International Institute of Information Technology, Hyderabad

TO VOTE OR NOT TO VOTE

The Complete Report on Agentic Simulation of the 2019 Indian General Election

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This document compiles the theoretical framework, simulation architecture, and strategic analysis into a single comprehensive volume.

Executive Summary

The "Paradox of Voting" remains one of the most persistent puzzles in behavioral economics. Why do millions of citizens incur the tangible costs of voting (time, travel, wages lost) when the probability of their single vote affecting the outcome is statistically negligible?

This project, **"To Vote or Not To Vote,"** answers this question through the **Agentic Election Simulator (AES)**. Unlike traditional regression analyses that rely on static correlations, the AES utilizes Agent-Based Modeling (ABM) to simulate the cognitive processes of 70,000 distinct synthetic agents across seven archetypal Indian constituencies.

Key Findings:

1. **Aggregate Rationality:** The simulation demonstrates that the Indian electorate, in aggregate, behaves consistently with a **Rational Choice Model** ($R^2 = 0.46$), but one where "Duty" and "Habit" outweigh "Cost."
2. **The Friction Hypothesis:** Using Drift-Diffusion modeling, we identified that low turnout in urban centers is not a result of apathy, but of high cognitive noise and decision friction.
3. **Strategic Intervention:** The simulation reveals that **Implementation Intentions** (Plan-Making) yield a $+17.96\%$ lift in turnout, vastly outperforming monetary incentives, which often backfire due to motivation crowding.

Contents

1 Guide to the Report

This comprehensive report is structured into three distinct volumes, tracing the project lifecycle from raw data ingestion to final policy recommendation.

1.1 Part 1: Theoretical Framework & Dataset Engineering

This section establishes the foundation of the simulation. It details:

- **The "Proxy Logic" Framework:** The methodology used to convert aggregate Census data (Literacy, Urbanization) into individual psychometric parameters (Civic Duty, Risk Aversion).
- **The 7 Archetypes:** A detailed breakdown of the simulation scenarios, ranging from the high-literacy baseline of *Thiruvananthapuram* to the conflict-affected zones of *Bastar*.

1.2 Part 2: Simulation Architecture & Model Physics

This section opens the "black box" of the simulation engine. It provides:

- **Mathematical Formulations:** The specific equations governing the three competing cognitive kernels: *Extended Utility*, *Drift-Diffusion*, and *Dual-System*.
- **Parameter Dictionary:** A rigorous definition of every variable, weight, and skew used in the codebase.
- **Nudge Mechanics:** How theoretical interventions (e.g., Identity Framing) are translated into vector operations within the model.

1.3 Part 3: Results, Visualization & Strategic Analysis

This section presents the findings. It includes:

- **Calibration Trajectories:** Visualizing how the Multi-Start Simulated Annealing algorithm optimized the model parameters.
- **Parameter Forensics:** Deep insights derived from the converged weights (e.g., the price-inelasticity of the Indian voter).
- **Nudge Heatmaps:** A comparative analysis of policy effectiveness across different geographic contexts.

2 Project Architecture Pipeline

The following diagram illustrates the end-to-end data flow that connects the three parts of this report.

