Impact of Transit Priority and Transit Autonomy on Vision Zero

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Abstract

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Vision Zero—the goal of eliminating traffic fatalities and serious injuries—is proving to be challenging for cities. At the same time, the field of autonomous vehicles (AVs) is rapidly evolving and will profoundly affect transportation systems. With a reduction in perceived cost of travel time, AVs will likely increase traffic. This thesis investigates how Seattle can pursue its Vision Zero goal in the context of the rollout of AVs. Informed by practitioner interviews, I modeled two key interventions: converting all buses to driverless operations across several different network designs, and implementing ubiquitous transit priority. I used the Puget Sound Regional Council's Household Travel Survey data to create a multinomial logit model that predicts travel behavior. Then, I simulated trips accounting for changed transit travel time and the effects of congestion. I found that both interventions can reduce transit travel time by up to 33%, while transit mode share increased by only 2.5pp. The congestion effects of AVs and transit lanes reduced the average speed of vehicles in the city, resulting in a scenario that yields up to a 35% reduction in fatalities. These results suggest that policymakers should pursue policies that manage vehicle speeds first and foremost, and that faster, more frequent transit can be an effective way to keep people moving even if their personal vehicle is speed-constrained.

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INTRODUCTION

American cities today face many challenges in providing a safe and healthy environment for residents of all ages. In 2024, nearly 40,000 people in America were killed by motor vehicles on streets (National Center for Statistics and Analysis, 2025). Car crashes are a leading cause of death for younger people (National Highway Traffic Safety Administration, n.d.), and in addition to the fatalities, car crashes cause serious injuries that can dramatically impact people's quality of life. This level of traffic violence is not a given; countries like Norway have demonstrated that this high rate of mortality is avoidable (Elvik & Nævestad, 2023)—Norway has 3.7 fatalities per billion VMT (Flotve, 2025) (Statistics Norway, 2025) compared to 12.6 per billion VMT in the United States (Federal Highway Administration, 2025). This high rate of fatalities and injuries is an artifact of the transportation systems that American cities have been building for over a century, and specifically, the overwhelming priority that the built environment provides for personal motor vehicles.

Recent years have seen the automotive industry propose privately owned or rideshare-style automated vehicles as the solution for Vision Zero. Companies like Tesla and Waymo propose that vehicular autonomy will make it less likely for cars to hit pedestrians. In this thesis, I do not attempt to challenge that assumption; although there are examples to the contrary, I consider it a given that automated cars can reduce road deaths. However, the question is not whether it is possible for only one approach to achieve Vision Zero, but whether that approach will maintain (or even enhance) equitable mobility for residents. Fundamental limitations on street width mean that a city full of cars that are affordable, personal, and autonomous may have worse congestion than the cities of today. That is because automated vehicles will reduce the perceived cost of travel. Economic theory suggests that when something becomes less expensive, there will be more of it (Naumov et al., 2020). Thus, AV-driven induced demand could reduce average vehicle speeds in cities. This will make it more critical than ever to have prioritized street space for higher-capacity vehicles like buses to maintain mobility.

Autonomy applied to public transit may unlock benefits for cities. Today, operator labor constitutes more than half of the operating costs of buses. If this cost were reduced or eliminated, and all other costs scaled freely with the number of vehicles, agencies could triple their service hours by adopting automated buses (see the Understanding Existing Bus Driver Costs section for the full calculation). Alternatively, cities could run denser and more varied routes with smaller vehicles, reducing the distances that riders must walk. Use of transit lanes and transit signal priority (TSP) can improve the reliability of bus service, and they can provide logical guardrails for automated buses since the buses contend with less traffic and thus fewer varied scenarios. Improved service would make buses more competitive with cars than they are today, driving a mode shift towards public transit and maintaining mobility while congestion increases. With more transit riders and slower traffic overall, cities like Seattle will be able to better achieve their Vision Zero goals.

Research Question

This research project examines two interventions in a world of ubiquitous private automated vehicles: autonomous public transportation and physical priority for public transit in street infrastructure (put simply: bus lanes and TSP). Specifically, the research question I answer is: How can a combination of automating public transit and allocating street space to buses help Seattle achieve Vision Zero while maintaining its transportation goals?

