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Perspective

Towards zero-emission urban mobility: Leveraging AI and LCA for targeted interventions

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Abstract

Urban mobility is a critical contributor to greenhouse gas emissions, accounting for over 30% of urban carbon emissions in the United States in 2021. Addressing this challenge requires a comprehensive and data-driven approach to transform transportation systems into sustainable networks. This paper presents an integrated framework that leverages artificial intelligence (AI), machine learning (ML), and life cycle assessment (LCA) to analyze, model, and optimize urban mobility. The framework consists of four key components: AI-powered analysis and models, synthetic urban mobility data generation, LCA for environmental footprint analysis, and data-driven policy interventions. By combining these elements, the framework not only deciphers complex mobility patterns but also quantifies their environmental impacts, providing actionable insights for policy decisions aimed at reducing carbon emissions and promoting sustainable urban transportation. The implications of this approach extend beyond individual cities, offering a blueprint for global sustainable urban mobility.

Keywords

urban mobility
artificial intelligence (AI)
life cycle assessment (LCA)
sustainable transportation
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1 Introduction

Urban mobility significantly influences the environmental footprint of our cities, contributing to more than 30% of carbon emissions in urban centers (EPA 2023) in 2021 in the U.S., equivalent to about 180 million metric tons of carbon dioxide. It's the biggest single source of greenhouse gas emissions in the country. The demand for sustainable and environmentally friendly mobility systems increases as urban areas continue to expand and evolve (Fulton et al. 2009; Li et al. 2022).

However, our current understanding and approach toward sustainable urban mobility are hindered by two significant gaps. The first gap concerns the scarcity of large-scale, high-spatiotemporal, high-accuracy, individual-level, and openly accessible mobility data (Zheng 2015). Existing mobility data often lacks the scale and granularity necessary to accurately capture the diverse and dynamic nature of urban mobility. This limitation impedes our ability to fully comprehend and effectively address the environmental impact of various transportation modes and practices tailored to each individual citizen. Additionally, most existing data is proprietary and not available for public access, which restricts opportunities for research and innovation in this vital field. The second gap relates to the insufficient integration of life cycle assessment (LCA) methodologies in urban mobility studies. LCA provides a thorough approach to evaluating the environmental impacts of a product or system throughout its entire life cycle, from production to disposal. However, the application of LCA in urban mobility is still limited (Van Mierlo et al. 2017; Chester and Horvath 2009), preventing a comprehensive understanding of the environmental impacts of our transportation systems, particularly those associated with the production and disposal of vehicles, infrastructure, and fuels. Bridging these gaps is essential for advancing sustainable urban mobility.

This Perspective article advocates for an integrated approach to studying urban mobility. It envisions a future where the power of artificial intelligence (AI) and machine learning (ML), interwoven with robust LCA methodologies, unlocks a deeper understanding of urban mobility patterns and their intricate environmental consequences. By leveraging the capabilities of these transformative technologies, urban planners can shift from merely responding to issues as they

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arise to implementing proactive strategies that anticipate and prevent congestion. This approach empowers cities to make more informed decisions, ultimately improving the quality of life for residents.

2 Shaping the future of urban mobility: An integrated approach

The transformation of urban mobility systems into sustainable and efficient networks requires a holistic and integrated approach that addresses the multifaceted challenges of modern transportation. This section introduces a framework designed to achieve this goal by combining the strengths of cutting-edge technologies and analytical methodologies. As illustrated in Figure 1, the framework is built upon four key components: AI-powered analysis and models, synthetic urban mobility data generation, LCA for environmental footprint analysis, and data-driven policy interventions. Together, these elements form a cohesive strategy that not only deciphers complex mobility patterns but also quantifies their environmental impacts and informs actionable policy decisions. Each of the following subsections delves into these components in detail, outlining how they contribute to the overall objective of fostering sustainable urban mobility.

