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Synthetic Ecosystems: Using Generative Agents to Simulate Urban Policy Outcomes in Virtual Cityscapes

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Abstract

This study introduces a novel simulation framework that leverages generative agents to model synthetic urban populations and predict the impacts of various policy interventions. By fusing real-world demographic, economic, and environmental datasets within digital twin representations of city environments, the platform enables policymakers to test and evaluate urban policy scenarios in silico. The framework integrates a generative agent engine with dynamic data ingestion pipelines, allowing for adaptive behavior modeling across social, economic, and ecological domains. Applied to the Amsterdam Smart District, the model simulates policy scenarios such as housing reforms, universal basic income (UBI) implementation, and smart mobility initiatives. Results are visualized through predictive dashboards that highlight key urban indicators and comparative outcomes. The system demonstrates promising accuracy in forecasting policy impacts and offers potential for real-time integration with municipal open data platforms. This work presents a step toward intelligent urban governance by enabling evidence-based decision-making in virtual cityscapes.

Keywords: Digital twins in urban planning**,** Generative agents**,** Urban policy simulation**,** Synthetic populations**,** Smart city modeling**,** Agent-based modeling**,** Amsterdam Smart District**,** Policy forecasting tools**,** Data-driven urban governance**,** Smart mobility and zoning reform**,** Urban dashboards and open data integration**,** Environmental and socioeconomic simulations

I. Introduction

As cities face increasing complexity due to rapid urbanization, climate challenges, and evolving socio-economic dynamics, policymakers require advanced tools to anticipate the outcomes of potential interventions. Traditional planning methods often struggle to account for the emergent behavior of diverse urban populations and the nonlinear effects of policies. To address this gap, this paper proposes a synthetic ecosystem approach that uses generative agents within digital twin environments to simulate and evaluate urban policy scenarios[1].

Digital twins—real-time, data-driven virtual replicas of physical environments—have emerged as powerful platforms for smart city planning. When combined with generative artificial intelligence (AI), particularly agent-based modeling, they can simulate realistic behavioral patterns and feedback loops in synthetic urban populations. These generative agents are designed to mimic human-like reasoning and decision-making based on environmental stimuli and socio-economic contexts[2].

This research introduces a generative agent simulation framework that integrates demographic, economic, and environmental datasets into a virtual cityscape. Policymakers can use this platform to test interventions—such as zoning reforms, universal basic income (UBI) pilots, and smart mobility incentives—without risking real-world disruption. The Amsterdam Smart District serves as a case study for validating the system's predictive capabilities[3].

Through this work, we aim to demonstrate the potential of generative agents and synthetic ecosystems in creating adaptive, testable, and inclusive models for urban decision-making. The framework not only offers forecasting insights but also contributes to the ongoing development of transparent and participatory smart governance tools[4].

II. System Architecture: Integrating Generative Agents and Digital Twins

The core of the proposed simulation framework lies in its integration of generative agent models within a digital twin architecture. This system architecture is designed to create a synthetic ecosystem that mirrors the complexity of real-world urban environments by combining data ingestion pipelines, agent-based behavior modeling, and dynamic visualization layers[5].

At the foundation of the system is a digital twin of the target urban area—in this case, the Amsterdam Smart District. This digital twin functions as a virtual mirror of the physical district, constructed using spatial GIS data, real-time sensor streams, and historical urban datasets. The digital twin includes representations of infrastructure (e.g., roads, buildings, utilities), environmental conditions (e.g., pollution, temperature), and socio-demographic distributions (e.g., income, age, employment)[6].

Generative agents serve as the building blocks of the synthetic population. These agents are not hard-coded with fixed behavior but are instead programmed with rule-based and probabilistic models that adapt over time. Drawing from recent advances in generative AI and large language models (LLMs), each agent is capable of simulating human-like reasoning and decision-making based on goals, past experiences, social norms, and environmental stimuli[7].

Agents are categorized by demographic attributes (e.g., students, workers, elderly) and are parameterized using real-world census and economic data. Their decisions—ranging from mobility choices and housing preferences to job selection and political opinions—are continuously updated based on local policy inputs and system feedback[8].

