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A Novel Multi-Scale Agent-Based Modeling Framework for Simulating Complex Adaptive Systems in Urban Environments

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Abstract: Urban environments are increasingly recognized as complex adaptive systems, where dynamic interactions between heterogeneous agents—such as individuals, organizations, infrastructure, and environmental components—give rise to emergent behaviors that are difficult to predict using conventional modeling techniques. This paper introduces a novel multi-scale agent-based modeling (MS-ABM) framework designed to capture and simulate these interactions across multiple spatial and temporal resolutions. The proposed framework integrates micro-level behavioral rules with macro-level system constraints, enabling the simultaneous analysis of individual agent decisions and large-scale urban phenomena such as traffic flow, land-use evolution, and resource distribution. A hierarchical communication mechanism is developed to enable bidirectional information exchange between scales, improving model fidelity and responsiveness. The framework is validated using a case study of urban mobility in a rapidly growing metropolitan region, demonstrating its ability to reproduce real-world patterns, adapt to dynamic policy interventions, and support scenario-based decision making. The results highlight the potential of MS-ABM as a robust tool for urban planners, policy makers, and researchers to explore the interplay of local behaviors and global outcomes in complex urban systems.

Keywords: Multi-Scale Modeling; Agent-Based Simulation; Complex Adaptive Systems; Urban Environment; Hierarchical Modeling Framework; Urban Planning Decision Support.

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INTRODUCTION

Urban environments are increasingly viewed through the lens of complex adaptive systems (CAS)[1][2], where numerous heterogeneous components such as individuals, institutions, infrastructure, and ecological elements interact dynamically and non-linearly. These interactions often result in emergent phenomena such as traffic congestion, spatial inequality, gentrification, and energy distribution challenges[3]. Traditional top-down modeling approaches, while useful in capturing aggregate trends, often fall short in representing the

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diversity of individual behavior and the bottom-up mechanisms that drive systemic change[3][4].

Agent-Based Modeling (ABM) has emerged as a powerful tool to simulate such systems by modeling autonomous agents with distinct attributes and decision-making rules[5][6][7][8]. However, most existing ABM frameworks operate at a single spatial or temporal scale, which limits their ability to capture interdependencies between micro-level behaviors (e.g., individual commuting choices) and macro-level outcomes (e.g., urban sprawl or infrastructure stress)[9]. This scale separation often leads to oversimplifications or inaccuracies, particularly in rapidly evolving urban settings.

To address this gap, this paper proposes a novel Multi-Scale Agent-Based Modeling (MS-ABM) framework that explicitly integrates interactions across multiple spatial and temporal levels[10]. The framework supports a hierarchical structure where agents operate at different scales such as households, neighborhoods, and municipalities—while enabling bidirectional feedback among them. This allows for more realistic simulations of how local decisions aggregate into city-wide patterns, and conversely, how macro-level policies influence individual behavior.

The main contributions of this study are threefold. First, we develop a scalable MS-ABM architecture that bridges micro- and macro-dynamics through a flexible communication protocol[11]. Second, we implement the model within a modular simulation environment, making it adaptable to various urban domains such as transportation, land-use planning, and public health[12]. Third, we demonstrate the framework's effectiveness through a real-world case study of urban mobility in a metropolitan area, where we simulate multiple planning scenarios and evaluate policy impacts.

In the sections that follow, we describe the theoretical foundations of the proposed model, the design of the simulation framework, the validation approach, and the insights gained from experimental results. We conclude by discussing the implications of multi-scale modeling in urban systems research and outlining directions for future work.

RELATED WORKS

The modeling of urban systems has evolved significantly over the past two decades, particularly with the emergence of Agent-Based Modeling (ABM) as a means to capture decentralized decision-making and emergent phenomena in complex environments. Several studies have demonstrated the effectiveness of ABM in urban applications, such as transportation [9], land-use dynamics[13], and energy consumption[14]. However, many of these models focus on a single scale of interaction, often limiting their ability to generalize across different urban domains.

