# Large Population Models: Executive Summary

## 1 Introduction

Many of society's most pressing challenges—from pandemic response to supply chain disruptions to climate adaptation—emerge from the collective behavior of millions of individuals making decisions over time. Understanding how individual choices aggregate into system-level outcomes requires computational tools that can simulate realistic populations, learn from diverse data sources, and integrate with real-world systems.

Traditional approaches to modeling population behavior have faced significant limitations. While large-scale statistical models can capture broad trends, they often miss nuanced interactions that drive emergent phenomena. Meanwhile, agent-based models that simulate individual decision-making have typically been limited to small populations or simplified behaviors. The result is a critical gap in our ability to understand and address complex societal challenges.

Large Population Models (LPMs) bridge this gap by enabling the simulation of entire populations with realistic behaviors and interactions at unprecedented scale. Unlike current AI advances that focus primarily on creating sophisticated "digital humans" with individual capabilities, LPMs develop "digital societies" where the richness of interactions reveals emergent phenomena. This approach offers a complementary path in AI research—illuminating collective intelligence and providing testing grounds for policies before real-world deployment.

## 2 The COVID-19 Pandemic: A Case Study for Large Population Models

Imagine you are the public health leader for New York City during the COVID-19 pandemic. You face critical questions that will impact millions of lives: When will the next wave emerge? Which testing strategy would be most effective—PCR or antigen tests? How would a $500 stimulus check affect people's behavior and disease spread?

Finding answers to these questions requires understanding the complex interplay between three key elements:

1. **Citizen behavior**: How individuals make decisions based on their circumstances, risk perceptions, and financial constraints
2. **Disease dynamics**: How the virus spreads through a population via complex networks of interactions
3. **Intervention strategies**: How testing, vaccination, and economic policies affect both disease spread and human behavior

For the NYC pandemic scenario, we constructed a synthetic population of 8.4 million individuals, with demographic profiles derived from census data. Each person in our digital city had both static attributes (age, gender, income, occupation) and dynamic properties (disease status, employment status) that evolved over time. These digital citizens interacted through realistic networks—living in households, commuting to workplaces, and moving around the city—creating channels for both disease transmission and economic influence. This virtual society became a testing ground where we could observe individual choices—whether to wear a mask, get tested after exposure, or reduce social activities due to financial pressures — aggregate into system-level outcomes like infection waves and

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economic impacts. Most importantly, this approach enabled us to test different intervention strategies, like targeted testing programs or financial incentives, before implementing them in the real world.

Building these models revealed three key challenges that prevented earlier approaches from being effective.

- First is the **"detail vs. scale" challenge** – like trying to film a stadium of people while capturing each person's facial expressions simultaneously. Traditional approaches could either simulate realistic behaviors for a small neighborhood or track simplified movements for an entire city, but not both.
- Second is the **"puzzle piece" problem** – information came from many different sources (hospital data, cell phone movements, survey responses) that didn't fit together easily.
- Third is the **"privacy vs. usefulness" dilemma** – the most valuable data for prediction was often the most sensitive personal information that people were reluctant to share.

Our innovations in Large Population Models tackle these challenges head-on, creating digital worlds where we can see how millions of individual decisions combine to shape our collective future.

| Method | Simulation | Calibration | Analysis |
|---|---|---|---|
| Conventional ABM* | 50 hours | 100,000 hours | 5,000 hours |
| **LPM** | 5 minutes | 20 minutes | 10 seconds |
| | + 600x | + 3000x | + 5000x |

Figure 1: Performance benchmarking comparing computational efficiency of LPMs versus conventional ABMs for simulating 8.4 million agents representing NYC's population. LPMs demonstrate orders-of-magnitude improvements in simulation (600x), calibration (3000x), and analysis (5000x) runtimes, enabling previously infeasible large-scale agent-based modeling applications.

