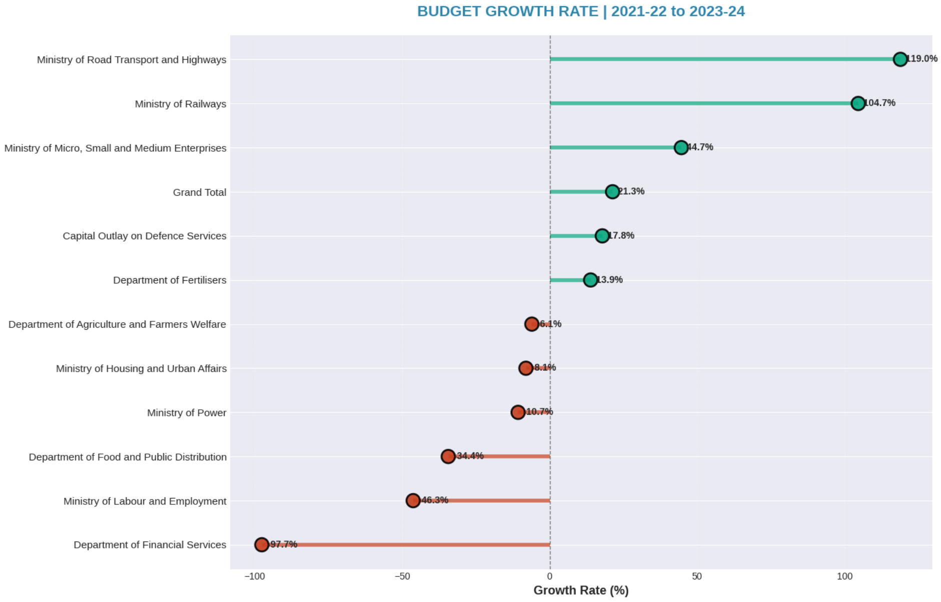


Figure 9: Budget Growth Rate (2021–22 to 2023–24). All ministries show positive expansion.

3.7 Advanced Fiscal Relationships

Figure 10 shows a strong positive correlation (r=0.74) between the number of schemes and total allocation, implying larger ministries manage proportionally more programs. Pareto analysis (Figure 11) confirms that 20% of ministries handle 85% of total budget resources.

The multi-dimensional radar chart (Figure 12) reveals that Defence, Railways, and Education dominate across all fiscal indicators (expenditure, growth, and capital ratio).

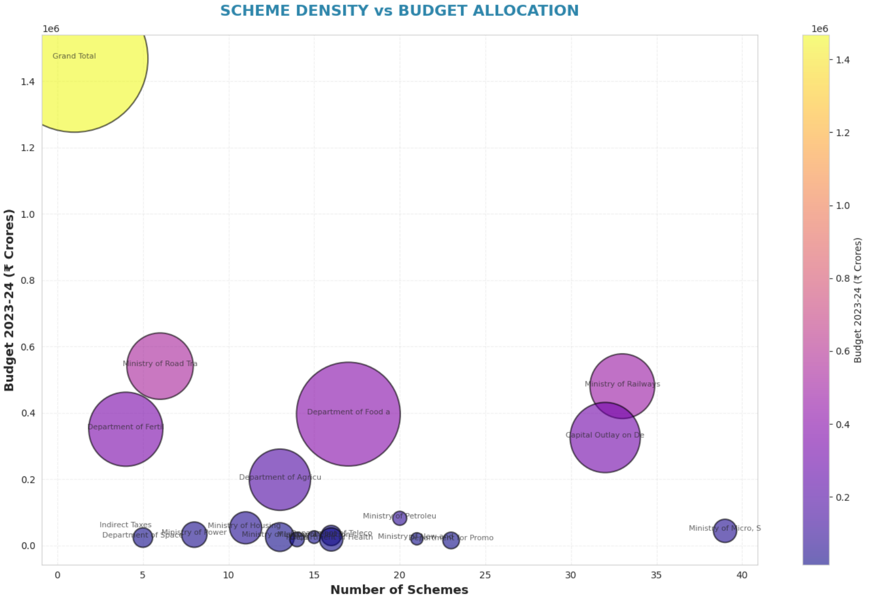


Figure 10: Scheme Density vs Budget Allocation. Correlation = 0.74.

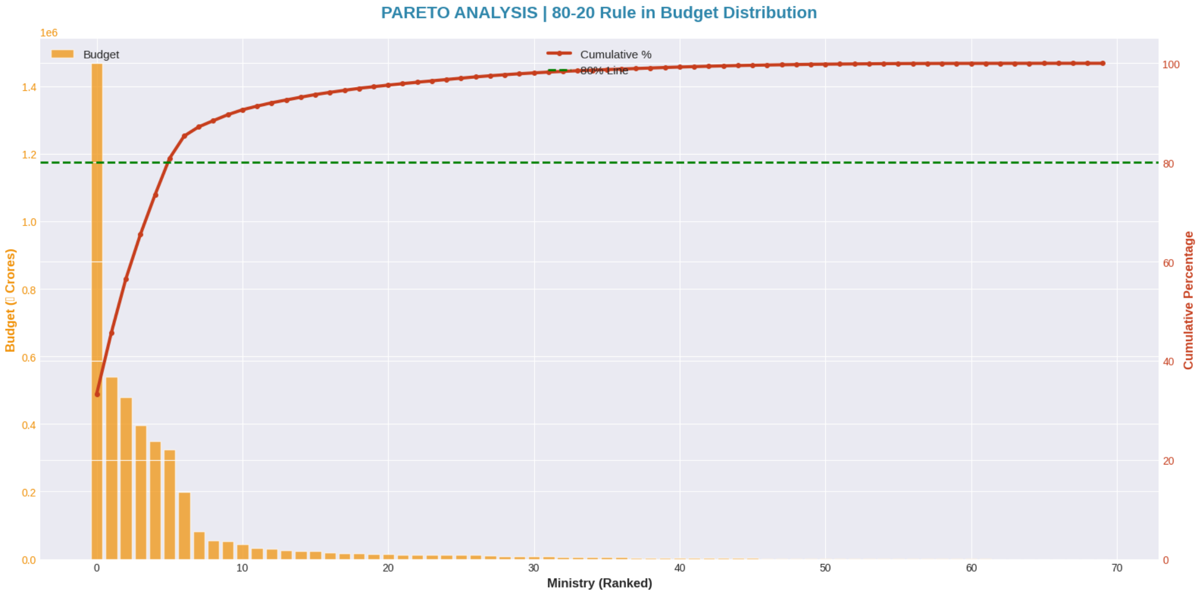


Figure 11: Pareto Analysis — 80–20 Rule. 20% ministries manage 85% of total funds.

