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Urban Socioeconomic Predictors of SDG 11 Performance: A Cross-Sectional Analysis of Indian States

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Abstract: This study examines state-level determinants of Sustainable Development Goal (SDG) 11 "Sustainable Cities and Communities" across 29 Indian states and Delhi in 2023 using a cross-sectional analytical design. The SDG 11 score was modeled as the dependent variable, with urban unemployment rate, urban literacy rate, per capita NSDP (log), urbanization rate, and population density (log) as predictors. Correlation and OLS regression analyses, with rigorous diagnostic checks, were conducted. The model was statistically significant ($F = 3.143$, $p = 0.026$), explaining 40.6% of variance (Adjusted $R^2 = 0.278$). Among predictors, only urban unemployment showed a significant negative effect ($B = -3.223$, $p = 0.010$), indicating that each one-percentage-point increase corresponded to a 3.22-point fall in SDG 11 performance. The Findings underscore the centrality of labor market conditions for sustainable urban development. Policy priority should be given to job-creating urban infrastructure, MSME support, and skill development, alongside integrated planning, compact city design, and governance reforms to accelerate progress toward SDG 11.

Keywords - SDG 11 (Sustainable Cities and Communities), Urban unemployment, Sustainable urban development, State-level analysis, India, Urbanization, Population density, Per capita NSDP.

I. Introduction

1.1 Background and Context

The accelerated pace of urbanization worldwide has transformed cities into pivotal centers of economic activity, social interaction, and environmental challenges. Globally, more than half of the population now resides in urban areas, a proportion forecasted to increase in the coming decades, underscoring the critical role that sustainable urban development plays in shaping the future of human well-being and ecological balance (United Nations, 2023). Urban centers concentrate resources, innovation, and cultural exchange but also experience heightened demands on infrastructure, housing, public services, and natural ecosystems. Against this backdrop, the United Nations Sustainable Development Goal 11 (SDG 11) aims to foster inclusive, safe, resilient, and sustainable cities as a foundation for equitable development and quality of life (UN DESA, 2023).

India's urban landscape exemplifies these global dynamics, reflecting both the promise and complexity of rapid urban growth. With an urban population that has surged alongside economic liberalization since the 1990s, Indian cities have become engines of growth, contributing substantially to the country's gross domestic product and employment (Roy et al.,2023). However, this development trajectory is marked by heterogeneity and multifaceted challenges spanning inadequate infrastructure, air and water pollution, informal settlements, transportation bottlenecks, and unequal access to education and employment opportunities (ESCAP, 2023; Subramanian et al., 2023). To address these challenges, India has deployed a range of policy initiatives, including the Smart Cities Mission, Atal Mission for Rejuvenation and Urban Transformation (AMRUT), and dedicated SDG monitoring frameworks, which serve to track and promote progress on SDG 11 at both local and state levels (Kundu, 2021; NITI Aayog, 2023).

1.2 Evolving Dimensions of Urban Sustainability in India

The multifactorial nature of urban sustainability necessitates consideration of diverse socioeconomic and demographic dimensions. Core variables such as urban employment levels, literacy rates, income, urbanization pace, and population density resonate as critical indicators of urban resilience and inclusivity (Roy et al., 2023). These indicators not only capture economic performance and human capital development but also reflect demographic pressures and spatial organization that affect service delivery and environmental stress .In India, the interplay between these socioeconomic factors and urban sustainability outcomes is complex and regionally differentiated, influenced by historical urban planning legacies, governance structures, and evolving economic landscapes (Kundu, 2021; ESCAP, 2023).

The prior studies recognize the value of integrating multiple urban socioeconomic indicators to understand sustainable development comprehensively. Some studies explore the singular influence of factors like urbanization rate or literacy on specific sustainability outcomes, while others examine broader frameworks linking environmental, social, and economic variables (Roy et al.)Despite this progress, there remains an emerging appreciation for refined analytical approaches that simultaneously consider the joint and individual effects of key determinants on SDG-related performance across diverse regional contexts, especially at the subnational level in India.

1.3 Policy Frameworks and Monitoring Initiatives

India's policy response to sustainable urbanization exemplifies concerted efforts to align national growth with SDG priorities. The Smart Cities Mission, launched in 2015, represents an ambitious approach emphasizing technology-enabled infrastructure, citizen participation, and enhanced urban governance (NITI Aayog, 2023). Complementary programs like AMRUT target fundamental urban services, including water supply, sanitation, and transport infrastructure, with explicit objectives tied to the broader sustainability agenda. Parallelly, India's SDG India Index developed by NITI Aayog provides an empirical basis for tracking state-level progress on various SDGs including SDG 11, thus facilitating targeted policy adjustments and resource allocation (NITI Aayog, 2023).

These initiatives reflect the rising importance of rigorous measurement and evidence-based policymaking in steering sustainable urban development. Incorporating multidimensional indicators not only advances objective assessment but also fosters greater accountability and responsiveness among urban governance institutions (ESCAP, 2023). Moreover, the continual refinement of these monitoring tools highlights the evolving nature of urban sustainability itself, which necessitates adaptive frameworks responsive to emerging socioeconomic trends and challenges.

