

Sustainable Transit through Public Agency Leadership: Policies, Economics, and AI

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**Abstract**

Sustainable Transit through Public Agency Leadership: Policies, Economics, and AI

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Urban Design and Planning

This dissertation integrates three empirical studies to advance planning and decision-making for Transit-oriented Development (TOD) and Transit-Incorporating Mobility-on-Demand (TIMOD) services led by public agencies in regional growth centers and low-density areas. The first study develops a multi-criteria tool to prioritize TOD on public land through a suitability assessment. The tool incorporates 14 indicators across five domains, including public transit service, land use, sociodemographics, real estate market conditions, and planning context. It is applied under three development scenarios: affordable housing, market-rate housing, and mixed-use development. This tool enables public agencies to strategically leverage land assets to support transit-supportive and equitable development.

The second study evaluates the comparative cost-effectiveness of TIMOD relative to fixed-route transit, driving, and commercial ride-hailing services in low-density settings. A comprehensive social cost estimation framework is employed, incorporating traveler and service provider costs alongside transportation externalities. Findings indicate that TIMOD

generally incurs higher social costs than other mobility alternatives due to its higher operating costs, while it provides time-cost savings and improved access for travelers in areas with limited fixed-route transit coverage. These insights inform more nuanced subsidy strategies and service deployment models for underserved populations in such contexts.

The third study develops a context-aware probabilistic spatiotemporal graph neural network (CA-STPGNN) to predict sparse demand for TIMOD services and quantify the associated uncertainty in low-density areas. The model integrates contextual information, temporal features, and multi-task learning as regularization to capture spatiotemporal dependencies in TIMOD trip patterns. Using data from real-world TIMOD programs in Washington State, the proposed model demonstrates superior predictive accuracy and uncertainty estimation compared with traditional approaches, while also revealing spatial heterogeneity in the influence of spatial and temporal features. This model can be applied to predict TIMOD demand in regions lacking observed data, thereby supporting public agencies in design and implementing cost-effective mobility solutions in low-density contexts.

Together, these three studies contribute adaptive tools, empirical evidence, and methodological innovations to support equitable, efficient, and context-sensitive transportation and land use planning in low-density contexts.

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been my greatest source of strength throughout this journey.

# Chapter 1 Introduction

## 1.1 Research Background

In recent years, public agencies and transit operators have increasingly explored integrated land-use and mobility strategies to enhance accessibility and promote equitable development, particularly in low-density areas. A substantial body of research underscores the importance of aligning transportation and land-use policies to foster sustainable growth, reduce automobile dependence, and improve mobility for underserved populations (Cervero & Murakami, 2010; Bertolini, et al., 2012; Ratner & Goetz, 2013; Dong, 2021). One promising opportunity lies in leveraging publicly owned land, such as park-and-ride (P&R) facilities located near transit corridors, as catalysts for Transit-Oriented Development (TOD). These facilities are often situated in strategic locations with high potential for mixed-use development and affordable housing given their proximity to transit infrastructure, established travel patterns, and sizable land parcels.

Despite these advantages, systematic approaches for identifying and prioritizing publicly owned sites for TOD remain limited. Much of the TOD literature focuses on privately owned parcels or high-density urban contexts (Vale, 2015; Guerra, et al., 2012), leaving a gap in guidance for public agencies seeking to redevelop their own assets in suburban or low-density settings. Addressing this gap can support more proactive land-use planning and ensure that TOD investments align with regional growth and equity goals (Kamruzzaman, et al., 2014).

In parallel, the limitations of fixed-route transit in low-density contexts have prompted agencies to explore alternative service models. Fixed-route systems often face low ridership, long headways, and high per-passenger operating costs in areas with dispersed populations and limited demand density (Mulley & Nelson, 2009; Guerra & Cervero, 2011; White, 2016). As

a result, many agencies have adopted Demand-Responsive Transportation (DRT) services to complement or replace underperforming routes. More recent DRT services have been more successful due to lower costs enabled by advanced ICT technologies (Currie & Fournier, 2020; RideCo, 2025). Within this spectrum, Transit Incorporating Mobility-on-Demand (TIMOD), a transit agency-led form of DRT, has emerged as a promising option for addressing mobility gaps where traditional service is infeasible (Wong, et al., 2020; Wang & Shen, 2023). In the TIMOD service model, the transit agency typically manages service design, funding, and management, while private companies may provide vehicles or booking technology. TIMOD services can include dynamically dispatched on-demand trips as well as pre-scheduled rides, allowing agencies to flexibly adapt service to varying conditions.

Although TIMOD can improve accessibility and travel times for residents in low-density areas, its cost-effectiveness varies widely depending on local demographics, built environment factors, and operational design (Kaufman, et al., 2021; Patel, et al., 2022). When accounting for the full scope of societal costs, including traveler expenses, service provider costs, and transportation externalities, TIMOD's relative performance compared with fixed-route transit, driving, or ride-hailing can shift considerably (Wang & Shen, 2023). This underscores the need for evaluation frameworks that fully integrate both internal and external costs to inform sustainable service delivery strategies.

Furthermore, as TIMOD services expand in suburban and rural areas, planners face growing challenges in accurately forecasting demand for the services in such contexts. Traditional prediction methods, such as classical regression models and Euclidean space-based approaches, can fall short in capturing the sparse, irregular, and context-dependent travel patterns in low-density settings (Wu, et al., 2019; Jin, et al., 2020; Ke, et al., 2021b). These methods typically rely on fixed spatial units and assume homogeneous travel behaviors between neighbors. They ignore non-Euclidean structural features in mobility landscapes,

which can limit model's generalizability across regions. In comparison, graph-based modeling provides a flexible framework to learn non-Euclidean dependencies across connected locations and handle irregular mobility structures. Recent advances in graph-based deep learning models, particularly probabilistic spatiotemporal graph neural networks (Wang et al., 2024a; Zhuang et al., 2024), offer promising tools for addressing these limitations by modeling complex spatial and temporal dependencies and incorporating uncertainty in demand estimation.

## 1.2 Problem Statement

Collectively, these land-use, service planning, and demand modeling challenges highlight the need for an integrated approach that connects asset prioritization for TOD, comprehensive evaluation of TIMOD cost-effectiveness, and advanced modeling techniques for travel demand prediction. Public agencies should simultaneously leverage publicly owned infrastructure and land, assess emerging mobility options like TIMOD, and anticipate demand in areas where data is sparse, yet current frameworks treat these issues in isolation.

Specifically, public agencies currently face a threefold planning challenge:

- 1) Underutilized publicly owned lands for development: Park-and-ride facilities are strategically located and well suited for TOD, but guidance on systematically prioritizing such public assets remains scarce.
- 2) Uncertain and uneven cost-effectiveness of service models: Fixed-route transit often proves economically unviable in low-density areas, while agency-led TIMOD services presents flexibility but variable cost-effectiveness depending on sociodemographic, operational, and built environment factors. Moreover, other mobility alternatives, such as commercial ride-hailing and driving, may offer cost advantages for certain traveler groups. A consistent evaluation of their cost-effectiveness, accounting for both internal and external transportation costs, requires further development.

- 3) Inadequate demand prediction methods in sparse contexts: Traditional models fail to capture the irregular, sparse, and context-specific demand patterns of demand-responsive mobility services in low-density settings, and limited studies incorporate uncertainty quantification in the service demand prediction. This highlights the need for advanced model architectures that can better adapt to the service demand dynamics in such contexts.

These interrelated challenges, public land underuse, service-model evaluation gaps, and deficient demand forecasting, hamper efforts to design sustainable, equitable, and effective mobility strategies in low-density suburban contexts.

### **1.3 Research Objectives**

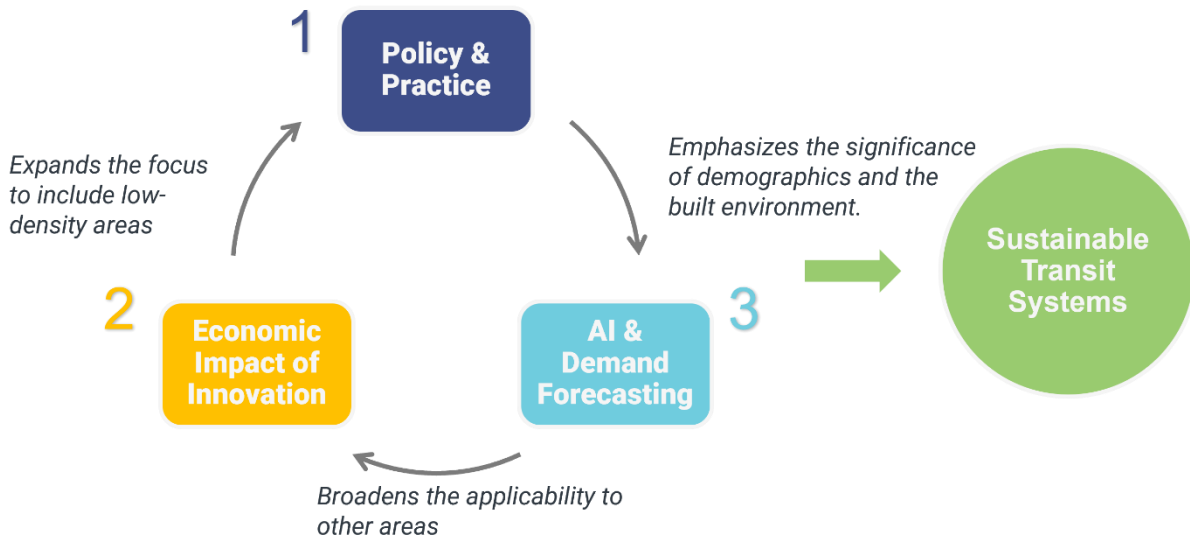
This dissertation addresses these gaps by pursuing three interlinked objectives:

- 1) To develop a multi-criteria prioritization framework for publicly owned park-and-ride sites to identify those with the highest potential for TOD under varying scenarios. This tool will support TOD decision-making by evaluating site potential across varied scenarios, factoring in indicators of public transportation, land use, socio-demographic characteristics, real estate market, and urban planning context.
- 2) To evaluate the comparative cost-effectiveness of TIMOD, fixed-route transit, driving, and ride-hailing in low-density areas. The assessment will integrate traveler costs, service provider costs, and costs and benefits of transportation externalities to provide a comprehensive societal cost view.
- 3) To design and implement a context-aware probabilistic spatiotemporal graph neural network (CA-STPGNN) to predict TIMOD demand in low-density areas. The model will incorporate sociodemographic and built environment factors, quantify uncertainty, and be generalizable to areas lacking observed service data.

By integrating land-use prioritization, cost-effectiveness evaluation, and advanced demand modeling, this research provides public agencies and policymakers with tools to guide investment decisions that align mobility services with community needs and long-term sustainability goals in near suburban and more remote areas.

## **1.4 Research Structure**

Based on empirical studies, the following three chapters of this dissertation respectively discuss the leading roles of public agencies in promoting sustainable transit systems from the perspectives of policy and practice, economic impact of emerging mobility services, and the application of advanced artificial intelligence models in demand forecasting for the mobility services in low-density areas (Figure 1-1). Specifically, the first study (Chapter 2) discusses the importance of publicly-owned park-and-ride (P&R) areas in catalyzing transit-oriented development (TOD). It develops a multi-criteria prioritization tool for identifying the most promising locations for TOD, in order to support the decision making under different TOD scenarios. The tool includes 14 TOD-related indicators divided into 5 categories: transit supportive land-use zoning, job accessibility, land price, land-use mix, and household income. This chapter emphasizes the role of public agencies in catalyzing sustainable transit development in regional growth centers and near suburban areas, as well as the impact of sociodemographic and the built environment factors on the effectiveness of transit policy implementation.



**Figure 1-1 The connections between the three chapters**

The second study (Chapter 3), which expands the geographic scope of the first chapter by explicitly incorporating low-density areas into the discussion, investigates and compares the cost-effectiveness of mobility alternatives in such contexts. Through a comparative cost-effectiveness evaluation, this chapter discusses the social impacts of demand-responsive mobility when public agencies take the leading role in planning and financing the services in low-density areas. This concept is defined as Transit Incorporating Mobility-on-Demand (TIMOD), which is a sub-category of DRT services. In this concept, demand-responsive mobility services are provided through transit agencies, while the ownership of assets (technology, vehicles, and drivers) depends on the type of public-private partnership. The research further develops a framework to evaluate the cost-effectiveness of TIMOD compared with fixed-route transit, driving, and commercial ride-hailing in low-density settings. It uses real-world TIMOD trip data as the baseline for simulation and estimates the marginal social costs (including the costs of travelers, service providers, and transportation externalities) for each mobility alternative. The study examines the conditions for the cost-effective adoption of transit agency-led demand-responsive mobility in low-density contexts. The expected outcomes of this research will enable planners and policymakers to consider the costs and

benefits of traditional and innovative public transportation solutions more effectively.

The third study (Chapter 4) aims to broaden the applicability of the second study's framework to a wider range of areas where transit agency-led demand-responsive mobility trip data is currently unavailable. To this end, the study develops a context-aware probabilistic spatiotemporal graph neural network (CA-STPGNN) to predict demand for transit incorporating on-demand services in low-density areas. It captures spatiotemporal correlations and uncertainty in the sparse demand for this mobility option and integrates sociodemographics and built environment characteristics to improve model's generalizability. This study explores the application of AI-driven modeling in assisting planners and policymakers in estimating the mobility needs of local communities and making decisions on service delivery.

# **Chapter 2 A Multi-Criteria Tool for Prioritizing Transit-Oriented Development on Public Land**

## **2.1 Introduction**

Transit-oriented development (TOD) provides vibrant streetscapes and pedestrian- and bicycle-friendly built environments that make it convenient and safe for people to engage in daily activities. It can help create more sustainable, livable, and equitable communities by increasing the use of public transit, spurring economic and residential development, improving jobs-housing balance, and facilitating healthy lifestyles (Appleyard et al. 2019; Calthorpe, 1993; Cervero 2004; Wang, et al., 2022; Shen, et al., 2018). It has also been shown that TODs can lead to more cost-efficient car usage, resulting in large savings for households living in TOD areas (Dong, 2021). TOD is a critical component of smart urban growth (Goetz, 2012).

Public agencies can play a leading role in catalyzing TOD in market economies, especially in regional growth centers where every inch of land is valuable and in suburban areas that hold promise for future intensive development. They may own land that is vacant, underutilized, or no longer used for its original purpose, even in areas where land resources are scarce. These public lands can be made available to developers, potentially at a reduced cost, in exchange for a commitment to develop a portion of the land for affordable housing or other uses deemed consistent with community goals. Public agencies can use such land as a catalyst for TOD, working with developers to make TOD projects financially feasible while helping to create mixed-income, mixed-use neighborhoods with economic, social, and environmental benefits. This idea has been put into practice in American cities. In California, for example, the Surplus Land Act requires the public sector to give preference to developers who commit to creating at least 25 percent of their buildings as affordable housing on the land to be developed (California Department of Housing and Community Development, 2021). Sound Transit, a

major transit agency in the state of Washington, is required to set aside 80 percent of its surplus land for affordable housing development upon completion of transit station construction (Sound Transit, 2018). Park-and-ride (P&R) facilities are a common form of publicly owned land that provide spaces for people to park vehicles and transfer to public transportation, such as rail and bus rapid transit. Many public transportation authorities in the U.S. own large tracts of land that are used as surface parking, and the value of these lands may increase as a result of urban growth and transportation improvements. As emerging nodes in the urbanization process, some of these lands can be suitable for affordable housing and commercial or mixed-use development, thus catalyzing TOD, while continuing to serve the parking function of the P&R through multi-story parking structures. P&R sites often have good potential for TOD due to their proximity to both residential communities and transit, although this potential varies depending on the land area, location, market conditions, and regulatory environment.

To help identify the most promising P&R sites for TOD, this research developed a multi-criteria prioritization tool and tested it on selected P&R sites owned by the Washington State Department of Transportation. The resulting tool can be used to identify P&R sites that are most suitable for TOD, as well as to prioritize other forms of publicly owned land that are potentially suitable for TOD. To achieve this goal, the research sought to answer three questions: (1) What indicators should be included to measure the suitability of public land for TOD? (2) How do these indicators contribute to TOD suitability in order to develop a prioritization tool? (3) How to extend the application of this tool to catalyze TOD on other publicly owned land areas in different geographic contexts?

We chose the Delphi method as the key component of our research methodology because it is an effective approach for selecting important indicators by building consensus among experts from different backgrounds. Three scenarios (Scenario (1) affordable housing emphasis, Scenario (2) market-rate housing emphasis, and Scenario (3) mixed-use emphasis)

were designed to stimulate discussion of different land-use plans and to help experts reach consensus on the relative importance of the indicators. The resulting tool was used to calculate TOD suitability scores to determine the priority for TOD at three selected P&R sites.

## **2.2 Literature Review**

### **2.2.1 Challenges in TOD Planning and Implementation in the United States**

The implementation of TOD in the U.S. usually faces several challenges. First, development near transit hubs often takes developers a long and hard time to complete due to the cumbersome approval process for land acquisition and even perceived inhibitive policies for construction permit (Guthrie & Fan, 2016). Meanwhile, developers may also have to deal with land assemblage and control issues because there are usually multiple property owners on the sites (City of Seattle Department of Planning & Development, 2013). This may result in developers facing high land development costs to create TODs, making TOD projects less attractive to them. Second, in densely populated areas TOD developers must pay for scarce and expensive land resources, while in sparsely populated suburban areas developers often do not consider TOD market-ready. Developers and public agencies may choose to implement TOD in non-residential areas, which has been shown in previous TOD studies (Cervero & Dai, 2014; Dumbaugh, 2004; Yang et al., 2016), often with trade-offs in terms of environmental qualities. This might be because authorities and developers want to avoid opposition to TOD projects from residents in surrounding neighborhoods, while still being able to control urban growth (Ibraeva et al., 2020). Unfavorable market conditions may make these residential areas less attractive to authorities and developers, resulting in inequitable transit-oriented development. Third, local transportation policies may prioritize development for parking spaces in transit station areas. Much of the land around high-capacity transit stations/stops is used primarily for parking, often surface parking, and lacks the upfront infrastructure to support TOD. It

encourages the use of automobiles rather than a people-oriented public transportation system, making future TOD less promising. In addition, there is competition for TOD investments among potential locations due to limited funding (Atkinson-Palombo & Kuby, 2011). This competition requires public authorities to be more effective in allocating resources to the most suitable areas.

To address these issues, public agencies can redevelop the land they own to achieve higher land use densities and offer a part of the land to developers, potentially at a below-market price. The P&R lots owned by public agencies can be used more efficiently by concentrating parking spaces (potentially eliminating some, depending on use) and providing additional space for the development of housing units and local businesses. This can facilitate TOD in regional central areas where there is an imbalance between demand and supply of transit services, as well as in low-density suburbs or urban fringes. It is also worth considering how the potential for TOD in one location can influence the development priorities of other, competing locations. Efforts can be focused on areas with higher TOD potential to maximize the social benefits of redevelopment.

### **2.2.2 The Role of Public Agencies in Catalyzing TOD: Examples from Different Countries**

The use of public land as a catalyst for TOD varies across cities and countries. To capitalize on the effects of TOD, the economic context and institutional framework play an important role and influence the level of success of TOD projects (Knowles and Ferbrache, 2019; Mathur and Gatdula, 2023). In some Asian and Middle Eastern cities, such as Dubai, Singapore, and Hong Kong, centralized land ownership, government-controlled or authorized infrastructure development, and independent corporate operation allow for comprehensive long-term TOD planning and a good balance between costs and revenues generated by TOD implementation (Hannawi, et al., 2019; Jauregui-Fung, 2022; Yang and Lew, 2016). These political and

economic forces efficiently accelerate the delivery of transit investments, promote the development of surrounding real estate, and generate fiscal returns (Suzuki et al., 2015; Hannawi, et al., 2019; Musil, 2020). In mainland China, the dominant role of public agencies in controlling the development of designated TOD areas promotes the integration of the transit system and land use, and the realization of transit-oriented benefits (Zhang, 2007). It requires effective city governance in terms of transit service coordination and proactive planning (Mu & de Jong, 2012).

In other Asian cities (e.g., Taipei and Tokyo), despite the separation between privately owned land and publicly operated transit system, the emerging public-private partnership plays an important role in promoting TOD through joint land development (Suzuki et al., 2015; Yen, et al., 2023). However, great efforts must be made to reduce the burden on public finances, and an effective coordinating umbrella organization needs to be created for the involved stakeholders (Mu & de Jong, 2016; Yen, et al., 2023).

In addition to the successful examples of cities like Hong Kong and Singapore using publicly owned land as an instrument for local governments and transit agencies to influence TOD planning and implementation, there are also examples of success in European countries. A well-known example is Ørestad New Town in Copenhagen (Knowles, 2012). Land along the metro route, owned by the city and the Danish government, was sold to developers to finance the construction and expansion of the metro system. In Stockholm, public transportation and land use planning were organized and integrated under the authority of the City of Stockholm during an early period of TOD, contributing to the current multi-level collaboration between the public transport authority, municipalities, and the national government (Paulsson, 2020). Land purchase by public agencies in some other European cities has also produced successful TOD cases (Pojani and Stead, 2018). Municipalities in Amsterdam and Vienna were able to purchase land in advance for future expansion needs. This

facilitated integrated TOD in these cities by encouraging land value capture through land consolidation led by public agencies.

The above examples suggest that available funding sources, centralized land use control, and integrated land development contribute to the success of TOD projects. Support for local funding packages for transit agencies and subsidy programs for developers (e.g., tax abatements) can reduce their costs and lead to sustainable development (Guthrie & Fan, 2016; Goetz, 2019). However, obtaining financial support is usually a challenge, especially for pluralistic democracies (Bonvino, 2019; Papa, 2019). Meanwhile, transit agencies in the United States lack the authority to regulate land use and zoning to implement TOD and therefore need to work with local governments (Mathur and Gatdula, 2023).

### **2.2.3 Assessing TOD Potential in Urban Areas using Criteria Identification**

The literature has identified several dimensions of TOD and associated metrics for assessing a location's TOD potential. Cervero and Kockelman (1997) first developed criteria for evaluating TOD potential from three dimensions of the built environment: density, diversity, and design ("3Ds"). These three dimensions were thought to influence residents' travel rates and mode choices. The three dimensions were later expanded to five dimensions by adding destination accessibility and distance to transit ("5Ds") (Ewing & Cervero, 2001; Ewing & Cervero, 2010). Demand management (i.e., policy interventions for reducing vehicle trips and contributing to a more efficient use of transportation) and demographics (i.e., a social-friendly neighborhood environment for promoting demand for public transit) have also been identified as two additional dimensions to assess TOD potential ("7Ds") (Ewing, et al., 2017).

Common metrics used to measure the density needed to support TOD include population, residence, and employment densities (Cervero and Kockelman, 1997). Land use entropy and population composition can be used to characterize the diversity for supporting

TOD. Design characteristics, including walkability, cyclable streets, and network intersections, should also be considered to assess the walking and bicycling environment for facilitating TOD (Vale, 2015; Lyu et al., 2016). Transit system performance is essential to characterize the level of accessibility and quality of transit service of a TOD area, which can be quantified by transit ridership, transit network connectivity, and job accessibility by transit (Renne, 2009; Mu & De Jong, 2012; Barrieau, 2019). Providing accessible public safety facilities is also necessary for equitable TOD (Wey et al., 2016).

There is also evidence that household income is positively associated with transit use frequency among transit riders (Lin & Shin, 2008). Car ownership, as an important performance measure for modeling trip generation and estimating parking demand, can be used to test whether TODs are working well (Renne, 2009; Kamruzzaman et al., 2014). While it can be used to evaluate the effects of an implemented TOD project, it may not be appropriate for measuring the potential of TODs. A lower car ownership rate may be a result, rather than a cause, of a well-functioning TOD that leads to a higher transit mode share among transit riders (Koizumi, et al., 2013). However, low vehicle ownership alone does not necessarily lead to higher demand for transit, as it can be associated with lower income levels and trip rates (Federal Highway Administration, 2017). The elasticity of demand for transit relative to car ownership varies with household income (Paulley, et al., 2006). In addition, by providing affordable housing, TOD areas can attract people who are willing to use transit. Housing affordability can be measured by household housing expenditures. However, data on household housing expenditures are usually not available at a disaggregated level. Alternatively, housing affordability could be captured by household income and home value.

In addition to these measurements, land use and fiscal policies, such as TOD districts for financing the improvement of public transportation and TOD supportive zoning for encouraging the development of adjacent housing units, can also contribute to successful TOD

(Kim and Li, 2021; Mathur and Gatlula, 2023; Renne et al., 2011). These policy tools can help capitalize on the accessibility effects of transit on surrounding properties and integrate TOD into the overall urban planning system (Cervero et al., 2002; Zhang, 2007). Meanwhile, TOD is closely related to adjacent land and home values. TOD has been shown to have a significant positive impact on adjacent property values, while high property values can generate high tax revenues that contribute to local public finances (Shen, et al., 2018; Sharma and Newman, 2018; Conrow, et al., 2021). Therefore, this research identified indicators in five categories to measure TOD potential: public transportation services and demand, land use mix and walkability, socio-demographic characteristics, real estate market conditions, and planning context.

#### **2.2.4 Evaluating the Importance of TOD Indicators Through a Delphi Process**

To develop a multi-criteria analysis tool, in addition to identifying a list of indicators, it is also necessary to evaluate the relative importance of each indicator. Although previous studies have considered uncertainty in the weights of TOD indicators and conducted sensitivity analyses to examine this uncertainty, a practical method for calculating weights is still lacking (Singh et al., 2017). The Delphi method can provide generally reliable results for identifying criteria and quantifying the relative importance of indicators while requiring a limited budget and small number of participating experts (Boulkedid et al., 2011). It is a systematic and qualitative approach used to predict outcomes by collecting opinions from a group of experts through several rounds of evaluation. This method has been widely used in the analysis of urban issues.

The Delphi method has also been used to identify criteria for transit-oriented development. Focusing on TOD in U.S. inner cities, Loukaitou-Sideris (2000) conducted a three-round Delphi survey in which a panel of 25 experts was asked about the various goals and objectives of TOD practice, as well as the preconditions and constraints of such

development in economically disadvantaged inner-city areas. Wey et al. (2016) used a fuzzy Delphi method to select TOD evaluation criteria that meet the principle of sustainable transportation and applied a fuzzy analytical network process to determine the weights of relevant planning criteria. In a manner similar to the Delphi process, Searle et al. (2013) conducted semi-directed interviews with urban stakeholders for various TOD case studies and evaluated the implementation process and outcomes of TOD projects according to various criteria. These studies suggest that the Delphi method is an appropriate approach for identifying TOD criteria and assessing their relative importance. In addition, there is no consensus in the literature as to what constitutes an optimal number of experts in the Delphi process. Previous research used different panel sizes for their Delphi studies<sup>1</sup>. This study invited 9 experts to participate in the Delphi process of defining and evaluating TOD indicators, allowing sufficient diversity of background while providing a manageable number to meet synchronously to have an in-depth conversation of the potential indicators and build consensus. These experts came with diverse backgrounds and work experiences at local, national, and international levels in urban and regional planning, real estate, and transit demand forecasting and management.

### **2.2.5 Developing a TOD Planning and Implementation Support Tool**

In TOD case studies, various planning tools have been developed for TOD planning and implementation. First, TOD typology based on identified criteria has been widely used to inform regional TOD planning (Reusser et al.,2008; Chen and Lin, 2015; Monajem and Nosratan, 2015). The TOD typology indicates the full potential for TOD in a location. Locations that are closer to the urban core and have a more balanced transportation demand and supply would have a higher full potential for TOD, as they can contribute to a more

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<sup>1</sup> For example, Delbecq et al. (1975) suggested that ten to fifteen persons could be sufficient if their background was homogeneous.

sustainable transportation system. The best-known approach to creating a TOD typology is the node-place model (Bertolini, 1996; Bertolini, 1999). This model has been modified by incorporating a more comprehensive list of TOD indicators (Kamruzzaman et al., 2014; Groenendijk et al., 2018).

Capital Metro, a transit agency in Austin, Texas, has developed a planning support tool to separately assess a transit station's TOD readiness and full potential for TOD (Capital Metropolitan Transportation Authority, 2013). TOD readiness represents how much a location has been developed toward its full TOD potential, while the full potential for TOD indicates how much progress that the location can make in promoting TOD in the future. The full TOD potential of a transit station was measured by applying a place typology based on its location advantages in terms of achievable highest land use intensity, multi-modal connectivity, and building form. The TOD readiness score of a transit station was calculated using four categories of metrics: transportation connectivity, market strength, land availability, and government support. The transit stations with higher TOD readiness scores would be prioritized for further development.

The existing studies establish the foundations for the development of a priority tool for identifying TOD potential on public land in transit station areas. First, the TOD typology differentiates TOD sites by considering their competition and synergy effects in a given market area. The investments made to support TOD in one location will influence the investments made in other locations. However, this method relies on either knowledge of future development of the entire urban area or the classification results from data analysis. Second, criteria for measuring TOD readiness and the full potential for achieving the highest levels for TOD should be distinguished. TOD projects typically take several years to be fully implemented but their success is linked to the current conditions as well as potential in the location. Assessing TOD readiness using quantifiable indicators based on current conditions is

therefore an important planning effort for prioritizing potential TOD sites.