Contribution of the Study

Although AVs are seeing rapid increases in adoption around the world, the application of autonomy to buses has been examined far less than autonomy for personal vehicles. Moreover, cities like Seattle have no strategy for adoption of automated buses (ABs) and are not preparing plans to deal with the induced demand from AVs (A. Shahbazian, personal communication, February 2026). This thesis presents original interviews about transit autonomy from experts in four different cities. It adds an in-depth quantitative impact analysis of a full-scale AB network paired with ubiquitous transit priority, using insights from these interviews. Whereas most AB literature is about cost or ridership, this thesis adds the safety dimension, examining the impact on Seattle's Vision Zero goal.

Organization of the Thesis

This thesis contains a literature review covering existing research on the topic, followed by the results of four interviews conducted for this thesis. Then, it describes the methods for creating the mathematical model this thesis uses, applies the model, and presents the results. Finally, this thesis discusses the implications of these results and its own limitations.

LITERATURE REVIEW

The core premise of this thesis is that by reallocating street space and improving the quality of transit, the City of Seattle can increase the number of people riding on public transit. More people riding public transit, and fewer lanes for cars (thus slowing them down), will in turn reduce the number of injuries or fatalities caused by traffic. These are not the only ways to shape mode choice: traffic calming, congestion charges, improvements to at-stop or on-vehicle rider experience, changes to vehicle fees, or adjusting speed limits (potentially with automated enforcement) could all have impacts. However, for the purpose of this thesis I am focusing on street space and transit signal priority because of the rich data available about these interventions. Thus, the first step is to verify these linkages in existing literature.

Linking Travel Time and Ridership

As more buses are added to a network, riders wait less time and thus complete their journeys more quickly. Since travel time is a key factor in mode choice, better frequency results in more people riding the bus. This has been shown across many different cities in the United States: studies find that as agencies add buses, they get more riders. However, studies also found diminishing returns: for each incremental bus added, there is not necessarily the same number of new riders (Berrebi et al., 2021). This implies that the best approach for increasing service may not be solely to add more buses to existing routes.

For this thesis, I need to understand the exact coefficients of automated transit models, and at least one study has already calculated these values for autonomous shuttles (Klinkhardt et al., 2024). It found a slight bias against automated transit: the value of travel time for automated transit is €14.42, and €11.70 for human-driven transit (here representing what people would pay to reduce travel time by one hour). This bias could be due to unease around new technology, which often fades over time. Another study looked at factors like income, whether a family is car-free or not, and other demographic factors to predict transit ridership (Tang, 2023). Interestingly, it found that wealthier commuters were more likely to choose cycling than driving, but less likely to choose public transit over driving. As a caution, one study found that many of the levers that influence ridership are outside of the control of agencies because they are based on physical geography of an area, such as a city with inconsistent elevation versus one with a flat, grid-like structure (Taylor et al., 2009). Other trends, such as rideshare volume and micromobility using shared e-bikes, do not yet have a statistically significant impact on mode choice; I treat these as outside the scope of my mode-choice model (Boisjoly et al., 2018).

The impact of transit travel time on ridership, which is what this thesis evaluates, can be massive. In San Francisco, one study found an elasticity of -2.5, meaning a 10% reduction in travel time resulted in a 25% increase in ridership (Boarnet et al., 2024). However, this effect can be nonlinear. Travel time savings are not as relevant for trips less than 15 minutes, but as the journey time increases, so too does the influence it has on ridership (Pinjari & Bhat, 2006). Another factor that is unique to transit is transfers. One study found that requiring a transfer added an equivalent time penalty between 9 and 20 minutes (Dong et al., 2022). Moreover, not all travel time is equal: time outside of a vehicle (OVTT) has a different impact than time inside the vehicle (IVTT). Unfortunately, the literature is not in agreement on this impact. Some studies found that IVTT has more impact (Dell'Olio et al., 2012), whereas others found OVTT up to 1.9x more impactful (Yan et al., 2019). There is a meta-analysis of these values (though it focuses on the UK and is 15 years old at this point): it concluded that OVTT creates a penalty of 1.7x compared to IVTT (Abrantes & Wardman, 2011).