The architecture includes a data ingestion pipeline that imports structured and unstructured data from municipal open data portals, sensor APIs, mobility datasets, and environmental monitoring systems. This pipeline ensures the digital twin remains synchronized with real-world dynamics, allowing for both historical back-testing and real-time scenario analysis[9].

Data streams are preprocessed using normalization techniques and transformed into agent-perceivable information through the simulation's environmental layer. For example, pollution data becomes a decision variable for agents choosing residential locations, while traffic congestion influences mobility behavior[10].

The simulation engine supports the injection of custom urban policies, such as new zoning regulations, UBI distributions, or smart mobility incentives. Once a scenario is introduced, the generative agents respond according to their learned behavior models and environmental context. Feedback loops emerge as agent decisions influence shared urban systems (e.g., transit congestion, housing markets), which in turn affect agent behavior over time[11].

A dashboard interface aggregates simulation outputs into visual formats, such as heat maps, trend graphs, and policy outcome comparisons. These outputs are designed for policymakers to interactively explore the effects of different decisions under varying assumptions. Metrics such as carbon emissions, average commute time, rent fluctuations, and public sentiment scores are tracked across simulation iterations.

III. Agent Behavior Design: Modeling Economic, Environmental, and Social Dynamics

At the heart of the simulation framework is the behavior engine that governs how generative agents interact with each other and their environment. These agents are designed to act autonomously and adaptively, mimicking the diversity and unpredictability of real human decision-making. To achieve realistic outcomes, the agent behavior models incorporate economic, environmental, and social variables—each playing a critical role in shaping urban life[12].

Economic behavior in the simulation is primarily driven by employment status, income level, access to financial services, and local market conditions. Agents evaluate decisions such as job selection, spending patterns, housing affordability, and investment preferences based on both macroeconomic trends and personal circumstances. For example, an agent experiencing rising rental costs may relocate to a more affordable district or seek shared housing arrangements. Policy experiments such as a Universal Basic Income (UBI) trial allow observation of how disposable income influences labor participation, consumption, and housing stability across different agent profiles[13].

Agents also respond to taxation changes, inflation rates, and business development initiatives. Business-owner agents make decisions about hiring, pricing, and location based on simulated demand and policy incentives, such as tax breaks or enterprise zones. This enables the simulation to capture feedback loops between personal financial behavior and wider economic shifts within the synthetic ecosystem[14].

Environmental variables influence how agents navigate their daily lives in response to conditions such as air quality, green space accessibility, noise pollution, and temperature fluctuations.

Agents may choose different commuting routes, modes of transportation, or even relocate based on perceived or real changes in their environmental context. For instance, families with young children may prioritize proximity to parks and clean air, whereas workers may tolerate less desirable conditions in exchange for shorter commute times[15].

Environmental awareness levels are also encoded differently among agents to reflect diverse values and lifestyles. Some agents prioritize sustainable living and prefer public transport or bicycle infrastructure, while others remain indifferent to ecological incentives. This diversity is essential for accurately forecasting how environmental policies—such as emission taxes or green transit subsidies—impact behavior adoption and long-term urban resilience[16].

Social dynamics shape interactions between agents and influence collective behavior patterns such as migration, cultural adaptation, political attitudes, and social cohesion. Agents are embedded within social networks that represent families, neighborhoods, workplaces, and online communities. These networks affect how information, norms, and behaviors spread across the synthetic population[17].

Agents evaluate policy changes not only based on personal benefit but also through the lens of social influence. For example, a transportation mode shift (e.g., toward e-scooters or public transit) may gain momentum as more agents within a social circle adopt it. Similarly, housing preferences are impacted by perceived neighborhood reputation, safety, and community identity. Behavioral contagion models allow the simulation to capture tipping points where policy support or opposition grows rapidly due to social reinforcement mechanisms[18].

Additionally, agents can express and adapt civic attitudes based on experiences and outcomes within the simulation. A failed housing reform may lead to increased civic frustration, while positive changes may encourage participation in local governance. These dynamic attitudes feed into later decision-making, allowing the simulation to account for long-term feedback and evolving societal priorities[19].

