Mapping, Modeling, and Measuring Walking and Walkability: The Role of AI in Enhancing Urban Pedestrian Networks

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Abstract*—Urban mobility is rapidly evolving as cities aim to enhance sustainability, walkability, and active transportation. This paper presents our ongoing research on how machine learning and AI-driven techniques can transform urban active transportation planning. We first explore the use of computer vision to map sidewalks from imagery data, offering an innovative approach to urban infrastructure management. Although AI-based models demonstrate high accuracy in detecting pedestrian infrastructure, challenges such as occlusions and network completeness persist, highlighting the need for further refinement of these approaches. In the second part, we explore machine learning approaches for estimating walking trips across large-scale networks, addressing key challenges like scalability and data biases. Additionally, we demonstrate the potential of spatially transferable models, highlighting machine learning's adaptability to diverse urban environments to estimate pedestrian travel demand. Finally, we discuss the role of AI in measuring visually perceived walkability through street-level images, identifying factors that influence pedestrian experiences. Together, these approaches contribute to a holistic understanding of pedestrian travel dynamics and infrastructure networks, laying the foundation for smarter, more walkable cities.

I. Introduction

Urban mobility is undergoing significant transformations as cities strive to promote more sustainable, accessible and pedestrian-friendly environments. In this context, walking and walkability are increasingly recognized as crucial components of accessible active transportation systems (De Vos et al., 2023; Iroz-Elardo et al., 2020). This paper presents our ongoing research on the role of AI and machine learning in enhancing urban pedestrian networks through the mapping, modeling, and measurement of walking activities and walkability. Using AI-driven techniques such as computer vision for sidewalk mapping, machine learning to estimate walking demand, and new approaches to assess visual perceptions of walkability, our objective is to address key challenges in urban planning, including data gaps, scalability, and biases. Our research contributes to a more comprehensive understanding of pedestrian infrastructure network and travel dynamics, offering valuable insights for urban planners to design more walkable, inclusive, and accessible cities.

II. Mapping Pedestrian Infrastructure

The use of AI in mapping pedestrian infrastructure is crucial to address gaps in the coverage and quality of sidewalk data. Traditional methods, such as surveying and collaborative mapping through platforms such as OpenStreetMap (OSM), have been useful but come with significant limitations, including inconsistencies in data quality and sparse pedestrian network information. AI-assisted approaches, particularly deep learning models, offer a promising alternative by automating the detection and mapping of pedestrian infrastructure from aerial imagery, street view images, and remote sensing data. Tools such as Tile2Net (Hosseini et al., 2023), which use hierarchical multiscale attention architectures to detect sidewalks and crosswalks from orthorectified imagery, have been developed to create detailed city-wide pedestrian maps. Despite these advancements, AI models still face challenges, such as disjointed networks caused by occlusions and detection inaccuracies. Although some studies have employed techniques such as image inpainting to address these issues (Senlet and Elgammal, 2012), more research is required to improve network completeness. The integration of AI with collaborative mapping tools such as OSM is seen as a future direction to improve pedestrian infrastructure datasets, making them more accurate and reliable for urban planning. The lack of accurate and up-to-date pedestrian network data remains a significant obstacle in urban planning, especially as the demand for sustainable and accessible transport infrastructure grows. To overcome these limitations, we are developing an AI-assisted approach that automates pedestrian network mapping, improving both scalability and precision. Our method leverages computer vision techniques and machine learning to extract pedestrian networks from aerial imagery and other sources, such as street view images. See Figure 1. Given the shortage of high-quality datasets for pedestrian pathway detection, we aim to create our own dataset for pathway segmentation using public and private data. This involves extracting existing network data from OSM and projecting it onto imagery to generate segmentation masks for training. Drawing inspiration from road network extraction studies (He et al., 2020; Hetang et al.,

Fig. 1: (a) Aerial shot of Jordan Springs, NSW, highlighting minimal occlusion in the urban landscape. (b) Tile2net Network (c) Resulting network after applying our post-processing heuristic

2024; Xu et al., 2022), our approach introduces a graph neural network to predict the network topology and fill the gaps in the mapped infrastructure. A custom heuristic algorithm is also incorporated to address common neural network errors, such as missing or falsely connected links, ensuring a higher-quality network. Additionally, this research aims to explore human-AI collaboration, where the AI model adapts to the expertise of human operators (Madras et al., 2018; Mozannar et al., 2023). This collaboration, facilitated by an allocation module, balances the strengths of both AI and human input, focusing on areas where AI excels while allowing human judgment to handle challenges the AI may struggle with. By combining AI's efficiency with human expertise, the approach provides a scalable, high-quality solution for pedestrian network mapping, essential for developing active transport infrastructure and fostering more walkable, livable cities.

