Optimizing Household Waste Segregation Policy in the Municipality of Bacolod: An Agent-Based Modeling and Deep Reinforcement Learning Approach

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Abstract—The implementation of the Ecological Solid Waste Management Act (RA 9003) remains a critical challenge for Local Government Units (LGUs) in the Philippines. Compliance is often hindered by budget constraints, lack of behavioral data, and the complexity of enforcing segregation at the household level. This study presents a novel policy optimization framework combining Agent-Based Modeling (ABM) with Deep Reinforcement Learning (DRL). We model the Municipality of Bacolod, Lanao del Norte, as a dynamic environment where household agents react to policy interventions based on the Theory of Planned Behavior (TPB). A custom Heuristic-guided Deep Reinforcement Learning (HuDRL) agent acts as the LGU policymaker, learning to maximize segregation compliance under strict budget constraints. Our simulations reveal that the HuDRL agent outperforms traditional "Status Quo" policies and standard PPO agents by discovering a "Sequential Saturation" strategy—focusing resources on specific zones to build social norms before expanding. Furthermore, Global Sensitivity Analysis using Sobol Indices identifies "Cost of Effort" as the primary driver of non-compliance, suggesting that LGUs should prioritize logistical support over purely punitive measures.

Index Terms—Agent-Based Modeling, Deep Reinforcement Learning, Waste Management Policy, Smart Governance, Sobol Sensitivity Analysis, Theory of Planned Behavior

I. INTRODUCTION

The implementation of the Ecological Solid Waste Management Act (R.A. 9003) in the Philippines has faced significant hurdles at the local government level, particularly in achieving consistent household segregation compliance. While the law mandates a decentralized approach through barangay-level management, many municipalities continue to struggle with high waste generation and low participation rates. Traditional governance strategies often rely on static, linear policy models that fail to account for the complex, adaptive nature of human behavior and the socio-economic heterogeneity of local communities. This research proposes a computational shift toward smart governance by leveraging Agent-Based

Modeling (ABM) and Deep Reinforcement Learning (DRL) to simulate and optimize policy interventions specifically tailored for the Municipality of Bacolod, Lanao del Norte.

A. Statement of the Problem

This study systematically quantified and determined the optimal settings for policy instruments, specifically incentive, punitive, and information and educational campaign measures, required to maximize sustained household solid waste segregation compliance within the Municipality of Bacolod, Lanao del Norte, by taking into account local socioeconomic determinants and budget-constraints.

This study answered the following specific questions:

1) How did variations in the synthesized household behavioral parameters (e.g., the relative weight of Subjective Norms vs. Perceived Behavioral Control, derived from literature and LGU records) affect the stability and efficacy of policy outcomes within the Agent-Based Model?

2) What was the optimal long-term resource allocation ratio among the three policy levers (monetary incentives, punitive enforcement, and educational campaigns) that maximized compliance per peso spent, as determined by the Reinforcement Learning agent?

3) Which dynamic policy strategy yielded the highest overall compliance and cost-benefit ratio for the LGU while strictly adhering to the defined annual budget constraint?

B. Research Objectives

The primary objective of this study was to develop and apply a coupled Agent-Based Model (ABM) and Deep Reinforcement Learning (DRL) framework to determine the optimal, budget-constrained allocation of resources across policy levers for maximizing household solid waste segregation compliance in the Municipality of Bacolod.

Specific objectives were:

1) To conduct a comprehensive synthesis of academic literature and utilize contextual financial and operational data from the Philippine Statistics Authority and LGU records, including interviews with key implementing officers, to rigorously parameterize the ABM.
2) To develop a Multi-Level Agent-Based Model where household agent behavior was governed by a utility function incorporating Theory of Planned Behavior constructs and socioeconomic variables, and where policy levers dynamically updated behavioral constructs.
3) To integrate a Reinforcement Learning algorithm that enabled the LGU agent to autonomously learn the optimal policy (allocating funds among incentives, enforcement staff, and education campaign) that maximized a composite reward function balancing compliance and financial cost, while adhering to a defined budget constraint.
4) To simulate and validate the efficacy and cost-effectiveness of budget allocation strategies (Pure Incentive, Pure Penalty, Pure Information Education Campaign, and Hybrid regimes) and provide actionable, data-driven recommendations on the optimal resource mix for the LGU enforcing RA 9003.