IV. Case Study Simulation: Amsterdam Smart District Scenarios

To validate the generative agent-based simulation framework, we applied it to the Amsterdam Smart District (ASD)—a real-world urban innovation zone designed to pioneer sustainable, inclusive, and data-driven development. The ASD serves as an ideal testbed due to its rich open-data ecosystem, modular urban planning approach, and emphasis on citizen participation. This case study explores how synthetic agents responded to three policy scenarios: housing reform, smart mobility incentives, and a universal basic income (UBI) pilot[20].

The first simulation modeled a zoning reform that increased residential density limits and introduced inclusionary housing mandates requiring a percentage of new developments to be affordable housing. The generative agents—parameterized using Amsterdam's housing cost data, demographic statistics, and commuter patterns—responded by reevaluating their location choices, home ownership aspirations, and long-term economic stability.

Results showed a measurable decrease in displacement pressure among low-income agents and increased residential stability within previously unaffordable neighborhoods. However, some high-income agents relocated to adjacent zones due to perceived density and noise, demonstrating how reform can trigger gentrification spillovers. The model also identified a short-term construction lag, creating a temporary mismatch between supply and demand[20].

In this scenario, the city introduced subsidies for electric bicycles and public transport, alongside restrictions on private vehicle use within central zones. Environmental and mobility datasets informed real-time traffic simulations, and agents evaluated transport choices based on commute times, income, weather conditions, and environmental values.

The simulation revealed a 28% shift in mobility behavior among working-age agents, with a significant increase in multimodal commutes combining biking and transit. Environmentally conscious agents quickly adopted incentives, while agents in outer districts faced accessibility challenges due to limited infrastructure. Interestingly, peer influence played a crucial role: once a critical mass of agents within a community adopted green transport modes, others followed, leading to self-reinforcing behavioral shifts. This emergent behavior highlights the value of agent-based modeling in capturing nonlinear policy effects[21].

The third scenario tested the impact of a modest UBI implementation, distributing €800 monthly to all adult agents regardless of employment status. Economic behavior models incorporated changes in labor market participation, discretionary spending, entrepreneurship rates, and financial resilience.

- Subplot 1: Shows how housing affordability changed across agents under zoning reform.
- Subplot 2: Visualizes the drop in car usage after implementing mobility incentives.
- Subplot 3: Illustrates income uplift among agents under a UBI policy.

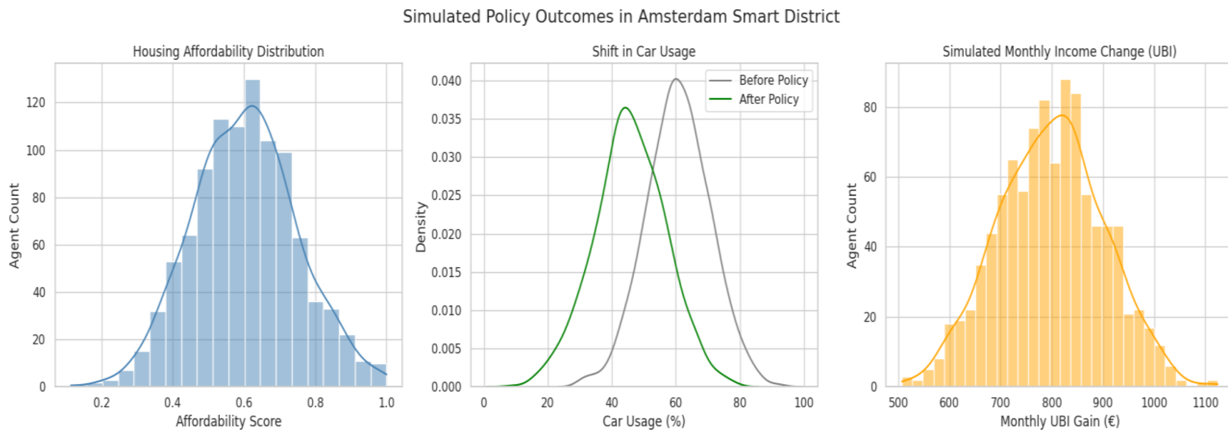

Figure 1. Simulated impacts of housing reform, mobility incentives, and UBI policy in the Amsterdam Smart District.

