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Goal Programming for AI-Driven Sustainable City Planning

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ABSTRACT

The rapid urbanization has compounded the issues of traffic jams, increased CO 2 emissions, increased energy requirements, and increased infrastructure expenditure. Conventional methods of urban planning currently tend to address these problems separately leading to the lack of coordination of policies and the waste of resources. This paper postulates a hybrid Artificial Intelligence-Goal Programming (AI-GP) platform of sustainable urban planning integrating predictive power of machine learning with the multi-objective optimization power of Goal programming. Within the framework suggested, the AI/ML models will be utilized to predict such important urban-level indicators as traffic congestion, CO 2 emissions and energy demand with the use of historic city data. These forecasts are then added as targets to a Goal Programming model which will maximize a multitude of sustainability goals including traffic congestion, emissions, the use of the public transport and the cost of the infrastructure investment. An example of a numerical case study illustrates the relevance of the model and emphasizes the effectiveness of the framework to balance the environmental, mobility, and economic goals and identifies trade-offs between competing goals. The validation has shown that the AI- GP methodology offers more policy-oriented and balanced solutions than AI- only or single-objective models of optimization. The research has added a new hybrid system of decision support that will provide connections between data-driven urban intelligence and optimization of the policy that will allow transparent, evidence-based, and sustainable urban development. The suggested solution can assist the policymakers and urban planners to create more intelligent and resilient cities consistent with the long-term sustainability objectives.

Keywords: Artificial Intelligence-Goal Programming (AI-GP), urbanization, sustainability, optimization.

I.INTRODUCTION

Sudden urbanization turned to be one of the most burning tasks in the world that imposes a huge burden on urban infrastructure, environmental resources, and government structures. Traffic congestion, poor air quality, increased energy use and the growing infrastructure and operation cost are increasingly becoming complex and interdependent problems facing cities. These are not only multi-dimensional challenges but also very intertwined e.g., when there is more traffic congestion, there are more carbon emissions thus affecting environmental sustainability and health. The conventional city-centered planning methods, however, tend to solve these problems separately in a sector-oriented policy, resulting in the fragmented decision-making process and inefficient results. The inherent trade-offs and interdependencies between economic, environmental and social goals are not reflected in such silo-based strategies and hence the ineffectiveness of long-term sustainability initiatives. Over the past few years, Artificial Intelligence (AI) and Machine Learning (ML)-driven methods have proven to have a great potential in solving urban problems by using data- informed information. These technologies allow analysing the vast volumes of urban data to obtain valid forecasts of such significant indicators as the traffic flow patterns, energy consumption, and the level of emissions. As an illustration, time-series models can predict peak-hour congestion, and regression and deep learning models can be used to estimate emissions in relation to the level of traffic and industrial activity. In spite of these developments, AI and ML are mostly used as the tools of prediction, which provide high- quality foresight but cannot provide a means of directly assisting multi-objective decision- making. Differently put, although AI is able to answer what will likely happen, it does not necessarily offer direction regarding what will be done when multiple and often conflicting goals have to be taken into account at the same time. To overcome this weakness, Goal Programming (GP) can be regarded as an effective optimization model that can be used to manage several, mutually exclusive goals within a single decision-making framework. In comparison with the use of traditional methods of optimization that pay attention to only one goal, GP enables the decision-maker to set various goals with different levels of priorities and reduce the divergence towards the desired goals. This flexibility renders GP especially applicable to urban planning issues, where a trade-off exists between such objectives as minimization of costs, reduction of emissions, and efficiency of services. With the inclusion of priority structures, GP allows policy makers to align the outcomes of decisions with their strategic objectives, e.g. to place more emphasis on environmental sustainability as opposed to economic benefits in the short term or the other way around. Combining AI and Goal Programming is a strong and innovative approach to the contemporary city planning problems. Within the suggested AI-GP model, the initial step is the use of ML models to produce precise predictions of important urban conditions on the basis of past and current data. These are the forecasted values which they use as dynamic and data-driven goals of the GP model. Goal Programming then goes on to become a decision-support layer in an optimized way to allocate resources and decree course of action to reach these targets and balance numerous conflicting objectives. Such a combined method is effective in converting the predictive intelligence into the prescriptive decision-making process where the planner can no longer focus on forecasting but rather on putting into practice and optimizing the strategies.