C. Significance of the Study

This research contributes to the interdisciplinary fields of environmental science and computational social science by advancing the integration of the Theory of Planned Behavior (TPB) with Deep Reinforcement Learning (DRL) [?]. Academically, it demonstrates the utility of Deep Neural Networks (DNNs) in processing high-dimensional state spaces—specifically varying compliance rates across seven heterogeneous barangays—to discover adaptive policy strategies that traditional linear programming fails to capture [?], [?].

Practically, the study provides Local Government Units (LGUs) with a low-risk, data-driven decision-support tool to test policy mixes (incentives vs. enforcement) without the costs of real-world trials. On a national level, the successful implementation of these recommendations supports environmental sustainability and climate mitigation goals by improving waste segregation at the source, thereby promoting a circular economy and reducing landfill methane emissions.

D. Scope and Limitations

The study is geographically bounded to the seven coastal and urban barangays of the Municipality of Bacolod, Lanao del Norte, currently served by the municipal collection system. The remaining nine barangays are excluded due to logistical inaccessibility.

The scope is strictly focused on household-level segregation and the executive implementation of existing legislation (Municipal Ordinance No. 2018-05), rather than the drafting of new laws. While the model utilizes high-fidelity proxy data for behavioral weights [?] and primary qualitative data from Key Informant Interviews (KIIs) with MENRO and local officials, it remains an abstraction of reality. Specific limitations include:

- The model excludes downstream operations such as landfill management and collection routing.
- Micro-level agent values are derived from a meta-analysis of regional empirical data rather than primary household surveys.
- The simulation assumes honest interactions and excludes informal bypass mechanisms, such as tipping collectors to accept unsegregated waste, to focus on official policy optimization.

II. RELATED WORK

A. Solid Waste Management in the Philippines

The national framework for waste management is governed by the Ecological Solid Waste Management Act of 2000 (R.A. 9003), which mandates source segregation, recycling, and the establishment of Materials Recovery Facilities (MRFs). However, implementation remains sub-optimal across various Local Government Units (LGUs), necessitating computational approaches to bridge the gap between national policy and local practice.

1) Systemic and Budgetary Constraints on LGUs: The primary challenge in implementing R.A. 9003 is the significant operational and financial burden placed on LGUs as the chief implementers. Solid waste management constitutes a high financial drain on municipal budgets, a situation compounded by a scarcity of compliant sanitary landfills and chronic underfunding for local initiatives. These deficiencies often lead to systemic institutional failures that weaken the effectiveness of the law. Consequently, overcoming these constraints requires significant political will and initiative from local officials to substantially improve municipal performance.

2) Behavioral Drivers and Resident Non-Compliance: Understanding the behavioral drivers of residents is essential for effective policy design. Non-compliance is frequently driven by structural friction—specifically, frustration with irregular collection services—rather than a simple lack of awareness. In some communities, minor environmental offenses have become normalized, requiring targeted interventions. While educational campaigns such as the SURWEM project raise awareness, they do not guarantee sustained behavioral change without accompanying structural support. Therefore, building trust through participatory governance and community involvement is vital for increasing compliance rates.

3) Heterogeneity and Policy Equity: Policy design must account for the socio-economic diversity of the population to ensure justice. Purely financial penalties, such as fines, are known to be regressive as they disproportionately affect low-income groups. To address this, reinforcement learning agents must optimize for both cost-efficiency and policy equity. This requires simulating agents with varying sensitivities to incentives and penalties based on their distinct socio-economic profiles.

III. METHODOLOGY

A. Research Design

This study employed a computational simulation research design that integrated Agent-Based Modeling (ABM) with Deep Reinforcement Learning (DRL) optimization. This design created a virtual laboratory for testing Solid Waste Management (SWM) policies, allowing for the autonomous discovery of the optimal resource allocation strategy without the cost and risk of real-world trials. The research followed three main phases: (1) Model parameterization using literature synthesis, (2) DRL integration and training, and (3) Policy scenario simulation and analysis.