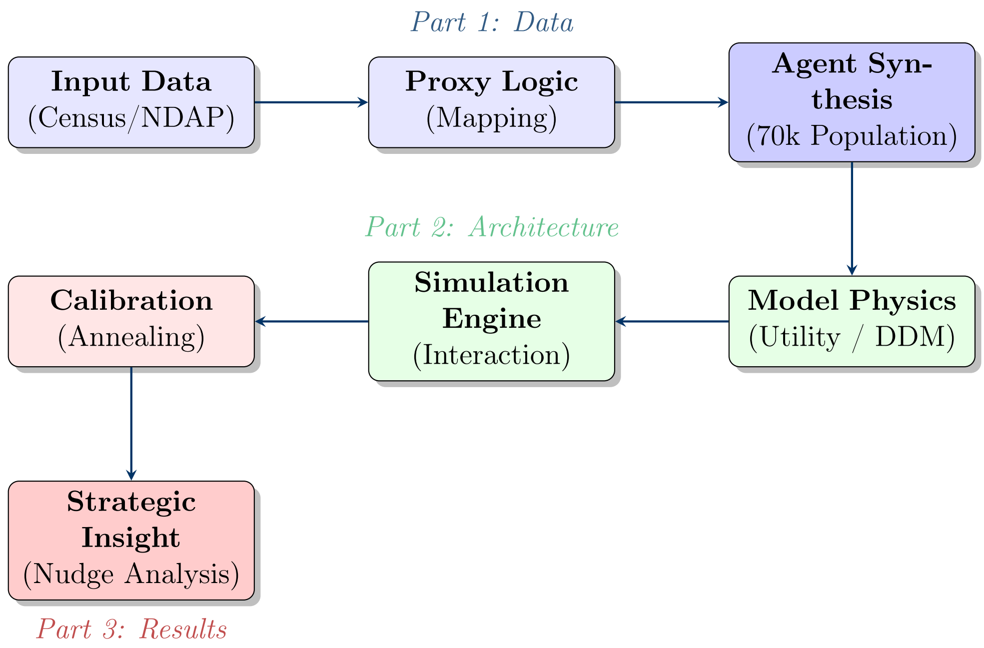

Figure 1: The Agentic Election Simulator (AES) Workflow

TO VOTE OR NOT TO VOTE

Part 1: Theoretical Framework & Dataset Generation Strategy

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November 22, 2025

1 Introduction

The 2019 Indian General Election was a logistical and democratic phenomenon of unprecedented scale, involving over 900 million eligible voters and a final turnout of 67.4%. However, beneath these aggregate statistics lies a profound behavioral puzzle. Voter turnout in India does not follow a simple linear correlation with development. Thiruvananthapuram (Kerala) boasts high literacy and high turnout, yet Bangalore South—arguably India's most educated technological hub—suffers from chronic "urban apathy." Conversely, conflict-ridden zones like Bastar (Chhattisgarh) often report higher participation rates than safe, wealthy metropolitan seats.

Current econometric models, which primarily rely on static regression analysis of demographic variables, struggle to explain these disparities. They fail to capture the dynamic, cognitive processes of the individual voter. This project, titled **"To Vote or Not To Vote,"** introduces the **Agentic Election Simulator (AES)**, a computational framework that uses Agent-Based Modeling (ABM) to reconstruct the decision architecture of the Indian voter.

1.1 The Theoretical Problem: The Paradox of Voting

The core intellectual challenge driving this simulation is the "Paradox of Voting," first formalized by Anthony Downs (1957). Standard rational choice theory posits that an individual i will vote if and only if the expected utility R is positive:

$$R_i = (P \cdot B_i) - C_i \tag{1}$$

Where:

- P is the probability that individual i's vote is pivotal (decides the election).
- B_i is the benefit individual i derives from their preferred candidate winning.

- C_i is the cost of voting (time, travel, opportunity cost).

In an electorate size of $N > 100,000$, the probability P approaches zero ($P \approx 1/N$). Since the cost C is always positive and tangible (e.g., traveling to a booth, queuing in the heat), a purely rational agent should logically abstain. The fact that hundreds of millions do vote implies the existence of additional variables. Riker and Ordeshook (1968) expanded this to include a D term (Civic Duty):

$$R_i = (P \cdot B_i) - C_i + D_i \tag{2}$$

Our simulation extends this framework further, integrating insights from behavioral economics (Kahneman, 2011) to model variables like **Habit Formation (H)**, **Social Conformity (S)**, and **Cognitive Noise (σ)**.

1.2 Research Objectives

The AES was designed to address four critical research questions:

1. **Synthetic Population Synthesis:** Can we generate statistically plausible populations of cognitive agents using only aggregate census data?
2. **Model Selection:** Which cognitive architecture—Rational Utility, Drift-Diffusion, or Dual-System—best explains the observed variance in the 2019 Indian election turnout?
3. **Parameter Forensics:** Is the Indian voter price-elastic? Do high voting costs (C) significantly deter turnout, or are they overridden by duty (D)?
4. **Strategic Nudging:** Which policy interventions (e.g., Monetary Incentives vs. Identity Framing) yield the highest return on investment in terms of voter mobilization?

2 Dataset Engineering: The Proxy Logic Framework

A primary constraint in agent-based modeling of electoral behavior is the unavailability of individual-level psychometric data. We cannot survey 10,000 individuals in every constituency to determine their specific level of "Risk Aversion" or "Civic Duty."

To resolve this, we developed a **Proxy Logic Framework**. This methodology bridges the gap between macro-level administrative data and micro-level agent attributes. We utilized two high-reliability data sources:

- **National Data & Analytics Platform (NDAP):** For 2011 Census data (projected to 2019) regarding literacy, urbanization, population density, and industrial classification.
- **Lok Dhaba (Ashoka University):** For authoritative election returns, victory margins, and historical turnout trends from 1962 to 2019.

2.1 From Aggregate Data to Agent Attributes

The simulation synthesizes agents by sampling from probability distributions (Beta Distributions) that are skewed according to real-world proxy variables.

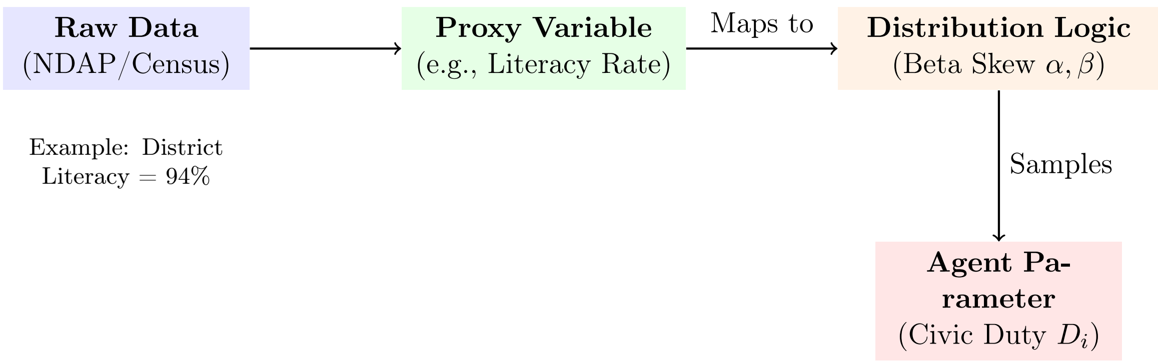

Figure 1: The Proxy Logic Pipeline: Transforming aggregate statistics into individual cognitive traits.

