



Modeling and Simulation of Village Fund Allocation Distribution Using Regional Cluster-Based System Logic Approach

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Submitted: November 23, 2025

Accepted: December 28, 2025

Published: January 31, 2026

Abstract

The inequitable distribution of Village Funds remains a critical issue in Indonesia's fiscal decentralization, often exacerbating regional development disparities due to static and uniform allocation mechanisms. This study aims to develop a budget distribution simulation model that integrates Data Mining with System Logic to formulate a more equitable allocation strategy. Using a quantitative approach with a case study in Majalengka Regency, the research methodology involves two stages: first, mapping regional characteristics using the K-Means Clustering algorithm based on historical data (2019-2022), and second, applying a Scenario-Based System Simulation using a Weighted Growth Model. The system logic applies an affirmative policy where underdeveloped regions (Low Cluster) receive a higher growth weight (8%) compared to developed regions (High Cluster, 2%). The simulation results demonstrate that the proposed model successfully reduces fiscal disparity by significantly increasing the nominal allocation for the Low Cluster without burdening the total regional budget, which only increased by 4.4%. This study concludes that the integration of clustering and rule-based simulation provides a scientifically accountable Decision Support System (DSS) for local governments to perform "What-If Analysis" in planning fair and targeted fiscal policies.

Keywords: Village Fund, K-Means Clustering, System Logic, Budget Simulation, Affirmative Policy

1. Introduction

Fiscal decentralization has become a primary paradigm in modern governance in Indonesia, concretely manifested through the Village Fund policy as mandated by Law Number 6 of 2014. This policy represents a fundamental shift from a centralized (top-down) development approach to a participatory (bottom-up) one, where village entities are granted autonomous authority to manage financial resources for accelerating local community welfare. Over the past decade, fund transfers from the central government to villages have increased significantly with strategic objectives to alleviate structural poverty, accelerate basic infrastructure development, and improve public service quality at the grassroots level.

The importance of effective village fund management cannot be underestimated; it serves as the backbone of rural economic stability. As confirmed in recent research by Nazila, Nugroho, and Nurmilah (2025), accountable village fund management-ranging from planning, execution, to reporting has a strong linear correlation with the success of physical infrastructure development and community economic empowerment [1]. When funds are managed through transparent mechanisms based on real needs, the economic multiplier effect is directly felt by villagers, creating sustainable economic independence. The relevance of village fund allocation to socio-



economic resilience was further tested during global crises. Village Fund Allocation (ADD) has a dominant, positive, and significant influence on community welfare levels, even amidst severe external pressures such as the COVID-19 pandemic [2]. These findings confirm the hypothesis that fiscal intervention through village funds is not merely an administrative obligation of the state, but a vital instrument of the social safety net. However, the effectiveness of this social safety net relies heavily on transparent and accountable governance. Research by Asrul (2023) emphasizes that Village Fund management has a significant influence on community welfare, where a robust transparency system-guaranteeing open access to information regarding policy formulation and implementation plays a vital role in building public trust and development participation [3]. Without transparency and clear allocation logic, even substantial funds will fail to alleviate poverty effectively. Furthermore, Nugroho and Sulyono (2024) add that social assistance programs, such as the Village Fund Direct Cash Assistance (BLT-DD), are specifically designed to accelerate national economic recovery and reduce extreme poverty in accordance with the Village Medium-Term Development Plan (RPJM-Desa) targets [4]. Consequently, failure to formulate a precise allocation distribution is not merely an administrative error but a strategic failure in realizing social justice and equitable regional development mandated by law. Therefore, precision in determining the allocation distribution for each region becomes a highly determinant variable.

If the budget distribution logic is determined inappropriately, the goal of equitable development (inclusive development) will not be achieved, and trillions of rupiah will be depleted for routine expenditures without providing tangible structural impacts for alleviating regional disparities. Although the urgency of village funds is high, there is a concerning Phenomenon Gap in its implementation reality. Current distribution and budget absorption mechanisms often operate inefficiently, slowly, and are ill-targeted. A recurring classic problem is the widening development disparity between regions; villages with good human resource (HR) capacity and initial infrastructure tend to progress faster, while underdeveloped villages that should receive affirmative intervention (larger allocation) often fail to absorb the budget or receive allocations disproportionate to their urgent needs. An in-depth analysis of local budget (APBD) absorption, highlighted that the main obstacle to budget optimization lies in planning quality and the competence of apparatus HR [5]. Poor planning unsupported by a strong regional database causes budgets to accumulate as Remaining Budget Financing (SiLPA) or be spent on non-priority programs.