III. MODELING PEDESTRIAN ACTIVITIES AND DEMAND

Modeling pedestrian activities and demand using machine learning approaches is critical for understanding urban mobility, especially in large and complex networks. A comprehensive approach requires combining data from various sources (Nelson et al., 2021), addressing scalability challenges, and ensuring transferability of models across different regions. To tackle the issue of scalability in large-scale networks, we conducted a study across the New South Wales (NSW) Six Cities Region network consisting of 188,999 links and applied machine learning models to estimate walking volumes (Saberi and Lilasathapornkit, 2024). See Figure 2. This study highlighted the challenges of scaling localized models to regional applications due to the biases and gaps in mobile phone data that may underrepresent short trips like walking. To mitigate these issues, the research proposed an extensive cross-validation approach and the integration of various auxiliary datasets, such as population and land use data, which ultimately improved model performance and made the predictions more robust across the region.

In addition to scalability, transferability of pedestrian models is crucial when applying models in different urban settings (Sikder et al., 2013). To address this challenge, we have conducted a study examining the spatial transferability of pedestrian trip generation models in Sydney, Melbourne, and Brisbane (Nourmohammadi et al., 2024). The study aimed to understand how well models developed in one city could be applied to another without a significant drop in accuracy. The findings revealed that aggregated models, such as those using zonal-level data, transferred better across cities compared to disaggregated models, which are more sensitive to local variations. The study also introduced a framework, Spatially Transferable Pedestrian Demand and Network (STePNet) Model, for integrating pedestrian demand and network models to improve model transferability. This is particularly valuable for urban planners and policymakers in regions with limited pedestrian data, as it allows them to use models trained elsewhere and apply them effectively to their local contexts.

The effectiveness of machine learning in pedestrian demand and activity estimation also hinges on the choice of modelling methodologies and the ability to handle large datasets while avoiding overfitting. Different machine learning techniques have been employed to predict pedestrian volumes based on features such as street connectivity, land use, and Points of Interest (POI) density. These models offer flexibility in capturing non-linear relationships between variables and can scale to larger networks. However, ensuring model generalizability remains a challenge, particularly in regions with scarce pedestrian data. To address this, the use of spatial cross-validation and outlier detection methods, has proven effective in improving the reliability of pedestrian volume estimates. This approach ensures that machine learning mod-

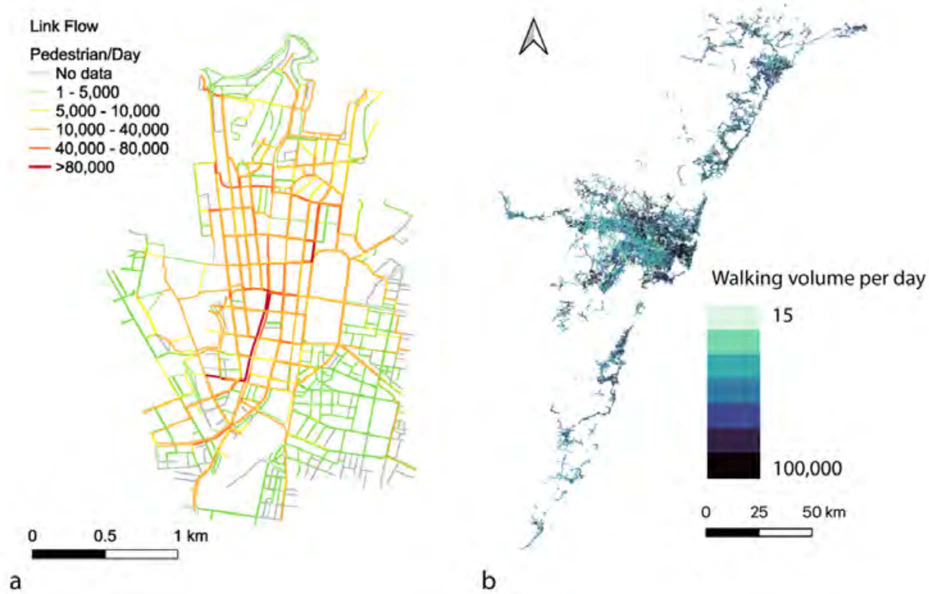

Fig. 2: (a) Estimated daily pedestrian volumes at the sidewalk level for Sydney CBD network using an approximated daily walking origin-destination demand matrix and a stochastic route choice model. (b) Estimated daily pedestrian volumes for the large-scale network of New South Wales Six Cities Region in Australia using machine learning approaches and mobile phone data

els remain robust, scalable, and transferable across different urban settings, ultimately supporting the development of more pedestrian-friendly and sustainable cities.