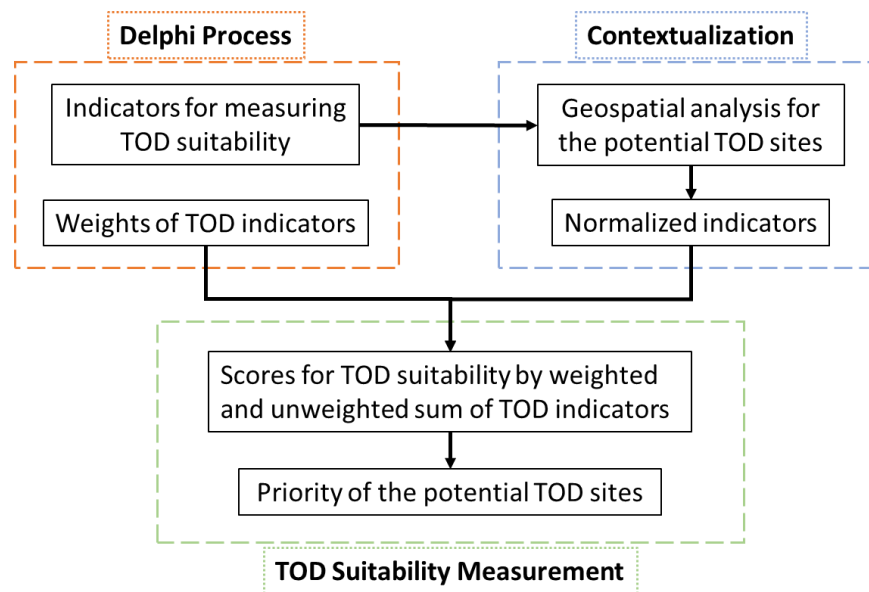
## **2.3. Data and Methodology**

### **2.3.1 Developing TOD Suitability Criteria using the Delphi Method**

The TOD Prioritization Tool was designed to provide a comparison of the TOD potential of P&R sites across a large region and to track changes in the level of TOD potential over time. This tool was intended to guide planning efforts prior to implementing TOD at P&R locations. The research team aimed to help inform decision making on transit investments in a region by identifying locations with relatively high potential for creating a sustainable transportation system and obtaining financial benefits. While recognizing that such a tool cannot address all nuances of local TOD implementation, we aimed to design this tool by including a relatively comprehensive list of TOD indicators. The inherent loss of some of the nuances of local TOD implementation issues was balanced against the ability of the tool to provide a relatively simple way to measure and compare the TOD potential of different P&R locations. Both regional-scale indicators for measuring the distribution of TOD areas and micro-scale indicators of built environment conditions in TOD areas were included. Indicators for measuring TOD potential can be adapted for different regions and other types of publicly owned land.

Developing the TOD Prioritization Tool followed these three steps: First, we identified a list of TOD-related indicators that are important in measuring the TOD suitability of a particular location. The importance of the TOD indicators was evaluated through the Delphi process, in which the inputs from multiple experts were obtained and synthesized, building consensus on indicators that are key to the success of TOD. Second, we measured and normalized the values of the identified TOD indicators for the selected P&R sites, which were then used to calculate TOD suitability scores. Finally, we used the obtained TOD suitability scores to determine the priority for TOD at selected P&R sites. The conceptual framework for

developing the TOD prioritization tool is shown in Figure 2-1.



**Figure 2-1 Framework for developing the TOD prioritization tool**

The process of identifying the TOD suitability criteria was as follows. First, we developed an initial list of potential TOD indicators through a systematic review of the literature (Cervero and Kockelman, 1997; Ewing and Cervero, 2001; Wey, et al., 2016; Singh, et al., 2017), which produced a list of 25 indicators organized into five categories: public transportation services and demand, land use mix and walkability, socio-demographic characteristics, real estate market conditions, and planning context. This initial list of potential TOD indicators was then used in our Delphi process, which consisted of three rounds of evaluation. We invited nine experts<sup>2</sup> with backgrounds and work experience in urban and regional planning, real estate, and transit demand forecasting and management to participate in the evaluation process. In the first two rounds of evaluation, the nine experts were requested to rate and rank the importance of the indicators and send back the results via email. No discussion between the participants was allowed in the first two rounds. After each of the first two rounds,

<sup>2</sup> Composition of the experts: four experts were professors from academic institutions, specializing in real estate development, transportation policy, and urban planning; the remaining five experts were professionals from planning organizations and transportation agencies in the state of Washington.

the research team summarized the results of ratings and rankings given by all experts and sent a summary report to them. The experts were encouraged to comment on the existing indicators and suggest additional indicators, resulting in a total of 28 indicators (Table 2-1). Based on these first two rounds, the third-round evaluation was a 90-minute online discussion session on Zoom with the experts, in which the experts were invited to discuss the relative importance of the indicators. After that, the final list of the TOD indicators and their weights in different scenarios was obtained.

**Table 2-1 Potential TOD indicators included in the Delphi process (“x” means the indicator was eventually eliminated from the list through the Delphi process)**

No.	The domain of indicators	Indicators	First Round	Second Round	Third Round	Final List for Priority Tool
1	Public transportation services and demand	Population in proximity to P&R site and current adjacent transit services	√	√	√	√
2		10- or 20-years population projection in proximity to P&R site and planned adjacent transit services	√	√	×	×
3		Current transit ridership at P&R site	√	×	×	×
4		Job accessibility from P&R site and current adjacent transit services	√	√	√	√
5		Job accessibility from P&R site and planned adjacent transit services	√	√	×	×
6		Commute travel time	√	×	×	×
7		Non-SOV commuters	√	×	×	×
8		Distance to CBD	√	×	×	×

9		Traffic volume	√	×	×	×
10		Transit network connectivity	×	√	√	√
11		Presence of special generators of transit demand (universities, colleges, or hospitals)	×	√	√	√
12	Land use mix and walkability	Land use mix	√	√	√	√
13		Walkscore	√	√	√	√
14		Street intersections	√	×	×	×
15		Neighborhood safety regarding crime	×	√	√	×
16	Sociodemographic characteristics	Employment	√	√	√	√
17		Car ownership	√	×	×	×
18		Racial diversity	√	√	√	√
19		Household income	√	√	√	√
20	Real estate market conditions	Land price/value	√	√	√	√
21		Housing unit rent	√	√	√	√
22		Home value	√	√	√	√
23		Commercial Market	√	×	×	×
24	Planning context	Transit supportive policies	√	√	√	√
25		Transit supportive land use zoning	√	√	√	√
26		Future upzoning potential	√	√	√	×
27		Housing affordability	√	×	×	×
28		Development activity	√	×	×	×

Because experts with different professional backgrounds had different opinions about the relative importance of each TOD indicator, in the third round three alternative TOD scenarios were presented, in which the indicators could be rated as having different levels of importance. Scenario (1) emphasized affordable housing to meet low-income housing demand,

for which TOD would provide a majority of the housing units for lower- and middle-income families. Scenario (2), in contrast, emphasized market-rate housing to generate more revenue to support public transit service expansion. Finally, Scenario (3) emphasized mixed-use development to improve transit accessibility to jobs and services and enhance residents' quality of life. The relative importance of the indicators under each scenario was discussed.

The experts were asked to rate the entire list of indicators using five levels of importance in the first two rounds and nine levels of importance in the third round. The five-level ratings consisted of (1) most important, (2) more important, (3) moderate, (4) less important, and (5) least important. For the nine-level ratings, four intermediate importance levels between two consecutive levels of the five-level ratings were added as compromise options. The rating results were then used to calculate the inter-rater agreement to determine the degree of agreement between the experts on the rating of each of the indicators. Given the overall low inter-rater agreement for the indicators using the five-level ratings, we consolidated the "most" and "more important" levels, as well as the "less" and "least important" levels, to obtain the three-level ratings. The calculation of the inter-rater agreement was based on the three-level ratings. Inter-rater agreement ranged from 0 to 1, with a higher value indicating a greater degree of consensus. The inter-rater agreement was measured by using the following equations.

$$IR_{ij} = \begin{cases} 1 & \text{if } R_i = R_j \\ 0 & \text{if } R_i \neq R_j \end{cases} \quad (1)$$

$$IR = \frac{\sum_{j>i}^n \sum_{i=1}^{n-1} IR_{ij}}{n_{ij}} \quad (2)$$

where  $R_i$  and  $R_j$  ( $i < j$ ) are respectively the rating of the  $i$ th and  $j$ th experts;  $IR_{ij}$  is the comparison between  $R_i$  and  $R_j$ ;  $IR$  refers to the value of the interrater agreement; and  $n_{ij}$  is the number of pairs of  $i, j$ .

The selection of potential TOD indicators depended on the results of the ratings and rankings. The indicators rated as less important and having a low ranking with a high inter-

rater agreement were considered for elimination from the next round of evaluation. In this study, a low ranking was defined as an average above a threshold (which was 10 for the final round) with a high inter-rater agreement defined as above 0.4. The additions and eliminations of potential TOD indicators in the Delphi process are shown in Table 2-1.

After the online discussion session (i.e., the third round of evaluation), the experts were asked to rate and rank the indicators again. The results of this final round of evaluation were used by the research team to determine the final list of TOD indicators. The final list contained 14 indicators because they were rated as more important with a high inter-rater agreement and a relatively high ranking at the end of the Delphi process. Each of the five domains was measured by at least two indicators. Among these indicators, 12 were identified as common indicators used in all three scenarios, while two were optional indicators used only in some of the scenarios.

### **2.3.2 Measuring TOD Suitability using the Prioritization Tool**

To measure the TOD suitability of the P&R sites, we computed the values of the TOD indicators in the final list (shown in Table 1) for 800-meter (i.e., 0.5-mile or about a 10-minute walk) and 1600-meter (i.e., 1.0-mile or about a 20-minute walk or about a 5-minute bike) buffer areas around the P&R sites using geospatial data. These buffer areas were slightly larger than the boundaries that had been defined in some previous studies (Calthorpe, 1993; Guerra, et al., 2012) because the centers of the buffer areas were the centroids of the P&R sites rather than the TOD stations/stops, while the nearest TOD stations/stops were included in the buffer areas. The data sources and measurements of the TOD indicators are shown in Table 2-2.

**Table 2-2 Data sources and measurements of the TOD indicators selected through the Delphi process (\* refers to the auxiliary variables used to measure the selected TOD**

indicators)

No.	Category	Indicator	Measure(s)	Unit	Data source	Data resolution
1		Transit network connectivity	Mean of the Z-scores of transit routes and transit frequency	Z-score	Derived from transit routes and transit frequency	Census Block Group
		* Transit routes	Total number of transit lines that pass through the buffer area	Number of transit routes	<a href="#">WSDOT Geospatial Database – Transit Routes</a>	Line
		* Transit frequency	Average of transit frequency density of the intersecting block groups by their proportions in the buffer	Transit frequency density per hour during evening peak period	<a href="#">2021 Smart Location Database of US Environmental Protection Agency</a>	Census Block Group
2	Common indicators	Presence of special generators of transit demand (universities, colleges, or hospitals)	Whether there exists at least one special generator intersects with the buffer	0: no special generator nearby 1: at least one special generator nearby	<a href="#">OpenStreetMap</a>	Point
3		Job accessibility in proximity to P&R site and adjacent transit services	Mean of the Z-scores of the job accessibility within 10, 20, 30 minutes transit and auto travel time	Z-scores	Derived from the job accessibility within 10, 20, 30 minutes transit and auto travel time	Census Block
		* Jobs within 30 minutes transit travel time	Total number of accessible jobs from the centroid of the P&R site	Number of jobs	<a href="#">Accessibility Observatory of University of Minnesota</a>	Census Block
		* Jobs within 20 minutes transit travel time	Total number of accessible jobs from the centroid of the P&R site	Number of jobs	<a href="#">Accessibility Observatory of University of Minnesota</a>	Census Block

		* Jobs within 10 minutes transit travel time	Total number of accessible jobs from the centroid of the P&R site	Number of jobs	<a href="#">Accessibility Observatory of University of Minnesota</a>	Census Block
		* Jobs within 30 minutes auto travel time	Total number of accessible jobs from the centroid of the P&R site	Number of jobs	<a href="#">Accessibility Observatory of University of Minnesota</a>	Census Block
		* Jobs within 20 minutes auto travel time	Total number of accessible jobs from the centroid of the P&R site	Number of jobs	<a href="#">Accessibility Observatory of University of Minnesota</a>	Census Block
		* Jobs within 10 minutes auto travel time	Total number of accessible jobs from the centroid of the P&R site	Number of jobs	<a href="#">Accessibility Observatory of University of Minnesota</a>	Census Block
4		Population density in proximity to P&R site and adjacent transit services	Average population density of the intersecting block groups by their proportions in the buffer	Density of household persons	<a href="#">2020 American Community Survey 5-Year Estimate</a>	Census Block Group
5		Transit supportive land use zoning	Proportion of the land with transit supportive zoning type (including mixed use, multi family, downtown, commercial/office)	%	GIS Open Databases of <a href="#">Snohomish</a> , <a href="#">Clark</a> , and <a href="#">Spokane</a> County	Land Use Parcel
6		Transit supportive policies	Lynnwood: Regional Transit Authority Tax in Snohomish Spokane: Multi-Family Tax Exemption (MFTE) Zones/Boundary; special taxing districts - Public Transportation Benefit Area (PTBA) Clark: None	Number of relevant policies	Comprehensive plan/MPO of Snohomish, Clark, and Spokane	County

7		Land price/value	Mean land value per acre of the intersecting tracts by their proportions in the buffer	Price per square meters	<a href="#">Federal Housing Finance Agency 2020 land value dataset</a>	Census Tract
8		Housing unit rent	Average of median gross rent of the intersecting block groups by their population proportions in the buffer	Median monthly gross rent per unit (dollars)	<a href="#">2020 American Community Survey 5-Year Estimate</a>	Census Block Group
9		Land use mix	Land use entropy <sup>3</sup> in the buffer area; Land use types include single family, multi family, mixed use, downtown, commercial/office, industrial, school/public facilities, water, parks/wildlife refuge	Land use entropy ranged from 0 to 1	GIS Open Databases of <a href="#">Snohomish</a> , <a href="#">Clark</a> , and <a href="#">Spokane</a> County	Land Use Parcel
10		Walkscore	Walkability to nearby amenities at a location	Score ranged from 0 to 100	<a href="#">Walk Score</a>	Point
11		Household income	Average income level of the intersecting block groups by their population proportions in the buffer	Median household income (1000 dollars)	<a href="#">2020 American Community Survey 5-Year Estimate</a>	Census Block Group
12		Employment density	Average density of employees living in the intersecting block groups by their population proportions in the buffer	Density of employees	<a href="#">2020 American Community Survey 5-Year Estimate</a>	Census Block Group

<sup>3</sup> The land use entropy was calculated using the equation:  $Entropy = -\frac{\sum_{i=1}^k p^i \ln(p^i)}{\ln(k)}$ , where  $p^i$  is the percentage of each land-use type in the buffer area,  $k$  is the total number of land use types.

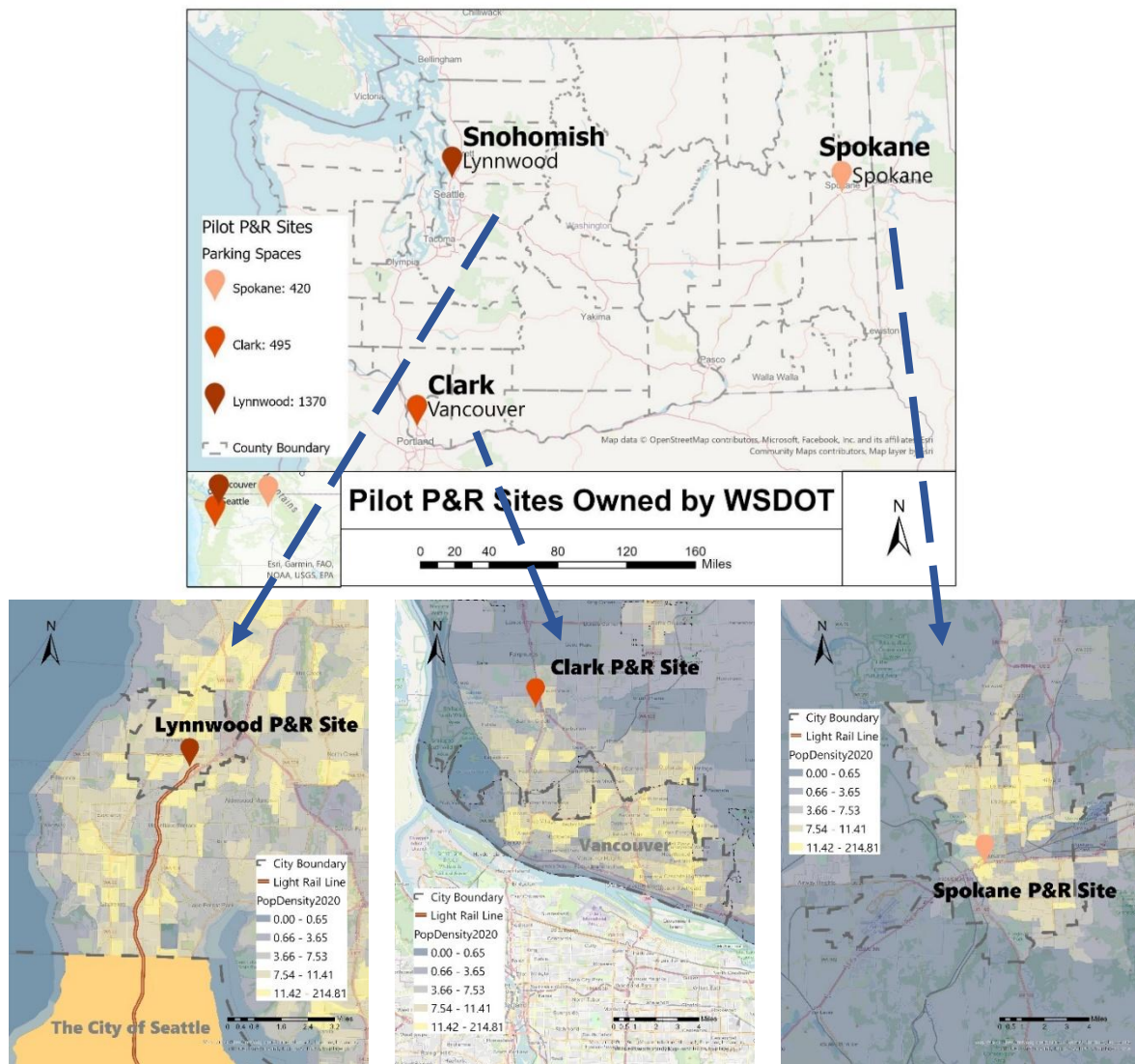
13	Optional indicators	Racial diversity	Average race diversity of the intersecting block groups by their proportions in the buffer	Race entropy <sup>4</sup> ranged from 0 to 1	<a href="#">2020 American Community Survey 5-Year Estimate</a>	Census Block Group
14		Home value	Average median home value of occupied housing unit of the intersecting block groups by their proportions in the buffer	Median house value per unit (1000 dollars)	<a href="#">2020 American Community Survey 5-Year Estimate</a>	Census Block Group

We selected three P&R sites to test the TOD prioritization tool. The three sites were located in the regional growth centers of Snohomish, Clark, and Spokane counties in Washington state, as shown in Figure 2-2. They were selected for their relatively advantageous locations in the metropolitan areas of Washington state in terms of population density and transportation connectivity. The Snohomish County site is a transit center in the city of Lynnwood. It had a relatively large parking area and is close to the planned Link light rail station (operated by Sound Transit). Lynnwood, part of the Seattle metropolitan area, is 16 miles north of Seattle and 13 miles south of Everett, near the intersection of Interstate 5 and Interstate 405, making the P&R site, with its large number of available parking spaces, important for TOD. (2) The Clark County site, the only WSDOT-owned P&R site in the region, is in Vancouver and is important for TOD because of its location. Vancouver is part of the Portland-Vancouver metropolitan area, near the intersection of Interstate 5 and Interstate 84. It is the largest city in Clark County and the fourth largest city in the state of Washington. (3) The Spokane County site was chosen because Spokane, where the site is located, is the second largest city in Washington state after Seattle, and the site is relatively centrally located within

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<sup>4</sup> The race entropy was calculated using the equation:  $Entropy = -\frac{\sum_{i=1}^k p^i \ln(p^i)}{\ln(k)}$ , where  $p^i$  is the percentage of each racial group in the buffer area,  $k$  is the total number of racial groups.

that city. It is a critical region in the far east of the state of Washington, bordering the state of Idaho.



**Figure 2-2 Distribution of the pilot P&R sites owned by WSDOT**

As an application of the TOD prioritization tool, we calculated the weighted and unweighted sums of the z-scores of these indicators to obtain a TOD suitability score for each site. We identified the most promising site for TOD by comparing their suitability scores.

$$S_i = \sum_{j=1}^{n_j} \beta_j Z_{ij} \tag{3}$$

$$Z_{ij} = \frac{(V_{ij} - \text{Aver}(V_{1j}, V_{2j}, V_{3j}))}{\text{Std}(V_{1j}, V_{2j}, V_{3j})} \tag{4}$$

where  $S_i$  is the TOD suitability score of the site  $i$ ;  $\beta_j$  is the weight of the indicator  $j$ ;  $n_j$

is the number of the TOD indicators;  $V_{ij}$  and  $Z_{ij}$  are the values of indicator  $j$  and its z-score of the site  $i$ ;  $V_{1j}, V_{2j}, V_{3j}$ , respectively, refer to the values of indicator  $j$  for the three sites;  $Aver(V_{1j}, V_{2j}, V_{3j})$  and  $Std(V_{1j}, V_{2j}, V_{3j})$ , respectively, refer to the mean and the standard deviation of  $V_{1j}, V_{2j}, V_{3j}$ .

The weights of the TOD indicators were derived from the principal right eigenvector of the pairwise comparison matrix of indicator importance levels obtained from the rating results. The concept of the pairwise comparison matrix came from the Analytic Hierarchy Process (AHP) method, which can be used for complex decision making based on ratings (Saaty & Katz, 1990; Strong et al., 2017). Specifically, the nine levels of TOD indicators' importance were assigned values of 1 to 9, where 9 referred to the most important and 1 was the least important. For each expert, the values of the indicator importance levels were compared in pairs to obtain that expert's pairwise comparison matrix. The principal right eigenvector of the pairwise comparison matrix was then computed to obtain the indicator weights given by that expert. Finally, the indicator weights used to calculate the TOD suitability score were obtained by averaging the weights derived from the rating results of all experts. The pairwise comparison matrix was calculated as in Equations (5) through (7).

$$C_{ij} = R_i - R_j + 1 \quad \text{if} \quad R_i \geq R_j \quad (5)$$

$$C_{ij} = \frac{1}{R_j - R_i + 1} \quad \text{if} \quad R_i \leq R_j \quad (6)$$

$$C_{ij} = \frac{1}{C_{ji}} \quad (7)$$

where  $R_i$  and  $R_j$ , respectively, are the importance values of the  $i$ th and  $j$ th indicator.  $C_{ij}$  is the ratio of the weight of the  $i$ th indicator to the weight of the  $j$ th indicator. If  $C_{ij}$  is equal to 1, then the  $i$ th and  $j$ th indicators are equally important and have the same weight. If  $C_{ij}$  is greater than 1, then the  $i$ th indicator is more important than the  $j$ th indicator and therefore has a lower weight. Conversely, if  $C_{ij}$  is below 1, then  $i$ th indicator is less important than the  $j$ th

indicator and thus has a smaller weight. In addition, the eigenvalue corresponding to the principal eigenvector is the largest eigenvalue of the pairwise comparison matrix.

The pairwise comparison matrix obtained by comparing the importance levels of the indicators was then normalized by dividing by the sum of the values in each column. The principal right eigenvector of this matrix was obtained by calculating the sum of each row. It was also the vector of the factor weights. Since the TOD indicators in the list were grouped into five domains, we also calculated the weights of each domain by using the average importance levels of the indicators in the domain. The method used to calculate the domain weights was the same as that used to calculate the factor weights. The final weights of the TOD indicators were equal to the factor weights multiplied by the domain weights.

## **2.4. Results**

### **2.4.1 Evaluating the Importance of the TOD Indicators**

Table 2-3 shows the rating and ranking results of the final round of evaluation for the TOD indicators. The mean rating and inter-rater agreement were measured based on the three-level Likert scale. For Scenario (1), all indicators in the public transportation and planning context domains were rated and ranked as relatively more important in the list, with an agreement level higher than 0.4. Housing unit rent, walking score, household income, employment density, and racial diversity were rated and ranked lower, and with a level of agreement lower than 0.4. As for Scenarios (2) and (3), transit network connectivity, the presence of special generators of transit demand, and transit-supportive policies had lower mean ratings and rankings than in Scenario (1), where the level of agreement on the importance of these indicators became lower than 0.4. The other indicators in the public transportation and planning context domains were still considered more important, with a higher level of agreement. Land-use mix and household income became more important in Scenario (2), whereas job accessibility and the land-use mix

became more important in Scenario (3). In addition, the other indicators in the list still had a level of agreement lower than 0.4 in Scenarios (2) and (3).

**Table 2-3 Rankings and ratings of the TOD indicators for different scenarios**

Indicators	Scenario 1: affordable housing			Scenario 2: market-rate housing			Scenario 3: mixed-use development		
	Mean rating	Inter-rater agreement	Mean ranking	Mean rating	Inter-rater agreement	Mean ranking	Mean rating	Inter-rater agreement	Mean ranking
Transit supportive land use zoning	1.11	0.78	3.56	1.11	0.78	3.28	1.11	0.78	3.39
Job accessibility (both by transit and automobile)	1.44	0.44	5.78	1.44	0.44	6.17	1.22	0.61	5.33
Population density	1.44	0.44	7.72	1.22	0.61	5.61	1.11	0.78	5.28
Transit supportive policies	1.22	0.61	7.94	1.56	0.36	8.17	1.56	0.36	8.39
Land price/value	1.44	0.61	6.89	1.33	0.58	5.28	1.33	0.5	6.06
Transit network connectivity	1.22	0.61	6.89	1.56	0.36	7.06	1.67	0.33	8.17
Land use mix	1.44	0.44	6.72	1.22	0.61	6.72	1.33	0.5	5.83
Household income	1.78	0.28	9.06	1.44	0.44	8.22	2	0.25	10
Walkscore	1.78	0.36	8.61	1.89	0.28	9.28	1.78	0.28	8.89

Presence of special generators of transit demand (universities, colleges, or hospitals)	1.33	0.5	6.61	1.67	0.33	8.56	1.56	0.36	7.44
Housing unit rent	1.78	0.36	10.06	1.56	0.44	9.44	1.67	0.33	9.83
Employment density	2	0.33	11.67	2	0.33	11.28	1.78	0.36	10.72
Home value	2.22	0.36	11.28	1.67	0.33	10.56	1.67	0.33	10.39
Racial diversity	1.89	0.28	9.61	2.44	0.44	11.94	2.56	0.44	12.44

Table 2-4 shows the weights of the TOD indicators, which varied among the scenarios. The weight ranged from 4.5 percent to 13.9 percent. The public transportation and planning context domains were generally considered more important than the other domains in the three scenarios, while the socio-demographic characteristics domain was considered less important. Transit supportive land use zoning had the highest weight in all three scenarios, followed by job accessibility by both transit and automobiles. The indicators with the lowest weights differed among these scenarios. Compared with the other indicators in the list, employment density in proximity to the P&R sites had a relatively lower weight in all three scenarios.

