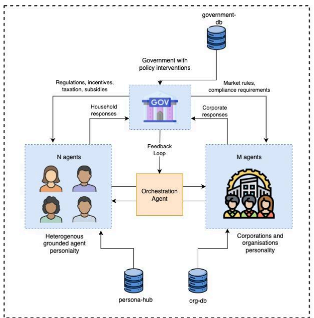
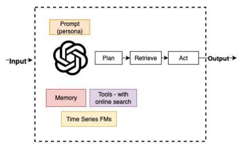
Multi-Agent-based Simulation for Climate Policy Evaluation

Traditional climate policy evaluation approaches, particularly Integrated Assessment Models (IAMs), which commonly aggregate populations into representative, rational agents, often fail to capture the heterogeneity, bounded rationality, and emergent dynamics of real socio-economic systems, resulting in policy recommendations that lack realism and may miss important distributional effects and unintended consequences [1]. We propose a novel framework that leverages LLMs instantiated as diverse households and organizational agents, each equipped with theory-informed personas and calibrated through empirical data, enabling richer modeling of actual behavioral diversity and adaptive responses [2]. A central government policymaker agent iteratively generates, tests, and refines policies in response to observed simulation outcomes, while adhering to explicit ethical guardrails that mitigate the risks of bias and ensure the inclusion of equity considerations.



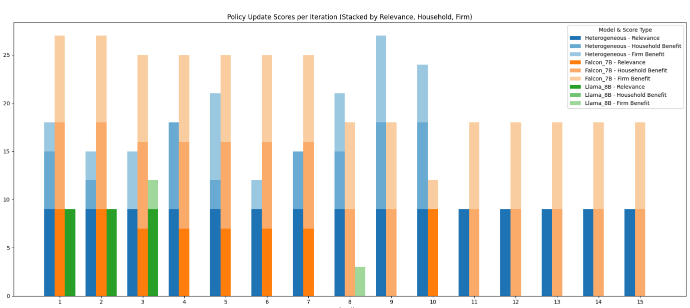
Social Technical System



Agent Architecture

Our proposed method distinguishes itself from traditional Agent-Based Modeling (ABM) by using LLMs, thus introducing human-like reasoning, social learning, and context-sensitive decision-making into the simulation environment [3]. Agents are designed with modules for role-adaptive behavior, scenario-based planning, and environmental context retrieval. This allows the system to represent both individual and organization-level goals and constraints along with causal feedback loops governing their interactions. In the feedback loop, the policy is generated, disseminated through the simulated population, responses and outcomes are collected and analyzed by the policymaker agent which refines the policy with guardrail checking. This iterative process is run for multiple epochs, enabling exploration of dynamic, potentially out-of-equilibrium behaviors like bubbles or tipping points that traditional IAMs cannot capture.

We implemented a multi-agent simulation using Falcon-7B-Instruct, Meta-Llama-8B, and a heterogeneous setup, applied to a short description of the EU's Carbon Border Adjustment Mechanism with six personas (three households, three firms). GPT-5 judged each iteration based on policy relevance and benefits to households and firms. Policy refinements evolved from sector-specific proposals (iteration 3) to balanced industry concerns (iteration 5), then to broader compliance guidelines (iteration 10). This shows that moderate feedback cycles surface targeted adjustments, while excessive iteration produces generic outcomes. Falcon-7B excelled early, the heterogeneous model outperformed at iterations 8–10, and both plateaued later. Llama returned few results and performed worst overall.



Our framework provides a "testbed" in which climate policy scenarios can be evaluated for aggregate impacts, distributional consequences, rebound effects, and social robustness. It thus offers policymakers insight into plausible societal responses, trade-offs, and resilience under deep uncertainty, serving as a complement to IAMs by supplying micro-founded, simulation-driven perspectives. This enables the design of climate interventions that are both cost-effective and socially and politically feasible. The methodology can be extended to incorporate multi-level governance and non-state actors to help guide equitable and adaptive climate transitions in increasingly complex policy landscapes.

[1] Frank Ackerman et al. "Limitations of integrated assessment models of climate change." Climatic Change 95.3 (2009), pp. 297–315. DOI: 10.1007/s10584-009-9570-x.
[2] Tao Ge et al. "Scaling Synthetic Data Creation with 1,000,000,000 Personas." 2025. arXiv: 2406.20094 [cs.CL].
[3] So Kuroki et al. "Reimagining ABM with LLM Agents via Shachi." ICML 2025 Workshop on Computer Use Agents. 2025.