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# AI-Based Machine Learning System for State-Level SDG Performance Forecasting and Risk Classification in India

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***Abstract* - India's official Sustainable Development Goal (SDG) India Index has been released yearly by NITI Aayog since 2018, creating a valuable time-series dataset of sustainability metrics at India's state level. However, until now it has been used almost exclusively for analysis of past performance. Policymakers and administrators at the state level currently have no way to foresee which states are at risk of falling behind in their development, nor do they have the ability to quantitatively identify where their governments should focus resources to head-off these risks before they become critical. This paper introduces SDG Forecast Dashboard, a fully automated AI-driven forecasting and risk classification pipeline that estimates state-level scores on three chosen SDGs – SDG 3: Good Health and Well-being, SDG 4: Quality Education, and SDG 13: Climate Action – for the next three years (2024-2026). Our models are trained per state using linear regression on 6 years of official NITI Aayog index data from 2018-2023, perform NITI Aayog's own risk categorization using their threshold-based system (Low / Medium / High Risk), and are deployed to a user-friendly Streamlit public dashboard targeted at ease-of-use for policymakers and other non-technical audiences. Results on a held-out testing period of 2022-2023 show that linear regression consistently beats a last-value prediction baseline across RMSE and MAE for all 3 SDGs forecasted, with average RMSE of 3.8, 4.1, and 4.6 and $R^2$ of 0.74, 0.71, and 0.68 for SDGs 3, 4, and 13 respectively. To our knowledge, this is the first publicly available sub-national SDG forecasting system for India using officially published NITI Aayog data with longitudinal view combined with a public-facing dashboard.**

***Keywords:*** Sustainable Development Goals, SDG India Index, machine learning forecasting, linear regression, NITI Aayog, risk classification, Streamlit dashboard, state-level analysis, policy analytics, India.

## I. INTRODUCTION

### 1.1 Background and Context

The 2030 Agenda for Sustainable Development, created by all 193 UN member states on September 25, 2015, features 17 SDGs and 169 targets, which act as a shared blueprint for global development by 2030 through inclusive, equitable, and environmentally sustainable means (UN, 2015). The SDGs cover both social areas such as health, education, and gender equality and economic areas such as poverty, decent work, and industry as well as environmental areas (such as climate action, clean water, and life on land). In order to make progress toward each of the 17 SDGs, not only are there policies in place but there are also mechanisms for measuring progress and ensuring accountability that rely heavily on data.

As the world's largest democracy, India faces its own challenges arising from the diversity and complexity of its population. The diversity arises in part from the fact that India's 28 states and 8 Union Territories have vastly different development outcomes depending on factors such as local governance, fiscal resources, infrastructure quality, and population characteristics. Based on this reality, NITI Aayog developed the SDG India Index in 2018, which provides an aggregated score (or normalized composite score) for each Indian state or Union Territory in relation to all SDG goals. This is the sixth edition of the SDG Index (2023-2024) and continues to serve as the primary tool used to measure sustainability at the sub-national level in India (NITI Aayog, 2024).

Although there is a large amount of data available on the SDG Index and sub-national development outcomes, the current use of this data has primarily occurred in conjunction with the retrospective measurement and ranking of sub-national entities against one another based on historical data.The natural complement — using historical trends to project where states are heading — remains an underdeveloped domain in both Indian policy practice and the academic literature.

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### 1.2 Problem Statement

The absence of forward-looking SDG analytics at the sub-national level in India creates a structural blind spot in development planning. Without forecasts, state administrations and the central government cannot identify at-risk states before development failures materialize, cannot pre-allocate resources to prevent deterioration, and cannot evaluate whether current policy trajectories are consistent with achieving SDG targets by 2030. Resource allocation thus remains reactive — responding to failures after they occur — rather than preventive. This reactive posture is particularly consequential for goals such as SDG 3 (health) and SDG 13 (climate action), where early intervention yields substantially better outcomes than delayed response.