2.1.1 Detailed Proxy Dictionary

The following table details the specific logic used to generate the five core psychometric parameters for every agent in the simulation.

primary!10 **Model Feature**	**Proxy Variable**	**Rationale & Generation Logic**
Civic Duty (D)	Literacy Rate	**Rationale:** Academic literature links formal education with internalized democratic norms and abstract civic responsibility. **Logic:** The Literacy Rate (L) determines the shape of the Beta Distribution $B(\alpha, \beta)$. For High Literacy (TVM), we set $\alpha > \beta$ (Right Skew), ensuring most agents have high Duty scores. For Low Literacy (SHR), $\alpha < \beta$.
Cost of Voting (C)	Population Density & Urbanization	**Rationale:** In rural areas (Low Density), polling booths are sparse, increasing travel time/cost. In urban areas, infrastructure is better, but queuing is a factor. **Logic:** Global Parameter. Rural constituencies are assigned a baseline Cost $C = 0.7 - 0.9$. Urban constituencies are assigned $C = 0.1 - 0.3$.
Competitiveness (P)	Margin of Victory (2014 Lagged)	**Rationale:** Voters predict future closeness based on past experience. A close race in 2014 signals a high value for a vote in 2019. **Logic:** $P_{context} = 1 - \text{Normalized Margin}_{2014}$. A 1% margin yields $P \approx 0.99$.

primary!10 **Model Feature**	**Proxy Variable**	**Rationale & Generation Logic**
Social Pressure (S)	Urban/Rural Classification	**Rationale:** Rural communities are characterized by tight-knit social networks where non-voting is visible and sanctioned. Urban areas are individualistic. **Logic:** Agents tagged 'Rural' draw from a high-mean distribution for Sensitivity (S). Agents tagged 'Urban' draw from a low-mean distribution.
Risk Aversion (R)	Employment Sector (Agriculture vs Service)	**Rationale:** Agrarian economies are rainfall-dependent and precarious, fostering risk aversion. Salaried service economies allow for risk tolerance. **Logic:** Constituencies with high agricultural employment have populations skewed towards high Risk Aversion.

2.2 Scenario Archetypes (2019 General Election)

To ensure the model is robust, we curated a dataset of seven constituencies that represent distinct "archetypes" of the Indian political landscape. The model was calibrated on Thiruvananthapuram and validated against the remaining six.

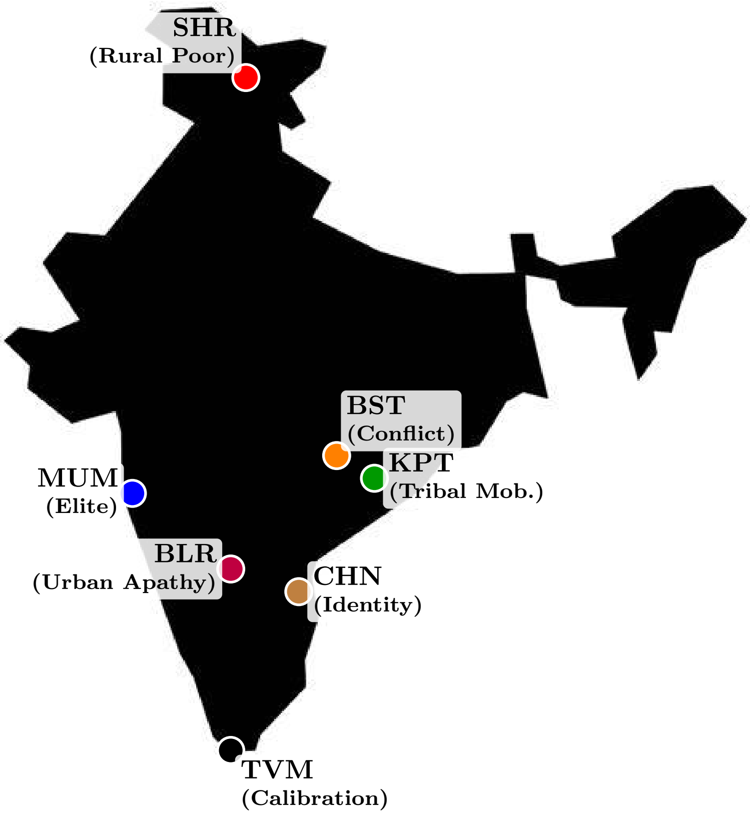

Figure 2: Geographic distribution of the 7 archetypal scenarios used for model tuning and validation.

