Perspectives

Mobility AI Agents and Networks

Haoxuan Ma, Yifan Liu, Qinhua Jiang, Brian Yueshuai He, Xishun Liao, and Jiaqi Ma, *Senior Member, IEEE*

***Abstract*—Intelligent vehicles and smart mobility systems are at the forefront of transportation evolution, yet effective management of these new mobility technologies and services are non-trivial. This perspective presents an Intelligent Mobility System Digital Twin (MSDT) framework as a solution. Our framework uniquely maps human beings and vehicles to AI agents, and the mobility systems to AI networks, creating realistic digital simulacra of the physical mobility system. By integrating AI agents and AI networks, this framework offers unprecedented capabilities in prediction and automated simulation of the entire mobility systems, thereby improving planning, operations, and decision-making in smart cities.**

***Index Terms*—Artificial intelligence, intelligent transportation system, mobility system digital twin.**

I. Introduction

RAPID urbanization and technological advancements have intensified the complexity of mobility management in cities [1]. The digital twin concept offers a promising solution, facilitating efficient planning, operations, and decision-making in mobility systems [2], [3]. This approach is particularly valuable for intelligent vehicles and smart mobility systems [4].

The key to establishing a mobility system digital twin (MSDT) lies in accurately modeling the intelligent behavior of all system components, such as humans, vehicles, and roadway networks.We propose Mobility AI agents and network modeling as core components. AI agents serve as simulacra of human beings, learning and replicating complex behavior patterns. AI networks represent an intelligent and adaptive model of the mobility infrastructure system, incorporating real-time data and self-learning capabilities. Together, they create a dynamic and realistic representation of mobility systems.

This perspective presents a conceptual framework for developing an MSDT that integrates diverse data sources, as illustrated in Fig. 1. Through data fusion and analytics, we construct accurate digital representations mirroring real-world mobility systems. This approach enables the creation of sophisticated AI agents and networks, supporting various applications from simulation tools to mobility system inference. These capabilities enhance planning processes, inform policy formulation, and facilitate strategic decision-making. The digital twin operates in a continuous feedback loop with the physical mobility system, allowing for real-time adjustments and long-term improvements in mobility management.

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Haoxuan Ma, Yifan Liu, Qinhua Jiang, Xishun Liao, and Jiaqi Ma are with the UCLA Mobility Lab and Mobility Center of Excellence, University of California, Los Angeles, Los Angeles, CA 90095 USA (e-mail: xishunliao@ucla.edu).

Brian Yueshuai He is with the Department of Civil and Environmental Engineering, University of Louisville, Louisville, KY 40292 USA.

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II. System Framework of MSDT

The MSDT is a comprehensive framework designed to enhance mobility analytics by integrating digital and physical systems. As illustrated in Fig. 1, this system relies on AI agents and AI networks to create a detailed digital replica of the physical mobility system, with the data warehouse serving as a critical foundation.

A. Data Warehouse

Our framework begins by constructing a comprehensive data warehouse that feeds into the digital twin. This data warehouse encompasses three key categories: Foundation, Processed, and Synthetic Data. Foundation Data includes human-sourced information (e.g., surveys [5] and tracked GPS points [6]) and infrastructure (e.g., Open Street Map [7], traffic count data [8], crash data [9], and aerial videos and images). Processed data, derived through data mining, includes aggregated traffic states and individual travel trajectories. Synthetic Data, generated via simulation or pre-trained models, encompasses synthetic population information, travel trajectories, and multi-modal networks. These datasets are crucial for developing and validating AI agents and networks, and for use case analyses like understanding travel patterns or network congestion.

B. Mobility System Modeling

The Mobility System Modeling process is central to our framework, bridging the data warehouse and Digital Simulacra to create an autonomous, intelligent digital twin of the mobility system. Agent Behavior Modeling, a critical component, focuses on three key models: human mobility, social relationships, and

