Advancements in Agent-Based Modeling for Travel Demand Forecasting (2020–2024)

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Abstract. This study aims to identify recent advancements in agent-based modeling (ABM) within the field of travel demand forecasting. To achieve this, peer-reviewed articles published between 2020 and 2024 were sourced from leading academic databases, including Web of Science, Scopus, TRIP (Transportation Research Integrated Database), and ScienceDirect. A total of 1,360 papers were initially retrieved. After a thorough review, 16 papers were selected for detailed analysis based on their strong alignment with the study's objectives.The selected studies were analyzed to uncover key advancements in the application of ABM to travel demand forecasting. Four main areas of progress were identified: (1) spatial-temporal demand modeling, (2) incorporation of multiple influencing factors, (3) utilization of diverse data sources, and (4) integration of multiple frameworks.To the best of our knowledge, few review studies have specifically addressed the use of ABM for travel demand forecasting. The insights from this research provide a foundation for further improvements to ABM, enabling more accurate and robust travel demand forecasting in future studies.

Keywords: Agent-based model; travel demand forecasting; development.

1. Introduction

Travel demand forecasting is a crucial field in transportation planning that predicts future travel patterns based on current and historical data [1,2]. It helps urban planners and policymakers understand how changes in transportation infrastructure [3], policies [4], or technologies will impact traffic flow [5], public transit [6]. Accurate forecasting ensures that cities can allocate resources efficiently, plan for sustainable development, and reduce congestion.

Traditional travel demand forecasting model is the Four-Step Travel Demand Model [7,8], which divides the forecasting process into four steps: trip generation, trip distribution, mode choice, and traffic assignment. This model used for urban planning, road infrastructure development, and transportation policy analysis. However, giving the shortcomings of this model, such as, it assumes that travel behavior is relatively static, so it excludes the changing factors like weather, policy. And it often relies on aggregate data, such as overall population numbers or traffic counts, and assumptions about group behavior. As a result, they may fail to capture the complexities and variations in travel choices, limiting their accuracy and effectiveness, particularly in rapidly changing or diverse urban environments. Researchers developed an alternative model – activity-based model for the travel demand forecasting – to overcome those shortcomings of the four-step model. One activity-based model is the agent-based modeling (ABM). Each agent operates independently according to specific rules and adapt to dynamic environments and interact with each other. ABM captures the complexity of agent interactions and the dynamic nature of transportation systems, which makes ABM particularly powerful in travel demand forecasting and transportation policy testing and transportation infrastructure planning.

Since the emergence of ABM dating back to the early 1990s, ABM in travel demand forecasting has evolved significantly over time. It first began to simulate individual behaviors and interactions. Initially, ABM applications were focusing on traffic flow [9] and basic route selection. Early applications often utilized simple models with limited agent interaction. With advancements in computational power and the availability of richer data, ABM expanded to simulate more complex travel behaviors, including responses to economic changes and policies. Technological advancements like machine learning, real-time data integration, and improved computational techniques have significantly enhanced the accuracy and applicability of ABM in transportation planning. Over those years, researchers raised various practical models, [10] summarized some important models in their book, they are ALBATROSS [11]; Feathers [12]; MATSim [13]; TRANSIMS [14, 15]; SimMobility [16]; POLARIS [17].

Although ABM has emerged as a tool for travel demand forecasting for almost 40 years, ABM still has limitations, as [10] listed in their book, ABM has following limitations: high computational complexity; no transparency in the mechanical process of agents interacting with other agents and environments which depends on the parameters' values; requires well-defined conditions and constraints; non-reproducibility due to the non-streamlined process of calibrating and imputing parameters for the models.

To assist future researchers in developing improved agent-based models (ABMs) to overcome existing limitations, [18] reviewed the applications of ABMs in urban transportation, categorizing them into nine distinct clusters, among them, the cluster 6 specifically focuses on the use of ABMs for travel demand forecasting. [18] observed that the trend in ABM research "tends to focus on how to generate synthetic populations of travelers." However, travel demand forecasting is just one aspect of their study. This research narrows its focus to papers published between 2020 and 2024 on the use of ABMs in travel demand forecasting, summarizing the key advancements in this area.