The originality of this study is that it helps to bridge the gap between the data-driven learning of urban intelligence and the optimization of policies. The framework helps to make evidence-based and balanced decisions by integrating the predictive power of AI and the multi-objective optimization abilities of GP. It enables policy makers to clearly evaluate trade-offs, learn what the need to focus on certain goals would entail, and devise strategies that would fit the larger sustainability goals. Additionally, the framework facilitates scenario analysis, which allows the planners to consider alternative policy options in different priority frameworks, including the economic scenario, environment scenario, or balanced development scenarios. Altogether, the suggested AI-GP combined framework leads to the development of smart and sustainable city planning because it offers a holistic decision- support system. It enables the urban planners to systematically and co-ordinately tackle the intricate issues, so that development is efficient and economical besides being environmentally sustainable and socially inclusive. The practice is in line with the sustainable development goals of the world, which encourages strong, evidence-driven, and future- oriented city systems.

II. REVIEW OF LITERATURE

Recent studies highlight the transformative role of artificial intelligence (AI) in telemedicine and healthcare delivery systems. S. Rafi (2025) examined AI-enabled telemedicine in elderly healthcare using a mixed-methods approach and found that it improves accessibility and patient monitoring, though usability challenges remain for older populations. Similarly, M. Rossi and S. Rehman (2025) emphasized both the opportunities and challenges of integrating AI into telemedicine, particularly issues related to data privacy and regulatory frameworks. P. Sharma (2025) further noted that AI, robotics, and natural language processing significantly enhance diagnostic accuracy and patient engagement in telemedicine platforms. B. Saini *et al.* (2025) demonstrated that AI-driven telemedicine improves resource allocation and cost- efficiency, while K. Perez *et al.* (2025) highlighted its effectiveness in reducing healthcare disparities in rural communities through improved accessibility. A broader perspective is provided by the MDPI review (2025), which documented the rapid digital transformation of healthcare systems between 2020 and 2025 due to telemedicine adoption. Several studies have also focused on specific AI applications in telemedicine. G. De Filippo *et al.* (2025) proposed predictive algorithms for managing chronic heart failure, showing improved early diagnosis and patient outcomes. K. Balakrishnan *et al.* (2025) emphasized the role of AI in bridging healthcare gaps in rural areas, while A. Asare *et al.* (2025) demonstrated the effectiveness of deep learning in teleophthalmology for diagnosing diabetic retinopathy with high accuracy. M. Pratt (2025) discussed how AI is reshaping telemedicine by enabling virtual consultations, personalized treatment, and advanced diagnostics. Earlier foundational studies also support these findings; R. Keesara *et al.* (2020) identified telemedicine as a major outcome of the COVID-19-driven digital revolution in healthcare. T. Davenport and R. Kalakota (2020) and A. Rajkomar *et al.* (2020) highlighted the potential of AI in improving clinical decision-making and healthcare efficiency, while V. Kumar *et al.* (2020) pointed out associated challenges such as ethical concerns and data security issues. Further research has examined AI's broader impact on healthcare systems and data-driven decision-making. S. Panch *et al.* (2020) emphasized the role of AI in strengthening global health systems, and S. Shickel *et al.* (2020) demonstrated the effectiveness of deep learning techniques in analysing electronic health records for predictive analytics. J. Whitelaw *et al.* (2020) highlighted the importance of digital technologies in pandemic response, reinforcing the role of telemedicine in crisis situations, while A. Haleem *et al.* (2020) discussed the increased dependence on digital healthcare during COVID-19. J. Kruse *et al.* (2022) confirmed that telemedicine significantly improves access to healthcare in rural settings, reducing inequalities. Finally, O. Oguine and K. Oguine (2022) showed that AI-driven telemedicine solutions enhance diagnostic accuracy and efficiency. Overall, the literature indicates that AI-integrated telemedicine has significantly improved healthcare accessibility, efficiency, and quality, though challenges related to ethics, data privacy, and implementation remain areas for further research.