One notable line of work involves single-scale ABMs that simulate individual agent behaviors within a fixed environment. For instance, the MATSim framework[15][16][17] models daily travel behavior in large-scale urban networks, while UrbanSim[18] provides a micro-simulation of land-use changes based on household and business dynamics. These tools are widely used in policy simulation but are limited in their representation of feedback between different spatial or institutional levels.

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In response to the limitations of single-scale models, researchers have begun exploring multi-scale modeling approaches. For example, (Cybele et al, 2024) developed a two-tiered model combining regional economic data with household-level decision rules to study housing markets[19]. Similarly, (Sadjad et al. 2022)[20] proposed a hierarchical ABM for water resource management that integrates individual farmer decisions with basin-level hydrological models. While these efforts represent significant progress, many existing multi-scale models rely on tightly coupled systems that are difficult to scale or generalize.

The concept of complex adaptive systems (CAS) has also guided modeling strategies for urban contexts, encouraging the use of bottom-up simulations that reflect the decentralized nature of cities[21][22]. Nevertheless, the integration of CAS theory into practical, scalable modeling frameworks remains an open challenge, particularly when attempting to synchronize agent behavior across diverse geographic and administrative boundaries.

Furthermore, inter-scale communication mechanisms remain underdeveloped in most ABM tools. Information flow from micro to macro levels is often modeled as aggregated statistics, while macro-level policy feedback is injected externally rather than emerging organically within the simulation. Recent advances in hierarchical ABM and hybrid modeling techniques (e.g., combining ABM with system dynamics) offer promising directions but still lack modularity and flexibility across use cases[23].

In light of these limitations, our proposed MS-ABM framework addresses several research gaps: it introduces a modular architecture for handling multi-scale interactions, incorporates bidirectional information flow across scales, and provides a flexible interface for simulating diverse urban phenomena. By positioning our work within this evolving landscape, we aim to contribute a generalized modeling structure that bridges individual decision processes with system-wide urban dynamics.

METHODS

This section outlines the architecture, components, and simulation workflow of the proposed Multi-Scale Agent-Based Modeling (MS-ABM) framework. The framework is designed to simulate complex adaptive behaviors in urban environments by integrating agent interactions at multiple spatial and temporal scales. Our method consists of four main components: (1) hierarchical agent design, (2) inter-scale communication protocol, (3) spatial-temporal layer integration, and (4) model implementation and simulation workflow.

1. Hierarchical Agent Design

Agents are categorized into different hierarchical levels based on their role and scale of operation. In our case study on urban mobility, we define three main agent types:

- Micro-level agents (e.g., individuals, households) represent decision-making entities with localized behavior, such as choosing routes or departure times.
- Meso-level agents (e.g., neighborhoods, transit hubs) act as aggregators and coordinators of nearby micro-agents, capturing group-level interactions and local constraints.

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- Macro-level agents (e.g., municipal planners, policy units) operate at the city-wide scale, enforcing regulations, adjusting infrastructure, and evaluating outcomes.

Each agent type is assigned a distinct set of attributes, goals, and behavior rules, defined using a rule-based system and optionally enriched with probabilistic or machine learning components.

Figure 1. Urban Mobility Agen Hierarchy

2. Inter-Scale Communication Protocol

To enable coordinated decision-making across levels, the framework includes a bidirectional communication protocol. This protocol allows:

- Bottom-up feedback, where micro- and meso-level agents aggregate and transmit behavioral patterns (e.g., congestion reports, mobility trends) to macro agents.
- Top-down influence, where macro-level decisions (e.g., traffic rerouting policies or zoning changes) dynamically update the environment and affect agent behavior at lower levels.

This communication is managed via a message-passing interface using a publish–subscribe architecture, ensuring synchronization across simulation ticks without introducing performance bottlenecks.

