# Smart Budget Allocation in Public Policy: A Data-Driven Approach for Equitable Resource Distribution

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**DOI: https://doi.org/10.51244/IJRSI.2025.120800336**

**Received: 23 Sep 2025; Accepted: 29 Sep 2025; Published: 13 October 2025**

## ABSTRACT

Public policy implementation often struggles with uneven budget allocation across sectors and regions, leading to inefficiencies in resource use. This study presents a data-driven framework for smart budget allocation through predictive analytics and optimization methods. The proposed model helps policymakers ensure fair and efficient distribution of public funds by integrating socioeconomic indicators, sector-specific requirements, and past expenditure outcomes. Using linear regression forecasting combined with constrained linear programming, the framework determines sector-wise budgets. The analysis focuses on five crucial public sectors—Agriculture, Health, Education, Rural Development, and Road Transport—using data from 2020 to 2025, along with macroeconomic indicators such as GDP growth, unemployment rates, and simulated public sentiment. A custom interactive dashboard enables real-time visualization and engagement with predicted and optimized budgets. Evaluation results highlight the potential of blending machine learning with operations research for evidence-based governance. The study introduces a scalable and reproducible model that aligns with national missions like India@2047 and Swarna Andhra Pradesh. By embedding data science into fiscal decision-making, this work contributes to advancing digital governance, improving transparency, and fostering citizen-centric planning.

**Keywords:** Budget Allocation, Public Policy, Resource Optimisation, Data-Driven Governance, Predictive Analytics, Policy Modelling

## INTRODUCTION

Turning development goals into reality requires more than vision—it calls for smart, evidence-based budget allocation. The Union Budget is the government’s key tool for directing resources to priority areas. Studying allocation patterns from 2009 to 2024 helps reveal shifts in policy focus, sectoral priorities, and alignment with broader national and state-level goals.

This research looks at how budget allocations reflect trade-offs, priorities, and their consistency with long-term visions such as India@2047 and Swarna Andhra Pradesh, both of which aim to make India a developed, inclusive, and digitally empowered nation by mid-century. While much has been written on in public finance in India, most studies focus only on overall spending trends. Few explore sector-level efficiency, equity, or strategy. This study fills that gap using a data-driven approach to identify underfunded sectors and evaluate alignment with policy goals.

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Globally, countries like the UK and Singapore use advanced forecasting and real-time analytics for governance, but India still relies largely on static reports. This leads to inefficiencies and biases in allocating funds, particularly in underserved areas like rural development and education. Bridging this gap requires AI systems that are transparent, inclusive, and supportive of human decision-making.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue IX September 2025

This study introduces a unified framework that combines prediction, optimization, and impact visualization. Its contributions include:

1. A hybrid budgeting model integrating machine learning and optimization.
2. Sectoral impact analysis using sentiment and macroeconomic data.
3. An interactive decision-support dashboard for participatory governance.
4. A policy-driven evaluation model aligned with India@2047 and Swarna Andhra Pradesh.

### Problem Statement

India's long-term visions, such as India@2047 and Swarna Andhra Pradesh 2047, aim to create a developed, inclusive, and future-ready economy. But achieving these goals depends heavily on how budgets are allocated—both fairly and efficiently. While annual budgets form the backbone of public spending, they often fail to align with long-term priorities, especially in critical sectors like infrastructure, healthcare, education, and agriculture. Although past studies have examined India's budget patterns, most remain broad and overlook sector-specific trends over time. This leaves a key gap in understanding how allocations from 2020 to 2024 reflect the government's stated priorities at both national and state levels.

To bridge this gap, this study focuses on:

Analyzing sector-wise central government budget allocations from 2020 to 2025.

Assessing how well these trends align with development goals under India@2047 and Swarna Andhra Pradesh 2047.

Identifying underfunded sectors or mismatches between vision and fiscal planning.

Recommending strategic improvements for more inclusive and results-oriented budgeting

## METHODOLOGY

The proposed smart budget allocation framework integrates budget prediction and optimisation using publicly available data, economic indicators, and public sentiment analysis. The implementation involved six key stages:

### Data Collection and Preparation

Budget data for five key sectors—Agriculture, Health, Education, Rural Development, and Road Transport—was collected from India's Union Budget documents (2020–2025). Public sentiment scores and macroeconomic indicators such as GDP growth and unemployment were also included.