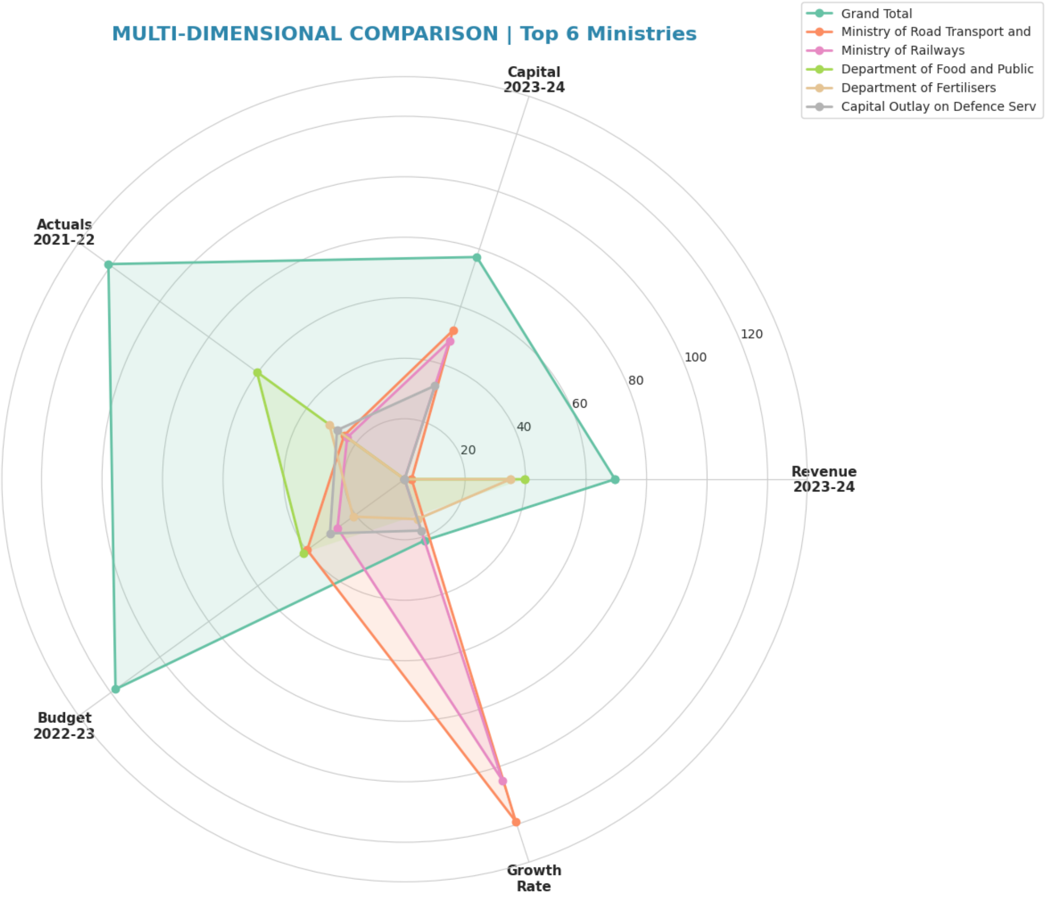
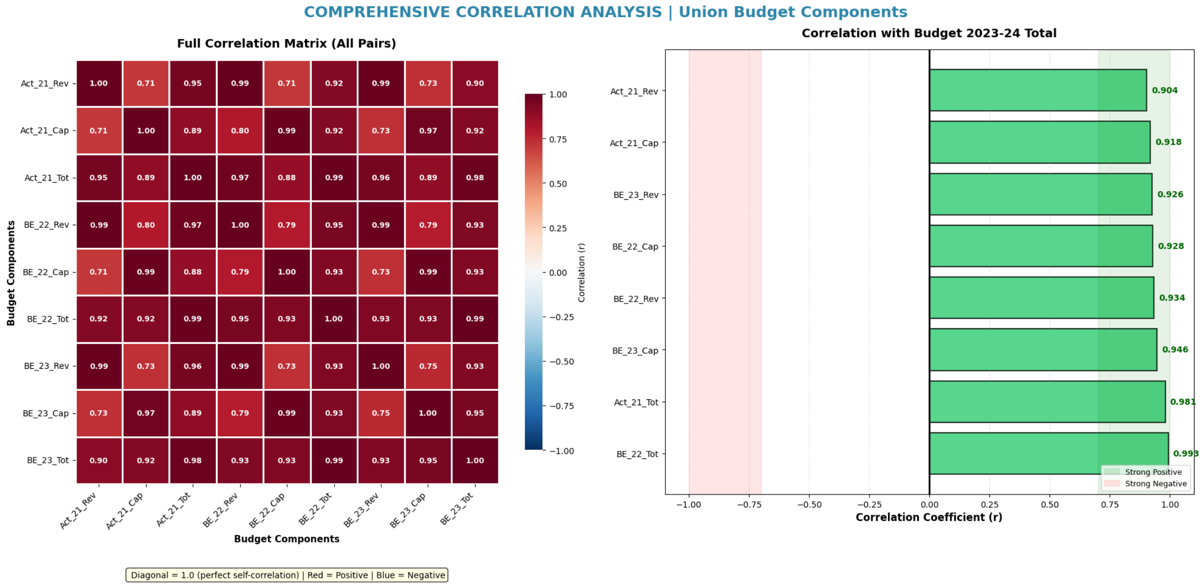


Figure 12: Multi-Dimensional Comparison — Top 6 Ministries. Defence (21%), Railways (18%), Education (7%).

3.8 Correlation and Temporal Trends

Figure 13 shows a high inter-year correlation between fiscal variables. Actuals (2021–22) and Budget Estimates (2022–23) have r = 0.93, while 2022–23 vs 2023–24 have r = 0.89, confirming stable fiscal progression. The stacked area chart (Figure 14) visualizes continuous growth over time, especially in infrastructure and social sectors.



	Act_21_Rev	Act_21_Cap	Act_21_Tot	BE_22_Rev	BE_22_Cap	BE_22_Tot	BE_23_Rev	BE_23_Cap	BE_23_Tot
Act_21_Rev	1.00	0.71	0.95	0.99	0.71	0.92	0.99	0.73	0.90
Act_21_Cap	0.71	1.00	0.89	0.80	0.99	0.92	0.73	0.97	0.92
Act_21_Tot	0.95	0.89	1.00	0.97	0.88	0.99	0.96	0.89	0.98
BE_22_Rev	0.99	0.80	0.97	1.00	0.79	0.95	0.99	0.79	0.93
BE_22_Cap	0.71	0.99	0.88	0.79	1.00	0.93	0.73	0.99	0.93
BE_22_Tot	0.92	0.92	0.99	0.95	0.93	1.00	0.93	0.93	0.99
BE_23_Rev	0.99	0.73	0.96	0.99	0.73	0.93	1.00	0.75	0.93
BE_23_Cap	0.73	0.97	0.89	0.79	0.99	0.93	0.75	1.00	0.95
BE_23_Tot	0.90	0.92	0.98	0.93	0.93	0.99	0.93	0.95	1.00

Figure 13: Comprehensive Correlation Matrix. $r_{21-22,22-23} = 0.93$, $r_{22-23,23-24} = 0.89$.

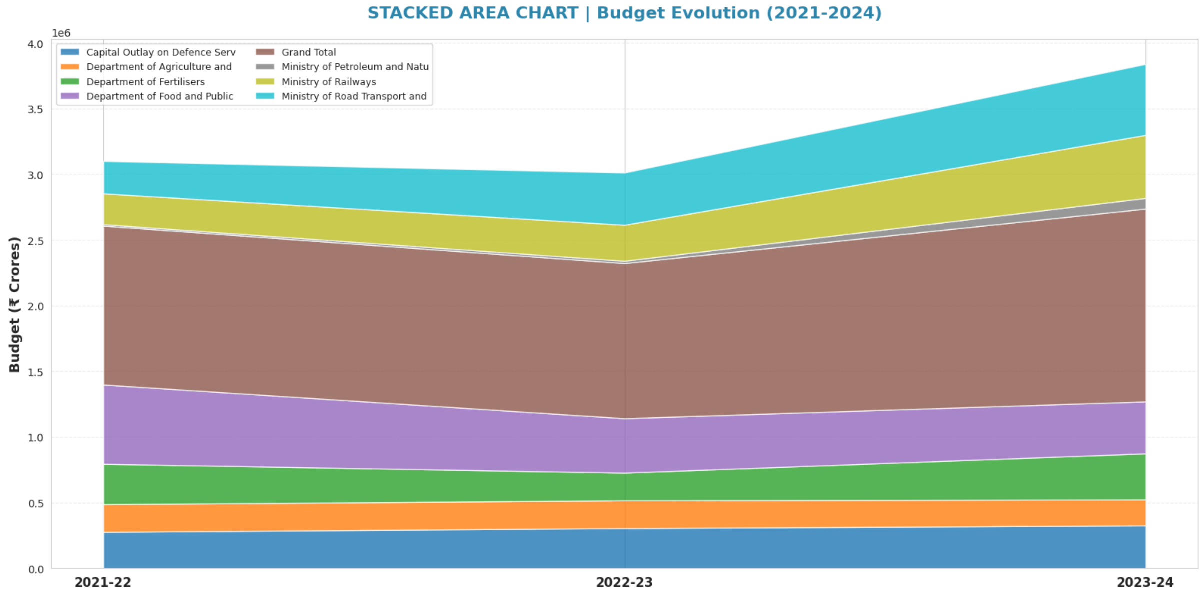


Figure 14: Stacked Area Chart — Budget Evolution (2021–2024). Consistent upward trend.