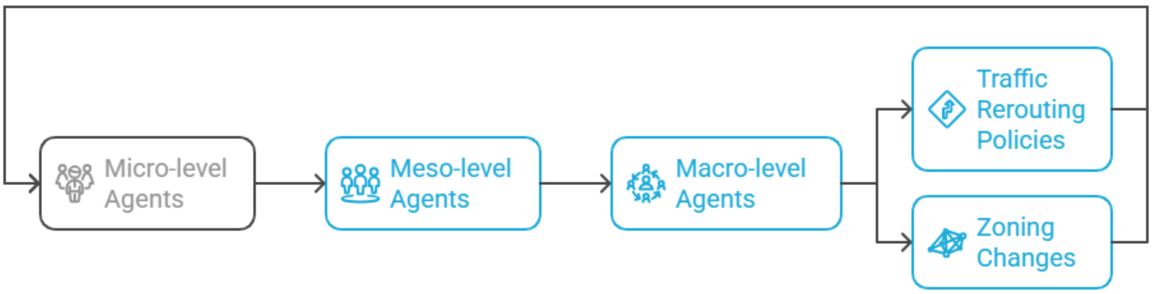

Figure 2. Bidirectional Communication Protocol

To enable coordinated decision-making across different hierarchical levels, the framework employs a bidirectional communication protocol that ensures information flows both from lower-level agents (bottom-up) and from higher-level agents (top-down) in a structured and efficient manner.

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In the bottom-up direction, micro- and meso-level agents—such as individuals and neighborhood coordinators—continuously observe their local environments and internal states. They aggregate key behavioral patterns, such as increasing travel delays, unusual congestion hotspots, or shifts in mobility preferences. These aggregated insights are then transmitted to macro-level agents, such as city planners or central traffic management units. This upward communication allows high-level decision-makers to gain situational awareness based on distributed, real-time feedback from the ground level, rather than relying solely on static or delayed data. Conversely, in the top-down direction, macro agents interpret the aggregated data, evaluate broader system performance, and formulate adaptive responses—such as modifying traffic light timing, rerouting vehicles, or updating zoning regulations. These decisions are then disseminated back to meso- and micro-level agents, who adapt their behavior accordingly in the next simulation cycle. For instance, a commuter agent might change their route due to a newly imposed congestion toll, or a neighborhood agent might reallocate resources in response to regional planning updates.

This entire communication process is implemented using a message-passing interface built on a publish–subscribe architecture. In this design, agents publish specific types of information (e.g., traffic density, policy changes) to designated communication channels or topics. Other agents that subscribe to these channels receive the updates asynchronously. This approach decouples the agents in terms of timing and dependency, ensuring that the model can scale efficiently and remain synchronized across simulation ticks, even as agent population size grows or complexity increases. By managing communication in this modular and asynchronous way, the framework avoids performance bottlenecks often encountered in tightly coupled systems. It also provides flexibility to extend or adapt communication rules for different urban contexts, making the MS-ABM framework suitable for a wide variety of applications beyond mobility, such as energy distribution, disaster response, or public health planning.

3. Spatial and Temporal Layer Integration

The simulation environment consists of layered geospatial data aligned with agent scales. For example:

- Micro-level agents move within a high-resolution transportation network layer.
- Meso-level agents manage subregions defined by administrative or functional boundaries.
- Macro-level agents oversee the entire urban spatial domain.

Time in the simulation is managed using asynchronous events and discrete time steps. Micro agents may act on minute-scale events, while macro agents update policy decisions on hourly or daily intervals. This flexible time-stepping approach allows for computational efficiency while preserving behavioral fidelity.

