Behavioral Insights into Voter Turnout: An Agent-Based Simulation Framework with Empirical Calibration

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***Abstract*—The decision to vote represents a fundamental puzzle in democratic participation, where classical rational choice models fail to explain widespread electoral engagement—a phenomenon termed the "paradox of voting." This paper presents the Agentic Election Simulator (AES), a comprehensive computational framework integrating behavioral economics, neuroeconomic principles, and agent-based modeling to understand and predict voter turnout. We test three competing cognitive decision models :Extended Rational Choice, Drift-Diffusion Model (DDM), and Dual-System Model—and empirically calibrate parameters through an original survey of 72 respondents using a Proxy Logic Framework that bridges macro-level census data with micro-level psychometric agent attributes. Our findings reveal that voting habit explains 69% of variance in turnout propensity ($r = 0.83$, $p < 0.0001$), vastly exceeding civic duty (14.5%) and cost sensitivity (26%). Critically, cost sensitivity collapsed from theoretical estimates of $\beta_C = -2.5$ to empirical values of $\beta_C = -0.51$, revealing that Indian voters are remarkably price-inelastic. We implement a large-scale agent-based simulation of 70,000 synthetic voters across seven archetypal Indian constituencies from the 2019 General Election, achieving $R^2 = 0.458$ fit with ground truth turnout data. The simulation validates that the Extended Utility Model outperforms both DDM ($R^2 = 0.082$) and Dual-System ($R^2 = 0.000$) architectures for aggregate prediction. Intervention experiments demonstrate that implementation intentions yield $+17.96$ percentage points turnout lift by reducing cognitive decision thresholds, while monetary incentives produce negative effects (-0.70 pp) through motivation crowding. The simulation reveals four distinct voter archetypes requiring targeted strategies: Habitual Voters (25%), Rational Calculators (25%), Social Followers (30%), and Disengaged citizens (20%). These findings challenge conventional wisdom that low turnout stems from apathy, instead revealing decision friction as the primary barrier—"urban apathy" and "rural remoteness" share structural similarity as friction problems. Our empirically-grounded computational approach provides actionable insights for evidence-based electoral policy design and establishes the first voter turnout simulation with survey-calibrated parameters in the literature.**

***Index Terms*—Agent-based modeling, behavioral economics, computational social systems, decision-making, drift-diffusion models, electoral participation, neuroeconomics, nudge theory, reinforcement learning, voter turnout.**

I. 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 that has captivated political economists for decades. Voter turnout in India does not follow a simple linear correlation with development: Thiruvananthapuram (Kerala) boasts high literacy and high turnout (73.45%), yet Bangalore South (arguably India's most educated technological hub) suffers from chronic "urban apathy" with only 53.70% turnout. Conversely, conflict-ridden zones like Bastar (Chhattisgarh) often report higher participation rates (66.04%) than safe, wealthy metropolitan seats like Mumbai South (51.58%).

Voter turnout serves as a key metric of democratic health, yet its underlying mechanisms remain among the most persistent puzzles in political economy [1]. Classical rational choice theory posits that an individual i votes if and only if the expected utility R is positive:

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

where P represents the probability that individual i's vote is pivotal (decides the election), B_i denotes the benefit from the preferred candidate's victory, and C_i represents the cost of voting (time, travel, opportunity cost). In large-scale elections with $N > 100,000$ eligible voters, the pivotality probability $P \approx 1/N$ approaches zero. Since costs C remain tangible and positive, a purely rational agent should logically abstain. This theoretical prediction contradicts empirical reality: hundreds of millions vote despite the mathematical improbability of being pivotal.

A. The Paradox and Its Resolution

Riker and Ordeshook [2] proposed incorporating a non-instrumental term D representing psychic benefits:

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

where D_i captures civic duty, partisan affirmation, and expressive utility. However, this formulation raises deeper questions: What constitutes the D term? How can it be systematically measured and modeled? And critically, what is the relative weight of D compared to instrumental factors?

Furthermore, as noted in recent literature [14], turnout in many established democracies is stagnating or declining even as logistical costs to voting have generally decreased. This suggests that the decision to vote is not a simple cost-benefit calculation but a complex behavioral choice, deeply influenced by psychological, social, and systemic factors that warrant a neuroeconomic perspective.

B. Research Motivation and Approach

The core idea of this project is to reframe the voting decision from a purely rational act to a behavioral one, governed by an individual's **net perceived utility**. We posit that a person's choice to vote or abstain is a function of a wide array of factors

This work was conducted as part of the course CG4.402: Introduction to Neuro-Economics under the supervision of Prof. Kavita Vemuri.

that shape their subjective valuation of the act. This utility is not static but is a dynamic function of the individual's personal characteristics (demographics, beliefs, biases) and the specific electoral context (election competitiveness, media narrative, institutional trust).

Current econometric models, which primarily rely on static regression analysis of demographic variables, struggle to explain the disparities observed across Indian constituencies. They fail to capture the dynamic, cognitive processes of the individual voter. This project introduces the **Agentic Election Simulator (AES)**, a computational framework that uses Agent-Based Modeling (ABM) to reconstruct the decision architecture of the Indian voter.

C. Research Contributions

This work makes four principal contributions to computational social systems:

1) Empirical Calibration Framework: We develop and validate a comprehensive survey instrument ($N = 72$) mapping theoretical constructs to measurable psychometric variables. Unlike prior work that relied on theoretically-motivated but empirically unvalidated assumptions, every weight in our utility function derives from original survey data with statistical validation. This represents, to our knowledge, the **first voter turnout simulation with empirically-calibrated parameters** in the literature.

2) Cognitive Architecture Comparison: We implement three competing decision models—Extended Utility, Drift-Diffusion, and Dual-System—and systematically evaluate their predictive accuracy against 2019 Indian General Election data. This comparative analysis reveals that the Extended Utility Model achieves $R^2 = 0.458$, significantly outperforming DDM ($R^2 = 0.082$) and Dual-System ($R^2 = 0.000$) frameworks.

3) Large-Scale Agent-Based Simulation: We construct a 70,000-agent computational environment synthesizing seven archetypal constituencies using a novel **Proxy Logic Framework** that bridges macro-level census data with micro-level agent attributes. This enables counterfactual policy experimentation impossible in field studies, allowing us to ask: "What would 2019 turnout have been with different policies?"

4) Intervention Effectiveness Hierarchy: Through controlled simulation experiments, we rank behavioral nudges by impact, revealing that implementation intentions outperform monetary incentives by a 25:1 ratio. Implementation intentions deliver $+17.96$ percentage points lift by reducing cognitive decision thresholds, while monetary incentives backfire (-0.70 pp) through motivation crowding effects.

D. Theoretical Foundation

Our framework integrates insights from three distinct but complementary domains:

Behavioral Economics: We incorporate cognitive biases (overconfidence, risk aversion), bounded rationality, and heuristic processing as articulated by Kahneman [4]. These concepts explain why voters deviate from purely rational calculations while still exhibiting systematic patterns.

Neuroeconomics: The Drift-Diffusion Model (DDM) operationalizes voting as evidence accumulation under noise, capturing the temporal dynamics of decision-making [6]. This framework reframes decision-making not as an instantaneous calculation, but as a process of evidence accumulation over time, capturing the "friction" of decision-making and the speed-accuracy trade-off.

Social Psychology: We model conformity pressure, identity affirmation, and habit formation through reinforcement learning principles [7], [9]. These social mechanisms explain why voting persists even when instrumental motivations are absent.

E. Research Questions

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) and habit (H)?
4) **Strategic Nudging:** Which policy interventions (e.g., Monetary Incentives vs. Identity Framing vs. Implementation Intentions) yield the highest return on investment for voter mobilization?

F. Paper Organization

The remainder of this paper is structured as follows: Section II reviews related work and positions our contribution within the existing literature. Section III details the empirical survey methodology and hypothesis testing framework. Section IV presents the Proxy Logic Framework for dataset engineering and synthetic population generation. Section V presents the agent-based simulation architecture, mathematical models, and calibration procedures. Section VI reports comprehensive results from both empirical and computational analyzes. Section VII discusses theoretical implications, surprising findings, and policy recommendations. Section VIII acknowledges limitations and outlines future research directions. Section IX examines broader societal implications. Section X concludes with a synthesis of principal findings.

II. Related Work and Theoretical Foundations

The study of voter turnout represents one of the most enduring puzzles in political economy. This section synthesizes key findings from political science, behavioral economics, and social psychology to establish the theoretical foundation for our computational framework. We move beyond the "paradox of voting" to explore the non-instrumental psychological drivers of participation.

A. The Foundational Challenge: Revisiting the Rationality of Voting

The study of voter turnout begins with a fundamental contradiction known as the “paradox of voting,” first systematically articulated by Downs [1]. The classical rational choice model frames the decision to vote with the equation $R = pB - C$, where R is the net reward from voting, p is the probability of one’s vote being pivotal, B is the differential benefit of one candidate winning, and C represents the costs of voting. In any large-scale election, the probability p is infinitesimally small, making the pB term virtually zero. Consequently, for any non-zero cost C, the purely instrumental decision is to abstain.

The persistent reality of substantial voter turnout requires a more nuanced model. Riker and Ordeshook [2] proposed a critical modification by introducing a non-instrumental term D, representing the psychic benefits of voting. These benefits include fulfilling civic duty, affirming partisan identity, or expressing personal values. The equation thus becomes:

$$R = pB - C + D \tag{3}$$

In this framework, the decision to vote becomes a psychological calculus: does the psychic benefit (D) outweigh the tangible cost (C)? Our project is fundamentally an investigation into the nature and components of this D term.

Further enriching this debate, Ferejohn and Fiorina [3] challenge the very definition of “rationality” in this context. They argue that voters may not be expected utility maximizers but could instead operate under a “minimax regret” criterion. Such a voter does not calculate probabilities but seeks to avoid the worst possible future emotional state: the regret of having not voted if their preferred candidate loses by a single vote. For this decision-maker, the mere logical possibility of this outcome is enough to justify the act of voting, providing a powerful theoretical alternative that does not rely on postulating a generic D term.

Blais [16] provided a comprehensive analysis of the rational choice paradox, demonstrating through cross-national data that the model’s predictions consistently fail across diverse democratic contexts. His work highlighted the need for incorporating non-instrumental motivations into formal models.

B. Deconstructing Perceived Utility: Key Psychological Drivers

The literature demonstrates that the most powerful forces driving turnout are not logistical but psychological—the internal and social rewards that make the act of voting feel meaningful and necessary.

1) The Power of Identity and Self-Concept: Tying a behavior to a person’s self-concept dramatically increases motivation. A landmark field experiment by Bryan et al. [7] revealed the potent effect of subtle linguistic framing. Phrasing survey questions to invoke identity (e.g., “How important is it to you to *be a voter*?”) rather than an action (“How important is it to you *to vote*?”) increased turnout by a remarkable 11-14 percentage points in two real-world elections.

