IMPROVING PUBLIC TRANSIT ACCESSIBILITY BY LEVERAGING EMERGING MULTIMODAL MOBILITY OPTIONS

FINAL RESEARCH REPORT

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INTRODUCTION

Cities aiming to enhance their transportation systems are quickly adopting shared mobility modes and improving their connectivity. These changes are intended to provide residents with more flexibility as they construct routes to various points of interest throughout the city. Specifically, the goal of integrating more mobility modes is to expand access to goods and services in a safe, affordable, and reliable way (*1–3*).

As cities invest in their transportation networks, they require a way to quantify accessibility. In the transportation literature, accessibility is typically defined on the origin, destination, or origin-destination (O-D) level. Origin-level metrics often measure how many points of interest (e.g., jobs) can be reached by a given origin within some travel cost contour (*4, 5*). Destination-based metrics are calculated from the opposite perspective, measuring instead how many origins can reach a given destination within some travel cost threshold (*6, 7*). More generally, O-D accessibility is measured strictly as the travel cost between a given O-D pair (*8–10*), which is the convention adopted in this paper.

Regardless of the metric of accessibility selected, early literature that sought to evaluate accessibility in a transportation network assumed the only modes available were personal vehicle, fixed-route public transit, and walking (*6, 9, 11, 12*). Recently, researchers have also begun including personal bike (*13, 14*) and shared modes such as bikeshare and transportation network companies (TNCs) into accessibility evaluations (*15, 16*). These studies aimed to discover whether additional modes can increase access to jobs by better connecting travelers to public transit (i.e., solving the first/last-mile problem). This research showed that bikes are a plausible solution when bikeway infrastructure is available, whereas TNCs do not provide the same benefit due to their high monetary cost.

In these studies, researchers considered the fact that the disutility of travel encompasses additional factors such as risk and monetary cost. This reflects a shift in the way that accessibility is defined. The travel cost associated with accessibility metrics is no longer solely based on travel time; rather, other factors like reliability, affordability, and safety are also included. For example, El-Geneidy et al. (*17*) consider public transit fare cost, Gehrke et al. (*7*) account for bike safety, and Cui and Levinson (*18*) introduce a "full cost accessibility" framework that integrates travel time, crash risk, emissions, and monetary cost into a single generalized travel cost function.

It is also common that accessibility metrics are reported for a single departure time (*11, 19*). However, the accessibility of an O-D pair depends on departure time due to the reality of a fixed-schedule public transit network. Some studies compute time-dependent accessibility (*10, 14, 20, 21*), demonstrating how schedule deficits can leave regions underserved for extended periods of time.

Furthermore, there is a sizeable body of literature whose objective is to identify gaps in accessibility across socio-demographic groups. Their approach is typically to calculate origin-level accessibility metrics and then compare these metrics by the origin's average income level (*21–23*). Though this approach allows us to make generalizations about the relationship between income and accessibility, it assumes a uniform population surrounding each origin and neglects other demographic characteristics such as age, disability status, and household composition that influence traveler preferences (*24*).

A review of the transportation literature related to accessibility reveals a renewed focus on four elements: new mobility modes, additional traveler costs, time-dependency, and population group-specific measures. However, a framework that simultaneously accounts for all of these dimensions has yet to be introduced. In our work, we address this challenge by developing a time-dependent, multi-cost, multimodal network model capable of discovering optimal O-D paths by population group. In particular, we account for the following travel modes: personal vehicle, TNC, carshare, fixed-route public transit, personal bike, bikeshare, scooter, and walking. The traveler costs we consider are day-to-day mean travel time, monetary expense, reliability, risk, and discomfort, all of which are assigned on the minute-level. With this framework, decision-makers can identify mobility disparities across time and space, as well as determine opportunities for network investments that may improve accessibility for desired groups and O-D pairs.

METHODOLOGY

Evaluating and comparing time-dependent accessibility across O-D pairs requires three steps: 1) construct a routable multimodal network, 2) assign a generalized travel cost to each edge and selected nodes, and 3) determine the shortest path between O-D pairs.