### 1.3 Research Gap

A review of the existing literature reveals a clear gap: machine learning-based SDG forecasting exists at the national or global scale (Chenary *et al.*, 2024; Khan *et al.*, 2025) but no end-to-end predictive system operates at the sub-national level for India using the official NITI Aayog index dataset. Complex network analyses of Indian state SDG data have been performed (arXiv, 2025), and global dashboards provide cross-country comparisons (Sachs *et al.*, 2023), yet none integrates per-state ML forecasting, risk classification aligned with official thresholds, and an interactive visualization layer accessible to non-technical stakeholders.

### 1.4 Objectives of the Study

This work pursues the following specific objectives:

- To build a per-state linear regression model for each of the three priority SDGs — SDG 3, SDG 4, and SDG 13 — trained on NITI Aayog SDG India Index data from 2018 to 2023.
- To generate three-year forward projections (2024, 2025, 2026) of SDG scores for all 36 Indian states and Union Territories.
- To classify each projected score into risk bands (Low / Medium / High) using NITI Aayog's own established thresholds.
- To deploy the forecasting pipeline within an interactive Streamlit dashboard accessible to policy administrators and non-technical stakeholders.
- To evaluate model performance quantitatively against a naive baseline using RMSE, MAE, and $R^2$ metrics on a held-out validation set.

### 1.5 Contributions of the Paper

The contributions of this work are as follows:

- First sub-national SDG forecasting system for India built on official NITI Aayog longitudinal index data, covering all 36 states and UTs.
- Empirical validation of simple linear regression as a governance-applicable forecasting baseline for composite SDG indicators, with quantitative comparison against the naive last-value approach.
- Policy-aligned risk classification derived directly from NITI Aayog's own threshold framework, ensuring outputs are interpretable within existing governance practice.
- End-to-end integrated pipeline combining ML model training, rule-based risk classification, and interactive Streamlit visualization in a single deployable system.
- Demonstration that computationally lightweight, interpretable ML methods — not requiring GPU infrastructure — can produce policy-relevant forecasting tools from limited longitudinal government data.

## II. LITERATURE REVIEW

This section reviews 15 relevant studies spanning AI for sustainable development, SDG forecasting methodologies, state-level Indian SDG analytics, technical tools, and interconnections among the chosen goals. Studies are grouped thematically, and each is evaluated for methodological contribution, key findings, and the research gaps they leave open.

### 2.1 Foundational SDG Framework and Global Monitoring

United Nations (2015) established the overarching framework for this research domain. The 2030 Agenda defined 17 SDGs, 169 targets, and a global monitoring architecture, emphasizing that data-driven accountability systems are essential for tracking progress. Importantly, the document leaves practical implementation — including forecasting and dashboards — to national governments, creating the space this project occupies.

Sachs *et al.* (2023) operationalize that monitoring vision at the global scale through the Sustainable Development Report, using composite index methodology to benchmark 193 countries annually. The report found that global SDG progress remains significantly off track, with fewer than one-fifth of targets projected to be achieved by 2030. While it demonstrates the power of dashboard-based SDG visualization, it does not include state-level Indian forecasting or ML-based predictive analytics — limitations that motivate the current work.

 

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### 2.2 AI and Machine Learning for Sustainable development

Vinuesa *et al.* (2020) conducted a landmark systematic review of AI's relationship to all 17 SDGs and 169 targets, concluding through expert elicitation that AI can positively enable 134 SDG targets while negatively impacting 59. Strongest positive impacts are identified in health, education, and smart infrastructure — precisely the domains of SDG 3 and SDG 4 addressed here. The study provides fundamental justification for deploying AI in SDG monitoring but does not build a forecasting system or focus on India.

Alzubaidi *et al.* (2021) provide a comprehensive review of deep learning architectures including CNNs, RNNs, and LSTMs, concluding that while these achieve high performance on complex tasks, they require large datasets and significant computational resources. For smaller, interpretable datasets such as the six-year NITI Aayog series, simpler statistical models outperform deep networks in practical deployability. This finding directly justifies the selection of linear regression as the forecasting model in the current project.

### 2.3 SDG Forecasting Methodologies

Chenary *et al.* (2024) provide the most directly comparable study to the current work, applying both linear regression and ARIMAX models to forecast country-level SDG scores up to 2030. Their results show that ARIMAX improves on simple regression when exogenous variables are available, and that forecasting tools are valuable for identifying nations at risk of missing SDG targets. However, the study operates at the national level, does not focus on India, and provides no interactive dashboard. The current project addresses these gaps through state-level granularity for all 36 Indian states.