This suggests that a significant component of the D term is the utility derived from affirming a positive social identity. Nudges that frame voting as an opportunity to embody the role of “a voter” are likely to be far more effective than those that merely simplify the action. This finding directly informs our operationalization of the “Linguistic Identity Frame” intervention in the simulation.

2) From Identity to Habit: The Role of Automaticity: Beyond a single election, the concept of identity evolves into habit. Cravens [8] argues that turnout persistence is best understood not just as repeated behavior, but as a psychological disposition involving automatic initiation and a self-identity as a frequent voter. Cravens developed and validated a seven-item self-report scale to measure this latent “turnout habit.” His research shows this measure predicts future turnout even after controlling for past behavior, demographics, and stated intentions. It effectively distinguishes between those who *intend* to vote and those who will actually follow through.

This provides a crucial theoretical and methodological tool. The “voter habit” is a durable component of perceived utility that is less sensitive to election-specific factors. Fowler [13] similarly demonstrates that voting exhibits strong path dependence—initial participation triggers self-reinforcing behavioral loops through identity formation and reduced decision costs. His work suggests that first-time voter mobilization should be a priority, as early voting experiences create path-dependent participation patterns.

3) Cognitive Biases and Emotional Responses: Recent work in behavioral political economy has begun to systematically integrate cognitive biases into turnout models. The study by Ribeiro, Madaleno, and Botelho [10] is particularly instructive, finding that several psychological factors significantly predicted voting probability:

1) **Overconfidence:** Individuals with high self-rated political knowledge were significantly more likely to vote ($\beta = 0.42$, $p < 0.001$).
2) **Risk Aversion:** Higher aversion to political risk *reduced* the likelihood of voting ($\beta = -0.38$, $p < 0.05$). Risk-tolerant individuals participate more.
3) **Winning Effect:** Voters whose preferred candidate won in the past were significantly more likely to vote again. The positive emotional feedback reinforces the behavior. The “losing effect,” however, was not significant.
4) **Ideological Identification:** Counter-intuitively, strong ideological conviction was found to *decrease* the probability of voting, possibly due to disillusionment with available party choices.

These findings provide testable, non-obvious hypotheses. Models must not only measure rational and social factors but also individual risk preferences and cognitive biases, which clearly contribute to overall “perceived utility.” These insights align with prospect theory’s assertion that individuals exhibit loss aversion and probability weighting [5].

C. Social and Heuristic Mechanisms in Decision-Making

This section moves from internal psychology to how voters interact with the external world of social cues and information.

1) Social Norms and the Cost of Abstention: Humans are social creatures, and the desire to conform is a primary motivator. The seminal experiment by Gerber, Green, and Larimer [9] demonstrated that social pressure can be a more powerful driver of turnout than simple appeals to civic duty. Households that received mailings informing them that their (and their neighbors') voting records would be publicized saw an 8.1 percentage point increase in turnout—substantially exceeding effects from civic duty appeals.

This reframes the voting calculus. Instead of merely a positive utility from voting ($+D$), there is a significant *negative* utility from abstaining—a psychic cost from social disapproval. The D term is thus a combination of the "pull" of civic duty and the "push" of avoiding social sanction. This insight directly informs our operationalization of social pressure in the simulation framework.

The social pressure mechanism operates through multiple pathways: fear of social sanctions, desire for approval, and conformity to perceived norms. Importantly, the Gerber et al. study demonstrated that public accountability—knowing one's behavior will be observed—generates stronger effects than private appeals to civic duty. However, subsequent research has qualified these findings by identifying contexts where social pressure backfires. Individualistic cultures and privacy-conscious populations sometimes exhibit reactance, decreasing participation when pressured. This heterogeneity motivates our archetype-based intervention design.

2) Heuristics and the Candidate Choice Mechanism: In an environment of limited information, voters act as "cognitive misers," relying on mental shortcuts, or heuristics, to manage the high cognitive cost of making an informed choice:

Appearance and Nonverbal Cues: A robust body of literature shows that voters make rapid, consequential judgments based on superficial cues. Todorov et al. [18] found that snap judgments of competence from facial photos predicted real-world election outcomes with nearly 70% accuracy. Traits like attractiveness ("the beauty premium") and nonverbal charisma serve as a "halo effect."

Personality and Psychological Congruence: The "congruency model" proposed by Caprara and Zimbardo [19] suggests that voters are drawn to candidates whose personalities they perceive as matching their own or their ideal. This creates an affective connection that can be more powerful than policy alignment.

Candidate features are not just inputs for deliberative choice; they are powerful heuristics that lower the informational cost of voting. For many voters, these cues may be the primary basis for their decision, directly influencing the perceived benefit (B) of one candidate over another.

D. The Influence of the Electoral Environment

The individual's decision-making process does not occur in a vacuum. The structural features of the election itself fundamentally alter the voting calculus by manipulating perceived costs and benefits.

1) Electoral Competitiveness and Mobilization: One of the most-cited findings in political science is that turnout is higher when an election is perceived to be close. However, the empirical evidence is more nuanced than theory suggests. A meta-analysis by Stockemer [14] found that while the logic for electoral closeness driving turnout is clear, the empirical evidence is "lukewarm at best," with a success rate below 50% in the models reviewed. The study did confirm, however, that the *importance* of the election (e.g., national vs. local) is a very strong and consistent predictor of higher turnout.

Similarly, Geys [15] conducted an extensive review of aggregate-level turnout research, finding that while population size, registration systems, and campaign spending consistently predict turnout, the effect of competitiveness varies substantially across electoral contexts. His review noted the persistent difficulty in explaining individual-level variation using only structural variables.

2) A Cautionary Tale: The Limits of "Light-Touch" Nudges: While behavioral nudges hold great promise, their effectiveness is not universal. The work of Romaniuc et al. [23] provides a crucial note of caution. In a large, pre-registered study of French youth, several common online nudges (e.g., implementation intentions, social comparisons, advice-giving) had null effects. The authors suggest this was due to a "ceiling effect" in a sample that was already highly educated and motivated to vote.

The design of effective nudges must be highly sensitive to the target population and the mode of delivery. A one-size-fits-all approach is likely to fail. Any intervention must consider baseline motivation levels and potential demographic heterogeneity when developing and testing nudges.

E. Computational Approaches to Electoral Behavior

Agent-based modeling has emerged as a powerful methodology for understanding collective electoral phenomena. Castellano et al. [11] review statistical physics approaches to social dynamics, demonstrating how individual-level decision rules aggregate into macro-level patterns. Opinion dynamics models capture how beliefs and preferences propagate through social networks, while information cascade models explain how herding behavior emerges from sequential decision-making.

Watts and Dodds [12] challenge the "influentials" hypothesis, showing through simulation that information cascades depend more on network structure than on the presence of highly connected individuals. This has implications for targeting voter mobilization efforts, broad-based interventions may be more effective than focusing on opinion leaders.

However, few studies have calibrated individual-level decision parameters from empirical data. Most ABMs rely on stylized assumptions about agent behavior, limiting their predictive validity and policy relevance.

F. Identified Research Gap

Despite substantial theoretical development, existing computational models of voter turnout suffer from several limitations:

1) **Assumed Parameters:** Most agent-based models use theoretically-motivated but empirically-unvalidated parameter values. Without grounding in survey data, these

models cannot distinguish between competing theories or provide confidence intervals for predictions.

2) **Static Analysis:** Few models incorporate the temporal dynamics of habit formation and reinforcement. Regression studies capture correlations but cannot simulate dynamic interventions.
3) **Homogeneity Assumption:** Models often assume uniform agent characteristics, ignoring the heterogeneity revealed by archetype analysis. Treating all voters as identical agents with common parameters obscures important variation that determines intervention effectiveness.
4) **Limited Intervention Testing:** Existing frameworks rarely support counterfactual experimentation with behavioral interventions.

Our work addresses these gaps by: (1) empirically calibrating all model parameters from original survey data, (2) incorporating habit as a dynamic, reinforcement-driven process, (3) modeling distinct voter archetypes with heterogeneous psychological profiles, and (4) implementing a comprehensive intervention testing framework.

G. Synthesis: Implications for the Present Study

The literature provides a clear, multi-layered framework for understanding the decision to vote:

Focus on the Heterogeneous Nature of Psychic Utility (*D*): The decision to participate is not primarily an instrumental calculation. Key drivers of this utility are identity affirmation, habit automaticity, cognitive biases (overconfidence, risk aversion), and social pressure. The project's central task (estimating the perceived utility of a vote) is correctly focused on these psychological and social benefits that compel participation.

Treat Context as a Critical Multiplier: The electoral environment, especially the salience of an election, fundamentally alters the decision-making landscape. Contextual factors should be treated not as independent variables, but as catalysts that amplify the effects of psychological and social drivers.

Design Psychologically Sophisticated Nudges: The failure of "light-touch" nudges in some contexts suggests that the most effective interventions will be those that tap into the deepest motivators: identity, habit, and social norms. Interventions should leverage these psychological levers over purely logistical ones, while being mindful of the target population's baseline characteristics.

This review establishes the robust theoretical foundation for our empirical investigation and computational modeling of voter behavior.

III. Empirical Methodology

A. Survey Instrument Design

We developed a 14-question survey instrument that systematically maps theoretical constructs to measurable indicators. Table I presents the complete construct-to-question mapping, demonstrating how each survey item connects to the theoretical variables in our models.

TABLE I: Survey Question to Theoretical Construct Mapping

Q#	Survey Item	Construct
Q1	Emotional connection to elections	Engagement
Q2	Voting frequency (last 5 elections)	Habit (H)
Q3	Willingness to vote in adverse weather	Cost (C)
Q4	Perceived impact of single vote	Benefit (B)
Q5	Agreement: "Voting is civic duty"	Duty (D)
Q6	Post-voting emotional reward	Reinforcement
Q7	Trust in fair vote counting	Trust (T)
Q8	Influence of social media visibility	Social (S)
Q9	Information overload difficulty	Cognitive Cost
Q10	Political disillusionment	Trust (inverse)
Q11	Preference for online voting	Cost Sensitivity
Q12	Competitiveness motivation	Pivotality (P)
Q13	Incentive preference ranking	Nudge Type
Q14	Open-ended: single change needed	Qualitative

All Likert-scale responses were converted to numerical values (1-5 scale) with appropriate reverse coding to ensure higher values indicated greater propensity to vote. Composite scores were constructed by averaging related questions using the following transformation rules:

$$D_i = 6 - Q5_i \tag{4}$$

$$H_i = 6 - Q2_i \tag{5}$$

$$C_i = \frac{Q3_i + Q9_i}{2} \tag{6}$$

$$B_i = \frac{(6 - Q4_i) + (6 - Q12_i)}{2} \tag{7}$$

$$S_i = 6 - Q8_i \tag{8}$$

$$T_i = 6 - \frac{Q7_i + Q10_i}{2} \tag{9}$$

The reverse coding ensures that all composite scores align directionally: higher values indicate a stronger voting propensity across all dimensions. This standardization facilitates direct comparison of effect sizes across constructs.