The absence of reliable System Logic in budget planning causes local governments to often take heuristic shortcuts in compiling the Regional Revenue and Expenditure Budget (RAPBD). The commonly used approach is the static incremental method, i.e., increasing the budget of all villages by the same percentage (flat rate), without considering the unique characteristics and urgency of each regional cluster. This phenomenon of mistargeting due to weak decision support systems is further validated in the case of social assistance distribution sourced from village funds. Village Fund Direct Cash Assistance (BLT-DD) revealed empirical facts that elementary errors often occur in determining beneficiaries (exclusion/inclusion errors) due to manual data processing filled with subjective bias [2]. Village deliberation mechanisms unsupported by valid quantitative data often produce biased decisions, where assistance does not reach the citizens who need it most. This targeting inaccuracy is often rooted in conventional approaches that still dominate decision-making processes at the local level. Hasugian, Sagala, and Sulindawaty (2022) highlight that selection or decision-making processes conducted manually are often time-consuming and lack standardized criteria, making it difficult for policymakers to determine worthy priorities objectively. In a broader context, reliance on subjective judgment without the support of computerized systems is highly susceptible to interest bias and human errors. Puscefa, Sundari, and Mulyani (2025), in their research on decision support systems, emphasize that the absence of structured methods frequently leads to unfair assessments, where subjective approaches dominate the logic of resource distribution [6]. This necessitates a transformation

from intuitive or 'flat rate' allocation methods toward a system logic-based approach capable of managing various complex criteria simultaneously to produce accurate priority rankings.

Similarly, Zuhendra, Hidayat, and Hendrawaty (2024) emphasized the cruciality of accurate poverty data clustering. Without the use of Data Mining technology on Integrated Social Welfare Data (DTKS), government intervention becomes "blind" and fails to target actual pockets of poverty [7]. The application of Data Mining technology, particularly through the Knowledge Discovery in Databases (KDD) approach, becomes a crucial solution for handling the complexity of large and diverse beneficiary datasets [8][9][10][11]. Syaefullah, Martanto, and Hayati (2024) explain that the stages of KDD ranging from data selection, preprocessing, to transformation enable governments to cleanse data of inconsistencies before the clustering process is undertaken [12]. Furthermore, the reliability of any simulation model is intrinsically tied to the quality of its input data. As emphasized within the Knowledge Discovery in Databases (KDD) framework, Syaefullah, Martanto, and Hayati (2024) argue that the pre-processing stage specifically data cleaning and transformation is critical to eliminate noise and inconsistencies that often plague manual village administration reports. This aligns with findings by Nugroho and Sulyono (2024), who demonstrated that proper data handling significantly reduces the error rate in eligibility determination, ensuring that the resulting clusters truly reflect the socio-economic reality of the region.

By utilizing the K-Means algorithm, heterogeneous data can be grouped into clusters based on attribute similarities (such as economic conditions, infrastructure, or poverty counts), thereby clearly mapping distribution patterns [13]. This clustering approach has been proven to enhance targeting effectiveness, as found by Nugroho and Sulyono (2024), where data partitioning into priority groups successfully increased accuracy in selecting recipients who truly meet eligibility requirements [4]. The integration of this clustering capability with budget allocation system logic is the key to resolving the issues of misallocation and budget inefficiency that have occurred thus far.

To address these distribution complexities, various information technology approaches have been offered in academic literature, specifically the use of Machine Learning algorithms and Decision Support Systems (DSS) [14]. However, a deep review of previous studies shows a significant Research Gap, where there is no comprehensive integration between regional mapping and budget policy simulation. First, the use of K-Means Clustering algorithms has indeed been widely used and proven reliable for mapping regional characteristics. For instance, Nugroho, Wijiyanto, and Pradana (2025) successfully utilized K-Means to map the distribution of business permits in Sragen Regency [15]. However, this study was limited to spatial distribution visualization and descriptive analysis. It did not integrate clustering results into financial decision-making models or policy simulations. The final result was merely labeling regions as "dense" or "sparse," without any output in the form of nominal budget recommendations.