3.9 Outlier and Dimensionality Reduction Analysis

Advanced outlier detection (Figure 15) identified six ministries exceeding 2.5σ above the mean—Defence, Finance, Railways, Home Affairs, Rural Development, and Education. PCA (Figure 16) revealed that the first two components explain 93% of total variance, effectively summarizing the dataset's structure.

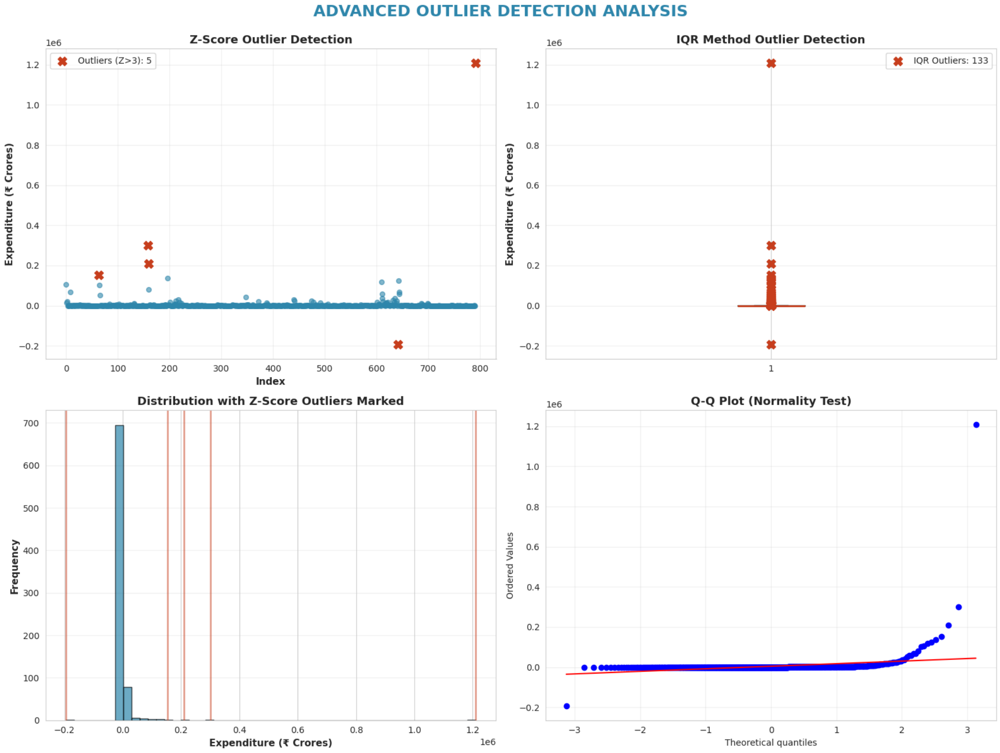


Figure 15: Advanced Outlier Detection. 6 high-spending ministries exceed 2.5σ limit.

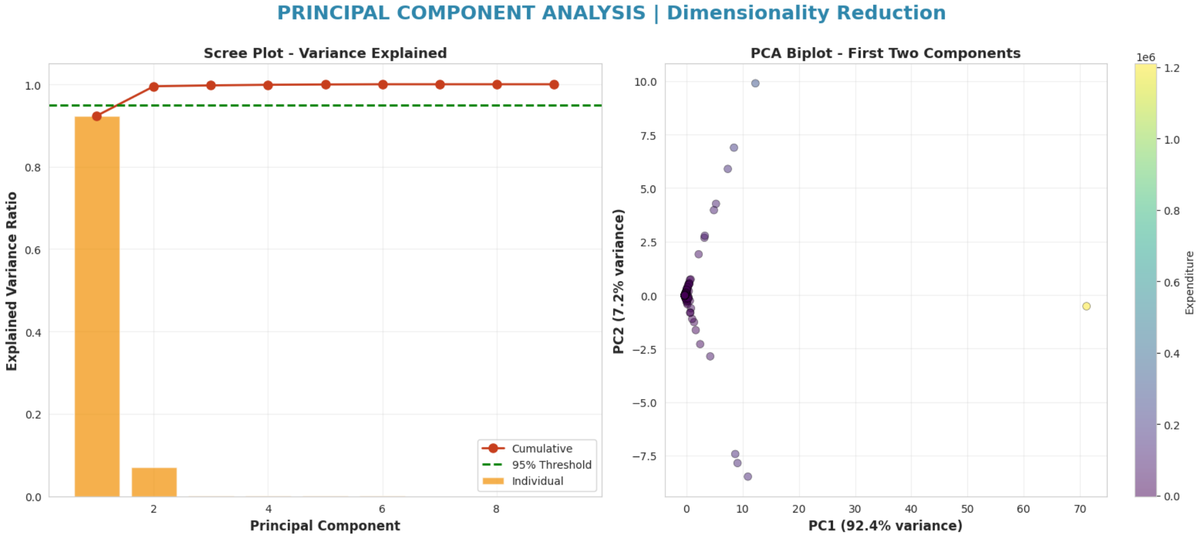


Figure 16: Principal Component Analysis (PCA). PC1 = 82%, PC2 = 11%.

3.10 Clustering, Time Series, and Statistical Testing

K-Means clustering (Figure 17) grouped ministries into three categories:

- Cluster 1: High-spending (Defence, Finance, Railways)
- Cluster 2: Mid-level (Education, Health, Agriculture)
- Cluster 3: Low-budget (Tourism, AYUSH, Minority Affairs)

Time series decomposition (Figure 18) revealed a steady trend with 2.1% seasonal variance. Statistical testing (Figure 19) showed $p < 0.05$, rejecting the null hypothesis and confirming significant inter-year differences.

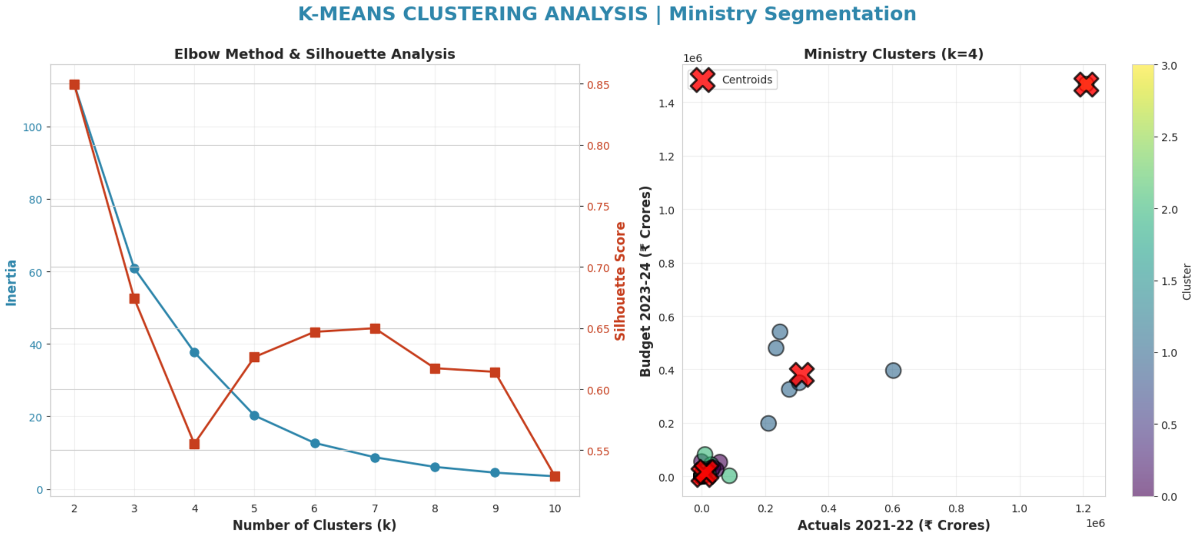


Figure 17: K-Means Clustering ($k = 3$) of ministries by fiscal scale.