Multimodal Network Model

Our method involves designing a multimodal network model that accounts for the personal vehicle, TNC, carshare, fixed-route public transit, personal bike, bikeshare, scooter, and walking modes (*25*). The set of all travel modes, with the exception of the walking mode, is denoted by M. To construct the model, we first represent the network for each mode $m \in M$ as a unimodal graph $G_m = (N_m, A_m)$, where N_m and A_m are the set of graph nodes and edges, respectively, associated with mode m. The network for each mode must be modeled as a unique graph so that a path that crosses multiple modes can be found. We illustrate the unimodal graph for each mode in Figure 1, where each graph is derived based on the original transportation network in Figure 2.

In a multimodal network model, the unimodal graphs are connected by transfer edges in order to facilitate multimodal route-finding. A transfer edge is an edge that connects two nodes which are members of different unimodal graphs. Prior to building transfer edges, we first decide which transfers are permissible based on practical intuition; for example, we permit transfers between public transit and any other mode, while we do not allow transfers between personal bike and TNC assuming a TNC vehicle lacks bike storage. We subsequently construct transfer edges between unimodal graph nodes where transfers could possibly occur (e.g., bus/train/etc. stops of the public transit graph, bikeshare stations of the bikeshare graph). Finally, we add the origin (O)/ destination (D) nodes along with O/D connector edges, which represent network ingress/egress, respectively. The final result is a routable multimodal graph, G_{MM}, also called a "supernetwork." It should be noted that transfer and O/D connector edges are assumed to be traversed by the walking mode.

Figure 3 displays an example supernetwork based on the original network shown in Figure 2, but only inclusive of the mode set $M = \{\text{TNC}, \text{public transit}, \text{bikeshare}\}$. The walking mode is included by way of transfer edges and O/D connector edges. Figure 3 also shows a plausible multimodal path that begins at the origin, traverses two unimodal graphs, and ends at the destination.

Generalized Travel Cost

After designing the multimodal network topology, we assign a generalized travel cost function to each edge that is a combination of five time-dependent traveler disutilities: monetary expense, mean travel time, reliability, risk, and discomfort. These five attributes were selected because they are measurable and known to impact travelers' decisions (*26*). The generalized travel cost is given