The rest of this paper is organized as follows. The next section presents the research methodology of this paper. This methodology tries to collect all relevant papers on the topic of ABM development and travel demand forecasting. Then, the findings of the selected papers. The final section summarizes the findings, and limitations of this research.

2. Research method

To get an understanding on the topic of the recent advancement of ABM in forecast travel demand, this study uses literature review method to collect all related literature published from 2020 to 2024. This method goes through following steps:

Step 1: Define the Scope and Objectives

- Clarify the Purpose: Analyzing the major advancements and methodological innovations.
- Set Boundaries: We set the time range from 2020 to 2024 October, focus on travel demand forecasting and agent-based modeling. Include journal papers, book chapters, conference papers.

Step 2: Search Strategy

- Keywords and Search Terms: Use terms like "agent-based modeling," "agent-based simulation," "multi-agent systems," "advances in ABM," and "ABM methodology." Combine these with application areas ("travel demand forecasting").
- Databases and Sources: Use relevant academic databases: General Databases: Science Direct, Scopus, Web of Science and Domain-Specific Databases: TRID (Transportation Research Integrated Database, for transportation focus).

After this step, we got 12 papers from Science Direct; 11 papers from Scopus; 529 papers from Web of Science; 808 papers from TRID.

Step 3: Screen and Select Studies

- Title and Abstract Screening: Quickly scan titles and abstracts to exclude irrelevant papers.
- Full-Text Screening: For selected studies, read the full text to ensure they are highly relevant. When reading all those papers, consider factors like: Focus on advancements in ABM methodology or discussions on the evolution of ABM applications or comparative analyses of ABM with other modeling approaches.

Step 4: Remove duplicate articles

After all those steps, we got 16 papers that closely related to the aim of this study.

3. Findings

The innovation of ABM in those 16 papers can be classified into the following groups: spatial-temporal demand modeling, incorporation of multiple influencing factors, utilization of diverse data sources, and integration of multiple frameworks.

3.1 Spatial-temporal demand modeling.

Spatial-temporal demand forecasting is essential for predicting travel demand in the complex dynamics of modern urban life, accounting for both geographic and temporal variations. It captures how travel behavior changes across different locations and times, enabling more accurate planning and management of transportation systems. This approach is especially valuable in urban environments, where demand patterns are highly complex and subject to significant fluctuations driven by factors such as time of day, day of the week, and local events.

[19] developed an agent-based model to forecast high-resolution spatial-temporal battery electric vehicle (BEV) charging demand. The model incorporates the travel and charging behaviors of BEV users, allowing for detailed predictions of charging station needs across various locations and times. This approach combines travel demand forecasting with electric vehicle charging infrastructure planning, offering more precise insights into future charging demands to optimize infrastructure development and reduce operational costs in large-scale BEV adoption.

[20] explores spatial resolution's impact on the efficiency of fleets of shared automated vehicle mobility services. The authors find that higher spatial resolution forecasts (short-term demand forecast) improve operational performance by enabling more precise fleet management and vehicle repositioning.

[21] investigates the use of social media data to refine ABMs. By leveraging geolocated social media data, such as Twitter and check-ins, the authors propose methods to detect local events and activities that significantly influence mobility patterns. These insights allow ABMs to better capture irregular travel behaviors, improving the accuracy of travel demand forecasting. The research highlights how social media data can enhance the granularity and dynamic response of traditional ABMs, especially in real-time demand prediction.

3.2 Utilization of diverse data sources.

Integrating non-traditional data sources, such as open-source data and social media, into ABM can significantly enhance model accuracy. By leveraging these data, ABM can more dynamically simulate the movement of individuals and groups, incorporating real-world events and social interactions that impact travel behavior. This advancement marks a significant step toward more responsive and data-driven travel demand models, with applications ranging from urban planning and real-time transportation management to forecasting disease spread.