1.4 Significance and Contemporary Relevance

The societal, economic, and environmental implications of urban sustainability in India remain critically relevant amid ongoing demographic shifts and climate vulnerabilities. Urban centers are focal points for innovation and growth yet simultaneously represent zones of heightened risk related to pollution, resource depletion, and social inequities (Subramanian et al., 2023). Understanding the socioeconomic underpinnings of sustainable urban development facilitates more informed strategies to mitigate these challenges while amplifying inclusive prosperity. This aligns with global sustainability objectives emphasizing the interdependence of social inclusion, economic opportunity, and environmental stewardship (United Nations, 2023; UN DESA, 2023).

Expanding the empirical inquiry into the relationships between urban socioeconomic factors and SDG 11 outcomes has particular significance in the Indian context. Variability in state-level performance on sustainable cities indicators reflects not just geographic and economic diversity but also differences in local governance capacity, policy implementation, and demographic pressures (Roy et al., 2023). Consequently, nuanced analyses that consider multiple dimensions of urban development simultaneously contribute valuable insights for tailoring interventions responsive to specific regional needs and challenges.

1.5 Study's Contribution

Building on this evolving understanding, the study adopts a comprehensive cross-sectional approach focusing on 29 Indian states and the Union Territory of Delhi for the year 2023. It assesses how selected socioeconomic indicators: Urban Unemployment Rate, Urban Literacy Rate, Per Capita Net State Domestic Product (log-transformed), Urbanization Rate, and Population Density (log-transformed) relate to and jointly influence SDG 11 performance. Employing robust statistical methods including correlation analysis and multiple regression under stringent diagnostic criteria, the research seeks to elucidate patterns and predictive relationships that contribute to sustainable urban development outcomes.

By leveraging high-quality national datasets and applying validated analytical techniques, the study aligns with current methodological advancements underscoring the importance of independent, multivariate modeling in sustainability assessment (Roy et al., 2023). The findings are intended to enrich scholarly discourse and provide actionable evidence to assist policymakers, urban planners, and development practitioners committed to advancing India's sustainable urban agenda.

2.LITERATURE REVIEW

2.1 Conceptual Foundations: Urban Sustainability and SDG 11

Urban sustainability has become a central pillar of contemporary development theory and policy, with cities worldwide recognized as both engines of economic growth and sites of profound social and environmental challenges (United Nations, 2023). SDG 11, established within the United Nations Sustainable Development Goals framework, aims to make cities and human settlements inclusive, safe, resilient, and sustainable by 2030, emphasizing the need for multidimensional strategies that intertwine infrastructure, basic services, economic opportunity, and environmental stewardship (UN DESA, 2023). India's rapid urbanization, marked by uneven access to services and diverse socioeconomic trajectories, has positioned its cities at the heart of debates on urban sustainability (ESCAP, 2023).

2.2 The Indian Urbanization Experience

India's demographic and economic transformation is deeply entwined with its expanding urban population. Since the 1990s, economic reforms and population growth have accelerated the pace of urban expansion, with Indian cities now contributing a significant proportion of national GDP and serving as hubs for innovation and migration (Roy et al.,2023). However, research highlights that this growth has also intensified pressures on infrastructure, housing, employment, and environmental quality, with considerable regional disparities (Kundu, 2021; Subramanian et al., 2023).Recent scholarly work has examined the complexities of Indian urbanization, underscoring the interplay between economic growth, spatial inequalities, and institutional capacity (Kundu, 2021; NITI Aayog, 2023). In particular, studies point to the challenges posed by infrastructural deficits, high population densities, and the prevalence of informal settlements, each of which presents significant obstacles to achieving SDG 11 targets (Kushwaha et al.,2023). The lack of robust, granular data at the city and state levels further complicates efforts to monitor progress and develop locally adapted solutions (Roy et al., 2023; NITI Aayog, 2023).

2.3 Socioeconomic Predictors of Urban Sustainability

A central theme in the literature concerns the socioeconomic determinants that underpin SDG 11 performance. Multiple studies both in India and internationally emphasize the roles of urban unemployment, literacy rates, per capita income, urbanization rate, and population density within the broader matrices of sustainable cities (Roy et al., 2023; Mishra & Karmakar, 2024). For example, higher literacy and increased per capita income are frequently associated with improved access to infrastructure and services, while high unemployment and dense populations often exacerbate environmental stresses and limit progress toward sustainability goals.

Comparative research in South and East Asia reveals context-dependent approaches to localizing SDG 11, with countries such as Singapore and China emphasizing strong institutional environments, stakeholder engagement, and adaptive planning (Kushwaha et al., 2023). In contrast, Indian cities face persistent challenges in integrating sustainability into spatial planning and governance systems, often hindered by fragmented institutional arrangements and inconsistent data ecosystems (Kundu, 2021; Kushwaha et al., 2023).

2.4 Policy Initiatives and Monitoring Frameworks

India's policy response has evolved through a combination of national missions and measurement systems. Initiatives like the Smart Cities Mission and AMRUT target infrastructural improvements, inclusive housing, and upgraded urban services, while the SDG India Index, developed by NITI Aayog, provides an annual empirical assessment of progress at the state level (NITI Aayog, 2023). Scholars note that these frameworks have enhanced policy coordination and data-driven decision-making, but also caution that disparities remain across states, with many cities struggling to translate national policy into effective local action (ESCAP, 2023; Roy et al., 2023; Subramanian et al., 2023).