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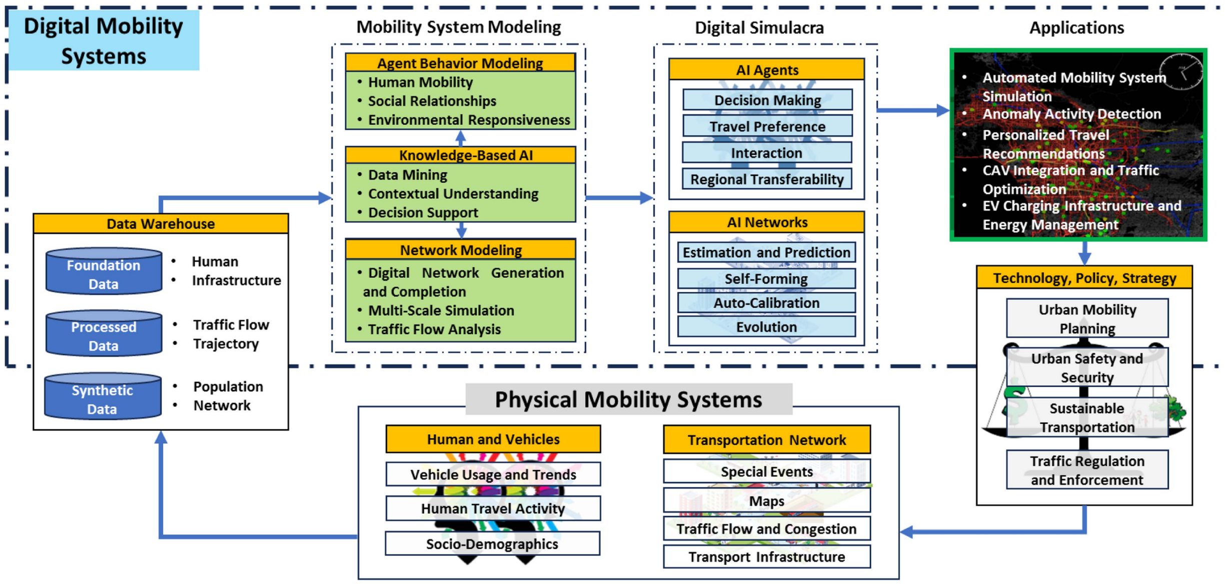

Fig. 1. Integrated intelligent mobility system: a digital twin framework with AI agent and network modeling.

environmental responsiveness. **Human Mobility** modeling examines how individuals with varying socio-economic and demographic backgrounds exhibit different daily activities and travel patterns, considering travel demand as derived from needed activities. This helps predict diverse mobility needs across populations [10]. **Social Relationships** modeling captures interpersonal dynamics influencing travel decisions, recognizing that an agent's activities are often affected by others, crucial for simulating interactions between AI agents. **Environmental Responsiveness** modeling examines agent decision-making under diverse conditions, from traffic scenarios to special events, ideally reflecting network changes including new technologies like EVs and AVs [11], [12], [13]. This equips AI agents with realistic decision-making capabilities, enabling interaction with evolving AI networks.

Network modeling, another crucial component, focuses on digital network generation and completion, multi-scale simulation, and traffic flow analysis. **Digital Network Generation and Completion** involves creating a digital representation of the physical mobility network using real-world data. Acknowledging data incompleteness, an AI-driven automatic completion process [14] is employed, utilizing nearby traffic network data, infrastructure sources, and human activity patterns to fill gaps. Next, **Multi-Scale Simulation** models is built on the digital network and ranges from individual agent-based simulations to large-scale transportation system simulations, capturing both micro-level interactions and macro-level patterns [15], [16], [17], [18]. The third aspect, **Traffic Flow Analysis** models traffic flow and congestion patterns, enabling the AI network to estimate and predict traffic conditions [19].

Moreover, knowledge-based AI, such as large language models (LLMs) and vision-and-language models (VLMs), enhances mobility system modeling by interpreting multi-source data. This equips AI agents and networks with the ability to extract crucial information and understand real-time mobility situations effectively.

C. Digital Simulacra: AI Agents and Networks

1) AI Agents: AI agents in our digital twin represent a significant advancement in simulating human mobility behavior. Each agent has a unique identity with specific socio-economic and demographic information, enabling decision-making based on complex situational factors, like traffic, weather, and time constraints.

These AI agents serve as foundation for next-generation activity-based travel demand models. They learn activity patterns for different identity types, form travel preferences, and adapt choices based on past experiences and new situations. Moreover, AI agents interact not only with other AI agents but also with the AI networks. For example, an agent might adjust its route based on real-time traffic conditions provided by the AI network, or the network might update its congestion predictions based on the collective behavior of multiple agents. This interaction simulates real-world network effect in transportation decisions, such as how individuals influence each other's travel decisions or how large events can cause shifts in traffic patterns.

The transferability of a pre-trained AI agent model allows for seamless behavior adaptation across different regions and cultures, making it versatile for various mobility systems. This transferability is achieved through fine-tuning techniques. We start with a base model trained on a large, diverse dataset, then adapt it to specific regions or cultures by training on smaller, localized datasets [10]. This approach allows the model to retain general mobility patterns while learning region-specific behaviors, enabling efficient deployment across different urban environments with minimal additional training.