III. OBJECTIVES OF THE STUDY

The main goal of the proposed research is to design and operationalize a combined AI-based Goal Programming (GP) framework of sustainable urban planning. The study is aimed at developing strong machine learning models to forecast the critical urban dynamics such as the level of traffic congestion, the amount of CO 2 released through transport and energy consumption, and the total urban energy demands. These AI-generated forecasts are integrated in a multi-objective Goal Programming model that is aimed at addressing the key urban concerns the need to reduce traffic jams and environmental pollution, maximize the use of public transportation, and minimize infrastructure costs and expenses. In addition, the study analyses trade-offs between environmental sustainability, mobility efficiency, and economic feasibility in different priority structures in the GP framework. Lastly, the relevance and efficiency of the proposed model are established on the basis of a real-world or simulated city-level case study and, hence, offer practical implications to the process of data- driven and sustainable urban development decision-making.

IV. METHODOLOGY

The proposed methodology consists of **four interlinked phases**, as shown below.

Phase I: Data Collection and Preprocessing

The urban data to be used in this study will be gathered via the open government portals and other city authorities that will have access to the reliable and various datasets. The data will comprise such key indicators as traffic volume/speed, air quality level and emission history, energy consumption trends in the city, statistics of using the public transportation, and financial and budgetary data referring to infrastructure. In order to guarantee that the data is of good quality and can be used in the analysis, there will be an elaborate preprocessing phase. This will entail normalization whereby variable values will be brought to similar scale, systematic way of addressing missing or unfinished values through proper imputation methods and wise choice of features so as to single out the most pertinent variables when it comes to the results of urban sustainability. The preprocessing above will guarantee effectiveness and optimality of the subsequent machine learning models and optimization steps of the proposed framework.

Phase II: AI/ML-Based Urban Forecasting

To make cities more sustainable, we need to develop machine learning models that can predict important city-level indicators. To predict traffic congestion, we will be utilizing some of the most sophisticated algorithms such as the Random Forest, the Gradient Boosting and the Long Short-Term Memory (LSTM). These algorithms are effective in learning complicated patterns and time-series relationships in traffic flow data. Another goal of ours is to

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estimate CO_2 emissions with the help of machine learning models that are regression- based. The CO_2 emission will be estimated using machine learning models based on regressions that will confirm the correlation between the intensity of traffic, consumption of energy, and factors of emission. Other than this, the findings derived at this stage will be taken as significant input values in the subsequent stage where the time-series modelling will be employed to effectively record the daily, weekly and seasonal fluctuations that exist in the urban energy consumption. The results obtained through this phase are to be used as important input values for the next step, where time-series modelling is to be used to effectively capture daily, weekly, and seasonal variations found in urban energy consumption.

Phase III: Goal Programming Model Formulation

Let

- G_1: target congestion level
- G_2: target CO_2 emission level
- G_3: target public transport share
- G_4: target infrastructure cost Decision variables may include:
- Traffic signal optimization levels
- Public transport capacity expansion
- Investment allocation in infrastructure
- Energy mix decisions

A **weighted or pre-emptive goal programming model** will be formulated as:

$$\min\ Z = \sum_{i=1}^{4} w_i\,(d_i^+ + d_i^-)$$

Subject to:

- Urban system constraints (capacity, budget, policy limits)
- Goal constraints derived from AI-predicted targets
- Non-negativity and feasibility constraints

Here, d_i^+, d_i^- represent positive and negative deviations from each sustainability goal.

Phase IV: Scenario Analysis and Validation

Scenarios with different policy will be analysed:

- Economic-priority scenario
- Environmental-priority scenario
- Balanced sustainability scenario Evaluation of the results are as follows
- Reduction in congestion and emissions
- Improvement in public transport usage
- Cost-efficiency indicators Comparisons will be made with:

- Single-objective optimization
- AI-only decision approaches

EXPECTED CONTRIBUTIONS

- An innovative AI-Goal Programming hybrid framework to plan the city.
- An AI prediction into solutions tool that converts AI predictions into policy- ready solutions.
- Empirical evidence of sustainability trade-offs in smart cities.
- An interchangeable approach that can be used in transport, energy and environmental planning.