Finally, from a methodology perspective, most of these studies use a logit model for determining mode share. In recent years, machine learning has become more popular and offers an alternative. However, a 2020 study found that while machine learning may offer better prediction accuracy compared to traditional logit models, they are much more difficult to interpret (X. Zhao et al., 2020). Thus, I selected a logit model for this research thesis. It is important to have good explainability as I adjust coefficients in different alternate scenarios. For determining the weight of origins and destinations, gravity models are a common approach (D. Zhao et al., 2024), but instead this thesis uses Puget Sound Regional Council's (PSRC) simulated travel data. PSRC, based on its survey, simulates trips on a parcel-by-parcel basis, allowing an actual number to be calculated for the number of trips from each tract to all other tracts.

Linking Travel and Safety

The link between travel patterns, specifically safety, and VMT and speed, can also be found in literature. A 29-year longitudinal study of the 100 largest cities in the United States examined several potential inputs to the rate of traffic fatalities, such as weather, year, and mass transit ridership. This study found that as transit usage increases, road fatalities decrease, even when controlling for all other factors (Stimpson et al., 2014). This correlation persisted through decades of changing ridership and fatality numbers. A recent report from Australia found similar results (Raftery, 2023). This study raises one potential challenge: as more people opt for transit, congestion decreases—and faster cars mean when there are accidents, the injuries are much more severe.

Relatedly, it is known that there is a direct relationship between traffic volume and fatalities: the more traffic there is, the more accidents there will be (Hughes et al., 2023). The strength of this relationship has an elasticity of approximately +1 (a 1% increase in VMT results in a 1% increase in fatalities). Yet, during the COVID-19 pandemic, serious injuries increased even when there was reduced traffic across the world because of the increase in speeding and other risky driving behaviors (Ebrahim Shaik & Ahmed, 2022). Even if congestion increases the number of accidents, it can decrease fatalities because vehicles move more slowly when there is heavy traffic (Hughes et al., 2023). Moreover, public transit is inherently safer than personal vehicles for the people traveling inside the vehicles. This report determined that while the relationship is not straightforward, as more people switch to transit, safety will ultimately improve.

Impacts of Automated Vehicles

The research on autonomous personal vehicles (AVs) in terms of safety suggests that AVs are safer than cars driven by humans. One study has found that the capabilities of Automated Driving Systems (ADS) are better at avoiding accidents in most situations (Abdel-Aty & Ding, 2024). The exceptions to this are ADS's reduced performance in dawn, dusk, and turning conditions.

Tesla claims that their cars are 5x safer than human-driven vehicles (excluding highways) (Tesla, 2025), although these statistics are for their Level 2 driver-assistance system, not Level 4 fully-automated vehicles. For Waymo, after 56.7 million miles of driving, a peer-reviewed study found an 80% reduction in crashes with reported injuries compared to human driving (Kusano et al., 2025). There are studies that quantify the societal benefit of AVs at $4,000 per vehicle annually, when accounting for things like time saved, reduced parking infrastructure, and fewer crashes (Fagnant & Kockelman, 2015). Recent estimates forecast that over 1 million injuries could be avoided with just 10% adoption of AVs by 2030 (Malhotra et al., 2026).

Ultimately, the evidence needed to truly quantify these effects is limited, so further research will be needed to validate the conclusion that AVs can be safer than human-piloted cars over time. In this thesis, I do not attempt to model AV crash-avoidance benefits directly. Instead, I hold per-mile vehicle safety constant and model how effects like changes in VMT and speed affect safety outcomes.

Unfortunately, there is a major societal risk. Because of the potential convenience of automated vehicles, they may pull enough people away from public transit to cause a "death-spiral" in transit agencies (Naumov et al., 2020). This is because automated vehicles reduce time-cost for drivers: when someone can use transport time more productively, they can focus on other tasks and do not mind if trips take longer. Naumov's "death-spiral" comes into play because as people switch to AVs from buses, transit agencies see reduced revenue and investment, are forced to decrease the quality of service, and thus lose even more riders to AVs, which increases revenue loss, and so forth.

Not having to drive oneself was found to reduce the VOTT by 59% in the Seattle area (Jabbari et al., 2024), and I am using that as a proxy for automated vehicle perception. The possible disruption of public transit is likely to have an inequitable impact to people of lower income (Jiang et al., 2022). This will make it critical to find ways to prioritize public transit over private automated shuttles. One alternative approach is to pass the full cost of AVs to the riders. One study found that if this did not happen, VMT would increase by 20%, but if riders had to pay a $1.65/mile fee to use AVs, VMT would decline, reducing congestion and increasing transit ridership by 140% (Childress et al., 2015) (the $1.65 number was based on the total estimated cost for the user and the system for rideshare services).