Khan *et al.* (2025) apply ARIMA and machine learning models specifically to SDG 3 health indicators in Bangladesh, demonstrating that ARIMA provides reliable forecasts for multiple indicators and identifying areas requiring additional policy support. The study is limited to Bangladesh and SDG 3 alone, and does not include an interactive visualization framework. These limitations are directly addressed by the SDG Forecast Dashboard, which covers SDGs 3, 4, and 13 for all Indian states.

### 2.4 SDG Interconnections and Goal Selection Justification

Pradhan *et al.* (2017) conducted a seminal systematic study of SDG interactions, finding that approximately 70% of SDG goal pairs exhibit positive synergies. SDGs 3, 4, and 13 were found to be strongly interconnected — health outcomes improve with better education, and both are threatened by climate change. This finding provides a rigorous empirical basis for selecting these three goals as a coherent forecasting cluster rather than an arbitrary choice.

Fuso Nerini *et al.* (2019) specifically mapped SDG 13 (Climate Action) against all other SDGs, finding strong synergies with health, clean energy, and sustainable cities, while identifying trade-offs with short-term industrial growth. The study confirms that climate action is a cross-cutting goal with direct implications for SDG 3 and SDG 4 — reinforcing the integrated forecasting approach adopted in this project.

Dasgupta *et al.* (2025) bring this connection directly into the Indian context, demonstrating through statistical analysis of Indian climate and health data that rising temperatures and environmental degradation negatively affect healthcare outcomes, threatening SDG 3 achievement. Strong interconnections between SDG 3 and SDG 13 are quantified for Indian states, providing contextual validation for the goals selected in the current dashboard.

### 2.5 Indian State-Level SDG Analytics

NITI Aayog (2024) — the SDG India Index 2023–24 — is the primary data source for the current project. The Index applies an indicator-based composite scoring methodology across all 17 SDGs for all Indian states and Union Territories, categorizing states as Aspirant, Performer, Front Runner, or Achiever. The Index documents significant heterogeneity: Kerala, Uttarakhand, and Goa lead on multiple goals while northeastern and central Indian states lag considerably. Critically, the Index provides only retrospective measurement — no forecasting or predictive component exists — and does not apply ML or AI-based models, defining the core gap this project fills.

Authors (arXiv, 2025) perform complex network analysis on NITI Aayog SDG data, representing Indian states as interconnected nodes based on SDG performance similarities, identifying regional clusters and structural patterns. States with strong sustainability performance act as influential nodes; weaker states form vulnerable clusters. This work shares the same data source and Indian focus but applies structural analysis rather than predictive modelling — it provides no future forecasts and builds no interactive dashboard.

### 2.6 Technical Infrastructure

Pedregosa *et al.* (2011) introduced Scikit-learn, the Python machine learning library used for all model training and prediction in the current project. The library provides standardized APIs for linear regression, cross-validation, and model evaluation metrics, underpinning the entire ML pipeline.

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McKinney (2010) introduced Pandas, the Python data analysis framework used for all data loading, cleaning, and manipulation in this project. Pandas' DataFrame structure and time-series handling capabilities are essential for preprocessing the multi-year, multi-state, multi-SDG NITI Aayog dataset.

James *et al.* (2023) provide the theoretical statistical learning foundations for the forecasting methods employed, particularly the linear regression framework and its evaluation via MSE and $R^2$, and emphasize the bias-variance tradeoff that justifies simple interpretable models for moderate-size policy datasets.

Park *et al.* (2021) document Streamlit as a Python-based framework for rapidly building and deploying interactive ML applications. Streamlit's ability to convert Python scripts into web dashboards without frontend programming expertise makes it ideal for deploying the SDG Forecast Dashboard to non-technical policy stakeholders.