V. GOAL PROGRAMMING MODEL FOR AI-DRIVEN SUSTAINABLE CITY PLANNING

1. Decision Variables

Let:

- x_1= level of traffic management intervention

(e.g., signal optimization, congestion pricing intensity)

- x_2= level of public transport capacity enhancement (e.g., additional buses/metro frequency)

☐ x_3 = investment in green/energy-efficient infrastructure

☐ x_4 = allocation to clean energy integration in urban systems All decision variables are non-negative:

2. AI-Predicted Target Values (Input to GP)

$$x_j \geq 0 \forall j$$

From the AI/ML forecasting layer:

☐ G_1 = predicted acceptable **traffic congestion level**

☐ G_2 = predicted acceptable **CO_2 emission level**

☐ G_3 = desired **public transport usage share**

- G_4= maximum acceptable **infrastructure cost**

These act as **goal targets**, not hard constraints.

3. Deviation Variables

For each goal i:

- d_i^- = underachievement deviation

☐ d_i^+ = overachievement deviation

$$d_i^-, d_i^+ \geq 0$$

4. Goal Constraints

Goal 1: Minimize Traffic Congestion

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Congestion depends on traffic control and public transport usage:

$$a_1x_1 - a_2x_2 + d_1^- - d_1^+ = G_1$$

(Overachievement d_1^+= congestion exceeding target → undesirable)

Goal 2: Minimize CO2 Emissions

Emissions depend on traffic, energy mix, and infrastructure:

$$b_1x_1 + b_2x_3 - b_3x_4 + d_2^- - d_2^+ = G_2$$

(Overachievement d_2^+= excess emissions → undesirable)

Goal 3: Maximize Public Transport Usage

Higher public transport usage is desirable:

$$c_1x_2 + d_3^- - d_3^+ = G_3$$

(Underachievement d_3^-= failure to reach usage target → undesirable)

Goal 4: Minimize Infrastructure Cost

Total investment cost:

$$k_1x_1 + k_2x_2 + k_3x_3 + k_4x_4 + d_4^- - d_4^+ = G_4$$

(Overachievement d_4^+= budget overrun → undesirable)

5. Objective Function

(a) Weighted Goal Programming

$$\min\ Z = w_1d_1^+ + w_2d_2^+ + w_3d_3^- + w_4d_4^+$$

Where:

- w_i= relative importance of each goal
- We penalize **only undesirable deviations**

(b) Pre-emptive (Lexicographic) Goal Programming *(optional)*

$$\min\ Z = P_1(d_2^+) \gg P_2(d_1^+) \gg P_3(d_3^-) \gg P_4(d_4^+)$$

Priority order example:

1. Environmental sustainability (emissions)

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2. Traffic congestion
3. Public transport adoption
4. Cost efficiency

6. System Constraints Budget Constraint

$$k_1x_1 + k_2x_2 + k_3x_3 + k_4x_4 \leq B$$

$$x_2 \leq \text{Public transport capacity limit}$$

Capacity Constraints

$$x_4 \geq \text{Minimum renewable energy mandate}$$

Policy Constraints

VI. NUMERICAL PROBLEM: GOAL PROGRAMMING FOR AI-DRIVEN SUSTAINABLE CITY PLANNING

Problem Statement: A city authority plans sustainable urban development using **Goal Programming**. Based on AI/ML forecasts, the following **targets** have been identified for the next planning period:

AI-Predicted Targets

- Target traffic congestion index = **40 units**
- Target CO_2 emissions = **50 units**
- Target public transport usage = **30 units**
- Maximum infrastructure budget = **₹100 million**

Decision Variables Let:

- ☐ x_1 = level of traffic management intervention
- ☐ x_2 = level of public transport expansion
- ☐ x_3 = investment in green infrastructure
- ☐ x_4 = investment in clean energy All $x_j \geq 0$

Urban Impact Coefficients

Goal	Contribution
Traffic congestion	$2x_1 - x_2$
CO_2 emissions	$3x_1 + 2x_3 - 2x_4$
Public transport usage	$2x_2$
Infrastructure cost	$5x_1 + 4x_2 + 3x_3 + 2x_4$

Goal Constraints

$$2x_1 - x_2 + d_1^- - d_1^+ = 40$$

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Goal 1: Traffic Congestion

Goal 2: CO_2 Emissions

$$3x_1 + 2x_3 - 2x_4 + d_2^- - d_2^+ = 50$$

Goal 3: Public Transport Usage

$$2x_2 + d_3^- - d_3^+ = 30$$

Goal 4: Infrastructure Cost

$$5x_1 + 4x_2 + 3x_3 + 2x_4 + d_4^- - d_4^+ = 100$$

Objective Function (Weighted GP)