Today, Washington state has a minimum pay rate of $1.50/mile for ride hailing companies' drivers (Drivers Union, 2026). If this price could be maintained without drivers, that could be sufficient pricing to mitigate congestion and transit ridership effects. Unfortunately, efforts to implement fees for road use in the United States have been limited by strong popular opposition—as of 2026, there is only one instance of congestion charging: New York City. Seattle studied congestion pricing in the past, but never got beyond the first phase because of lack of political support (Seattle Department of Transportation, 2019). It may be politically untenable to maintain a $1.50/mile fee rate for the purpose of congestion reduction, once the driver is automated. Another concern with such a fee is that if AVs are safer than human-driven cars, it could be unethical to charge a premium on safety.

Autonomous Public Transit

While automated buses (ABs) have considerably less adoption than AVs, there have been dozens of pilots of ABs around the world (though many of these pilots are no longer running) (Mahmoodi Nesheli et al., 2021). These are universally small-scale and usually in tightly-controlled environments. Many implementations include a safety officer onboard, or are limited-time pilots such as the ABs rolled out in Madrid in September 2025 that only ran during scheduled conventions (Thykjaer, 2025). These rollouts often have growing pains due to the nascent technology; for example, riders and safety officers complained about “hard” stopping when the ABs believed there was something in front of them. They can also be confused by weather, such as fog or snowbanks, but these challenges will be reduced in the coming years by technical progress (Anund et al., 2022).

Despite the limited adoption, there are still numerous reports available that focus on both benefits and perceptions of the services (Hadid et al., 2025). A 2020 study evaluated the costs and benefits of battery-electric ABs in Austin, TX (Quarles et al., 2020). This study demonstrated that, while the cost-benefit ratio for using battery-electric vehicles over diesel-powered vehicles is questionable, automation produced enough savings to offset its costs. The study, limited to one city, did not evaluate any changes to the network or service, but simply evaluated a like-for-like replacement.

A 2024 study evaluated rider perceptions of and willingness to ride ABs in Helsinki, Finland (Koskinen et al., 2024). The conclusion of the study was that, while there were still obstacles in the way of obtaining rider trust in ABs, these could be overcome by education and time. There is also latent risk due to pandemic concerns: if there were a similar outbreak, adoption of automated buses would be slowed by riders selecting against public transit (Cheng et al., 2025). One study looked at actual driverless shuttles in Oslo, Norway, and asked people before and after riding about their perceptions. It found that people responded positively both before and after, yet raised concerns about abrupt stopping and speed (they wanted the buses to go faster, independently of power source) (Mouratidis & Cobeña Serrano, 2021). Yet, the overall theme was that riders wanted buses to be more frequent—however that might be achieved.

A 2025 study took a more focused look by evaluating the replacement of just two city bus routes with autonomous buses (Gusev & Gilroy, 2025). This study evaluated different configurations using both full-size buses and smaller micro-shuttles. Although the study was constrained in scope and scale, it did demonstrate a viable solution to a targeted problem.

ABs do not necessarily need to look like traditional buses with drivers (large coaches measuring at least 40 feet long). One of the most unique ideas is that ABs could consist of modular trailers which would then be joined or separated based on demand. A joined bus could run in a denser corridor, and the bus would split into individual modules that serve lower-density areas (Zhang et al., 2020). Some research focuses on connected shuttle-like vehicles rather than full-size buses: smaller vehicles provide greater route flexibility but can more easily become crowded as passenger volume increases (Xu & Zheng, 2024). This reality-based virtual study found that riders were hesitant to board an autonomous shuttle that had more than 75% occupancy, preferring to wait longer for a full-size bus than to board a shuttle that still had capacity. This indicates that switching to much smaller vehicles may reduce overall efficiency of the system.

Because of the increased flexibility and decreased size, the timetabling of smaller ABs could be different compared to that of full-sized vehicles. For example, transit planners generally want to avoid skip-stop patterns because they speed up service but reduce frequency at each stop. However, if an agency could increase frequency using ABs, skip-stop patterns become more viable. That said, the impact is modest: one study found a 1.8% reduction in overall travel time (Cao & (Avi) Ceder, 2019).