Second, comparative research by Salman et al. (2025) compared the performance of K-Means and K-Medoids algorithms in grouping schools based on facilities [16]. This research focused heavily on technical algorithm accuracy metrics (Silhouette Coefficient) but neglected the practical utility aspect of such grouping for policymakers. There was no answer to the strategic question: "After schools are grouped based on facilities, how much budget should be allocated to each group to achieve equity?". Third, conventional DSS approaches such as Analytical Hierarchy Process (AHP) or Weighted Product (WP) also have fundamental limitations when applied in the context of continuous budget distribution simulation. Arfan et al. (2023) used the AHP-TOPSIS method to determine village development priorities [17]. Although this method is reliable in producing rankings (ordinal priority order: 1, 2, 3), it is static and less flexible for simulating dynamic budget scenarios. This method can determine that Village A is a higher priority than Village B, but it is difficult to automatically determine how much nominal rupiah should be added to Village A and how much should be reduced from Village B based on the available total budget ceiling. Similar limitations were found in Vikki (2022), which used a fuzzy

logic approach for selecting student council presidents; although the approach was logical in criteria weighting, its application had not touched the complexity of public finance distribution simulation involving budget constraint variables [18].

Based on the state of the art above, there is a clear literature gap in the integration between regional clustering methods and budget policy simulation models. No research has developed an integrated framework where regional cluster status (as an output of unsupervised learning) is used directly as an input variable in a System Logic to calculate projected fund allocations automatically. Most research models are disconnected: stopping at the clustering stage (labeling) or performing budget calculations without an objective data clustering basis. This research aims to fill this gap by offering Novelty in the form of developing a "Budget Distribution Simulation Model Based on Regional Cluster System Logic." Unlike previous partial studies, this study proposes a hybrid approach. The first stage uses the K-Means Clustering algorithm to map villages in Majalengka Regency into clusters (Low, Medium, High) based on objective historical data. The second stage, which is the core novelty of this research, is the application of Rule-Based System Logic. In this model, a Weighted Growth Model concept is applied, where the percentage of budget increase is simulated differently based on cluster status (Affirmative Policy). Villages identified in the "Low" cluster will automatically receive a larger percentage increase weight compared to villages in the "High" cluster within the system simulation.

The urgency of this research lies in its ability to provide "What-If Analysis" capabilities for stakeholders. With this model, the Majalengka Regency Local Government no longer relies on guesswork in compiling the budget but can simulate various policy scenarios (e.g., "What is the impact on the total APBD if we increase the budget of underdeveloped villages by 8% while advanced villages only by 2%?") before the policy is politically ratified. This minimizes the risk of fiscal policy failure and ensures distributive justice principles are met measurably. Thus, this research aims to prove that the integration of Clustering and System Simulation can produce budget formulations that are fairer, more equitable, and scientifically accountable (scientific-based policy).

2. Methodology

This research applies a quantitative approach using a Scenario-Based System Simulation method. The research framework is designed to integrate Data Mining techniques (as the initial state input) with System Logic (as the decision-processing engine).

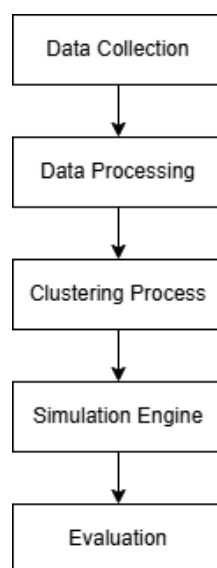


Figure 1. Research Stage.

2.1 Data Collection and Preprocessing

The data used in this study is secondary data in the form of historical reports of Village Fund Allocation per district (Kecamatan) in Majalengka Regency. The dataset covers the fiscal years 2019 to 2024. However, through the Data Cleaning stage, data from 2023 and 2024 were eliminated because they were found to contain null values in the source dataset. Thus, the valid data used as the modeling basis (training set) is the 2019–2022 period.

The main variables extracted from this dataset include:

1. Entity: 26 Districts in Majalengka Regency.
2. Attributes: Fiscal Year and Nominal Fund Allocation (Rupiah).

2.2 Regional Clustering Model (K-Means)

The first stage in this system is State Mapping. The K-Means Clustering method was chosen due to its efficiency in grouping unlabeled numerical data (unsupervised learning). This algorithm aims to minimize the variance within a cluster and maximize the variance between clusters[13].