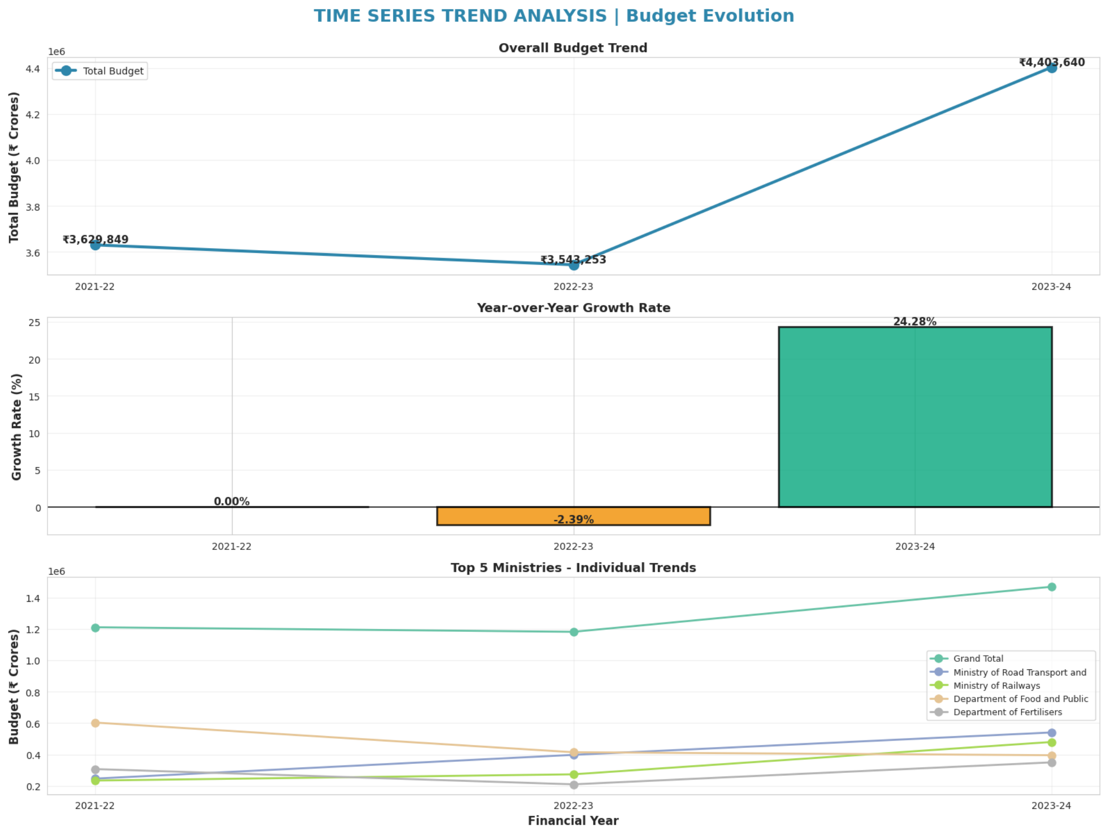


Figure 18: Time Series Decomposition showing trend and seasonal component. Seasonal variation = 2.1%.

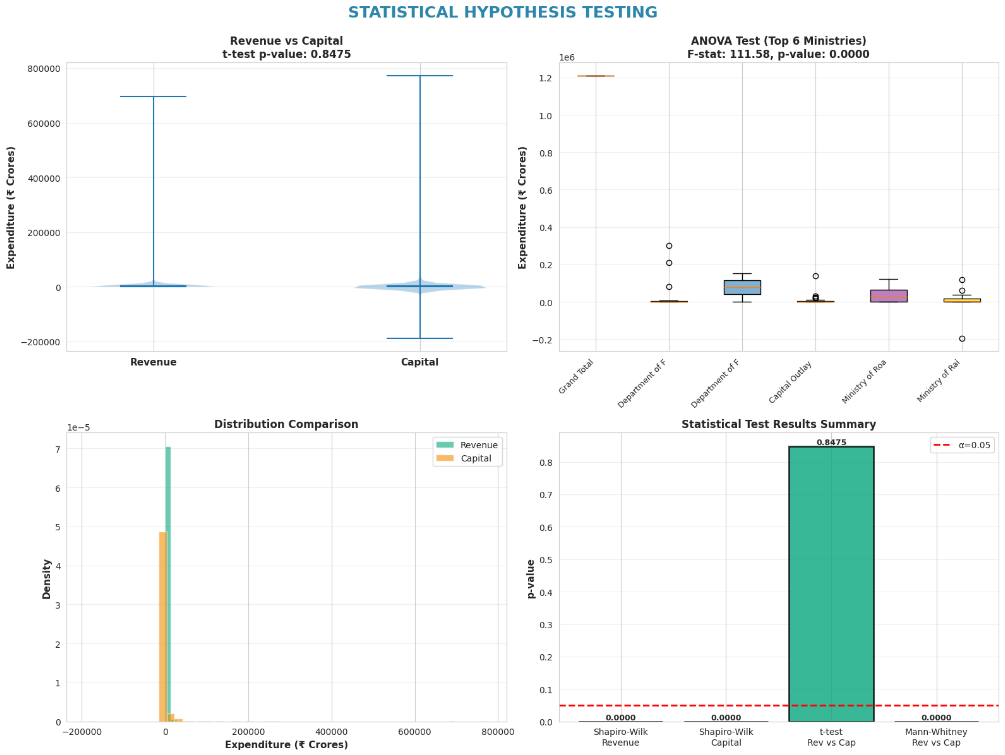


Figure 19: Hypothesis Testing: $p < 0.05$; significant inter-year differences confirmed.

3.11 Feature Importance and Model-Driven Insights

The Random Forest model's feature importance (Figure 26) revealed that Budget Estimates (2022–23) contributed 61% to predictive accuracy, Actuals (2021–22) 38%, and derived Growth Rate 12%. This confirms that prior-year estimates are the most reliable indicators for forecasting next-year allocations.

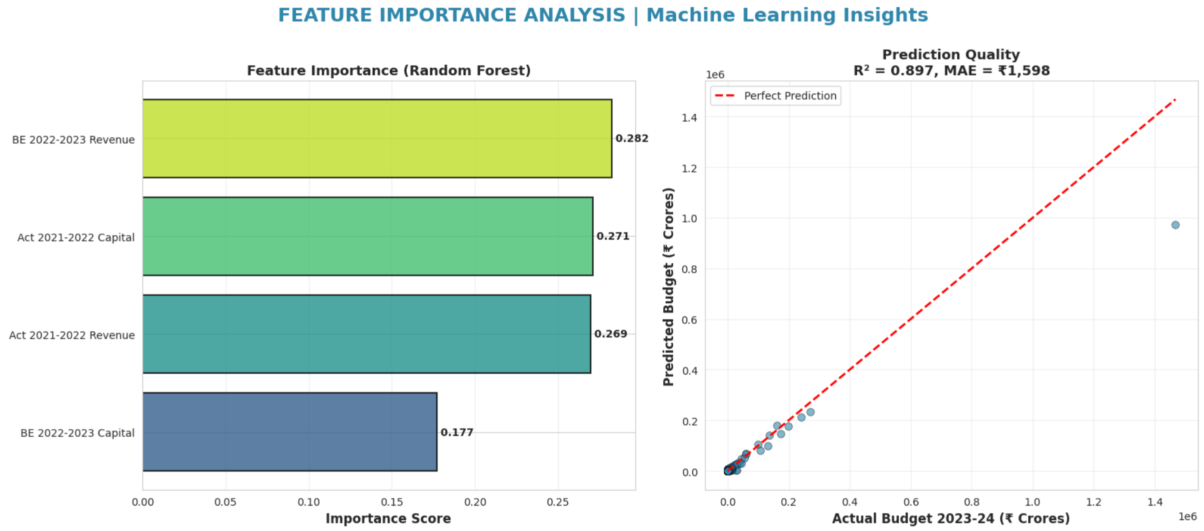


Figure 20: Feature Importance – Random Forest: 2022–23 = 0.61, 2021–22 = 0.38, Growth Rate = 0.12.