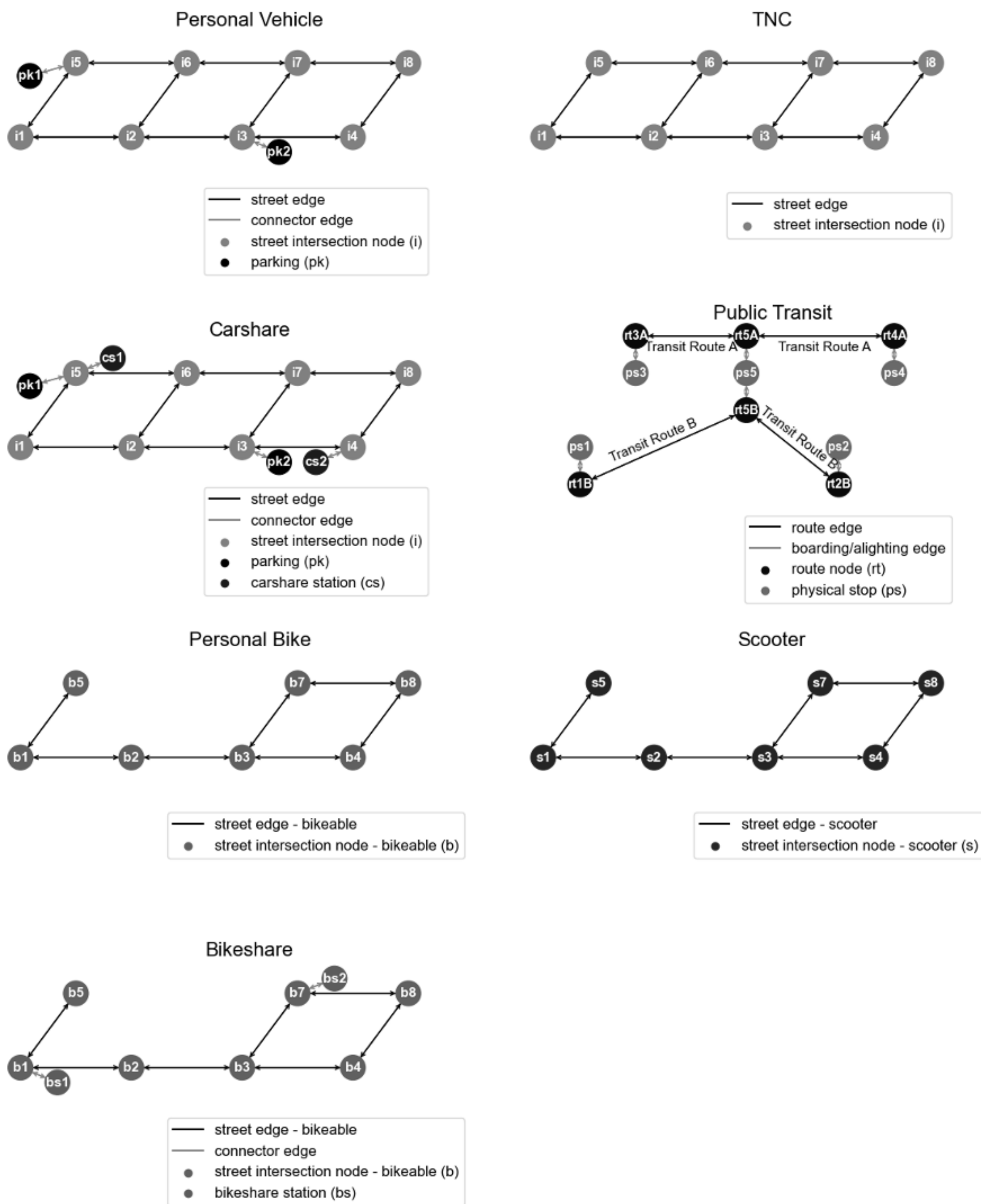


FIGURE 1: The unimodal graph model for various travel modes, including $m \in \{\text{personal vehicle}, \text{bikeshare}, \text{TNC}, \text{carshare}, \text{personal bike}, \text{public transit}, \text{scooter}\}$.

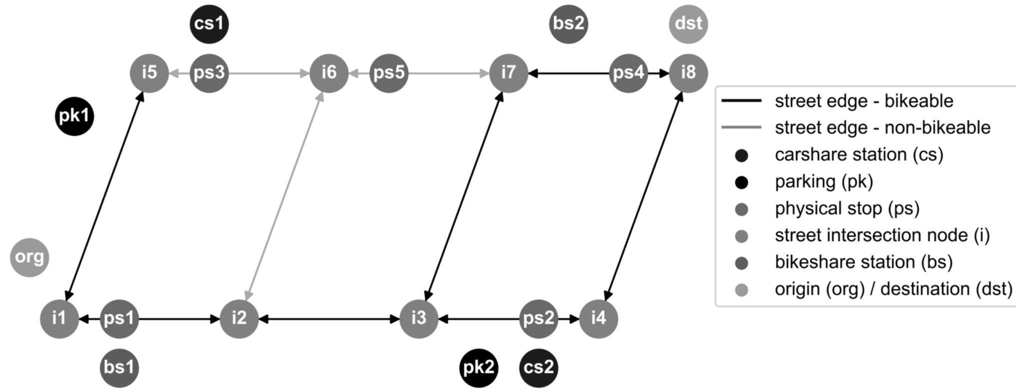


FIGURE 2: A toy transportation network with 20 directional street segments and 8 street intersection nodes. Other significant nodes include carshare stations, bikeshare stations, parking spots, and bus stops.