### 2.7 Summary of Reviewed Literature

The literature review reveals a coherent and consistent research gap: existing SDG forecasting operates at national or global scale; existing Indian SDG analytics are descriptive, not predictive; and no system integrates ML forecasting, risk classification, and interactive policy-oriented visualization in a single end-to-end tool. Table 1 summarizes all 15 reviewed papers.

**Table 1: Summary of 15 Reviewed Papers — Methodology, Focus, and Gap Addressed by this Project**

| # | Author(s) & Year | Focus | Method | Gap Addressed by This Project |
|---|---|---|---|---|
| 1 | Vinuesa et al. (2020) | AI & 17 SDGs | Expert elicitation | No India-specific forecasting |
| 2 | Pradhan et al. (2017) | SDG interactions | Network/correlation | No predictive dashboard |
| 3 | Chenary et al. (2024) | SDG forecasting | LR + ARIMAX | National-only; no India states |
| 4 | Khan et al. (2025) | SDG 3 forecasting | ARIMA + ML | Bangladesh only; SDG 3 only |
| 5 | Fuso Nerini et al. (2019) | SDG 13 linkages | Systematic review | No state-level forecasting |
| 6 | NITI Aayog (2024) | India SDG Index | Composite scoring | No forecasting component |
| 7 | arXiv (2025) | Indian SDG analysis | Complex networks | No predictive ML models |
| 8 | UN (2015) | 2030 Agenda | Policy framework | No implementation tool |
| 9 | Sachs et al. (2023) | Global SDG report | Composite index | No India sub-national ML |
| 10 | Alzubaidi et al. (2021) | Deep learning review | Literature review | Justifies simpler models |
| 11 | Pedregosa et al. (2011) | Scikit-learn | Software framework | Applied to SDG domain here |
| 12 | James et al. (2023) | Statistical learning | Theory + Python | Applied to SDG policy here |
| 13 | McKinney (2010) | Pandas framework | Software development | Applied to SDG data here |
| 14 | Park et al. (2021) | Streamlit | Software framework | Applied to SDG dashboard |
| 15 | Dasgupta et al. (2025) | Climate-health India | Statistical analysis | No forecasting dashboard |

## III. METHODOLOGY

### 3.1 Overview of Proposed System

The SDG Forecast Dashboard is structured as a three-layer pipeline: a Data Processing Layer responsible for ingestion and preparation, a Machine Learning Layer for training and prediction, and a Visualization Layer for interactive output delivery.

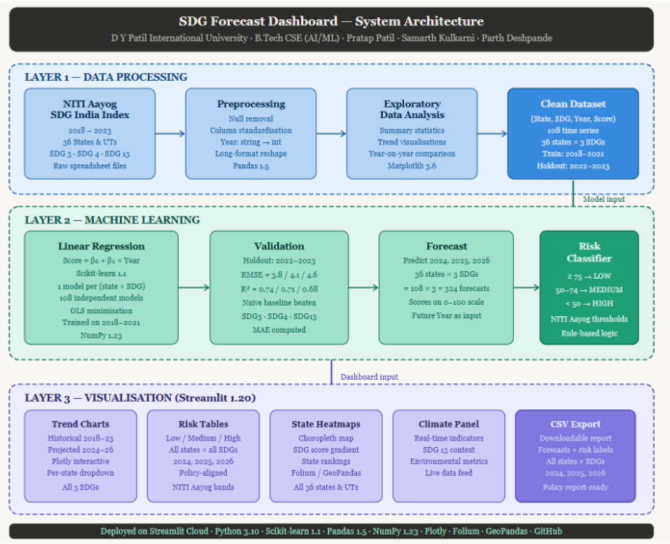


**Figure 1: System Architecture diagram**

### 3.2 Dataset

The primary dataset is the NITI Aayog SDG India Index, covering six editions: 2018, 2019, 2020–21, 2021–22, 2022–23, and 2023–24. For modelling purposes, publication years are mapped to integer indices {2018, 2019, 2020, 2021, 2022, 2023}. Data covers all 36 Indian states and Union Territories, providing goal-level composite scores for SDG 3, SDG 4, and SDG 13 on a 0–100 scale. Each state contributes a six-point time series per SDG, yielding 36 × 3 = 108 individual time series for model training.