IV. Measuring Visual Walkability Perception

Visual walkability perception has gained significant attention in recent years due to advancements in computer vision techniques and the widespread availability of street view images (Ito et al., 2024). However, several key limitations in current approaches still persist. The two primary challenges are the diversity in perception and the potential biases inherent in using street view images (SVI) when measuring walkability. The globally recognized Place Pulse dataset (Dubey et al., 2016; Salesses et al., 2013), while providing valuable insights into urban perception from cities worldwide, was not specifically designed to assess walkability. Moreover, it assumes that a single index can represent urban perception for all people, disregarding individual socioeconomic differences. Further research suggests that walkability perceptions are shaped by people's socioeconomic backgrounds (Liu et al., 2023). For instance, individuals living in affluent areas may perceive their urban environments differently from those in less privileged settings. Additionally, many past studies have relied on SVI for walkability analysis due to its wide geographic coverage (Liu et al., 2023). Despite its usefulness, SVI introduces potential biases and inaccuracies (Koichi Ito and Biljecki, 2024). See Figure 3 A significant limitation of SVI is that it captures the driver's perspective, not the pedestrian's, whose experience is the central focus of walkability assessments.

To address these challenges, our research aims to bridge the gaps by collecting data on both socioeconomic backgrounds and walkability perceptions using high-quality 360-degree sidewalk view images. These images offer a pedestrian-centered perspective, which is more appropriate for understanding walkability perceptions. Our ongoing research aims to analyze how perceptions differ across demographic groups and identifies key attributes that shape each group's experience of walkability. By utilizing sidewalk view images, we aim to minimize biases in both physical and perceived walkability indices, improving the accuracy and generalizability of walkability assessments. Ultimately, our goal is to develop a personalized walkability index that reflects the unique needs and preferences of diverse populations. This personalized index will provide urban planners with critical insights to enhance urban design and create more inclusive and equitable environments for all communities.

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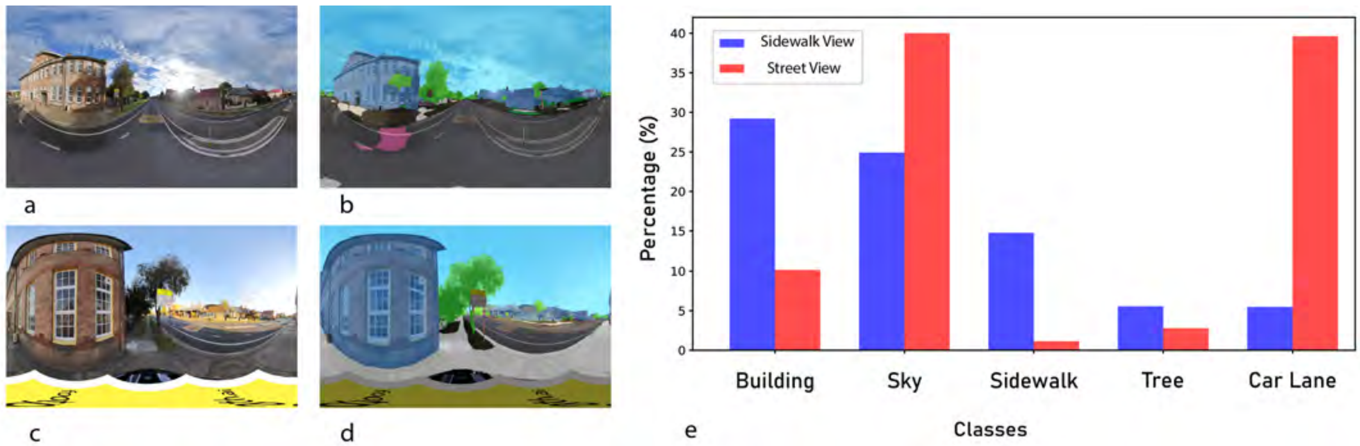

Fig. 3: Images illustrating the comparison between sidewalk and street view perspectives: a) Sidewalk view image, b) Semantic segmentation of the sidewalk view, c) Street view image, d) Semantic segmentation of the street view, and e) Comparison of Class Percentages Between Sidewalk View and Street View Images for a single location, showing differences in object class distributions including building, sky, sidewalk, tree, and car lane.

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