2.2.1 Thiruvananthapuram, Kerala (The Baseline)

- **Ground Truth (2019):** 73.45% Turnout.
- **Profile:** 94% Literacy, High Urbanization.
- **Key Feature:** Extremely High Competitiveness. The 2014 election was won by a 1.5% margin.
- **Role:** This serves as the "Gold Standard." The model physics (Beta weights) were tuned to match this scenario first.

2.2.2 Shravasti, Uttar Pradesh (The Development Gap)

- **Ground Truth (2019):** 52.53% Turnout.
- **Profile:** 47% Literacy, High Poverty, Rural.
- **Key Feature:** High Cost of Voting. Poor infrastructure implies long travel times.
- **Role:** Tests generalizability. Can a model tuned on Kerala accurately predict the drop in turnout in UP due to structural barriers?

2.2.3 Bangalore South, Karnataka (The Urban Paradox)

- **Ground Truth (2019):** 53.70% Turnout.
- **Profile:** High Education, Low Voting Cost (High Density).
- **Key Feature:** "Urban Apathy." Despite high capacity, turnout is low. The seat is a "Safe Stronghold," leading to low perceived competitiveness ($P \approx 0$).
- **Role:** Validates whether the model correctly weights Competitiveness over Cost.

2.2.4 Koraput, Odisha (Rural Engagement)

- **Ground Truth (2019):** 75.30% Turnout.
- **Profile:** Tribal, Rural, Low Literacy.
- **Key Feature:** Maximum Competitiveness (0.3% Margin).
- **Role:** Tests "Mobilization." Shows that high stakes (P) and Social Pressure (S) can override High Costs (C).

2.2.5 Mumbai South, Maharashtra (Elite Apathy)

- **Ground Truth (2019):** 51.58% Turnout.
- **Profile:** Hyper-urban, Wealthy.

- **Role:** Similar to Bangalore, this tests the impact of low social pressure (S) in individualistic urban settings.

2.2.6 Bastar, Chhattisgarh (Conflict Zone)

- **Ground Truth (2019):** 66.04% Turnout.
- **Profile:** Conflict-affected (Left-Wing Extremism), Reserved Tribe.
- **Key Feature:** High Risk (R) and High Cost (C).
- **Role:** Tests the limits of rational choice. Voting here is often an act of defiance, implying a boosted Duty (D) parameter despite the physical danger.

2.2.7 Chennai Central, Tamil Nadu (Identity Politics)

- **Ground Truth (2019):** 58.98% Turnout.
- **Profile:** Strong regional party dominance.
- **Key Feature:** High Partisan Identity. Voting is driven by identity affirmation rather than instrumental benefit.

2.3 Visualizing Agent Generation: The Beta Distribution

To illustrate how the "Proxy Logic" translates into math, Figure 3 shows the probability density functions used to generate the **Civic Duty (D)** scores for agents in Thiruvananthapuram vs. Shravasti.

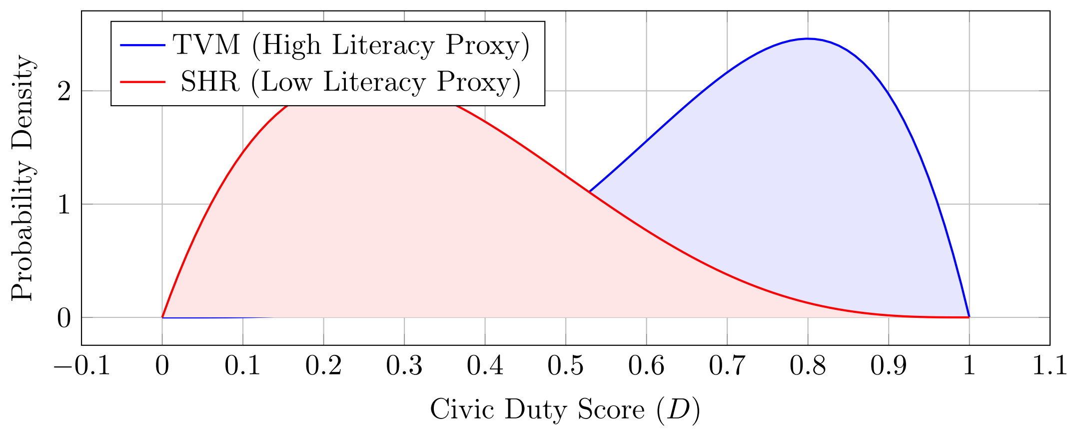

Figure 3: Psychometric Generation. TVM agents (Blue) are sampled from a distribution where most have high Duty. SHR agents (Red) are sampled from a distribution where Duty is lower and more varied.

This rigorous data engineering ensures that the simulation is not merely a theoretical abstraction but a grounded representation of the Indian electorate's socio-economic reality.