**Table 2-4 TOD indicators' weights in different scenarios**

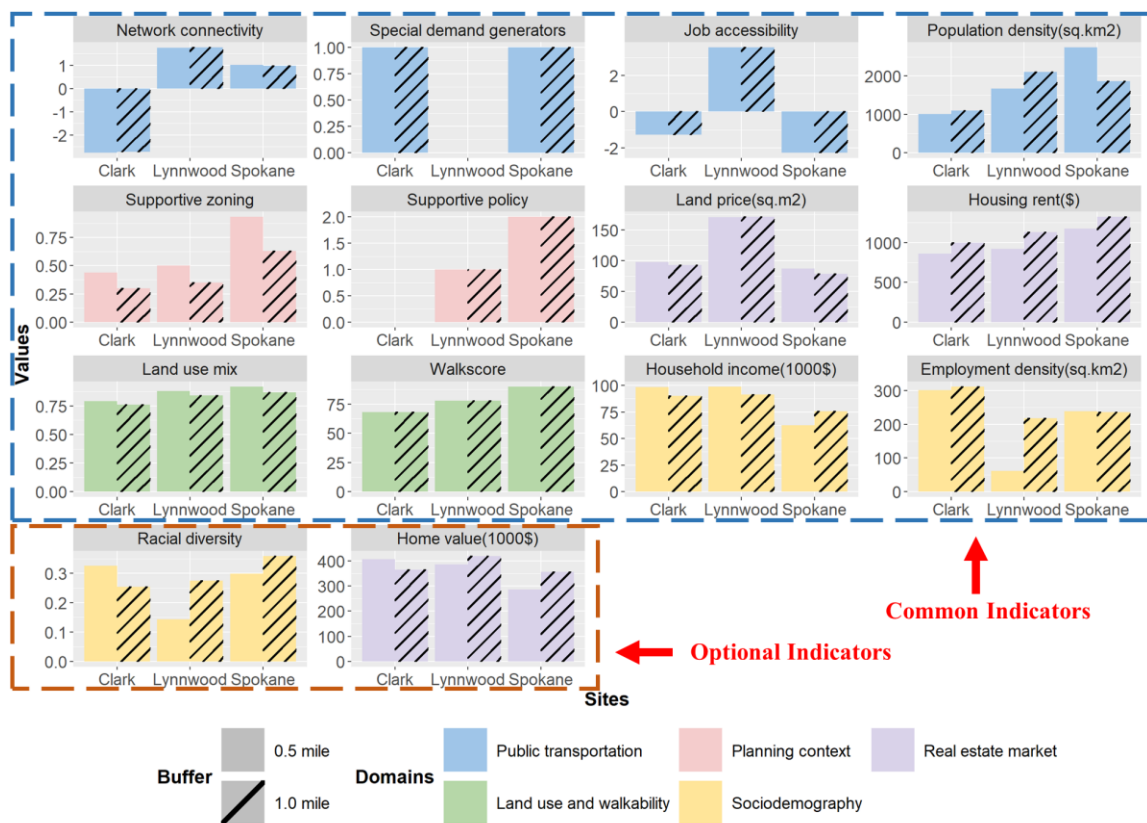
No.	Category	Indicators	Scenario (1): affordable housing (%)	Scenario (2): market-rate housing (%)	Scenario (3): mixed-use development (%)	Average weights of the scenarios (%)
1	Common indicators	Transit supportive land use zoning	13.56	13.85	13.76	13.02
2		Job accessibility (both by transit and automobile)	10.36	9.29	10.2	9.44

3		Population density	8.98	11.6	12.05	10.32
4		Transit supportive policies	8.67	8.81	8.02	8.06
5		Land price/value	8.29	9.28	8.66	8.3
6		Transit network connectivity	8.26	7.79	6.1	7
7		Land use mix	7.39	7.12	7.55	6.98
8		Household income	6.94	7.48	5.88	6.42
9		Walkscore	6.4	4.92	5.17	5.21
10		Presence of special generators of transit demand (universities, colleges, or hospitals)	6.13	4.48	5.01	4.94
11		Housing unit rent	5.21	5.55	6.04	5.31
12		Employment density	4.61	4.69	5.16	4.57
13	Optional indicators	Home value	/	5.13	6.39	5.46
14		Racial diversity	5.22	/	/	4.95
Sum of weights			100	100	100	100

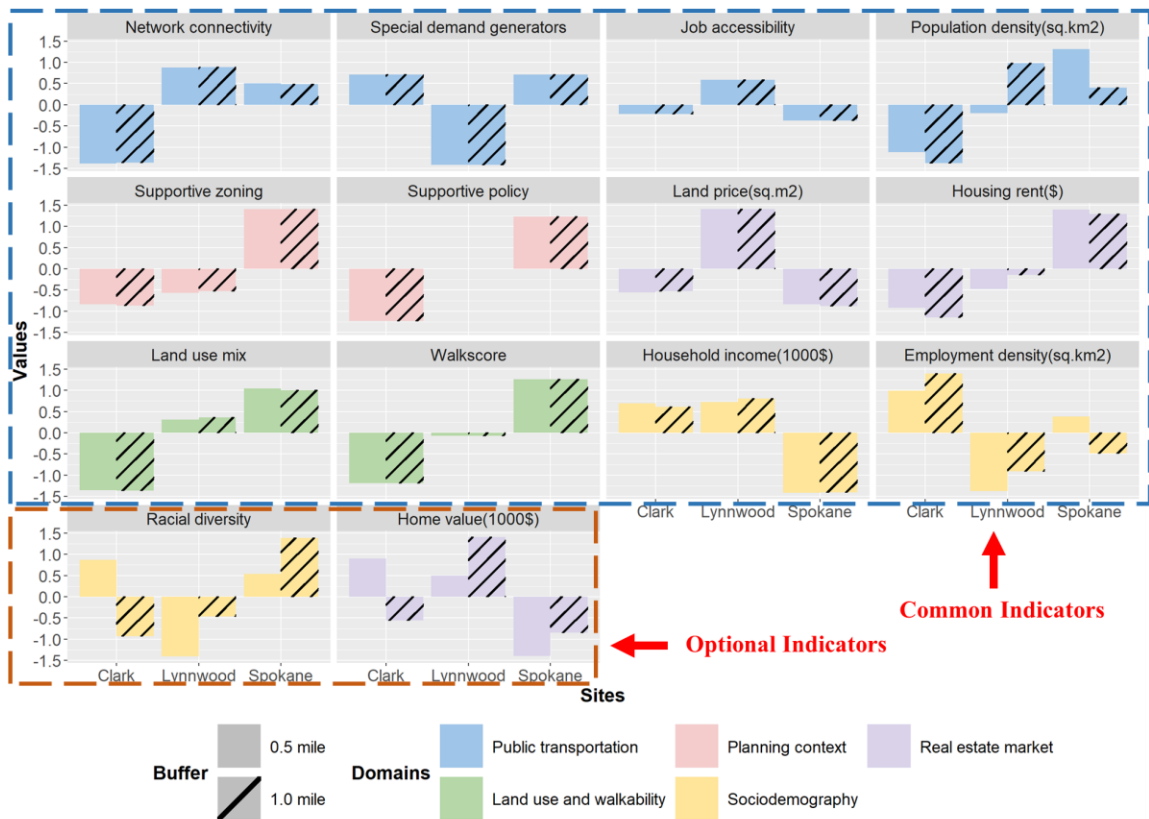
### 2.4.2 Measuring TOD Suitability for Pilot Park-and-Ride Sites Using the Prioritization Tool

Figure 2-3(a) and Figure 2-3(b) show, respectively, the unstandardized and the standardized values (i.e., Z-scores) of the TOD indicators for the 0.5-mile and 1.0-mile buffer areas of the three P&R sites. The figures show that the unstandardized and the standardized values of the TOD indicators for the three P&R sites are obviously different. This suggests that these sites may have different potentials of TOD. For some of the indicators, the values for the 0.5-mile and 1.0-mile buffers of a given P&R site were obviously different. Specifically, for the Spokane

site, the densities of population and transit-supportive zoning areas within the 0.5-mile buffer area were significantly higher than those within the 1.0-mile buffer area. In contrast, the average household income, racial diversity, and average home value within the 0.5-mile buffer area were substantially lower than those within the 1.0-mile buffer area of the Spokane County site. For the Lynnwood site, the density of transit zoning areas and average household income were higher inside the 0.5-mile buffer area, while population density, average housing rent, employment density, racial diversity, and average home value were higher inside the 1.0-mile buffer area. For the Clark site, only the average housing rent was significantly lower for the 0.5-mile buffer than the 1.0-mile buffer.



(a) Not standardized



(b) Standardized to Z-scores

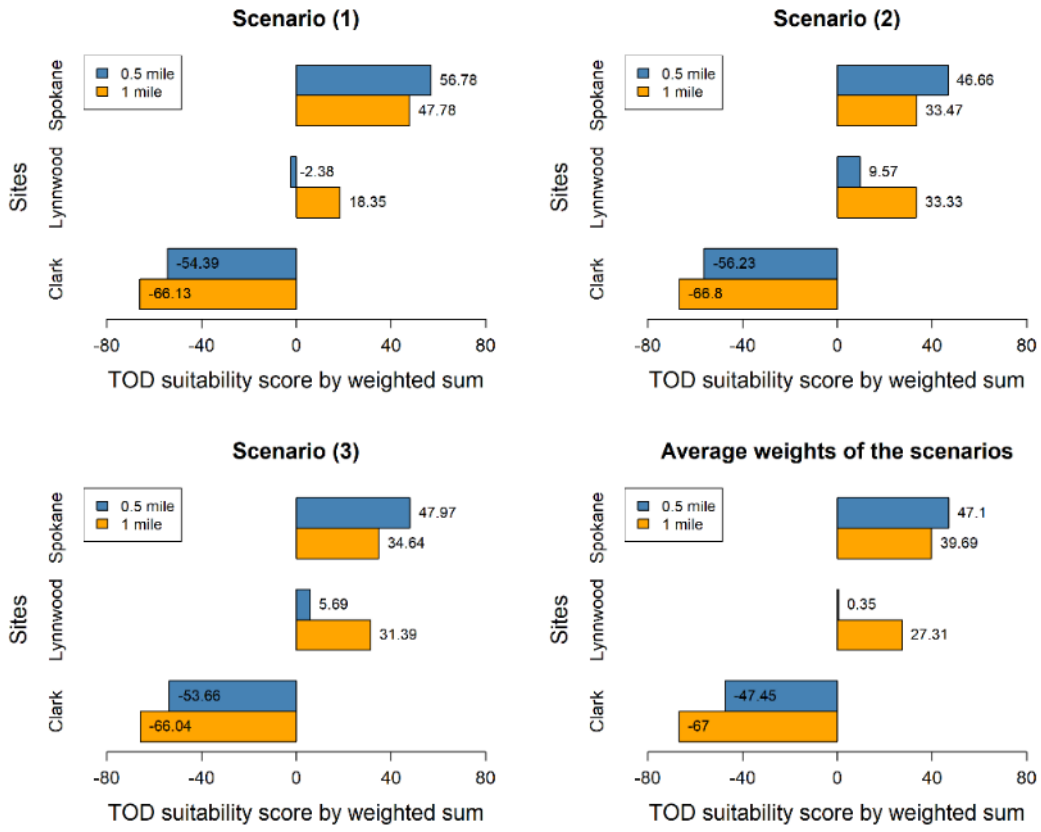
**Figure 2-3 TOD indicator values of the 0.5-mile and 1.0-mile buffers of the P&R sites**

In comparing the results in Figure 2-3(a) to those in Figure 2-3(b), it is worth noting that the orders of the TOD indicator values among the three pilot P&R sites were consistent between standardized and unstandardized results, as well as between the results for the 0.5-mile and the 1.0-mile buffer areas. To make the indicator values directly comparable across different sites and different scenarios, standardized values should be used to measure TOD suitability.

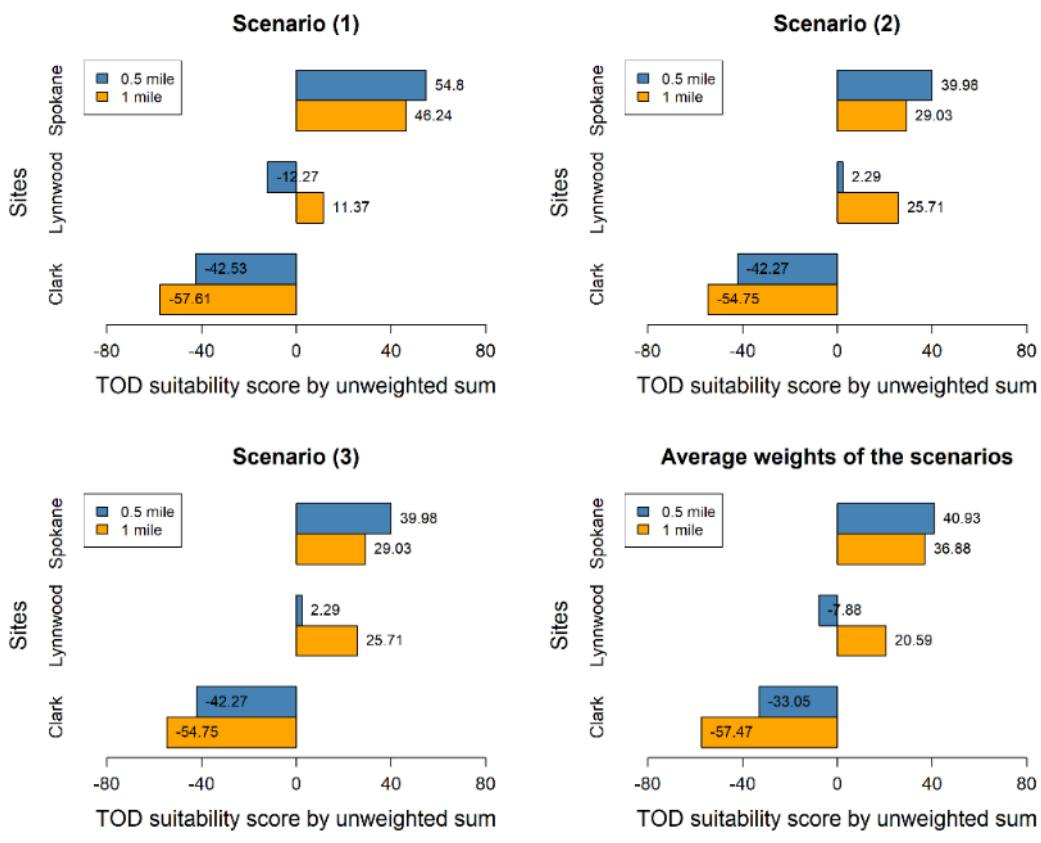
As shown in Figure 2-3, the differences between the current TOD conditions of the three sites are obvious. The Clark site's network connectivity is lower because it is served by only 4 bus routes with relatively low frequencies, compared with more than 20 routes with relatively high frequencies at the other two sites. There is no university, college or hospital in the vicinity of the Lynnwood site, so it has a zero value for the indicator of “special demand generators”. However, the Lynnwood site has the highest job accessibility among the three

selected sites because it has easy and quick access to the neighboring city of Seattle, which is one of the largest employment centers in the U.S. The Clark site area has a higher employment density, but a lower population density compared with the other two sites. It is located in a commercial area with many grocery stores and restaurants. The Spokane site has relatively well-developed supportive zoning and policies to capitalize on TOD effects. Land prices are higher around the Lynnwood site reflecting expectations of sustained growth in demand for this location due to its proximity to Seattle and the concentration of residents who live and work in Seattle, while housing rents are higher and home values are lower around the Spokane site due to its location in the center of Spokane City and the concentration of tenants. In addition, the Spokane site area has a higher land use mix and walkability due to its central location in Spokane City.

Figure 2-4(a) and (b) show the TOD suitability scores for the three scenarios at the P&R sites. To ensure the robustness of the resulting suitability scores, both the weighted and unweighted sum of the Z-scores of the TOD indicators were calculated and compared. Theoretically, the TOD suitability score had the same range of values as the Z-score multiplied by 100.



(a) Weighted



(b) Unweighted

**Figure 2-4 TOD suitability scores for different scenarios at the P&R sites**

The unweighted sum means that all indicators listed had the same weight and the sum of the weights was 100 percent. As Scenarios (2) and (3) had the same list of TOD indicators, the unweighted sum of these two scenarios was the same, whereas the weighted sum was different. In addition to the scores for the different scenarios, we also calculated the TOD suitability scores by using the average indicator weights of the three scenarios. Average indicator weights were calculated for all the 14 indicators (the 12 common indicators and two optional indicators) across the three scenarios and normalized to a sum of 100 percent. The average indicator weights were intended to be used for a more general case in which the implementation scenario of a TOD project was not clearly specified.

As shown in Figure 2-4(a), the TOD suitability scores of the three pilot sites ranged from -100 percent to 100 percent. Among the three pilot P&R sites, the Spokane site had the best suitability for TOD in each of the three scenarios, but the Lynnwood site had only a slightly lower score for the 1.0-mile buffer area for Scenarios (2) and (3) that respectively emphasized market rate housing and mixed-use development. The Lynnwood site showed a clear difference between the TOD suitability scores for the 0.5-mile and 1.0-mile buffer areas. This difference in suitability scores was due to the significantly different population densities, housing rents, employment densities, racial diversity, and home values in the two buffers (shown in Figure 2-3(b)), especially the population density that has a relatively high weight. For the Spokane and Clark sites, TOD suitability within the 0.5-mile buffer was slightly better than within the 1.0-mile buffer for all three scenarios, while the opposite was true for the Lynnwood site.

Compared with the results based on weighted indicators, the TOD priorities of the three sites remain the same across all three scenarios (Figure 2-4(b)). The Spokane site still has the best suitability for TOD across the scenarios. However, the difference in TOD suitability

between the Spokane site and the site with the lowest suitability scores becomes smaller. This suggests that the Spokane site's stronger performance on higher-weighted indicators further enhances its TOD potential compared with other sites. The TOD suitability of the Clark site became higher, although it was still the lowest among the three P&R sites. The TOD suitability of the Lynnwood site became lower.

## **2.5. Discussion and Conclusions**

This research developed a multi-criteria TOD prioritization tool and used it to measure the suitability of TOD at publicly owned P&R sites. The tool consisted of a total of 14 indicators in five domains: public transportation services and demand, land-use mix and walkability, sociodemographic characteristics, real estate market conditions, and planning context. We also designed three TOD scenarios emphasizing affordable housing, market-rate housing, and mixed-use development, respectively, for a more focused application of this tool. Different TOD indicators were selected and applied to prioritize potential TOD sites under these scenarios.

A Delphi process was used to select the most relevant TOD indicators and assign weights to them based on the experts' ratings and rankings. It is worth acknowledging that the small number of experts who participated in the Delphi process probably limited the number of disciplines and the range of professional experience represented in the process of rating and ranking TOD indicators. On the other hand, the small number of experts made it possible for the research team to organize the online discussion session for the experts to exchange different opinions and build consensus on the relative importance of the indicators. The weights developed represent experts' consensus of the relative importance of the indicators in measuring TOD suitability. The results, shown in Table 4, indicated that the importance of most TOD indicators did not vary much across the scenarios. If a scenario for future

development cannot be decided due to uncertainty in practical projects, then the average weights of the indicators of the scenarios can be applied.

All TOD indicators in the list were calculated, normalized, and weighted to measure the TOD suitability of publicly owned P&R sites. The results of this research indicated that the weighted scores differed for some locations and for different TOD scenarios. This TOD prioritization tool can be customized and applied to measure the development priorities of other public lands in the future. For a sensitivity analysis, these TOD indicators were also unweighted to obtain the TOD suitability scores of the selected sites and compare them with the weighted results.

The tool can help facilitate the use of public transit and support a more sustainable urban transportation system by prioritizing the locations with higher levels of transit service, denser population and employment, more diverse land uses, higher land values, and a more transit-supportive regulatory environment. The tool can also contribute to equitable improvements in workforce development and quality of life for racial groups by prioritizing the locations with greater racial diversity, better job accessibility, and higher walkability. Because it was designed around three TOD scenarios in which different housing units and land-use types primarily provided for different groups of people, the tool is more generally applicable to various TOD projects in practice. It can support the construction of diverse housing in more transit-accessible and walkable neighborhoods, which is particularly important for urban revitalization (Yin, et al., 2022).

It is important to note that this TOD prioritization tool does not include all indicators that are commonly perceived to be highly relevant. For example, TODs have been shown to be significantly more attractive to lower-income aging adults than to their higher-income counterparts because of the transportation savings (Wood et al., 2016). Another example of excluded indicators is car ownership, which is associated with demand for transit service. Even

though our Delphi study did not identify them as key indicators for measuring potential for TOD, their effects are partially captured by household income, home value, and auto accessibility (Paulley, et al., 2006; Federal Highway Administration, 2017). In addition, this tool is contextualized with 800-meter and 1600-meter buffer areas of the selected P&R sites. To apply the tool to other cities that are more bike-friendly, the buffered areas could be extended.

This TOD prioritization tool can be modified and applied to measure the suitability of and development priorities for a broader set of publicly owned land areas across the U.S. in the future. First, the datasets used to measure the TOD indicators in the tool are public and available to regions across the U.S. and could be adapted to work in other contexts. Second, the tool takes into account a comprehensive list of TOD indicators, both common TOD characteristics (i.e., public transportation, land use, sociodemographic characteristics, and real estate market domains) and local characteristics that support TOD (i.e., planning context domain). To contextualize and evaluate a public land for TOD suitability, various dimensions related to TOD can be included by applying this TOD prioritization tool. In addition, this tool uses the standardized values of the TOD indicators to compare the TOD potential of the public lands assessed. This establishes the relative competitiveness or readiness of different locations for TOD, as well as the changing TOD potential in the locations.

The applicability of this tool is currently limited to the U.S., but the idea of using publicly owned land to catalyze TOD is relevant to other market economies where urban land is predominantly under private ownership. The political climate, institutional framework, and economic context in different countries may affect the performance of TOD projects differently. Therefore, similar tools need to be developed for other market economy countries by considering such differences. In particular, indicators that are more sensitive to local contexts should be identified and included.

# **Chapter 3 Improving Mobility in Low-Density Areas: An Economic Evaluation of Innovative Transit Solutions**

## **3.1 Introduction**

Public transportation in areas with low population density encounters distinct difficulties due to dispersed settlement patterns and limited demand for transit services (Bronsvoort, et al., 2021; Tirachini & Cats, 2020). In such contexts, residents often struggle to access essential destinations like healthcare facilities, educational institutions, and shopping areas via public transit (Pucher & Renne, 2005). Conventional fixed-route systems are generally inefficient and cost-ineffective in these areas, and they often fail to adequately serve residents' mobility needs, resulting in limited mode shift from single-occupancy vehicles (SOVs) to public transit (Bronsvoort, et al., 2021; Pucher & Renne, 2005). A survey found that nearly 50% of municipalities with populations under 2,500 lack public transit services, compared with 29% in areas with 2,500 - 49,999 residents (Dumas, et al., 2021). Low-density areas are significantly more likely to be transit-underserved than high-density ones. These limitations drive transportation planners to explore alternative service models capable of providing more adaptive and cost-effective mobility in areas where fixed-route transit underperforms.

The proliferation of app-based ride services has opened new possibilities for public transit agencies to collaborate with innovative mobility providers. These partnerships offer flexible and demand-responsive services that can enhance existing public transportation systems (Clewlow & Mishra, 2017; McCoy, et al., 2018; Schaller, 2018; Shen, et al., 2021; Yan, et al., 2019; Wang & Shen, 2023). Demand-responsive transportation (DRT)—including ride-hailing services operated by transportation network companies (TNCs), as well as transit agency-provided on-demand and dial-a-ride programs—offers potential solutions for addressing first-mile/last-mile (FM/LM) gaps, facilitating guaranteed ride-home services, and

replacing underperforming fixed-route services in low-demand areas (Bronsvoort, et al., 2021; Wang & Shen, 2023; Maretić & Abramović, 2020). These services can be tailored based on demographic and environmental considerations to improve accessibility and system efficiency (Dytckov, et al., 2022).

This study adopts the concept of Transit Incorporating Mobility-on-Demand (TIMOD), introduced by Wang and Shen (2023), to describe programs in which transit agencies integrate DRT services into their operations, either as supplements or substitutes for traditional fixed-route services. TIMOD constitutes a distinct subcategory within the broader spectrum of DRT, distinguished by public transit agency leading service design, funding, and management, with technical support provided by private companies. TIMOD services include both dynamically dispatched on-demand trips and pre-scheduled services, offering flexible options to accommodate travelers' demand. Microtransit is the most common form of TIMOD, though vehicle type and service configurations may vary by area and travel demand level. For example, some TIMOD programs may utilize larger vehicles than those used in typical microtransit operations. While other forms of demand-responsive and flexible transit share operational features—such as flexible routing and dynamic scheduling—with TIMOD, these services are typically booked in advance and not always operated on a real-time basis.

A growing number of transit agencies have started piloting TIMOD initiatives, most commonly to strengthen FM/LM connections, which is one of the major barriers to increasing transit ridership (Curtis, et al., 2019). TIMOD has also been implemented in low-density and suburban areas where maintaining high-quality fixed-route service is economically unsustainable due to sparse demand and high per-passenger service costs (Shen, et al., 2021; Wang & Shen, 2023; Maretić & Abramović, 2020). Although TIMOD offers a promising solution for improving mobility in such contexts, its cost-effectiveness is influenced by a range of sociodemographic, built environment, and service operational variables. Therefore, rigorous

evaluation of cost-effectiveness of TIMOD services and their mobility alternatives is essential for identifying the conditions under which these services can be more effectively deployed. This is critical to inform strategic decision-making and support the integration of economically sustainable mobilities into broader public transportation networks. Cost-effectiveness analysis (CEA) provides a systematic approach to comparing alternative services based on their relative costs and benefits, thereby supporting evidence-based policy and investment decisions.

Despite increasing interest in TIMOD, the literature on its cost-effectiveness remains relatively sparse. Wang and Shen (2023) proposed a foundational framework for assessing TIMOD's cost-effectiveness relative to other transportation modes. Cai et al (2025) further develops this framework by integrating a more comprehensive measurement of transportation externalities and a broader comparison across alternatives, including TNC services. The improved framework would allow for comparative evaluations of various mobility services across different low-density areas. However, further development is needed, particularly through the incorporation of more low-density cases with different sociodemographic, environmental, and service operational contexts. Current understanding regarding the contextual conditions necessary for the cost-effective deployment of TIMOD and its alternative modes, especially in various low-density environments, needs further exploration. Identifying the strengths and limitations of existing service models in diverse geographic settings is critical to optimizing deployment strategies and ensuring these services deliver the greatest benefit in a financially sustainable way. Beyond the scope of FM/LM trips linked to transit stations, this study examines point-to-point travel within the designated TIMOD service areas. For these point-to-point trips, passengers are required to walk to pre-assigned pick-up locations designated by the service provider before beginning their trips. The assigned pick-up locations may be situated anywhere within the service area or at designated spots located several minutes' walking distance from the requested places.

This study aims to advance the existing evaluation framework by broadening the comparison of mobility alternatives and extending the application of the framework to diverse low-density settings. The study also incorporates a more comprehensive measurement of transportation externalities, including air pollution, greenhouse gas emissions, crashes, congestion, noise, and health impacts associated with physical activity. Seven distinct low-density areas in Washington State, U.S. are examined, where TIMOD services have been implemented. Although these areas are characterized by relatively low population density compared with dense urban centers, they differ in terms of demographic profiles, transit accessibility, and built environment features. Utilizing real-world TIMOD trip data from these settings, the cost-effectiveness of TIMOD services in comparison to counterfactual alternatives is evaluated. The alternatives include fixed-route transit, private vehicle use, and commercial ride-hailing services (i.e., TNCs). The analysis compares actual TIMOD trips with simulated trips using alternative modes to assess the relative efficiency of TIMOD within the existing transportation system. It aims to quantify the economic impacts of providing different mobility options on travelers, service providers, and society at large through comparative cost analysis of accommodating marginal travel demand.

The study aims to address the following questions: 1) What methods allow for consistent measurement and meaningful comparison of the economic costs across various mobility services? 2) From a societal perspective, accounting for both internal transportation costs incurred by travelers and service providers, as well as external costs stemming from associated externalities, what factors influence the relative cost-effectiveness of different mobility options? For each alternative, what are the key cost components? 3) How does the cost-effectiveness of mobility alternatives differ across low-density areas, and what underlying factors drive these variations? The findings can assist transit agencies and planning organizations in exploring and implementing innovative transit solutions both within the region

and in broader contexts.

The remainder of this chapter is organized as follows. Section 3.2 reviews relevant theoretical and empirical literature on demand-responsive transportation (DRT), with a particular emphasis on TIMOD services and their comparative cost-effectiveness relative to alternative mobility options. This review establishes a foundational context for the study. Section 3.3 outlines the methodological approach, including the conceptual framework, case study background, TIMOD service data, and the methods employed for cost-effectiveness evaluation. Section 3.4 presents the evaluation results, detailing total costs incurred by travelers, service providers, and environmental and health-related externalities. These costs are analyzed for an average rider across seven low-density case study areas in Washington State, with comparisons made to highlight variations associated with population density, income, and transit service levels. A sensitivity analysis is also conducted to examine the impact of key parameters on the cost-effectiveness outcomes. Section 3.5 provides a discussion of the findings, evaluating the economic competitiveness of TIMOD relative to other alternatives and assessing the robustness of the results to underlying assumptions. Finally, Section 3.6 concludes the chapter by summarizing the key insights derived from the study.

## **3.2 Literature Review**

### **3.2.1 Transit Incorporating Mobility-on-Demand (TIMOD)**

Information and communication technology (ICT) advancements changed mobility services, resulting in a new class of private mobility providers that leverage mobile apps and digital platforms to connect riders. These demand-responsive services, including ride-hailing, ridesharing, car-sharing, microtransit, and micromobility, provide attractive features such as enhanced flexibility, comfort, and operational efficiency. By incorporating these new mobility services, transit agencies can achieve some crucial goals, such as filling service gaps,

increasing demand-responsive options, and lowering the costs of certain services (Schaller, 2018; Yan, et al., 2019; Circella & Alemi, 2018; Feigon & Colin, 2016).

Many public transit agencies have recognized this potential and have started exploring, testing, or even implementing partnerships with private entities to deliver demand-responsive mobility services (Curtis, et al., 2019; Ashour & Shen, 2022). Numerous studies have explored the conditions under which these collaborations are most effective. Researchers examining DRT public-private partnerships in the United States have identified four key service models: first-mile/last-mile (FMLM) services connecting to transit systems, door-to-door services in low-density areas, off-peak hour services, and paratransit (Patel, et al., 2022; Lucken, et al., 2019). For instance, Southeastern Pennsylvania Transportation Authority (SEPTA) initiated a partnership with UberX in 2016 to enhance access to its rail stations and fill FM/LM gaps. Similarly, the Metropolitan Transit System (MTS) in San Diego offered a \$5 discount on FM/LM connections to and from its transit stations during certain events (Lucken, et al., 2019). Moreover, many pilot projects target low-density areas. Dallas Area Rapid Transit (DART) aimed to integrate TNCs (Uber and Lyft) and other DRT providers like carpool services and bike-share programs to replace inefficient fixed-route services in low-density areas (Patel, et al., 2022; Cordahi, et al., 2018). Austin's transit agency, in collaboration with TNCs, offers both FMLM and door-to-door microtransit services to low-density areas (Zuniga-Garcia, et al., 2022).

Lessons learned from the literature on DRT public-private partnerships include the following: 1) If transit agencies play a leading role in partnerships, they can gain better control over current DRT service provisions, ensure data accessibility, manage fare integration across transportation systems, and plan for future integration of DRT services into public transportation networks (Lucken, et al., 2019; Patel, et al., 2022). However, limited research exists on the integration of DRT services under transit agency leadership. 2) Accurate metrics

and measures are critical for assessing the performance of DRT services and identifying opportunities for operational improvements (Martin et al., 2021). Evaluation results can inform decision-makers, enabling collaborations with stakeholders to achieve societal benefits such as increased ride sharing and decreased environmental externalities (Rupert, 2020). 3) The transferability of evaluation results from a pilot program to other regions should be explored to provide guidance for future projects (Cordahi, et al., 2018; Patel, et al., 2022).

Building on these studies, Wang and Shen (2023) proposed the concept of TIMOD and explored how transit agencies may play the leading role in integrating public transportation with demand-responsive mobility services. Compared with demand-responsive transit, flexible transit, and microtransit, TIMOD primarily uses minivans, offering greater adaptability to demand variability through more customized and economical vehicle sizes. It also offers enhanced routing flexibility strategically planned by transit agencies, extending beyond first-mile/last-mile connections to include point-to-point trips from origins to destinations, to accommodate local travel demand. Some areas use small buses instead of minivans. However, this emerging concept remains underexplored, necessitating further studies to examine additional scenarios and investigate how TIMOD services can better serve communities with different sociodemographic characteristics and built environments while offering greater societal benefits compared with other alternatives.

### **3.2.2 Evaluation of TIMOD**

Several studies have highlighted potential challenges in integrating DRT services into transit systems. Patel et al. (2022) identified the most prevalent issues as ensuring equitable access to services and accurately estimating the costs of service provision. While reducing costs is often not the main objective of these partnerships, providing cost-effective alternatives is essential. Zhou (2019) and Yan et al. (2019) demonstrated that low-demand transit routes could be replaced by TNCs at lower costs, with the primary benefit stemming from reduced wait times.