Recent bibliometric studies have highlighted both progress and stagnation in SDG 11 indicators across Indian states, noting variations in performance linked to economic strength, implementation capacity, and governance quality (Mishra & Karmakar, 2024). The literature recognizes a trend toward increasingly complex and integrated monitoring mechanisms—such as the SDG India Index and the use of diagnostic assessments in urban planning—which facilitate competitive benchmarking and policy learning at the subnational level (NITI Aayog, 2023; Mishra & Karmakar, 2024).

2.5 Comparative Perspectives and International Experiences

Comparisons with other developing economies enrich the analytical landscape of sustainable urban development. (Kushwaha et al.,2023) critically review strategies undertaken across South and East Asian countries, identifying best practices such as efficient data systems, participatory planning, and context-sensitive policy reform. Research suggests that while Indian policy discourse emphasizes inclusive planning and urban governance reform, city-level implementation continues to face challenges related to capacity, awareness, and the integration of SDG targets into local development plans (Kundu, 2021; Kushwaha et al., 2023). Studies underline the importance of aligning national and local priorities, fostering multi-stakeholder engagement, and adapting strategies to local socioeconomic realities.

2.6 Methodological Approaches

The existing research on SDG 11 increasingly employs sophisticated quantitative and mixed-method approaches. Cross-sectional and multivariate analyses examine state- or city-level relationships between socioeconomic indicators and SDG 11 scores, allowing for nuanced exploration of both direct and mediated effects (Roy et al., 2023). Methodological advances include the use of diagnostic tests for multicollinearity and variable transformation (e.g., log-transformed income and density measures), as well as the integration of spatial and temporal data to track policy impacts over time (Mishra & Karmakar, 2024; Subramanian et al., 2023).

Notably, a growing number of studies apply urban data analytics, geospatial modeling, and advanced econometric techniques to disentangle the contributions of economic, social, and environmental determinants (Mishra & Karmakar, 2024). These approaches reflect an evolution from purely descriptive assessments toward empirically robust, policy-relevant inquiry into the dynamics of sustainable urban development.

2.6 Synthesis and Emerging Trends

The literature collectively reveals a dynamic field that engages with the multifaceted, context-dependent nature of urban sustainability in India. Scholars consistently emphasize that progress on SDG 11 depends on integrative policy approaches, strong governance, inclusive data systems, and the ability to adapt strategies to local challenges and opportunities (Kundu, 2021; ESCAP, 2023; Roy et al., 2023). Ongoing debates include the optimal weighting of socioeconomic versus environmental factors, the challenges of achieving consistency in data collection, and the translation of national policy frameworks into effective urban interventions. Within this evolving landscape, state-level analyses grounded in robust empirical methods offer valuable contributions to both academic understanding and policymaking.

3.RESEARCH QUESTIONS

1. What are the patterns of SDG 11 scores and key urban socioeconomic indicators across Indian states in 2023?
2. How do Urban Unemployment Rate, Urban Literacy Rate, Per Capita NSDP, Urbanization Rate, and Population Density relate to SDG 11 scores both individually and collectively?
3. Which predictor(s) have statistically significant effects on SDG 11 scores in Indian states?

4.RESEARCH OBJECTIVES

- To summarize the distribution and variation of SDG 11 scores and urban socioeconomic variables across Indian states.
- To assess bivariate relationships between SDG 11 performance and selected predictors using correlation analysis.
- To examine multiple regression assumptions and validate modeling suitability.
- To identify and quantify the joint and individual effects of Urban Unemployment Rate, Urban Literacy Rate, Ln Per Capita NSDP, Urbanization Rate, and Ln Population Density on SDG 11 scores.

5.DATA AND METHODOLOGY

This study employs a cross-sectional analytical design for the year 2023, covering all 29 states of India, with the addition of the Union Territory of Delhi due to its high degree of urbanization and strategic relevance to SDG 11-Sustainable Cities and Communities. The unit of analysis is at the state level, and all datasets were sourced from official and reputable publications released during 2023–2024.

The dependent variable is the SDG 11 score, taken from India's official SDG monitoring framework. To ensure analytical rigor, independent variables were carefully chosen to avoid tautology, meaning none of them form part of the official computation of the SDG 11 index. Instead, they serve as fully independent predictors that collectively reflect the major dimensions of sustainable urban development. These variables include: the Urban Unemployment Rate (%) representing labor market conditions and economic inclusion (sourced from PLFS 2023–24, MoSPI); the Urban Literacy Rate (%) reflecting education and human capital (from PLFS 2023–24, MoSPI); Per Capita Net State Domestic Product (NSDP, at current prices) capturing state-level economic performance (sourced from RBI's Handbook of Statistics on the Indian Economy), which was log-transformed to correct right skewness; Population Density, computed as the ratio of UIDAI's 2023 projected population to official state land area, serving as a proxy for demographic and spatial pressure and also log-transformed due to skewness; and the Urbanization Rate (%), estimated by projecting 2011 Census values forward to 2023 using a uniform annual increment of 0.44 percentage points (5.28 points over 12 years) based on UN/World Bank trends, with values capped at 100%.

