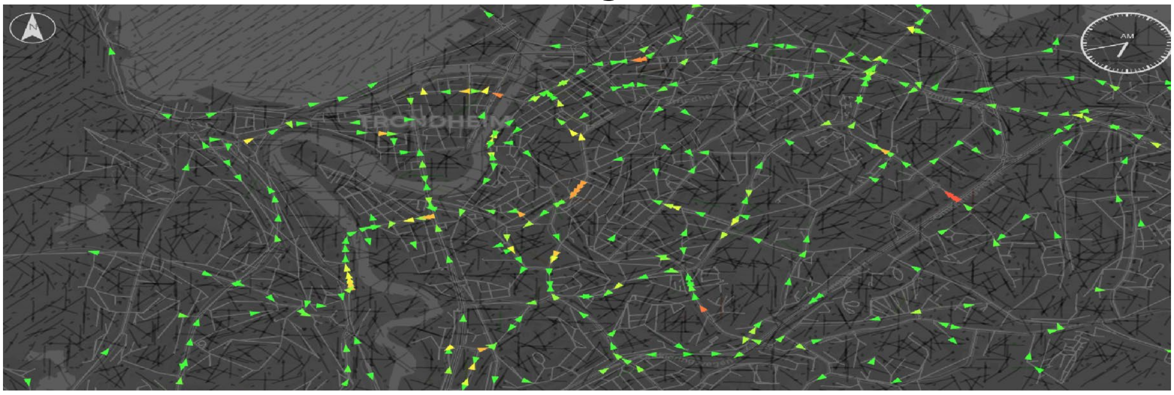
Four Step or Agent Based Models for Urban Mobility



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Sustainable transport initiatives are changing urban travel behaviour and challenge traditional transport modeling. This article compares the Four Step Model (FSM) and the Agent Based Model (ABM) to evaluate their capability of modeling urban mobility dynamics by examining their data needs, methodologies, and modeling trends.

SUMMARY

While the Four-Step Model (FSM) remains the cornerstone of strategic and long-term transport planning because of its simplicity and transparency, recent developments such as tour-based extensions, staged modeling with Dynamic Traffic Assignment (DTA), and the integration of shared mobility have considerably enhanced its capacity to represent time-dependent, urban-scale dynamics. In contrast, Agent-Based Models (ABMs) simulate individual travelers, providing richer behavioral realism but demanding higher data quality and computational resources. Overall, the comparison indicates that current FSMs have closed much of the gap with ABMs, though opportunities for further improvement still remain.

INTRODUCTION

In recent years, sustainable urban transport policies and technological advancements have been transforming how people travel in cities by reducing car dependency and enabling emerging mobility modes such as shared mobility systems, Mobility-as-a-Service (MaaS), and, in the near future, autonomous vehicles (Ciari, Balac and Axhausen, 2016; Narayanan and Antoniou, 2023). While these modes can significantly support the transition toward sustainable and human-centric urban mobility, they may also introduce new challenges if their behavioral dynamics are not well understood such as induced demand, competition with public transport, and equity concerns. Planners therefore rely on transport modeling tools to evaluate the system-wide impacts of new mobility modes and policy interventions.

For decades, the Four-Step Model (FSM) has been the foundation of transportation planning, particularly for evaluating policies and infrastructure investments (de Dios Ortúzar and Willumsen, 2024). In recent years, however, Agent-Based Models (ABMs), such as the open-source MATSim framework, have gained increasing attention for their ability to simulate individual behaviors, capture population heterogeneity, and represent dynamic mobility patterns (W Axhausen, Horni and Nagel, 2016). This paper compares the data requirements, methodological structures, and effectiveness of FSM and ABM approaches in modeling urban mobility based on empirical studies.

DATA REQUIREMENTS

Both FSM and ABM rely on similar inputs, such as population and land-use data, multimodal networks, public-transport service data, travel surveys, and counts. Their primary distinction lies in their level of resolution, as summarized in Table 1. While FSMs aggregate input data, such as population, employment, and level of service, at the Traffic Analysis Zone (TAZ) level, ABMs use disaggregated data at the individual and household levels, including coordinate level activity locations and time-dependent multimodal networks. To model emerging mobility modes, both approaches rely on revealed and stated preference surveys alongside supply-side data(W Axhausen, Horni and Nagel, 2016; de Dios Ortúzar and Willumsen, 2024).

METHODOLOGIES

Workflow

The primary purpose of all transport models is to explain how and why people travel within a given area, but they differ in behavioral realism and methodological structure (see Figure 1). FSM divides the modeling process into four sequential stages. The first stage, trip generation, estimates the number of trips produced and attracted by each zone. Trip distribution then connects origin and destination TAZs based on their socioeconomic characteristics and network connectivity. The mode choice stage determines how trips are divided among available travel modes, and finally, traffic assignment identifies the specific routes travelers use on the network while accounting for congestion and travel times (de Dios Ortúzar and Willumsen, 2024) .