2) AI Networks: AI networks form the backbone of our digital mobility infrastructure, offering real-time insights into system conditions, even in areas with limited data due to signal loss or low sensor coverage. They predict traffic by considering factors such as weather and special events, accurately forecasting future traffic states and understanding underlying causes and

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chain effects. For instance, an AI network can predict how a highway incident might lead to congestion on nearby roads or how severe weather might impact public transit ridership and road traffic.

AI networks form the backbone of our digital mobility infrastructure, powered by deep learning and generative models. These models enable the networks to dynamically evolve and autonomously generate adaptations [20], [21], like optimized pedestrian paths and bicycle routes based on real-time movement patterns. It also features auto-calibration, continuously fine-tuning its parameters based on observed discrepancies without human intervention.

Moreover, the network's evolution capability enables it to adapt to long-term changes in urban forms, policy, and human behavior, adjusting its model over time to accommodate new infrastructure, shifts in population density, or evolving transportation policies.

The synergy between AI agents and AI networks creates our Digital Simulacra, a comprehensive digital ecosystem. AI agents, loaded onto the AI network, influenced by network predictions, shape and are shaped by network conditions, capturing complex phenomena like emergent traffic patterns and the ripple effects of local disturbances. For instance, AI agents' route choices and travel times are affected by the network's traffic predictions, while the collective behavior of agents shapes the network's state and evolution. This integration allows scenario testing, where changes to agent behaviors or network conditions can be simulated to predict system-wide outcomes, providing valuable insights for urban planning and mobility management.

D. Applications

Digital Simulacra achieves digital autonomy and opens the door to numerous downstream applications.

- AI Agent Anomaly Detection: AI agents learn typical human movement patterns across different times, locations, and social contexts. These models identify deviations from the norm, allowing for the detection of anomalous activities within global human trajectory data [22], [23].
- Automated Mobility System Simulation: By integrating AI agents and networks, we can automate comprehensive simulations of entire mobility systems. AI networks create digital mobility networks, predict traffic patterns, and perform dynamic traffic assignments based on real-time conditions, while AI agents collectively lead to advanced activity-based travel demand models [14], [15].
- New Mobility Intelligence: AI agents learn travel preferences based on socio-demographic data, offering personalized travel recommendations [24]. Additionally, AI networks simulate the impact of CAVs on traffic flow, safety, and efficiency. Modeling human interactions with CAVs helps optimize integration strategies and predict adoption rates [25].

III. Progress and Results

Building on the comprehensive overview of the MSDT, this section provides a detailed examination of the AI agent and network modeling processes, as well as the outcomes and progress of ongoing research by the UCLA Mobility Lab. These processes form the core of our framework, enabling the creation of digital twins. The work started with LA as a testbed and is being extended to other places in the US and other parts of the world.

A. Data Warehouse Construction

Developing a high-quality data warehouse involves organizing, integrating, cleaning, and enriching raw data while annotating it with contextual information to enhance its utility for analysis, discovery, and decision-making. To build the data warehouse, we gathered and curated datasets from diverse sources.

- *Population Data:* American Community Survey [26], National Household Travel Survey [5], and Synthetic Population data from Southern California Association of Governments [27] for building AI agent profile.
- *Human Travel Behavior Data:* Household Travel Surveys [5], [28] and synthetic trajectory from LA-Sim [15] for AI agent travel activity modeling.
- *Location-Based Data:* GPS data provided by Veraset [6], and Point-of-interest (POI) data provided by Open Street Map [7] for learning the movement pattern of AI agent in the network.
- *Transportation Network:* Open Street Map for building road network [7], General Transit Feed Specification data for public transit behavior study [29].
- *Traffic Data:* PeMS [8] for traffic flow modeling, Regional Integrated Transportation Information System [30] and Work Zone Data Exchange [31] for work zone traffic impact modeling;
- *Stated/Revealed Preference Survey Data:* Southern California Autonomous Vehicle Preference Survey [32] for learning CAV impact on travel choices.

B. Implementation for AI Agents

Gathering socio-demographic information, travel diaries, and trajectories is essential to construct AI agents. However, collecting such data using location-based services raises significant privacy concerns [33], particularly regarding the identification of specific POIs within trajectories. To address privacy concerns, AI agents are developed as anonymous digital simulacra of human beings, designed to emulate travel behaviors while safeguarding personal privacy. By masking the link to any specific person, these agents can process and simulate detailed information without leaking personal data.