The K-Means objective function is calculated using the Euclidean Distance formula as shown in Equation (1):

$$J = \sum_{j=1}^k \sum_{i=1}^n ||x_i - c_j||^2 \quad (1)$$

Where:

J : Objective function (variance).

k : Number of clusters (determined as k=3 for Low, Medium, High categories).

n : Number of district data points.

x_i : Fund allocation value of the i -th district.

c_j : Centroid point of the j -th cluster.

The iteration process is carried out until the centroid positions converge (do not change). The output of this stage is a category label (L) for each district, where $L \in \{Low, Medium, High\}$.

2.3 System Logic and Affirmative Policy Model

This section constitutes the core novelty of the research. Once the regional status is identified, the system applies the Weighted Growth Simulation Model. Unlike conventional linear approaches, this model utilizes Rule-Based Logic to determine different growth rate variables (α) for each cluster.

The system logic is defined as follows:

Rule 1 (High Priority): IF district x belongs to the Low Cluster (C_{low}), THEN a maximum growth weight (α_{high}) is assigned to accelerate development.

$$IF x \in C_{low} THEN \alpha = 8\% (1.08) \quad (2)$$

Rule 2 (Moderate Priority): IF district x belongs to the Medium Cluster (C_{med}), THEN a moderate growth weight (α_{med}) is assigned.

$$IF x \in C_{med} THEN \alpha = 5\% (1.05) \quad (3)$$

Rule 3 (Stability): IF district x belongs to the High Cluster (C_{high}), THEN a minimal growth weight (α_{low}) is assigned to maintain fiscal stability.

$$IF x \in C_{high} THEN \alpha = 2\% \quad (1.02) \quad (4)$$

2.4 Mathematical Formulation for Simulation

Based on the system logic above, the mathematical formulation to calculate the projected budget for the following year (D_{t+1}) for each district i is expressed in Equation (5):

$$D_{i,t+1} = D_{i,t} \times (1 + \alpha_k) \quad (5)$$

Where:

$D_{i,t+1}$: Simulation result of fund allocation for district i in the prediction year (2025).

$D_{i,t}$: Fund allocation data for district i in the base/last year (2022).

α_k : Growth factor corresponding to cluster category k .

2.5 Evaluation Scenario

To measure the effectiveness of the model, a comparative evaluation is conducted using the *What-If Analysis* technique. Two scenarios are tested:

1. Baseline Scenario: Simulation of a flat rate increase of 5% for all districts (reflecting conventional policy).
2. Proposed Scenario (Affirmative): Simulation using cluster-based *System Logic* (8%, 5%, 2%).

The model's success indicators are measured based on two parameters:

Nominal Equity: Do districts with small budgets receive competitive nominal increases compared to large districts?

Budget Efficiency: Is the total APBD burden from the simulation result still within reasonable regional budget increase limits (not exceeding 5-10% of the total budget)?

3. Results and Discussion

This section presents the empirical findings obtained from the integration of the K-Means Clustering algorithm and the System Logic Simulation. The analysis focuses on three key aspects: the regional clustering profile, the simulation of budget scenarios, and the effectiveness of the proposed affirmative policy in reducing fiscal disparity.

3.1 Regional Clustering Analysis

The initial stage of the system involves mapping the 26 districts in Majalengka Regency based on historical Village Fund allocation data (2019-2022). Using the K-Means algorithm with $k=3$, the system successfully identified distinct characteristics of regional fiscal capacity.

As visualized in Figure 1., the clustering results reveal a significant gap in the baseline allocation:

1. High Cluster (Cluster 1): Consists of districts with large historical allocations ($> \text{IDR } 6 \text{ Billion/year}$), such as Lemahsugih and Jatiwangi. These districts have historically absorbed the largest portion of the budget.
2. Medium Cluster (Cluster 2): Represents the majority of districts with allocations ranging between $\text{IDR } 4 \text{ Billion}$ to $\text{IDR } 5.5 \text{ Billion}$.

- Low Cluster (Cluster 0): Consists of districts with the smallest allocations (< IDR 3 Billion/year), such as Cigasong and Majalengka.