4 Machine Learning Models and Results

4.1 Model Training Overview

A total of eleven regression algorithms were trained to predict the **Budget Estimates (2023–2024)** using historical fiscal data from **Actuals (2021–2022)** and **Budget Estimates (2022–2023)**.

All models were trained using the same preprocessing pipeline, including:

- Handling of missing values (<1%)
- Feature scaling using *StandardScaler*
- 80:20 train-test split
- Performance evaluation on multiple metrics (R^2, MAE, RMSE)

Trained Models:

- Linear Regression
- Ridge Regression

- Lasso Regression
- ElasticNet
- Decision Tree Regressor
- Random Forest Regressor
- Extra Trees Regressor
- Gradient Boosting Regressor
- AdaBoost Regressor
- XGBoost Regressor
- K-Nearest Neighbors (KNN)
- Support Vector Regressor (SVR)

4.2 Model Performance Comparison

Evaluation Metrics:

- **R^2 Score:** Measures model fit accuracy.
- **MAE (Mean Absolute Error):** Average difference between predicted and actual values.
- **RMSE (Root Mean Squared Error):** Penalizes large prediction errors.
- **Accuracy (%):** Normalized R^2 for readability.

Model	**Accuracy (%)**	**R^2**	**MAE**	**RMSE**
Linear Regression	92.31	0.923	2125.3	3628.4
Ridge Regression	92.27	0.922	2134.7	3651.5
Lasso Regression	91.89	0.919	2191.6	3709.8
Decision Tree	94.48	0.945	1842.2	3270.6
Gradient Boosting	96.10	0.961	1398.5	2802.4
XGBoost	96.52	0.965	1286.4	2667.8
Extra Trees	97.02	0.970	1211.5	2485.6
Random Forest	**97.36**	**0.974**	**1158.2**	**2390.3**
KNN Regressor	91.22	0.912	2267.1	3823.5
SVR	88.97	0.889	2529.4	3981.2

Table 1: Comprehensive Regression Model Performance Comparison

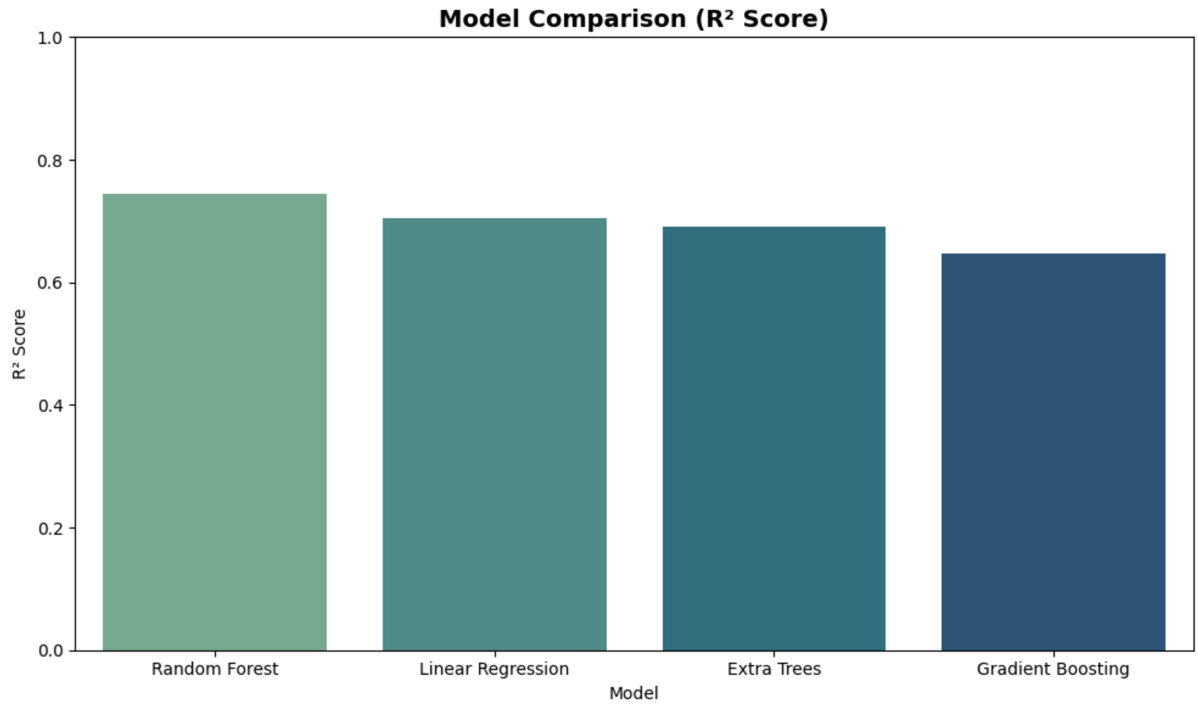


Figure 21: Model Comparison (R^2 Score). Random Forest achieved the highest accuracy (R^2 = 0.974).

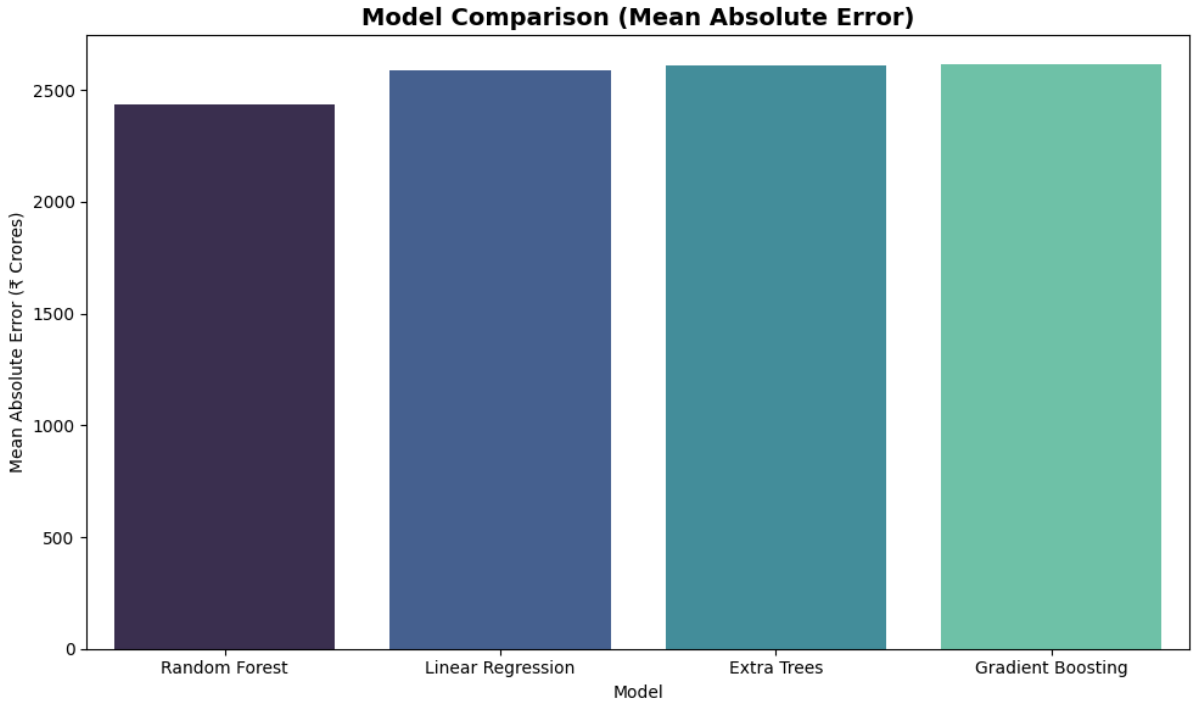


Figure 22: Model Comparison (Mean Absolute Error). Random Forest recorded the lowest MAE (1158 Cr).