1) AI Agent Mobility Pattern Modeling: We develop the Deep Activity Model [10], a generative deep learning approach to model human mobility patterns using socio-demographic information, travel diaries, and travel trajectories. The model is trained to learn the relationship between an AI agent's socio-demographic information and mobility (activity and travel) patterns. Importantly, the input data includes information about the AI Agent's household members and social network, allowing the model to learn interactive behaviors and their impact on activities across multiple AI agents. The Deep Activity Model learns the dependencies between activities, considering factors such as start and end times, duration, and location for each activity. It employs an auto-regressive generation method, sequentially creating a full day's travel activities starting from midnight. As shown

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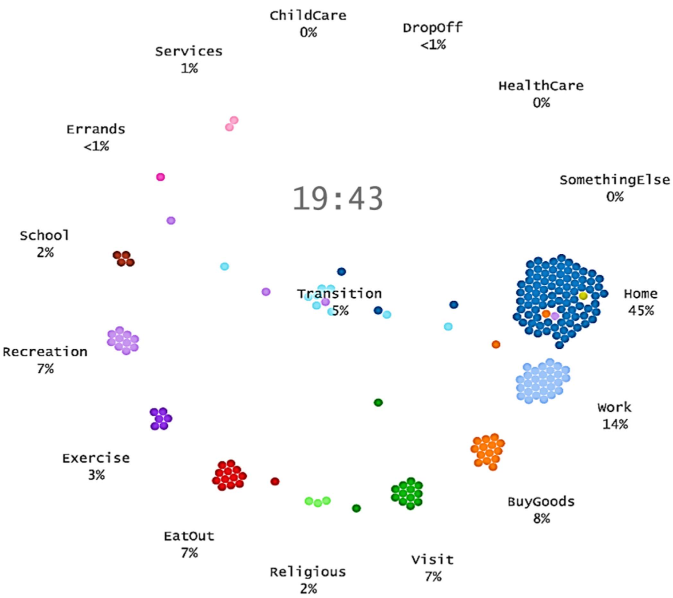

Fig. 2. Activity of 200 AI agents on a weekday at 19:43. Each bubble stands for an AI agent, and its travel behavior is displayed by the movement from one activity to another.

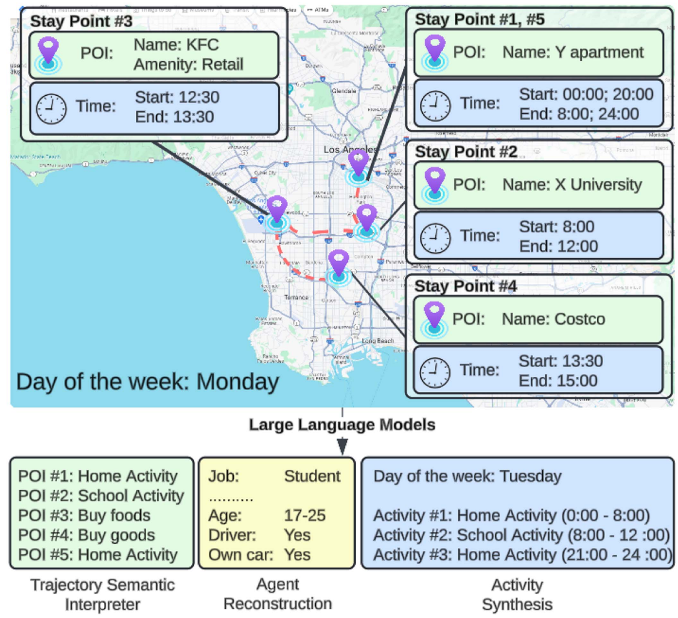

Fig. 3. Semantic trajectory analysis. (top) Raw trajectory data visualization and (bottom) analysis results using LLM.

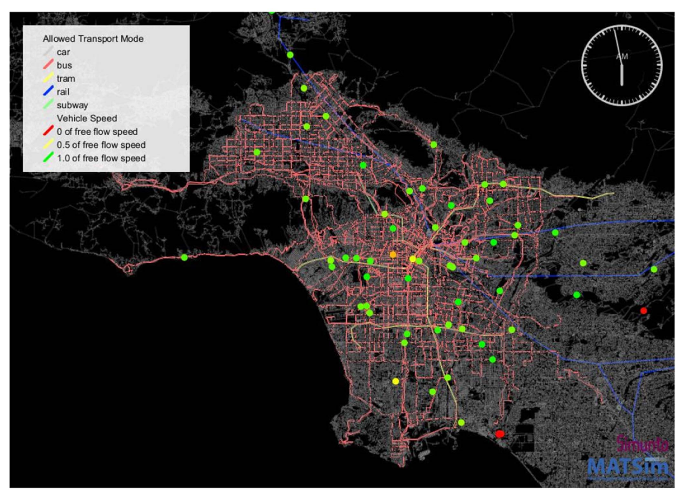

Fig. 4. Multi-modal mega-city macroscopic simulation in Los Angeles County.