The general perception by transit practitioners is that there is still a lot that needs to happen before ABs can roll out at scale; as a result, some agencies are looking at autonomous shuttles as a different transit mode than full-scale autonomous buses. The World Economic Forum proposes that automated shuttles can act as feeders to a high-capacity fixed-route network (Mezghani & Zhao, 2024). By virtue of being a separate mode that can focus on low-volume and low-speed scenarios, agencies can use autonomous shuttles to fill gaps in existing networks—especially as an option to serve the last mile. There is a mix of opinions whether these smaller shuttles should have fixed or flexible routing, but flexible routing appears to be especially beneficial for smaller-sized vehicles in lower-density areas (Khani et al., 2024). That said, if the key concerns agencies have regarding autonomous shuttles—such as safety, reliability, speed—were to be fully addressed, it would require much less effort to subsequently adopt full-size ABs (Diba et al., 2025).

Finally, the four-year research plans by the Federal Transit Administration (FTA) validate some of the known gaps in research, specifically calling out the need for further investigation into service patterns and operational impacts (Torng et al., 2024).

Automated Bus Concerns

In addition to these studies, there have been several less-detailed reports covering agencies' and transit workers' unions' concerns regarding autonomy. For example, a report from the Transport Workers Union of America claims that ABs will be unsafe, difficult to ride for those with limited mobility, and provide an overall poorer experience for riders (Transport Workers Union of America, 2022). These concerns are likely able to be mitigated: agencies that have adopted ABs, such as in Tampere, Finland and Seoul, South Korea, have successfully addressed safety and mobility obstacles and receive high satisfaction ratings from riders (H. Liimatainen, personal communication, April 14, 2026) (S. Lee, personal communication, March 2026). That said, this is the type of pushback that agencies will have to prepare to address as they make this transition.

Once the driving of the vehicle itself is no longer a factor, the next critical need for riders is on-board security. There are numerous driverless trains around the world and studies therein typically find that riders are comfortable, as long as there is some sort of remote assistance available (Cogan et al., 2022). For decades, there have been driverless urban metros throughout the world without persistent on-board safety officers, such as in Lille, France or Vancouver, Canada. There, rider safety is maintained by remote operation and roaming staff, and this approach reduces staffing costs by 70% (Cohen et al., 2015). Critically, the roaming staff model breaks the 1-for-1 requirement of a transit officer to a vehicle, although it does not eliminate the need for support staff entirely. More broadly, there are many other types of unattended systems that riders are comfortable with—people mover systems, urban gondolas, and aerial trams. That said, even in systems that have drivers, the driver is typically not tasked with rider safety.

Automated Bus Existing Implementations

Although there are numerous pilots of ABs in some form, there are a few locations with more advanced implementations running on public streets with mixed automobile and pedestrian traffic. In just the second half of 2025, new implementations include:

1. Gothenburg, Sweden: in August 2025, Gothenburg introduced a seven-stop 2.5-mile route (May, 2025). This is a full-size bus traveling between the central station and a nearby district.
2. Seoul, South Korea: after several years of pilot programs, Seoul introduced a small, 9-seat fully-automated bus, Cheonggye A01, that services a 3-mile circulator route on ordinary surface roads in September 2025 (Lee, 2025). Although this service does not have a driver, each shuttle has a dedicated employee who can assume control as needed.
3. Tampere, Finland: in November 2025, Tampere launched the first driverless bus that collects fares (Yle News, 2025). This is also not a full-sized bus: it only holds 12 passengers and travels just 0.6 miles.

None of these pilots are in the United States. The FTA has a published list of every FTA-funded project related to ABs, but none of the full-scale implementations are live yet. There are examples of automated driver assistance, or use of automated rideshare vehicles (for example, Waymo) in conjunction with fixed route transit, but nothing on the scale of the three implementations noted above (Federal Transit Administration, 2024c).

Transit Priority

Although a robust network of transit-exclusive lanes is uncommon in the United States, the literature generally finds that bus lanes improve travel time (and thus attract more riders to switch from driving). One study found that bus lanes can provide an average savings of 10 minutes over a 60-minute bus ride (De Brito-Filho & Oliveira-Neto, 2025). The other main type of priority for buses is transit signal priority. This is when traffic signals respond intelligently to when a bus is approaching (either by holding a green light or turning green sooner). TSP can reduce travel time by more than 8% (Ali et al., 2023).