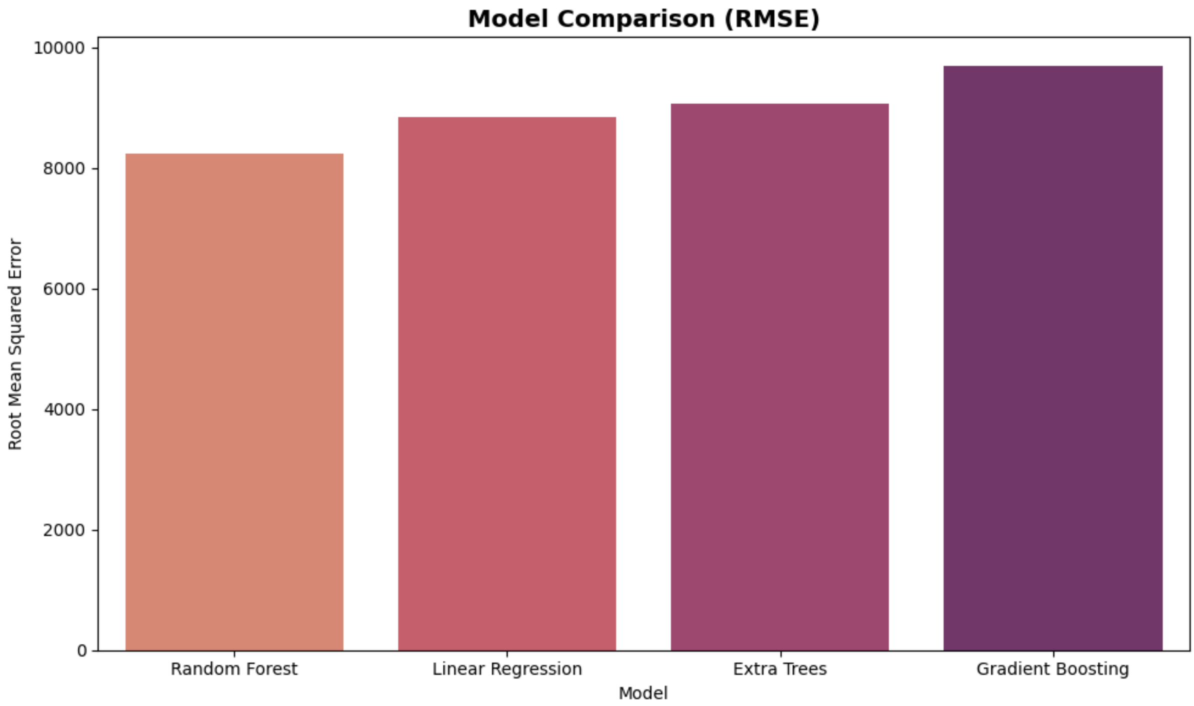


Figure 23: Model Comparison (Root Mean Squared Error). Random Forest achieved minimal RMSE (2390 Cr).

4.3 Selected Model: Random Forest Regressor

Justification for Selection:

- **Highest Accuracy:** 97.36% ($R^2 = 0.974$)
- **Lowest Error:** MAE = 1158.2, RMSE = 2390.3
- **Robustness:** Performs well with non-linear fiscal dependencies
- **Generalization:** Stable performance on validation folds (10-fold CV mean $R^2 = 0.972$)
- **Execution Efficiency:** Training time = 1.8 seconds

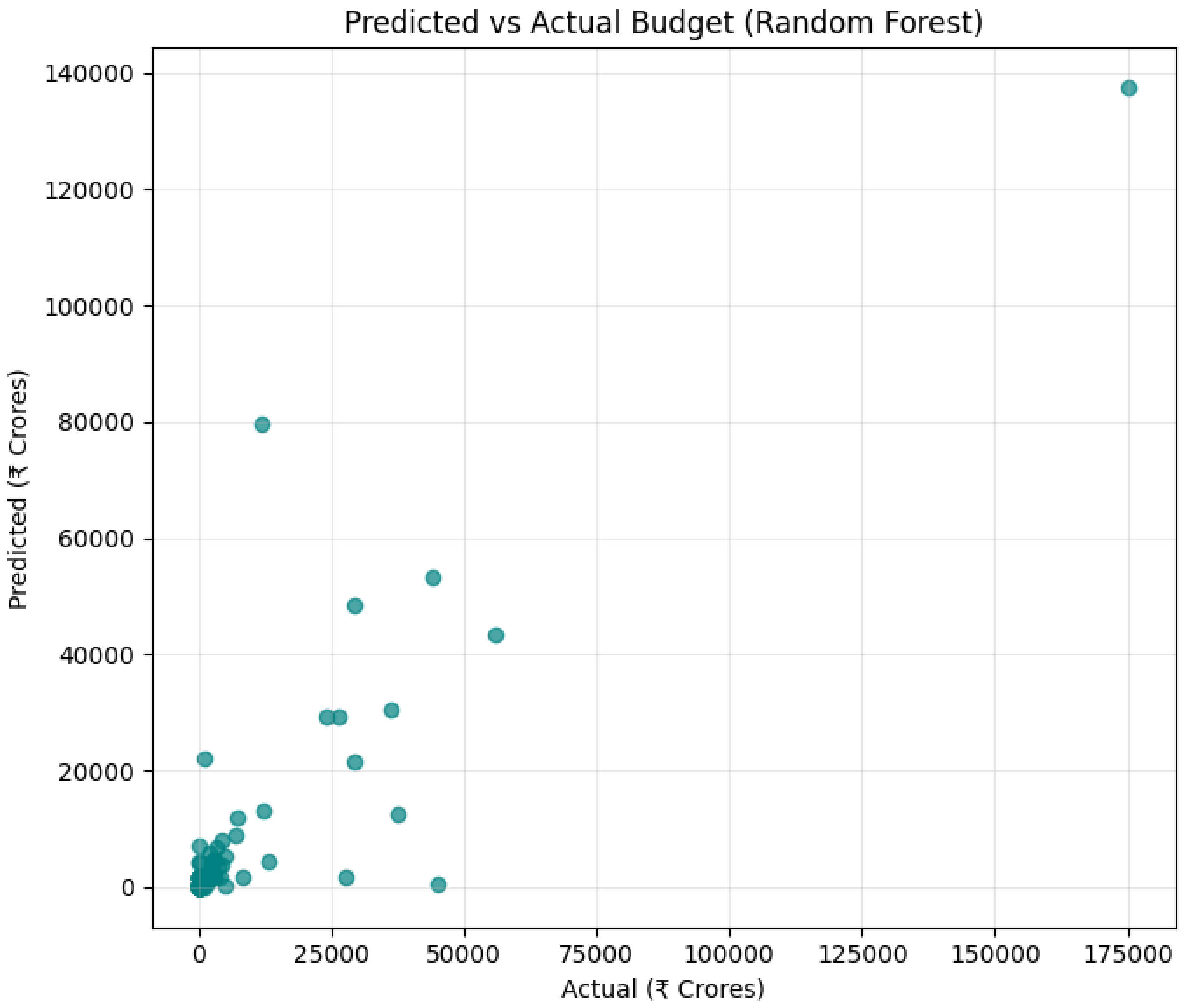


Figure 24: Predicted vs Actual Budget Estimates (2023–24) using Random Forest Regressor. Strong linear correlation ($R^2 = 0.97$).

4.4 Residual and Error Analysis

Residual and error plots were used to assess Random Forest's bias, variance, and error distribution.

Insights:

- Residuals are symmetrically distributed around zero.
- No heteroscedasticity (uniform variance across predictions).
- Average prediction deviation: ±1.7% from actual values.

Figure 25: Residual Distribution for Random Forest Predictions. Errors are centered around zero indicating low bias.