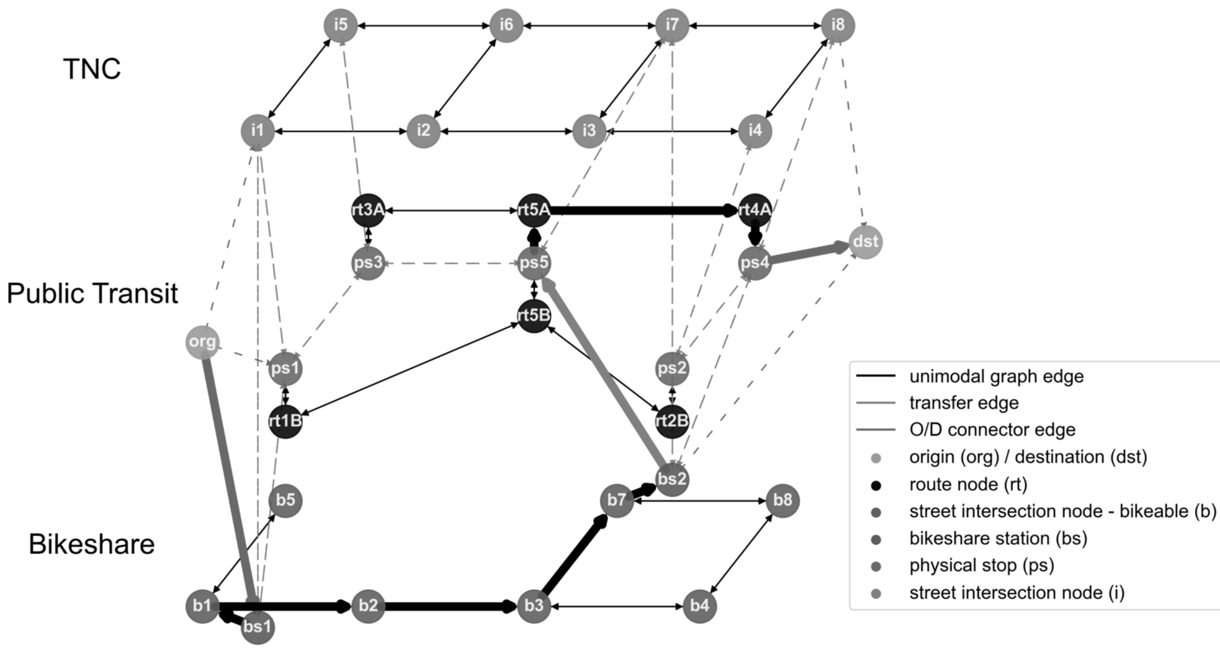


FIGURE 3: Supernetwork model for $M = \{\text{TNC}, \text{public transit}, \text{bikeshare}\}$. The unimodal graphs are connected via transfer edges. The origin and destination are connected by O/D connector edges. We offset the unimodal graphs slightly for the ease of visualization. A multimodal path leveraging bikeshare, public transit, and walking (for transfer and O/D connector edges) is bolded.

by Equation 1.

$$GTC_e(t) = \beta_x \cdot c_e^x(t) + \beta_T \cdot c_e^T(t) + \beta_r \cdot c_e^r(t) + \beta_k \cdot c_e^k(t) + \beta_D \cdot c_e^D(t) \tag{1}$$

where $c_e^x(t), c_e^T(t), c_e^r(t), c_e^k(t), c_e^D(t)$ denote the monetary expense, mean travel time, reliability measure, risk measure, and perceived discomfort measure, respectively, of edge e when entering the edge at time t.

The β parameter of a given cost attribute is defined as dollar value associated with a single unit of that cost attribute. Thus, β_x is always equal to \$1.00/\$1.00, while β_T is given by the dollar value that a traveler assigns to a unit of their time. The benefit of defining the cost function in this way is that the β parameters can be assigned depending on the population group of interest or the goals of the transportation planner. For example, a planner conducting an analysis on the modal options for risk-averse cyclist may choose to assign a relatively high value to β_k. Another advantage of this cost function formulation is that it may be simplified to a subset of the individual cost factors by simply setting any of the β parameters to zero.

Below we provide the definition of each cost factor that composes the generalized cost function:

- Monetary expense $c_e^x(t)$: sum of fixed and operational monetary costs
- Mean travel time $c_e^T(t)$: day-to-day average travel time
- Reliability $c_e^k(t)$: 95$^{\text{th}}$ percentile travel time, estimated by the mean travel time $c_e^T(t)$ multiplied by a scalar that is time-dependent and mode-specific
- Risk $c_e^r(t)$: predicted number of crashes within a given time period, where the prediction is calibrated based on observed crash data and accounts for road length, road class, speed limit, and micromobility infrastructure
- Discomfort $c_e^D(t)$: discomfort-weighted-length, where the discomfort weight is mode-specific and indicative of physical exertion required to traverse edge e

In addition to edge costs, movement-based node costs are assigned as necessary. Node costs are imposed to either penalize or benefit movement from one edge to another edge via a specific node. For example, free transfers within the public transit network or discounted transfers between different modes can be implemented by node costs.