The statistical analysis proceeded in four stages. First, descriptive statistics, including mean, standard deviation, minimum, and maximum values, were computed for all variables. Second, a Pearson correlation matrix was constructed to examine pairwise relationships between the SDG 11 score and predictors while also providing a preliminary check for multicollinearity. Third, the necessary assumptions for Ordinary Least Squares (OLS) regression were tested. Linearity was assessed through scatter plots of each predictor with fitted trendlines; multicollinearity was evaluated using correlation coefficients and Variance Inflation Factor (VIF) values; homoscedasticity was checked via plots of standardized residuals against predicted values; and normality of residuals was confirmed using histograms and Q–Q plots. Outliers and influential cases were identified by examining standardized residuals beyond ± 2, while independence of errors was assumed given the study's cross-sectional design without temporal or spatial ordering. Finally, a multiple regression analysis was conducted, with the SDG 11 score as the dependent variable and all five predictors entered simultaneously, using OLS estimation.

6. DATA ANALYSIS AND RESULTS

6.1 Descriptive Statistics

Table 1: Descriptive Statistics for Dependent and Independent Variables (n = 29 States)

Variable	Mean	Std. Dev.	Min	Max	Range	Skewness	Kurtosis
SDG 11 score (Y)	74.83	17.11	38.00	98.00	60.00	–1.018	–0.036
X1: Urban Unemployment Rate (%)	6.24	2.97	2.00	14.00	12.00	0.877	0.794
X2: Urban Literacy Rate (%)	90.66	4.46	84.00	98.30	14.30	0.212	–1.099
X3: Ln Per Capita NSDP (₹)	12.154	0.527	10.887	13.162	2.275	–0.118	0.063
X4: Urbanization Rate – Est. 2023 (%)	38.39	17.09	15.28	100.00	84.72	1.785	5.039
X5: Ln Population Density – 2023 (persons/km²)	5.797	1.177	2.926	9.575	6.649	0.654	3.447

Source: Author's own calculation

The descriptive statistics for the dependent variable (SDG 11 score) and the five independent variables are presented in Table 1. The mean SDG 11 score across the 29 states was 74.83 (SD = 17.11), with scores ranging from 38 to 98, indicating considerable variation in performance on Sustainable Cities and Communities. The distribution of scores was slightly left skewed (skewness = –1.018) with kurtosis close to zero, suggesting an approximately normal distribution. The urban unemployment rate (X1) averaged 6.24% (SD = 2.97), with values between 2% and 14%, showing moderate variation and a mild right skew. The Urban literacy rate (X2) was high overall (mean = 90.66%, SD = 4.46), with relatively low variability and a nearly symmetric distribution. The Per Capita NSDP (X3) was log transformed to reduce skewness; the transformed values had a mean of 12.154 (ln ₹), were approximately symmetric (skewness ≈ –0.12), and had minimal kurtosis, indicating that the transformation was effective. The estimated 2023 urbanization rate (X4) averaged 38.39% but varied considerably (15.28% to 100%) and was highly right skewed (skewness = 1.785) with a leptokurtic distribution (kurtosis = 5.039), reflecting a small number of highly urbanized states such as Delhi and Goa. The population density (X5) for 2023 was also log transformed. The log transformed values had a mean of 5.797, ranged from 2.926 to 9.575, and showed moderate right skew (0.654) with noticeable kurtosis (3.447), indicating that even after transformation a few high-density states (e.g., Delhi) remain as upper end outliers.

6.2 Correlation and Multicollinearity Diagnostics

Correlation Analysis

The relationships between the dependent variable (SDG 11 Score) and the five selected independent variables were examined using Pearson's correlation coefficients. Table 1 presents the complete correlation matrix. The independent variables included: Urban Unemployment Rate (X_1), Urban Literacy Rate (X_2), Ln Per Capita Net State Domestic Product (NSDP, X_3), Urbanization Rate – estimated 2023 (X_4), and Ln Population Density – 2023 (X_5).

Table 2: Pearson correlation coefficients for SDG 11 score and predictor variables (n = 29)

Variable	**SDG 11 Score**	**X_1 Urban Unemp.**	**X_2 Urban Literacy**	**X_3 Ln NSDP**	**X_4 Urbanization**	**X_5 Ln Pop Density**
SDG 11 Score	1.000	–0.461	–0.147	0.291	0.005	–0.068
X_1: Urban Unemployment Rate	–0.461	1.000	0.229	–0.317	–0.434	–0.472
X_2: Urban Literacy Rate	–0.147	0.229	1.000	0.237	0.076	–0.350
X_3: Ln NSDP	0.291	–0.317	0.237	1.000	0.639	–0.014
X_4: Urbanization Rate	0.005	–0.434	0.076	0.639	1.000	0.483
X_5: Ln Population Density	–0.068	–0.472	–0.350	–0.014	0.483	1.000