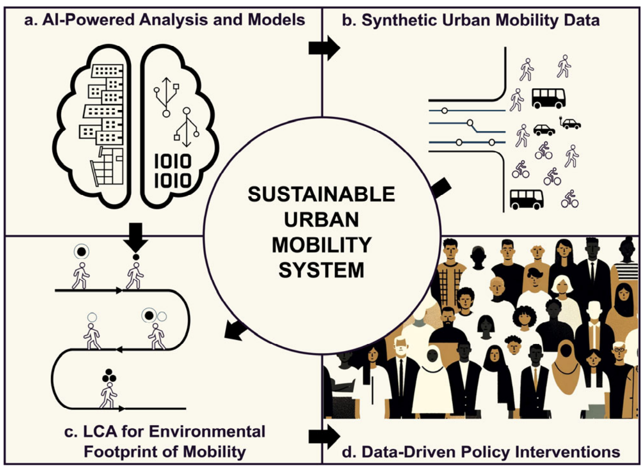

Fig. 1 Integrated framework for sustainable urban mobility systems. The framework consists of four interrelated components: (a) AI-powered analysis and models, which leverage advanced machine learning techniques to uncover complex urban mobility patterns; (b) synthetic urban mobility data, which uses AI-generated datasets to model and simulate realistic mobility scenarios for data-scarce environments; (c) LCA for environmental footprint of mobility, where individualized LCA profiles assess the environmental impacts of different transportation modes based on real or synthetic data; and (d) data-driven policy interventions, which utilize insights from mobility patterns and LCA profiles to craft targeted, non-intrusive policies aimed at reducing carbon emissions and promoting sustainable urban transportation

To accurately capture the complexity of urban transportation networks, our framework considers travel modes that encompass both public and private forms of transport, including buses, subways, shared bikes, private cars, and pedestrian travel. By incorporating data from these varied modes, it ensures that the generated trajectories for each individual reflect the multimodal nature of urban mobility. However, it is important to recognize that transportation choices are deeply influenced by cultural factors, which vary significantly across different urban environments. Therefore, in specific studies, it is practical and necessary to focus on the transportation modes that are most prevalent and culturally relevant in particular city settings. This approach allows for a more accurate and context-sensitive analysis of urban mobility patterns, ensuring that the findings are applicable and meaningful within the specific cultural context of each study area.

2.1 Unlocking mobility insights through AI-powered analysis and models

AI and ML provide transformative power to analyze and model urban mobility. These rapidly advancing technologies offer unprecedented opportunities to unravel the complexities of urban transportation systems. By leveraging AI and ML, we will be able to better understand how individuals navigate urban environments (Figure 1(a)) (Simini et al. 2021; Pappalardo et al. 2023). The new knowledge will provide new strategies to optimize transportation systems and mitigate their environmental impacts.

However, current travel data often lack the necessary scale, granularity, and accuracy required to fully capture the diversity and dynamics of urban travel. Privacy concerns and data confidentiality further complicate data collection efforts. To address these challenges, future research must focus on integrating diverse data sources, such as crowdsourced data, sensor networks, and data from mobile devices. These sources can provide high-resolution, real-time information that enhances our understanding of individual and collective movement patterns. Moreover, innovative data collection methods, including the use of privacy-preserving techniques like differential privacy and federated learning, can help balance the need for detailed mobility data with the requirement to protect individual privacy. By adopting standardized data collection protocols and frameworks, we can improve the interoperability of datasets, enabling more accurate and comprehensive analysis.

AI models, particularly those trained on extensive datasets of GPS trajectories, hold immense potential for uncovering intricate patterns in both individual and collective movement. These models, which utilize advanced architectures such as trajectory sequencing and temporal encoding, are capable of identifying recurrent mobility patterns, predicting future movements, and revealing previously unnoticed correlations between mobility behaviors and external factors, including weather conditions, public events, and urban infrastructure. Additionally, the scalability of these AI models is a critical factor in their applicability across diverse urban contexts. As these models are designed to process and adapt to the vast and continuously expanding volume of mobility data, they can provide detailed insights into transportation dynamics across a range of urban environments—from large metropolitan areas to smaller cities.