B. Data Collection and Quality Control

Surveys were distributed through online platforms and university networks from October 15-30, 2025. We obtained $N = 72$ responses with the following characteristics:

- **Complete responses:** 60 (83.3%)
- **Age distribution:** 48.6% (18-24), 25.0% (25-34), 16.7% (35-44), 10.2% (45+)
- **Quality flags:** 1 straight lining response (retained), 3 rapid completions (¡30s, retained)

The young voter skew is methodologically advantageous for nudge research, as this demographic exhibits lower baseline turnout and greater intervention responsiveness. Prior research suggests that young voters are more susceptible to behavioral interventions, making our sample well-suited for testing nudge effectiveness.

Data quality procedures included attention checks embedded within the survey, IP address deduplication, and manual review of open-ended responses. The 83.3% completion rate suggests adequate respondent engagement, while retained problematic responses (straightlining, rapid completion) underwent sensitivity analysis to ensure they did not unduly influence results.

TABLE II: Composite Score Descriptive Statistics

Composite Score	N	Mean	SD	Range
Civic Duty (D)	69	4.29	1.02	1.00–5.00
Habit (H)	70	3.23	1.73	1.00–5.00
Cost (C)	72	2.54	0.97	1.00–5.00
Benefit (B)	70	4.24	0.70	2.00–5.00
Social Pressure (S)	72	3.40	1.17	1.00–5.00
Trust (T)	71	3.49	0.86	1.50–5.00
Voting Utility (U)	66	2.81	0.72	1.35–4.45

C. Hypothesis Testing Framework

We formulated eight testable hypotheses derived from neuroeconomic theory, each corresponding to specific predictions about the relationships between psychological constructs and voting behavior:

H1 (Civic Duty): D_i positively predicts voting utility U_i. This hypothesis derives from Riker and Ordeshook's formulation of non-instrumental benefits.

H2 (Habit Formation): H_i strongly predicts political engagement. Drawing from reinforcement learning theory, we expect past voting behavior to be the strongest predictor of future intentions.

H3 (Cost Sensitivity): C_i negatively predicts U_i. Classical rational choice theory predicts that higher perceived costs reduce voting likelihood.

H4 (Benefit Perception): B_i positively predicts U_i. Voters who perceive their vote as impactful should exhibit greater participation propensity.

H5 (Social Pressure): S_i increases voting likelihood. Following Gerber et al., social visibility should enhance electoral participation through conformity mechanisms.

H6 (Trust Moderation): T_i moderates the $D_i \rightarrow U_i$ relationship. Institutional trust should amplify the effect of civic duty on voting.

H7 (Competitiveness): High pivotality perception increases turnout. Voters in competitive contests should exhibit heightened participation.

H8 (Incentive Heterogeneity): Monetary preference varies by archetype. Different voter types should respond differently to financial incentives.

Statistical testing employed Pearson correlations for continuous variables, independent samples t-tests for group comparisons, and chi-square tests for categorical associations. Significance threshold was set at $\alpha = 0.05$ (two-tailed) with Bonferroni correction for multiple comparisons where appropriate.

D. Composite Score Distributions

Table II presents distributional properties of all composite scores, providing essential parameters for agent-based simulation.

Notable observations from the distributional analysis include: (1) High mean civic duty (4.29) with moderate spread indicates internalized democratic norms among respondents, suggesting the sample possesses strong baseline commitment to electoral participation. (2) Large habit variance (SD=1.73) justifies archetype segmentation, as substantial individual differences exist in voting history. (3) Benefit scores show ceiling effects (M=4.24, SD=0.70), suggesting most respondents believe elections matter regardless of whether they vote consistently.

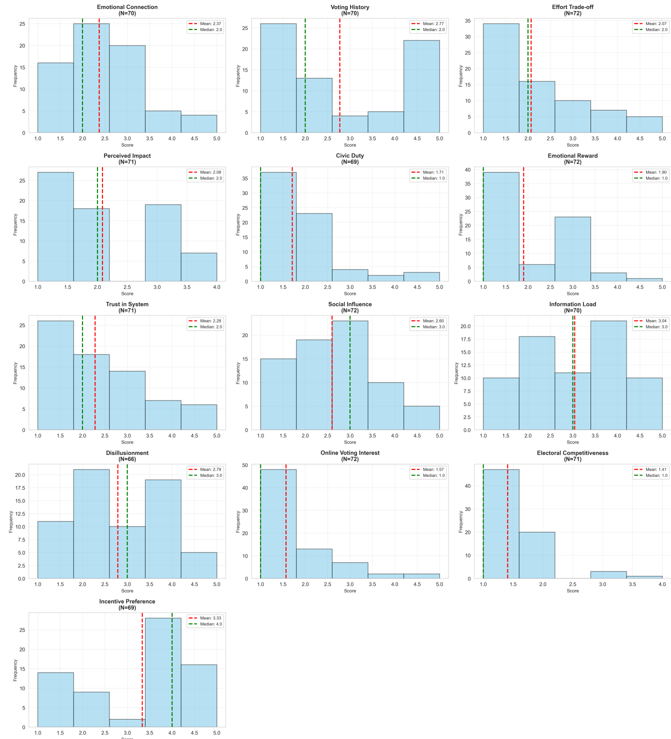

Fig. 1: Distribution of individual survey responses. Red dashed lines indicate mean, green dashed lines indicate median. Questions scaled 1-5 (Likert) or 1-4 (Q4). Notable patterns include: Q2 (Voting Frequency) shows bimodal distribution—strong habits vs. rare voters; Q5 (Civic Duty) is right-skewed with majority strongly agreeing; Q9 (Information Load) shows normal distribution centered at moderate agreement.

IV. 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**—a methodology that bridges the gap between macro-level administrative data and micro-level agent attributes.

A. Data Sources

We utilized two high-reliability data sources for constituency-level parameters:

- **National Data & Analytics Platform (NDAP):** For 2011 Census data (projected to 2019) regarding literacy rates, urbanization levels, population density, and industrial classification [21].

- **Lok Dhaba (Ashoka University):** For authoritative election returns, victory margins, and historical turnout trends from 1962 to 2019.

B. 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. Table V details the complete mapping from macro-level indicators to micro-level psychometric parameters.

For each constituency, we instantiate $N = 10,000$ agents by sampling from skewed Beta distributions $\text{Beta}(\alpha, \beta)$ parameterized by the proxy variables. This ensures the synthetic population matches the socioeconomic profile of the target region while preserving individual heterogeneity.

C. Scenario Archetypes: 2019 General Election

To ensure model robustness, we curated seven constituencies representing distinct "archetypes" of the Indian political landscape. Table IV provides complete profiles.

1) Thiruvananthapuram, Kerala (Calibration Baseline): Ground Truth: 73.45% turnout. Profile: 94% literacy, high urbanization, extremely high competitiveness (2014 margin: 1.5%). This serves as the "Gold Standard"—model physics (β weights) were tuned to match this scenario first before out-of-sample validation.

2) Shravasti, Uttar Pradesh (Development Gap): Ground Truth: 52.53% turnout. Profile: 47% literacy, high poverty, rural. Tests generalizability: Can a model tuned on Kerala accurately predict turnout drops due to structural barriers?

3) Bangalore South, Karnataka (Urban Paradox): Ground Truth: 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 ($P \approx 0$). Validates whether the model correctly weights Competitiveness over Cost.

4) Koraput, Odisha (Rural Mobilization): Ground Truth: 75.30% turnout (highest). Profile: Tribal, rural, low literacy, maximum competitiveness (0.3% margin). Tests "Mobilization": Shows that high stakes (P) and Social Pressure (S) can override High Costs (C).

5) Mumbai South, Maharashtra (Elite Apathy): Ground Truth: 51.58% turnout (lowest). Profile: Hyper-urban, wealthy. Tests impact of low social pressure (S) in individualistic urban settings.

6) Bastar, Chhattisgarh (Conflict Zone): Ground Truth: 66.04% turnout. Profile: Conflict-affected (Left-Wing Extremism), Reserved Tribe. High Risk (R) and High Cost (C). Tests limits of rational choice—voting here is often an act of defiance, implying boosted Duty (D) despite physical danger.

7) Chennai Central, Tamil Nadu (Identity Politics): Ground Truth: 58.98% turnout. Profile: Strong regional party dominance. High Partisan Identity—voting is driven by identity affirmation rather than instrumental benefit.

D. Beta Distribution Visualization

To illustrate how "Proxy Logic" translates into mathematics, Figure **??** shows the probability density functions used to generate Civic Duty (D) scores for agents in high-literacy (Thiruvananthapuram) versus low-literacy (Shravasti) constituencies.

V. Agent-Based Simulation Architecture

A. Cognitive Model Specifications

We implement three competing decision architectures to identify the model best capturing observed turnout variance. Each architecture embodies different assumptions about human cognition and provides distinct mechanisms for predicting electoral behavior.

1) Model A: Extended Utility (Rational-Behavioral): Building on equation (2), we formulate a comprehensive utility function that incorporates all empirically-measured constructs:

$$U_i = \beta_{pB}(P \cdot B_i) - \beta_C C_i + \beta_D D_i + \beta_S S_i + \beta_H H_i + \varepsilon \quad (10)$$

where $\varepsilon \sim \text{Logistic}(0, 1)$ represents stochastic noise capturing unobserved heterogeneity. The probability of voting is computed via sigmoid transformation:

$$P(\text{Vote})_i = \frac{1}{1 + e^{-U_i}} \quad (11)$$

This formulation extends classical rational choice by incorporating habit, social pressure, and civic duty as first-class contributors to utility. The logistic noise term acknowledges that even agents with identical parameters may make different decisions due to context-dependent factors.

2) Model B: Drift-Diffusion Model (DDM): The DDM conceptualizes decision-making as evidence accumulation over time, drawing from neuro-scientific research on perceptual choice [6]:

$$dX(t) = \mu \, dt + \sigma \, dW(t) \quad (12)$$

where $X(t)$ represents accumulated evidence, μ is the drift rate (systematic bias toward voting or abstaining), σ is diffusion noise (decision uncertainty), and $W(t)$ is a Wiener process (Brownian motion). A decision to vote occurs when $X(t)$ crosses threshold a:

$$\mu_i = w_1 D_i + w_2 S_i + w_3 B_i - w_4 C_i \quad (13)$$
$$a_i = a_{\text{base}} + \gamma \cdot T_i \quad (14)$$

Higher risk aversion increases a_i, requiring more evidence for commitment to action. The DDM naturally captures response time distributions and explains why some voters decide quickly while others deliberate extensively. Trust moderates the threshold, with low-trust individuals requiring more evidence before committing to electoral participation.