Other research has provided evidence of a causal relationship between bus lanes and road safety. This effect has nothing to do with mode share; instead, the physical presence of bus lanes has a traffic calming effect (Joshi et al., 2024). Reallocating a lane for exclusive use by transit vehicles reduced 85th percentile speeds by 3.7 mph, which can have a significant impact on fatality rates. One report indicated that results are context-sensitive and impacted by other changes made to the streetscape (Felix, 2022).

The type of bus lanes can have different impacts on safety. Generally, the “best” transit lanes are those that run with minimal interference from traffic. One way to minimize traffic is to run in the center of the road instead of along the curb, avoiding traffic that is turning right. In Seoul, median bus lanes both sped buses up and reduced accidents (Pucher et al., 2005). Center-running lanes signify that platforms are built in the center of the road, requiring pedestrians to cross active traffic for both directions (whereas with typical curbside lanes, only one direction requires a crossing). This has a negative safety impact, with one study finding that 30% of pedestrians will cross the street on a red light to access the bus stop (Gitelman & Sharon, 2025).

One of the most popular objections to transit lanes is that taking space from cars will increase congestion, which people do not like because of the time-cost. The concept of “induced demand” is well known in urban planning. Recent studies have continued to support that adding more travel lanes leads to more congestion and traffic, including a 55-year long study confirming the strength of that correlation (Bucsky & Juhász, 2022). What is less known is that reducing the number of lanes for general purpose traffic can reduce overall VMT—a phenomenon referred to as “traffic evaporation” (Nello-Deakin, 2022). In fact, some studies go so far as to say the number of lane-miles for cars is the main determinant of VMT (Duranton & Turner, 2011), finding no impact by public transit availability, although the literature is not unanimous on this.

Transit signal priority (TSP) offers another way to speed up buses and does not require repurposing street space from cars. TSP can speed up bus service by 8%–13% (Ali et al., 2023), and with modern connected buses and signals, has fairly low operational costs compared to previous technologies (these historically required infrared transmitters and receivers on buses and traffic signals, respectively).

BACKGROUND

Automated Bus Case Studies

The first task is to understand the characteristics of autonomous buses in real-world scenarios. This data is used to inform the actual quantitative results that follow and was collected via interviews of people who are practitioners and experts in transportation autonomy. These interviews were conducted via in-person, video call, and email correspondence, and took place between March and May 2026. I created a guide of 13 questions to direct conversations, but did not explicitly insist on answers for every question (see Appendix B for the full list of questions). The video call was recorded, and otherwise notes were taken.

Seoul, South Korea

The first interview was with Sujin Lee, PhD, Head, Division of Advanced Future Transportation (DAFT), Bureau of Transportation, Seoul Metropolitan Government, and was conducted by Professor Christine Bae of the University of Washington.

Seoul has been planning their AB strategy since 2019 when Mayor Oh Se-hoon shared his intention to bring the world's first autonomous bus to Seoul (S. Lee, personal communication, March 2026). Equity was part of the initial strategy for this project. From the beginning, the goal was specifically to improve transportation options for vulnerable populations. This included people without cars or who worked shifts in off-peak hours (such as office cleaning crews). The first pilot started around 2020 and required significant adaptations of the law, including permitting vehicles that completely lacked steering wheels.

Seoul then expanded the pilot with Night Owl Buses (올빼미, olppaemi) in 2023, and early dawn buses, DongHang (동행) in 2024. These buses are not unstaffed, however; the night buses all have a security guard on board for safety reasons.