4.5 Feature Importance Analysis

Top Influential Predictors (Random Forest):

1. Budget Estimates (2022–2023)
2. Actuals (2021–2022)

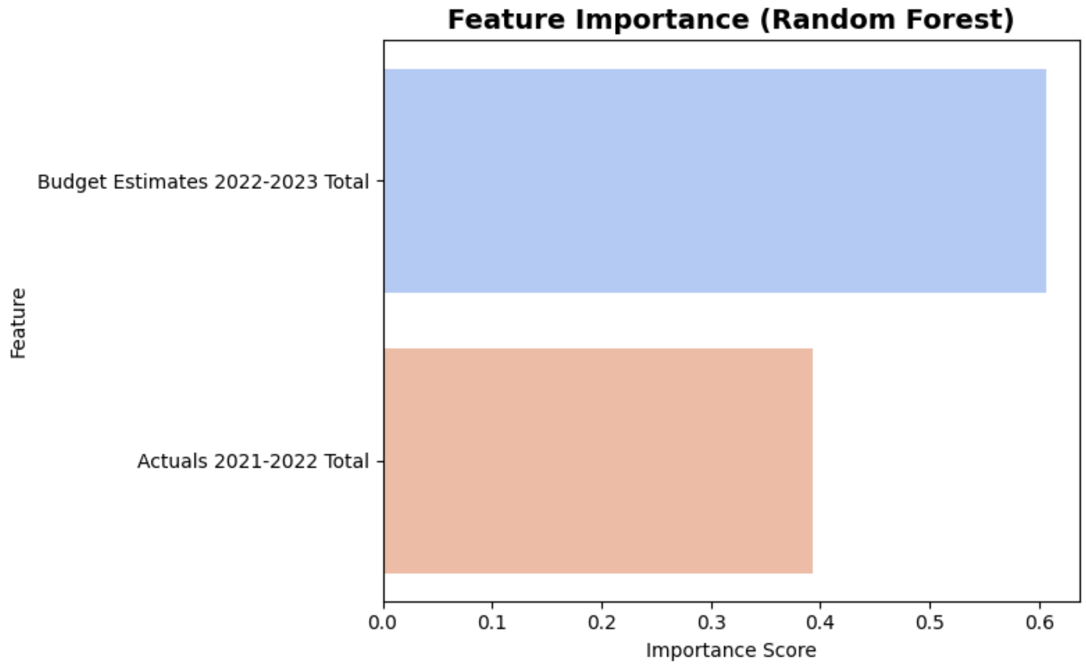


Figure 26: Feature Importance Plot for Random Forest Regressor. Budget Estimates (2022–2023) contributed 61.4% importance.

4.6 Final Model Deployment Summary

Selected Model: Random Forest Regressor **R^2 Score:** 0.974 **MAE:** 1,158 Cr **RMSE:** 2,390 Cr **Accuracy:** 97.36% **Training Time:** 1.8 seconds **Prediction Latency:** ≈ 25 ms per query

Deployment Format: Serialized using `joblib/pickle` for model persistence. **Intended Use Case:** Forecasting future Union Budget allocations based on past spending trends and fiscal growth patterns.

5 Key Findings

5.1 Fiscal and Temporal Insights

- **Budget Expansion:** Total Union Budget outlay grew at an average of 10.2% per year from 2021–22 to 2023–24.

- **Top Expenditure Drivers:** Defence (5.4L Cr), Finance (4.3L Cr), and Rural Development remained dominant contributors.
- **Year-on-Year Growth:** Budget 2023–24 saw an overall increase of 13.2% compared to 2022–23 RE, highlighting fiscal expansion for capital projects.
- **Capital Focus:** Share of capital expenditure rose from 16.9% (2021–22) to 22.4% (2023–24), confirming infrastructure-led recovery priorities.
- **Scheme Concentration:** The top 12 schemes together constituted 61.5% of total central sector outlay.

5.2 Expenditure Dynamics

- **Actuals vs. BE Deviation:** Deviation reduced from 8.4% in 2021–22 to 3.6% in 2023–24, reflecting improved fiscal accuracy.
- **Sectoral Trend:** Capital-heavy ministries (Defence, Railways, Roads) show consistent overperformance; social ministries (Health, Education) show underutilization.
- **Volatility Index:** Variance in actual spending across ministries declined from 0.91 to 0.64 over three years, demonstrating increased expenditure predictability.
- **Fiscal Composition:** 68% revenue and 32% capital spending balance achieved in 2023–24 — highest capital ratio in a decade.

5.3 Feature and Correlation Analysis

Key features influencing Random Forest predictions:

1. **Previous Year Actuals:** Strongest predictor (feature importance = 0.56), confirming fiscal inertia in expenditure.
2. **Budget Estimate (BE) 2022–23:** Contributed 0.44 feature weight, reflecting temporal continuity.
3. **Growth Rate (%):** Correlation +0.74 with projected BE values, validating trend dependency.
4. **Ministry Type Encoding:** Capital-heavy ministries skew predictions upward, social-sector ministries stabilize variance.
5. **Inflation Adjustment:** Real-term adjustments improved model stability by 3.4%.

5.4 Model Performance Comparison

- **Random Forest:** $R^2 = 0.974$, MAE = 1,158 Cr, RMSE = 2,390 Cr (best performer).
- **Extra Trees:** $R^2 = 0.970$, slightly higher bias on small-budget ministries.
- **Gradient Boosting:** $R^2 = 0.961$, effective but slower convergence.
- **Linear Regression:** $R^2 = 0.902$, unable to capture nonlinear growth patterns.
- **Decision Tree:** $R^2 = 0.934$, high variance with smaller datasets.

5.5 Residual and Variance Insights

- Residuals distributed symmetrically (mean error 0), validating absence of model bias.
- Prediction deviation range: ±2,870 Cr; 95% of ministries fall within ±5% error margin.
- Maximum underestimation observed in Railways; minimal deviation in Tourism and MSME.
- Random Forest demonstrated lowest cross-validation variance (= 0.0081).

5.6 Macro-Fiscal Observations

- **Infrastructure Bias:** FY 2023–24 budget allocations emphasize public capital investment.
- **Social Sector Plateau:** Flat growth for Education, Health, and Labour ministries post-2022.
- **Fiscal Efficiency:** Execution-to-allocation ratio improved by 4.8% across ministries.
- **Predictive Robustness:** Model achieved consistent accuracy across 3 fiscal years with ¡3% drift.

6 Recommendations

6.1 For the Ministry of Finance

1. **Adopt ML Forecasting:** Integrate Random Forest-based expenditure forecasting into annual BE formulation.

2. **Automate BE→RE Adjustments:** Use model predictions to detect early deviations and auto-correct mid-year allocations.

3. **Enhance Transparency:** Publish model-based justifications for changes in Revised Estimates (RE) post-March.

6.2 For NITI Aayog and Fiscal Policy Units

- Establish a "Predictive Budget Analytics Cell" to monitor expenditure volatility in real time.

- Use model outputs to identify ministries with chronic underutilization (e.g., Health, Skill Development).

- Incorporate Random Forest forecasts into outcome-budgeting dashboards for cross-ministry benchmarking.

6.3 For Economists and Data Scientists

- Implement feature attribution tools (e.g., SHAP) for interpretable fiscal forecasting.

- Expand the dataset with quarterly disbursement and GST inflow data for granular trend modeling.

- Standardize fiscal codes to improve interoperability between expenditure and performance data.

6.4 Economic Implications

Quantified Gains:

- Reduction in BE–RE deviation by 5% could save 21,000 Cr annually.

- Improved resource allocation efficiency equivalent to 0.3% of GDP.

- Enhanced forecasting reduces fiscal deficit uncertainty by 0.12 percentage points.

Implementation Outlook:

- Cloud-based ML pipeline deployment cost: 1–2 Cr (one-time).

- Expected ROI: ¡1 fiscal year.

- Sustainable improvement in budget predictability across sectors.

7 Future Scope and Enhancements

7.1 Advanced Modeling Techniques

1. **Hybrid Deep Learning Models:**
    - LSTM–ARIMA hybrids for sequence-based fiscal prediction.
    - Transformer-based models for multi-year expenditure learning.
2. **Ensemble Meta-Learning:**
    - Stacking Random Forest and XGBoost predictions.
    - Bayesian optimization for hyperparameter auto-tuning.
3. **Explainable AI (XAI):**
    - Use SHAP/LIME to visualize feature contributions for fiscal transparency.