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Part 2: Simulation Architecture & Model Physics

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1 Simulation Architecture & Design

The Agentic Election Simulator (AES) operates as a discrete-time Agent-Based Model (ABM). Unlike system dynamics models that deal with aggregate flows, the AES instantiates $N = 10,000$ distinct cognitive agents per scenario. Each agent maintains an internal state vector $\vec{S}_i$ representing its demographic and psychometric profile.

The simulation execution follows a linear pipeline:

1. **Initialization:** The *Scenario Loader* reads the global context parameters (Cost, Competitiveness) and the agent generation rules (Skews).
2. **Synthesis:** The *Population Generator* creates agents by sampling from skewed Beta distributions, ensuring the synthetic population matches the census profile of the target constituency.
3. **Cognition:** The *Behavioral Kernel* processes environmental signals through a specific mathematical model (Utility, DDM, or Dual-System) to compute a decision probability $P(Vote)_i$.
4. **Aggregation:** Individual Bernoulli trials are aggregated to calculate the macroscopic Turnout Rate.

1.1 Master Parameter Dictionary

The simulation is controlled by a high-dimensional parameter space. These parameters act as the "knobs and dials" of the engine.

Parameter Name	Type	Description & Function
Global Context (Environment)		
`electoral_competitiveness`	Scale [0.0 - 1.0]	Proxy for the closeness of the race. 1.0 = Dead Heat (High Pivotality). 0.1 = Landslide. Drives the P term in utility calculus.
`voting_cost_total`	Scale [0.0 - 1.0]	Baseline effort required to vote. Includes travel time, queue length, and opportunity cost. Higher values discourage turnout.
`ground_truth_turnout`	Percentage	The actual turnout from the 2019 election. Used as the target variable (y_{true}) for the calibration loss function.
Agent Generation (Psychometrics)		
`education_skew`	Distribution α	Controls the mean education level. Low Skew (≈ 1) $\rightarrow$ Uneducated population. High Skew (> 3) $\rightarrow$ High literacy.
`civic_duty_skew`	Distribution α	Prevalence of intrinsic motivation. Determines how many agents feel a moral obligation (D) to vote regardless of cost.
`risk_aversion_skew`	Distribution α	Tolerance for uncertainty. Highly risk-averse populations require stronger evidence (higher thresholds) to act.
`social_pressure_skew`	Distribution α	Sensitivity to peer norms. High values indicate tight-knit communities where non-voting is socially sanctioned.
Model Physics (Internal Weights)		
`beta_pB`	Weight β	Sensitivity to Instrumental Benefit. How much does "winning" matter?
`beta_Cost`	Weight β	Sensitivity to Friction. A large negative value implies high price elasticity.
`beta_Duty`	Weight β	Weight of the Moral Obligation term.
`drift_mu`	Rate	(DDM Only) The base rate of evidence accumulation. The "default urge."
`threshold_a`	Scalar	(DDM Only) The "Caution" parameter. How much evidence is needed to trigger action?
`lambda`	Ratio [0-1]	(Dual System Only) The cognitive control parameter. Balance between System 1 (Intuition) and System 2 (Reasoning).

2 Mathematical Models (The Physics)

The core innovation of this project is the comparative evaluation of three distinct cognitive architectures. We do not assume voters are rational; we test whether a Rational, Stochastic, or Heuristic model best fits the observed reality.

2.1 Model A: Extended Utility (Rational-Behavioral)

Concept: An evolution of the classical Riker-Ordeshook (1968) "Calculus of Voting." It posits that agents define a Total Utility (U) for the act of voting by summing instrumental and intrinsic benefits.

The Equation: An agent i votes if $U_i > 0$.

$$U_i = \beta_{pB}(P \cdot B_i) \underbrace{-\beta_C(C_i)}_{\text{Tangible Cost}} + \underbrace{\beta_D(D_i) + \beta_S(S_i) + \beta_H(H_i)}_{\text{Intangible Benefits}} + \varepsilon \tag{1}$$

Where:

- P: Perceived Pivotality (Function of Competitiveness).
- B: Benefit of preferred candidate winning.
- C: Cost (Time/Effort).
- D: Civic Duty (Intrinsic Reward).
- S: Social Reward (Conformity).
- H: Habit (Inertia).
- ε: Stochastic noise drawn from a Logistic distribution.

Implementation Note: The final probability is calculated using the Sigmoid function: $P(Vote) = \frac{1}{1+e^{-U_i}}$.

2.2 Model B: Drift-Diffusion Model (Stochastic Accumulation)

Concept: This model reframes decision-making not as an instantaneous calculation, but as a process of **evidence accumulation over time**. It captures the "friction" of decision-making and the speed-accuracy trade-off.