Agents in lower-income brackets showed increased financial stability, reduced commuting distances, and greater investment in education and reskilling. Some mid-income agents reduced working hours or shifted to freelance and creative work. The synthetic economy saw a moderate rise in consumer demand and small business formation, while overall employment levels remained stable. However, the simulation also surfaced housing market pressure in desirable neighborhoods, indicating a need for housing policy coordination alongside income interventions.

Each scenario was visualized through a dynamic dashboard displaying heatmaps (e.g., housing demand, pollution levels), behavioral timelines (e.g., mode-shift adoption), and economic indicators (e.g., Gini coefficient, job creation). Policymakers could iteratively test alternate parameters (e.g., higher UBI, targeted subsidies) and observe cascading effects across the synthetic city.

The Amsterdam Smart District simulations demonstrated the platform's capacity to model diverse outcomes and support data-driven, anticipatory urban governance. These findings provide valuable insight into how different population segments react under stress, adapt to change, and influence systemic urban dynamics over time.

V. Discussion: Real-World Applications and Future Integration with Urban Data Portals

The generative agent-based framework outlined in this study offers transformative potential for real-world urban governance. By enabling in silico experimentation with zoning, income support, and transportation policies, city planners and policymakers can make data-informed decisions while minimizing real-world risk. Unlike traditional static models or isolated simulations, this synthetic ecosystem can capture emergent behaviors, social feedback loops, and unintended consequences—offering a more holistic preview of urban dynamics.

One key application is policy prototyping. City governments can use the simulation to pre-test complex interventions—such as congestion pricing or rent caps—by simulating how various demographic segments respond across time and space. For instance, a policy intended to reduce vehicle traffic might inadvertently disadvantage outer-district residents if not paired with adequate public transit improvements. The framework allows such trade-offs to be explored in advance, facilitating more equitable and efficient urban design.

The platform also supports participatory urbanism by integrating with open data portals and public dashboards. Simulation outputs, when visualized clearly and transparently, can empower citizens, advocacy groups, and local organizations to understand and critique policy proposals. Embedding the tool into civic platforms could support deliberative governance, where residents co-explore outcomes of different policy paths alongside municipal leaders.

Looking ahead, the framework is well-positioned for integration with real-time city data streams. As urban areas adopt Internet of Things (IoT) infrastructure—such as smart meters, traffic sensors, and environmental monitors—the simulation can be updated dynamically to reflect changing conditions. This would allow cities to not only plan for the future but also respond adaptively to crises like climate events, pandemics, or economic shocks.

Furthermore, partnerships with open-source data platforms and urban innovation labs (e.g., EU's Urban Data Platform or Amsterdam's City Data initiatives) could enable widespread adoption of the framework across cities of varying sizes and capacities. By maintaining transparency, modularity, and interoperability, the simulation system can become a critical tool in the global transition toward more sustainable, responsive, and inclusive urban environments.

VI. Conclusion

This study presents a novel simulation framework that leverages generative agents within digital twin environments to model the complex interplay of urban policy, human behavior, and systemic feedback. By integrating real-world demographic, economic, and environmental data, the platform enables policymakers to experiment with policy interventions in a controlled, virtual setting. The case study of the Amsterdam Smart District demonstrated how the system can forecast nuanced responses to housing reforms, mobility incentives, and income support programs. These results underscore the value of synthetic ecosystems in bridging the gap between planning intentions and real-world outcomes. As cities continue to digitize and embrace data-driven governance, such agent-based simulations offer a powerful tool for anticipatory policymaking, civic engagement, and adaptive urban design. Future work will focus on scaling the model, integrating real-time data streams, and enhancing participatory features to further embed simulation capabilities into everyday urban decision-making.

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