However, this replacement faces practical challenges, including barriers to information sharing between public agencies and private companies, social equity issues, financial and legal concerns associated with integrating private ride-sharing services into public transit systems (Zhou, 2019). Shen et al. (2018) and Gurumurthy et al. (2020) employed agent-based modeling to examine deployment scenarios where DRT services could either support first-mile-last-mile (FMLM) connections to transit system or serve door-to-door trips. Their findings suggest that subsidized DRT services for FMLM trips can enhance transit coverage and shift demand away from private vehicle use, yielding potential performance gains. However, subsidizing DRT services for door-to-door trips in dense areas without restrictions may significantly reduce transit demand. Additionally, studies have shown that residents who frequently use ride-hailing services and live in areas with low transit service density are more likely to prefer demand-responsive services over fixed-route transit (Wang et al., 2022; Yan et al., 2021). However, for low-income travelers, limited access to reliable technological resources can pose a significant barrier to adopting these services (Wang et al., 2022).

While these studies provide initial insights into the integration of DRT services, they failed to discuss the potential advantages of transit agencies in leading the integration. Furthermore, these studies were exploratory and had limitations restricting their applicability in guiding transportation decision-making. Some studies used simulations based on hypothetical scenarios, which may only partially reflect the complexities of designing and implementing TIMOD. Other studies relied on respondents stated preferences, which may not always align with their actual behavior for various reasons such as habit, convenience, or external factors. A recent study conducted by Wang and Shen (2023) used real-world TIMOD trip data to evaluate the service performance with respect to the costs of travelers, service providers, and the society. By analyzing real behavior and outcomes, transportation researchers can better understand the comparative cost-effectiveness of TIMOD services and better inform

relevant decision-making. Nevertheless, a more comprehensive list of cost components, particularly the external costs associated with different travel modes, should be considered to assess the comparative cost-effectiveness of TIMOD services across various geographic contexts.

### **3.2.3 Cost-Effectiveness of TIMOD Services**

The comparative cost-effectiveness of providing mobility options in low-density areas has been a topic of interest in transportation research. One study highlights the cost-effectiveness challenges of fixed-route transit in low-demand and sparsely populated areas (Bauchinger, et al., 2021). The authors argue that demand-responsive services can be a more cost-effective alternative in such areas compared with solely operating conventional transit system. Another study argues that fixed-route services are expensive and do not provide good service at nighttime in low-density areas. In contrast, demand-responsive services with flexible and dynamic routing systems are more cost-effective in these areas (Sanaullah, et al., 2021). These studies highlight the potential cost-effectiveness of TIMOD services relative to fixed-route transit. However, more explicit estimations from the perspectives of travelers, service providers, and society are required to substantiate the findings.

Both traveler's time costs and service provider's operating costs are critical for evaluating the cost-effectiveness of a transportation mode. Some studies have focused on the costs incurred by service providers, aiming to optimize service supply. These studies typically assume that service providers bear all service-related expenses and manage vehicle assignments in response to incoming requests. The optimization generally includes the provider's operating costs (such as vehicle dispatch, fleet size, and labor) and users' time costs (including waiting and in-vehicle times) (Quadrioglio & Li, 2009; Nourbakhsh & Ouyang, 2012; Grahn, et al., 2022). In contrast, other studies have focused exclusively on minimizing users' costs, arguing that fixed-route transit increases users' access and egress times due to its

fixed pick-up and drop-off locations (Kumar & Khani, 2021).

The value of travelers' time varies across different time components of a trip, including access time, waiting time, in-vehicle time, and egress time. However, some factors that could affect travelers' costs, such as perceived discomfort during the trip and the freedom to arrange waiting time, are often overlooked in literature. Additionally, service performance under varying levels of demand density has been explored (Zhou, 2019; Nourbakhsh & Ouyang, 2012). These factors should also be considered when evaluating the cost-effectiveness of a mode of transportation.

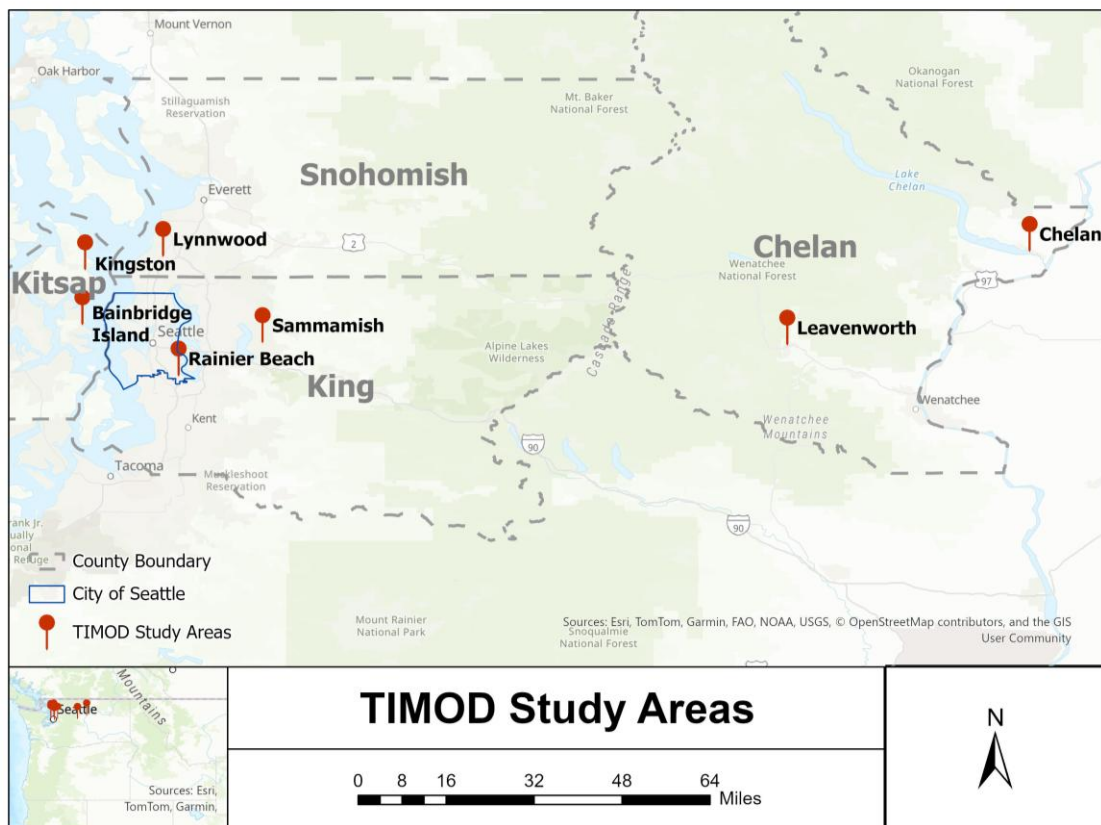
To quantify transportation externalities, previous studies have employed modeling software such as SUMO for microsimulation and MATSim for large-scale simulation. These tools simulate externalities such as emissions, noise, and congestion for individual vehicles under specific scenarios, and results are then aggregated for further analysis (Rendel & Bachmann, 2023). Other studies have directly utilized historical data to estimate externalities across entire transport systems (Schröder, et al., 2023). These studies provide useful information about externalities in large-scale transportation systems using aggregated traffic data. However, estimating and monetizing the effects of individual trips on transportation externalities remain challenging, necessitating further adjustments of relevant parameters tailored to the specific contexts of different study cases.

### **3.3 Data and Methodology**

#### **3.3.1 Case Background and Data**

This study evaluates the comparative cost-effectiveness of TIMOD services in seven representative low-density areas in WA, including Sammamish, Rainier Beach, Leavenworth,

Chelan, Lynnwood, Bainbridge Island, and Kingston<sup>5</sup>. TIMOD service offers convenient, fast, and affordable rides in the designated areas. Depending on the area, riders either pay a fare equivalent to the bus fare or can use these services for free. The vehicle capacity and the maximum number of passengers per ride also vary by area, typically ranging from 5 to 14 seats. The service also provides ADA-accessible vehicles for passengers with mobility devices. Service hours vary depending on the location. The service can be booked through either an app or a phone call, with pick-up and drop-off times available upon request. TIMOD provides point-to-point demand-responsive services within the designated service area limits, irrespective of the trip purpose.



**Figure 3-1 The areas of study**

The trip-level data for completed rides consists of request, pick-up, and drop-off times,

<sup>5</sup> This chapter includes fewer study areas than the next. For the TIMOD service areas operated by King County Metro, only 2 of the 6 are selected as representatives.

origin and destination geo-coordinates, trip distances, and the number of seats requested. A representative day is selected for each of the case areas to estimate the comparative cost-effectiveness of mobility alternatives on that day. The selection is based on the most recent date when the ridership started to stabilize and reached the average level over time. The case areas' sociodemographic characteristics obtained from the 2019-2023 American Community Survey (ACS) 5-year estimates and the 2023/2024 Labor Statistics (U.S. Census Bureau, 2023; Bureau of Labor Statistics, 2023; Bureau of Labor Statistics, 2024), as well as the characteristics of TIMOD service operation and the selected representative days of trip data are shown in Table 3-1.

**Table 3-1 The characteristics of the case areas**

<i>Service provider</i>	<i>King County Metro</i>		<i>Link Transit</i>		<i>Community Transit</i>	<i>Kitsap Transit</i>	
<i>Urban hierarchy of the service areas (WSDOT, 2024)<sup>6</sup></i>	Urban		Small Urban		Urban	Small Urban	
<i>Service area</i>	Sammamish	Rainier Beach	Leavenworth	Chelan	Lynnwood	Bainbridge Island	Kingston
<b><i>Sociodemographic characteristics</i></b>							
<i>Median hourly wage</i>	\$31.38 (2023)	\$31.38 (2023)	\$23.04 (2024)	\$23.04 (2024)	\$32.46 (2024)	\$29.37 (2024)	\$29.37 (2024)
<i>Population density (sq. mi)</i>	3,188	5,008	1,841	644	5,199	891	1,225
<i>Median age</i>	41.3	39	42.3	46.7	39.2	49	40.6
<i>Ratio of bachelor's degree or higher</i>	83.4%	43.1%	45.6%	26.5%	32.6%	75.0%	42.4%
<i>Median household income (\$)</i>	\$238,750	\$101,436	\$74,653	\$71,996	\$76,439	\$159,882	\$99,345

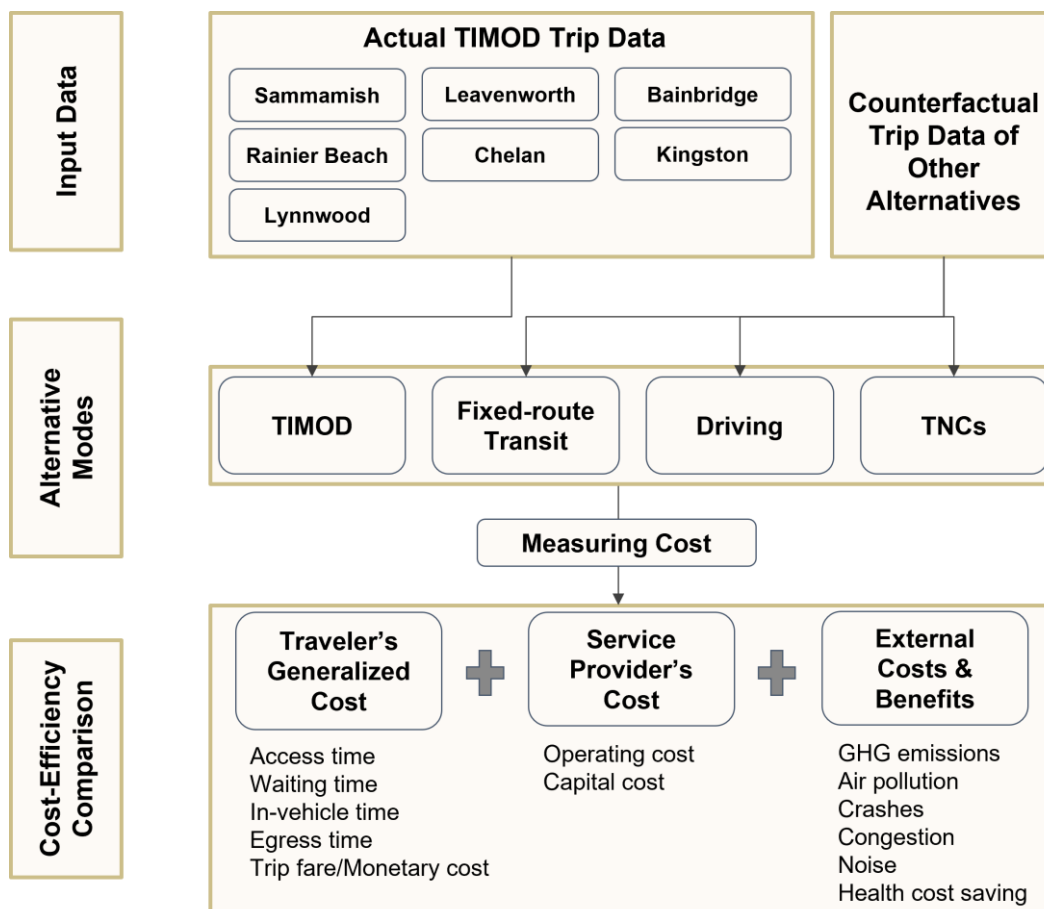
<sup>6</sup> WSDOT defines rural transit service areas as regions with populations of 50,000 or fewer, which is the same as the definition reported by the Federal Highway Administration (FHWA Highway Functional Classification Concepts, 2013). This definition differs from that used by the U.S. Census Bureau.

<b>TIMOD Service operation<sup>7</sup></b>							
<i>Service hours</i>	5:00am – 1:00am	7:00am – 6:00pm	5:30am – 8:30pm	7:30am – 6:00pm	5:00am – 10:00pm	8:00am – 6:30pm	7:30am – 5:00pm
<i>Service type</i>	Point-to-point	Point-to-point	Point-to-point	Point-to-point	Point-to-point	Point-to-point	Point-to-point
<i>Vehicle capacity</i>	5	5	14	14	6	14	14
<i>Vehicle type</i>	Minivan	Minivan	Bus	Bus	Minivan	Bus	Bus
<b>Trip-level data</b>							
<i>Number of trips</i>	67	301	38	38	193	61	13
<i>Number of riders</i>	89	336	38	41	206	91	13
<i>Median trip distance (mi)</i>	4.69	4.07	2.20	1.80	1.60	4.61	5.35
<i>Period of data availability</i>	Mar 6, 2023 – May 30, 2023	Mar 6, 2023 – May 30, 2023	Feb 1, 2024 – Mar 23, 2024	Feb 1, 2024 – Mar 23, 2024	Jan 1, 2024 – Dec 31, 2024	Jan 1, 2024 – Dec 31, 2024	Jan 1, 2024 – Dec 31, 2024
<i>Selected representative day</i>	Thu, May 4, 2023	Thu, May 4, 2023	Wed, Feb 28, 2024	Wed, Feb 28, 2024	Tue, Sep 10, 2024	Wed, Sep 4, 2024	Wed, Sep 4, 2024

### 3.3.2 Methodological Framework

This study builds upon an analytical framework proposed by Wang and Shen (2023) for quantifying and comparing the economic costs of expanding mobility services in new or underserved areas. The framework emphasizes using marginal cost instead of system-wide average cost when considering service expansion or new mobility options, as it provides more pertinent information for decision-making. “Marginal cost” refers to the costs for serving an increment of trips generated by an additional group of travelers. The framework also highlights the importance of accounting for both the service provider's and the users' costs, including monetary and time costs, and externalities such as environmental impacts. To accurately estimate the user's travel time, the time cost should include access, waiting, in-vehicle, and egress times. The framework is shown in Figure 3-2.

<sup>7</sup> This map is available at <https://www.communitytransit.org/services/zip-shuttle/alderwood>.



**Figure 3-2 Methodological framework**

The study addresses the research questions with two methodological components. First, the evaluation of alternative travel modes' cost-effectiveness is conceptualized from a societal perspective by considering traveler's generalized cost, service provider's cost, and transportation external costs and benefits. Second, a transportation simulation procedure is built to allow transit agencies to empirically compare the costs of serving TIMOD trips to the counterfactual trips of other mobility alternatives: 1) fixed-route transit, 2) driving, and 3) commercial ride-hailing services (i.e., TNCs). Specifically, traveler's generalized cost is estimated by monetizing actual travel times of TIMOD trips and simulated travel times of the counterfactual trips of other alternatives. Travel times are monetized using travelers' values of time as percentages of the median hourly wage in each area. The service provider's cost is estimated using the statistics obtained from the collaborated transit agencies. The transportation

externalities include air pollution (harmful air pollutants), greenhouse gas emissions, crashes, congestion, noise, and health benefits from physical activities.

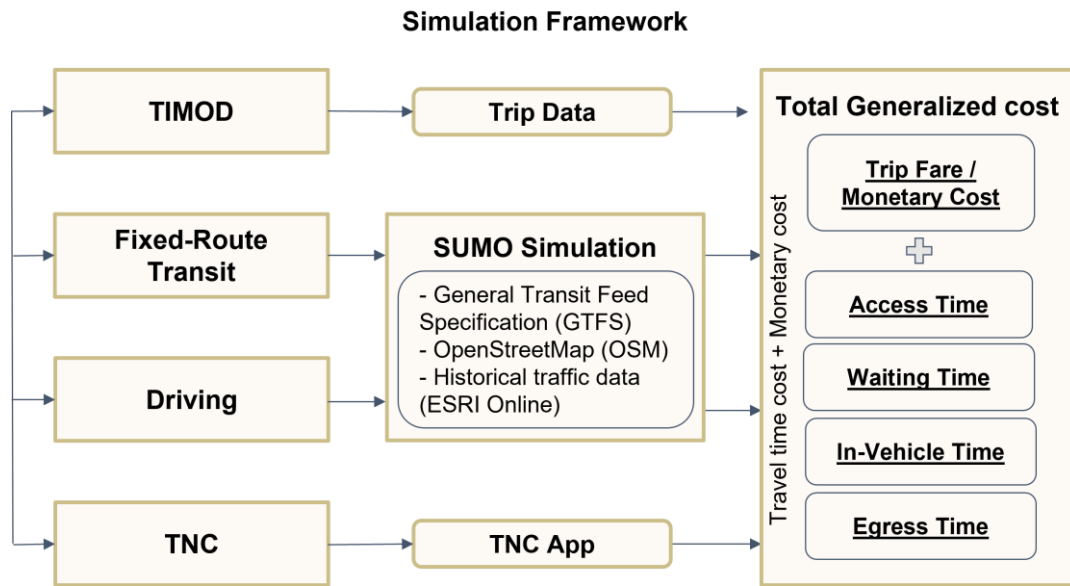
### *3.3.2.1 Conceptualizing Cost-Effectiveness of Alternative Travel Modes*

Economic cost variables are quantified to assess the cost-effectiveness of TIMOD relative to alternative modes. These variables include:

- 1) Generalized costs for travelers from different socioeconomic backgrounds include travel time components, such as access time, waiting time, in-vehicle time, and egress time, and monetary costs, such as ride fares or parking fees.
- 2) Costs for mobility service providers, including public transit agencies and private operators. These typically cover the costs of labor (wages for drivers, managers, and planners), fuel or propulsion, capital, and maintenance.
- 3) Costs and benefits of transportation externalities, primarily environmental and health externalities.

### *3.3.2.2 Estimating Travel Times and Costs*

Figure 3-3 illustrates the simulation framework. Because TIMOD is a shared-ride service, users can either request specific pick-up locations or be directed to walk to a designated spot at a nearby corner. For the cases where pick-up locations as requested can be almost anywhere within TIMOD service areas, the access time of a TIMOD trip is estimated as the interval between pick-up arrival and departure time. If pick-up arrival time equals departure time, it means the access time would be zero. The waiting time of a TIMOD trip is estimated as the interval between reported pick-up arrival time and promised or requested pick-up time. If the reported pick-up arrival time is earlier than the promised or requested pick-up time, the waiting time is assumed to be zero. The above estimation methods of access time and waiting time apply to the cases of Leavenworth, Chelan, Lynnwood, Bainbridge, and Kingston.



**Figure 3-3 Alternative modes simulation framework**

For the cases where users will be directed to walk to a designated spot to meet their vehicles, it is assumed that they would spend no more than 5 minutes accessing the pick-up locations. If the interval between requested and reported pick-up time of a TIMOD trip is longer than 5 minutes, it is assumed that users would spend 5 minutes accessing the pick-up location, with the remaining time spent waiting for the vehicle to arrive. On the other hand, if the interval is shorter than 5 minutes, users are assumed to access the pick-up location throughout the time interval. These methods apply to the cases of Sammamish and Rainier Beach.

Based on actual TIMOD trips, the counterfactual trips by other alternative travel modes are simulated by using Eclipse SUMO, a free and open-source software. Eclipse SUMO is highly customizable and can directly model real-world road networks and individual-traveler-level traffic flows (Lopez, et al., 2018). It allows the data import of bus schedules and road network to simulate the trips of fixed-route transit and driving. Data for bus schedules is obtained from General Transit Feed Specification (GTFS). Road network data is from OpenStreetMap (OSM), including the number of lanes, speed limits, permitted vehicle types, sidewalks, pedestrian crossings, and traffic signals. In simulating counterfactual trips by fixed-

route transit and private vehicle, it is assumed that travelers would depart at the same time as when they requested TIMOD services. Depending on the departure time, an estimated speed factor is applied to each trip to account for varying traffic speeds throughout a typical weekday. The speed factor reflects the ratio of traffic speed at a certain time of day to the road speed limit. It is estimated based on historical traffic data from ESRI online<sup>8</sup>. The outputs of the simulation include access, waiting, in-vehicle travel, and egress times required for travelers using each mode.

Travel times and costs of TNC trips are estimated using Uber's Guest Trip Estimates endpoint<sup>9</sup>. It returns estimated waiting time, trip duration, and trip fare based on the input of trip information, including addresses of origin (pick-up location) and destination (drop-off location), along with trip departure time. It is assumed that the trips would occur on a similar weekday and during the same time period as the actual TIMOD trips. The option with the lowest price is selected for the estimation of each trip. The study also assumes that travelers who choose TNC would spend similar time on accessing their pick-up locations as the corresponding TIMOD trips.

### *3.3.2.3 Estimating the Generalized Costs for Travelers*

Travel time for each mode was monetized using percentages of the median hourly wage rate as the values of travelers' time during trips, under the simplified assumption that the trips were either commuting trips or non-commuting trips made by average working adults during a typical weekday. Travelers' values of time for various trip components are listed in Table 3-2. These values were determined for the following reasons:

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<sup>8</sup> Retrieved from: <https://pro.arcgis.com/en/pro-app/latest/help/data/streetmap-premium/use-live-traffic-with-streetmap-premium.htm>

<sup>9</sup> Retrieved from <https://www.uber.com/global/en/price-estimate/>;  
<https://developer.uber.com/docs/guest-rides/references/api/v1/guest-trips-estimates-post>

- 1) The U.S. Department of Transportation recommended plausible ranges for personal trip values of travel time savings for surface modes other than high-speed rail (U.S. Department of Transportation, 2016). These were 35% to 60% of hourly earnings for time spent in a vehicle and 80% to 120% of hourly earnings for time spent on walking.
- 2) For the value of in-vehicle time as a percentage of hourly earnings, TIMOD and TNCs were assigned the lowest value rounded to the nearest 10 (i.e., 40%), while driving was assigned the highest value (60%) (Wang & Shen, 2023). TIMOD and TNC vehicles were expected to have a higher level of comfort than buses given their available seats for all passengers, which contributes to their lower opportunity cost of in-vehicle time than transit. Compared with other modes, drivers of private vehicles cannot use their in-vehicle time freely, and therefore they were expected to have the highest opportunity cost of in-vehicle time.
- 3) TIMOD and TNC were also set to have a lower wait time value than transit (Schwieterman, 2019). TIMOD and TNC riders have more control over the distribution and use of their time waiting and walking to pick-up locations. Even if they were a few minutes later than the estimated pick-up time, drivers would stay for a short time (about 2 minutes) to allow riders to arrive at pick-up locations.
- 4) Due to the lack of information about the ultimate destination, the egress walking time is assumed to be zero for TIMOD and TNC. For most cases, the drop-off locations are believed to be quite close to the eventual destination. The egress walking time for bus trips is included as part of the total walking time, alongside access walking time.

**Table 3-2 Travelers' values of time for trip components as percentages of hourly wage**

<i>Time</i>	<i>TIMOD</i>	<i>Fixed-route</i>	<i>TNC</i>	<i>Driving</i>
<i>Access time</i>	100%	100%	100%	100%
<i>Waiting time</i>	50%	75%	50%	NA

<i>In-vehicle time</i>	40%	50%	40%	60%
<i>Egress time</i>	NA	100%	NA	100%

TIMOD ride fare per person of each case area is shown in Table 3-3 in Section 3.3.2.4. Trips made by driving do not have to pay a ride fare. Instead, these trips pay for the costs of fuel consumption, maintenance, and vehicle ownership divided by the miles traveled. The gasoline price per gallon of each area is estimated as the average price of local gas stations. They are Sammamish (\$4.82), Rainier Beach (\$4.82), Leavenworth (\$4.63), Chelan (\$4.02), Lynnwood (\$4.02), Bainbridge Island (\$4.32), and Kingston (\$3.82)<sup>10</sup>. Fuel consumption from driving is estimated using SUMO simulation, which accounts for the effects of vehicle speed and acceleration on fuel usage during a trip (Krajzewicz, et al., 2014). Additionally, the average costs of car maintenance and car ownership (including insurance, license, and depreciation) are respectively \$0.098<sup>11</sup> and \$0.832<sup>12</sup> per mile in 2023 (AAA, 2023); \$0.101 and \$0.854 in 2024 (AAA, 2024).

### 3.3.2.4 Estimating Service Provider’s Operating Costs

The operating cost per vehicle per hour of TIMOD service in each case area is also shown in Table 3-3. The data for TIMOD operating costs is obtained from the transit agencies. The TIMOD operating cost typically includes wages for drivers, dispatchers, and immediate supervisors, as well as costs of maintenance, fuel, and insurance divided by the hours of service. For the estimation of counterfactual operating costs of fixed-route transit, it is assumed that an increase in passengers would necessitate additional investments in the current transit system if TIMOD option is unavailable, such as using larger buses and adding more seats. Due to the lack of available data to quantify this additional investment, the current operating cost allocated

<sup>10</sup> These figures are obtained from <https://www.gasbuddy.com/gasprices/washington/>

<sup>11</sup> This was obtained by calculating the average of different vehicle types.

<sup>12</sup> The same as above, assuming 10,000 miles traveled per year.

to the number of TIMOD riders was used as an approximate estimate of the marginal cost of accommodating this additional amount of travel demand within the transit system. Given this assumption, the agency's total operating costs for TIMOD and transit are calculated using equations (1) and (2). The total vehicle hours of TIMOD service on the selected day are provided by the collaborated transit agencies. The total vehicle hours of fixed-route transit and the average weekday transit boardings in the month of the selected day were also obtained from the collaborated transit agencies.

**Table 3-3 Service operation by case area**

<i>Service provider</i>	<i>King County Metro</i>		<i>Link Transit</i>		<i>Community Transit</i>	<i>Kitsap Transit</i>	
<i>Service area</i>	Sammamish	Rainier Beach	Leavenworth	Chelan	Lynnwood	Bainbridge Island	Kingston
<i>Ride fare per person</i>	\$2.75 or less	\$2.75 or less	\$0	\$0	\$2.50 or less	\$2.00 or less	\$2.00 or less
<i>Hourly operating cost per vehicle</i>	\$56	\$56	\$148	\$148	\$70	\$283	\$283

The equations below show how service providers' total operating costs of trips of TIMOD and fixed-route transit are measured.

$$C_{MF} = O_{MF} * H_{MF} \quad (1)$$

$$C_{transit} = O_{transit} * H_{transit} * D / (R_{transit} + D) \quad (2)$$

Where  $C_{MF}$  is the total operating cost of TIMOD vehicles on the selected day,  $O_{MF}$  is the TIMOD's operating cost per vehicle per hour,  $H_{MF}$  is the total vehicle hours of TIMOD on the selected day.  $C_{transit}$  is the total operating cost of buses traveling through the study areas on the selected day,  $O_{transit}$  is the operating cost per bus vehicle per hour,  $H_{transit}$  is the total vehicle hours of buses traveling through the study areas on the selected day,  $D$  is the total number of persons generating the demand for the observed trips of TIMOD on the selected day, and  $R_{transit}$  is the total ridership of those buses on the selected day.

For driving<sup>13</sup>, it is assumed that additional parking spaces might need to be constructed to accommodate the increased parking demand resulting from the shift of TIMOD trips to private car trips. The parking cost per space by type consists of land costs, construction costs, and the costs of operation and maintenance. The types of parking facilities in suburban and rural areas include on-street parking, off-street parking, surface parking (parking lots directly on land), and structured parking space (multi-story parking buildings called parkades, garages or ramps). Underground parking is assumed to be not typical in suburban and rural areas. Moreover, this study assumes that each parking space serves two trips per day and would be offered to drivers at no charge. Therefore, the minimum number of parking spaces needed in each area can be calculated based on the total number of trips. Daily and monthly costs per parking space for different types of facilities are shown in Table 3-4<sup>14</sup>. In addition, TNC operating costs are not known, nor are they a direct, public financial cost; they are assumed to be fully covered by fares collected from the users.

**Table 3-4 Parking cost per parking space by type of facility adjusted by inflation  
(Litman, 2022; Litman, 2025)**

<i>Type of facility</i>	<i>Land cost</i>	<i>Construction cost</i>	<i>Operating and maintenance cost</i>	<i>Total daily cost</i>	<i>Total monthly cost</i>
<i>2023</i>					
<i>On-street parking</i>	\$0.20	\$0.75	\$0.86	\$1.81	\$54.25

<sup>13</sup> The cost of road maintenance is assumed to be included in car ownership expenses, as part of the taxes paid. It is acknowledged that the government may face deficits in road maintenance cost. In this case, car ownership expenses may not be able to fully cover this cost.

<sup>14</sup> For cross-area comparisons, the data used to calculate parking costs differs from the case-specific values reported in the previous study (Cai, et al., 2025).