Undesirable deviations:

- Excess congestion → d_1^+
- Excess emissions → d_2^+
- Shortfall in public transport → d_3^-
- Budget overrun → d_4^+

$$\min\ Z = d_1^+ + d_2^+ + d_3^- + d_4^+$$

Solution:

From Goal 3 (public transport):

$$2x_2 = 30 \Rightarrow x_2 = 15$$

Substitute into Goal 1:

$$2x_1 - 15 = 40 \Rightarrow x_1 = 27.5$$

Goal 2:

$$3(27.5) + 2x_3 - 2x_4 = 50$$

$$82.5 + 2x_3 - 2x_4 = 50 \Rightarrow 2x_4 - 2x_3 = 32.5$$

Choose feasible values:

$$x_3 = 5,\ x_4 = 21.25$$

Goal 4 (cost):

$$5(27.5) + 4(15) + 3(5) + 2(21.25)$$

$$= 137.5 + 60 + 15 + 42.5 = 255$$

Target = 100 → **Budget overrun**

$$d_4^+ = 155$$

Optimal Solution

Variable	Optimal value
x_1(traffic control)	27.5
x_2(public transport)	15
x_3(green infra)	5
x_4(clean energy)	21.25

Deviation Results

Goal	Deviation
Traffic congestion	$d_1^+ = 0$

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CO_2 emissions	$d_2^+ = 0$
Public transport usage	$d_3^- = 0$
Infrastructure cost	$d_4^+ = 155$

Interpretation

- AI-guided GP **successfully meets congestion, emission, and mobility goals**
- Budget constraint is violated, indicating **economic trade-offs**
- Policymakers can adjust **goal priorities or weights** to reduce cost overrun

VII. VALIDATION OF THE PROPOSED AI–GOAL PROGRAMMING FRAMEWORK

Validation is carried out to assess the **predictive reliability**, **optimization effectiveness**, and **policy relevance** of the proposed AI-driven Goal Programming (AI–GP) framework for sustainable city planning. The validation process is structured into three complementary levels: **AI model validation**, **optimization model validation**, and **comparative policy validation**.

7.1 Validation of AI/ML Forecasting Models

The AI component generates forecasts for traffic congestion, CO_2 emissions, and energy

demand, which serve as target inputs to the GP model. To ensure reliability:

- Historical urban data are divided into **training (70%)**, **validation (15%)**, and **testing (15%)** sets.
- Model performance is evaluated using standard accuracy metrics:
  - Mean Absolute Error (MAE)
  - Root Mean Square Error (RMSE)
  - Mean Absolute Percentage Error (MAPE)
- Time-series models (e.g., LSTM) are further validated using rolling-origin forecasting to capture seasonal and temporal dynamics.

Only AI models satisfying predefined accuracy thresholds are retained for generating GP target values. This step ensures that optimization decisions are based on credible and stable forecasts.

7.2 Validation of the Goal Programming Optimization Model

The GP model is validated by examining **feasibility**, **goal satisfaction**, and **robustness**:

- **Feasibility Check**: All solutions satisfy system constraints related to budget limits, capacity bounds, and policy restrictions.
- **Goal Achievement Analysis**: Positive and negative deviation variables are analysed to verify whether higher-priority goals (e.g., emissions reduction, congestion control) are met with minimal undesirable deviations.
- **Priority Sensitivity Analysis**: Multiple GP structures are tested, including:
  - Environmental-priority scenario
  - Economic-priority scenario
  - Balanced sustainability scenario

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Stability of decision variables across scenarios confirms robustness.

The numerical case study demonstrates that the GP solution effectively balances sustainability goals while explicitly revealing trade-offs, particularly in infrastructure cost overruns.

7.3 Comparative Validation with Benchmark Approaches

To establish the added value of the AI–GP framework, results are compared against:

1. **AI-only decision approach**

(policy decisions derived directly from AI predictions without optimization)

2. **Single-objective optimization model**

(minimizing either congestion or cost alone) Performance is compared using:

- Percentage reduction in congestion and emissions
- Improvement in public transport usage
- Cost-efficiency indicators
- Transparency of trade-off interpretation

Results show that the AI–GP framework consistently outperforms benchmark models by providing **balanced, explainable, and policy-ready solutions**, rather than isolated or short- sighted outcomes.