## 3 The Three Fundamental Challenges and Our Solutions

Building Large Population Models requires overcoming three fundamental challenges that have limited traditional approaches:

### 3.1 Challenge 1: The Scale vs. Expressiveness Trade-off

**The Challenge**: Traditional modeling approaches force an artificial choice between scale and sophistication. Conventional epidemiological models can simulate millions of individuals but rely on simplified behavioral rules. Recent AI approaches using large language models demonstrate sophisticated adaptive behaviors but remain limited to small populations of 25-1000 agents—far from the scale needed to model metropolitan dynamics.

**Our Solution**: LPMs resolve this tension through compositional design with tensorized execution. We've created a domain-specific language (FLAME) that decomposes complex environmental dynamics into modular components that can be efficiently executed across millions of agents. For agent behavior, our breakthrough insight is that while agent states are highly heterogeneous, their decision-making often follows similar patterns based on demographic and socioeconomic characteristics. This allows us to identify representative "agent archetypes" that capture behavioral variations while dramatically reducing computational cost.

**The Impact**: Our approach achieves a 600× speedup compared to traditional implementations when simulating 8.4 million agents representing New York City's population. This makes previously intractable scenarios computationally feasible, enabling more accurate representation of how individual behaviors aggregate to population-level outcomes.

This is represented in the following papers:

- Chopra et al. flame: a framework for learning in agent-based models (AAMAS 2024, Oral) [link here]

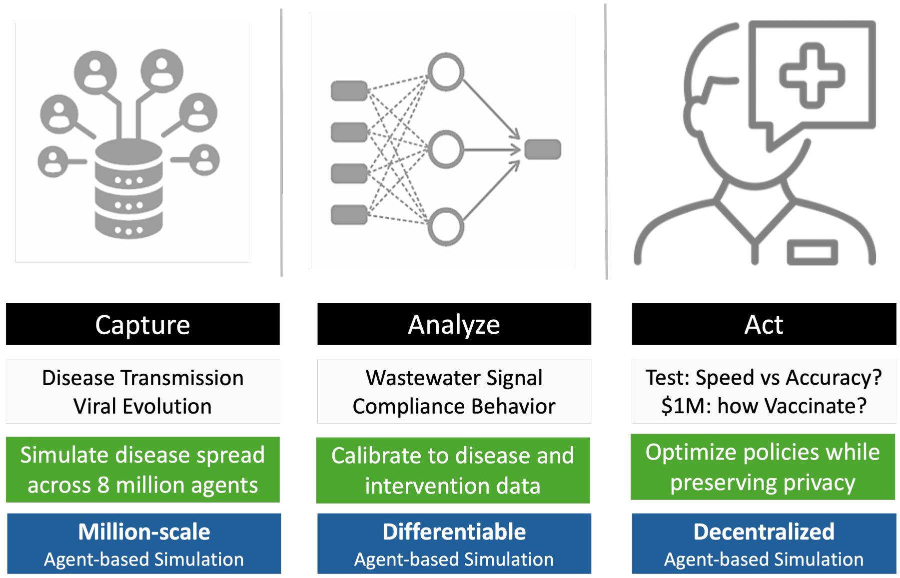


Figure 2: Research Pillars: LPMs alleviate the three challenges of ABMs by making simulations scalable, differentiable and decentralized. In Public Health, this enables LPMs to capture disease transmission and viral evolution across millions of agents; analyze outcomes by ingesting multi-modal disease, behavior and intervention data and securely deploy policies while preserving privacy.

- Chopra et al. on the limits of agency in agent-based models (AAMAS 2025, Oral) [link here]
- Romero-brufau, Chopra et al. Public health impact of delaying second dose of BNT162b2 or mRNA-1273 covid-19 vaccine (British Medical Journal 2021) [link here]

### 3.2 Challenge 2: Heterogeneous Data Integration

**The Challenge**: During COVID-19, decision-makers faced a paradoxical situation: data abundance coupled with information scarcity. Public health departments received heterogeneous streams of information—clinical reports, wastewater samples, mobility patterns, social media surveys—yet struggled to integrate these signals into coherent, actionable insights.

**Our Solution**: LPMs transform simulations from black-box entities into first-class computational objects amenable to modern optimization techniques. By ensuring that every component remains differentiable, we can efficiently compute gradients of simulation outputs with respect to parameters, enabling gradient-based calibration and zero-shot sensitivity analysis. This mathematical innovation allows simulations to learn directly from heterogeneous data sources without requiring surrogate models or prohibitively large numbers of simulation runs.