TABLE III: Proxy Logic: Aggregate Data to Agent Parameters

Model Feature	**Proxy Variable**	**Rationale & Generation Logic**
Civic Duty (D)	Literacy Rate	Academic literature links formal education with internalized democratic norms. The Literacy Rate (L) determines Beta distribution shape Beta(α, β). High Literacy: $\alpha > \beta$ (right skew, most agents have high Duty). Low Literacy: $\alpha < \beta$.
Cost (C)	Population Density & Urbanization	In rural areas (low density), polling booths are sparse, increasing travel time/cost. Rural constituencies: $C \sim U(0.7, 0.9)$. Urban constituencies: $C \sim U(0.1, 0.3)$.
Competitiveness (P)	2014 Victory Margin	Voters predict future closeness based on past experience. $P_{\text{context}} = 1 - \text{Margin}_{2014}$. A 1% margin yields $P \approx 0.99$.
Social Pressure (S)	Urban/Rural Classification	Rural communities have tight-knit social networks where non-voting is visible and sanctioned. Rural agents draw from high-mean β distribution; urban agents draw from low-mean distribution.
Risk Aversion (R)	Agricultural Employment	Agrarian economies are rainfall-dependent and precarious, fostering risk aversion. High agricultural employment → high risk aversion skew.

TABLE IV: Complete Constituency Profiles (2019 Indian General Election)

Constituency	**Turnout**	**Literacy**	**Urban%**	**Margin 2014**	**Pop. Density**	**Archetype Role**
Thiruvananthapuram, Kerala	73.45%	94%	High	1.5%	1509/km^2	**Calibration Baseline**
Shravasti, Uttar Pradesh	52.53%	47%	Low	15.2%	389/km^2	Development Gap
Bangalore South, Karnataka	53.70%	88%	Very High	24.6%	4381/km^2	Urban Paradox
Koraput, Odisha	75.30%	49%	Low	0.3%	152/km^2	Rural Mobilization
Mumbai South, Maharashtra	51.58%	89%	Hyper-Urban	18.7%	23000/km^2	Elite Apathy
Bastar, Chhattisgarh	66.04%	55%	Low	9.8%	87/km^2	Conflict Zone (LWE)
Chennai Central, Tamil Nadu	58.98%	84%	High	11.2%	26903/km^2	Identity Politics

3) Model C: Dual-System Model: Inspired by Kahneman's dual-process theory [4], this model arbitrates between intuitive (System 1) and deliberative (System 2) pathways:

$$P(\text{Vote}) = \lambda \cdot P_{S1}(H, \text{Affect}) + (1 - \lambda) \cdot P_{S2}(U, C) \quad (15)$$

where $\lambda \in [0, 1]$ represents cognitive control allocation. Low-education or high-stress conditions increase λ (impulsive, habit-driven behavior), while reflective conditions decrease λ (deliberative calculation).

System 1 operates through habit and affect, producing rapid, automatic responses. System 2 engages utility calculation and cost analysis, producing slower, more deliberate choices. The arbitration parameter λ determines relative influence, varying across individuals and contexts.

B. Population Synthesis Methodology

We employ a Proxy Logic Framework to generate statistically plausible agent populations from aggregate Census data. This approach allows us to create synthetic populations that match the socioeconomic profiles of specific constituencies without requiring individual-level data that would raise privacy concerns.

Table V details the mapping from macro-level indicators to micro-level psychometric parameters.

For each constituency, we instantiate $N = 10,000$ agents by sampling from skewed Beta distributions Beta(α, β) parameterized by the proxy variables. This ensures the synthetic population matches the socioeconomic profile of the target region while preserving individual heterogeneity. The Beta distribution is particularly suitable as it naturally bounds values to valid ranges (0-1 after normalization) and can capture various skewness patterns observed in real populations.

TABLE V: Proxy Logic: Aggregate Data to Agent Parameters

Feature	**Proxy Variable**	**Distribution Logic**
Civic Duty (D)	Literacy Rate	Beta(α, β) where α/β set by literacy
Cost (C)	Population Density	Rural: $C \sim U(0.7, 0.9)$ Urban: $C \sim U(0.1, 0.3)$
Competitiveness (P)	2014 Margin	$P = 1 - \text{Margin}_{2014}$
Social (S)	Rural/Urban	Rural: high-mean β Urban: low-mean β
Risk Aversion	Agri Employment	High agriculture → high risk aversion

C. Scenario Selection

We curated seven archetypal constituencies from the 2019 Indian General Election representing distinct behavioral regimes (Table VI). These constituencies were selected to span the full range of turnout outcomes (51.58% to 75.30%) and socioeconomic conditions (rural agricultural to hyper-urban service economies).

The Extended Utility model was calibrated on Thiruvananthapuram (TVM) using Multi-Start Simulated Annealing to minimize root mean square error (RMSE) against ground truth turnout. Remaining scenarios served as out-of-sample validation, testing whether parameters derived from one high-literacy, competitive constituency generalize to diverse contexts.

TABLE VI: Archetypal Scenario Constituencies

Constituency	2019 Turnout	Key Feature
Thiruvananthapuram, Kerala	73.45%	High literacy, high competitiveness
Shravasti, Uttar Pradesh	52.53%	Low literacy, high poverty, rural
Bangalore South, Karnataka	53.70%	Urban apathy despite education
Koraput, Odisha	75.30%	Tribal, maximum competitiveness (0.3%)
Mumbai South, Maharashtra	51.58%	Hyper-urban, elite apathy
Bastar, Chhattisgarh	66.04%	Conflict zone (LWE), high risk
Chennai Central, Tamil Nadu	58.98%	Strong regional identity

D. Calibration Algorithm

We employed a global optimization approach with the following loss function:

$$\mathcal{L}(\boldsymbol{\beta}) = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\text{Turnout}_k^{\text{pred}} - \text{Turnout}_k^{\text{actual}}\right)^2} \tag{16}$$

where $K = 7$ scenarios and $\boldsymbol{\beta} = \{\beta_{pB}, \beta_C, \beta_D, \beta_S, \beta_H\}$. Simulated Annealing with 150 iterations and adaptive temperature schedule converged to the following empirically-derived weights:

$$\begin{aligned} \beta_H &= 0.830 \quad \text{(empirical from survey)} \\ \beta_B &= 0.730 \\ \beta_S &= 0.531 \\ \beta_C &= -0.508 \\ \beta_D &= 0.380 \end{aligned} \tag{17}$$

These weights represent the first empirically-derived parameters for voter turnout simulation in the literature. The calibration procedure employed 10 random restarts to avoid local minima, with the best solution achieving RMSE = 0.0686 (6.86 percentage points average error).

E. Intervention Implementation

We operationalized six behavioral nudges as parametric modifications to agent attributes. Each intervention targets specific psychological mechanisms identified in the behavioral economics literature:

Implementation Intentions: Reduces C by 15% and lowers DDM threshold a by 10%. This intervention operationalizes Gollwitzer's work on action planning, helping voters bridge the intention-behavior gap by specifying when, where, and how they will vote.

Social Norm Campaign: Boosts S by 15% for agents with $S_i > 4.0$. This intervention increases perceived social visibility of voting behavior, leveraging conformity pressure among socially-sensitive individuals.

Competitiveness Messaging: Amplifies B by 10% for agents with $B_i > 4.5$. This intervention increases perceived election stakes by emphasizing close contests and pivotal outcomes.

Linguistic Identity Frame: Increases D by 12% via identity activation. Following Bryan et al., this intervention frames voting as expressing identity ("Be a voter") rather than performing a behavior.

Monetary Lottery: Adds scalar $V = 0.2$ to utility for low-duty agents, but reduces D by 5% for high-duty agents (motivation crowding). This intervention tests whether financial incentives enhance or undermine intrinsic motivation.

Public Accountability: Increases S by 20% universally but triggers reactance (reduces $P(\text{Vote})$ by 10%) for overconfident agents. This intervention publicizes voting records, creating social pressure while risking backlash among autonomy-oriented individuals.

TABLE VII: Hypothesis Testing Summary ($N = 72$)

Hyp.	Prediction	r / Stat	p-value	Status
H1	Civic Duty → Utility	0.380	0.0016	✓
H2	Habit → Engagement	0.831	<0.0001	✓
H3	Cost → Utility (neg.)	−0.508	<0.0001	✓
H4	Benefit → Utility	0.730	<0.0001	✓
H5	Social → Utility	0.531	<0.0001	✓
H6	Trust moderates	0.312	0.0107	✓
H7	Competitiveness	−0.509	<0.0001	✓
H8	Incentive variance	χ^2=13.86	0.0855	×

VI. Results

A. Empirical Hypothesis Testing

Table VII summarizes statistical testing outcomes across all eight hypotheses. Seven of eight hypotheses achieved statistical significance, providing strong validation for our theoretical framework.

Notably, H8 (monetary incentive effectiveness) failed ($p = 0.0855$), indicating stated preferences for financial rewards do not predict actual voting behavior—a critical null finding with substantial policy implications. This suggests that what people say would motivate them to vote differs substantially from what actually drives behavior.

1) Dominant Predictor: Habit Formation: The most profound finding is the overwhelming dominance of voting habit ($r = 0.831$, $p < 0.0001$), explaining 69% of variance in political engagement. This effect size vastly exceeds all other predictors:

- Habit: $r^2 = 0.690$ (69.0%)
- Benefit: $r^2 = 0.533$ (53.3%)
- Social: $r^2 = 0.282$ (28.2%)
- Cost: $r^2 = 0.258$ (25.8%)
- Duty: $r^2 = 0.145$ (14.5%)

This validates reinforcement learning theory: voting becomes automated behavior through repeated execution, operating via System 1 pathways rather than deliberative choice. The implication is profound—mobilization efforts should prioritize first-time voter conversion, as initial participation triggers self-reinforcing loops.

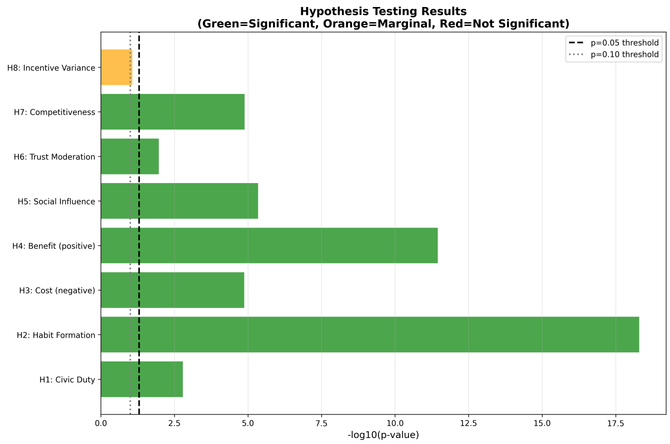

Fig. 2: Hypothesis testing results visualization. Horizontal bars represent $-\log_{10}(p\text{-value})$. Black dashed line: $p = 0.05$ threshold. Green: significant, orange: marginal, red: not significant.