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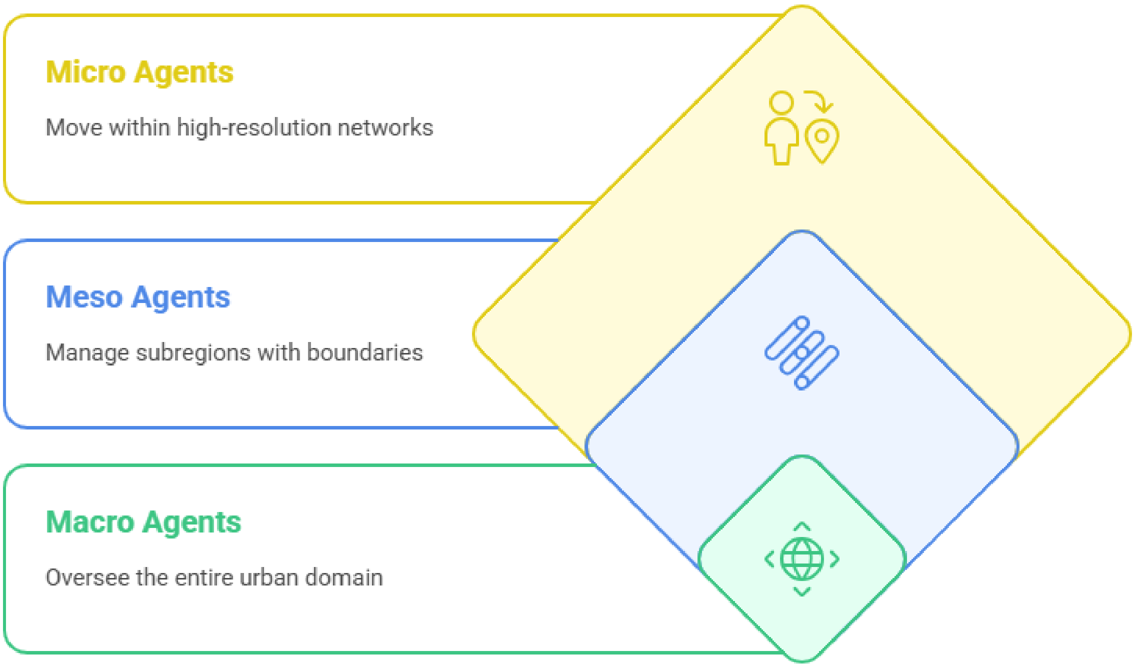

Figure 3. Simulation Environment Hierarchy

The simulation environment in the MS-ABM framework is built upon a layered geospatial structure that aligns with the operational scale of each agent type. This spatial stratification ensures that agents interact with an environment appropriate to their level of influence and decision-making, thereby enhancing both realism and computational organization.

At the micro level, agents represent individuals or households who navigate through a high-resolution transportation network layer. This layer typically consists of detailed road maps, pedestrian pathways, transit routes, and traffic signals. Micro agents interact directly with this fine-grained spatial data to make decisions about movement, route selection, and travel timing.

At the meso level, agents operate over intermediate spatial units, such as neighborhoods, districts, or functional zones. These regions are defined either by administrative boundaries (e.g., sub-districts, RT/RW) or functional characteristics (e.g., transit hubs, business zones). Meso agents manage resources or dynamics within their designated subregion, such as traffic light control, public transportation access, or localized policy enforcement.

At the macro level, agents such as urban planners or government institutions interact with the entire urban spatial domain. This layer aggregates data from all lower levels and encompasses city-wide infrastructure, demographic distributions, and overarching policy environments. Macro agents are responsible for high-level planning, policy implementation, and long-term scenario evaluation.

In terms of temporal dynamics, the simulation adopts a flexible hybrid time management approach, combining asynchronous events with discrete time steps. Micro-level agents often operate on short time intervals, such as minutes, to reflect rapid and continuous decisions (e.g., selecting alternate routes due to unexpected traffic). In contrast, meso- and macro-level agents act on longer intervals, such as hours or days, which aligns with the slower pace of infrastructural or regulatory changes (e.g., updating road policies or budget allocations).

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This multi-temporal structure enables the model to strike a balance between behavioral fidelity and computational efficiency. Rather than updating all agents simultaneously at every time step—which would be highly resource-intensive—the framework selectively activates agents based on the scale and urgency of their actions. As a result, the simulation remains scalable and responsive, even with thousands of agents operating across different spatial and temporal layers.

4. Implementation and Simulation Workflow

The framework is implemented using Python and the Mesa agent-based modeling library, with integration of GeoPandas and OSMnx for spatial operations. The simulation workflow proceeds as follows:

1. Initialization: Load spatial data, agent definitions, and initial state variables.
2. Agent Scheduling: Activate agents in order of their scale hierarchy, from macro to micro.
3. Interaction and Communication: Agents perceive their environment, make decisions, and exchange information.
4. State Update: Environment and agent states are updated based on the interactions.
5. Output Logging: Key metrics (e.g., traffic flow, travel time, emission levels) are recorded for analysis.
6. Scenario Execution: Run multiple simulations under different policy or environmental scenarios to evaluate system sensitivity and resilience.