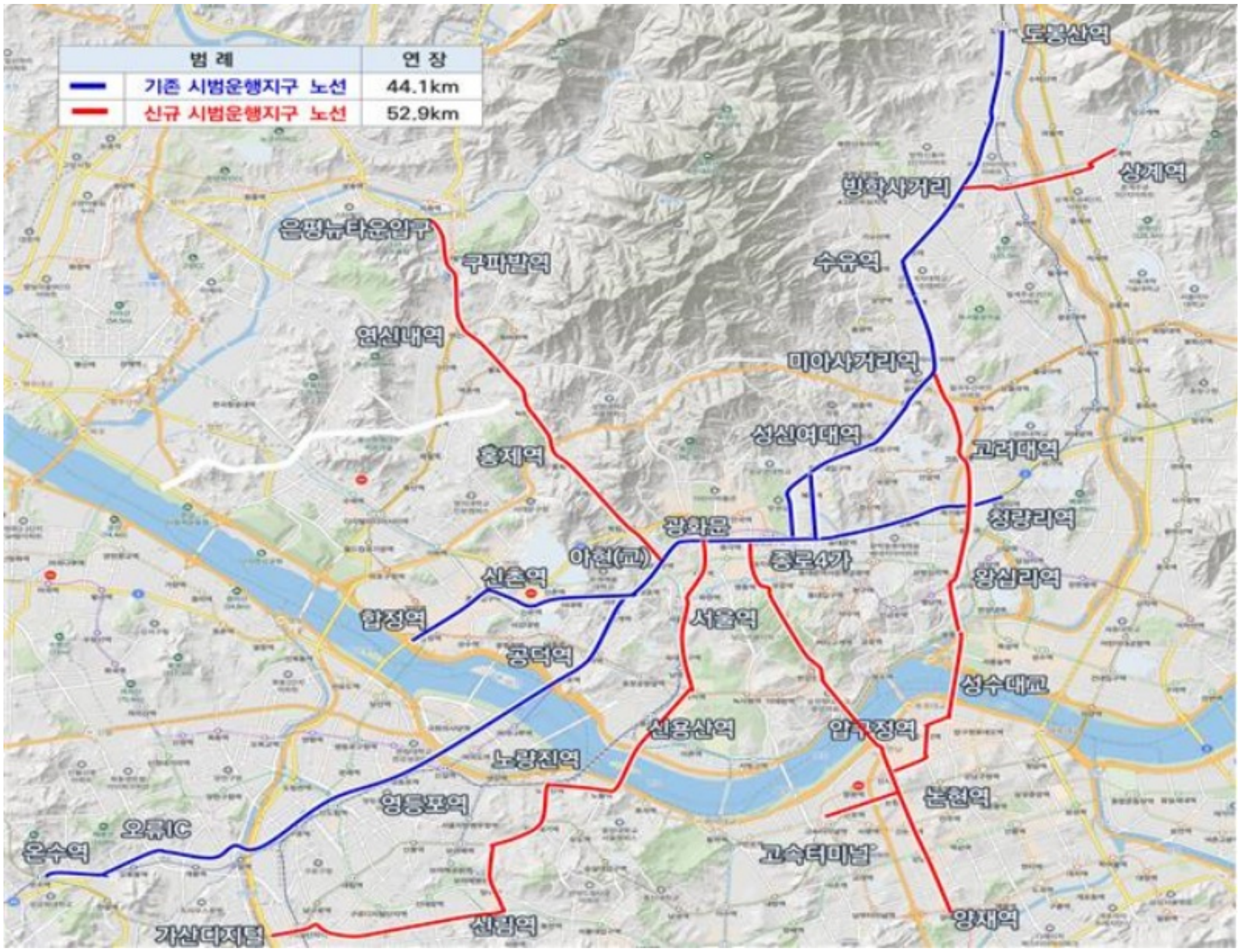

Figure 1 *Map of Automated Bus Pilots in Seoul (Korea Policy News, 2024)*

From an infrastructure perspective, Seoul's ABs almost exclusively use bus-only lanes except Cheonggye A01. Seoul has an extensive network of such lanes, and there are two reasons for using this approach: 1) these buses go faster than cars in terms of speed, but also 2) the safety concerns are reduced because there are fewer points of contact with other vehicles. Given the complexity of road conditions in Seoul and the nascency of this technology, the more variables that can be reduced, the better. These buses also use Seoul's "Cooperative Intelligent Transportation System" which communicates with traffic signals and provides real-time data on different components of the transportation system.

There is one route which does not have bus lanes due to the narrow road width. Because of the complexity of this environment (frequent traffic lights and high pedestrian traffic volumes), this bus is limited to 30 km/h (18.6 mph).

Labor organizations have raised some concerns in terms of job loss. However, agencies tend to face a labor shortage and already have difficulty finding bus drivers (there may be a cultural aspect to this as well since driving a bus is an undesirable occupation). Ultimately, this drives high operational costs for agencies: in Seoul, bus drivers account for 70% of bus operating costs. Another aspect of the labor concerns is the imminent arrival of AV taxis. Their use is now permitted in specific areas (Gangnam) as of 2026, but only 200 licenses are projected to be issued this year which is small in comparison to a total taxi driver population of 70,000.