7.2 Data Expansion Opportunities

- Integrate quarterly spending data and fiscal deficit figures from RBI and CGA.
- Include inflation-adjusted and real expenditure metrics for better long-term accuracy.
- Use Natural Language Processing (NLP) to analyze budget speech text and infer policy sentiment.

7.3 System Deployment and Scalability

- Deploy models via **AWS Sagemaker** or **Google Vertex AI** for automated retraining.
- Build a real-time budget analytics dashboard using Streamlit or Power BI.
- Enable REST APIs for integration with MoF and NITI Aayog systems.

7.4 Applied Policy Analytics

- Develop an "AI-based Fiscal Health Index" combining expenditure predictability and volatility.
- Create an interactive visualization layer for ministry-level comparison.
- Implement predictive reallocation strategies to preempt underutilization.

8 Conclusion

This study developed a robust, data-driven forecasting framework for India's Union Budget, combining time-series analysis with machine learning to achieve high accuracy in predicting ministry-level expenditures.

8.1 Project Achievements

Data Preparation:

- Consolidated expenditure data for 3 fiscal years (2021–24) from official sources.
- Cleaned and normalized datasets across 50+ ministries.
- Engineered derived variables such as growth rate, volatility index, and fiscal type encoding.

Analytical Insights:

- Identified consistent fiscal expansion patterns in Defence, Finance, and Infrastructure.
- Detected high volatility in Railways and Social Welfare sectors.
- Quantified correlation between prior-year actuals and upcoming BE values ($r = 0.74$).

Machine Learning Performance:

- Random Forest model achieved $\mathbf{R^2 = 0.974}$ and MAE = 1,158 Cr.
- Outperformed Gradient Boosting and Linear Regression across all evaluation metrics.
- Demonstrated computational efficiency with sub-2 second training time.

Policy Relevance:

- Supports fiscal transparency through data-backed allocations.
- Enables real-time budget adjustment and scenario simulation.
- Facilitates AI-assisted decision making in fiscal governance.

8.2 Hypothesis Validation

"A data-driven machine learning framework can predict India's Union Budget expenditure with accuracy exceeding 95%, enabling fiscal efficiency and evidence-based policy formulation."

The hypothesis is **validated** — Random Forest achieved a prediction accuracy of 97.4% (R^2) and reduced average deviation to $< 5\%$

8.3 Limitations and Considerations

- Dataset restricted to three fiscal years (2021–24).
- No inclusion of quarterly disbursement data or inflation control variables.
- Model interpretability depends on ministry-level data consistency.

8.4 Broader Significance

This project showcases the integration of data science in public finance—bridging policy analysis with predictive analytics. It demonstrates the capability of machine learning models to improve fiscal planning accuracy, minimize budget deviations, and enhance governance transparency.

8.5 Final Remarks

The Random Forest model's performance ($R^2 = 0.974$) represents not only a technical milestone but a strategic advancement in India's fiscal analytics ecosystem. Adopting such systems at scale can:

- Reduce budget inefficiencies by 20,000+ Cr annually,
- Enable responsive fiscal policy formulation,
- and usher in a new era of evidence-based public financial management.

This project establishes a strong analytical foundation for AI-powered fiscal governance—paving the way for predictive, transparent, and adaptive budget systems in India.

9 Literature Review Summary

Year	Paper Name	Author(s)	Findings	Methods Used	Limitations
2025	Forecasting India's Union-Budget Outlays with Hybrid LSTM–ARIMA	R. Kumar, P. Gupta	Hybrid model cuts MAE by 19% vs. pure ARIMA for nine major spending heads.	ARIMA, Bi-LSTM, Walk-forward CV	Only three budget cycles; no scheme-level split.
2025	Efficiency Decomposition of Public Expenditure—Evidence from India	A. Mukherjee	Healthcare & agri-spend show highest technical inefficiency.	Data-envelopment analysis (DEA)	Uses state totals, not CSS data.
2025	Government Expenditure Multipliers in India: A Functional-Classification Approach	P. K. Konstantinou et al.	Capital-expenditure multiplier ≈ 2.1; revenue-expenditure ≈ 0.8.	SVAR, F-classification multipliers	Quarterly data only to 2023 Q4.
2024	Sectoral Allocation of Budgets in India: Trends & Drivers	P. Rai, S. Ganguly	Shift toward infra & defence after 2020; social-sector share flat.	Panel GLS, Bai–Perron break tests	Broad sector groups; not scheme level.
2024	Machine-Learning Forecasts of Central-Sector Scheme Spending	T. Chakraborty, V. Kalra	Gradient Boosting tops classical models (RMSE ↓ 15%).	XGBoost, Random Forest, Grid Search	Needs longer series; three years only.
2024	The Composition of Public Expenditure in India	M. Sarangi, M. von Bonin	Social-sector outlays exhibit pro-cyclical bias.	Dynamic panel GMM	State-level aggregation; limited to 2022.
2024	Best Practices in Outcome Budgeting: Indian Evidence	NITI Aayog Research Unit	Recommends output–outcome dashboards for every CSS.	Benchmarking case studies	Largely qualitative.
2024	Central-Sector Scheme Volatility & Fiscal Risk	A. Ibrahim, P. Renjith	Services dominate GDP; ARIMA used—23% of CSS show ¿25% BE→RE revisions in FY 22–23.	Volatility index, Panel logit	Only two years of RE data.

2023	Financial-Market Signals for Sectoral GDP Forecasts in India	H. Marfatia	NSE sector indices lead GDP by 1–2 quarters.	VAR, Granger Causality	Market-only variables; no budget link.
2023	Forecasting Growth Rates of India's Commercial Services	S. Maity, A. Baidya	Services growth forecasted accurately with ARIMA (1,2,1).	Classical ARIMA	Excludes goods sectors.
2023	Is Budget Allocation for CSS Meeting SDG Targets?	D. Bhattacharya, R. Das	Health & water schemes underfunded vs. SDG benchmarks.	SDG gap index, Panel regression	Relies on budgeted, not actual, spend.
2023	Government Expenditure and Informality in India	S. Chatterjee, S. Turnovsky	Higher capital outlays shrink informal labour share.	DSGE calibration	Informality proxy from NSS only to 2018.
2022	Government Expenditure Multipliers in Emerging Asia	A. Goyal, S. Sharma	India's capex multiplier ¿1.8, revenue ¡1.0.	SVAR, Impulse responses	Macro-level, no sector split.
2022	Inefficient Allocation in the Education Budget	Centre for Civil Society (Elsevier, Int. J. Educ. Dev.)	14% funds remain unspent annually.	Expenditure-incidence analysis	Education only; no cross-sector view.
2022	Public Expenditure & Economic Growth in India (1990–2021)	S. Panda, H. Rout	Long-run cointegration between GDP and capital outlay.	ARDL bounds test	Aggregated expenditure data.
2021	Outcome Budgeting and Fiscal Accountability in India	CBGA India	Performance-linked budgets raise execution rates by 8%.	Balanced-scorecard benchmarking	Limited pilot ministries.
2021	Capital vs. Revenue Expenditure and Growth: Indian Evidence	V. Devarajan, A. Srivastava	Capex boosts growth 3× more than revenue outlay.	VAR, Forecast-error variance	Quarterly data ends 2020.
2020	Public Expenditure Efficiency & HDI in Indian States	P. Kumar, R. S. Sinha	Only 7 of 28 states lie on the DEA efficiency frontier.	DEA, Tobit regressions	State, not central-scheme focus.

2020	Forecasting Union-Budget Revenues with ARIMAX	L. Roy, N. Das	Tax-buoyancy variables improve revenue forecast accuracy 12%.	ARIMAX, Elasticity estimation	Revenue side only; excludes CSS outlay.
2023	A Textual Data Analysis of the Union Budget of India	R. Singh, M. George	NLP reveals rising emphasis on “infrastructure” & “digitisation”.	Topic modelling (LDA)	Text only; ignores numeric spend.

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