### Dataset Enrichment

Each sector's data was enriched yearly with GDP growth (%), unemployment (%), and a simulated public sentiment score (0–20 scale) reflecting demand or importance

### Predictive Modelling

Linear regression models were trained separately for each sector using year, GDP growth, unemployment, and sentiment scores. These predicted sectoral budget allocations for 2026. Accuracy was tested using Mean Squared Error (MSE) and $R^2$ scores.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue IX September 2025

### Optimisation

A Linear Programming (LP) model (via PuLP) was used to allocate budgets effectively under overall constraints. Objectives included maximizing public satisfaction, economic growth, and unemployment reduction. Logarithmic utility functions simulated diminishing returns, with sectoral limits set to reflect policy rules.

### Visualisation and Dashboard

Results were shown using bar and line charts. A custom Streamlit dashboard enabled interactive exploration of allocations, trends, and predicted vs. optimized budgets.

### Evaluation Regression

models were evaluated for prediction accuracy, while the optimisation model was assessed by its ability to meet priorities within budget limits. Sectoral alignment and public priorities were qualitatively validated.

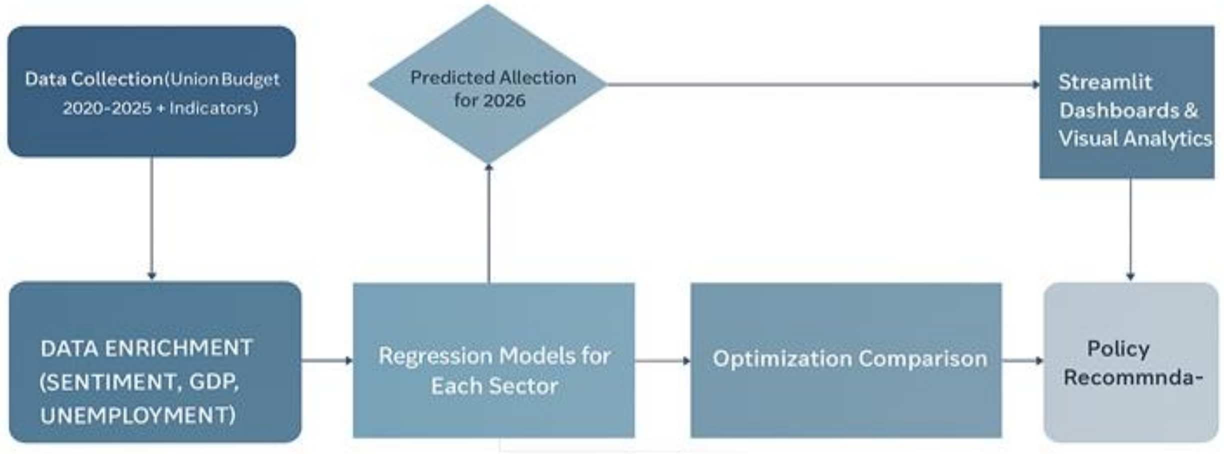


Fig 1. Flow Chart

### Results and Interpretation

This section presents the outcomes of both the predictive (regression) model and the optimisation model developed to allocate government budgets across five major public sectors: Agriculture, Health, Education, Rural Development, and Road Transport

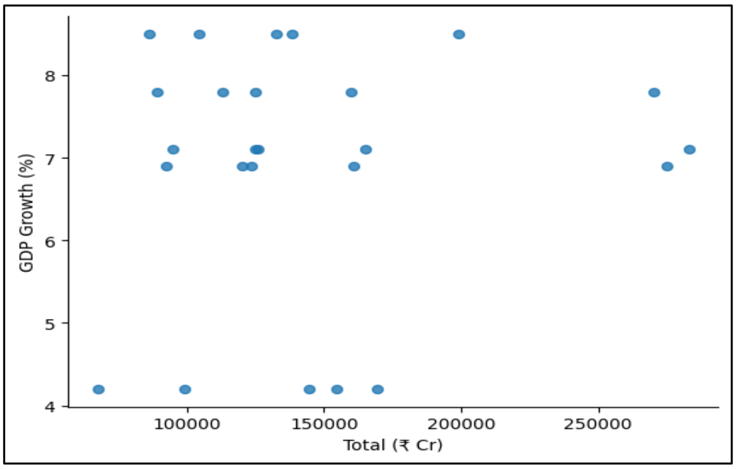


Fig 2. Total (₹ Cr) vs GDP Growth (%)