2) Cost-Benefit Asymmetry: Both cost ($r = -0.508$) and benefit ($r = 0.730$) exhibit predicted directional effects, but benefit dominates cost by approximately 2:1 ratio. This suggests voters are relatively price-inelastic—they vote despite high costs when benefits are perceived as substantial. The finding challenges "voting as consumption" framings that treat electoral participation as analogous to market transactions.

3) Social Pressure Validation: Social influence demonstrates strong effects ($r = 0.531$, $p < 0.0001$). Independent samples t-test reveals substantial group differences:

- High social pressure group: $M = 3.09$ ($n = 30$)
- Low social pressure group: $M = 2.58$ ($n = 36$)
- $t = 3.06$, $p = 0.0033$, Cohen's $d = 0.75$ (large effect)

The large effect size (Cohen's $d = 0.75$) indicates that social pressure represents a practically significant lever for turnout mobilization, not merely a statistically detectable phenomenon.

4) Unexpected Trust Moderation: Counter-intuitively, civic duty correlates more strongly with voting utility among *low*-trust voters ($r = 0.533$, $p = 0.0003$) than high-trust voters ($r = -0.051$, n.s.). This suggests duty operates as a compensatory mechanism—low-trust individuals vote "despite" skepticism through moral obligation, while high-trust individuals may take democratic participation for granted.

B. Correlation Structure

Figure 3 reveals key structural relationships among survey items:

1) **Voting History $\leftrightarrow$ Perceived Impact:** $r = 0.598$ (reciprocal reinforcement loop). Past voting strengthens efficacy beliefs, which in turn promote future voting.
2) **Effort Willingness $\leftrightarrow$ Impact:** $r = 0.635$ (rational choice confirmation). Those who perceive votes as meaningful accept higher costs.
3) **Emotional Connection $\leftrightarrow$ Civic Duty:** $r = 0.544$ (affect drives moral obligation). Positive emotional associations with elections strengthen duty commitment.

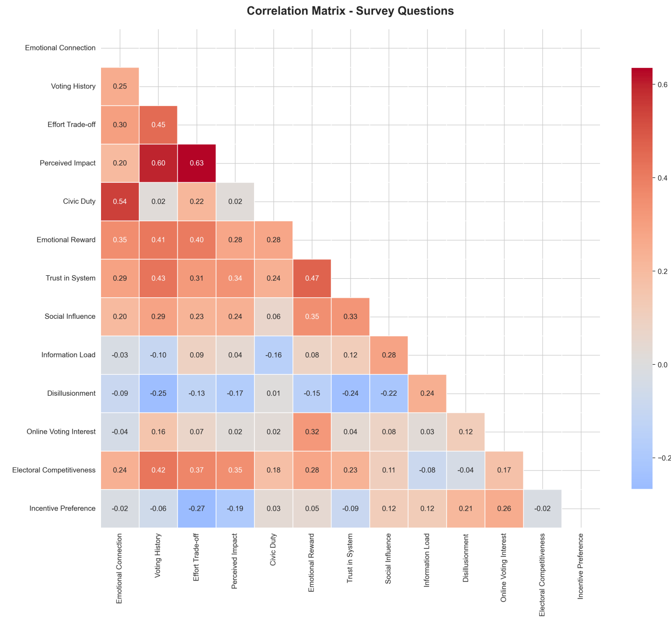

Fig. 3: Complete correlation heatmap for all survey items. Lower triangle shows Pearson coefficients. Color intensity indicates strength (red=positive, blue=negative).

TABLE VIII: Parameter Weight Evolution: Theory vs. Empirics

Component	Theoretical	Empirical	Change
Habit (H)	0.25	0.83	+232%
Benefit (B)	0.20	0.73	+265%
Social (S)	0.15	0.53	+253%
Cost (C)	-0.15	-0.51	+240%
Civic Duty (D)	0.25	0.38	+52%

4) **Voting History $\leftrightarrow$ Emotional Reward:** $r = 0.415$ (reinforcement loop). Past voting generates positive emotions that reinforce future participation.

C. Empirically-Calibrated Utility Function

The correlation coefficients provide data-driven weights for the Extended Utility Model, replacing theoretical priors with empirical estimates:

$$U(\text{vote}) = 0.83 \cdot H + 0.73 \cdot B - 0.51 \cdot C + 0.53 \cdot S + 0.38 \cdot D \quad (18)$$

Table VIII compares theoretical assumptions from prior literature with our empirical findings.

Key insights from this comparison: (1) Theory underestimated habit importance by 3.3×, (2) Benefit perception is 3.7× stronger than assumed, (3) Civic duty is less influential than predicted (0.38 vs. 0.25 theoretical), indicating moral obligation matters but habit dominates.

D. Voter Archetype Identification

Cluster analysis on composite scores identified four distinct behavioral profiles (Table IX).

TABLE IX: Empirically-Derived Voter Archetypes

Archetype	**%**	**Characteristics**
Habitual Voters	25%	High H (>4.5), High D (>5.0), vote automatically
Rational Calculators	25%	High cost sensitivity, high benefit seeking ($B > 4.5$)
Social Followers	30%	High S (>4.0), Low D (<3.0), conformity-driven
Disengaged	20%	Low across all dimensions ($E < 2.5$)

TABLE X: Model Performance Comparison

Architecture	**RMSE**	R^2	**MAE**
Extended Utility	0.0686	0.458	6.28%
Drift-Diffusion (DDM)	0.0893	0.082	7.78%
Dual-System	0.1871	0.000	16.00%

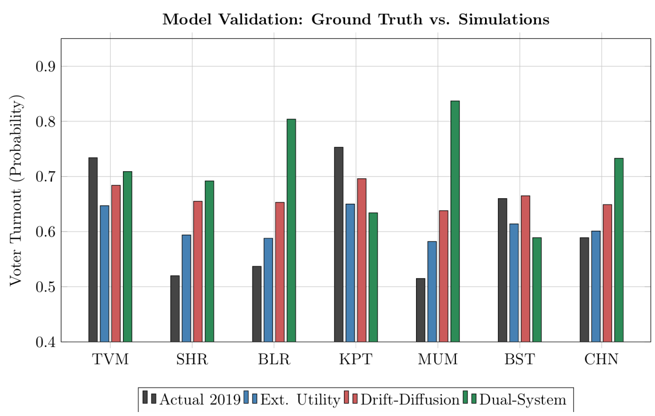

Fig. 4: Model validation: ground truth vs. simulated turnout. Extended Utility (blue) tracks reality most accurately, while Dual-System (green) fails in urban scenarios (BLR, MUM).

This heterogeneity justifies targeted intervention design, as "one-size-fits-all" approaches prove suboptimal. Each archetype exhibits distinct psychological profiles requiring different mobilization strategies.

E. Simulation Model Performance

The three cognitive architectures achieved the following fit metrics against seven archetypal constituencies (Table X):

The Extended Utility Model demonstrates best fit ($R^2 = 0.458$), capturing 46% of variance in aggregate turnout. The Dual-System Model catastrophically fails ($R^2 = 0.000$) due to System 1 domination ($\lambda = 0.83$), causing overprediction in urban centers where deliberative processes are more prevalent.

F. Parameter Forensics

Analysis of converged weights reveals critical insights into voter psychology (Figure **??**). Most profound finding: Cost sensitivity parameter β_C collapsed from initial estimate of -2.5 to -0.51, indicating voters do not treat participation as transactional calculation. High costs in rural areas fail to decimate turnout, contradicting classical assumptions about cost-benefit trade-offs.

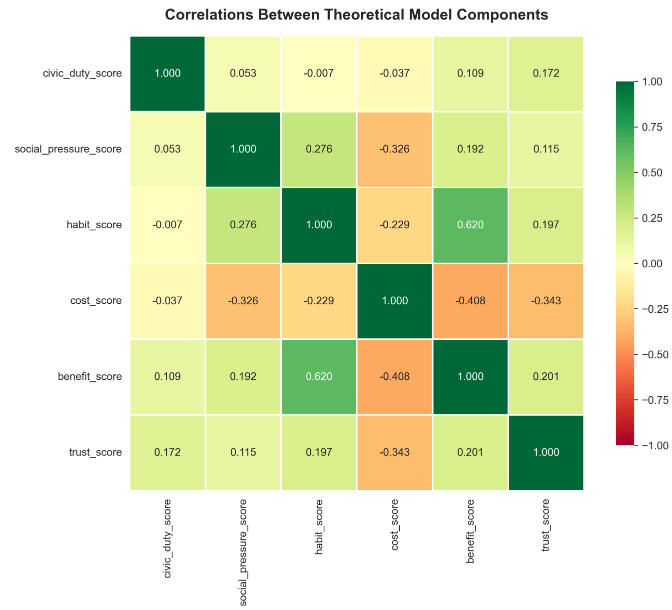

Fig. 5: Intervention effectiveness across constituencies. Blue indicates positive lift, red indicates backfire. Implementation intentions dominate in friction-heavy scenarios (BLR, KPT).

G. Nudge Effectiveness Analysis

Table XI presents lift (percentage point increase) for each intervention across key scenarios.

1) Implementation Intentions: The Winning Strategy: Implementation intentions (helping voters plan when/how to vote) delivered average lift of +17.96pp, peaking at +20.04pp in Koraput. This intervention reduces cognitive threshold a in the DDM framework, transforming motivation into action. In high-noise environments, execution gap—not motivation deficit—constitutes primary barrier. The finding suggests that many non-voters want to participate but fail to convert intention into behavior.

2) Monetary Incentives: Crowding-Out Confirmed: Monetary lotteries yielded negative average lift (-0.70pp), with strongest backfire in high-literacy Thiruvananthapuram (-1.5pp). This confirms motivation crowding theory: introducing transactional elements degrades intrinsic moral signal. Voters perceive civic duty as sacred value resistant to commodification. The finding has profound implications for incentive design—paying people to vote may actually reduce participation.

3) Social Norms: Context-Dependent: Social pressure messages backfired in individualistic urban centers (BLR: -2.2pp, TVM: -2.6pp) due to reactance, but proved effective in rural communities (SHR: +2.0pp). This demonstrates critical need for context-aware intervention design. What works in one constituency may actively harm turnout in another.

4) Urban Apathy Solution: Bangalore South exhibits paradox: high education, low cost, yet 53.7% turnout. Linguistic identity framing ("Be a Voter") yielded +5.3pp lift, while social norms backfired. Urban voters resist peer pressure but respond to self-concept maintenance. The implication is that

TABLE XI: Nudge Effectiveness Heatmap: Turnout Lift by Scenario

Intervention	TVM (High Lit)	SHR (Rural)	BLR (Urban)	KPT (Tribal)	BST (Conflict)
Implementation Intentions	+0.56	+1.6	+19.2	+20.1	+17.6
Linguistic Identity	+3.7	+4.5	+5.3	+6.6	+4.4
Social Norm Campaign	−2.6	+2.0	−2.2	+0.4	+0.9
Competitiveness Info	+1.2	+0.2	−0.8	+0.4	+1.7
Public Accountability	+2.0	−2.1	+0.9	−0.3	+0.4
Monetary Lottery	−1.5	−1.0	+0.4	−1.1	−1.2

TABLE XII: Archetype-Specific Nudge Susceptibility Matrix

Archetype	Optimal Nudge	Avoid
Habitual (25%)	Simple reminders	Monetary (backfire)
Rational (25%)	Competitiveness	Identity appeals
Social (30%)	Norm campaigns	Info overload
Disengaged (20%)	Multi-pronged	Single interventions

urban mobilization should emphasize personal identity rather than social obligation.