<i>Surface parking with free land</i>	\$0.00	\$1.25	\$1.14	\$2.39	\$71.76
<i>Surface parking</i>	\$0.45	\$1.25	\$1.14	\$2.85	\$85.40
<i>Structured parking</i>	\$0.23	\$3.74	\$1.72	\$5.69	\$170.55
<b>2024</b>					
<i>On-street parking</i>	\$0.21	\$0.77	\$0.88	\$1.86	\$55.83
<i>Surface parking with free land</i>	\$0.00	\$1.28	\$1.18	\$2.46	\$73.85
<i>Surface parking</i>	\$0.47	\$1.28	\$1.18	\$2.93	\$87.89
<i>Structured parking</i>	\$0.23	\$3.85	\$1.77	\$5.85	\$175.52

### 3.3.2.5 Estimating Transportation Externalities

The estimation of transportation externalities includes the costs of air pollutants on health and materials, greenhouse gases on global climate and ecosystems, crashes, congestion, noise, and health impacts associated with physical activity. To estimate these externalities, vehicle miles or passenger miles of travel are converted into corresponding monetary costs by travel mode.

**Greenhouse gases:** Greenhouse gases have significant and far-reaching effects on the Earth's climate and ecosystems. The cost of greenhouse gases is estimated based on life-cycle CO<sub>2</sub> or CO<sub>2</sub> equivalent (CO<sub>2</sub>E) emissions of trips by mode. While CO<sub>2</sub>E includes CO<sub>2</sub> emissions and the emissions of other greenhouse gases (such as methane, nitrous oxide, or fluorinated gases), CO<sub>2</sub> emissions account for 95% of all transportation-related greenhouse gas emissions (Federal Transit Administration, 2010). In this regard, the estimates based on CO<sub>2</sub> and CO<sub>2</sub>E can be considered approximate. A typical minivan (make and model: Toyota Sienna

or Chrysler Pacifica) used for operating TIMOD service in some case areas would generate 502 grams<sup>15</sup> of CO<sub>2</sub>E per vehicle mile traveled (which approximates to the emissions of a standard SUV), while a passenger car used by TNC and a single driver would generate 410 grams of CO<sub>2</sub>E per vehicle mile traveled (Bieker, 2021). Furthermore, a TIMOD trip can be a shared ride, while its counterfactual trip by TNC (Uber or Lyft) or driving cannot be shared by more than one ride in the study areas. Uber or Lyft do not offer ride-pooling services outside of major markets, according to the company's statement (Schaller, 2021)<sup>16</sup>. Compared with non-shared rides for the same level of demand, shared rides can result in fewer miles traveled with passengers in vehicles, and thus lower associated external costs. This has been considered when estimating the external costs for TIMOD and other alternatives. This study has also taken into account the effect of deadheading on the emission costs of both TIMOD services and TNCs as an additional proportion of the trip distance. According to the statistics provided by the collaborated transit agencies, the average deadhead mile ratio of a TIMOD trip on the selected day for each case area is as follows: Sammamish (58%), Rainier Beach (58%), Leavenworth (62%), Chelan (18%), Lynnwood (9%), Bainbridge Island (6%), and Kingston (36%). The average deadhead mile ratio of a TNC trip in the Seattle Metropolitan Area is 46.9% (Balding et al., 2019). The other case areas outside the Seattle Metropolitan Area are assumed to have a similar deadhead mile ratio on average.

From a national average perspective, a typical bus generates 291 grams of CO<sub>2</sub> per passenger mile traveled (APTA, 2018). CO<sub>2</sub> emissions were then monetized using the marginal abatement cost of \$313.73 per ton of CO<sub>2</sub> emissions in the United States (Liu & Feng, 2018). Therefore, the CO<sub>2</sub> emission abatement cost of a TIMOD minivan is \$0.16 per vehicle mile

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<sup>15</sup> The CO<sub>2</sub> emission equivalents per kilometer from the original estimates have been converted to the equivalents of per mile.

<sup>16</sup> The areas where the UberX Share service is available can be found at: <https://www.uber.com/us/en/ride/uberx-share/>. The Seattle metropolitan area is not included in this list.

driven, compared with \$0.13 per vehicle mile driven for a typical passenger vehicle of TNC and personal driving, and \$0.09 per passenger mile traveled for a bus. We used equation (3) to estimate the emission cost of each mode.

$$C_E = M * E_{mode} * L_{mode} \quad (3)$$

Where  $C_E$  is the CO<sub>2</sub> emission abatement cost of a mode,  $M$  is the abatement cost per gram of CO<sub>2</sub> emissions,  $E_{mode}$  is the CO<sub>2</sub> emission equivalents per vehicle/passenger mile traveled,  $L_{mode}$  is the total miles traveled by passengers on the selected day.

**Air pollution:** Air pollutants harm the health of humans and other living beings, as well as damages materials. Air pollutants consist of harmful gases (such as carbon monoxide, sulfur dioxide, or nitrogen oxide), particulate matters (such as PM10 or PM2.5), and biological molecules (such as volatile organic compounds). On the basis of estimates of vehicles in line with the Euro 6 emission standard for European countries, the air pollution cost per vehicle mile traveled by a small passenger car or a large SUV on an urban road is estimated as \$0.0025 (European Commission, 2019; US Department of Transportation, 2021)<sup>17</sup>. When compared with European emission standards, U.S. Environmental Protection Agency (EPA) emissions standards for passenger cars and light-duty vehicles align most closely with the Euro 6 standard. Therefore, a typical passenger car used by TNCs and private drivers and a typical minivan used for TIMOD in some areas would generate an air pollution cost of \$0.0025 in 2023 and \$0.0026 in 2024 per vehicle mile traveled. The air pollution cost per passenger mile traveled by bus on an urban road is estimated as \$0.0015 in 2023 and 2024 (European Commission, 2019). These estimates are lower than the converted estimates reported by Delucchi and McCubbin (2011)

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<sup>17</sup> The original estimates were reported in 2016-euro cents per passenger kilometer. These estimates have been converted to per passenger mile and per vehicle mile, respectively, by assuming an average of 1.6 passengers per vehicle (US Department of Transportation, 2021). They have also been adjusted for the exchange rate between EURO and USD in 2016 (i.e., 1 EURO in 2016 = 1.1069 USD in 2016) and for inflation from 2016 to 2023 and 2024 (i.e., 1 USD in 2016 = 1.27 USD in 2023= 1.31 USD in 2024).

for year-2006 because new emission standards for light-duty vehicles in the U.S. and Europe are set to lower air pollution emissions.

**Crashes:** Based on the estimates of Lemp and Kockelman (2008), the crashes cost per vehicle mile driven by a TIMOD minivan is \$0.150 in 2023 and \$0.155 in 2024, while it is \$0.110 (2023) and \$0.113 (2024) for a passenger vehicle of TNC and personal driving<sup>18</sup>. In comparison to the proportions of crash costs of light-duty passenger vehicles and heavy-duty freight trucks, only 0.7% of the annual crash costs for the entire U.S. vehicle fleet is attributable to buses (Delucchi & McCubbin, 2011). Because this is only a minor factor to the total external cost, we estimate the crash cost of a bus to be zero in align with the prior study. The sum of crash costs of a travel mode is calculated by the cost per vehicle mile driven times the total number of miles traveled by mode.

**Congestion:** Congestion cost can be estimated as the value of added delays based on the current traffic, which is a function of traffic volume relative to road capacity and the value of time spent in vehicles. Lemp and Kockelman (2008) estimated the value of added delay for different vehicle types by using their passenger car equivalents at signalized intersections on roadways with an average road capacity of 2,000 vehicles per hour per lane and under standard congested conditions (reaches 95% of capacity), assuming that the value of in-vehicle time was \$8 per hour in 2006. The results show that the congestion cost per mile driven of a minivan (assuming the make and model are Toyota Sienna) was \$0.0935 in 2006, while for a passenger car (assuming the make and model are Toyota Corolla), it was \$0.0698. The 2006 values are adjusted to 2023 and 2024 levels using the ratio of in-vehicle time values for those years. The estimated congestion cost per vehicle mile traveled by mode of each case area is shown in

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<sup>18</sup> The costs have been adjusted for [inflation from 2006 to 2023 and 2024](#) (i.e., 1 USD in 2006 = 1.51 USD in 2023 = 1.56 USD in 2024). They were calculated using the cost of the Toyota Sienna minivan and the average cost of small cars from the original estimates, adjusted for inflation from 2006 to 2023 and 2024.

Table 3-5. The sum of congestion costs of a travel mode is calculated by the cost per vehicle mile traveled times the total number of miles traveled by mode. In addition, buses are assumed to have zero marginal impact on congestion, as their schedules are assumed to remain unchanged regardless of additional travelers<sup>19</sup>. Consequently, the number of bus miles does not increase, and the congestion cost for buses is considered to be \$0.

**Table 3-5 Congestion cost per vehicle mile travelled by mode**

<i>Area</i>		<i>Sammamish</i>	<i>Rainier Beach</i>	<i>Leavenworth</i>	<i>Chelan</i>	<i>Lynnwood</i>	<i>Bainbridge Island</i>	<i>Kingston</i>
<b>Mode</b>	<b>Year</b>							
<b>TIMOD</b>	<b>2023</b>	\$0.194	\$0.194	\$0.138	\$0.138	\$0.194	\$0.173	\$0.173
	<b>2024</b>	\$0.201	\$0.201	\$0.142	\$0.142	\$0.201	\$0.182	\$0.182
<b>TNC</b>	<b>2023</b>	\$0.145	\$0.145	\$0.103	\$0.103	\$0.145	\$0.129	\$0.129
	<b>2024</b>	\$0.150	\$0.150	\$0.106	\$0.106	\$0.150	\$0.136	\$0.136
<b>Driving</b>	<b>2023</b>	\$0.218	\$0.218	\$0.155	\$0.155	\$0.218	\$0.194	\$0.194
	<b>2024</b>	\$0.226	\$0.226	\$0.160	\$0.160	\$0.226	\$0.204	\$0.204

**Noise:** Noise cost of vehicle use depends on the density of the population exposed to the noise and the existing noise level (which is affected by the existing traffic volume, traffic speed, and mix of vehicle types) (European Commission, 2019). It varies by road type, from local roads to interstate highways. The assumed average noise cost of a light-duty vehicle is \$0.062 (2023) and \$0.064 (2024) per vehicle mile traveled and \$0.039<sup>20</sup> (2023) and \$0.040 (2024) per passenger mile traveled, assuming 1.6 passengers per vehicle (Delucchi & McCubbin, 2011; US Department of Transportation, 2021). The noise cost per passenger mile traveled by bus is similar to that of a passenger car (European Commission, 2019). Therefore, we estimate the noise cost per passenger mile traveled by bus to be \$0.039 (2023) and \$0.040 (2024).

**Health cost saving:** The health cost savings reflect the monetary values for the health

<sup>19</sup> This assumes no additional buses are required in the counterfactual scenario when passengers switch from TIMOD.

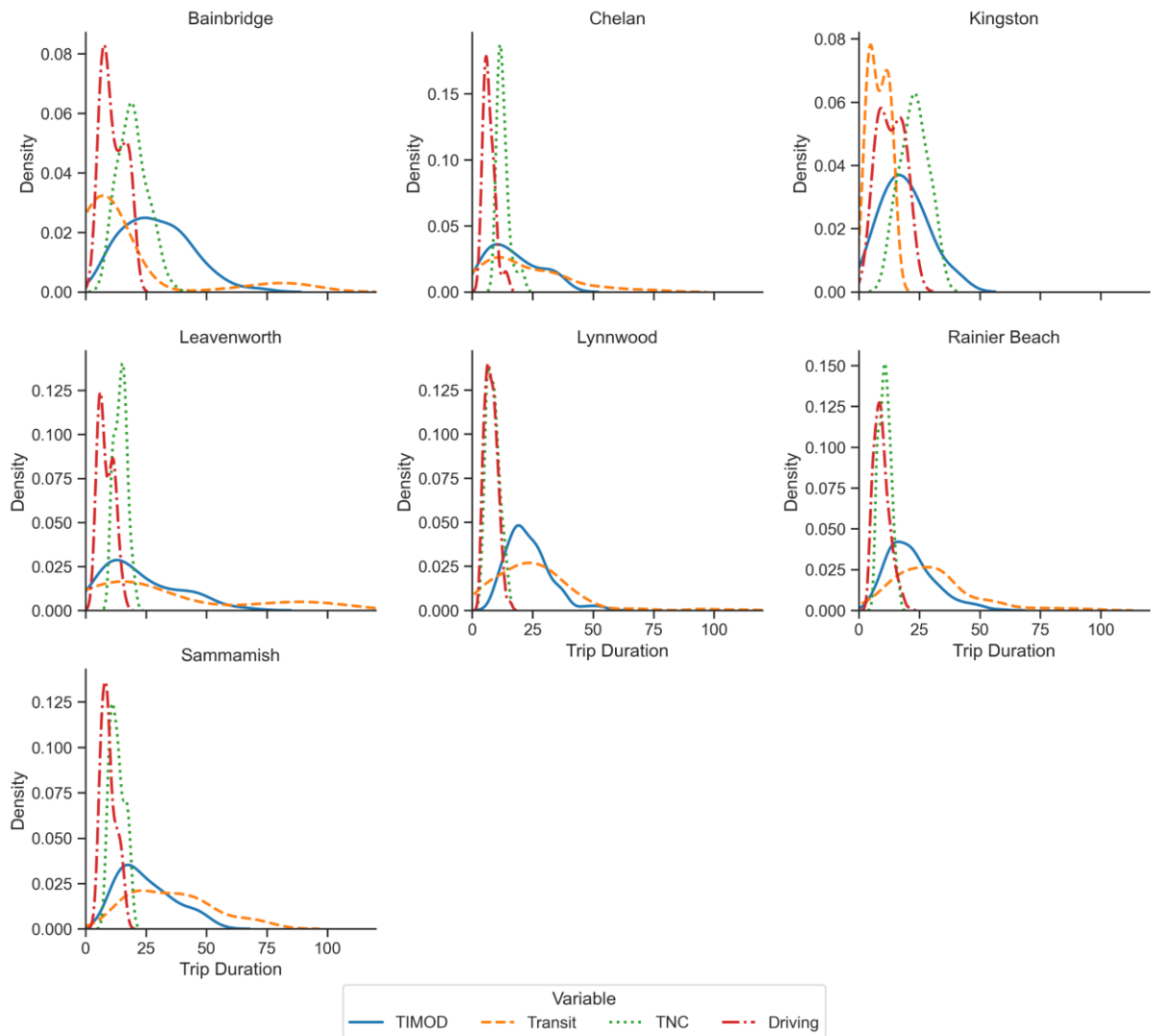
<sup>20</sup> The pre-converted estimates fall within the range provided by Delucchi & McCubbin (2011), at approximately 80% of the upper bound.

benefits of increased walking and cycling, including the benefits internal to the people who increase their activities and external benefits to society due to medical cost savings and thus the reduction in public financial burden of illness. With inflation considered, the health cost savings per mile in 2023 and 2024 are estimated at \$0.28 (2023) and \$0.29 (2024) for increased cycling and \$0.70 (2023) and \$0.72 (2024) for increased walking (LTNZ 2006; Litman, 2016). These values are multiplied by the increased walking distances associated with access to and egress from fixed-route transit to account for the resulting benefit savings. The estimated health savings are then subtracted from the sum of other external costs to determine the final external cost.

## **3.4 Results**

### **3.4.1 Comparing Travel Time by Mode of Transportation**

Figure 3-4 shows the distributions of travelers' total travel time by transportation mode and area. Table 3-6 provides a breakdown of travel time by mode for all the areas. Based on the overall distribution of trip durations, except in Kingston, TIMOD takes more time than driving and TNCs but less time than transit on average. Compared with driving and TNCs, TIMOD trips have longer in-vehicle times due to ride sharing. They also involve longer waiting times than counterfactual TNC trips. Additionally, long transit trips with extended access and waiting times reflect the limited transit service coverage in the study areas.



**Figure 3-4 Distribution of total travel time by mode**

**Table 3-6 Breakdown of travel time by mode**

<b>Mode</b>	<b>Mean</b>	<b>Std.</b>	<b>Min.</b>	<b>Max.</b>
<b>TIMOD</b>	22.70	10.80	3.00	70.70
Access time + Wait time	12.36	8.09	0.00	45.13
In-vehicle time	10.34	6.49	0.00	50.00
<b>Transit (bus)</b>	27.33	19.23	0.00	111.10
Access time + Wait time	21.74	18.39	0.00	101.47

In-vehicle time <sup>21</sup>	5.65	5.60	0.00	32.85
<b>TNC</b>	11.67	4.52	4.00	35.00
Access time + Wait time	4.81	3.08	1.00	23.00
In-vehicle time	6.86	3.00	0.86	19.00
<b>Driving</b>	9.05	3.40	3.40	21.40
In-vehicle Time	7.05	3.40	1.40	19.40
Parking Time	2	0	2	2

### 3.4.2 Costs for Travelers, Service Operation, and Externalities

Table 3-7 shows the costs of travelers, service operation, and externalities in total and per rider of each case area. From a societal perspective, driving is the least expensive mobility option for riders across all areas even when parking costs are considered. Except in Rainier Beach, TNC services are more cost-effective than both TIMOD and fixed-route transit. The comparative cost-effectiveness of TIMOD compared with fixed-route transit depends on the service provider's operations. In some areas, TIMOD is less costly than fixed-route transit, while in others, it is more expensive. From the traveler's perspective, TIMOD has a cost advantage over fixed-route transit and TNCs due to its demand-responsive nature and subsidized fares. In Leavenworth and Chelan, where TIMOD services are offered for free, TIMOD services are even more cost-effective than driving for travelers. From the service provider's perspective, TIMOD is more costly than fixed-route transit in most areas, though it is less expensive in Bainbridge Island and Kingston. In terms of total external cost, fixed-route transit is less expensive than other alternatives. Except in Sammamish, TIMOD has an

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<sup>21</sup> The relatively low in-vehicle time of fixed-route transit arises because, for some trips, transit is not even an option due to limited service coverage. In such cases, travelers are assumed to walk to their destinations, leading to long access times.

advantage over TNCs, largely due to reduced VMT resulting from more common shared rides. In some areas, the use of buses instead of minivans for TIMOD service further contributes to lower external costs.

**Table 3-7 Estimated cost components by mode and area**

Service provider		King County Metro			Link Transit			Community Transit	Kitsap Transit			
Area		Sammamish <sup>22</sup>	Rainier Beach	Total for the areas	Leavenworth	Chelan	Total for the areas	Lynnwood	Bainbridge Island	Kingston	Total for the areas	
Number of trips		67	301	368	38	38	76	195	61	13	74	
Number of riders		89	336	425	38	41	79	208	91	13	104	
Estimated parking spaces for serving mobility demand per day		34	151	184	19	19	38	98	31	7	37	
Modes	Cost estimates											
TIMOD	Travelers' generalized costs	Sum	\$884.70	\$3,085.75	\$3,970.45	\$154.79	\$123.00	\$277.79	\$1,710.46	\$768.28	\$76.14	\$844.41
		<i>Per rider</i>	\$9.94	\$9.18	\$9.34	\$4.07	\$3.00	\$3.52	\$8.30	\$8.44	\$5.86	\$8.12
	Daily operating costs	Sum	\$2,000.88	\$4,390.82	\$6,391.70	\$2,326.56	\$1,499.24	\$3,825.80	\$6,187.64	\$5,094.00	\$237.72	\$5,331.72
		<i>Per rider</i>	\$22.48	\$13.07	\$15.04	\$61.23	\$36.57	\$48.43	\$30.04	\$55.98	\$18.29	\$51.27
	External costs	Sum	\$135.73	\$505.10	\$640.84	\$43.91	\$29.72	\$73.64	\$195.47	\$114.83	\$41.29	\$156.13
		<i>Per rider</i>	\$1.53	\$1.50	\$1.51	\$1.16	\$0.72	\$0.93	\$0.95	\$1.26	\$3.18	\$1.50
Total social costs <sup>23</sup>	Sum	\$2,776.56	\$7,057.68	\$9,834.24	\$2,525.26	\$1,651.96	\$4,177.22	\$7,578.57	\$5,821.11	\$331.15	\$6,152.26	

<sup>22</sup> The results of Sammamish and Rainier Beach are obtained from the study published in Transportation Research Part D (Cai et al., 2025).

<sup>23</sup> For Metro Flex and fixed-route transit, the ride fares paid by passengers but collected by transit agencies were excluded from the total cost. The total ride fares by fixed-route transit are lower than those by Metro Flex because transit is not available for some trips in the study areas. When simulating the cost of traveling by transit, it is assumed that those trips for which transit is not available

		<i>Per rider</i>	\$31.20	\$21.00	\$23.14	\$66.45	\$40.29	\$52.88	\$36.79	\$63.97	\$25.47	\$59.16	
Driving	Travelers' generalized costs		Sum	\$541.72	\$2,019.35	\$2,561.06	\$162.38	\$142.04	\$304.42	\$996.58	\$604.94	\$116.39	\$721.33
			<i>Per rider</i>	\$6.09	\$6.01	\$6.03	\$4.27	\$3.46	\$3.85	\$4.84	\$6.65	\$8.95	\$6.94
	Parking cost	On-Street parking	Sum	\$61.87	\$274.77	\$334.82	\$35.58	\$35.58	\$71.16	\$181.65	\$58.05	\$13.11	\$69.29
			<i>Per rider</i>	\$0.70	\$0.82	\$0.79	\$0.94	\$0.87	\$0.90	\$0.88	\$0.64	\$1.01	\$0.67
		Surface parking with free land	Sum	\$81.71	\$362.90	\$442.21	\$46.99	\$46.99	\$93.99	\$239.91	\$76.67	\$17.31	\$91.51
			<i>Per rider</i>	\$0.92	\$1.08	\$1.04	\$1.24	\$1.15	\$1.19	\$1.16	\$0.84	\$1.33	\$0.88
		Surface parking	Sum	\$96.89	\$430.30	\$524.34	\$55.72	\$55.72	\$111.44	\$284.47	\$90.91	\$20.53	\$108.51
			<i>Per rider</i>	\$1.09	\$1.28	\$1.23	\$1.47	\$1.36	\$1.41	\$1.38	\$1.00	\$1.58	\$1.04
		Structured parking	Sum	\$193.78	\$860.60	\$1,048.68	\$111.44	\$111.44	\$222.88	\$568.94	\$181.83	\$41.06	\$217.02
			<i>Per rider</i>	\$2.18	\$2.56	\$2.47	\$2.93	\$2.72	\$2.82	\$2.76	\$2.00	\$3.16	\$2.09

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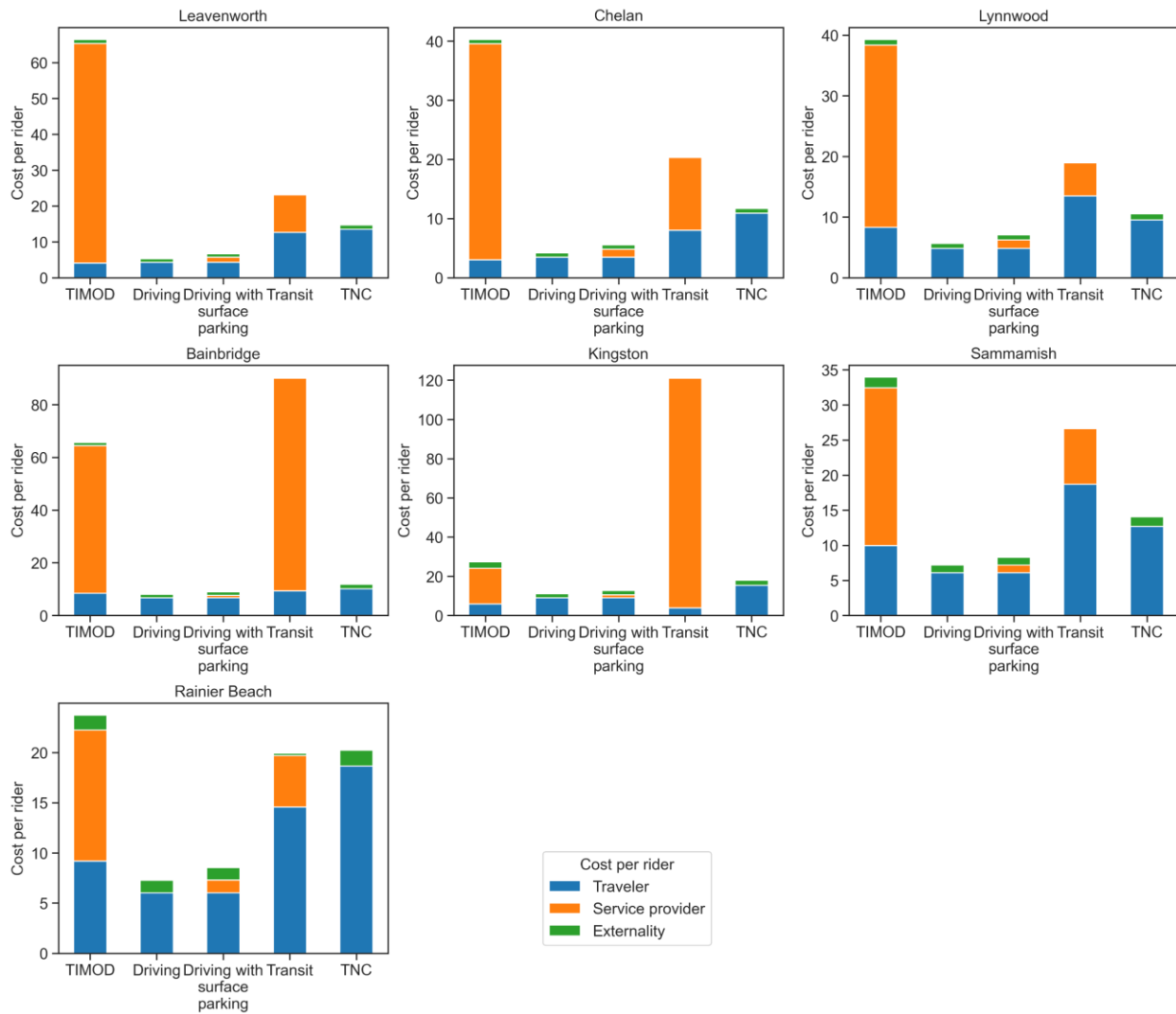
would choose to walk.

	External costs		Sum	\$97.01	\$97.04	\$418.72	\$515.75	\$36.53	\$29.20	\$52.74	\$172.77	\$120.38	\$27.57	
			<i>Per rider</i>	\$1.09	\$1.09	\$1.25	\$1.21	\$0.96	\$0.71	\$0.67	\$0.84	\$1.32	\$2.12	
	Total social costs without parking space		Sum	\$639.02	\$638.75	\$2,438.07	\$3,076.82	\$198.91	\$171.24	\$354.15	\$1,169.35	\$725.32	\$143.97	
			<i>Per rider</i>	\$7.18	\$7.18	\$7.26	\$7.24	\$5.23	\$4.18	\$4.48	\$5.68	\$7.97	\$11.07	
	Total social costs with parking space	On-Street parking	Sum	\$700.62	\$2,712.84	\$3,411.64	\$234.49	\$206.82	\$425.31	\$1,351.00	\$783.37	\$157.08	\$938.58	
			<i>Per rider</i>	\$7.87	\$8.07	\$8.03	\$6.17	\$5.04	\$5.38	\$6.56	\$8.61	\$12.08	\$9.02	
		Surface parking with free land	Sum	\$720.47	\$2,800.97	\$3,519.03	\$245.90	\$218.23	\$448.13	\$1,409.26	\$801.99	\$161.28	\$960.80	
			<i>Per rider</i>	\$8.10	\$8.34	\$8.28	\$6.47	\$5.32	\$5.67	\$6.84	\$8.81	\$12.41	\$9.24	
		Surface parking	Sum	\$735.64	\$2,868.37	\$3,601.16	\$254.63	\$226.96	\$465.59	\$1,453.82	\$816.23	\$164.50	\$977.80	
			<i>Per rider</i>	\$8.27	\$8.54	\$8.47	\$6.70	\$5.54	\$5.89	\$7.06	\$8.97	\$12.65	\$9.40	
		Structured parking	Sum	\$832.53	\$3,298.67	\$4,125.50	\$310.35	\$282.68	\$577.03	\$1,738.29	\$907.14	\$185.03	\$1,086.30	
			<i>Per rider</i>	\$9.35	\$9.82	\$9.71	\$8.17	\$6.89	\$7.30	\$8.44	\$9.97	\$14.23	\$10.45	
	Transit	Travelers' generalized costs		Sum	\$1,663.23	\$4,898.46	\$6,561.68	\$480.19	\$329.03	\$809.22	\$2,774.90	\$848.80	\$50.23	\$899.02
				<i>Per rider</i>	\$18.69	\$14.58	\$15.44	\$12.64	\$8.03	\$10.24	\$13.47	\$9.33	\$3.86	\$8.64
Daily operating		Sum	\$706.29	\$1,725.00	\$2,431.29	\$397.15	\$503.10	\$900.25	\$1,126.73	\$7,348.29	\$1,522.35	\$8,870.64		

	costs	<i>Per rider</i>	\$7.94	\$5.13	\$5.72	\$10.45	\$12.27	\$11.40	\$5.47	\$80.75	\$117.10	\$85.29
	External costs	Sum	\$10.17	\$75.11	\$85.28	\$3.49	\$1.67	\$5.15	\$33.02	\$31.50	\$7.50	\$39.00
		<i>Per rider</i>	\$0.11	\$0.22	\$0.20	\$0.09	\$0.04	\$0.07	\$0.16	\$0.35	\$0.58	\$0.38
	Health savings	Sum	\$62.50	\$145.51	\$208.01	\$42.63	\$26.90	\$69.53	\$111.62	\$13.53	\$0.00	\$13.53
		<i>Per rider</i>	\$0.70	\$0.43	\$0.49	\$1.12	\$0.66	\$0.88	\$0.54	\$0.15	\$0.00	\$0.13
	Total social costs <sup>24</sup>	Sum	\$2,182.44	\$5,816.05	\$7,998.49	\$838.19	\$806.90	\$1,645.09	\$3,495.53	\$8,065.05	\$1,556.08	\$9,795.13
		<i>Per rider</i>	\$24.52	\$17.31	\$18.82	\$22.06	\$19.68	\$20.82	\$16.97	\$88.63	\$119.70	\$94.18
TNC	Travelers' generalized costs	Sum	\$1,128.39	\$6,271.51	\$7,399.90	\$512.31	\$446.49	\$958.80	\$1,958.92	\$922.95	\$199.53	\$1,122.48
		<i>Per rider</i>	\$12.68	\$18.67	\$17.41	\$13.48	\$10.89	\$12.14	\$9.51	\$10.14	\$15.35	\$10.79
	External costs	Sum	\$122.63	\$529.16	\$651.79	\$46.77	\$33.34	\$80.11	\$216.23	\$152.11	\$34.84	\$186.96
		<i>Per rider</i>	\$1.38	\$1.57	\$1.53	\$1.23	\$0.81	\$1.01	\$1.05	\$1.67	\$2.68	\$1.80
	Total social costs	Sum	\$1,251.02	\$6,800.67	\$8,051.69	\$559.08	\$479.83	\$1,038.91	\$2,175.15	\$1,075.06	\$234.38	\$1,309.44
		<i>Per rider</i>	\$14.06	\$20.24	\$18.95	\$14.71	\$11.70	\$13.15	\$10.56	\$11.81	\$18.03	\$12.59

<sup>24</sup> For Metro Flex and fixed-route transit, the ride fares paid by passengers but collected by transit agencies were excluded from the total cost. The total ride fares by fixed-route transit are lower than those by Metro Flex because transit is not available for some trips in the study areas. When simulating the cost of traveling by transit, it is assumed that those trips for which transit is not available would choose to walk.