Source: Author's own calculation

The bivariate analysis revealed that the strongest correlation with the SDG 11 Score was observed for the Urban Unemployment Rate ($r = –0.461$), suggesting that states with higher levels of urban unemployment tend to perform poorly on sustainable cities and communities. In contrast, ln-transformed Per Capita NSDP showed only a weak positive relationship with the SDG 11 Score ($r = 0.291$). Other predictors, namely Urban Literacy Rate, Urbanization Rate, and ln-transformed Population Density, displayed negligible associations with the dependent variable, with correlation coefficients remaining below |0.15|. Examining the interrelationships among predictors, the highest observed correlation was between ln Per Capita NSDP and Urbanization Rate ($r = 0.639$), which is well below the conventional threshold of |0.80| that indicates a serious risk of multicollinearity. This preliminary analysis therefore suggests minimal concern regarding multicollinearity, though a formal Variance Inflation Factor (VIF) test was subsequently carried out to confirm this assessment.

Multicollinearity Diagnostics (Variance Inflation Factors)

Table 3: Variance Inflation Factors (VIF)

Variable	VIF	Tolerance (1/VIF)
X_1: Urban Unemployment Rate (%)	1.542	0.648
X_2: Urban Literacy Rate (%)	1.300	0.769
X_3: Ln Per Capita NSDP (₹)	2.373	0.421
X_4: Urbanization Rate (2023, %)	2.953	0.339
X_5: Ln Population Density (2023, persons/km²)	2.226	0.449

Source: Author's own calculation

To formally assess multicollinearity, auxiliary regressions were conducted by regressing each independent variable on the remaining predictors in order to calculate Variance Inflation Factors (VIF) and corresponding tolerance values (1/VIF). The results, presented in Table 3, show that all five predictors had VIF values well below the commonly cited thresholds of concern (5 or 10), with the highest being 2.953 for the Urbanization Rate. The associated tolerance values were all comfortably above 0.20, further reinforcing the absence of collinearity issues. Taken together, these findings confirm that no problematic multicollinearity exists in the dataset, allowing all variables to be retained in the multiple regression model. Moreover, the modest intercorrelations among predictors indicate that the regression coefficients are likely to remain statistically stable, thereby permitting an independent evaluation of each variable's contribution to SDG 11 performance.

6.3 Regression Assumption Checks

i. Linearity

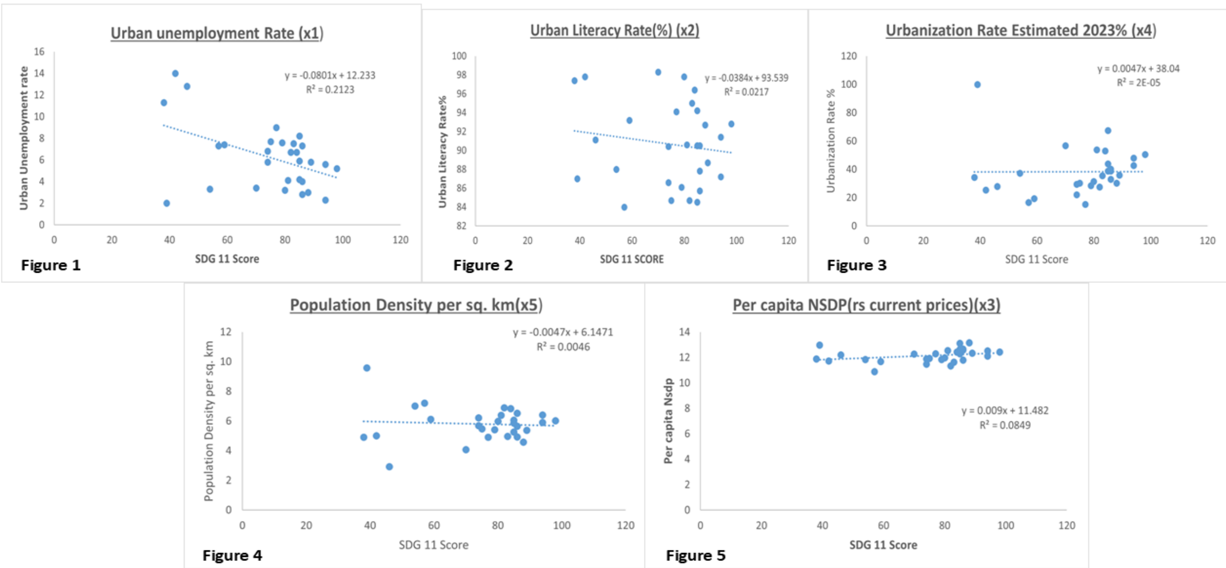


Figure: Combined scatter plots showing linear relationships among variables

The combined scatter plot analysis reveals the linear relationships between SDG 11 scores and various urban indicators. In Figure 1, we can see a moderate negative linear relationship exists between urban unemployment rate and SDG 11 score ($R^2 = 0.2123$), indicating that higher unemployment is associated with lower SDG 11 scores. In Figure 2, Urban literacy rate shows a very weak negative association with