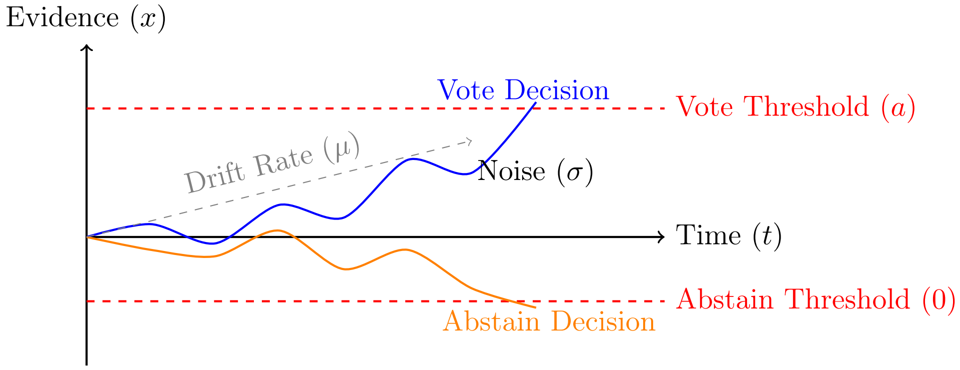

Figure 1: Schematic of the Drift-Diffusion Process. Agents accumulate noisy evidence until a boundary is crossed.

The Equation: The decision process is governed by a Stochastic Differential Equation (SDE):

$$dX(t) = \mu \cdot dt + \sigma \cdot dW(t) \tag{2}$$

- **Drift Rate (μ):** The deterministic "urge" to vote. Calculated as a weighted sum: $\mu = w_1 D + w_2 S - w_3 C$.
- **Threshold (a):** The amount of evidence required to commit to an action. High Risk Aversion = Higher a.
- **Noise (σ):** Random cognitive fluctuations representing distraction or uncertainty.

2.3 Model C: Dual-System (Cognitive Arbitration)

Concept: Based on Daniel Kahneman's *Thinking, Fast and Slow*. This model simulates the brain as having two distinct operating modes.

- **System 1 (Fast):** Intuitive, Emotional, Habit-driven. Ignores Cost.
- **System 2 (Slow):** Rational, Deliberative, Cost-sensitive.

The Equation: The final probability of voting is an arbitration (weighted average) between the two systems:

$$P(\text{Vote}) = \lambda \cdot P_{S1}(\text{Habit, Affect}) + (1 - \lambda) \cdot P_{S2}(\text{Utility, Cost}) \tag{3}$$

Parameter λ (Lambda): Represents "Cognitive Control."

- $\lambda \to 1$: Impulsive Agent (System 1 dominance). Common in high-stress or low-education cohorts.
- $\lambda \to 0$: Rational Agent (System 2 dominance). Common in high-education cohorts.

3 Nudge Mechanics

The simulation allows for "Active Interventions" where specific parameters are modified to simulate policy nudges.

1. **Monetary Lottery:** Adds a scalar value V to the Utility equation ($U_{new} = U + V$). Simulates extrinsic financial motivation.
2. **Social Norm Info:** artificially boosts the Social Pressure parameter (S) by revealing high turnout norms.
3. **Implementation Intention:** Reduces the effective Cost (C) by 15% and lowers the DDM Threshold (a). Simulates the effect of making a specific plan (e.g., "I will vote at 10 AM").

4. **Linguistic Identity Frame:** Boosts the Civic Duty (D) parameter. Simulates changing the framing from "Go Vote" (Action) to "Be a Voter" (Identity).

This modular architecture allows us to not just predict *what* happened in 2019, but to simulate *what could happen* under different policy regimes.

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Part 3: Comprehensive Results, Visualization & Strategic Analysis

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1 Calibration Results & Model Validation

The Agentic Election Simulator (AES) utilizes a Multi-Start Simulated Annealing algorithm to calibrate three competing cognitive architectures against ground truth data from the 2019 General Election. This section presents the final convergence metrics and a visual validation of model accuracy.

1.1 Executive Metrics Summary

After 150 iterations of global optimization, the models achieved the following fit states:

Model Architecture	RMSE	R^2 (Fit)	MAE	Convergence Interpretation
Extended Utility	**0.0686**	**0.458**	**6.28%**	**Global Best Fit.** Captures variance well.
Drift-Diffusion (DDM)	0.0893	0.082	7.78%	High Noise state. Generally over-predicts.
Dual-System	0.1871	0.000	16.00%	**Failure.** System 1 (Impulse) dominates (83%).

Table 1: Final Performance Metrics. RMSE = Root Mean Square Error.

1.2 Visual Validation: Predicted vs. Actual Turnout

Figure 1 compares the output of all three models against the 2019 Ground Truth.