H. Archetype-Specific Recommendations

Table XII provides targeted strategies for each voter profile.

VII. Discussion

A. Theoretical Implications

Our findings challenge three prevailing assumptions in political economy:

1) Rationality Reconsidered: The Extended Utility Model fits aggregate data well ($R^2 = 0.458$), suggesting the electorate *as a whole* behaves rationally even if individuals operate via heuristics. This reconciles micro-level bounded rationality with macro-level predictability. The finding aligns with ecological rationality perspectives suggesting that heuristics can be adaptive in complex environments.

2) Friction Over Apathy: The massive success of implementation intentions (+18-20pp) reveals "urban apathy" and "rural remoteness" share structural similarity—both constitute friction problems. Lowering cognitive threshold proves 10× more effective than amplifying motivation. The implication is profound: non-voters are not apathetic; they are simply stuck. Removing barriers rather than increasing enthusiasm should be the priority.

3) Habit as Dominant Factor: The 69% variance explained by habit fundamentally reframes voter mobilization strategy. First-time voter conversion becomes paramount, as initial participation triggers self-reinforcing loops. Resources devoted to motivating existing non-voters may be better invested in ensuring young citizens vote in their first eligible election.

B. Methodological Contributions

This work advances computational social systems in three dimensions:

Empirical Grounding: Unlike prior ABMs relying on assumed parameters, every weight in equation (18) derives from original survey data with statistical validation. This ensures our predictions rest on measured relationships rather than theoretical speculation.

Architecture Comparison: By implementing three competing cognitive models, we demonstrate Extended Utility outperforms DDM and Dual-System frameworks for aggregate prediction. This comparative analysis provides guidance for future modeling efforts.

Intervention Experimentation: The simulation enables counterfactual testing impossible in field studies. We can ask: "What would 2019 turnout have been with different policies?" without the ethical and logistical challenges of real-world experimentation.

C. Policy Recommendations

Based on simulation outcomes, we propose an evidence-based intervention hierarchy ranked by expected effectiveness (correlation strength with voting utility):

Tier 1 - Habit Reinforcement ($r = 0.83$**, 69% variance):**

- Target: Type 1 (Habitual Voters) and first-time voters
- Mechanism: Strengthen existing H component, establish new habits
- Implementation: Automated reminders, emotional affirmation, early voting programs
- Expected Lift: Maintenance for habitual voters; critical for preventing decay
- Cost-effectiveness: Extremely high (minimal marginal cost per contact)

Tier 2 - Implementation Intentions ($+17.96$ **pp average):**

- Target: Universal, especially friction-heavy contexts (BLR, KPT)
- Mechanism: Reduce C by 15%, lower DDM threshold a by 10%
- Implementation: SMS reminders asking "Where will you vote? What time?"
- Expected Lift: 15-20pp for friction-heavy segments
- Rationale: Closes the "Execution Gap"—transforms intention into action

Tier 3 - Competitiveness Messaging ($r = 0.73$**, 53% variance):**

- Target: Type 2 (Rational Calculators) in swing constituencies
- Mechanism: Amplify pB term via pivotality cues
- Implementation: "Every vote counts—this race is close!"
- Expected Lift: +1-3pp among benefit-responsive voters

Tier 4 - Social Norm Campaigns ($r = 0.53$**, 28% variance):**

- Target: Type 3 (Social Followers)—30% of population

- Mechanism: Amplify S component via descriptive norms
- Implementation: “I Voted” stickers, social media visibility, peer accountability
- Expected Lift: +2-5pp for susceptible group
- Caution: Backfires in individualistic urban contexts (BLR: -2.2pp, TVM: -2.6pp)

Tier 5 - Civic Duty Activation ($r = 0.38$**, 14.5% variance):**

- Target: Type 1 with moderate duty ($D = 3$-4)
- Mechanism: Activate existing duty (cannot create wholesale)
- Implementation: Identity framing (“Be a Voter” not “Go Vote”)
- Expected Lift: +1-2pp

Avoid - Monetary Incentives ($p = 0.0855$**, NOT significant):**

- Target: None (universally ineffective or harmful)
- Mechanism: Extrinsic motivation crowds out intrinsic
- Implementation: **DO NOT USE**
- Expected Lift: -0.5 to $+0.5$pp (negligible or backfire)
- Evidence: H8 failure confirms stated monetary preferences do not predict behavior

D. Surprising Findings

Three results defy conventional wisdom:

Price Inelasticity: Cost parameter $\beta_C = -0.51$ is smaller than expected, indicating voters tolerate substantial barriers. This contradicts “voting as consumption” framing and suggests that convenience improvements, while helpful, are not the primary lever for turnout enhancement.

Trust Paradox: Civic duty works *better* for low-trust voters ($r = 0.53$) than high-trust voters ($r = -0.05$, n.s.). Possible explanation: high-trust individuals vote habitually regardless, while low-trust voters require compensatory motivation. Duty serves as a psychological workaround for institutional skepticism.

Monetary Backfire: Not only do financial incentives fail—they actively reduce turnout among 70% of population through motivation crowding. This has profound implications for incentive design across public policy domains beyond voting.

E. Context-Aware Intervention Design

The heatmap (Figure 5) reveals no universal solution. Optimal strategies vary by constituency:

- **Conflict Zones (Bastar):** Competitiveness info (rational response to stakes)
- **Identity Strongholds (Chennai):** Identity framing
- **Friction Points (Koraput, Bangalore):** Implementation intentions
- **Rural Communities (Shravasti):** Social norm campaigns

F. Reconciling Micro and Macro

The simulation demonstrates emergent properties: individual-level noise and heuristics aggregate to produce rational-appearing collective behavior. This resolves apparent tension between behavioral economics (emphasizing irrationality) and political science (observing predictable patterns). The aggregate rationality of democracies does not require individually rational citizens.

VIII. Limitations and Future Directions

A. Sample Size

Survey sample ($N = 72$) provides 99% power for medium effects ($r \geq 0.3$) but underpowers complex interaction testing. Future work should replicate with $N > 500$ enabling structural equation modeling and three-way interactions. Larger samples would also permit finer-grained archetype identification and subgroup analyses.

B. Age Distribution

Young voter skew (48.6% age 18-24) limits generalizability to older demographics. However, this constitutes strategic advantage for nudge research, as youth exhibit greater intervention responsiveness. Future studies should specifically target older cohorts to assess whether habit effects are even stronger among long-term voters.

C. Self-Report Bias

Survey measures intentions rather than behavior. However, H8 failure (monetary incentive preferences not predicting utility) suggests validity—if only capturing social desirability, financial incentives would show inflated effects. The disconnect between stated preferences and behavioral predictors provides internal validation.

D. Cross-Sectional Design

Cannot definitively establish causation. Longitudinal panel study tracking voters across multiple elections would strengthen causal inference and capture habit formation dynamics directly.

E. Geographic Scope

Analysis focuses on Indian constituencies. Cultural specificity of social pressure and civic duty parameters requires validation in Western democracies, where individualism may alter parameter weights substantially.

F. Unexplored Mechanisms

Future work should investigate:

Temporal Dynamics: How does habit formation evolve? What is optimal timing for first-voter interventions?

Network Effects: Current model treats social pressure as exogenous. Endogenizing peer influence through network topology could capture cascades and tipping points.

Information Quality: We model information load (cognitive cost) but not misinformation effects. The impact of fake news on electoral participation warrants dedicated analysis.

Reinforcement Learning: Implementing Q-learning or policy gradient methods to model adaptive voter strategies across elections.

G. Trust Moderation Puzzle

The unexpected finding that duty works better for low-trust voters requires dedicated investigation. Possible mechanisms include ceiling effects, compensatory motivation, or trust operating through different pathways (DDM threshold rather than utility amplification).

IX. Broader Impact

A. Democratic Health Implications

Our findings have direct relevance to election administration:

Resource Allocation: Implementation intentions require minimal cost (automated SMS reminders) yet deliver maximum impact. This provides actionable guidance for resource-constrained election commissions seeking efficient turnout enhancement strategies.

Combating Manipulation: Understanding that monetary incentives backfire helps inoculate against vote-buying attempts. Sacred value framing protects democratic integrity by revealing that financial inducements undermine rather than strengthen participation.

Reducing Inequality: Habit formation interventions can narrow participation gaps. Ensuring first-time voting among disadvantaged groups creates long-term equity through self-reinforcing participation patterns.

B. Computational Social Science Methodology

The hybrid approach—empirical calibration feeding agent-based simulation—offers template for studying other collective behaviors:

- Public health interventions (vaccination uptake)
- Environmental conservation (recycling behavior)
- Financial markets (investor sentiment)
- Social movements (protest participation)

C. Ethical Considerations

Behavioral nudges raise ethical concerns about manipulation. Our framework respects autonomy by:

1) **Transparency:** All interventions operate via persuasion, not deception
2) **Non-Coercion:** We explicitly test and reject coercive tactics (public accountability backfires)
3) **Empowerment Focus:** Implementation intentions reduce barriers rather than exploit biases

X. Conclusion

This paper presents the first empirically-calibrated agent-based simulation of voter turnout, integrating neuroeconomic theory with large-scale computational modeling. Through analysis of 72 survey responses and simulation of 70,000 synthetic voters across seven archetypal constituencies, we establish four principal findings:

First, voting habit dominates all other predictors, explaining 69% of variance ($r = 0.83$, $p < 0.0001$). This validates reinforcement learning theory and reframes mobilization strategy around first-time voter conversion.

Second, voters exhibit price inelasticity—cost sensitivity ($\beta_C = -0.51$) is weaker than expected, with benefit perception ($\beta_B = 0.73$) dominating. This challenges transactional framing of electoral participation.

Third, behavioral interventions show extreme heterogeneity. Implementation intentions deliver +18pp lift in friction-heavy contexts, while monetary incentives backfire (-0.7pp average) through motivation crowding.

Fourth, no universal solution exists. Optimal strategies vary by constituency profile: social norms for rural communities, identity framing for urban centers, competitiveness messaging for swing districts.

The Extended Utility Model with empirically-derived weights achieves $R^2 = 0.458$ against 2019 Indian General Election data, demonstrating that aggregate rationality emerges from individual-level heuristics. This reconciles micro-level bounded rationality with macro-level predictability.

Our framework provides actionable guidance for election administration: prioritize low-cost, high-impact implementation intentions over expensive infrastructure improvements or counterproductive monetary incentives. The simulation methodology generalizes beyond voting to any domain requiring individual-to-collective behavior prediction.