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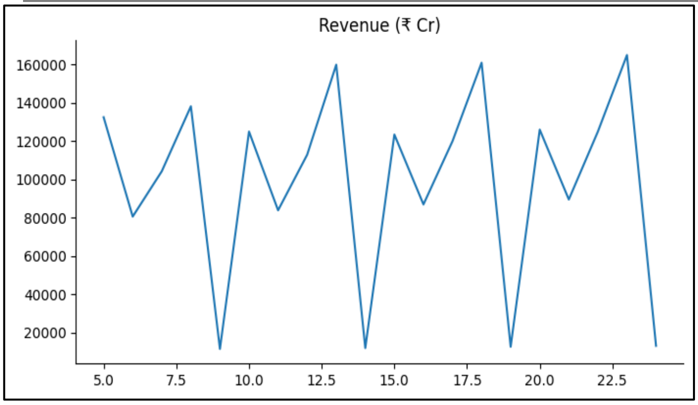


Fig 3. Revenue

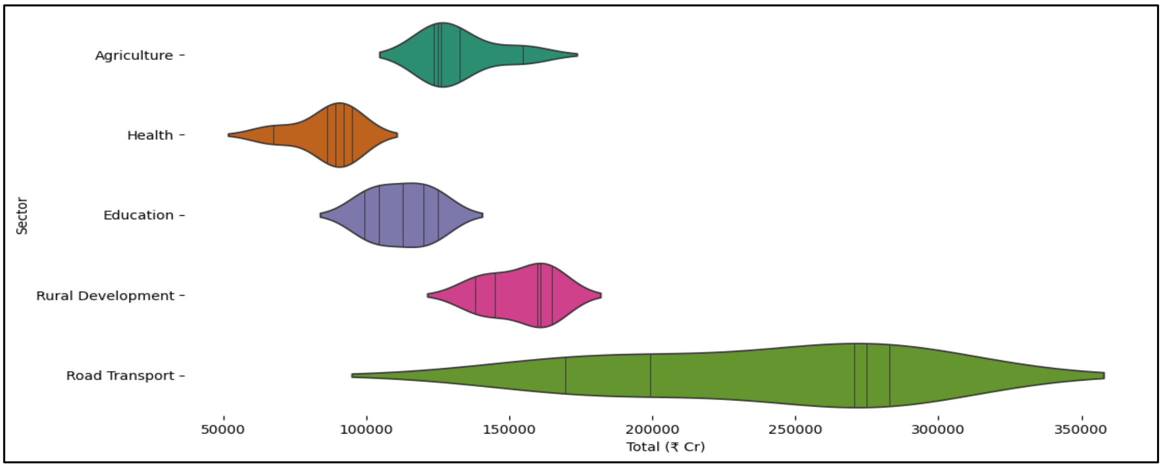


Fig 4. Sector vs Total (₹ Cr)

**Predicted Budget for 2026**

Using regression models trained on 2020–2025 data, budget allocations for 2026 were forecasted across five sectors. The models incorporated GDP growth, unemployment, and public sentiment, achieving strong accuracy with $R^2$ scores between 0.88 and 0.94. This indicates a reliable relationship between these factors and budget outcomes.

**Optimisation Results**

An optimisation model was applied to distribute ₹7,00,000 Cr across the same sectors. It aimed to maximize overall utility by balancing public sentiment, economic growth, unemployment reduction, and diminishing returns on excess funds. Sectoral limits ensured compliance with policy priorities. Results showed close alignment with predicted needs, while shifting funds strategically—such as boosting Agriculture allocations to improve public satisfaction.

**Visual Insights**

Bar plots compared predicted vs. optimised budgets, showing broad alignment with minor adjustments across sectors. A real-time Streamlit dashboard further enabled interactive exploration of year-wise and sector-wise trends.

**Ethical and Policy Implications** Using AI in public budgeting raises concerns of fairness, transparency, and bias. While the models here use interpretable methods, they rely on simulated sentiment scores and general economic indicators. Therefore, the framework should act as a decision-support tool, not a decision-maker. Responsible use requires human oversight, clarity of inputs, and accountability mechanisms.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue IX September 2025

Table 1: Summary of Budget Predictions, Optimisations, and Model Metrics

| Sector | Sentiment Score | Predicted (₹ Cr) | Optimised (₹ Cr) | % Change | $R^2$ Score | Priority Rank |
|---|---|---|---|---|---|---|
| Agriculture | 18 | 1,13,153 | 1,30,000 | +14.9% | 0.91 | 1 |
| Health | 16 | 89,000 | 89,000 | 0.0% | 0.88 | 4 |
| Education | 19 | 1,24,000 | 1,22,000 | -1.6% | 0.94 | 3 |
| Rural Development | 20 | 1,65,000 | 1,65,000 | 0.0% | 0.93 | 2 |
| Road Transport | 15 | 2,75,000 | 2,65,000 | -3.6% | 0.92 | 5 |