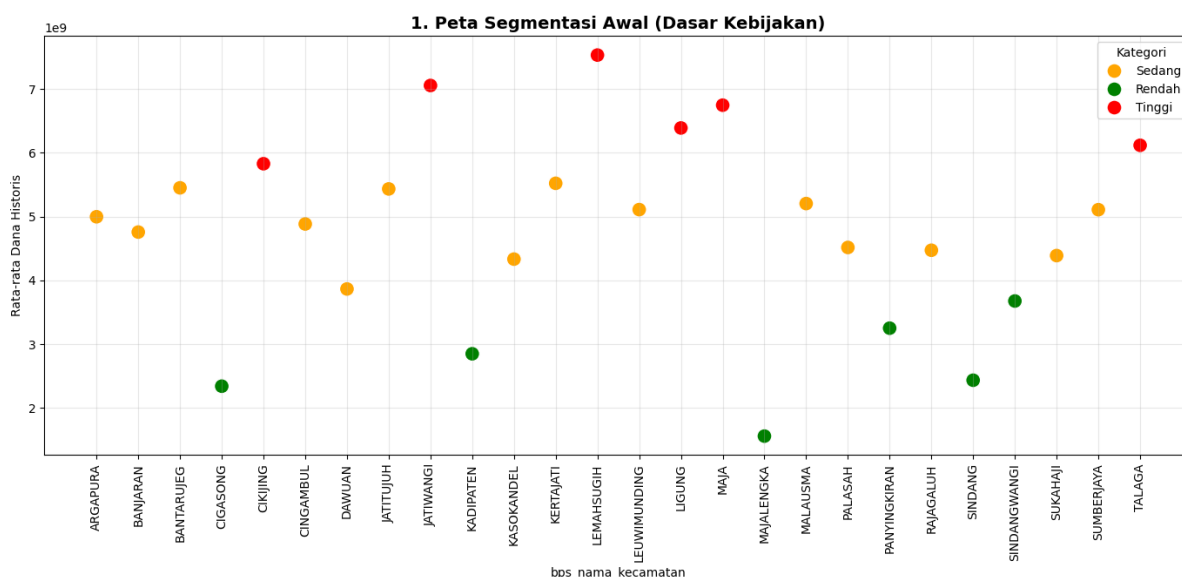


Figure 2. State Mapping of Districts using K-Means Clustering (Low, Medium, and High Clusters)

This mapping serves as the "State Variable" for the simulation engine. The distinct separation between the red dots (High) and green dots (Low) in Figure 1, empirically proves the existence of fiscal disparity, justifying the need for an affirmative intervention model.

3.2 Simulation of Affirmative Policy Scenarios

The core of this research is the "What-If Analysis" using the Weighted Growth Model. To demonstrate the model's performance, we compared the proposed scenario against a baseline scenario.

- Baseline Scenario (Status Quo): Applying a flat growth rate of 5% for all districts, reflecting a conventional budgeting approach without system logic.
- Proposed Scenario (Affirmative): Applying the *System Logic* where Low Cluster grows by 8%, Medium by 5%, and High by 2%.

The simulation results, as presented in Table 1, show a shift in budget distribution. In the Proposed Scenario, the system successfully redirects the flow of additional funds to the districts that need it most.

Table 1. Comparison of Budget Increment: Baseline vs. Proposed Model

District Name	Cluster Category	Baseline Increment (Flat 5%)	Proposed Increment (Affirmative)	Difference (Surplus for Affirmative)
Sindangwangi	Low	IDR 172,791,650	IDR 276,466,640	+ IDR 103,674,990
Panyingkiran	Low	IDR 156,401,908	IDR 250,243,053	+ IDR 93,841,145
Kertajati	Medium	IDR 271,444,158	IDR 271,444,158	IDR 0 (Neutral)
Ligung	High	IDR 315,095,758	IDR 126,038,303	- IDR 189,057,455
Jatiwangi	High	IDR 335,011,902	IDR 134,004,761	- IDR 201,007,141

3.3 Effectiveness of Disparity Reduction

The effectiveness of the simulation is best observed in the Nominal Increment Analysis shown in Figure 3. In a standard system, large districts (Red bars) would dominate the chart. However, the simulation results show a reversal of this trend.

Districts in the Low Cluster (Green bars), such as Sindangwangi, received a nominal increase of IDR 276.4 Million, which is significantly higher than Jatiwangi (High Cluster) which only received IDR 134 Million. This proves that the system logic successfully functions as a "fiscal equalizer."