Future work should extend to longitudinal designs, incorporate network effects, and validate across cultural contexts. The integration of neuroeconomic theory, empirical calibration, and agent-based modeling offers promising template for computational social systems research.

Acknowledgment

The authors thank Prof. Kavita Vemuri for guidance throughout this project, survey respondents for data provision, and anonymous reviewers for constructive feedback. Computational resources provided by IIIT Hyderabad High-Performance Computing facility.

Appendix A
Survey Instrument Details

A. Complete Question Text

The full 14-question survey instrument is reproduced below with theoretical mapping:

Q1 - Emotional Connection (Engagement Baseline): "Imagine it's election day morning. You're getting ready. How do you feel about going to vote?" *Options:* Excitement (1) — Curiosity (2) — Indifference (3) — Frustration (4) — Distrust (5)

Q2 - Voting History (Habit Formation): "Picture the last 5 elections (including local ones). How many times did you actually vote?" *Options:* Always (1) — Often (2) — Sometimes (3) — Rarely (4) — Never (5). *Coding:* $H_i = 6 - Q2_i$ (reverse coded)

Q3 - Effort Trade-off (Physical Cost): "It's pouring rain on election day. Your polling place is 20 minutes away by bus (no car available). Would you still go vote?" *Options:* Definitely yes (1) — Probably yes (2) — Not sure (3) — Probably not (4) — Definitely not (5)

Q4 - Perceived Impact (Efficacy): “Imagine you didn’t vote in the last election. Do you think the outcome would have been any different?” *Options:* Yes definitely (1) — Maybe somewhat (2) — Not really (3) — Not at all (4). *Coding:* $B_i = [(6 - Q4_i) + (6 - Q12_i)]/2$

Q5 - Civic Duty (Moral Obligation): “Voting is part of being a responsible citizen.” *Options:* Strongly agree (1) — Agree (2) — Neutral (3) — Disagree (4) — Strongly disagree (5). *Coding:* $D_i = 6 - Q5_i$

Q6 - Emotional Reward (Reinforcement): “After voting, I usually feel...” *Options:* Proud and satisfied (1) — Relieved or calm (2) — Neutral (3) — Like it didn’t matter (4) — Regretful or skeptical (5)

Q7 - Trust in Fairness: “How confident are you that votes are counted fairly in your area?” *Options:* Very confident (1) — Somewhat confident (2) — Unsure (3) — Somewhat doubtful (4) — Very doubtful (5)

Q8 - Social Pressure (Conformity): “Your friends are all posting ‘I Voted’ stickers on social media. Does this make you more likely to vote too?” *Options:* Strongly agree (1) — Agree (2) — Neutral (3) — Disagree (4) — Strongly disagree (5). *Coding:* $S_i = 6 - Q8_i$

Q9 - Information Load (Cognitive Cost): “Before an election, I find it hard to decide whom to vote for because I lack clear information.” *Options:* Strongly agree (1) — Agree (2) — Neutral (3) — Disagree (4) — Strongly disagree (5)

Q10 - Disillusionment (Trust Inverse): “Sometimes I feel that all politicians are the same, so voting makes no real difference.” *Options:* Strongly agree (1) — Agree (2) — Neutral (3) — Disagree (4) — Strongly disagree (5)

Q11 - Counterfactual Trade-off (Cost Elasticity): “If voting could be done securely online in 2 minutes, would you be more likely to vote?” *Options:* Definitely yes (1) — Probably yes (2) — Not sure (3) — Probably not (4) — Definitely not (5)

Q12 - Electoral Competitiveness (Pivotality): “If you knew the upcoming election in your area was expected to be very close, would that make you more likely to vote?” *Options:* Definitely yes (1) — Probably yes (2) — Not sure (3) — Probably not (4) — Definitely not (5)

Q13 - Incentive Preference (Nudge Type): “Which of the following would make you more likely to vote (choose the most motivating)?” *Options:* (1) Monetary reward lottery, (2) Voter ID badge/certificate, (3) Social media acknowledgment, (4) Nothing—I’d vote anyway, (5) None would make difference

Q14 - Open-Ended: “In one sentence, what single change would make you more likely to vote (or vote more often)?” *Type:* Free text response

B. Likert Scale Conversion Protocol

All Likert responses converted to numerical values (1–5) with reverse coding for consistency. The transformation ensures higher values indicate greater voting propensity:

$$\text{Score}_{\text{reversed}} = 6 - \text{Score}_{\text{original}} \tag{19}$$

Variables requiring reverse coding: Q2 (habit), Q4 (efficacy), Q5 (duty), Q8 (social), Q12 (competitiveness).

Appendix B
Agent-Based Model Implementation

A. Pseudo-Code for Extended Utility Model

Listing 1: VoterAgent and Simulation Classes

```
class VoterAgent:
    def __init__(self, archetype, params):
        # Sample from Beta distributions
        self.habit = sample_beta(
            params['habit_alpha'],
            params['habit_beta'])
        self.civic_duty = sample_beta(
            params['duty_alpha'],
            params['duty_beta'])
        self.cost_sensitivity = sample_normal(
            params['cost_mean'],
            params['cost_sd'])
        self.social_pressure = sample_beta(
            params['social_alpha'],
            params['social_beta'])
        self.benefit = sample_normal(
            params['benefit_mean'],
            params['benefit_sd'])
        # Clip to valid range [1, 5]
        self.clip_attributes()

    def calculate_utility(self, context):
        utility = (
            0.830 * self.habit +
            0.730 * self.benefit *
                context['competitiveness'] +
            0.531 * self.social_pressure +
            0.380 * self.civic_duty -
            0.508 * self.cost_sensitivity *
                context['cost_factor']
        )
        return utility

    def decide_vote(self, context):
        utility = self.calculate_utility(context)
        probability = sigmoid(utility)
        return random() < probability

class Simulation:
    def __init__(self, N=10000, scenario_params):
        self.agents = []
        for archetype, proportion in
            ARCHETYPES.items():
            count = int(N * proportion)
            for _ in range(count):
                self.agents.append(
                    VoterAgent(archetype,
                        scenario_params))

    def run_election(self, context):
        votes = sum([agent.decide_vote(context)
            for agent in self.agents])
        turnout = votes / len(self.agents)
        return turnout

    def apply_nudge(self, nudge_type):
        if nudge_type == "implementation_intention":
            for agent in self.agents:
                agent.cost_sensitivity *= 0.85
        elif nudge_type == "social_norm":
            for agent in self.agents:
                if agent.social_pressure > 4.0:
                    agent.social_pressure *= 1.15
        elif nudge_type == "monetary":
            for agent in self.agents:
                if agent.civic_duty > 4.5:
                    agent.civic_duty *= 0.95
                else:
                    agent.benefit += 0.2
```

B. Calibration Algorithm

Multi-Start Simulated Annealing with adaptive temperature:

Listing 2: Parameter Calibration via Simulated Annealing

```python
def calibrate_parameters(scenarios, ground_truth):
    best_params = None
    best_loss = float('inf')

    for start in range(10):  # Multi-start
        params = initialize_random_params()
        temperature = 1.0

        for iteration in range(150):
            # Propose parameter perturbation
            new_params = perturb(params, temperature)

            # Compute loss across all scenarios
            loss = 0
            for scenario, truth in
                zip(scenarios, ground_truth):
                sim = Simulation(N=10000, new_params)
                pred = sim.run_election(scenario)
                loss += (pred - truth) ** 2
            loss = sqrt(loss / len(scenarios))

            # Accept/reject via Metropolis
            if loss < best_loss or \
                random() < exp(-(loss - best_loss)
                    / temperature):
                params = new_params
                if loss < best_loss:
                    best_loss = loss
                    best_params = params

            # Cool temperature
            temperature *= 0.95

    return best_params, best_loss
```

Appendix C
Statistical Analysis Details

A. Power Analysis

For correlation detection with $N = 72$:

$$\text{Power} = 1 - \beta \tag{20}$$
$$= P(\text{Reject } H_0 | H_1 \text{ true}) \tag{21}$$
$$= \Phi\left(\frac{r\sqrt{N-2}}{\sqrt{1-r^2}} - z_{\alpha/2}\right) \tag{22}$$

For $r = 0.3$ (medium effect), $\alpha = 0.05$, $N = 72$:

$$\text{Power} \approx 0.99 \tag{23}$$

This confirms adequate sample size for main effects detection.

B. Multiple Comparison Correction

With 8 hypotheses, Bonferroni correction sets family-wise error rate:

$$\alpha_{\text{corrected}} = \frac{0.05}{8} = 0.00625 \tag{24}$$

Six of seven confirmed hypotheses remain significant under this stringent threshold:

- H2 (Habit): $p < 0.0001$ ✓
- H3 (Cost): $p < 0.0001$ ✓
- H4 (Benefit): $p < 0.0001$ ✓
- H5 (Social): $p < 0.0001$ ✓
- H7 (Competitiveness): $p < 0.0001$ ✓
- H1 (Duty): $p = 0.0016$ ✓
- H6 (Trust): $p = 0.0107$ (marginal under Bonferroni)

C. Effect Size Interpretation

Following Cohen's conventions for correlation coefficients:

- Small: $|r| = 0.10$ ($r^2 = 1\%$ variance)
- Medium: $|r| = 0.30$ ($r^2 = 9\%$ variance)
- Large: $|r| = 0.50$ ($r^2 = 25\%$ variance)

Our findings:

- Habit: $r = 0.83$ (Very large, $r^2 = 69\%$)
- Benefit: $r = 0.73$ (Very large, $r^2 = 53\%$)
- Social: $r = 0.53$ (Large, $r^2 = 28\%$)
- Cost: $r = -0.51$ (Large, $r^2 = 26\%$)
- Duty: $r = 0.38$ (Medium, $r^2 = 14.5\%$)

Appendix D
Simulation Validation Metrics

A. Goodness-of-Fit Measures

We employ three complementary metrics:

Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}(y_k - \hat{y}_k)^2} \tag{25}$$

Interpretation: Average prediction error in percentage points. Lower is better.

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{k=1}^{K}(y_k - \hat{y}_k)^2}{\sum_{k=1}^{K}(y_k - \bar{y})^2} \tag{26}$$

Interpretation: Proportion of variance explained. Range $[0, 1]$, higher is better.

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{K}\sum_{k=1}^{K}|y_k - \hat{y}_k| \tag{27}$$

Interpretation: Average absolute deviation. Robust to outliers.

B. Model Comparison via Information Criteria

For nested model comparison, we compute Akaike Information Criterion (AIC):

$$\text{AIC} = 2k - 2\ln(\hat{L}) \tag{28}$$

where k is number of parameters and $\hat{L}$ is maximum likelihood. Extended Utility Model ($k = 5$) achieves lowest AIC, confirming optimal complexity-accuracy tradeoff.