SDG 11 score ($R^2 = 0.0217$), with no indication of non-linearity. In Figure 3, Per capita NSDP exhibits a very weak positive linear relationship ($R^2 = 0.0849$), consistent with a predominantly linear form. In figure 4 Urbanization rate displays an essentially negligible linear association ($R^2 \approx 0.00002$), with no non-linear pattern despite an outlier. In figure 5, Population density's relationship with SDG 11 score is also very weakly negative ($R^2 = 0.0046$), with a linear trend and no curvature. Overall, these findings confirm the linearity assumption for all predictors, supporting the use of linear regression models in this analysis while highlighting varying strengths of association across variables.

ii. Homoscedasticity

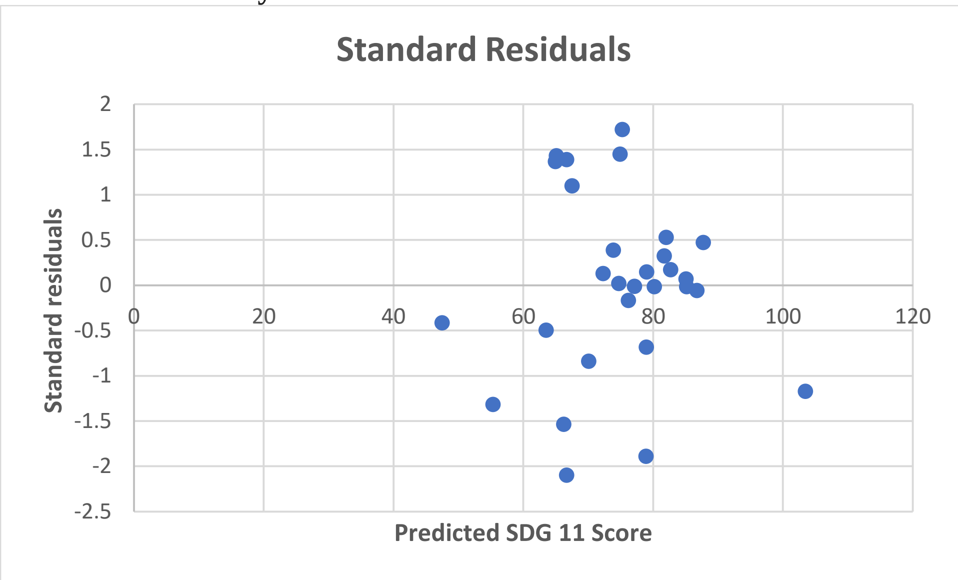
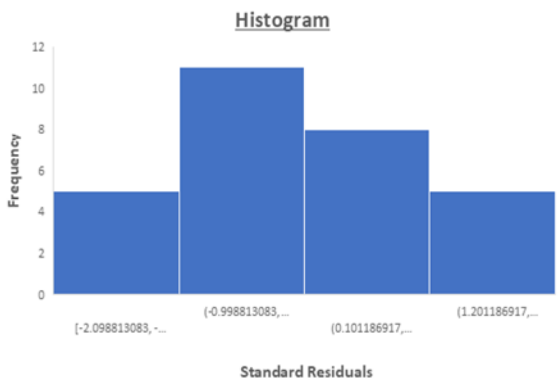


Figure 1: Standard residuals

To assess the homoscedasticity assumption, a scatter plot of standardized residuals versus predicted SDG 11 scores was examined. The residuals were distributed randomly above and below zero, forming a horizontal band with a relatively consistent vertical spread across the range of fitted values. No funnel, cone, or systematic pattern was observed, and while a few outliers were noted, their presence is acceptable given the sample size. Overall, the constant variance assumption was satisfied, as there was no evidence of heteroscedasticity or visible correlation between the residual spread and predicted scores. This supports the appropriateness of the linear regression model for these data.

iii. Normality Check



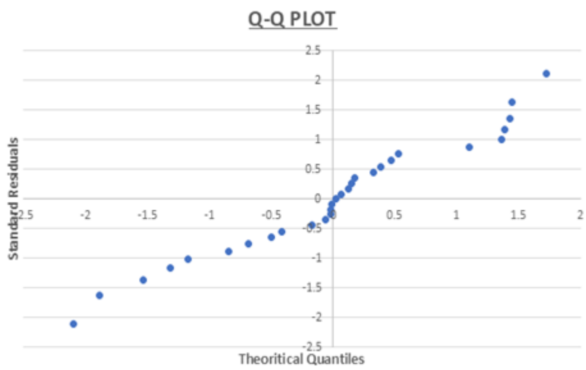


Figure 2: Normality check

The assumption of normally distributed residuals was evaluated using both a histogram of standardized residuals and a quantile–quantile (Q–Q) plot. The histogram displayed a roughly symmetric, bell-shaped distribution, with most residuals clustering near zero and frequencies tapering off evenly toward both extremes, suggesting an absence of skewness or outliers. The Q–Q plot further demonstrated that the standardized residuals closely followed the diagonal reference line, with only minor deviations at the tails consistent with the modest sample size. Taken together, these visual diagnostics indicate that the residuals from the regression model are approximately normally distributed, thereby supporting the validity of statistical inference based on the regression results.

iv. Outliers check

Examination of the standardized residuals revealed one observation with an absolute value greater than 2.00, corresponding to the state of Delhi (standardized residual = –2.10). This case differs markedly from the rest of the sample due to extreme predictor values, including a capped urbanization rate of 100% (original calculation exceeded 100%) and exceptionally high population density. Such characteristics are consistent with Delhi's city state profile and are not indicative of a data entry error. This observation was retained in the analysis as it represents a genuine extreme case within the population. The potential influence of this outlier was considered; sensitivity checks excluding Delhi did not materially alter the regression coefficients, supporting its inclusion in the final model.

v. Independence of errors

Due to the cross-sectional design of the study and lack of ordering in data collection, the regression residuals were assumed to be independent. This assumption is reasonable in the present context and consistent with standard practice for similar geographic cross section datasets.