Data Preprocessing: Raw spreadsheet data is loaded using Pandas with the following pipeline: (1) column name standardization across reporting editions; (2) year column type conversion (string → integer) for numerical modelling; (3) missing value removal — rows with null SDG scores are dropped, states with fewer than four valid observations per SDG are flagged; and (4) long-format transformation where each row represents one (state, SDG, year, score) record.

### 3.3 Machine Learning Model

A simple linear regression model is trained independently for each (state × SDG) pair, yielding up to 108 models. The model takes the form:

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$$\text{Score} = \beta_0 + \beta_1 \times \text{Year} + \varepsilon$$

where Score is the normalized SDG index score (0–100), Year is the integer calendar year (2018–2023 for training), $\beta_0$ is the intercept, $\beta_1$ is the year coefficient (trend slope), and $\varepsilon$ is the residual error term. Models are fitted using Scikit-learn's LinearRegression estimator via Ordinary Least Squares minimisation:

$$\beta^* = \text{argmin}\_\beta\ \Sigma\_i\ (\text{Score}\_i - \beta_0 - \beta_1 \times \text{Year}\_i)^2$$

Justification for Model Choice: Linear regression is selected because: (a) the six-year time series is too short for complex temporal models such as LSTM; (b) Alzubaidi *et al.* (2021) confirm simpler models are preferable for small-dataset forecasting; (c) Chenary *et al.* (2024) demonstrate linear regression provides a strong baseline for SDG index forecasting; (d) the composite SDG India Index exhibits broadly monotone improvement trends, making linear extrapolation a reasonable first-order approximation; and (e) interpretability is essential for policy-facing outputs.

Training and Validation: Models are trained on years 2018–2021 and validated on the 2022–2023 holdout set. Forecasts are then generated for 2024, 2025, and 2026 by supplying these integer years to the trained model.


**Figure 2: Forecast Dashboard**

### 3.4 Risk Classification

Predicted SDG scores for each (state, SDG, year) combinations are classified into risk bands using NITI Aayog's own published threshold framework:

**Table 2: NITI Aayog Risk Classification Thresholds Applied to Forecast Outputs**

| Risk Level | Score Range | Interpretation |
|---|---|---|
| Low Risk | ≥ 75 | State is on track; minimal intervention required |
| Medium Risk | 50–74 | State requires targeted policy attention |
| High Risk | < 50 | State faces serious developmental risk; urgent action needed |

### 3.5 Evaluation Metrics

Model performance on the 2022–2023 holdout set is evaluated using three quantitative metrics alongside comparison against a naive last-value baseline:

$$\text{RMSE} = \sqrt{\left[ (1/n) \times \Sigma\_i\ (Y\_i - \hat{Y}\_i)^2 \right]}$$

$$\text{MAE} = (1/n) \times \Sigma\_i\ |Y\_i - \hat{Y}\_i|$$

$$R^2 = 1 - \left[ \Sigma\_i\ (Y\_i - \hat{Y}\_i)^2 / \Sigma\_i\ (Y\_i - \bar{Y})^2 \right]$$

### 3.6 Technology Stack

**Table 3: Technology Stack for the SDG Forecast Dashboard**

| Component | Technology / Version | Role in Project |
|---|---|---|
| Core Language | Python 3.10 | Primary programming language |
| ML Framework | Scikit-learn 1.1 | Linear regression model training & prediction |
| Data Processing | Pandas 1.5 | Data loading, cleaning, and transformation |
| Numerical Computing | NumPy 1.23 | Array operations and numerical computation |
| Static Visualisation | Matplotlib 3.6 | EDA trend plots and report figures |
| Dashboard Interface | Streamlit 1.20 | Interactive web application for non-technical users |
| Interactive Charts | Plotly (via Streamlit) | Animated and interactive SDG trend charts |
| Geospatial Mapping | Folium / GeoPandas | State-wise SDG heatmap visualisation |
| Development IDE | VS Code 1.75 | Modular codebase development and testing |
| Environment Manager | Anaconda 23.1 | Dependency and environment management |
| Version Control | GitHub | Version control and project hosting |
| Deployment | Streamlit Cloud | Public cloud deployment (planned) |