B. Data Sources and Model Parameterization

In lieu of collecting large-scale primary survey data, this study constructed a high-fidelity Agent-Based Model (ABM) by synthesizing data from academic literature, public government statistics, and operational records obtained through key-informant interviews. The behavioral core of the household agents was grounded in the Theory of Planned Behavior (TPB), with parameters for Attitude (w_A), Subjective Norms (w_{SN}), and Perceived Behavioral Control (w_{PBC}) derived from a systematic review of environmental psychology literature Taraghi2025, Moeini2023. To ensure ecological validity, agent initialization utilized empirical Knowledge, Attitude, and Practices (KAP) data Paigalan2025, explicitly calibrating agents to reflect a realistic "Intention-Action Gap" (High Attitude $A_0 \approx 0.66$ vs. Low Compliance $B_0 \approx 0.58$). The simulation environment was further contextualized to seven specific barangays in the Municipality of Bacolod (e.g., Liangan East, Poblacion) using validated socio-demographic profiles and LGU operational data. The LGU-DRL agent operates within a strict annual budget of ₱1,500,000, discretized quarterly, to optimize a "Policy Mix" across three cost-constrained levers: (1) **Enforcement** (C_{Enf}), calculated via Equation **??** based on personnel wages and coverage ratios; (2) **Monetary Incentives** (C_{Inc}), modeled in Equation **??** as a variable function of $N_{\text{Compliant}}$ to introduce a fiscal "victim of success" risk; and (3) **IEC Campaigns** (C_{IEC}), defined in Equation **??** as tiered fixed costs for media dissemination.

C. Multi-Level Agent-Based Model Architecture

The simulation was developed using the Python library *MESA* Mesa2025, a choice supported by recent reviews of computational tools in solid waste management TianReview2024, Ma2023. The architecture employed a strict hierarchical design within a single Agent-Based Model (ABM) environment, containing seven distinct `BarangayAgent` objects (representing Liangan East, Esperanza, Poblacion, Binuni, Demologan, Mati, and Babalaya), which in turn encapsulated their respective populations of `HouseholdAgent` objects. This multi-level structure accurately captured the decentralized governance flow and heterogeneity of the Municipality of Bacolod Brugiere2022. The model operated on quarterly time steps, where `BarangayAgents` managed fiscal allocation, policy implementation (e.g., "No Segregation, No Collection"), and enforcement deployment, bridging municipal mandates with local execution Nishimura2022. `HouseholdAgents` made binary segregation decisions based on a Theory of Planned Behavior (TPB) utility function, weighing policy strictness, social norms, and infrastructure availability against the "cost of effort" Ceschi2021. To enable autonomous policy optimization, the system was formalized as a finite-horizon Markov Decision Process (MDP), where an LGU-DRL agent dynamically allocated a continuous budget across Enforcement, Incentives, and IEC levers to maximize long-term compliance while minimizing costs Kompella2020. Crucially, the model incorporated a "Norm Internalization Mechanism" to simulate behavioral hysteresis, where sustained high compliance ($> 70\%$) created internalized social habits that resisted decay even when external interventions were reduced Centola2018.

D. Heuristic-Guided Deep Reinforcement Learning (HuDRL) Framework

To overcome the "Sparse Reward Problem" inherent in high-dimensional municipal resource allocation ($d = 21$), this study implements a Heuristic-Guided Deep Reinforcement Learning (HuDRL) framework utilizing Deep Proximal Policy Optimization (Deep PPO). The agent employs a custom Actor-Critic architecture where two deep neural networks (64-neuron dense layers with ReLU activation) process a multi-modal State Vector (S_t) comprising barangay compliance rates, fiscal liquidity, and political capital. To strictly enforce the municipality's fiscal constraints, the Actor network utilizes a Softmax Normalization Layer, mathematically guaranteeing that the continuous action vector (A_t)—representing allocations for IEC, Enforcement, and Incentives—never exceeds the quarterly budget cap ($B_{\text{Quarterly}}$).

Crucially, the framework integrates "Reward Shaping" to guide the agent away from sub-optimal, equitable distributions (the "Status Quo" trap) and toward a "Sequential Saturation" strategy. The Composite Reward Function (R_{total}) balances environmental compliance against fiscal sustainability and political backlash, while adding heuristic bonuses ($+20,000$) when the agent concentrates $> 40\%$ of resources on the weakest performing barangay. This logic is operationalized in the HuDRL Algorithm (Algorithm **??**), which utilizes a "Targeted Amplification" mechanism to act as a saliency filter, multiplying intent signals to critical nodes by a factor of $\alpha = 100$ to accelerate the discovery of optimal tipping points.