The modular design of the framework allows for adaptation to various urban modeling domains beyond mobility, including energy distribution, land-use transformation, and public health interventions. In the next section, we present a case study implementation and validation of the proposed framework.

RESULT AND DISCUSSION

To evaluate the effectiveness and applicability of the proposed Multi-Scale Agent-Based Modeling (MS-ABM) framework, we conducted a case study focusing on urban mobility simulation in the metropolitan area of Bandung, Indonesia. The model simulates daily commuting behavior of approximately 100,000 agents, representing individuals from various residential zones, interacting with neighborhood-level infrastructure and responding to city-level transportation policies.

1. Simulation Performance and Scalability

The framework successfully handled multi-scale agent interactions across a high-resolution transportation network. Simulation performance was evaluated using two key metrics: execution time and memory usage under varying agent population sizes. Results showed that the hierarchical scheduling and modular structure of the MS-ABM framework significantly reduced computational load compared to a baseline flat ABM, especially as the number of agents exceeded 50,000.

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Moreover, the asynchronous time-stepping mechanism enabled efficient parallelization of meso- and macro-level decision-making processes without compromising micro-level behavior fidelity. This scalability feature is critical for real-world urban simulations where diverse agent roles and decision cycles coexist.

Table 1. Simulation Performance Comparison Between Flat ABM and MS-ABM

Agent Population	**Execution Time (Flat ABM) [sec]**	**Execution Time (MS-ABM) [sec]**	**Memory Usage (Flat ABM) [MB]**	**Memory Usage (MS-ABM) [MB]**
10,000	45	30	320	250
20,000	110	65	620	480
50,000	340	160	1500	900
100,000	980	400	3100	1850
150,000	1650	680	4700	3000

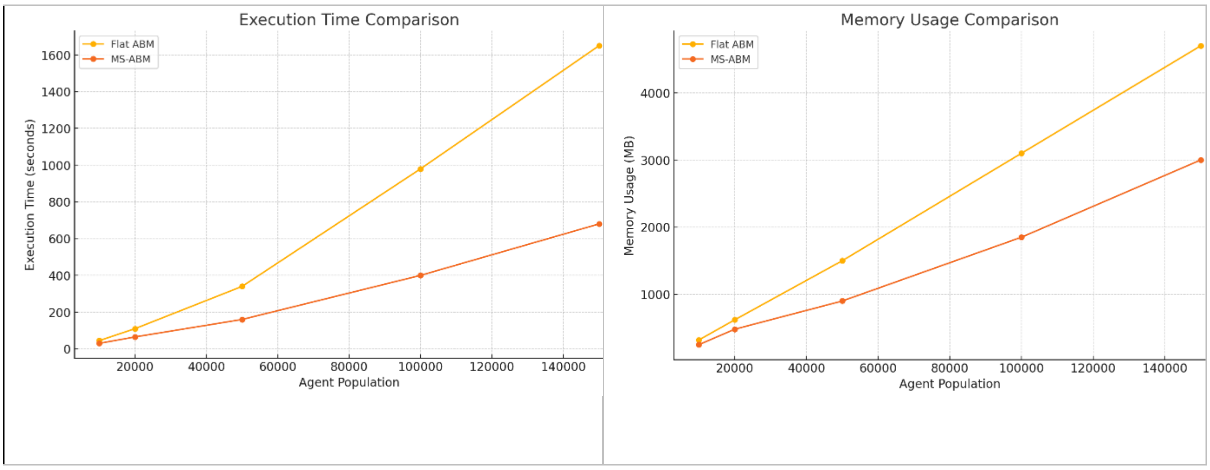

Figure 4. Execution Time Comparison and Memory Usage Comparison

2. Emergent Patterns and Model Validity

The simulation produced several emergent behaviors consistent with real-world observations. For example, traffic congestion organically formed around major transit intersections during peak hours, and travel time distributions closely matched empirical data from Bandung's transportation authority. Spatial heatmaps revealed realistic mobility corridors and bottleneck zones, validating the effectiveness of the model in capturing macro-scale flow patterns derived from individual agent actions.