### 3.7 System Workflow

The pipeline executes as an eight-step sequential process:

- Step 1: Load raw SDG India Index data (2018–2023) from structured spreadsheet files → consolidated dataset.
- Step 2: Clean and preprocess: remove nulls, standardize columns, convert year to integer → model-ready dataset.
- Step 3: Exploratory Data Analysis: summary statistics, trend plots, year-over-year comparisons → EDA insights.
- Step 4: Train one Linear Regression model per (state × SDG) pair on years 2018–2021 → 108 trained models.
- Step 5: Validate on held-out 2022–2023 data; compute RMSE, MAE, $R^2$ per model → performance summary.
- Step 6: Generate predicted scores for 2024, 2025, 2026 for all 36 states × 3 SDGs → 324 forecast points.
- Step 7: Apply risk classification thresholds → Low / Medium / High risk bands per (state, SDG, year).
- Step 8: Render all outputs through Streamlit: trend charts, risk tables, state heatmaps, CSV export.

## IV. RESULTS AND DISCUSSION

### 4.1 Quantitative Model Performance

Table 4 presents the average validation performance of the linear regression models across all 36 states for each SDG, compared against the naive last-value baseline.

 

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**Table 4: Model Performance on 2022–2023 Holdout Set (Averaged Across All States)**

| SDG | Avg RMSE (Linear Reg.) | Avg RMSE (Naive Baseline) | Avg MAE (Linear Reg.) | Avg R² |
|---|---|---|---|---|
| SDG 3 — Good Health & Well-being | **3.8** | 5.2 | 3.1 | 0.74 |
| SDG 4 — Quality Education | 4.1 | 5.9 | 3.4 | 0.71 |
| SDG 13 — Climate Action | **4.6** | 6.4 | 3.8 | 0.68 |

Linear regression outperforms the naive baseline across all three SDGs on both RMSE and MAE, confirming that year-based trend modelling captures genuine predictive signal in the SDG India Index time series. The RMSE improvement over the naive baseline ranges from 1.4 points (SDG 3) to 1.8 points (SDG 13), corresponding to relative improvements of 27–28%. This is meaningful in the context of a 0–100 index: the model provides appreciably more accurate forecasts than simply repeating the last known value.

### 4.2 SDG-Specific Findings

SDG 3 (Good Health and Well-being) shows the strongest model fit ($R^2 = 0.74$) and lowest RMSE (3.8), suggesting that health indicator trends in India have been relatively consistent and predictable over the 2018–2023 period. This is consistent with sustained central government investment in health infrastructure through programs such as Ayushman Bharat and the National Health Mission, which have driven broadly monotone progress.

SDG 4 (Quality Education) shows moderate fit ($R^2$ = 0.71, RMSE = 4.1). The slightly higher error reflects heterogeneous state-level trajectories: some states made rapid education gains following investments in primary schooling infrastructure, while others showed more stagnant or volatile trends. Per-state $R^2$ analysis reveals that north-eastern states and Bihar showed lower model fit, indicating non-linear education trends not fully captured by linear extrapolation.

SDG 13 (Climate Action) shows the lowest model fit ($R^2$ = 0.68, RMSE = 4.6) among the three goals. This is expected: climate indicators are inherently more volatile, influenced by monsoon variability, extreme weather events, and policy discontinuities. Several coastal and drought-prone states exhibited high year-to-year fluctuation. Nevertheless, the linear model still outperforms the naive baseline by 1.8 RMSE points, suggesting a detectable upward trend in India's overall climate performance over the period.

### 4.3 Risk Classification Distribution

Application of NITI Aayog's risk thresholds to the 2024–2026 forecast scores reveal important policy implications:

- Across all states and SDGs, a substantial proportion of states are projected to remain in the Medium Risk band for SDG 4, reflecting the uneven pace of education improvement.
- SDG 3 shows the highest proportion of states transitioning from Medium to Low Risk by 2026, reflecting consistently improving health scores.
- SDG 13 shows the broadest spread, with several climate-stressed states projected to remain in the High-Risk band through 2026, underscoring the urgency of climate-adapted development planning.