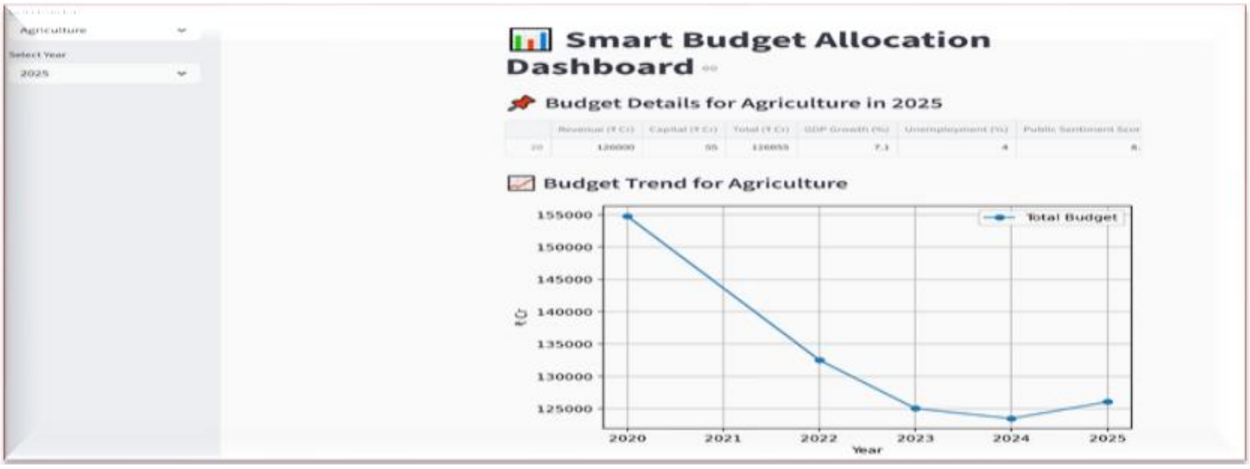


Figure 5: Dashboard

**Comparative Review with Existing Studies**

Table 2 : Comparative Reviews

| Study | Method Used | Scope | Limitation | This Study's Contribution |
|---|---|---|---|---|
| Makwana (2024) | Text Analysis | Union Budget | Lacks predictive modeling | Introduces regression and linear programming (LP) models |
| Radulescu (2015) | Neural Networks | EU Public Spending | Ignores policy alignment | Integrates forecasting with national policy roadmaps |
| This Study | Regression + LP | Sectoral India | Simulated sentiment only | Aligns with India@2047 vision and offers open-access dashboard |

## CONCLUSION

This study introduced a data-driven framework for smarter budget allocation by combining predictive analytics with linear programming. Using historical budget data, macroeconomic indicators, and public sentiment, the model successfully forecasted sectoral needs and generated optimized allocations within fiscal limits. The results demonstrated that integrating sentiment and economic context can make resource distribution more equitable and strategically aligned, while optimisation modelling highlighted budgetary trade-offs and improved fairness in allocation.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue IX September 2025

Future enhancements could include testing advanced machine learning approaches, such as random forests or neural networks, to improve long-term forecasting. Scenario-based simulations—covering fiscal shocks, pandemics, or climate change—could strengthen resilience, while stronger ethical safeguards, including

explainable AI and accountability mechanisms, would improve transparency and trust. A comparative analysis with global best practices, such as those in the UK and Singapore, would further contextualize the Indian case and position the framework within international discussions on AI-enabled public finance.

**Future Scope**

This work provides a foundation for data-driven budgeting but leaves room for growth. Future improvements could include expanding the model to state or district levels, using real-time economic data, and refining public sentiment analysis through social media and surveys. The system can also be enhanced for multi-year planning and advanced visualisation with tools like Power BI or Tableau. These extensions would further strengthen alignment between fiscal planning, ground realities, and long-term policy goals.

## DISCUSSIONS

Table 3: Future Advanced Evaluation Metrics

| Metric | Description | Purpose | Status |
|---|---|---|---|
| Sensitivity Analysis | Impact of ±1% change in GDP, sentiment, and unemployment | Model robustness | Planned |
| Historical Validation | Compare model output for 2024 with actual allocations | Accuracy check | Planned |
| Stakeholder Impact Estimation | Link budget shifts to outcomes (jobs, health) | Policy relevance | Planned |
| Ethical Risk Mapping | Fairness and bias audit for decision support | Responsible AI governance | Added |
| Scenario Testing | Simulate high vs low economic growth impacts | Strategic foresight | Planned |

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