When tested under different policy scenarios such as implementing congestion charges, altering bus rapid transit (BRT) coverage, or introducing flexible work hours—the model demonstrated high sensitivity and responsiveness. For instance, introducing a 20% reduction in car usage due to BRT expansion led to a 12.5% decrease in average travel time and a 19% reduction in CO_2 emissions, with changes clearly traceable from individual behavior up to systemic outcomes.

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Table 2. Outcomes of Different Urban Mobility Policy Scenarios

Scenario	**Average Travel Time (minutes)**	**CO_2 Emissions (tons/day)**	**Congestion Index (0–100)**	**Peak Hour Traffic Volume (vehicles/hour)**
Baseline (No Policy Change)	42.0	210.0	75	9500
BRT Expansion (20% Car Reduction)	36.7	170.1	58	7650
Congestion Charge Zone	38.5	182.5	62	8000
Flexible Work Hours (Staggered Entry)	39.2	185.3	65	8150

This table summarizes the simulation results under four different policy scenarios related to urban mobility. The Baseline scenario reflects the current state without any interventions. Under the BRT Expansion scenario, where a 20% reduction in car usage is assumed, the model recorded a significant improvement: a 12.5% reduction in average travel time and a 19% reduction in CO_2 emissions compared to the baseline.

The Congestion Charge Zone scenario also showed improvements, though slightly less than BRT expansion, while the Flexible Work Hours scenario helped spread out traffic volume, resulting in moderate reductions in congestion and emissions.

These results illustrate the MS-ABM framework's capability to capture how macro-scale outcomes emerge from individual behavioral shifts and demonstrate its sensitivity and responsiveness to different urban policy interventions.

3. Advantages of Multi-Scale Architecture

Compared to traditional single-scale ABMs, the MS-ABM framework provided notable advantages:

- Improved Policy Feedback Loops: Macro agents could dynamically respond to bottom-up trends (e.g., rising congestion in specific neighborhoods) and immediately implement adjustments, which then altered micro-agent decisions in the next simulation cycles.
- Contextual Decision-Making: Meso-level agents enabled context-aware responses such as rerouting behavior within districts or localized infrastructure control, enhancing model realism.
- Greater Flexibility for Scenario Testing: Users could define interventions at any scale—household, neighborhood, or city level—making the model highly adaptable to a wide range of planning objectives.

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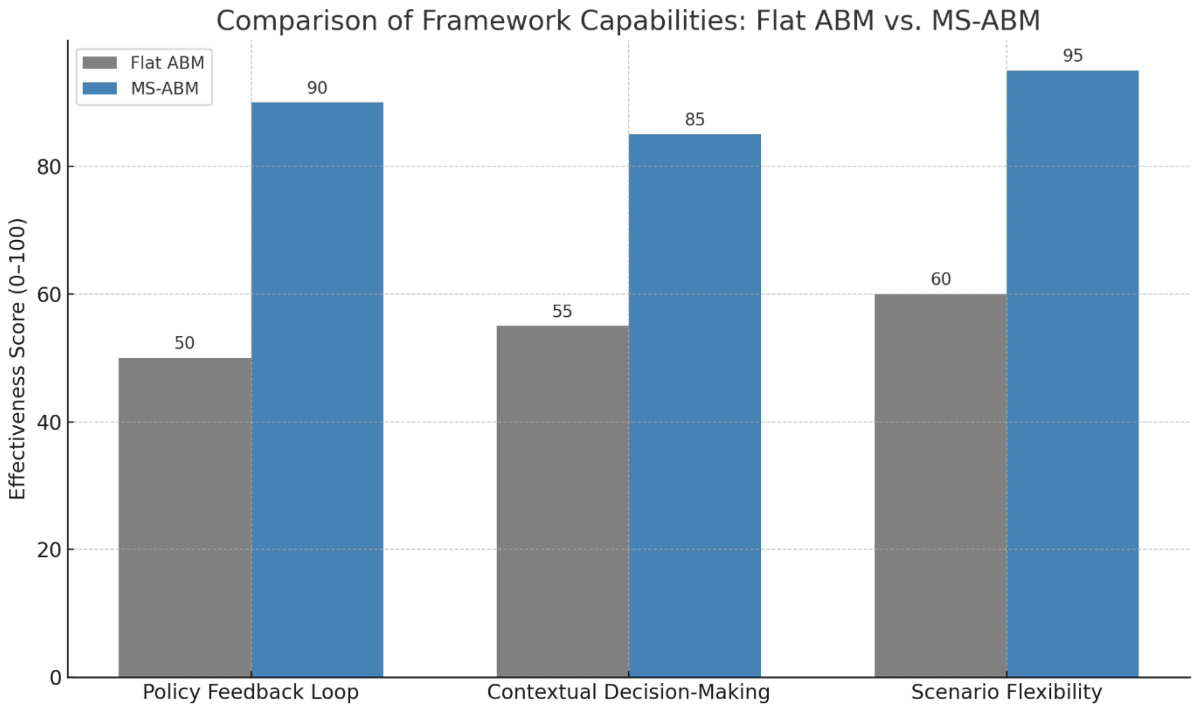