Figure 3-5 visualizes the stacked costs per rider of traveler, service provider, and externalities by mode across different areas. For TIMOD, the service provider’s cost contributes the most to its total social cost for all the areas. Rainier Beach have lower proportions of service providers’ costs than other areas. Leavenworth and Bainbridge Island incur higher TIMOD operating costs per rider, due to higher hourly operating expenses and longer service hours deployed to serve a small group of riders. For the operating cost per rider by fixed-route transit, Bainbridge Island and Kingston have significantly higher costs due to the substantially longer total service hours allocated.



### **Figure 3-5 Traveler, service provider, and external costs per rider by mode and area**

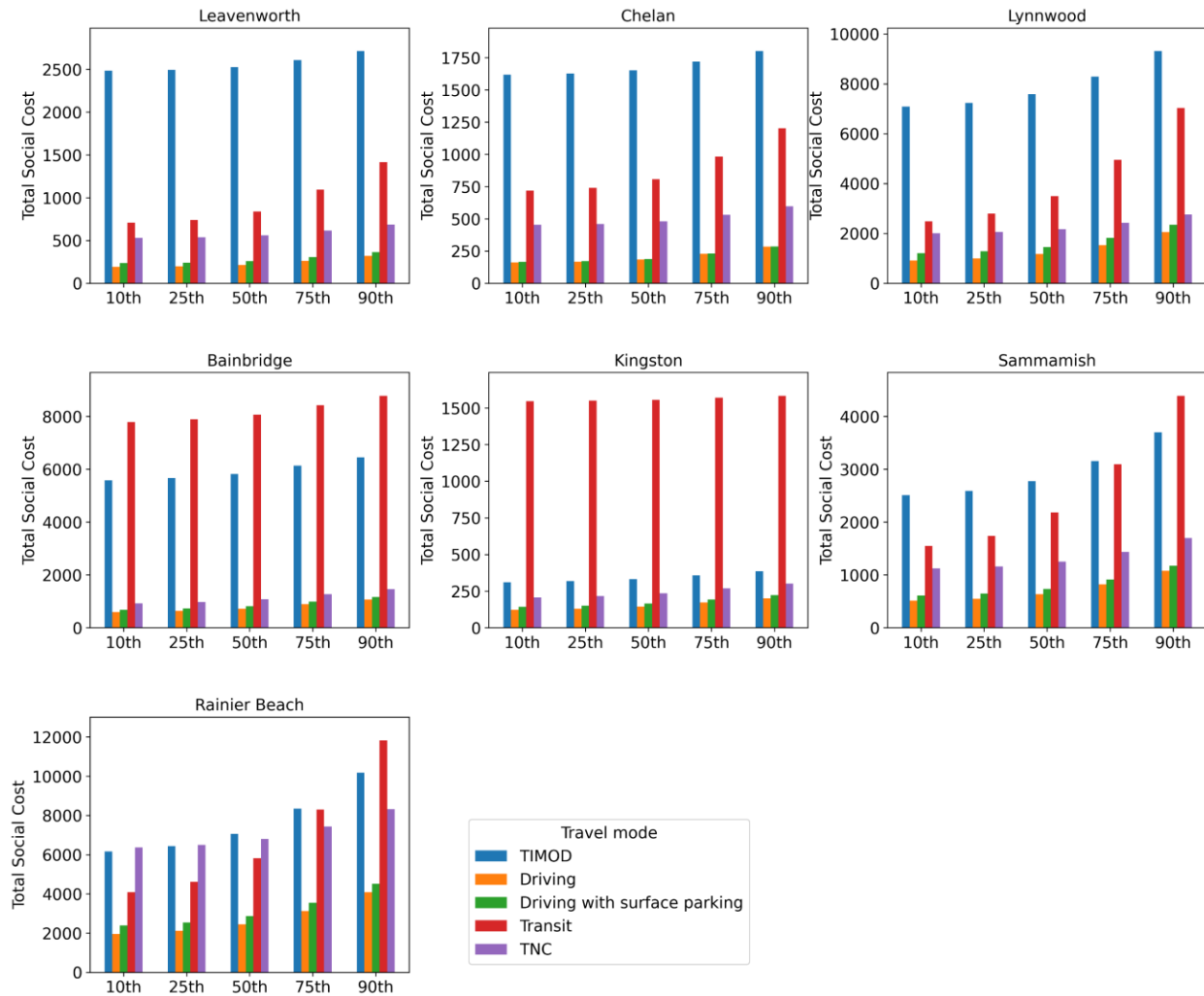
For the traveler's generalized cost per rider by TIMOD and driving, Leavenworth and Chelan have lower costs than other areas because of the lower hourly wage rate. Sammamish has the highest generalized cost for TIMOD riders due to the higher hourly wage rate and the longer waiting time on average. Moreover, in terms of the traveler's generalized cost per rider by fixed-route transit, Sammamish and Rainier Beach present higher costs induced by the longer waiting time. Additionally, Rainier Beach has the highest generalized cost for a TNC rider, which is caused by higher pricing in the area. Kingston also has a relatively high generalized cost for TNC riders, due to the longer wait times associated with TNC services in this area.

With regard to the external cost per rider, Chelan has the lowest cost for TIMOD due to the more common shared rides. Lynnwood also has a relatively low external cost per rider for TIMOD because of the shorter trips. For the external cost per rider by fixed-route transit and TNC, Bainbridge Island and Kingston have relatively higher costs than others due to the longer trips. Due to the shared rides, TIMOD induces smaller external costs than TNCs in most cases except for Sammamish and Kingston.

#### **3.4.3 Sensitivity analysis**

Figure 3-6 presents the total social cost by mode and area as changes in hourly wage. Driving, even considering the cost of constructing and maintaining parking spaces, remains the most cost-effective option across all hourly wage levels in each area. When serving higher-income groups, the comparative cost disadvantage of TIMOD becomes smaller compared with fixed-route transit. This is due to the demand-responsive nature of TIMOD service, which results in time savings. The effect would be opposite in comparison to driving and TNCs. In Sammamish and Rainier Beach, the total social cost of using TIMOD becomes lower than that of fixed-route transit for individuals

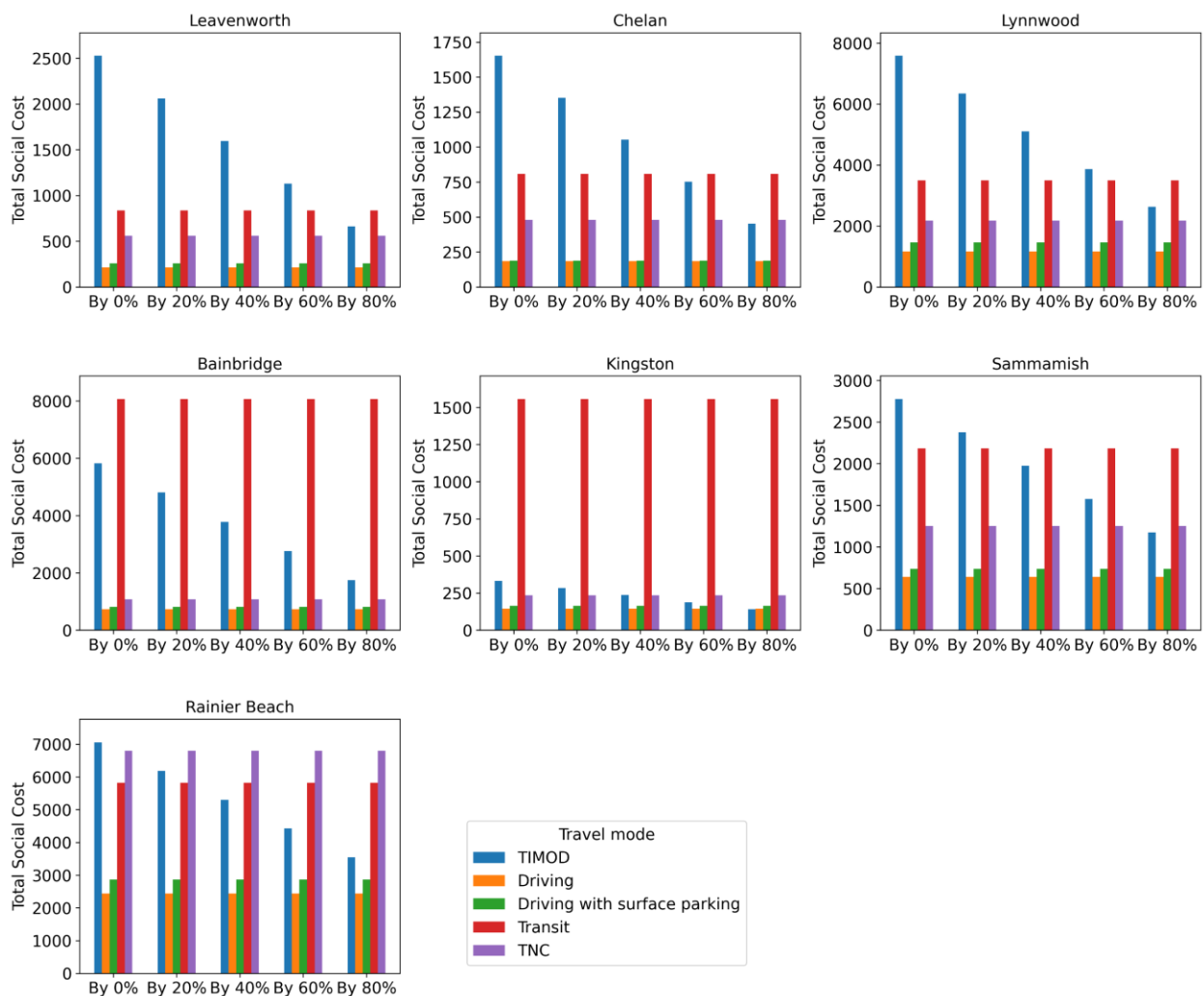
earning wages at the 90th percentile. In contrast, TIMOD remains the most expensive option across all wage percentiles in Leavenworth, Chelan, and Lynnwood. Moreover, the results suggest that both TIMOD and fixed-route transit are more sensitive to changes in the traveler's value of time, largely due to longer waiting times.



**Figure 3-6 Total social cost on a typical weekday as changes in hourly wage**

Figure 3-7 illustrates how the comparative cost-effectiveness of TIMOD changes with reductions in its hourly operating costs. Among the study areas, Leavenworth and Lynnwood require at least an 80% reduction in TIMOD’s hourly operating cost for its total social cost to fall below that of fixed-route transit. However, even with an 80% reduction, TIMOD's total social cost in these two areas remains higher than

that of TNCs. In Chelan, TIMOD's hourly operating cost must be reduced by at least 60% to be more cost-effective than fixed-route transit, and by 80% to be lower than TNCs. In Sammamish, reductions of at least 40% and 80% are needed for TIMOD to have a lower total social cost than fixed-route transit and TNCs, respectively. In contrast, Rainier Beach, which has high densities of population and transit services, only requires a 20% reduction for TIMOD to outperform TNCs and a 40% reduction to outperform transit. Additionally, TIMOD's total social cost in Bainbridge is higher than that of TNCs even with an 80% reduction. In Kingston, TIMOD can be more cost-effective than TNCs with at least a 60% reduction.



**Figure 3-7 Total social cost on a typical weekday as changes in TIMOD hourly operating cost**

### 3.5 Discussion

In most of the study cases, TIMOD is the least cost-effective option. The service provider's cost contributes the most to its total social cost for all the areas. The higher cost of TIMOD stems from the extended daily vehicle hours deployed to sustain personalized point-to-point service. This contrasts with the findings of Wang and Shen (2023), where the service was structured as point-to-station with a comparable number of daily trips. From the traveler's perspective, TIMOD has a cost advantage over fixed-route transit and TNCs due to its demand-responsive nature and subsidized fares. From a societal perspective, the comparative cost-effectiveness of TIMOD and fixed-route transit can be significantly affected by how transit agencies plan and deploy the services. The results do not show an obvious association between population density and the comparative cost-effectiveness of these two travel modes.

Compared with TNCs, TIMOD offers subsidized fares to riders, benefiting them through trip fare savings. Meanwhile, TIMOD has slightly lower external costs than TNCs due to the higher proportion of shared rides and the resulting reduction in vehicle miles traveled. The external costs of TIMOD, particularly the costs of crashes and congestion, could be further reduced if it can use existing bus lanes. Nevertheless, TIMOD is more sensitive to changes in travelers' value of time than TNCs, owing to its longer travel time resulting from detours for shared rides and longer waiting time.

Driving is shown to be the most cost-effective mode in the study areas, even considering the costs of additional parking spaces. This finding is consistent with Blumenberg et al. (2024)'s argument that policymakers should consider offsetting the costs of car ownership and access for disadvantaged groups. The comparative cost advantage of driving may be less pronounced in densely populated areas, where heavy traffic and induced congestion increase time costs and

transportation externalities. Additionally, providing parking spaces is more costly in the dense areas with high land values.

The findings of this study indicate that in low-density areas, TNCs are more cost-effective than TIMOD from a societal perspective. However, prior research has shown that TNCs' profit-driven model restricts service coverage in some suburban areas with low demand (Barajas & Brown, 2021). Additionally, its high fares and surge prices further limit service accessibility for disadvantaged groups (Bardaka et al., 2020). Given the comparative advantages and limitations of TIMOD and TNCs, transit agencies should explore subsidized TNCs as a mobility alternative to satisfy the travel demand of disadvantaged populations in low-density areas.

In Leavenworth and Chelan, where the density of transit service is relatively low, TIMOD shows a more significant advantage over fixed-route transit in terms of traveler's generalized cost. The generalized cost per rider of TIMOD is 32% and 37% of that of fixed-route transit in these two areas, respectively. However, the operating cost per rider for TIMOD is nearly 600% and 300% of that of fixed-route transit in these two areas, respectively. In Rainier Beach and Lynnwood, where the density of transit service is relatively high, the generalized cost per rider of TIMOD is 63% and 62% of that of fixed-route transit in these two areas, respectively. The operating cost per rider for TIMOD is nearly 550% and 250% of that of fixed-route transit in these two areas, respectively. This suggests that whether TIMOD can be a more cost-effective alternative for travelers than fixed-route transit depends on the context and the trade-offs between traveler benefits and service provider costs.

The cost-effectiveness of a transportation mode is sensitive to the assumptions made in this study. For instance, the operating costs of service providers could be lower if autonomous electric vehicles were widely adopted. The costs of service operation and the environmental externalities

could be affected by savings from drivers' wages and cleaner technologies, which may lead to different findings (Bösch, et al., 2018). However, adopting AEVs requires additional investment in charging infrastructure. Their efficiency depends on the placement and types of charging stations, as well as vehicle battery capacity (Vosooghi, et al., 2020). Determining whether this option is more cost-effective than other alternatives for meeting sparse mobility demand in low-density areas calls for more rigorous evaluation. Additionally, future evaluations of TIMOD operating costs should account for the potential increase in demand driven by greater market penetration. This heightened demand could enhance the economies of scale for TIMOD services.

This research has limitations. First, the transit waiting time may be overestimated, as departure times were based on the request time of TIMOD trips rather than actual transit schedules. Presumably, a transit rider would reduce waiting time by aligning their departure with expected bus schedules. Second, without access to detailed local traffic data, this study assumed average road capacity and standard congestion conditions for estimating congestion costs. A more precise estimation would require accounting for variations in road capacity and congestion levels in future studies. Additionally, future research could incorporate measurements of the impacts of increasingly frequent and intense heat waves and extreme heat events on travelers (Fraser & Chester, 2017; Klein & Anderegg, 2021). These conditions disproportionately impact travelers without private vehicles, who may face prolonged sun exposure while accessing transit stops or waiting for fleets, resulting in thermal discomfort and heightened heat-related health risks (Hsu, et al., 2021; Liu, et al., 2025).

### **3.6 Conclusions and Policy Implications**

This study further developed a framework to compare the cost-effectiveness of TIMOD to three

alternative modes – fixed-route public transit services, driving, and TNCs – using real-world TIMOD trip data. The study addressed questions related to the factors determining the comparative cost-effectiveness of TIMOD and alternative mobility options, measured and compared the social costs across different mobility services, and explored the conditions and arrangements under which TIMOD services are more cost-effective in low-density areas. While the selected case areas are considered as low-density suburban areas, they have distinct transit service provisions, built environments, and sociodemographic characteristics. The findings of this study provide an empirical basis for evaluating the economic costs of TIMOD in addressing the mobility needs of a segment of disadvantaged population in low-density areas currently relying on this service.

The study extended a conceptual framework for measuring the economic cost of a mobility option, taking into account service provider costs, user monetary and time costs, and transportation externalities. The results revealed various insights into the cost-effectiveness of different modes of transportation. Driving emerged as the least costly option for society, while TIMOD, as a demand-responsive mobility service with subsidized fares, demonstrated a competitive cost advantage over fixed-route transit and TNCs from a traveler's perspective. While driving may have the lowest social cost in the suburban areas, this mobility option may not be available to those who are financially or health disadvantaged. Given that the marginal costs to society are shown to be lower for driving and riding TNC in the study cases, transit agencies should explore alternative ways to improve mobility for disadvantaged suburban residents by offsetting costs for driving and subsidizing fares for riding TNCs. On the other hand, we are aware of the concerns about service availability and the varying waiting time of TNCs in suburban areas as discussed above, which may raise the question about whether TNCs are more cost-effective than TIMOD across all suburban areas. Another consideration is that the operating cost of TIMOD is sensitive to the level

of demand, which can be substantially higher in certain denser suburban locations. This potential economy of scale may also affect the comparative cost-effectiveness of TIMOD in comparison to TNCs.

The study also highlighted that the operating cost of TIMOD can be higher than that of fixed-route transit in some cases, indicating that TIMOD's service deployment and operating model need improvements to be more financially feasible. Additionally, the study shed light on the importance of accounting for externalities, including air pollution, greenhouse gas emissions, crashes, congestion, and noise. Although the current external costs are relatively minor compared with other cost components, they are not negligible and could become more prominent in the future given the growing climate change trends. TIMOD has demonstrated a slight reduction in external costs compared with TNCs, attributable to more common pooling of multiple rides in such services. These cost factors should be included in the framework of cost-effectiveness analysis.

The selected case areas have different built environments and sociodemographic characteristics, resulting in different estimated costs. Compared with transit riders, travelers in areas with lower transit service density experience greater cost benefits from using TIMOD due to a more substantial reduction in time costs. Such differences should be informative for transit agencies seeking to improve their TIMOD programs by considering the tradeoffs between travelers' benefits and service provider's costs.

# Chapter 4 Predicting Mobility-On-Demand Transit in Low-Density Areas Using Context-Aware Graph Neural Networks

## 4.1 Introduction

In a previously published paper, the term Transit Incorporating Mobility-on-Demand (TIMOD) was introduced to describe a flexible alternative to traditional fixed-route, fixed-schedule transit. It includes mobility services provided by public transit agencies that can dynamically adapt to user demand, such as on-demand and dial-a-ride services (Wang & Shen, 2023). It is a sub-category of Mobility-on-Demand (MOD) services differentiated by transit agencies playing the leading role in planning and financing demand-responsive mobility services (Pak, et al., 2023; Cai, et al., 2025). Unlike fixed-route and fixed-schedule systems, TIMOD provides both on-demand and pre-scheduled shared rides, with vehicles dispatched in response to individual ride requests. This flexibility makes TIMOD particularly well-suited for areas with dispersed populations, limited transit coverage, and varying travel needs across time and space.

However, the economic sustainability of TIMOD services hinge on achieving a balance between service supply and travel demand in low-density areas. To deliver cost-effective and equitable mobility, it is critical to estimate the potential demand for TIMOD based on the specific characteristics of service areas. This helps guide policymakers in selecting service models that align with local mobility patterns and resource constraints. While extensive research has focused on demand prediction for MOD services, many studies examine dense urban areas with high population density and developed fixed-route transit networks (Ke, et al., 2021a; Liang et al., 2022). In contrast, demand prediction in low-density suburban areas—where demand is inherently sparse—remains underexplored. Additionally, on-demand mobility in urban areas is

dominated by profit-driven TNCs, whereas transit agency-led demand-responsive services in low-density areas are designed to enhance mobility for residents rather than maximize revenue. This difference in service goals further underscores the need for exploration of TIMOD in low-density areas.

Traditional demand prediction methods, such as classical regression models and Euclidean space-based predictive models, often struggle to capture the irregular, sparse, and context-dependent patterns of demand observed in low-density settings (Wu, et al., 2019; Jin, et al., 2020; Ke, et al., 2021b). These approaches typically rely on fixed spatial units or assume homogeneous underlying travel patterns between neighbors, ignoring non-Euclidean structural features in mobility landscapes and limiting the generalizability across areas. Mobility networks are inherently complex and irregular, with spatial and temporal patterns that vary widely across different contexts. Traditional methods fail to adapt to these dynamics, limiting their effectiveness in capturing real-world mobility behaviors. In comparison, graph-based modeling offers a more flexible framework to learn non-Euclidean dependencies across connected locations and handle irregular mobility structures. Recent advances in graph-based deep learning models, particularly probabilistic spatiotemporal graph neural networks (Wang et al., 2024a; Zhuang et al., 2024), provide promising tools for modeling complex spatial and temporal dependencies and incorporating uncertainty in demand estimation.

There are several challenges that motivate the exploration of graph-based approaches. First, the structure of mobility networks varies across transportation modes, even within the same region. Fixed-route transit is typically stop- or station-based, while TIMOD is often operated as point-to-point service. This heterogeneity calls for a modeling approach that can learn the interactions within multimodal networks. Second, TIMOD demand is influenced by both

transportation networks and land use coverage of semantic neighbors. An effective predictive framework must incorporate these contextual features to enhance both accuracy and uncertainty of demand prediction. Third, TIMOD programs can be deployed in diverse geographic regions with different network sizes and topologies. The spatial heterogeneity in mobility networks requires predictive models that can generalize across varying graph structures and scales and learn invariant mobility patterns that transfer between regions. Graph neural networks (GNNs), particularly those incorporating spatiotemporal and contextual learning layers, can provide a promising path towards robust and scalable TIMOD demand prediction.

To address these challenges, this study develops a context-aware probabilistic spatiotemporal graph neural network (CA-STPGNN) model to predict the demand for TIMOD services in low-density areas based on local built environment factors and regional sociodemographic characteristics. It is used to predict TIMOD service demand between geographic units in regions where observed trip data is unavailable. The study aims to develop a predictive model that is generalizable to other low-density areas beyond the study cases. The predictions can help transit agencies assess the cost-effectiveness of TIMOD relative to other alternatives, design TIMOD services, and allocate resources for cost-effective implementation. They can also provide support for securing TIMOD program funding. The study intends to address the following three questions: 1) What model components are essential to ensure generalizability to areas lacking observed TIMOD trip data? 2) Which sociodemographic and built environment factors are relevant for predicting TIMOD demand? 3) How do these factors affect model prediction accuracy and uncertainty? The expected outcomes of this research will support planners and policymakers to estimate the mobility needs of local communities and make decisions on a TIMOD service delivery model that matches the needs.

## 4.2 Literature Review

### 4.2.1 Multi-scale Travel Demand Forecasting

Classical travel demand modeling techniques, such as gravity-based and utility-based models, have been extensively applied for travel demand prediction (Chen P., et al., 2023; Martín-Baos et al., 2023). However, these models often fall short in capturing the nonlinear relationships and complex interdependencies inherent in regional mobility patterns. The advent of machine learning techniques, including random forest and gradient boosting decision trees (GBDT), has significantly enhanced the accuracy of travel demand predictions by accounting for spatial nonlinearity (Witayangkurn et al., 2013; Rasouli and Timmermans, 2014; Ding et al., 2018; Xiao et al., 2021). Recently, deep learning models have gained increasing attention for predicting travel demand due to their ability to capture complex spatiotemporal relationships. Researchers have utilized convolutional neural networks (CNNs) to extract spatial correlations and recurrent neural networks (RNNs) to model the temporal dependencies of mobility patterns across areas (Zhang, et al., 2017; Li et al., 2021; Chen W., et al., 2023). Further studies have combined CNNs and RNNs to effectively capture the intricate spatiotemporal interdependencies in travel behavior across both neighboring and distant regions (Ai et al., 2019; Ren et al., 2020; Li et al., 2023). Given the inherent graph structure of transportation networks, graph neural networks (GNNs) have been employed to capture mobility similarities in non-Euclidean spaces. GNNs can be adapted to identify semantic neighbors of mobility flows while accounting for multiple graph structures and irregular spatial units of alternative travel modes (Geng et al., 2019; Li et al., 2020; Ke et al., 2021; Liang et al., 2022). The variants of GNNs, including graph convolutional networks (GCNs), graph attention networks (GATs), graph isomorphism network (GINs), and

graph sample and aggregation (GraphSAGE), can be employed for graph representation learning.

To capture mobility patterns at varying spatial scales and different levels of characteristics, various techniques have been used to integrate embeddings. At the disaggregated level, numerous studies have incorporated multiple node features, such as sociodemographic and built environment characteristics associated with the nodes, to predict demand for a travel mode across area (Rong et al., 2024). Recent research has also employed multi-task learning techniques to incorporate sociodemographic data as a regularization into learning latent features by deep learning models (Huang et al., 2019; Wang et al., 2024). This hybrid modeling approach has demonstrated superior training stability and predictive accuracy compared with traditional travel demand models and standalone deep learning methods. To learn aggregated-level features, the techniques that can be used to integrate embeddings include pooling methods that perform linear aggregation (mean, max, or sum), multi-layer perceptron (MLPs) acting as a non-linear aggregation (Guo et al., 2024), and spectral-based encoder capturing both local (high-frequency) and global (low-frequency) features in the spectral domain (Zhao, et al, 2023).

#### **4.2.2 Generalizable Graph Representation Learning**

For effective generalization to unseen graphs, a graph representation learning method must efficiently accommodate structural variability and node features without necessitating extensive retraining. Among various approaches, the most generalizable methods are those that leverage structural patterns and robust feature extraction, enabling them to adapt even to previously unseen graph structures.

There are various models that can generalize well depending on the nature of data. First, GATs can generalize well, especially for heterogeneous graphs with different types of nodes or edges (Zhang, et al., 2023). They have the flexibility to weigh the importance of different

neighboring nodes differently, which helps in capturing critical relationships even in unseen graphs. The use of attention mechanisms allows the model to focus on the most relevant parts of the graph, which can aid in generalization. Second, GINs are known for their strong discriminative power in capturing fine-grained structural differences between graphs. This is achieved by applying MLP-based aggregation on neighbors' information to learn graph representations. However, GINs can face challenges on generalizing to unseen graph structures when applied to graphs with novel patterns that diverge significantly from the training set. Third, GraphSAGE has also been argued to have good performance on generalization (Nguyen, et al., 2024). This approach uses neighbor sampling and pooling-based aggregation, which enables it to learn node representations from local structural and feature information of scalable neighbors. It is not tied to specific graph topologies. The learned aggregators can be reused on unseen graphs with different sizes or structures, making it more flexible when applied to unseen graphs.

#### **4.2.3 Influencing Factors of Demand for On-demand Mobility Services**

Considerable prior research has explored the factors influencing the demand for on-demand mobility services. One key finding is that ridehailing, when used as a feeder mode for mass transit, is particularly favored by young commuters, who often perceive it as more reliable than traditional feeder buses (Zgheib, et al., 2020). The frequency of on-demand service usage by a rider has demonstrated associations with public transit impacts: negligible impact for occasional ridehailing use (one to eleven times per month), a complementary effect for regular ridehailing use (eleven to thirty-two times per month), and a substitution effect for active ridehailing use (more than thirty-two times per month) (Zhang, et al., 2022). The proximity to a shared vehicle significantly influences the probability of choosing this mode, with the impact of access distance outweighing that of egress distance in terms of utility (Jin et al., 2020). Compared with traditional taxi,

ridehailing services tend to have a higher market share in remote areas characterized by low population density, sparse transportation facilities, lower household income, and a higher proportion of young residents (Yang, et al., 2022). This suggests that ridehailing services could contribute to more equitable services by serving underserved areas, while traditional taxis cater more to high-demand areas. In addition, ridehailing demand is significantly influenced by built environment variables, including population density, street design factors such as road and sidewalk densities, land use mix, and transit accessibility (Sun & Ding, 2019). These effects exhibit variations across areas, showing geographic trends from urban to suburban neighborhoods (Yu & Peng, 2019).