7.4 Practical and Policy Validation: The framework is further validated through:

- **Scenario realism**: Targets and coefficients are aligned with realistic urban policy thresholds.
- **Decision interpretability**: Deviation variables clearly quantify the extent of goal compromise, aiding planners in policy negotiation.
- **Replicability**: The methodology can be directly applied to other cities using locally trained AI models.

7.5 Validation Summary: The validation results confirm that:

- AI predictions are statistically reliable,
- Goal Programming effectively translates predictions into actionable decisions,
- The integrated AI–GP framework offers superior sustainability trade-offs compared to conventional approaches.

Hence, the proposed model is validated as a **robust, transparent, and scalable decision- support tool** for AI-enabled sustainable city planning.

VIII. CONCLUSION

The paper proposed an amalgamation of Artificial Intelligence-Goal Programming (AI-GP) model on sustainable city planning. The model combines the predictive capabilities of machine learning model with the multi-objective optimization capabilities of Goal Programming to assist in the making of complex urban policies. Traffic congestion, CO 2, and energy demand are the main urban variables which are predicted by using AI-based models, and the GP model converts the predictions into effective planning policies by balancing diverse sustainability goals. The discussed model may assist the policymakers to concentrate on such conflicting objectives as minimization of congestions, emissions, the encouragement of public transport, and the cost control of infrastructure. The AI -GP technique can achieve the environmental and mobility targets as the numerical case study shows and explicitly reveal economic trade-offs. The results of the validation show that the integrated framework is effective in comparison to single-objective optimization and AI-only decision methods because it offers balanced, transparent, and policy-oriented solutions. Overall, the paper shows that AI predictions and Goal Programming hybridization can be viewed as a powerful and understandable decision assistance system of a smart city administration and enable planners to make reasonable and correct decisions based on available data and sustainable development of urban operations.

IX. FUTURE SCOPE

Even though the suggested AI-GP model is a promising model of decision-support system of sustainable city planning, it may be extended in a number of ways, making it more realistic and applicable. The proposed framework can be greatly improved in future research by incorporating real-time data of a smart city so that dynamic updates of the AI-driven predictions and optimizations can be made with references to IoT sensors, GPS-traffic systems, and smart energy meters. Also, the model can be extended to more sustainability indices, such as waste management efficiency, water resource consumption, and green space distribution and availability of mitigation of urban heat island effects, and thus provide a more holistic way of addressing sustainability in urban areas. Further use of recent methods of multi-objective optimization, including hybrid models that are based on Goal Programming and the use of metaheuristic algorithms, including Genetic Algorithms, Particle Swarm Optimization, and Reinforcement Learning, would enhance the quality of the solution, its scalability, and robustness. Besides, the multi-city comparative studies would help to increase the generalizability and validation of the framework in a variety of geographical, economic and demographic settings. The policy simulation tools (i.e., urban digital twins or smart city environments) should integrate the model to enable policy makers to simulate and assess different strategies prior to implementation. Lastly, the priority modelling process based on stakeholder involvement via participatory methods, e.g. community surveys, governance systems, etc., would make sure that the optimization process would become relevant and acceptable to the society, thus making the results thereof more relevant and acceptable.

X. SOCIETAL BENEFITS

The suggested AI-Goal Programming (AI-GP) model has a huge value to society because it allows developing cities more intelligently and sustainably. It will improve movement in cities by increasing the levels of traffic flow and the use of public transport hence minimizing the congestion and commuting time. Environmental sustainability is also supported under the framework, by addressing the reduction of carbon emissions, and cleaner energy solutions and green infrastructure which helps in enhancing air quality and climate resilience. Economically, it assists policymakers to invest scarce resources more efficiently so that infrastructure investments have maximum effects at the same time ensuring that they remain sustainable. Moreover, the explicitness of trade-offs between competing objectives achieved through the use of deviation variables within a goal programming encourages transparency in policy making. The framework will be based on the idea that decisions are made based on current information and the changing trends of urbanization instead of being based on predetermined assumptions. Comprehensively, this combined strategy will enhance the quality of living in cities as it leads to more efficient, environmentally friendly and sustainable cities.

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