In contrast, Agent-Based Models (ABMs), such as the MATSim framework, simulate individual travelers as autonomous agents with daily activity plans. These plans can be generated using various approaches, such as rule-based scheduling, econometric modeling, or statistical matching, but they share the underlying assumption that travel is derived from the need to participate in activities. Each agent's plan specifies activities, locations, durations, and travel modes. Agents iteratively adjust their choices (e.g., departure time, route, or mode) through a co-evolutionary learning process until reaching behavioral equilibrium, thereby reflecting consistent travel patterns and stable network performance (Bowman and Ben-Akiva, 2001; W Axhausen, Horni and Nagel, 2016).

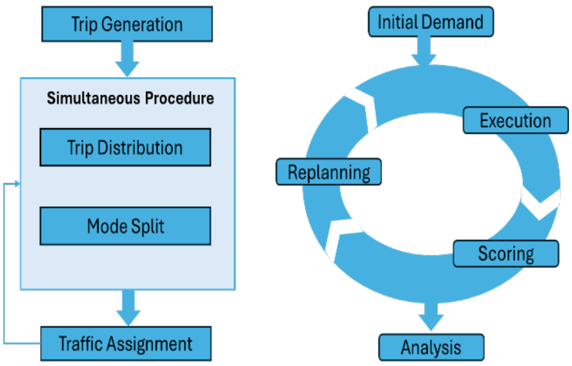

Figure 1:Methodological workflow of FSM(left) and AMB(right)

Limitations

FSM has been the backbone of transport planning for decades, yet it has been heavily criticized for its methodological limitations when applied to complex urban mobility systems. The classical FSM structure struggles to represent emerging mobility modes, short trips, time-dependent policies, and traveler heterogeneity, all of which require a more detailed behavioral foundation. These limitations led to the development of ABMs, which can simulate individual travelers and their interactions. Nevertheless, because of its user-friendliness, transparency, and policy interpretability, FSM remains widely used, and

considerable research has been devoted to enhancing its behavioral realism.

Table 1: Comparison of input data requirements for FSM and ABM Frameworks

DATA TYPES	**FSM AGGREGATE (ZONAL LEVEL)**	**ABM DISAGGREGATE (INDIVIDUAL LEVEL)**
POPULATION	Zonal demographics (e.g., age, income)	Synthetic populations with individual/household records
LAND-USE	Zonal employment, residential density	Point level activity locations (e.g., home, workplace coordinates)
MULTIMODAL NETWORKS	Zonal travel times/costs (skims matrices)	Time-dependent, link-level routable networks
PUBLIC TRANSPORT	Simplified or averaged schedules	GTFS-based schedules with vehicle capacities
TRAVEL SURVEYS	Trip rates and mode shares by purpose	Detailed activity chains and daily scheduling patterns
TRAFFIC COUNTS	Used for calibration and validation	Used for calibration and validation

To address the specific challenge of representing emerging mobility services, researchers have developed extended or hybrid FSM frameworks. These models retain the trip-generation and trip distribution stages of the classical FSM but integrate a disaggregate mode-choice layer that distinguishes between conventional modes and shared mobility systems such as car sharing and ride-hailing. The resulting shared-mobility demand is then linked to fleet-management components that simulate vehicle availability, matching efficiency, and system-level operations (Narayanan *et al.*, 2023).

Another long-standing limitation of FSM is its assumption that trips are independent events, ignoring the interdependencies between sequential activities. This limitation has been partially solved through the adoption of tour-based modeling, which links roundtrips (e.g., home–work–home) and captures behavioral consistency, particularly for private-vehicle users(Ferdous *et al.*, 2012).

FSM has also been criticized for its static representation of network conditions**.** While adequate for intercity or long-term strategic forecasting, it performs poorly in modeling urban dynamics, where congestion and travel times vary continuously. To overcome this, staged modeling processes have been introduced, segmenting travel demand into finer temporal intervals (e.g., 15-minute periods) and coupling it with Dynamic Traffic Assignment (DTA)**.** This integration enables city-scale, time-dependent simulations that capture congestion build up and feedback between network conditions and travel demand (Bottom and Chiu, 2011).

Despite these methodological advances, a fundamental bottleneck remains in the FSM's matrix-based formulation. This structure limits the model's ability to increase the spatial resolution of TAZs or to explicitly represent intra-zonal trips. Similarly, capturing traveler heterogeneity by further segmenting demand using additional socio-demographic variables is theoretically possible but practically challenging, as it leads to an exponential increase in the number of Origin-Destionation (OD) matrix and computation time. To address these limitations, the FSM framework implemented in PTV Visum has been extended to incorporate activity-based modeling features representing a significant step toward the principles of ABM.

In contrast, ABMs, such as MATSim, operate directly at the individual level, representing person-specific behavior, dynamic interactions, and adaptive responses to policies or network changes. Their open-source design and active community support have accelerated adoption, particularly in academic and research contexts.