## **4.3 Methodology**

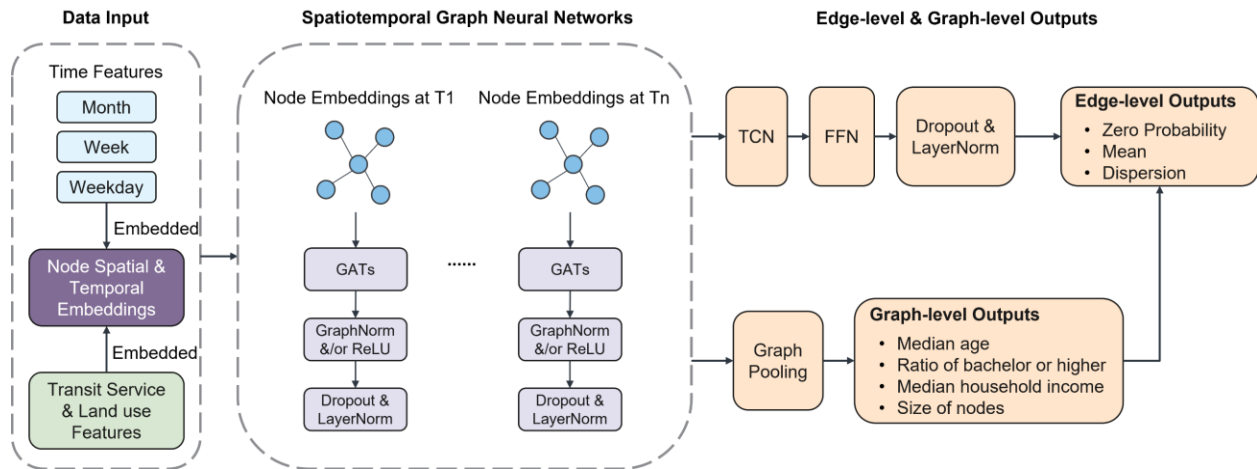
### **4.3.1 TIMOD Mobility Graph Representation Learning**

The architecture of the TIMOD mobility graph learning model is illustrated in Figure 4-1. Each node in the mobility graph represents a geographic unit of analysis, defined as a census block in this study. Edges denote origin-destination (OD) connections between pairs of geographic units via TIMOD trips, with daily trip volume and network distance taken as the edge attributes. Census blocks are defined by features like streets, roads, and other visible boundaries. Compared with the hexagonal grid units commonly used by TNCs for efficiently operating services in larger and denser areas, it is more beneficial for transit agencies to plan services in smaller and lower-density areas based on census blocks, as they are scalable to align with local contexts. The population data is also publicly available at the census block level.

The proposed model is a spatiotemporal graph neural network designed to predict edge-level parameters of probabilistic distributions of daily trip generation over time, along with graph-

level outputs for multi-task learning as supervision. Specifically, it incorporates both spatial and temporal features to learn node embeddings at different time steps. Temporal features, including month, weekday, and week indices, are first embedded and projected to a unified time embedding space. These embeddings are concatenated with embedded spatial attributes and used as inputs to a two-layer residual Graph Attention Network (GAT), applied sequentially across time steps. The second GAT layer can be skipped through a residual layer. The spatial attributes include population density, densities of transit stops/stations and daily trips, ratios of residential, manufacturing, transportation, retail, business services, cultural and recreational, and agriculture land coverages.

Each GAT layer is followed by GraphNorm (Chen, et al., 2018; Cai, et al., 2021), dropout, and LayerNorm to stabilize training and avoid overfitting. Only the first GAT layer applies ReLU activation after GraphNorm. The resulting node embeddings across time are then used to construct edge representations by concatenating the features of source and destination nodes. Temporal dependencies along edges over time are further modeled using a temporal graph convolutional network (TCN) and a feed-forward layer (FFN), followed by dropout and normalization. Simultaneously, node-level embeddings are aggregated using a graph pooling technique to generate graph-level representation for each time step, which is then passed through a separate head for graph-level prediction. Finally, edge-level outputs, representing the parameters of the probabilistic distribution (i.e., zero probability, mean, and dispersion), are produced by combining edge-specific outputs with graph-level temporal biases, ensuring coherent predictions across spatial and temporal dimensions.



**Figure 4-1 Architecture of TIMOD mobility graph learning model**

Given the nature of trip data, where some origin-destination pairs may have zero trips generated, probabilistic models can be employed to estimate the probability of trip occurrences and the expected non-zero trip counts. Specifically, zero-inflated models and hurdle models are widely used to address data with excessive zeros by distinguishing between two underlying processes: one generating structural zeros and another producing non-negative values. The former process estimates the likelihood of zero trips occurring due to contextual constraints, while the latter models the distribution of non-zero trips. Notably, zero-inflated and hurdle models operate under distinct assumptions. A zero-inflated model assumes that zeros in the data arise from two sources: (1) structural zeros, which result from underlying constraints preventing trip occurrences between certain areas, and (2) sampling zeros, which occur due to random fluctuations in the trip generation process. In comparison, a hurdle model separately models zero and non-zero values. While it similarly accounts for structural zeros, it truncates all zeros when modeling the generation of positive trip counts. Both models will be evaluated for their influence on model performance. Furthermore, due to the highly skewed nature of empirical trip data, this study employs negative binomial modeling to accommodate the overdispersion in trip counts.

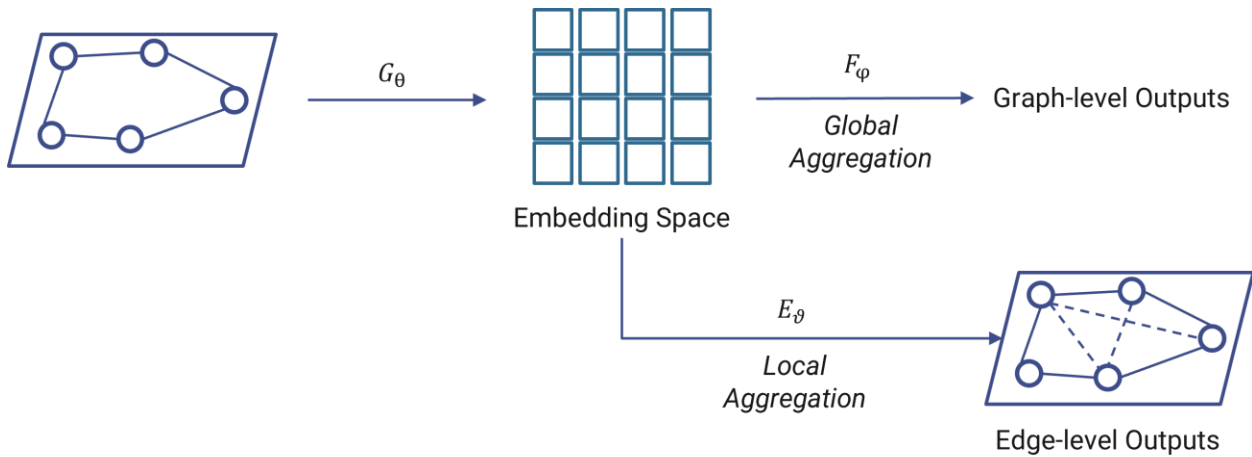
The baseline models used for prediction performance comparison include:

- 1) eXtreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016): a representative machine learning method based on gradient boosting decision trees.
- 2) Zero-inflated Negative Binomial Graph Neural Network (ZINB-GNN): A GNN-based model incorporating zero-inflated and negative binomial modeling. Below are the variants incorporated ZINB modeling.
  - a) Zero-inflated Negative Binomial Graph Attention Network (ZINB-GAT): A GAT-based method that models dependencies between travel flows. This model learns node embedding by aggregating neighboring node features based on a learnable weight matrix.
  - b) Zero-inflated Negative Binomial Graph Convolution Network (ZINB-GCN): A GCN-based method that models correlations across travel flows. This model learns node embeddings by a mean-based aggregation of neighboring node features.
- 3) Hurdle Negative Binomial Graph Neural Network (HNB-GNN): A GNN-based model incorporating hurdle and negative binomial modeling to predict the probabilistic distribution of TIMOD trip counts between areas.
  - a) Hurdle Negative Binomial Graph Attention Network (HNB-GAT): A GAT-based hurdle and negative binomial modeling.
  - b) Hurdle Negative Binomial Graph Convolution Network (HNB-GCN): A GCN-based hurdle and negative binomial modeling.

#### **4.3.2 Multi-task Learning by Incorporating Regional Sociodemographic Characteristics**

In Figure 4-2,  $G_\theta$  represents the GNN-based node embeddings learning function parameterized by  $\theta$ ,  $E_\vartheta$  represents the edge-level pooling function parameterized by  $\vartheta$ , and  $F_\phi$  represents the graph-

level supervision function parameterized by  $\varphi$ . By performing a multi-task learning framework, the supervised encoder of TIMOD mobility graph can predict flows between areas through a graph-based neural network and reconstruct sociodemographic information through an MLP-based aggregator (Le et al., 2018; Wang et al., 2024b). The supervision of regional sociodemographic statistics constrains the learning of graph latent space and enhances the stability of training by introducing sociodemographic supervision loss as regularization (Maurer et al., 2016; Huang et al., 2019). The global sociodemographic statistics are obtained from the 2019-2023 American Community Survey (ACS) 5-year estimates (U.S. Census Bureau, 2023), including median household income, median age, and the ratio of persons with bachelor's degree or higher. The size of graph nodes, namely the number of census blocks in the study area, is also taken into account as one of the graph-level features.



**Figure 4-2 Methodological framework of supervised learning for incorporating regional sociodemographic characteristics**

### 4.3.3 Probabilistic Modeling and Loss Function

#### 4.3.3.1 Zero-inflated Negative Binomial Loss Function

The ZINB model combines a Bernoulli component and a Negative Binomial component into the likelihood expression. This model assumes that zeros can arise from two separate processes: a

structural zero-generation process due to censoring or absence of demand and a sampling process from a Negative Binomial (NB) distribution.

The log likelihood of ZINB is computed as:

$$\log P(y|\pi, \mu, \theta) = \begin{cases} \log [\pi + (1 - \pi) \left(\frac{\theta}{\theta + \pi}\right)^\theta & \text{if } y = 0 \\ \log(1 - \pi) + \log NB(y|\mu, \theta) & \text{if } y > 0 \end{cases}$$

$$\log NB(y|\mu, \theta) = \log \Gamma(y + \theta) - \log \Gamma(y + 1) - \log \Gamma(\theta) + \theta \log \left(\frac{\theta}{\theta + \pi}\right) + y \log \left(\frac{\theta}{\theta + \pi}\right)$$

Where  $\pi \in (0,1)$  represents probability of excess zero (zero-inflation),  $\mu > 0$  represents mean of the Negative Binomial distribution,  $\theta > 0$  is dispersion parameter (shape), and  $y \in N$  refers to the observed trip count between census blocks.

The ZINB loss is defined as the negative average log-likelihood across all edges and forecast steps:

$$\mathcal{L}_{ZINB} = -\frac{1}{N} \sum_{i=1}^N \log P(Y = y_i | \pi_i, \mu_i, \theta_i)$$

Where  $y_i$  refers to the ground-truth value of the  $i$ th edge, and  $\pi_i, \mu_i$ , and  $\theta_i$  represents the predicted parameters of the ZINB distribution of the value of the  $i$ th edge.

#### 4.3.3.2 Hurdle Negative Binomial Loss Function

Hurdle Negative Binomial (HNB) model decomposes trip generation process into two stages: (1) a Bernoulli process modeling whether a count is zero or non-zero (the ‘‘hurdle’’), and (2) a truncated Negative Binomial distribution for the positive counts only (the NB is conditioned on  $y > 0$ ).

$$\log P(y|\pi, \mu, \theta) = \begin{cases} \log(\pi) & \text{if } y = 0 \\ \log(1 - \pi) + \log NB(y|\mu, \theta) - \log(1 - NB(0|\mu, \theta)) & \text{if } y > 0 \end{cases}$$

$$\log NB(y|\mu, \theta) = \log \left[ \frac{\Gamma(y + \theta)}{y! \Gamma(\theta)} \left( \frac{\mu}{\theta + \pi} \right)^y \left( \frac{\theta}{\theta + \pi} \right)^\theta \right]$$

$$NB(0|\mu, \theta) = \left( \frac{\theta}{\theta + \pi} \right)^\theta$$

Where  $\pi \in (0,1)$  represents probability of a zero outcome from Bernoulli process,  $\mu > 0$  represents mean of the NB component,  $\theta > 0$  is dispersion parameter (shape) of the NB component, and  $y \in N$  refers to the observed trip count between census blocks.

The HNB loss is defined as the negative average log-likelihood across all edges and forecast steps:

$$\mathcal{L}_{HNB} = -\frac{1}{N} \sum_{i=1}^N \log P(Y = y_i | \pi_i, \mu_i, \theta_i)$$

Where  $y_i$  refers to the ground-truth value of the  $i$ th edge, and  $\pi_i, \mu_i$ , and  $\theta_i$  represents the predicted parameters of the HNB distribution of the value of the  $i$ th edge.

#### 4.3.4 Model Evaluation Metrics

The edge-level prediction accuracy of the expected trip volumes between census blocks is evaluated using the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE).

$$MAE = \frac{1}{N} \sum_{n=1}^N |v_{ij} - \hat{v}_{ij}| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (v_{ij} - \hat{v}_{ij})^2} \quad (2)$$

$$\hat{v}_{ij} = (1 - \hat{p}_{ij}) \hat{\mu}_{ij} \quad (3)$$

Where  $v_i$  refers to the number of actual TIMOD trips occurred between census blocks  $i$  and  $j$ , and  $\hat{v}_{ij}$  is the predicted mean trip counts between census blocks  $i$  and  $j$ .  $N$  refers to the total number of predicted edge values across time.  $\hat{p}_{ij}$  and  $\hat{\mu}_{ij}$  represent the predicted zero probability and the

mean of the distribution, respectively.

The prediction uncertainty is evaluated by the Mean Prediction Interval Width (MPIW) and the Prediction Interval Coverage Probability (PICP) (Pearce, et al., 2018; Wang, et al., 2024). A model with a lower MPIW and a higher PICP demonstrates superior performance on prediction uncertainty compared with others.

MPIW measures the average width of prediction intervals, which is calculated as:

$$MPIW = \frac{1}{N} \sum_{i=1}^N (Q_{i_{1-\alpha/2}} - Q_{i_{\alpha/2}})$$

Where  $N$  is the number of edge values,  $\alpha$  is the significance level,  $Q_{i_{\alpha/2}}$  and  $Q_{i_{1-\alpha/2}}$  refer to the quantiles at  $\alpha/2$  and  $1 - \alpha/2$  respectively. In this study, a 0.001 significance level is used to compute MPIW, and thus  $Q_{i_{1-\alpha/2}} - Q_{i_{\alpha/2}}$  covers 99.9% confidence interval considering the high sparsity of demand and thus the high probability of zero trip occurrence in low-density areas. A higher MPIW indicates that the model is less confident in its predictions, leading to greater estimated uncertainty.

PICP measures the probability of ground-truth values that fall within the prediction interval bounded by  $Q_{\alpha/2}$  and  $Q_{1-\alpha/2}$ . It is computed as:

$$PICP = \frac{1}{N} \sum_{i=1}^N I_i$$

Where  $N$  is the number of edge values,  $\alpha$  is the significance level,  $I_i \in [0, 1]$  is an indicator variable of whether the ground truth value of the observation falls within the range bounded by  $Q_{i_{\alpha/2}}$  and  $Q_{i_{1-\alpha/2}}$ . In this study, a 0.01 significance level is used to compute PICP. A higher PICP suggests that the model predictions are more accurate and can be covered by the prediction intervals.

### 4.3.5 Data Description

#### *4.3.5.1 TIMOD Trip Data and Sociodemographic Characteristics of the Study Areas*

Real-world trip-level data of TIMOD programs in 11 low-density areas<sup>25</sup> across Washington State, U.S., are utilized to train the predictive demand model. These areas include Leavenworth, Chelan, Bainbridge Island, Kingston, Lynnwood, Sammamish, Rainier Beach, Juanita, Kent, Othello, and Tukwila. The data was obtained from the local transit agencies responsible for operating TIMOD services in these areas. Each trip record contains the trip date along with the geographic coordinates of the origin and destination. To quantify travel demand, daily trips are aggregated at the census block level to compute inter-block trip volumes. Given the variation in data availability periods across cases, a unified time window within the year for which data is available, from March 6 to May 30, is applied to ensure consistency in model training and testing. The sociodemographic characteristics of the study areas, derived from the American Community Survey (ACS) estimates, along with the periods of the TIMOD trip data, are summarized in Table 4-1. The areas of study are shown in Figure 4-3.

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<sup>25</sup> This chapter includes more study areas than Chapter 3. For the TIMOD service areas operated by King County Metro, all the 6 are selected.

**Table 4-1 The characteristics of the study areas**

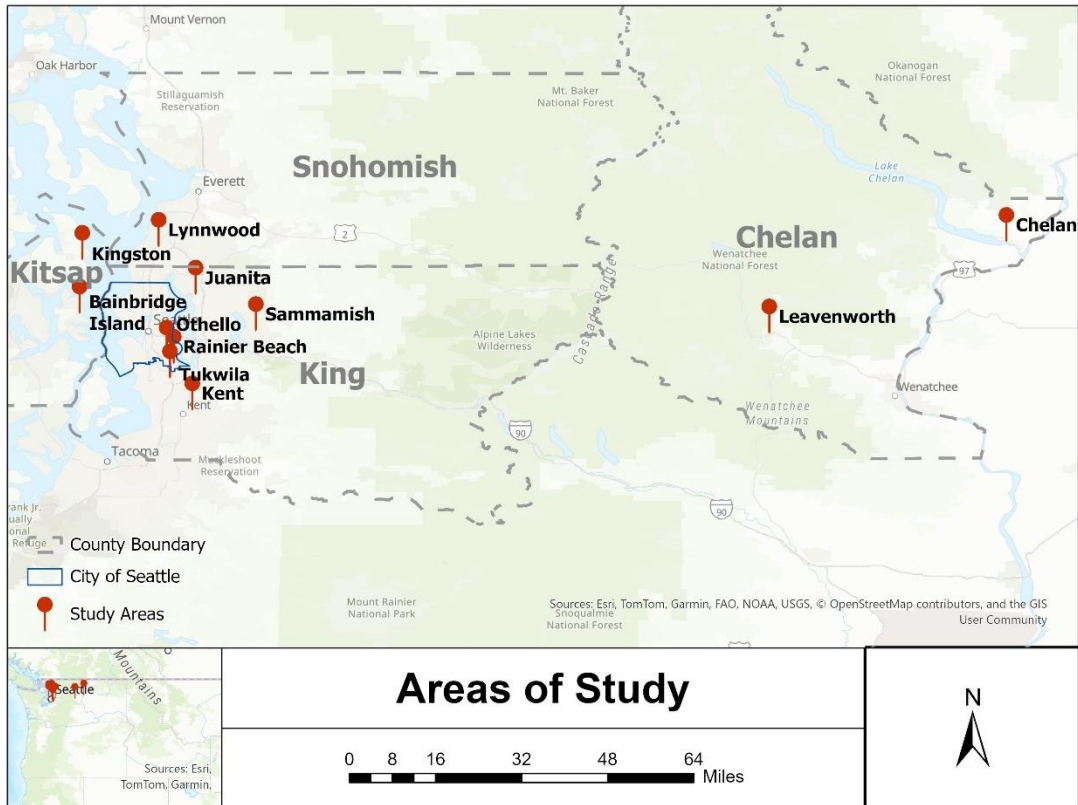
<i>Service provider</i>	<i>Link Transit</i>		<i>Community Transit</i>	<i>Kitsap Transit</i>			<i>King County Metro</i>				
<i>Study area</i>	Leavenworth	Chelan	Lynnwood	Bainbridge Island	Kingston	Sammamish	Rainier Beach	Juanita	Kent	Othello	Tukwila
<i>Median age</i>	42.3	46.7	39.2	49	40.6	41.3	39	37.1	37.6	24.6	35
<i>Ratio of bachelor's degree or higher</i>	45.6%	26.5%	32.6%	75.0%	42.2%	83.4%	43.1%	68.4%	33.1%	14.4%	23.9%
<i>Median household income (\$)</i>	\$74,653	\$71,996	\$76,439	\$159,882	\$99,345	\$238,750	\$101,436	\$144,080	\$85,982	\$65,757	\$80,534
<i>Number of geographic units (census blocks)</i>	59	104	173	65	38	121	462	185	215	301	153
<i>Sparsity of demand (probability of zeros across time)</i>	0.9945	0.9971	0.9950	0.9870	0.9918	0.9961	0.9989	0.9990	0.9990	0.9989	0.9980
<i>Period of data availability</i>	Jan 1, 2024 – August 31, 2024 <sup>26</sup>	Jan 1, 2024 – August	Jan 1, 2024 – Dec 31, 2024	Jan 1, 2024 – Dec 31, 2024	Jan 1, 2024 – Dec 31, 2024	Mar 6, 2023 – May 30, 2023	Mar 6, 2023 – May 30, 2023	Mar 6, 2023 – May 30, 2023	Mar 6, 2023 – May 30, 2023	Mar 6, 2023 – May 30, 2023	Mar 6, 2023 – May 30, 2023

<sup>26</sup> This differs from the range reported in Table 1 of Chapter 2 due to delays in the availability of the remaining portion of the data.

<i>Time range of selected data</i>	31, 2024 <sup>27</sup>	
	Mar 6, 2024 – May 30, 2024	Mar 6, 2023 – May 30, 2023

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<sup>27</sup> Same as above.



**Figure 4-3 The areas of study**

#### 4.3.5.2 Population Density, Land Use, and Road Network Data

The geospatial data of census blocks and their population densities in 2024 are obtained from Washington State Office of Financial Management’s Small Area Estimates<sup>28</sup>. The estimates are based on 2020 census blocks. The land use geospatial data is obtained from Washington State Geospatial Open Data Portal<sup>29</sup>. The data is based on 2010 estimates. It was produced from digital county tax parcel layers using Department of Revenue (DOR) two-digit land use codes. According to the land use codes, the land use coverage is classified into residential, manufacturing, transportation, retail, business services, cultural and recreational, agriculture, and undeveloped and

<sup>28</sup> <https://geo.wa.gov/datasets/wa-ofm::ofm-saep-block20/about>

<sup>29</sup> <https://geo.wa.gov/datasets/wa-geoservices::washington-state-land-use-2010/about>

water areas. Except for undeveloped and water areas, the ratio of each type of land use areas in a census block is calculated to capture land use characteristics. Additionally, road network data of the study areas comes from OpenStreetMap (OSM)<sup>30</sup>. This data is used to measure network distances between the centroids of census blocks.

#### *4.3.5.3 Transit service data*

On-demand mobility services have been argued to have both substitutive and complementary effects on fixed-route transit systems (Clewlow and Mishra, 2017; Gerte et al., 2019; Graehler et al., 2019; Kumar and Khani, 2021; Meredith-Karam et al., 2021). As an emerging travel alternative, on-demand mobility can provide access to and from transit stops/stations or replace transit services for the trips starting and ending at certain locations. The interaction between on-demand mobility and public transit varies across regions and time of day (Grahm et al., 2020). This dynamic relationship is influenced by the presence of special generators of transit demand (universities, colleges, or hospitals) and dedicated transit-oriented land uses. Given that, it is essential to consider the characteristics of fixed-route transit network in predicting TIMOD demand. In this study, the characteristics of fixed-route transit networks are captured by quantifying their service levels and embedding them into the TIMOD mobility graph node features. The service level of fixed-route transit in a census block is measured by transit stop/station densities and the average service frequency of transit routes on a typical weekday. The density of transit stops/stations and service frequencies of transit routes are obtained from General Transit Feed Specification (GTFS), an open-source data that provides the information of transit service schedule.

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<sup>30</sup> <https://download.geofabrik.de/north-america/us/washington.html>

## 4.4 Results

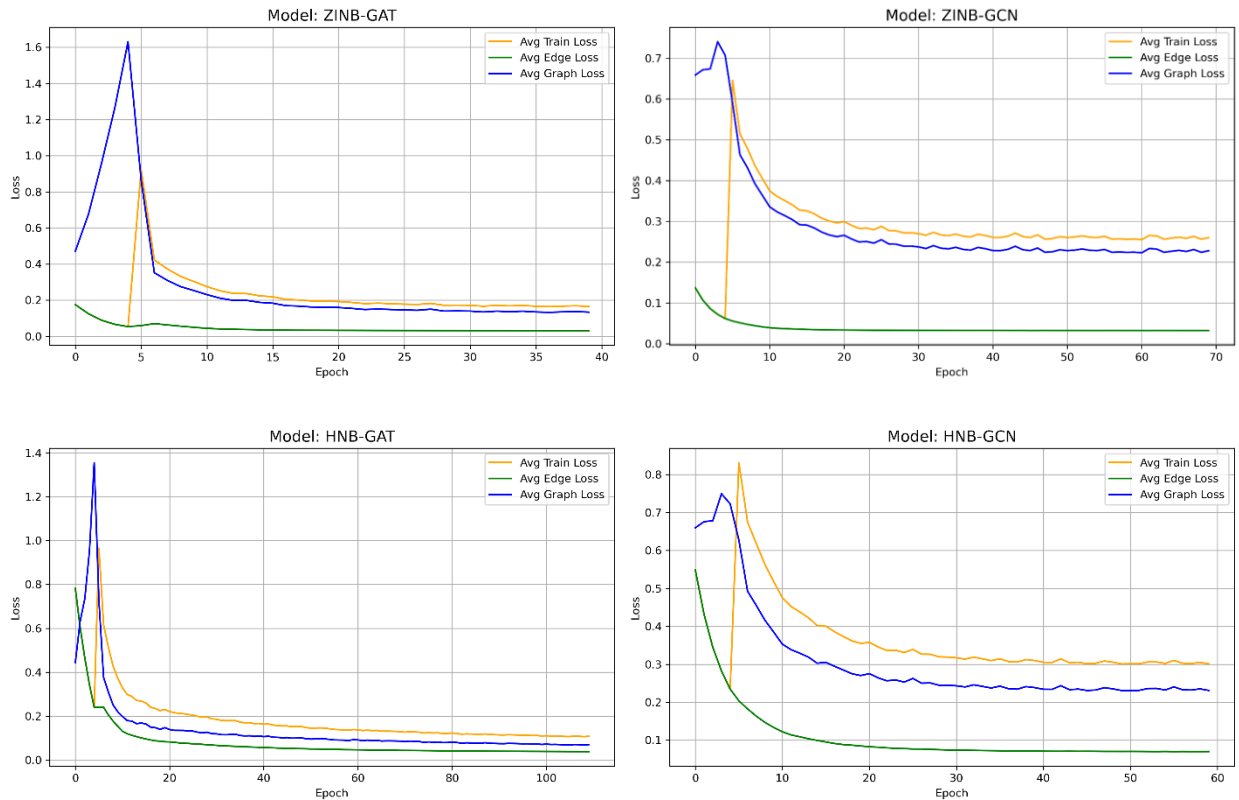
### 4.4.1 Experiment Setup

The 11 study areas, each corresponding to a mobility graph, are randomly split into training, validation, and test sets. 70% of the data (i.e., 8 areas) is used for training and validation, and the rest 30% for testing (i.e., 3 areas). The data for each case consists of 60 time steps in total, covering 12 weeks from March to May, excluding weekends. Each time sequence in the training set is chunked into 9 overlapping subsequences using a sliding window with a stride of five steps. Each subsequence spans 20 time steps. This splitting method enables the model to capture daily and weekly variations within a 30-day period. The time sequences in the test set are divided into 3 non-overlapping chunks. All spatial node features have been min-max scaled within each graph.

Due to the limited number of study areas, this study used Leave-One-Out Cross-Validation (LOO-CV) technique to tune the model’s hyperparameters. Among the 8 areas for training and validation, the data of each area serves as the test set exactly once, while the data of the remaining 7 areas are used for training. It trains on 7 graphs while leaving one out for testing each time until all areas have been iteratively taken as the test set. Early stopping with a patience of 10 epochs is applied to prevent overfitting on the training and validation data. Then, the data of all the 8 areas and the tuned hyperparameters are used to train predictive models. Because the learning of edge embeddings is more complex than that of graph embeddings, the first 5 epochs are used as a warmup to balance the convergence speeds of edge-level and graph-level embeddings learning tasks. The first 5 epochs are trained to only reduce edge-level losses and then graph-level losses are added since the 6<sup>th</sup> epoch. This is used to avoid the gradient updates to be dominated by the learning of a single task.

## 4.4.2 Model Performance Comparison

The GNN-based models' training curves are presented in Figure 4-4. As shown in the figure, all models demonstrated convergence<sup>31</sup> with the same learning rate, while the number of epochs required for convergence varies across the models.



**Figure 4-4 Training curves (first 5 epochs as warmup)**

Table 4-2 presents the metrics of prediction accuracy and prediction uncertainty of the models. The GNN-based models outperform XGBoost in terms of prediction accuracy. Among the GNN-based models, the GAT-based models achieve higher accuracy than the GCN-based models across the test areas. This suggests that graph convolution may be less effective than graph attention in capturing the local features of densely connected nodes, as the convolution operation

<sup>31</sup> Convergence refers to the process where the model's training curve stabilizes, indicating that further training is unlikely to significantly improve the model's performance.

averages the messages passed from neighbors. The generally lower MPIWs of GAT-based models suggest that these models are more confident in their predictions of the areas, although this comes at the cost of reduced PICPs and underestimation of variability in trip generation. This may be attributed to the attention mechanism, which assigns lower weights to non-zero neighboring interactions due to their sparsity. Among the GAT-based models, HNB-GAT yields lower MAEs than ZINB-GAT across the test areas. While it is more confident, it is less accurate in quantifying uncertainty, resulting in lower MPIWs and PICPs. This suggests that the HNB-GAT model is more conservative in predicting non-zero values, as it tends to overestimate the probability of zero trips. It raises concerns about the applicability of HNB-GAT in areas with relatively high TIMOD demand. Additionally, the models show different levels of prediction accuracy and prediction uncertainty across the areas for testing. The GAT-based models overestimate zero trip occurrences for Leavenworth, resulting in its poorer performance for this area compared with other areas with sparser TIMOD demand.