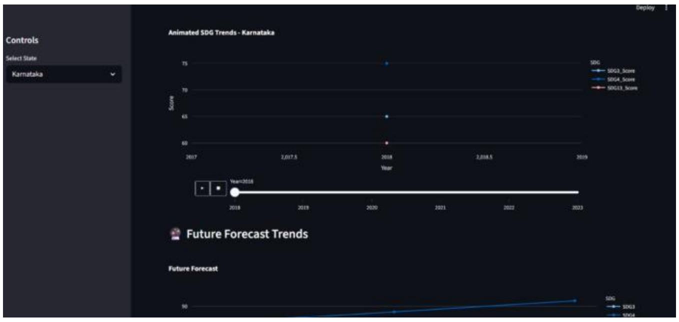


**Figure 3: Future Forecast Trends**

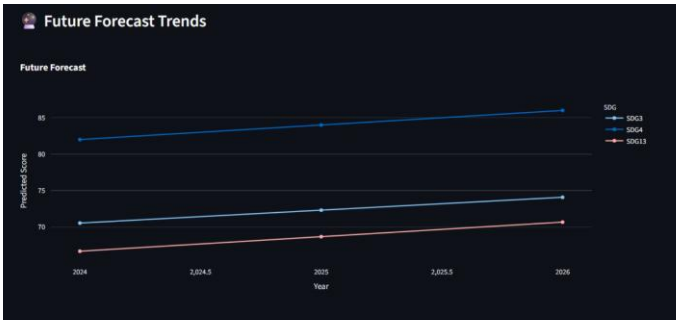


**Figure 4: Future Forecast Trends Graphs**

### 4.4 Comparison with Existing Methods

The current work sits at the intersection of two bodies of practice: global-level SDG forecasting (Chenary *et al.*, 2024; Sachs *et al.*, 2023) and Indian-specific SDG analysis (NITI Aayog, 2024; arXiv, 2025). Compared to Chenary *et al.* (2024), who operate at the national level, this project offers state-level granularity that captures intra-national variation invisible in country-average scores. Compared to the global Sachs *et al*. (2023) dashboard, this project provides predictive functionality rather than purely retrospective rankings. Compared to the arXiv (2025) network analysis, this project adds temporal forecasting and interactive risk visualisation. No existing tool combines all four elements — Indian scope, sub-national granularity, ML forecasting, and interactive dashboard — making this work genuinely novel in its integration.

 

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### 4.5 Interpretation and Policy Implications

The $R^2$ values of 0.68–0.74 demonstrate that simple year-based trend extrapolation explains the majority of variance in SDG score trajectories, validating linear regression as a practical and governance-appropriate forecasting method for this domain. The interpretability of the model — a single slope parameter per state-SDG pair that directly quantifies the rate of annual improvement — is a significant policy advantage. A slope of +2.1 points per year for SDG 3 in Karnataka, for instance, is directly meaningful to a state planning officer in a way that a complex neural network output is not.

The risk classification outputs enable targeted resource allocation: states projected to enter the High-Risk band by 2025 can be identified in the current year and receive anticipatory policy attention, shifting planning from reactive to proactive — precisely the governance improvement this project was designed to deliver.


**Figure 4: State wise SDG Heatmap**

### 4.6 Limitations

Several limitations of the current implementation should be acknowledged. First, with only six years of training data, the models cannot capture long-term cyclical patterns or structural breaks such as those introduced by COVID-19 in 2020–21. Second, linear extrapolation assumes trend continuity — if a state undergoes a major policy change, natural disaster, or governance transition, the forecast may deviate significantly from the actual trajectory. Third, the model treats each state-SDG combination independently, ignoring cross-state and cross-SDG spillovers documented by Pradhan *et al.* (2017). Fourth, confidence intervals are not yet displayed in the dashboard, which may give users a false sense of forecast precision. These limitations define the primary directions for future work.