However, a key limitation of ABMs lies in their extensive data requirements. Although they rely on similar input types as FSMs such as population, land use, and network data, they require these inputs at a much finer spatial and behavioral resolution. Accurately representing daily individual travel demand necessitates high-quality datasets that include detailed socio-demographic information and activity patterns. Besides the data requirement, model transparency is also considered as a limitation due to the mathematical complexity behind agent interactions and decision-making processes (Kagho, Balac and Axhausen, 2020).

USES CASES

Both FSM and ABM play critical roles in tackling urban mobility challenges. This section summarizes their key applications across various mobility domains based on recent literature.

Tolling. FSM models the effect by adjusting generalized travel costs within its mode choice step, influencing traveler behavior at an aggregate level (Tørset *et al.*, 2022). In contrast, ABM simulates time-dependent tolls directly by coding on links, allowing individual agents to dynamically reroute or adjust their schedules in response (W Axhausen, Horni and Nagel, 2016).

Parking. Similarly, parking is handled at different levels of detail. FSM incorporates parking costs as an aggregate explanatory variable for trip distribution (Flügel *et al.*, 1819), while ABM models the specific agent-level impacts of parking policies, including search behavior, pricing, and capacity constraints (W Axhausen, Horni and Nagel, 2016; Bischoff and Nagel, 2017).

Public transport reliability. When it comes to public transport reliability, FSM relies on schedule-based transit assignments with capacity constraints. ABM, however, uses dynamic GTFS schedules to more accurately capture real-world conditions, including fail-to-board events, crowding, and delays (Subbaraman, Adamidis and Drabicki, no date).

Active Travel. Active travel such as walking and cycling, FSM represents these modes at the zonal level within the mode choice model ((Flügel *et al.*, 1819).ABM offers a much finer resolution, modeling facility-level factors like slope and surface type, as well as complex intermodal connections (Ziemke, Metzler and Nagel, 2019; Balac and Hörl, 2021; Alvarez Castro *et al.*, 2024).

Ride hailing/pooling. Emerging services like ride-hailing and pooling are treated differently by the two frameworks. FSM typically adds them as a new mode within the mode choice step or requires additional tools to model them (Friedrich, Hartl and Magg, 2018). ABM can simulate the underlying complexities of these services, including driver-rider matching, wait times, and the dynamics of pooling (W Axhausen, Horni and Nagel, 2016; Maciejewski *et al.*, 2017).

Autonomous vehicles. FSM represents autonomous vehicles by modifying the parameters of the trip generation or mode choice steps (Friedrich, Sonnleitner and Richter, 2019; Liu, Haghighi, and University of Utah. Department of Civil and Environmental Engineering, 2022). ABM is much more robust, allowing for the city-scale simulation of fleet operations, including dispatching, pooling, empty vehicle mileage, and the effects of specific policies like pricing and access rules (Bischoff and Maciejewski, 2016).

Electrification. For electrification, FSM treats the car fleet as separate electric and conventional car segments, with their respective cost elements affecting travel choices (Tørset *et al.*, 2022). ABM, by contrast, simulates individual charging behavior and potential detours caused by charging needs (Hörl *et al.*, 2025).

Sharing System. Car, bike, and e-scooter sharing services are added as new modes within FSM's mode choice steps or can be modeled with extended FSM with external fleet management component (Narayanan and Antoniou, 2023). ABM provides a more detailed simulation that captures membership and eligibility, vehicle availability, and relocation or rebalancing operations (Chrisnawati and Susilo, 2024).

CONCLUSION

This article compared the FSM and ABM to assess their roles in addressing current urban mobility challenges. The traditional FSM, with its aggregated and structured approach, offers transparency and user-friendliness, making it well-suited for strategic, intercity, and long-term planning. However, its methodological framework struggles to capture individual-level heterogeneity, temporal dynamics, and emerging shared mobility services. These limitations led to the development of ABM frameworks.

Significant progress has been made to overcome the methodological limitations of FSMs through tour-based modeling, staged modeling processes, and the integration of Dynamic Traffic Assignment (DTA) to represent time-dependent network conditions and trip interdependencies. Moreover, extended FSM frameworks can now incorporate shared mobility options by linking disaggregate mode-choice layers with fleet management components. These developments enhance behavioral realism while preserving the model's simplicity and interpretability. Nevertheless, the FSM's matrix-based structure remains a major bottleneck, constraining further improvements in spatial resolution and behavioral detail

In contrast, ABMs simulate travelers at the individual level, capturing heterogeneity, adaptive behavior, and dynamic responses to policy and network changes. Their disaggregate nature enables realistic modeling of emerging modes such as ride-hailing, car sharing, and micromobility. Nonetheless, ABMs require high-quality data, significant computational resources, and face challenges related to model transparency due to the complexity of agent interactions and decision-making processes.

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