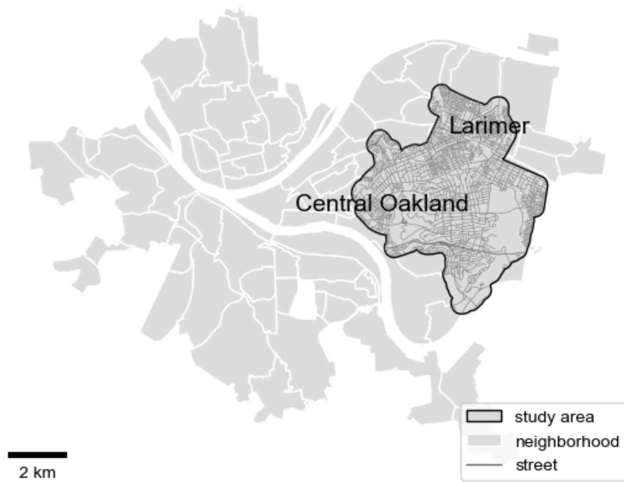
Accessibility Analysis

After building the network model and assigning edge and node costs, we conduct accessibility analysis. This requires finding the time-dependent shortest (lowest generalized travel cost) path between selected O-D pairs using the decreasing order of time algorithm provided by (*27*) and openly available on Github (*28*). We specifically examine O-D accessibility in this work. For an accessibility metric, we use the generalized travel cost of the shortest path as well as the individual cost attributes where appropriate.

EXPERIMENTS AND RESULTS

The real multimodal transportation network of Pittsburgh, PA was used to demonstrate the method. The nine-neighborhood study area is depicted in Figure 4a along with its street network in Figure 4b. Our case studies investigate the morning period accessibility of the Larimer-Central Oakland pair, which was selected to represent the commute from a low-income, high-unemployment neighborhood to an area with well-paying jobs. We assumed the population of interest lacked private modes of transportation such that the supernetwork model included the modes of TNC, carshare, public transit, bikeshare, scooter, and walking.

All of the data required to build the network topology in Pittsburgh is publicly available.



(a) The study area's street network is identified within the broader context of Allegheny County. The neighborhoods of Larimer and Central Oakland are considered in the case studies.

(b) The streets, bike lane information, and locations of bus stops, parking meters, bikeshare stations, and carshare stations within the study area are shown.

FIGURE 4: The study area in Pittsburgh, PA.

Most of the data used to assign edge costs is also open-source; the only exception is the data (provided by INRIX) we used for the reliability cost component, which was acquired via a license. The implementation of the method is also open-source and provided by the following link: `https://github.com/lgraff/Multimodal_Accessibility`.

Three case studies showcase the versatility of the proposed method. These sensitivity analyses highlight how the accessibility of the Larimer-Central Oakland O-D pair varies with three model elements: 1) β_T (value of travel time) in Equation 1, 2) origin departure time, and 3) usage pricing of shared scooter services.

Case Study 1: Sensitivity Analysis of Value of Travel Time

In the first case study, we varied the value of time parameter (β_T) in Equation 1 from \$0.00/hour to \$20.00 hour and evaluated how the mode combination and individual cost attributes of the shortest path change. The departure time was set at 8:00AM, and the other parameters were fixed as follows: β_r = \$15.00/hour, β_x = \$1.00/\$1.00, β_r = \$0.10/crash, and β_k = \$0.00/discomfort-weighted-km (indicating no value for physical discomfort).