The development and validation of these AI-driven tools necessitate rigorous testing and comparative analysis with existing models. Despite the challenges associated with this process, the potential benefits are substantial. By accurately capturing and analyzing mobility patterns, AI can facilitate a shift from reactive to proactive urban mobility planning, fostering the integration of transportation systems into the broader framework of sustainable urban development.

2.2 Creating synthetic worlds: The power of simulated mobility data

The ability to generate realistic synthetic mobility data represents a significant leap forward in our quest for sustainable urban transportation. By harnessing the power of AI models, we can create virtual "sandboxes" that accurately mirror the complexities of real-world urban mobility (Figure 1(b)). These synthetic datasets, crafted to adhere to the statistical characteristics of observed mobility patterns, offer a valuable tool for addressing data scarcity and exploring potential scenarios without compromising individual privacy.

The realism of these synthetic worlds is paramount as they should be able to capture the subtleties and complexities of individual travel behaviors, reflecting the diverse modes of transportation, trip purposes, and temporal dynamics that characterize urban mobility. This fidelity is crucial for ensuring that the insights derived from synthetic data are transferable to real-world scenarios. Moreover, the ability to generate synthetic data across different urban contexts allows us to test the generalizability of our models and identify common patterns as well as unique characteristics of specific cities. This "cross-city synthesis" approach is essential for developing robust and adaptable solutions that can be applied to a wide range of urban environments.

The validation of synthetic data is equally critical. Rigorous comparisons with real-world data such as national household travel survey, using metrics such as trip distance, travel modes, and temporal distributions, will ensure the accuracy and reliability of these synthetic worlds. By benchmarking against existing models and datasets, we can continually refine our synthetic data generation techniques and ensure their validity for informing policy decisions and shaping the future of urban mobility.

2.3 Beyond the journey: Quantifying the environmental footprint of individual mobility

Understanding and generating urban mobility patterns is only the first step in achieving sustainable transportation systems; quantifying the environmental impacts of these movements is equally critical. LCA provides a robust framework for this analysis, allowing researchers and policymakers to move beyond aggregate statistics and examine the specific contributions of individual mobility behaviors to the personal carbon footprint and environmental impact (Enlund et al. 2023). Thus, the integration of LCA methodology is pivotal in translating raw data into actionable insights regarding the environmental impacts of various transportation modes (Figure 1(c)). By applying LCA at an individual level, we can create a detailed environmental profile for each set of mobility patterns observed in the urban dataset, thereby addressing the critical gap of LCA application in urban mobility.

The creation of individualized LCA profiles begins with segmenting mobility patterns by transportation mode, which is critical for accurately assessing the environmental impacts of different transportation types. Using machine learning algorithms, we classify travel segments based on speed, location, and patterns to identify modes such as cycling, driving, or public transit. Once the modes are identified, we develop customized LCA models for each one, considering their entire lifecycle, including vehicle manufacturing, fuel emissions, and end-of-life disposal. For instance, driving models account for vehicle production, fuel consumption, and emissions, while public transit models consider infrastructure and energy use. For cycling, the LCA includes the production of bicycles and the environmental impacts of bike lane infrastructure.

Our LCA methodology is based on the ISO 14040 standard (ISO 2020), and its design and implementation follow these steps: first, we define the goal and scope, which for this study is to quantify the environmental impacts of various transportation modes. Next, we collect data from reliable sources like government reports and databases such as Ecoinvent, covering raw material extraction, manufacturing, fuel use, and disposal. For electric vehicles, regional energy mix data ensures accurate carbon footprint estimates, while human-powered modes consider the impacts of infrastructure. We then assess the environmental impacts using the ReCiPe methodology, covering impact categories such as global warming potential and resource depletion.

To ensure accuracy, we cross-verify data, perform sensitivity analyses on key assumptions like fuel efficiency, and benchmark our findings against existing LCA studies. This comprehensive approach enables us to provide reliable environmental impact assessments that offer valuable insights for policymakers and urban planners, promoting sustainable mobility options and supporting informed decision-making.

A central innovation of our approach is the LCA, which links each individual's mobility data, empirically collected or synthesized, to a detailed and tailored environmental profile. This profile includes metrics like carbon emissions, resource consumption, and potential ecological impacts. These profiles are derived from sophisticated analytics that calculate the environmental costs associated with different transportation choices.