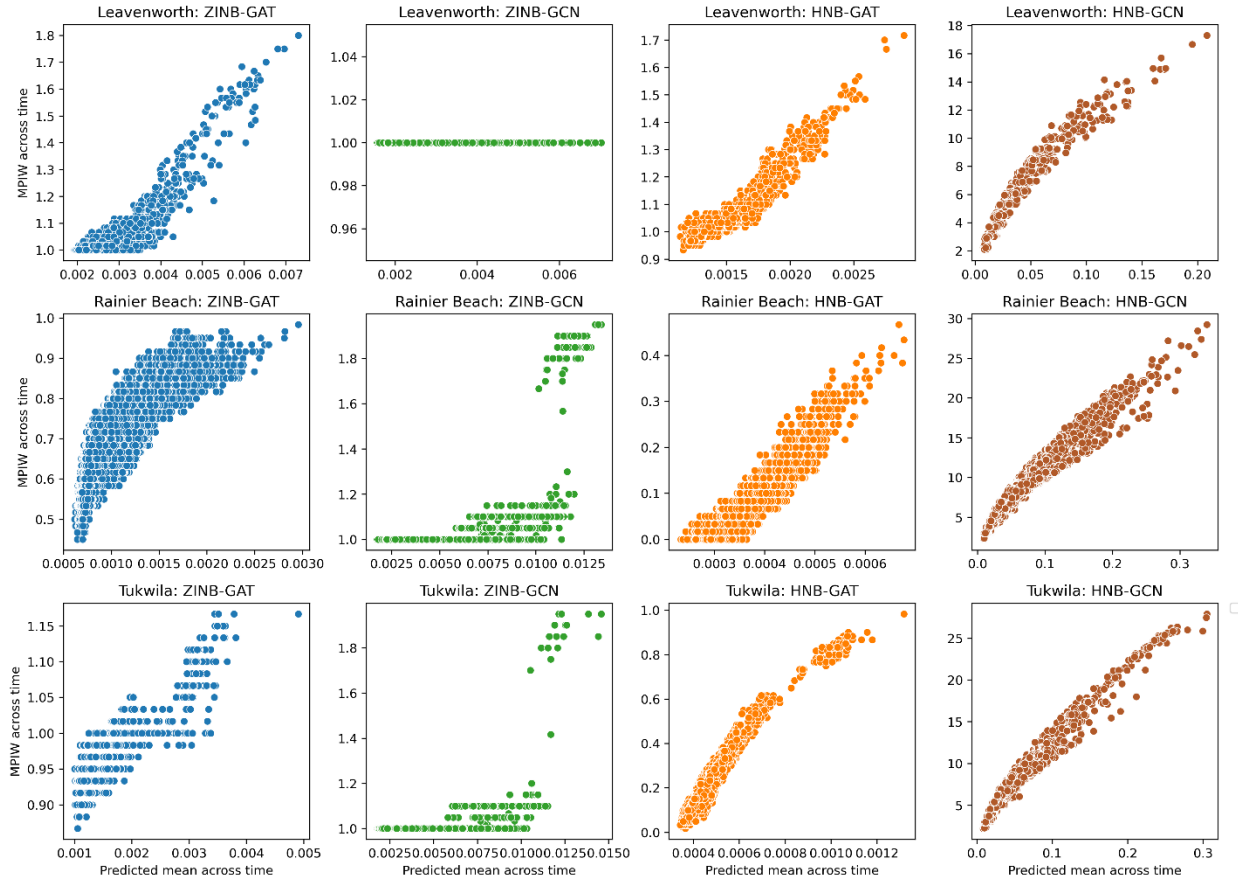
**Table 4-2 The comparison of model performance**

<i>Metrics</i>	<i>ZINB-GAT</i>	<i>ZINB-GCN</i>	<i>HNB-GAT</i>	<i>HNB-GCN</i>	<i>XGBoost</i>
<i>RMSE</i>	LEA: 0.1162	LEA: 0.1162	LEA: 0.1163	LEA: 0.1173	LEA: 0.1163
	RAI: 0.0471	RAI: 0.0472	RAI: 0.0472	RAI: 0.0584	RAI: 0.0507
	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600	TUK: 0.0705	TUK: 0.0610
<i>MAE</i>	LEA: 0.0103	LEA: 0.0103	LEA: 0.0090	LEA: 0.0256	LEA: 0.0102
	RAI: 0.0022	RAI: 0.0044	RAI: 0.0016	RAI: 0.0272	RAI: 0.0051
	TUK: 0.0038	TUK: 0.0056	TUK: 0.0028	TUK: 0.0294	TUK: 0.0055
<i>MPIW</i>	LEA: 1.0482	LEA: 1.0000	LEA: 1.0447	LEA: 3.7383	/
	RAI: 0.6586	RAI: 1.0008	RAI: 0.0198	RAI: 4.9555	

<b>PICP</b>	TUK: 0.9662	TUK: 1.0010	TUK: 0.1448	TUK: 5.1831
	LEA: 0.9987	LEA: 0.9986	LEA: 0.9987	LEA: 0.9999
	RAI: 0.9995	RAI: 0.9998	RAI: 0.9990	RAI: 0.9999 /
	TUK: 0.9996	TUK: 0.9997	TUK: 0.9982	TUK: 0.9998

**Note:** LEA - Leavenworth, RAI – Rainier Beach, TUK– Tukwila

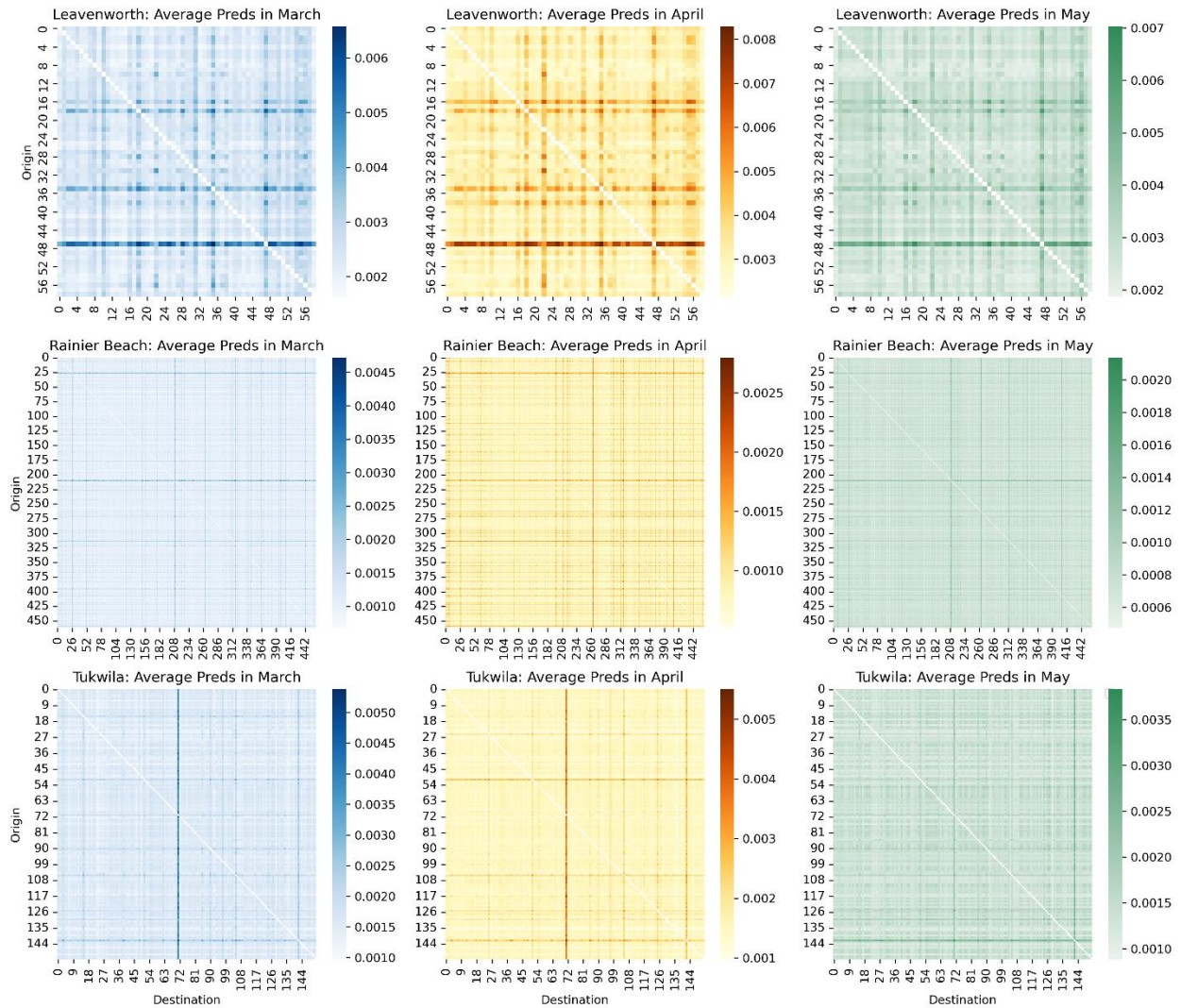
Figure 4-5 presents the mean prediction versus the MPIW over time for each OD pair (i.e., per edge), grouped by testing area. Across all the test areas, HNB-GCN exhibits the widest average prediction intervals, indicating lower model confidence compared with other models. In Rainier Beach and Tukwila, ZINB-GCN also produces wider intervals than the GAT-based models; however, in Leavenworth, its intervals are narrower, reflecting a more conservative prediction that compromises PICP. Moreover, ZINB-GAT generally produces wider prediction intervals than HNB-GAT across all areas.



**Figure 4-5 Predicted mean trip count versus mean prediction interval width (MPIW) over time for each OD pair**

Compared with HNB-GAT, ZINB-GAT is less conservative in predicting non-zero trips, thus avoiding overestimation of zero-trip probabilities. As it yields relatively low MAEs across all the test areas and achieves narrow MPIWs while maintaining high PICPs, providing confident and accurate predictions, it is selected for further comparison. The monthly average predictions of the ZINB-GAT model for the test areas are shown in Figure 4-6. The x- and y-axes represent the IDs of the origin and destination census blocks in the areas. TIMOD demand is imbalanced across space and time. For example, demand from census block ID 47 to other blocks in Leavenworth is higher than that between most other OD pairs. In Rainier Beach and Tukwila, the highest TIMOD demand occurs between different OD pairs in different months. This suggests that the model

effectively captures the spatially and temporally varying patterns of TIMOD demand.



**Figure 4-6 Monthly average predictions of the ZINB-GAT model**

#### 4.4.3 Influence of Node Features

Table 4-3 shows the performance of the ZINB-GAT model when various node features are excluded from the input. The Wilcoxon signed-rank test was applied to compare the predictions of each model variant with those of the full ZINB-GAT model. The results of the hypothesis testing indicate that excluding node features leads to significantly different predictions across all the test areas.

This analysis reveals pronounced spatial heterogeneity in how different features influence prediction uncertainty. Excluding the population density feature results in higher MPIW and PICP in Leavenworth, which means that the model becomes more uncertain in its predictions without this contextual variable. The absence of this feature leads the model to inflate uncertainty to account for the missing information in this area. In comparison, in Rainier Beach and Tukwila, excluding population density reduces the model’s ability to capture uncertainty accurately, resulting in lower MPIWs and PICPs.

**Table 4-3 Comparing model performance with regard to node features**

<i>Metrics</i>	<i>ZINB-GAT (full version as reference)</i>	<i>ZINB-GAT w/o population density</i>	<i>ZINB-GAT w/o transit services</i>	<i>ZINB-GAT w/o residential</i>	<i>ZINB-GAT w/o retail</i>	<i>ZINB-GAT w/o business services</i>
<b><i>RMSE</i></b>	LEA: 0.1162	LEA: 0.1161	LEA: 0.1161	LEA: 0.1162	LEA: 0.1162	LEA: 0.1161
	RAI: 0.0471	RAI: 0.0471	RAI: 0.0471	RAI: 0.0471	RAI: 0.0471	RAI: 0.0471
	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600
<b><i>MAE</i></b>	LEA: 0.0103	LEA: 0.0132	LEA: 0.0112	LEA: 0.0118	LEA: 0.0132	LEA: 0.0131
	RAI: 0.0022	RAI: 0.0019	RAI: 0.0024	RAI: 0.0028	RAI: 0.0021	RAI: 0.0034
	TUK: 0.0038	TUK: 0.0032	TUK: 0.0037	TUK: 0.0060	TUK: 0.0031	TUK: 0.0041
<b><i>MPIW</i></b>	LEA: 1.0482	LEA: 1.1827	LEA: 1.0011	LEA: 1.1686	LEA: 1.3591	LEA: 1.3055
	RAI: 0.6586	RAI: 0.4210	RAI: 0.9350	RAI: 0.8853	RAI: 0.6414	RAI: 1.0009
	TUK: 0.9662	TUK: 0.5513	TUK: 0.9499	TUK: 1.2001	TUK: 0.7468	TUK: 1.0008
<b><i>PICP</i></b>	LEA: 0.9987	LEA: 0.9990	LEA: 0.9986	LEA: 0.9989	LEA: 0.9989	LEA: 0.9990
	RAI: 0.9995	RAI: 0.9994	RAI: 0.9998	RAI: 0.9998	RAI: 0.9997	RAI: 0.9998
	TUK: 0.9996	TUK: 0.9990	TUK: 0.9996	TUK: 0.9997	TUK: 0.9992	TUK: 0.9980

**Note:** LEA - Leavenworth, RAI – Rainier Beach, TUK– Tukwila

The exclusion of transit service-related features leads to higher MPIW and PICP in Rainier Beach, suggesting that the model becomes more uncertain and conservative in its predictions when lacking this contextual information in this area. In contrast, in Leavenworth and Tukwila, these features are less informative; hence, their exclusion results in lower MPIWs and PICPs, indicating reduced uncertainty coverage and underestimation of variability. This pattern underscores spatial heterogeneity in feature relevance and highlights the importance of transit-related inputs in capturing demand uncertainty in different environments.

The model excluding the ratio of residential land consistently shows higher MPIW and PICP across all the test areas, indicating that the absence of this feature leads to broader and more conservative prediction intervals. Without including this feature, the model becomes less confident in its predictions, increasing the estimated uncertainty to compensate for the missing contextual information.

The model excluding the ratio of retail land shows a lower MPIW and a higher PICP in Rainier Beach. This suggests that the model becomes more confident in its predictions when excluding this contextual information in this area. In contrast, this feature is less informative for the predictions in Tukwila, resulting in lower MPIW and PICP in the area. In addition, the model becomes less confident in its predictions in Leavenworth, which leads to an increased uncertainty estimation.

The exclusion of the ratio of business services land leads to the model's lower confidence in the predictions of the three test areas. It even results in a lower PICP in Tukwila, suggesting that the model becomes less confident and less accurate in quantifying uncertainty when this feature is missing. The ratio of business service land might be a critical predictor of trip generation patterns,

potentially due to high demand associated with commercial activities. Removing this feature weakens the model's ability to learn meaningful spatial patterns, leading to overestimation of uncertainty without improving prediction coverage.

In summary, this analysis reveals pronounced spatial heterogeneity in how different features influence prediction uncertainty. Population density and transit service variables exhibit location-specific effects. Removing them increases uncertainty in some areas while reducing it in others. In contrast, land-use ratios show clearer patterns: excluding the residential land ratio consistently leads to higher MPIWs and PICPs, underscoring its broad and uniform importance across all regions. Business services land ratio also emerges as a strong predictor, with its removal decreasing both model confidence and accuracy across the study area. The influence of retail land ratio, however, varies by location, suggesting that its role in shaping travel demand depends on local demand patterns and urban context.

#### **4.4.4 Sensitivity Analysis of Model Architecture**

A sensitivity analysis is conducted to examine the influence of various components in the predictive model architecture. The results of Wilcoxon signed-rank test indicate that the predictions of each model variant in the sensitivity analysis are significantly different from those of the full ZINB-GAT model. First, this study examines the use of mean pooling instead of attention-based pooling in learning graph-level embeddings. The results are shown in Table 4-4. ZINB-GAT with graph-level mean pooling performs a more balanced prediction of uncertainty across the area. Compared with the ZINB-GAT model with attention-based graph pooling, it is less confident in the predictions of Rainier Beach and Tukwila, while it is more accurate in the prediction coverages of these two areas. Moreover, the ZINB-GAT model without the TCN layer exhibits larger MAEs across the test areas. While it achieves higher PICPs for Leavenworth and

Rainier Beach, this comes at the cost of increased prediction uncertainty. For Tukwila, it yields lower MPIWs and PICPs compared with the ZINB-GAT model with the TCN layer. The ZINB-GAT applied graph-level mean pooling and removed TCN layer achieves smaller MAEs for Leavenworth and Tukwila. However, compared with the ZINB-GAT with attention-based graph pooling and TCN layer included, it overestimates the probability of zero-trip occurrences and underestimates the probability of non-zero trip generation for these two areas, leading to lower MPIWs and PICPs. Additionally, the ZINB-GAT model without graph-level regularization overestimates the probability of zeros, which also results in lower MPIWs and PICPs. These results suggest that each model component is essential for achieving better performance.

**Table 4-4 Sensitivity analysis of model performance**

<i>Metrics</i>	<i>ZINB-GAT with attention-based graph pooling and TCN layer (reference)</i>	<i>ZINB-GAT with graph mean pooling instead</i>	<i>ZINB-GAT w/o TCN layer</i>	<i>ZINB-GAT applied graph mean pooling &amp; removed TCN layer</i>	<i>ZINB-GAT w/o graph-level supervision</i>
<b><i>RMSE</i></b>	LEA: 0.1162	LEA: 0.1163	LEA: 0.1162	LEA: 0.1163	LEA: 0.1163
	RAI: 0.0471	RAI: 0.0471	RAI: 0.0472	RAI: 0.0471	RAI: 0.0472
	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600	TUK: 0.0600
<b><i>MAE</i></b>	LEA: 0.0103	LEA: 0.0093	LEA: 0.0113	LEA: 0.0084	LEA: 0.0083
	RAI: 0.0022	RAI: 0.0029	RAI: 0.0039	RAI: 0.0023	RAI: 0.0014
	TUK: 0.0038	TUK: 0.0039	TUK: 0.0045	TUK: 0.0033	TUK: 0.0024
<b><i>MPIW</i></b>	LEA: 1.0482	LEA: 1.0317	LEA: 1.2425	LEA: 0.7024	LEA: 0.5568
	RAI: 0.6586	RAI: 1.0151	RAI: 1.0701	RAI: 0.8680	RAI: 0.0000

<i>PICP</i>	TUK: 0.9662	TUK: 1.0149	TUK: 0.9480	TUK: 0.7724	TUK: 0.0000
	LEA: 0.9987	LEA: 0.9987	LEA: 0.9989	LEA: 0.9978	LEA: 0.9972
	RAI: 0.9995	RAI: 0.9998	RAI: 0.9998	RAI: 0.9998	RAI: 0.9989
	TUK: 0.9996	TUK: 0.9997	TUK: 0.9995	TUK: 0.9992	TUK: 0.9980

**Note:** LEA - Leavenworth, RAI – Rainier Beach, TUK– Tukwila

#### 4.5 Discussion and Conclusions

This study proposes a context-aware probabilistic spatiotemporal graph neural network (CA-STPGNN) to model the sparse demand for TIMOD services in low-density suburbs. The model integrates graph attention networks and temporal convolutional networks to capture spatial dependencies of node-level features (e.g., population density, transit service, land use, temporal indicators) and temporal dynamics of edge-level interactions. A multitask learning framework regularizes edge-level predictions via graph-level characteristics, while probabilistic layers quantify uncertainty in predictions. Zero and non-zero trip probabilities are estimated via Bernoulli and Negative Binomial components.

The model is evaluated on 12 weeks of TIMOD trip data from 11 suburban areas in Washington State (March–May 2023/2024). Results show that GNN-based models consistently outperform XGBoost in accuracy, with GAT-based models outperforming GCN-based ones. GAT-based models produce narrower prediction intervals (lower MPIWs), indicating higher confidence, but often at the cost of lower coverage (PICPs), likely due to the underweighting of sparse nonzero neighbors. Among these, HNB-GAT achieves the lowest MAEs but shows the greatest overconfidence, with reduced MPIWs and PICPs compared with ZINB-GAT.

The results reveal spatial heterogeneity in how contextual features affect the model’s

ability to quantify uncertainty in TIMOD demand. Population density is crucial in Leavenworth—its removal increases uncertainty—but less informative in Rainier Beach and Tukwila. Transit service features are informative in Rainier Beach but contribute little elsewhere. The residential land ratio is consistently important, with its exclusion broadening and making predictions more conservative. Removing the retail land ratio has mixed effects: it improves performance in Rainier Beach but reduces confidence or coverage in other areas. Excluding the business service land ratio consistently lowers confidence and sometimes coverage, underscoring its value for capturing commercial demand. These results support the need for context-aware models that adapt to local feature relevance.

Architectural choices also impact model performance. Graph-level mean pooling improves uncertainty estimation across areas compared with attention-based pooling, though sometimes with lower confidence. Removing the TCN layer raises MAEs and can improve coverage in some areas but generally increases uncertainty and reduces confidence. Combining mean pooling with TCN removal yields lower MAEs but skews zero vs. non-zero trip predictions, reducing coverage. Eliminating graph-level regularization causes overprediction of zeros and unreliable intervals. Overall, temporal modeling and regularization are key to improving both accuracy and uncertainty estimation.

This study is limited by data availability. Future research could use data from additional months to capture TIMOD demand patterns over a longer period. Moreover, future studies could explore alternative assumptions regarding the distribution of trip counts. For example, Poisson–Inverse Gaussian and Poisson–Lognormal distributions could be used in place of the negative binomial model to better accommodate heavier tails and capture extreme variability. However, these methods are less commonly available in standard toolkits and often require approximation

techniques for integration. Additionally, the proposed model estimates trip counts between geographic units based on local contexts, providing data to assess TIMOD cost-effectiveness in regions considering future pilot programs.

## Chapter 5 Synthesis

### 5.1 Summary of three studies

The three studies advance the understanding of public agency's leadership in shaping sustainable transit systems around TOD and TIMOD services in regional growth centers and low-density areas by combining planning tools, cost-effectiveness analysis, and predictive modeling.

Chapter 2 develops a multi-criteria TOD prioritization tool tailored to publicly owned park-and-ride sites. Incorporating 14 indicators across five domains, including transit service, land use, demographics, market conditions, and planning context, the tool uses expert-informed weighting and scenario-specific prioritization to assess TOD suitability. It supports strategic decision-making by identifying locations that can best support affordable housing, market-rate development, or mixed-use projects. While adaptable to diverse U.S. contexts, the tool's applicability is limited by regional data availability and the exclusion of some potentially relevant indicators such as car ownership. Nevertheless, it offers a standardized and flexible framework for equitable, transit-supportive land development.

Chapter 3 examines the cost-effectiveness of TIMOD relative to fixed-route transit, driving, and TNCs using real-world TIMOD data and the counterfactual trips of other alternatives. It extends a framework incorporating traveler time and monetary costs, services provider costs, and transportation externalities. Results show that driving generally incurs the lowest cost from a societal perspective. From the traveler's perspective, TIMOD often outperforms fixed-route transit and TNCs, and even driving in some areas. However, TIMOD's operating costs are highly sensitive to transit agencies' budget allocations and service hour deployment, which are the primary contributors to its cost disadvantage in low-density areas. External costs, though currently minor, may become more significant in the future given the growing climate change trends. These

findings highlight the need for targeted subsidy strategies and service optimization based on local demand patterns and cost trade-offs.

Chapter 4 proposes a generalizable Context-Aware Spatiotemporal Graph Neural Network (CA-STPGNN) to predict sparse TIMOD demand while quantifying uncertainty. Using actual trip data across 11 suburban areas, the study demonstrates that GAT-based models outperform alternatives in accuracy but may exhibit overconfidence, particularly in less sparse contexts. Model performance is shown to vary across regions, reinforcing the need for context-sensitive modeling. The study identifies specific contextual features, including population density, transit service, and land use coverage, that result in spatial heterogeneity in model performance. Sensitivity analyses underscore the importance of including temporal convolution layer and graph-level regularization in improving prediction accuracy and uncertainty quantification.

In summary, these studies offer insights into optimizing TOD planning, evaluating transit agency-led demand-responsive service efficiency, and improving service demand prediction under uncertainty in low-density areas. They collectively support transit agencies' decision making on more equitable, efficient, and data-informed mobility and development strategies.

## **5.2 Contributions and Policy Implications**

The work of this dissertation makes contributions to public transportation planning. The findings from these three studies have policy implications for advancing equitable, cost-effective, and data-driven mobility and development strategies, particularly in suburban growth centers and lower-density contexts where traditional transit models often fall short.

### **5.2.1 Strategic Use of Public Land to Promote Equitable TOD**

The TOD prioritization tool developed in Chapter 2 offers a replicable framework for public

agencies to evaluate and prioritize publicly owned land, particularly park-and-ride sites, for TOD investments. Policymakers can use this tool to align land-use planning with broader equity and sustainability goals by prioritizing sites that support population diverse communities, offer broad access to employment opportunities, improve connections to transit systems, and enhance walkability. The inclusion of scenario-based weighting schemes (affordable housing, market-rate, and mixed-use) enables policymakers to tailor development strategies to specific policy objectives, such as addressing housing affordability or promoting economic revitalization.

### **5.2.2 Context-Sensitive Subsidy and Mobility Strategies**

Chapter 3 highlights the nuanced trade-offs involved in deploying TIMOD versus fixed-route transit, TNCs, or driving. Although driving is the least costly option from a social perspective, it is often inaccessible to lower-income or mobility-constrained populations. TIMOD emerges as a more equitable solution in such cases but is sensitive to operating costs and demand levels. Policymakers should consider context-sensitive operation and subsidy models that adjust support for TIMOD and TNCs based on local demand density, built environment characteristics, and user demographics. In areas where pooling and ride-matching are more feasible, public agencies might improve cost-effectiveness by redesigning TIMOD operations or establishing public-private partnerships with TNCs. Moreover, as external costs (e.g., emissions, congestion) grow in importance, incorporating environmental and health externalities into funding decisions will become increasingly relevant for sustainable transit policy. In addition, Autonomous electric vehicles (AEV) may be a cost-effective solution for serving scarce demand in low-density areas by savings from driver revenue and cleaner technologies.

### **5.2.3 Enhancing Predictive Capacity and Adaptive Planning**

Chapter 4 offers a methodological advance in TIMOD demand forecasting by modeling the uncertainty associated with its sparse usage. For policymakers, the ability to anticipate not just expected demand but also the confidence interval around those predictions is critical for planning scalable, resilient public transportation services. The finding that model performance varies by region underscores the importance of location-based planning, suggesting that one-size-fits-all approaches are insufficient. Policymakers should support the integration of predictive analytics into public transportation planning and require that models explicitly account for local context when predicting demand. Moreover, investments in data infrastructure to improve the quality and timeliness of local mobility and land use data will enhance the utility of such models.

### **5.2.4 Coordinated Land Use–Mobility Planning Frameworks**

These studies advocate for a more integrated approach to land use and public transportation planning. Policies that coordinate TOD investment with demand-responsive transit service—guided by cost-effectiveness and predictive modeling—can help optimize land and mobility resources. For instance, land near high-priority TOD sites identified in Chapter 2 could be paired with enhanced TIMOD services informed by the cost evaluation from Chapter 3 and the predictive insights from Chapter 4. This type of cross-sectoral coordination requires institutional alignment between transit agencies, planning organizations, and housing authorities, potentially supported through state-level policy mandates or funding incentives.

### **5.2.5 Advancing Equity Through Context-Aware Tools**

Across all studies, a consistent theme is the importance of adapting tools, subsidies, and models to local demographic and spatial contexts. Policies that promote the routine use of context-aware

tools can help ensure that investments in TOD and TIMOD truly address the needs of disadvantaged populations and do not inadvertently exacerbate existing inequities. For example, equity-focused grant programs can incentivize jurisdictions to use the prioritization tools and predictive models when proposing new transit supportive services.

## **5.3 Future research**

Building on the findings and policy implications of the three studies, here are some critical areas for future research to explore.

### **5.3.1 Advancing TOD Evaluation Frameworks**

The TOD prioritization tool developed in Chapter 2 provides a replicable framework for evaluating the potential of park-and-ride sites but could also be applied to other forms of publicly owned land and more broadly used in TOD planning and implementation across different regions. Future work should also examine how evolving data sources, such as up-to-date demographics and land use data, can improve the precision and adaptability of TOD assessment tools. In addition, longitudinal studies assessing the outcomes of prioritized sites would help validate the framework's effectiveness in supporting equitable and sustainable development.

### **5.3.2 Refining Cost-Effectiveness Models for Emerging Mobility**

Chapter 3 highlights the necessity of evaluating TIMOD relative to other mobility alternatives. Future studies could explore the long-term fiscal and social sustainability of TIMOD services by incorporating dynamic elements such as changing fuel prices, labor costs, and technology adoption. The integration of Autonomous Electric Vehicles (AEVs) into the cost-effectiveness estimation framework can also advance the exploration, as does the inclusion of hybrid public–

private service models. Additionally, more granular equity analyses, such as distributional impacts across income groups, age cohorts, and neighborhoods, would provide policymakers with richer insights into subsidy design and resource allocation.

### **5.3.3 Improving Predictive Modeling and Uncertainty Quantification**

The CA-STPGNN framework in Chapter 4 demonstrates the value of predictive modeling for low-density settings, but further research is needed to enhance its transferability and interpretability. Future studies could investigate model generalization across more diverse regions, the incorporation of multimodal travel data, and the development of hybrid models that combine deep learning with behavioral modeling. Advancements in explainable AI could also make predictive models more transparent for decision makers. Moreover, uncertainty quantification could be extended to scenario planning, helping agencies evaluate potential risks under varying demand, budget, and policy conditions.

### **5.3.4 Integrating Land Use and Mobility Research**

Future work should focus on building coordinated frameworks that connect TOD investments, demand-responsive services, and predictive modeling. This includes exploring institutional mechanisms for collaboration among transit agencies, planning organizations, and housing authorities. Comparative studies across metropolitan regions could reveal how governance structures and policy environments shape the effectiveness of integrated land use–mobility strategies.

### **5.3.5 Embedding Equity in Data and Methods**

Finally, equity considerations warrant more systematic integration into both modeling and

evaluation. Future research should develop equity-sensitive indicators within TOD prioritization, incorporate distributional weights into cost-effectiveness analyses, and explicitly model the demand of disadvantaged populations in predictive frameworks. These approaches will help ensure that future transit innovations do not simply enhance efficiency but also advance fairness and accessibility.

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