Algorithm 1 Heuristic-Guided Action Selection & Reward Shaping (HuDRL)

1: **Input:** S_t (State Vector), $\mathcal{B}_{list}$ (Barangay Agents), B_{cap} (Quarterly Budget)
2: **Output:** A_{final} (Optimized Budget Allocation)
3: **Step 1: Observation**
4: $S_t \leftarrow$ GetCurrentState()
5: **Step 2: Identify Critical Node**
6: $B_{crit} \leftarrow \min_{b \in \mathcal{B}_{list}}(b.compliance\_rate)$ {Identify weakest performing barangay}
7: **Step 3: Initial Policy Prediction**
8: $A_{raw} \leftarrow \pi_\theta(S_t)$ {Neural Network prediction}
9: **Step 4: Heuristic Targeted Amplification**
10: **if** $A_{raw}[B_{crit}] > \delta_{intent}$ **then**
     {If agent shows intent to fund critical node}
11:     $A_{raw}[B_{crit}] \leftarrow A_{raw}[B_{crit}] \times \alpha$ {Amplify signal (e.g., $\alpha = 100$)}
12:     Decrease other allocations to balance
13: **end if**
14: **Step 5: Budget Normalization (Softmax-style)**
15: $A_{final} \leftarrow$ Softmax$(A_{raw}) \times B_{cap}$
16: **Step 6: Execution**
17: Apply A_{final} to ABM Environment
18: **Step 7: Reward Shaping**
19: $R_{total} \leftarrow R_{base} + R_{bonus}$ {Includes Jackpot for Saturation Strategy}
20: **Step 8: Network Update**
21: PPO.Update(S_t, A_{final}, R_{total})

E. Simulation and Analysis

This study employed a rigorous four-stage experimental design to operationalize the coupled ABM-RL framework and isolate the causal impact of specific policy interventions. The process began with **Initialization and Calibration**, where the model was grounded in demographic and operational data from seven specific barangays and iteratively tuned to replicate the municipality's baseline compliance rate (approx. 10%) Villanueva2021, Jimenez2025. Following calibration, the Heuristic-Guided Deep Reinforcement Learning (HuDRL) agent underwent extensive training over 12 simulated lifetimes (approx. 10,000 periods) to explore the high-dimensional policy space Dey2025. To evaluate governance efficacy, the study simulated three distinct **Policy Scenarios**: a *Pure Penalty Regime* (representing the status quo/enforcement-heavy approach), a *Pure Incentive Regime* ("soft" governance), and a *Hybrid Regime* (an adaptive, AI-optimized mix of IEC, incentives, and enforcement) TianReview2024. System performance was quantified using four key metrics: Maximum Sustainable Compliance, Cost-Effectiveness (compliance gained per peso), Policy Equity (variance across barangays), and Optimal Resource Allocation. Finally, the model's structural robustness was validated through a **Global Sensitivity Analysis** using the Sobol method Sobol2001, which stress-tested the influence of core behavioral parameters $(w_a, w_{sn}, c_{effort})$ on global compliance outcomes.

IV. RESULTS

A. Data and Input Parameters Analysis

[cite$_s$start]$The validity of the Agent-BasedModel(ABM) was established through the rigorous empirical gro$ 1, 2]. [cite$_s$start]$The simulation environment was strictly bounded by a ha$ $-30,000 per enforcer) frequently crowded out funding for educationan$ 8, 14, 15].

[cite$_s$start]$As detailed in Table$ **??**, $the municipality exhibited profound$ $size - fits - all'' policy[cite$: 50, 51]. [cite$_s$start$Barangay Poblacion, termed the "Urban Resource Tro$ $capita spending power due to its massive population, forcing a legislative$ 22, 23]. [cite$_s$start$Conversely, Barangay Binuni represented a "Wealth$ 26, 42, 44].

TABLE I
BARANGAY DEMOGRAPHIC AND FINANCIAL INITIALIZATION PARAMETERS

Barangay	Households	Annual Budget (P)	Initial Compliance	Income Profile	
				Low	Mid
Brgy Poblacion	1,534	200,000	2%	70	25
Brgy Liangan East	608	30,000	14%	40	40
Brgy Ezperanza	574	90,000	14%	20	50
Brgy Binuni	507	126,370	15%	50	30
Brgy Demologan	463	21,000	11%	80	15
Brgy Babalaya	171	15,000	14%	80	10
Brgy Mati	165	80,000	11%	90	5

Note: Income profiles derived from Appendix B interviews.
[cite$_s$start]$Low Income agents have higher price sensitivity$ (γ) to fines[cite: 21].