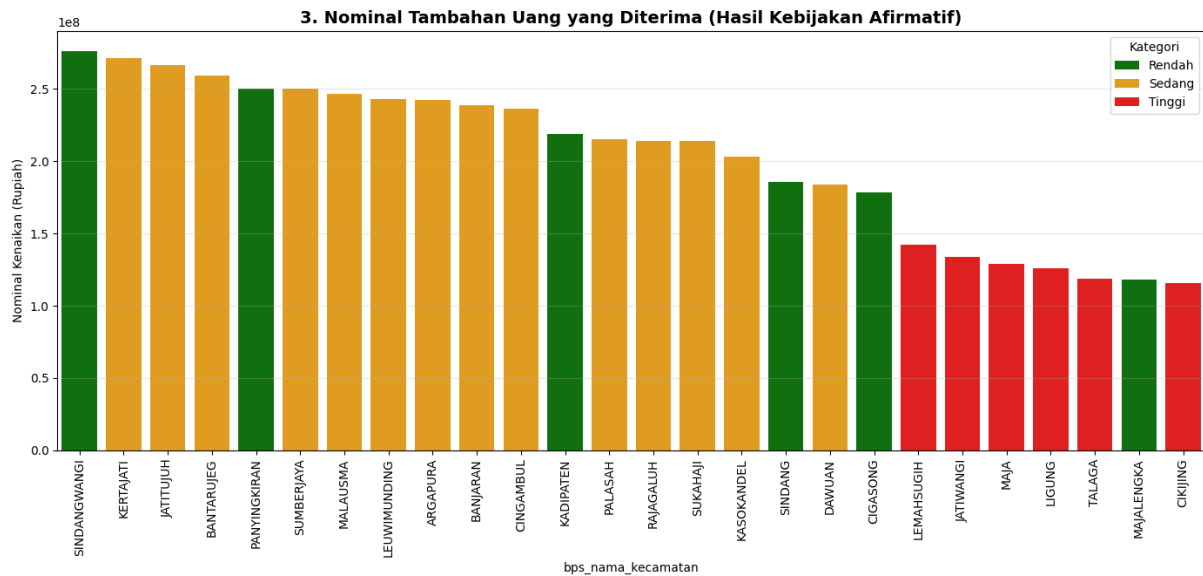


Figure 3. Nominal Budget Increment Distribution

3.4 Discussion

The findings of this study offer a significant novelty compared to previous research relying solely on AHP ranking [8] or static clustering [6]. While previous methods could only tell *which* village is poor, this proposed simulation model quantifies *how much* financial intervention is needed.

The "What-If" simulation demonstrates that achieving equity does not require an excessive budget explosion. The total budget required for the Proposed Scenario is IDR 124.6 Billion, representing a total increase of only 4.4% from the previous year. This indicates that the Affirmative Policy is fiscally realistic and implementable for the Local Government of Majalengka. The model ensures that the "gap" between developed and underdeveloped districts is narrowed over time without reducing the absolute budget of any district (Pareto Improvement).

4. Conclusion

This research has successfully demonstrated that the integration of the K-Means Clustering algorithm and System Logic Simulation serves as an effective instrument for optimizing Village Fund distribution. The empirical results from the case study in Majalengka Regency lead to three main conclusions. First, the K-Means algorithm effectively mapped the 26 districts into three distinct fiscal capacity clusters (Low, Medium, and High), providing an objective baseline for policy formulation. Second, the Weighted Growth Simulation Model proved superior to the conventional flat-rate method. The simulation confirmed that by applying an affirmative logic assigning an 8% growth rate to the Low Cluster and 2% to the High Cluster the system could redirect financial resources to the most needy regions. Specifically, districts in the Low Cluster received a nominal increment two times larger than those in the High Cluster, thereby narrowing

the development gap. Third, from a managerial perspective, the proposed model is fiscally realistic, as the total budget increase remains within a manageable range (4.4%), ensuring that the pursuit of equity does not compromise regional fiscal stability. This study contributes a novel framework for "Scientific-Based Policymaking," allowing local governments to simulate the impact of budgetary decisions before implementation. Future research may expand this model by incorporating more complex variables, such as poverty rates and infrastructure indices, into the system logic to enhance prediction accuracy.

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