3.2.1 Big data

[22] propose a new methodology that integrates ubiquitous big data to improve the scalability and realism of transport scenarios, focusing on activity-based modeling and its application to travel demand forecasting. The study highlights the use of aspatial scheduling models to enhance the agent-based framework for large-scale transportation systems.

3.2.2 Open-source data

[23] apply the mobiTopp multi-modal agent-based travel demand model to simulate1.9 million agents' behavior in the station-based bike sharing system when they choose pick-up and drop-off stations in Hamburg, Germany. [24] also use aggregated and anonymized mobile phone network datasets, which include trip-based and trip chains data to generate more accurate representations of travel patterns.

3.2.3 Synthetic population data

[25] discuss how ABMs can enhance travel demand forecasting by utilizing synthetic population data. They demonstrate how open, publicly available data—combined with travel behavior models—can generate detailed synthetic populations that reflect the diverse characteristics of real-world individuals. This approach improves the accuracy of travel demand simulations and provides better insights into mobility patterns across large urban areas like Paris .

3.2.4 Integrate Social Network

[26] explores the integration of social network dynamics with agent-based models to predict travel behaviors and their impact on disease transmission. The innovation here is in the application of social network structures — like household ties, neighborhood connections, and work relationships — into travel demand modeling. By simulating travel and contact patterns through social networks, the model assesses how these behaviors influence the spread of diseases like COVID-19. In the model, agents' travel patterns are linked with their social connections, which are dynamically updated. This allows the simulation to explore not only the effects of mobility on disease spread but also the impact of interventions like school closures and work-from-home policies. The research demonstrates that including social network interactions in travel demand forecasting can significantly improve the accuracy of simulations by reflecting real-world complexities in human movement and social contact.

3.3 Integration of multiple frameworks

Different frameworks offer unique advantages and face distinct limitations. Integrating them into a unified framework could yield more comprehensive and accurate results.

3.3.1 Integrate an activity-based model into an agent-based framework

[24] explores the role of ABM in forecasting demand for demand-responsive transport (DRT) and integrates it with traditional public transportation systems. The researchers utilized an activity-based ABM developed within the MATSim platform to simulate and predict mobility patterns using mobile phone network data. This model incorporates multimodal transport behaviors, helping to forecast demand for flexible, on-demand mobility services like ridesharing.

[27] explores the use of agent-based simulation to assess the potential impacts of automated mobility-on-demand (AMOD) systems on urban mobility, specifically in Singapore. The study uses the SimMobility simulation platform, which combines activity-based demand models with multimodal dynamic traffic assignment. This framework helps to simulate individual decisions, demand-supply interactions, and the overall system performance, providing insights into how AMOD could impact transportation networks, including congestion and modal shifts.

[28] discusses the integration of activity-based models with dynamic multimodal transit assignment, incorporating macroscopic road congestion estimation to achieve faster convergence. The study emphasizes the role of using such models in predicting travel demand more efficiently in complex urban environments. By dynamically adjusting the assignment of modes and activity patterns based on congestion data, the authors highlight improvements in simulation speed and accuracy, offering a more robust forecasting tool for urban transportation planning.

3.3.2 Integrate dynamic demand responses into the model

[29] presents an agent-based simulation framework for designing efficient, large-scale public transport networks. The model integrates dynamic demand responses to changes in both the transport network and external factors. Tested in Zurich, the framework suggests a sparser network with smaller vehicles, higher frequency, and ultimately, higher ridership at lower subsidies.

3.3.3 Integrate behavior models and multiple data sources to calibrate the simulation

[30] develops an agent-based microsimulation for predicting the demand for Bus Rapid Transit (BRT) in Dhaka, Bangladesh, using the MATSim framework. The study emphasizes integrating

behavior models and multiple data sources, including stated-preference data, to calibrate the simulation. Key findings highlight the influence of travel time, cost, and pricing on BRT demand, with multi-modal access leading to the highest demand. This work aims to enhance the planning of BRT systems and support future evaluations of innovative transport modes in Dhaka.