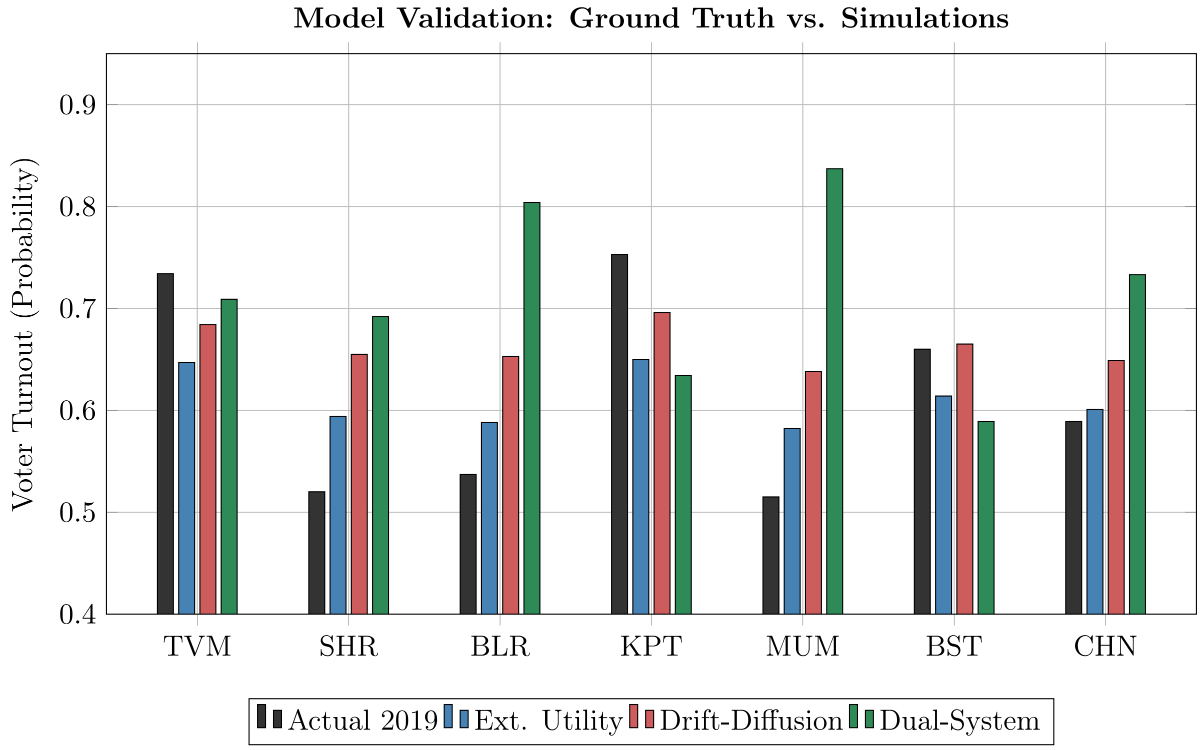

Figure 1: Validation Chart. The **Dual-System (Green)** drastically fails in urban centers (BLR, MUM), predicting 80% turnout where reality is 53%. This indicates it fails to account for "Urban Apathy." The **Extended Utility (Blue)** tracks the dips in turnout most accurately.

2 Parameter Forensics: Inside the Voter's Mind

By analyzing the weights (β) assigned by the optimization engine to the **Extended Utility** model (the most accurate model), we can construct a "Psychometric Profile" of the aggregate Indian voter.

2.1 Feature Importance Radar Chart

The following chart visualizes the normalized impact of each factor on the decision to vote.