The simulation further incorporated distinct psychosocial profiles for each barangay using Theory of Planned Behavior (TPB) weights, as summarized in Table **??**. [cite$_s$start]$The economic disparity between agrarian zones and commerci$ $income households in Mati and Demologan resulted in high price sensiti$ making uniform fines disproportionately punitive[cite: 53, 55]. [cite$_s$start]$Behavioral nuances were also encoded$: $Barangay Poblacion exhibited an "Urban Isolation" profile with low So$ 0.20), indicating that community pressure was ineffective in high-density areas[cite: 69, 70]. [cite$_s$start]$In contrast, agricultural areas like Barangay Mati showed hi$ 76].

V. MODEL CALIBRATION AND DATA RECONCILIATION

Model calibration was executed to align the simulation with the Municipal Environment and Natural Resources Office (MENRO) audit, reconciling significant discrepancies between self-reported data and ground-level reality. While barangay interviews suggested an aggregate compliance between 40% and 50%, the MENRO audit established a functional segregation rate of only 10% to 15%. This divergence highlighted a "Social Desirability Bias" and an "Intention-Action Gap," where officials overstated compliance or high awareness failed to translate into practice. To establish a valid "Status Quo" baseline of approximately 12.5%, the model treated the low reported compliance of Poblacion (2%) as an accurate "Anchor

TABLE II
CALIBRATED BEHAVIORAL WEIGHTS AND LEGISLATIVE ALLOCATION
STRATEGIES

Barangay	Agent Behavior Parameters				Budget Allocation (%)		
	Attitude (w_a)	Norms (w_{sn})	Effort (C_e)	Decay (γ)	Enf	Inc	IEC
Binuni	0.65	0.80	0.64	0.02	40	40	20
Ezperanza	0.40	0.70	0.55	0.03	50	30	20
Babalaya	0.60	0.90	0.62	0.05	90	5	5
Liangan East	0.65	0.60	0.58	0.04	25	65	10
Poblacion	0.55	0.20	0.48	0.03	60	20	20
Demologan	0.60	0.60	0.62	0.05	85	10	5
Mati	0.60	0.50	0.60	0.05	30	50	20

Note: Agent behavior parameters correspond to Theory of Planned Behavior (TPB) weights: w_a (Attitude), w_{sn} (Social Norms), C_e (Perceived Cost of Effort), and γ (Compliance Decay Rate). Budget allocation percentages reflect the legislative constraints under the Status Quo scenario.

Point" while drastically reducing inflated reports from other localities, such as Binuni and Liangan East, to filter out transient project-based spikes and theoretical awareness.

Fig. 1. *
A. Status Quo (Baseline)

TABLE III
COMPARISON OF ACQUIRED COMPLIANCE DATA VS. CALIBRATED
SIMULATION INITIALIZATION

Barangay	Acquired Data (Self-Reported)	Calibrated S_0 (Simulation Start)	Primary Calibration Factor
Brgy Babalaya	100%	14%	Adjusted for lack of funding/monitoring
Brgy Binuni	95%	15%	Decoupled awareness from actual practice
Brgy Mati	70%	11%	Adjusted for high habit decay rate
Brgy Liangan East	65%	14%	Removed temporary project-based spikes
Brgy Demologan	60%	11%	Standardized to municipal baseline
Brgy Ezperanza	20%	14%	Aligned with middle-class control group
Brgy Poblacion	2%	2%	Anchor Point (Aligned with Audit)

Note: "Acquired Data" refers to unverified compliance rates reported during Key Informant Interviews (Appendix B). "Calibrated S_0" refers to the initialized compliance state in the Agent-Based Model, tuned to match the aggregate municipal segregation rate of ≈12% verified by MENRO.

A. Comparative Results of Policy Strategies

The simulation experiments revealed a stark divergence in efficacy between static, equal-distribution strategies and the dynamic resource allocation discovered by the AI agent. [cite_start]The results unequivocally demonstrated that without the "Sequential Saturation" logic, no amount of static rebalancing betu widenon − compliance[cite : 31].

[cite_start]The ∗ ∗StatusQuo(Baseline) ∗ ∗scenario, whichdistributedfundsequally(53, 571/barangay), functionedasa"dilutionmechanism"[cite : 39]. [cite_start]Whilesmall, cohesivecommunitieslikeMatiandBabalayaachieved100%compliancethroughsocialmomentum, high− densitycriticalzoneslikePoblacionstagnatedat0.33%[cite : 35, 37]. [cite_start]ThisvalidatedtheUrban Resource Traphypothesis, whereanonymityanddensitydissolvethesocialpressurerequired intensityinterventionstowork[cite : 38].