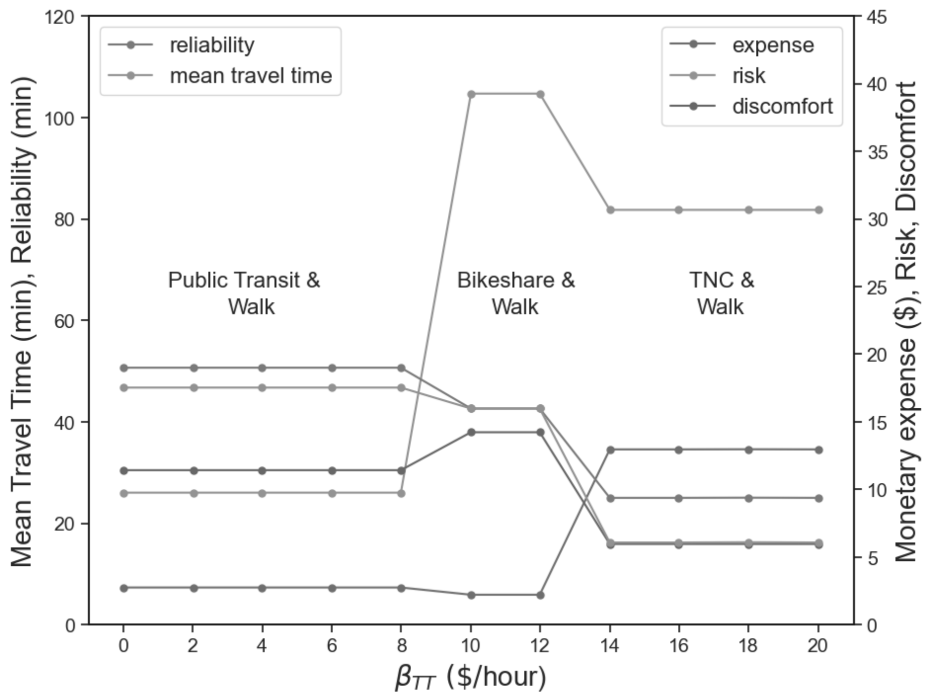


FIGURE 5: Individual cost attributes and mode combination along the optimal path as a function of β_T.

Figure 5 illustrates the sensitivity of the optimal path to changes in β_T, underscoring the influence of cost sensitivity on modal options. At lower values (\$0.00/hour to \$8.00/hour), the path includes walking and an express bus route, offering lower monetary expenses in exchange for higher mean travel time and reliability (95th percentile travel time).

As β_T increases to \$10.00/hour, the optimal path shifts to bikeshare and walking, resulting in slightly reduced expenses due to the lower usage price of bikeshare compared to fixed-price public transit. However, the path's risk and discomfort measures rise, reflecting the increased risks and physical effort associated with active transportation. The substantial increase in the risk measure suggests insufficient bikeway infrastructure along the chosen path. Although bikeshare offers shorter waiting times compared to buses, its travel time remains relatively high when compared to a Google Maps query suggesting a shorter 24-minute personal bike ride between Larimer and Central Oakland. This is due to the fact that the specified origin requires a lengthy walk to reach the nearest bikeshare station.

For β_T between \$14.00/hour and \$20.00/hour, the optimal path includes TNC and walking. The path's estimated monetary expense increases about five-fold, though all other cost factors expectedly decline since TNCs offer direct O-D travel after an initial waiting period. These results suggest that the high prices of TNC vehicles are justified for traveler groups with high values of travel time, since TNCs are usually quicker, more reliable under light traffic, more comfortable, and safer. Consequently, policymakers whose goals are to replace TNC vehicle trips with transit or active modes may choose to invest in micromobility safety infrastructure, new express bus routes, or additional bikeshare stations. For users with active mode restrictions, transit agency partnerships with TNC companies could be a plausible option.

Case Study 2: Sensitivity Analysis of Departure Time

The second case study investigates the sensitivity of accessibility to departure time, which is particularly relevant for regions with low-frequency transit service. The following parameters were used: β_T = \$12.00/hour β_r = \$15.00/hour, β_x = \$1.00/\$1.00, β_r = \$0.10/crash, and β_k = \$0.00/discomfort-weighted-km.