in Fig. 2, this approach enables the model to generate realistic activities for AI agents by capturing the complex interdependency within households, social networks, and individual activities. Our experiments validate the model's robustness and versatility. It demonstrates strong performance when fine-tuned with data from diverse regions, including California, the Puget Sound area, and Mexico City. It allows us to capture various travel behaviors and patterns across geographical and cultural contexts.

2) AI Agent Modeling Empowered by Knowledge-Based AI: To enhance our AI agents' intelligence, we incorporate embodied AI principles [34], [35], enabling them to understand complex contexts and make informed decisions. We utilize knowledge-based AI approaches, particularly LLMs, to improve agent reasoning capabilities.

LLMs, as one typical knowledge-based AI, are employed for data mining to interpret trajectory stay points and annotate them with possible POIs and activities [36], as illustrated in Fig. 3. This process enriches time series data by utilizing the knowledge embedded within LLMs, allowing AI agents to contextualize trajectories. In cases of missing social-demographic information, LLMs reconstruct AI agent profiles by inferring attributes from annotated trajectory data.

When social-demographic information is missing, LLMs infer AI agent attributes from annotated trajectories, such as occupation and income level. These reconstructed profiles enable the generation of realistic activities, guiding AI agents to exhibit human-like decision-making in complex mobility scenarios, incorporating both raw and contextualized data.

C. Implementation for AI Networks

1) Agent-Based Simulation: We developed a large-scale simulation platform to generate realistic travel trajectories and traffic conditions. Our Deep Activity Model creates accurate mobility patterns, incorporating diverse transportation modes for comprehensive representation [10]. As shown in Fig. 4, the network integrates local road and public transit infrastructures, with AI agents loaded into the system.

Our simulation uses the MATSim toolkit [37] as the base simulation platform, which allows detailed AI agent profiles and network models. We optimized the model using a data-driven approach by clustering highways based on traffic data. Future work will involve formulating this optimization as a meta-model for auto-calibration.

We applied our simulation platform to Los Angeles County [15], featuring multimodal networks, a million-level agent scale, and provisions for micro-mobility and electric vehicles. Adaptive traffic signal control algorithms [38], [39] is adopted to mimic real-world traffic. After validation against

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real traffic counts and extensive calibration, the model effectively predicted and analyzed traffic dynamics, offering insights for urban planners and policymakers. This supports decision-making to enhance transportation efficiency, reduce emissions, and improve urban mobility in densely populated areas.

2) Network State Modeling: Traffic state prediction is a crucial component of intelligent transportation systems (ITS), enhancing the AI network's estimation and prediction capability. We have made significant breakthroughs in estimating and predicting traffic state in special events. For example, We developed a novel deep-learning model to predict traffic speed and incident likelihood during planned work zone events [40]. Also, we model the long-term congestion and short-term speed patterns during hurricane evacuations [41]. These accurate and timely predictions, especially predictions under special weather and roadway conditions, enhance traffic management and support congestion prevention and mitigation efforts. These deep learning and generative models are embedded in and serve as the backbones of the AI Networks which automatically generate future network evolution.

3) Interactions Between AI Agents and AI Networks: The interaction between AI agents and networks, particularly in estimating how agents' behavior impacts the network, is central to our modeling approach. Our previous work explored how mobility agents using CAVs and Electric Vehicles (EVs) influence mobility patterns in large urban networks [32], [42], [43], [44], utilizing traditional choice models like activity-based models (ABMs). However, ABMs are time-consuming and resource-intensive, limiting scalability. To address this, we are integrating AI agents with network systems to establish a feedback loop that enhances our MSDT framework, aiming to dynamically refine interaction models, ensuring continuous adaptation to emerging traffic patterns and urban changes.

IV. Future Works

Looking ahead, this MSDT framework consists of AI agents and networks that have the potential to revolutionize the way we model and analyze mobility systems, by accurately simulate the impacts of new technologies, policies, and infrastructure changes leveraging the power of data and AI. Future work will focus on enhancing agent learning capabilities, improving the adaptability of AI agents and networks, and developing sophisticated interaction models. This approach will provide planners and engineers with valuable insights for creating increasingly efficient and sustainable mobility systems.

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