2.4 Shaping sustainable cities: Data-driven policy interventions for a greener future

The final part of this integrated approach capitalizes on the insights gained from the first three steps to develop and test passive, non-intrusive policy interventions (Figure 1(d)). These policies are specifically designed to substantially reduce carbon emissions to a target (e.g., 30%).

The policies will be intricately crafted using the insights gathered from the synthetic mobility data and LCA profiles developed. This data-driven approach ensures that each policy minimizes disruption while enhancing the efficiency of urban mobility systems. Some examples of the policies can include dynamic pricing for tolls and public transportation to manage peak demand times, zoning adjustments that promote transit-oriented development, and the implementation of smart traffic management systems that adjust signals in real-time to optimize traffic flow and reduce congestion. The synthetic mobility data provides a detailed understanding of traffic patterns, identifying peak travel times and heavily utilized routes. This information is crucial for designing targeted traffic flow measures, such as optimizing traffic light sequences or implementing smart traffic management systems that adapt to real-time conditions to alleviate congestion. Simultaneously, individual LCA profiles, which detail the environmental impacts associated with various transportation modes, will guide the development of specific interventions. For areas where LCA profiles highlight significant emissions from fuel-based vehicles, policies could promote the use of electric vehicles through tax incentives, subsidies, or by increasing the availability of charging stations. Similarly, in regions where short car trips significantly impact the environment, the introduction of better infrastructure for non-motorized transportation, like expanded bike lanes or pedestrian zones, could encourage walking and cycling, thereby reducing emissions. Enhanced public transit accessibility will also play a key role, especially during peak emission periods. Policies might include increasing the frequency of buses and trains or reducing fares during peak hours to shift commuter preference away from private vehicles.

Each policy can be rigorously tested through simulation models that leverage the synthetic mobility data to predict the outcomes of proposed interventions. These simulations will help forecast how changes could influence traffic flows and emissions levels, allowing for the refinement of policies based on these outcomes before they are implemented on a larger scale. This method ensures that the policies are not only grounded in robust data but also flexible enough to adapt to observed and unforeseen challenges, ultimately making them more effective in reducing carbon emissions while improving urban mobility.

3 Conclusion: Data-driven mobility towards a sustainable urban future

The escalating challenges of urban mobility demand innovative solutions that transcend conventional approaches. This Perspective presents a vision, where the convergence of AI, ML, and LCA unlocks a deeper understanding of mobility patterns, enabling data-driven policy interventions that pave the way for greener, more efficient, and equitable urban transportation systems. This integrated approach has the potential not only to significantly reduce carbon emissions but also to empower urban planners with granular insights to create more livable, resilient, and sustainable cities. The implications of this data-driven approach extend far beyond individual cities, offering a blueprint for a global movement towards smarter urban environments. As urbanization accelerates worldwide, the need for sustainable mobility solutions becomes increasingly urgent. By embracing open data principles and fostering collaboration among researchers, policymakers, and industry stakeholders, we can accelerate the development and adoption of these transformative technologies, ensuring a more sustainable future for generations to come.

The future of our cities hinges on our collective ability to embrace data-driven solutions. This Perspective is not just a vision for sustainable mobility research; it is a call to action for the present. Researchers, policymakers, and industry leaders must invest in the development and deployment of data-driven solutions, fostering a collaborative and multidisciplinary approach to reshape urban mobility. By harnessing the power of AI, ML, and LCA, we can unlock the potential for sustainable urban transportation and create cities that are not only vibrant and prosperous but also environmentally responsible. Let us embrace the power of data and innovation to pave the way for a brighter, more sustainable urban future for all.

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Declaration of competing interest

The author has no competing interests to declare that are relevant to the content of this article.

Ethical approval

This study does not contain any studies with human or animal subjects performed by any of the authors.

Author contribution statement

Qi R. Wang contributed solely to the conception and design of the study. Qi R. Wang drafted, revised, and approved the manuscript.

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