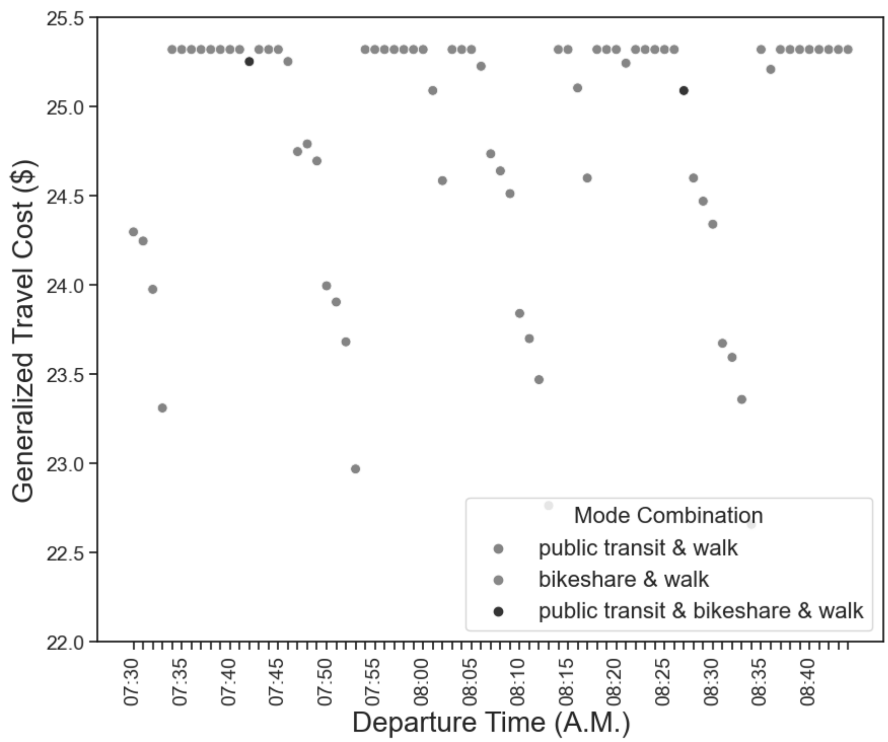


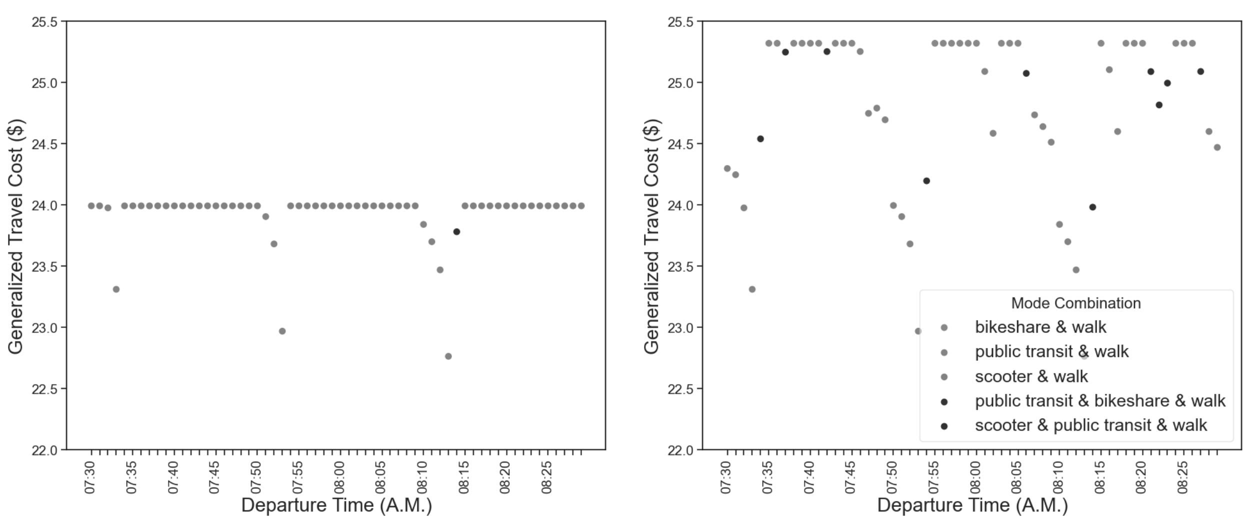
FIGURE 6: Generalized travel cost as a function of departure time.