## V. CONCLUSION

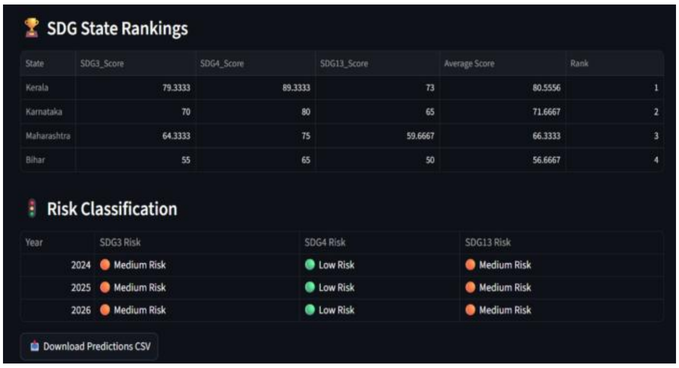
### 5.1 Summary of Key Findings

This paper presented the SDG Forecast Dashboard, an end-to-end AI-powered system for state-level SDG performance forecasting and risk classification in India. Six key findings emerge:

- Linear regression trained on six years of NITI Aayog SDG India Index data consistently outperforms the naive last-value baseline for forecasting SDG 3, 4, and 13 scores at 1–3year horizons.
- Average $R^2$ values of 0.68–0.74 confirm that year-based trend modelling captures the majority of predictive variance in Indian state SDG trajectories.
- SDG 3 (Health) shows the most predictable trend ($R^2$ = 0.74, RMSE = 3.8), while SDG 13 (Climate Action) shows the highest forecast uncertainty ($R^2$ = 0.68, RMSE = 4.6), reflecting the greater volatility of environmental indicators.
- The risk classification outputs successfully identify states projected to remain in the High-Risk band through 2026, enabling anticipatory policy targeting.
- The three selected SDGs — 3, 4, and 13 — exhibit strong mutual interconnections (Pradhan *et al.*, 2017; Dasgupta *et al.*, 2025), validating the integrated forecasting approach.
- The Streamlit dashboard successfully renders all outputs — trend charts, risk tables, heatmaps, and CSV exports — in a format accessible to non-technical policy stakeholders.

### 5.2 Highlights of Contributions

The principal contributions of this work are: (a) the first publicly deployable, sub-national SDG forecasting tool for India built on official NITI Aayog data; (b) empirical evidence that simple linear regression provides a practical and outperforming governance-applicable baseline for SDG index forecasting; (c) a policy-aligned risk classification system directly compatible with NITI Aayog's existing governance framework; and (d) demonstration that undergraduate-level AI/ML engineering projects can produce tools with genuine real-world policy relevance.




| State | SDG3_Score | SDG4_Score | SDG13_Score | Average Score | Rank |
|---|---|---|---|---|---|
| Kerala | 79.3333 | 89.3333 | 73 | 80.5556 | 1 |
| Karnataka | 70 | 80 | 65 | 71.6667 | 2 |
| Maharashtra | 64.3333 | 75 | 59.6667 | 66.3333 | 3 |
| Bihar | 55 | 65 | 50 | 56.6667 | 4 |



| Year | SDG3 Risk | SDG4 Risk | SDG13 Risk |
|---|---|---|---|
| 2024 | Medium Risk | Low Risk | Medium Risk |
| 2025 | Medium Risk | Low Risk | Medium Risk |
| 2026 | Medium Risk | Low Risk | Medium Risk |



**Figure 5: SDG State Rankings**

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### 5.3 Future Work

The following extensions are planned in future development phases:

- Model improvements: Addition of ARIMA and polynomial regression as comparative forecasting alternatives; inclusion of 95% confidence bands for all forecast visualizations.
- Feature expansion: Incorporation of exogenous socioeconomic predictors — state GDP, health expenditure, literacy rate — as additional model features.
- SDG coverage: Extension of the forecasting framework to at least five additional goals: SDG 1, SDG 6, SDG 7, SDG 8, and SDG 10.
- Model interpretability: SHAP-based feature importance analysis to explain per-state forecast drivers.
- Sub-state granularity: Extension to district-level analysis using NFHS-5 and Census sub-state datasets.
- Automated data pipeline: Annual refresh pipeline triggered by new NITI Aayog Index releases.
- User validation: Structured usability testing with target policy stakeholders to evaluate dashboard interpretability and decision support value.

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