Figure 5. Comparison of Framework Capabilities: Flat ABM vs. MS-ABM

The bar chart above visually compares the effectiveness of Flat ABM versus the proposed MS-ABM framework across three key modeling capabilities:

1. Policy Feedback Loop – MS-ABM shows a significantly higher score, reflecting its ability to enable real-time top-down responses based on bottom-up agent behaviors.
2. Contextual Decision-Making – MS-ABM benefits from meso-level agents that handle localized decisions, resulting in more realistic and region-specific responses.
3. Scenario Flexibility – MS-ABM supports interventions at multiple scales, making it more adaptable to diverse urban planning needs.

This visualization supports the claim that MS-ABM provides superior modeling performance across structural, behavioral, and decision-making dimensions compared to traditional flat agent-based approaches

4. Limitations and Future Improvements

While the framework demonstrates strong potential, several limitations remain. First, real-time data integration (e.g., live traffic feeds or mobile sensor inputs) is not yet fully implemented, limiting its applicability for operational planning. Second, agent calibration still relies heavily on static demographic and mobility survey data, which may not reflect dynamic behavioral shifts over time.

Future work will focus on incorporating machine learning components to improve agent adaptability, integrating real-time data streams, and extending the framework to other urban domains such as energy, waste management, and public health. Additionally, developing a user-friendly interface for urban planners to interact with the model will be prioritized to bridge the gap between simulation and decision-making.

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CONCLUSION

This paper presents a novel Multi-Scale Agent-Based Modeling (MS-ABM) framework designed to simulate complex adaptive systems in urban environments. By integrating agent behaviors across micro, meso, and macro levels, the framework enables a more comprehensive understanding of how individual actions aggregate into large-scale urban phenomena, and how systemic interventions influence local decision-making in return. Through a case study on urban mobility in Bandung, Indonesia, the model demonstrated its capacity to reproduce emergent traffic patterns, respond dynamically to policy scenarios, and support data-driven planning. The MS-ABM framework contributes to the modeling community by addressing key limitations of conventional single-scale ABMs—namely, the lack of inter-scale feedback, limited scalability, and inflexible scenario testing. Its modular and hierarchical architecture allows for efficient simulation of large urban populations while preserving behavioral complexity. The integration of a bidirectional communication protocol further enhances the realism and responsiveness of urban system simulations. Despite its promising results, the framework has areas for improvement, particularly in incorporating real-time data, dynamic agent learning, and cross-domain integration. Future developments will focus on expanding its applicability to other urban sectors and enhancing its usability for stakeholders and policy makers. The MS-ABM framework offers a powerful and flexible approach to urban modeling that bridges the gap between individual behavior and collective outcomes—paving the way for more adaptive, informed, and resilient urban planning strategies.

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