Single-instrument strategies performed even worse due to the economics of dilution. [cite_start]The ∗ ∗PureEnforcement ∗

Fig. 2. *
B. Pure Enforcement

$*strategy resulted in a collapse to 13.9\% global compliance [cite:$
$75].[cite_start]The data showed that dilute enforcement was effectively useless; without reaching a critical threshold of intensity, the$
$compliance in Poblacion remained zero [cite:$
$46,47].[cite_start]Similarly, the ** Pure Incentives **$
$*strategy plateaued at 34.3\%, as the fixed budget spread across large populations resulted in microscopic rewards that failed to offset the$
$53,54].$

$[cite_start]In contrast, the ** Heuristic -$
$Guided Deep Reinforcement Learning (HuDRL) *$
$*agent outperformed all manual strategies, achieving a terminal Global Compliance Rate of$ **92.8%** $[cite:$
$73].$

TABLE IV
COMPARATIVE GLOBAL COMPLIANCE RATES ACROSS POLICY REGIMES
$(Q_1 - Q_{12})$

Policy Regime	Q1 (Initial)	Q4 (Year 1)	Q8 (Year 2)	Q12 (Terminal)
Status Quo (Baseline)	10.7%	52.4%	55.3%	57.1%
Pure Incentives	10.7%	34.6%	34.2%	34.3%
Pure Enforcement	10.7%	14.9%	14.0%	13.9%
Adaptive (HuDRL)	**10.7%**	**45.3%**	**72.2%**	**92.8%**

[cite$_s$tart]

$[cite_start]The superior performance of the AI was attributed to its discovery of *$
$*Sequential Saturation ** | a "King of the Hill" logic where the agent concentrated 51\% to 69\% of the total municipal budget onto single ban$
$61,62].[cite_start]By rotating this "siege" tactic from Demologan (Q2) to Poblacion (Q8-$
$12), the agent ensured that intervention intensity always exceeded the resistance threshold of the target demographic before moving on [$
$62,68].[cite_start]This validated the hypothesis that resolving the$ **Urban Resource Trap** $requires prioritizing sequential efficacy over si$
$71].$

VI. GLOBAL SENSITIVITY ANALYSIS

To evaluate the structural validity and predictive reliability of the developed Agent-Based Model (ABM), a Global Sensitivity Analysis (GSA) using Sobol indices was executed. [cite$_s$tart]$Unlike local sensitivity analysis, GSA accounted for the non-$ $linear interactions between variables across the entire multi-$ $dimensional input space [cite: 92].This stress-$ $testing phase involved varying the five core behavioral paramet$ by $\pm 20\%$ to quantify their individual contributions (S_1) to the variance in global compliance rates.

The analysis revealed that the **Cost of Effort ($c_{\textbf{effort}}$)** was the overwhelming driver of the model's output, accounting for approximately **83%** of the variance in household compliance. [cite$_s$tart]$This result provided computational evidence for the$ $"Convenience Hypothesis," confirming that physical friction and logis$ $environmental intent [cite:$ $94,95].[cite_start]This aligns with observations by Yazawa 2025, who noted that structural deficiencies | such as lack of accessible collect$ $96,97].$

The secondary driver, **Social Norms (w_{sn})**, acted as a critical force multiplier. The sensitivity index indicated that individual decisions were heavily contingent on the perceived compliance of the neighborhood. [cite$_s$tart]$This validated the "Cultural Inertia" mechanism, where social pressure could either lock a community into non-$ $compliance or, once a threshold is reached, accelerate a "tipping$ $100,101].$

A significant revelation was the near-zero sensitivity of the **Attitude (w_a)** parameter. While traditional policy often prioritized IEC campaigns to change mindsets, the model

Fig. 6. Global Sensitivity Analysis Results illustrating First-Order Sobol Indices (S_1) for behavioral parameters.

demonstrated that "environmental awareness" alone was insufficient to drive behavior change when systemic barriers remained high. [cite$_s$tart]$This quantified the "Value-$ $Action Gap" documented by Zhao 2022, supporting the conclusion that ex$ $104,106].$

Usage of Generative AI

The authors used Gemini Pro for grammatical corrections only.