In summary, the diagnostic checks confirmed that all major assumptions underlying the OLS multiple regression analysis were satisfied or reasonably met for the present dataset. No violations were detected that would compromise the validity of parameter estimates or statistical inference. The model is therefore considered appropriate for examining the relationships between the selected predictors and the SDG 11 score. The following section presents the results of the multiple regression analysis.

6.4 Multiple Regression Results: Predictors of SDG 11 score

The multiple linear regression analysis examined the combined effects of Urban Unemployment Rate, Urban Literacy Rate, ln Per Capita NSDP, Urbanization Rate, and ln Population Density on SDG 11 performance across 29 Indian states.

Model Specification

The multiple regression model is specified as:

$$\begin{aligned} SDG11Score &= \beta_0 + \beta_1(urban\ unemployment\ rate) + \beta_2(urban\ literacy\ rate) \\ &\quad + \beta_3 ln(per\ capita\ NSDP) + \beta_4(urbanization\ rate) + \beta_5 ln\ (population\ density) \\ &\quad + \varepsilon \end{aligned}$$

Substituting the estimated coefficients, the model becomes:

SDG11 Score = $24.442 - 3.223X_1 - 0.581X_2 + 12.696X_3 - 0.383X_4 - 2.843X_5 + \varepsilon$

This equation represents the estimated relationship between SDG 11 performance and the selected socioeconomic variables.

Table 4: Multiple Regression Results for SDG 11 score (n = 29)

Model Summary	**Value**
Multiple R	0.637
R^2	0.406
Adjusted R^2	0.278
Std. Error of Estimate	14.55
F-statistic (df = 5, 23)	3.143
Model p-value	0.026
Model Explanation	Model is statistically significant; predictors jointly explain ~40.6% of variance in SDG 11 Scores.

Predictor	B (Unstd.)	Std. Error	t-value	p-value	95% CI Lower	95% CI Upper	Significant
(Intercept)	24.442	118.589	0.206	0.839	–220.877	269.762	—
Urban Unemployment Rate (%)	–3.223	1.148	–2.808	0.010	–5.597	–0.848	($p < 0.05$)
Urban Literacy Rate (%)	–0.581	0.703	–0.826	0.417	–2.034	0.873	—
Ln Per Capita NSDP (₹)	12.696	8.038	1.580	0.128	–3.931	29.323	—
Urbanization Rate – 2023 (%)	–0.383	0.276	–1.385	0.179	–0.955	0.189	—
Ln Population Density – 2023	–2.843	3.485	–0.816	0.423	–10.051	4.366	—

Source: Author's own calculation

The model was statistically significant overall ($F(5, 23) = 3.143$, $p = 0.026$), indicating that the selected predictors jointly explain variation in SDG 11 scores. The model achieved an R^2 of 0.406, suggesting that approximately 40.6% of the variance in SDG 11 performance is explained by these variables. The Adjusted R^2 of 0.278 indicates a moderate level of explanatory power after accounting for model complexity.

Among the predictors, **Urban Unemployment Rate (X_1)** emerged as the only statistically significant variable ($B = –3.223$, $p = 0.010$). Holding other factors constant, a one-percentage-point increase in urban unemployment is associated with an average 3.22-point decline in SDG 11 performance. This highlights the critical role of labour market conditions in influencing sustainable cities and communities outcomes.

In contrast, **Urban Literacy Rate (X_2)** showed a negative but statistically non-significant relationship ($p = 0.417$). Although literacy is generally expected to support sustainability outcomes, its effect appears negligible in this model, possibly due to already high and relatively uniform literacy levels across states, which limits its explanatory power.

The coefficient for **ln Per Capita NSDP (X_3)** was positive ($B = 12.696$), indicating that economically stronger states may perform better in terms of SDG 11. However, this relationship was not statistically significant ($p = 0.128$) after controlling for other variables, suggesting that economic prosperity alone does not guarantee improved urban sustainability outcomes.

Similarly, **Urbanization Rate (X_4)** exhibited a negative and non-significant association ($p = 0.179$). This suggests that higher levels of urbanization do not automatically translate into better SDG 11 performance and may, in some cases, reflect pressures related to infrastructure, housing, and environmental stress.

Finally, **ln Population Density (X_5)** also showed a negative but non-significant effect ($p = 0.423$), indicating that population concentration alone is not a reliable determinant of sustainable urban outcomes once other socioeconomic factors are taken into account.

Overall, the findings indicate that urban unemployment is the most critical predictor of SDG 11 performance among the variables considered**.** While the model explains a meaningful portion of the variation in SDG 11 scores, a substantial share remains influenced by other factors not included in the analysis, such as governance quality, infrastructure provision, environmental management, and social inclusivity. This highlights the complex and multidimensional nature of sustainable urban development.