Figure 6 illustrates the generalized travel cost and mode combination of the optimal path during the morning period. We observe a pattern indicative of schedule-based transit: for some departure time windows (e.g., 7:30AM-7:34AM, 7:46AM-7:53AM), the generalized cost decreases with time as a bus nears its arrival and waiting time for the bus decreases. Immediately after the bus arrives, the bikeshare mode is advantageous for a period until another bus arrival is imminent. The graph also shows two departure times (7:42AM and 8:27AM) for which optimal path involves transit, bikeshare, and walking, exemplifying the supernetwork model's ability to identify multi-modal paths. A comparison between the transit, bikeshare, and walking path and the bikeshare and walking path reveals improved travel time, risk, and reliability metrics for the former. This is likely due to the use of an express bus line with fewer stops and a dedicated bus lane. The fact that this mode combination is rarely selected suggests that bikeshare stations are not well connected with bus routes in the region surrounding this O-D pair.

Moreover, the study's findings highlight how emerging modes such as bikeshare can augment accessibility during periods when transit service is infrequent. In this example, the presence of bikeshare sets a practical upper limit on the generalized cost just below $25.50. The bikeshare option allows travelers to forgo longer waiting times for a bus that operates on a fixed schedule, thereby providing a more robust accessibility solution that does not depend on the time of day.

Case Study 3: Sensitivity Analysis of Scooter Usage Pricing

The objective of the third case study was to determine if lowering scooter prices could improve accessibility between the selected O-D pair. We conducted this analysis because the results of the second study revealed that, for the population group characterized by this set of β parameters, scooters were not a viable mode option at their current rate of $0.39 per minute. Figure 7, displays the optimal path results of two different usage rates: $0.10 per minute and $0.05 per minute. Note that the $1.00 fixed fee per ride was also removed for this study.



(a) Scooter price per minute: $0.05

(b) Scooter price per minute: $0.10

FIGURE 7: Comparison of generalized travel cost as a function of departure time for different scooter per-minute usage prices.

Figure 7a shows that the mode combination of scooter and walking is almost always optimal when scooters are priced at the very low rate of $0.05 per minute. The only exceptions are the few instances when almost no waiting time is required by the bus. At $0.10 per minute (Figure 7b), the optimal path is heavily dependent on departure time. Figure 7b is similar to Figure 6, though multimodal paths consisting of scooter, public transit, and walking replace bikeshare and walking paths in eight instances. In these cases, scooters are used as a first/last-mile solution that allows travelers to take advantage of a larger array of transit routes. The analysis suggests that scooters, if priced affordably, can complement transit in two ways: 1) spatially by increasing bus stop services areas, and 2) temporally by offering an alternative during schedule deficits. We also tested the scooter price of $0.15 per minute, but the results mimicked those displayed in Figure 6, which indicates that scooter rates must be greatly reduced for the mode to be part of the theoretical shortest path between this O-D pair.

CONCLUSION

In this research, we introduce a multi-cost, multimodal network modeling framework to evaluate time-dependent accessibility. The network model includes the personal vehicle, TNC, carshare, public transit, personal bike, bikeshare, scooter, and walking travel modes. Each edge is assigned a time-dependent generalized travel cost that is a function of monetary expense, day-to-day average travel time, reliability, risk, and discomfort. Differences in population groups are accounted for by way of differential treatment of cost sensitivities in the travel cost function. Movement-based node costs are also incorporated.

The network model can be used to determine and compare accessibility metrics across time and space. We illustrate the model's flexibility on a large-scale transportation network in Pittsburgh, PA, highlighting the flexibility of the model via three case studies. The first two studies showcase the model's ability to assess the current state of a transportation network. Specifically, we investigate how the mode and cost breakdown of the optimal path vary in accordance with value of time and origin departure time. In the third study, we use the model to test the effects of proposed pricing changes to scooters, finding that scooters can complement schedule-based transit if priced affordably.

In future work, we will develop additional use cases for the network model. A possible application involves determining the utilization pattern of the network for different modes and facilities. This involves aggregating the shortest paths for individuals across various O-D pairs. This analysis could enable decision-makers to make informed choices on mobility service investments based on accessibility goals and budget limitations.

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