3.4 Incorporation of multiple influencing factors

Personal preferences, constraints such as time and spatial limitations, and external factors—including costs, availability, and emerging modes of mobility—significantly shape individual travel decisions. ABM incorporates these elements into its frameworks to produce more accurate travel demand forecasts.

3.4.1 Innovative mobility solutions influence the travel behavior

The adoption of new modes of travel such as car sharing, dynamic ridesharing, micromobility services, and autonomous vehicles may affect travel behavior, but traditional aggregate models often overlook the influence. [31] examines the effects of innovative mobility solutions such as carsharing, dynamic ridesharing, micromobility services, and autonomous vehicles on travel behavior and their integration into travel demand models. The study highlights how these new solutions disrupt traditional travel behavior and require updated modeling techniques to better predict future transportation trends.

3.4.2 Multiple complex interactions among agents

The authors [32] apply multi-agent multimodal simulations to predict transportation dynamics in Los Angeles. This simulation model incorporates various modes of travel, including public transport, private vehicles, and emerging shared mobility options. The agent-based approach is effective in capturing individual-level decision-making, helping to forecast demand across different modes while also considering congestion, mobility policies, and urban growth. These developments improve the accuracy of forecasting by modeling complex interactions among agents, providing insights for transportation planning and policy adjustments in large urban areas.

3.4.3 Individual travel preferences with system constraints

[33] focus on the development of a novel agent-based model for travel demand simulation. This model integrates individual travel preferences with system constraints, providing a comprehensive simulation across all mobility choices. One of the key innovations of the model is its ability to simulate both long-term mobility decisions, such as mobility tool ownership and work location choices, and daily travel patterns, by incorporating activity frequency, duration, and destination decisions.

A significant advancement in the model's design is its consideration of two primary constraints: transport infrastructure capacity and natural time/space limitations during the execution of an individual's 24-hour day plan. These constraints help ensure the model realistically reflects both personal preferences and system limitations. The integration of activity-based modeling with agent-based simulation makes the model more adaptable to real-world transport planning, ensuring that agents can respond dynamically to changes in network service levels .

This approach marks a significant step forward in modeling the complex interactions between personal travel choices and broader system constraints, providing more reliable insights into future mobility schemes and urban planning decisions. It highlights the growing importance of balancing individual preferences with the real-time limitations of transportation networks in agent-based models for travel demand forecasting.

3.4.4 The heterogeneity of individual traveler behavior

[34] highlight key developments in using ABM for transit ridership forecasting. It emphasizes how ABM has evolved to better represent the heterogeneity of individual traveler behavior, including factors like socio-economic status, preferences, and travel choices. These models are

increasingly capable of simulating complex interactions between agents, helping predict ridership with higher accuracy. Additionally, ABM allows for testing various policies, such as fare adjustments and service expansions, to understand their impact on demand.

4. Summary

This research centers on advancements in ABM for travel demand forecasting. A growing trend in this field involves incorporating multiple influencing factors into ABMs, utilizing diverse data sources — particularly open-source data — to develop reusable models, merging various travel demand forecasting approaches, and placing greater emphasis on spatial-temporal travel behavior.

This paper’s primary limitation lies in its exclusive focus on the development of ABM for travel demand forecasting, excluding consideration of other innovative methodologies. For instance, [2] proposes integrating natural environmental factors (e.g., weather) and socioeconomic factors (e.g., population density) to capture the complexity of urban travel demand, which is characterized by significant noise and fluctuating patterns. Their predictive model employs machine learning techniques to enhance forecasting accuracy, supporting urban planning and transportation system optimization. Similarly, [1] introduce a Residual Spatial-Temporal Network (RSTN) for travel demand forecasting. This deep learning architecture combines convolutional and recurrent neural networks to effectively model both spatial and temporal dependencies in urban travel data. The model's innovative use of residual connections addresses challenges such as vanishing gradients and improving training efficiency. By integrating spatial features (e.g., geographic data) and temporal patterns (e.g., time-series data), the RSTN demonstrates superior prediction accuracy compared to traditional methods, making it a valuable tool for urban transportation planning and real-time traffic management.

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