**The Impact**: Our differentiable approach provides a 3000× speedup in calibration time (from 100,000 hours to 20 minutes) and a 5000× speedup in analysis time (from 5,000 hours to 10 seconds). This efficiency enables rapid integration of new data and timely analysis of intervention effects—critical capabilities during fast-evolving crises.

This is demonstrated in the following publications:

- Chopra et al. differentiable agent-based epidemiology (AAMAS 2023, Oral) [link here].
- Quera-bofarull, Chopra et al. Don't simulate twice: one-shot sensitivity analysis via automatic differentiation (AAMAS 2023, Oral) and (ICML-W 2022 Best Paper Award) [link here]
- Garg and Chopra. Distributed Calibration of Agent-based Models (KDD Workshop 2024) [link here]

- Chopra, Quera-bofarull and Zhang. differentiable agent-based modeling: systems, methods and applications (AAMAS 2024, Tutorial) [link here]

### 3.3 Challenge 3: The Simulation-Reality Gap

**The Challenge**: Current agent-based simulations rely primarily on aggregate census and mobility data that has been anonymized or made differentially private, significantly limiting model expressiveness. During COVID-19, attempts to capture real-time individual data via contact tracing apps faced two key limitations: privacy concerns that reduced adoption and data quality, and timeliness challenges where insights became outdated before implementation.

**Our Solution**: Instead of bringing data to simulations, LPMs bring simulations to data—enabling secure, decentralized computation directly where data resides while maintaining individual privacy. We extend differentiable simulation capabilities to distributed agents while preserving privacy through secure multi-party computation protocols. This creates a dual notion of an agent—an entity that can exist in both synthetic and physical environments.

**The Impact**: This approach transforms population modeling from a retrospective analysis tool into an integrated component of adaptive response systems. Most significantly, it can transform passive exposure notification apps into proactive exposure management tools. During COVID-19, contact tracing apps could only inform users about past exposures ("You were exposed 3 days ago"). With LPMs embedded in mobile devices, these apps can answer forward-looking questions like "How can I minimize my risk over the next week?" or "What activities should I modify based on current community transmission?" The simulation runs locally on the device, using privacy-preserved data about the individual's behavior patterns and community context to provide personalized guidance.

This is represented in the following publications:

- Chopra et al. Private Agent-based Modeling. (AAMAS 2024, Oral) [link here]

Beyond individual applications, with LPMs, public health systems can estimate personalized risk based on current contact patterns, calibrate disease models using privacy-preserved individual-level data, and evaluate policy interventions without compromising individual behavioral data. All of this happens while maintaining strict privacy guarantees that encourage wider adoption.

## 4 Real-World Impact and Future Applications

Large Population Models represent a significant advancement in our ability to understand and address challenges that emerge from the interactions of millions of individuals. Our approach has already begun to impact global health policy, helping to optimize vaccine distribution strategies for millions of people and improve pandemic preparedness.

Beyond public health, LPMs can be applied to numerous domains where individual decisions aggregate into collective outcomes:

- Climate adaptation: Modeling how behavioral changes, technology adoption, and policy incentives interact to influence emissions and resilience
- Supply chain management: Tracking billions of dollars in global supply flows to improve efficiency and reduce waste
- Urban planning: Simulating how transportation networks, housing development, and economic incentives shape city growth and resource use

As digital technologies increasingly mediate social interactions and generate unprecedented data about human behavior, LPMs provide a framework for responsibly leveraging this information to understand and improve social systems. LPMs offer a path toward modeling complex social dynamics at true population scale while respecting individual autonomy and privacy, with extreme computational efficiencies.

While current AI advances primarily focus on creating sophisticated individual agents, LPMs highlight the importance of understanding collective intelligence and emergent phenomena. As we continue to develop more powerful computational tools, LPMs serve as a reminder that many of our most pressing challenges require not just modeling individual cognition, but the complex web of interactions through which individual behaviors become social outcomes.