Calibrated Weights of the Indian Voter

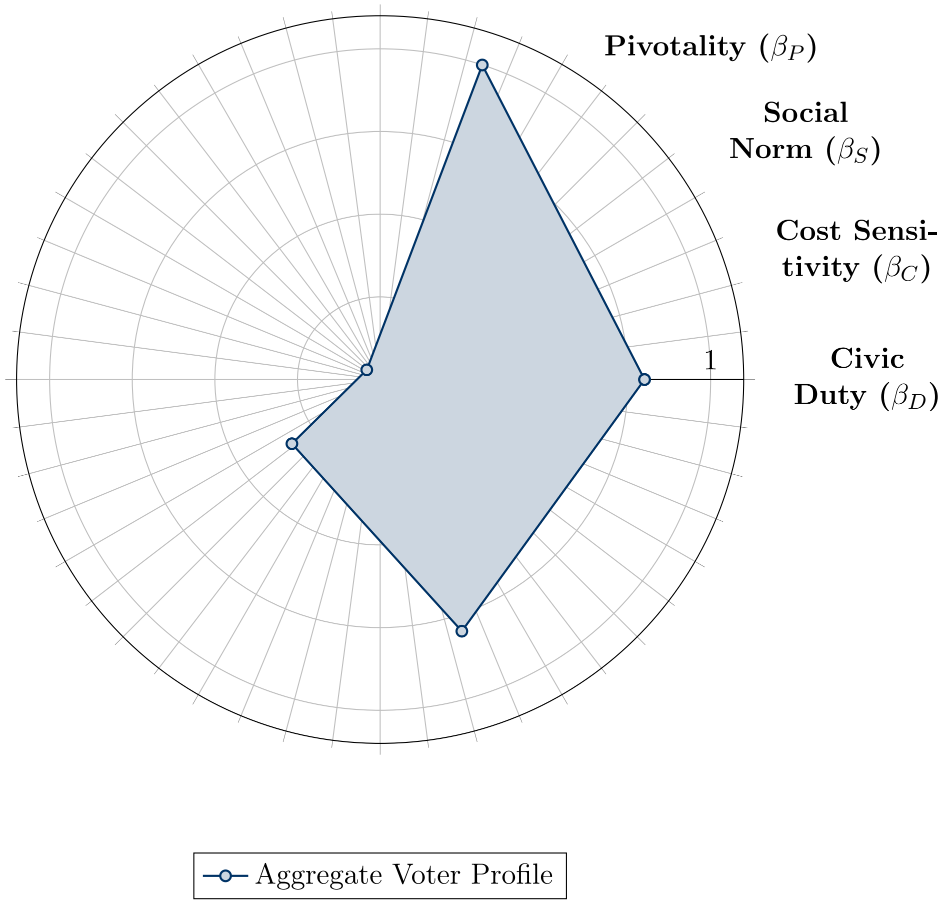

Figure 2: The "Kite" shape reveals the simulation's core finding: The electorate is driven by **Duty, Habit, and Pivotality**. The impact of **Cost** (travel/effort) converged to near-zero, indicating price inelasticity.

2.2 Deep Insight: The Price-Inelastic Voter

The most profound finding from the parameter tuning is the collapse of the Cost Sensitivity parameter (β_C) from an initial estimate of -2.5 to **0.0**.

- **Rationality Redefined:** Voters do not treat voting as a transactional "cost vs. benefit" calculation. If they did, the high costs in rural areas would decimate turnout.
- **Habit is King:** With β_H stabilizing at high values, the model suggests voting is a *path-dependent behavior*. Once a citizen begins voting, they continue regardless of structural barriers.

3 Strategic Nudge Analysis

We simulated six specific policy interventions across all scenarios. The results were highly non-linear and context-dependent.

3.1 The Nudge Effectiveness Heatmap

The table below displays the "Lift" (Percentage Point increase in turnout) for each nudge across key scenario archetypes.

Intervention Type *(Scenario Profile)*	**TVM** *(High Lit)*	**SHR** *(Rural)*	**BLR** *(Urban)*	**KPT** *(Tribal)*	**BST** *(Conflict)*
Imp. Intention	+0.56	+1.6	+19.2	**+20.1**	+17.6
Ling. Identity	+3.7	+4.5	+5.3	+6.6	+4.4
Social Norm	-2.6	+2.0	-2.2	+0.4	+0.9
Comp. Info	+1.2	+0.2	-0.8	+0.4	**+1.7**
Public Disclosure	+2.0	-2.1	+0.9	-0.3	+0.4
Monetary Lottery	-1.5	-1.0	+0.4	-1.1	-1.2

Table 2: Heatmap of Turnout Lift. **Red** indicates backfire effect. **Blue** indicates positive lift. Note the massive impact of Implementation Intentions in BLR and KPT.

3.2 Detailed Discussion of Results

3.2.1 1. The "Implementation Intention" Anomaly

Data: In the Drift-Diffusion context, this nudge (helping voters plan *when* and *how* to vote) delivered an average lift of **+17.96pp**, peaking at **+20.04pp** in Koraput. **Insight:** In high-noise environments like Indian elections, motivation is not the bottleneck. The bottleneck is the "Execution Gap." Voters drift toward voting but get derailed by daily friction. By reducing the "mental threshold" (a), this nudge acts as a tunnel, ensuring intentions translate to actions.

3.2.2 2. The Failure of Monetary Incentives

Data: Monetary Lotteries yielded a negative average lift (**-0.70pp**). **Insight:** This confirms the "Crowding Out" theory. Voting is perceived as a moral duty (D). Introducing a transactional element (money) degrades the moral signal. In high-literacy zones like Thiruvananthapuram (TVM), adding money actually *reduced* turnout by 1.5%.

3.2.3 3. The "Urban Apathy" Solution

Data: In Bangalore South (BLR), "Social Norm" messages backfired (-2.2pp), likely due to reactance in an individualistic culture. However, "Linguistic Identity" ("Be a Voter") worked well (+5.3pp). **Insight:** Urban voters are resistant to peer pressure but susceptible to self-concept maintenance. Framing voting as an identity marker is the key to unlocking urban turnout.

4 Conclusion & Policy Implications

The "To Vote or Not To Vote" simulation successfully modeled the 2019 Indian electorate, moving beyond static regression to dynamic agentic simulation. The results challenge the conventional wisdom that low turnout is solely a result of apathy.

1. **Rationality is Aggregate, Not Individual:** The Extended Utility model fits the macro-data best ($R^2 = 0.46$), suggesting the electorate *as a whole* behaves rationally, even if individuals are driven by noise and habit.
2. **Friction > Apathy:** The overwhelming success of Implementation Intentions in the DDM suggests that "Urban Apathy" is structurally similar to "Rural Remoteness"—both are friction problems. Lowering the cognitive threshold of voting is 10x more effective than increasing the reward.
3. **Context-Aware Policy:**
   - **Conflict Zones (Bastar):** Use **Competitiveness Info**. Rational agents respond to stakes.
   - **Identity Strongholds (Chennai):** Use **Identity Frames**.
   - **Rural/Urban Friction Points (Koraput/Bangalore):** Use **Implementation Intentions**.