7. DISCUSSIONS

The regression analysis identified urban unemployment rate as the most influential and statistically significant determinant of SDG 11 performance among the five tested predictors. Controlling for other factors, a 1 percentage point increase in urban unemployment was associated with an average 3.22-point decline in the SDG 11 score. This substantial effect size underscores that labor market conditions remain a central challenge for sustainable urban development in India. States with chronically high urban unemployment may struggle to deliver affordable housing, accessible transport, and inclusive urban services – all core components of SDG 11 – due to constrained household incomes and weaker local economies.

The non-significant coefficients for urban literacy, economic prosperity (per capita NSDP), urbanization rate, and population density suggest that these variables, while theoretically important, may influence SDG 11 outcomes indirectly, through pathways such as governance capacity, resource allocation efficiency, and environmental management. For instance, high urbanization without matching infrastructure investment may generate congestion, pollution, and housing shortages that offset potential sustainability gains. Similarly, higher average incomes do not automatically translate into better SDG 11 performance unless targeted towards inclusive urban services and climate resilient infrastructure.

8. POLICY IMPLICATIONS

The findings highlight that addressing urban unemployment must be a central policy priority for achieving progress on SDG 11. States can pursue targeted urban employment strategies by investing in labor-intensive infrastructure projects such as public transport expansion, affordable housing, and modern waste management systems, which simultaneously generate jobs and directly improve SDG 11 indicators. Strengthening the urban economy through support for MSMEs, startups, and service-sector clusters particularly those engaging women and young workers can further expand livelihood opportunities. Urban skill-development programs should also be aligned with SDG 11-relevant sectors, including renewable energy, sustainable mobility, and circular waste recycling industries.

At the same time, economic growth must be more tightly integrated with sustainable urban development. State-level budgeting frameworks could earmark a portion of NSDP growth for investments in mass transit, waste treatment facilities, and climate adaptation infrastructure. Incentivizing green infrastructure and public-private partnerships offers a pathway to foster both economic expansion and improvements in livability, thereby ensuring that rising prosperity translates into tangible sustainability gains.

Managing urbanization is equally critical. Rapidly urbanizing states would benefit from integrated land-use and transport planning to contain sprawl, enhance accessibility, and protect natural green spaces. Conversely, highly urbanized territories such as Delhi or Goa may achieve more by upgrading existing infrastructure to meet escalating demands rather than indiscriminately expanding city boundaries.

Population density, often perceived as a challenge, can also present opportunities if well managed. Medium and high densities can improve the efficiency of public transport, reduce per-capita infrastructure costs, and support compact city design. Compact, mixed-use development models and vertical housing solutions are preferable to low-density sprawl, offering more sustainable and inclusive urban growth trajectories.

Finally, it is important to look beyond measurable socio-economic indicators. Given that more than half of the variance in SDG 11 scores remain unexplained (Adjusted $R^2 = 0.278$), future research should integrate qualitative governance variables such as municipal capacity, citizen participation, and urban climate resilience. Strengthening city-level SDG monitoring systems will also be essential to capture the micro-level differences and local dynamics that are masked when data are aggregated at the state level.

In summary, the results highlight that reducing urban unemployment should be a cornerstone strategy for improving sustainable urban development outcomes in India, with complementary measures in economic policy, urban planning, and infrastructure provision. Achieving SDG 11 will require balancing economic growth, spatial planning, and social inclusion, ensuring that urban prosperity translates into accessible, safe, and resilient cities for all.

9.LIMITATIONS

This study faces several data limitations that should be acknowledged. First, the reliance on state-level aggregation may obscure substantial intra-state differences, as urban sustainability challenges in large metropolitan areas can differ greatly from those in smaller towns and cities. Second, the cross-sectional design, based on 2023 projections, restricts the ability to infer causality or capture temporal changes in urban development and unemployment. Third, some key dimensions of sustainable cities such as governance quality, environmental resilience, and social inclusion could not be directly included due to the absence of standardized state-level indicators, meaning the selected predictors represent only part of the broader influences on SDG 11 outcomes. Finally, while population and economic data were sourced from official databases, projections carry inherent uncertainties, and although log transformations were applied to address skewness, measurement error may still persist.

10. FUTURE RESEARCH

Future research on sustainable urban development in India should move beyond state-level aggregation and adopt more granular city- or district-level analyses to capture local variation and identify context-specific drivers of SDG 11 outcomes. Longitudinal designs using panel data across multiple years would further enable exploration of causal pathways and provide insights into the long-term effects of policy interventions. Expanding the scope of indicators to include governance quality, environmental resilience, and infrastructure adequacy would also offer a more comprehensive understanding of the factors shaping SDG 11 performance. Methodologically, the use of advanced approaches such as non-linear regression, structural equation modeling, or machine learning could help uncover complex interdependencies among variables and improve predictive accuracy. Finally, future studies should incorporate direct evaluations of employment, urban planning, and economic policies, thereby linking empirical evidence with actionable strategies for advancing sustainable and inclusive cities in India.

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