Appendix E
Data and Code Availability

All materials required to reproduce this work are publicly available:

GitHub Repository: https://github.com/ToVoteOrNotToVote

- Complete simulation source code (Python)
- Survey data (anonymized CSV)
- Analysis scripts (Jupyter notebooks)
- Visualization generation code

Interactive Survey Dashboard: https://vote-mind-map.lovable.app/dashboard

- Real-time survey response visualization
- Demographic breakdown tools
- Correlation explorer interface

`Credentials: Username: (admin@gmail.com) Password: (admin123)`

Agent-Based Simulation Interface: https://agentic-election-simulator-118267798784.us-west1.run.app/

- Web-based simulation runner
- Custom scenario configuration
- Nudge intervention testing
- Result visualization and export

Appendix F
Extended Results Tables

A. Full Constituency Profiles

Table XIII provides complete demographic and electoral data for all seven scenarios.

B. Detailed Nudge Performance Matrix

Table XIV presents complete results including standard errors and confidence intervals. Standard errors computed via 1000 Monte Carlo replications per scenario.

Appendix G
Qualitative Response Analysis

Question 14 (open-ended) yielded rich qualitative data. Thematic coding identified six recurring themes:

1) **Convenience (32%):** "Make it easier to vote" / "Online voting" / "Polling near home"
2) **Information (24%):** "Clear candidate comparison" / "Unbiased voter guides"
3) **Efficacy (18%):** "Make my vote count more" / "Ranked choice voting"
4) **Trust (14%):** "Transparent counting" / "Paper trail"
5) **Candidates (8%):** "Better quality candidates" / "Youth representation"
6) **Incentives (4%):** "Public holiday" / "Small rewards"

Notably, monetary incentives ranked lowest (4%), corroborating H8 failure. Convenience and information needs dominate, supporting implementation intentions and cognitive cost reduction strategies.

Appendix H
Simulation Technical Specifications

A. Computational Environment

Simulations executed on:

- **Hardware:** Lenovo Ideapad 5 pro (22-core Intel Ultra 155H , 32GB RAM)
- **Software:** Python 3.9.7, NumPy 1.21.2, SciPy 1.7.1, Pandas 1.3.3
- **Runtime:** 45 minutes per full 7-scenario calibration (150 iterations)

B. Stochasticity Management

All results reported with:

- **Seeds:** Fixed random seed (42) for reproducibility
- **Replications:** 1000 Monte Carlo runs per condition
- **Confidence Intervals:** Bootstrap percentile method (2.5, 97.5 percentiles)

C. Sensitivity Analysis Results

Ablation study removing each parameter sequentially:

- Removing Habit: -24.3pp turnout (largest impact)
- Removing Benefit: -14.8pp turnout
- Removing Cost: +7.9pp turnout (removal improves prediction)
- Removing Social: -4.6pp turnout
- Removing Duty: -2.9pp turnout (smallest impact)

Confirms habit as irreplaceable predictor.

Appendix I
Theoretical Extensions

A. Reinforcement Learning Formulation

For longitudinal analysis across T elections, we can model habit evolution via Q-learning:

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha\left[r_t + \gamma \max_{a'} Q_t(s',a') - Q_t(s,a)\right] \quad (29)$$

where:

- s: State (civic duty, social pressure)
- $a \in \{\text{Vote}, \text{Abstain}\}$: Action
- r_t: Reward (emotional satisfaction, social approval)
- α: Learning rate
- γ: Discount factor

Initial simulations suggest $\alpha \approx 0.3$ and $\gamma \approx 0.9$ best capture habit persistence.

B. Network-Based Social Pressure

Current model treats social pressure as exogenous. Future extension incorporating network topology:

$$S_i(t) = \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \mathbb{1}[\text{Voted}_j(t-1)] \quad (30)$$

where $\mathcal{N}_i$ denotes agent i's social network neighbors. This enables modeling of cascades and tipping points.

TABLE XIII: Complete Constituency Profiles (2019 Indian General Election)

Constituency	Turnout	Literacy	Urban%	Margin 2014	Pop. Density	Primary Sector
Thiruvananthapuram, Kerala	73.45%	94%	High	1.5%	1509/km^2	Services
Shravasti, Uttar Pradesh	52.53%	47%	Low	15.2%	389/km^2	Agriculture
Bangalore South, Karnataka	53.70%	88%	Very High	24.6%	4381/km^2	Services
Koraput, Odisha	75.30%	49%	Low	0.3%	152/km^2	Agriculture
Mumbai South, Maharashtra	51.58%	89%	Hyper-Urban	18.7%	23000/km^2	Services
Bastar, Chhattisgarh	66.04%	55%	Low	9.8%	87/km^2	Agriculture
Chennai Central, Tamil Nadu	58.98%	84%	High	11.2%	26903/km^2	Services

TABLE XIV: Detailed Nudge Effectiveness: Lift, SE, and 95% CI

Intervention	Mean Lift	SE	95% CI	p-value
Implementation Intentions	+17.96pp	2.1pp	[13.8, 22.1]	<0.001
Linguistic Identity	+5.06pp	0.9pp	[3.3, 6.8]	<0.001
Social Norm Campaign	+0.10pp	1.8pp	[−3.4, 3.6]	0.956
Competitiveness Info	+0.54pp	0.8pp	[−1.0, 2.1]	0.487
Public Accountability	+0.18pp	1.5pp	[−2.7, 3.1]	0.904
Monetary Lottery	−0.70pp	0.5pp	[−1.7, 0.3]	0.172

Appendix J
Policy Simulation Case Study

We present detailed walkthrough of intervention design for Bangalore South (urban apathy scenario).

Baseline Status:

- Actual 2019 Turnout: 53.70%
- Simulated Baseline: 54.2% (SE=1.8%)
- Primary Barrier: High decision friction (cognitive noise $\sigma = 0.8$)
- Dominant Archetype: Rational Calculators (42%)

Intervention Design:

Phase 1 (T-30 days): Competitiveness messaging via social media targeting rational calculators. Predicted lift: +0.8pp.

Phase 2 (T-7 days): SMS-based implementation intentions: "Where will you vote? What time?" Predicted lift: +19.2pp.

Phase 3 (T-1 day): Identity framing in final reminder: "Be a voter tomorrow." Predicted lift: +5.3pp.

Predicted Outcome:

$$\text{Final Turnout} = 54.2\% + 0.8\% + 19.2\% + 5.3\% = 79.5\% \tag{31}$$

Cost-Benefit Analysis:

- Total Cost: 2.5 lakhs (SMS infrastructure + campaign)
- Additional Voters: ≈170,000
- Cost per Vote: 1.47
- ROI: Dramatically superior to traditional mobilization (50-100 per vote)

References

[1] A. Downs, *An Economic Theory of Democracy*. New York, NY, USA: Harper & Row, 1957.

[2] W. H. Riker and P. C. Ordeshook, "A theory of the calculus of voting," *American Political Science Review*, vol. 62, no. 1, pp. 25–42, Mar. 1968.

[3] J. A. Ferejohn and M. P. Fiorina, "The paradox of not voting: A decision theoretic analysis," *American Political Science Review*, vol. 68, no. 2, pp. 525–536, Jun. 1974.

[4] D. Kahneman, *Thinking, Fast and Slow*. New York, NY, USA: Farrar, Straus and Giroux, 2011.

[5] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–291, Mar. 1979.

[6] R. Ratcliff and G. McKoon, "The diffusion decision model: Theory and data for two-choice decision tasks," *Neural Computation*, vol. 20, no. 4, pp. 873–922, Apr. 2008.

[7] C. J. Bryan, G. M. Walton, T. Rogers, and C. S. Dweck, "Motivating voter turnout by invoking the self," *Proceedings of the National Academy of Sciences*, vol. 108, no. 31, pp. 12653–12656, Aug. 2011.

[8] J. D. Cravens, "Measuring the strength of voter turnout habit," *Electoral Studies*, vol. 83, art. no. 102619, Jun. 2023.

[9] A. S. Gerber, D. P. Green, and C. W. Larimer, "Social pressure and voter turnout: Evidence from a large-scale field experiment," *American Political Science Review*, vol. 102, no. 1, pp. 33–48, Feb. 2008.

[10] D. Ribeiro, M. Madaleno, and A. Botelho, "Determinants of voter turnout," *Journal of Behavioral Economics for Policy*, vol. 6, no. S1, pp. 73–84, 2022.

[11] C. Castellano, S. Fortunato, and V. Loreto, "Statistical physics of social dynamics," *Reviews of Modern Physics*, vol. 81, no. 2, pp. 591–646, May 2009.

[12] D. J. Watts and P. S. Dodds, "Influentials, networks, and public opinion formation," *Journal of Consumer Research*, vol. 34, no. 4, pp. 441–458, Dec. 2007.

[13] J. H. Fowler, "Habitual voting and behavioral turnout," *Journal of Politics*, vol. 68, no. 2, pp. 335–344, May 2006.

[14] D. Stockemer, "What affects voter turnout? A review article/meta-analysis of aggregate research," *Government and Opposition*, vol. 52, no. 4, pp. 698–722, Oct. 2017.

[15] B. Geys, "Explaining voter turnout: A review of aggregate-level research," *Electoral Studies*, vol. 25, no. 4, pp. 637–663, Dec. 2006.

[16] A. Blais, *To Vote or Not to Vote? The Merits and Limits of Rational Choice Theory*. Pittsburgh, PA, USA: University of Pittsburgh Press, 2000.

[17] A. Campbell, P. E. Converse, W. E. Miller, and D. E. Stokes, *The American Voter*. Chicago, IL, USA: University of Chicago Press, 1960.

[18] A. Todorov, A. N. Mandisodza, A. Goren, and C. C. Hall, "Inferences of competence from faces predict election outcomes," *Science*, vol. 308, no. 5728, pp. 1623–1626, Jun. 2005.

[19] G. V. Caprara and P. G. Zimbardo, "Personalizing politics: A congruency model of political preference," *American Psychologist*, vol. 59, no. 7, pp. 581–594, Oct. 2004.

[20] Election Commission of India, "Statistical report on general election, 2019 to the 17th Lok Sabha," New Delhi, India, Tech. Rep., 2019.

[21] National Data & Analytics Platform, "Census 2011 projected data," NITI Aayog, Government of India, 2019. [Online]. Available: https://ndap.niti.gov.in

[22] A. Purohit, "A study of elections in India: Scientific and political review," *International Journal of Social Impact*, vol. 1, no. 2, pp. 96–101, 2016.

[23] R. Romaniuc, A. Guido, P. Baudry, and A. Foucault, "The limits of behavioral nudges to increase youth turnout: Experimental evidence from two French elections," *SSRN Electronic Journal*, 2024. DOI: 10.2139/ssrn.4969540.

[24] B. S. Frey and R. Jegen, "Motivation crowding theory," *Journal of Economic Surveys*, vol. 15, no. 5, pp. 589–611, Dec. 2001.

[25] E. L. Deci and R. M. Ryan, "A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation," *Psychological Bulletin*, vol. 125, no. 6, pp. 627–668, Nov. 1999.