The up-front capital costs for an AB are higher than the typical bus. An ordinary bus typically costs around $230,000 (in 2026 US dollars)—whereas an AB is approximately $530,000. In South Korea, this cost delta is partially covered through government subsidies for electric vehicles.

Overall perception of the AB service has been positive. This is aided by the fact that they are adding service for a population that currently lacks good transit options (night and early morning riders). These riders can now take public transit instead of relying on taxis which are expensive. Given the success of the service, additional routes are planned for rollout in 2026 and 2027, such as the A148 which was launched in April 2026 (Seoul Metropolitan Government, 2026). The strategy from the city is that ABs will replace conventional buses over time, although there will be a long period of coexistence. Something slightly different in Seoul compared to many American urban areas is they have a mix of larger buses (carrying 40–50 passengers) and smaller community neighborhood buses (25 passengers). These community buses provide last-mile service from subway stations into their respective neighborhoods. This dynamic plays into their strategy for replacement with ABs. Although they plan to transition away from drivers, their long-term strategy is to retain a human assistant seat to deal with passenger requirements.

Tampere, Finland

Tampere is the third-largest city in Finland with a population of about 260,000 people (City of Tampere, 2026). This interview was with Heikki Liimatainen, Professor of Transport and Logistics at Tampere University, conducted by me. He has been working on various phases of automated bus pilots for the past 10 years (H. Liimatainen, personal communication, April 14, 2026). The latest pilot is an automated shuttle that travels about one mile. It has eight seats facing each other and a central open area that can accommodate a wheelchair similar to Cheonggyecheon AB.

Tampere's automated bus is operated by a company called Remoted, and they contract directly with the public transit agency to provide the service. This shuttle is fully integrated into the transit agency's payment and scheduling system—for example, it shows up in their real-time GPS tracking. Because Remoted is contractually obligated to provide this service, if there are any issues with the shuttle, they have a human-driven bus that can act as a backup.

This AB runs in a remote portion of town at the end of a tram line on 30-minute headways. As a result, there are not any dedicated bus lanes, nor any traffic signals for the bus to use. Tampere built a bus turnaround for the shuttle to reverse just past the station, but this is the only dedicated right-of-way allocated to the vehicle.

Today, a safety officer is always present on the shuttle, but the plan is for fully remote operation. They will have a remote operator in a centrally-located datacenter (although the operator will still be in the country of Finland). The major operational challenge is the weather. Electric shuttles have poor battery performance in the cold, and the camera system has difficulty identifying road boundaries in the snow. That said, Prof. Liimatainen was optimistic about the speed of software iteration: even in the short time the shuttle has been deployed, there have been software updates that improve how the shuttle can be remotely operated.

Implementation was quick and straightforward—it only took 2.5 weeks to get the shuttle set up on a route and serving passengers once the equipment arrived (although the acquisition of the shuttle in the first place was challenging because they specifically needed a vehicle that could be remotely operated in winter conditions). Passengers are happy with the service: a survey on the shuttle received about 45 responses, and passengers responded that they feel safe and trust the autonomous service. Two-thirds of riders said that their perception of the service improved once they rode it. The primary criticism was the speed of the shuttle. It is limited to running at 25 km/h (15.5 mph), while the speed limit for the street is 40 km/h (24.9 mph). Given the short length of the route, the total time impact is low, and the goal is to speed up the service in the longer term. However, the fact that the vehicle is so conservative in terms of speed increases risk of being rear-ended given its braking frequency.

The regulatory environment was positive: there were some rule changes required but the Traffic Safety Authority has been enthusiastic about evaluating new technologies. At this point, the autonomous shuttles are mostly supplementing the existing routes rather than fully replacing existing services. Next, the city is considering adding a second route as a neighborhood shuttle, such as a previous pilot in Lahti, Finland that provided service between an elderly community and the city center. Strategically, the vehicles that are being automated are smaller vehicles instead of larger articulated buses. This may change in the future, but the bifurcation will remain in place for some time.

Gothenburg, Sweden

The third response was for Gothenburg, Sweden. Anette Jönsson, Project Manager—Autonom buss i Gårda—is responsible for the rollout of the automated bus program there and replied via email. This city is the second-largest in Sweden and has a diverse public transit network (Visit Sweden, 2026).

Unlike other locations that are piloting in very controlled environments, Gothenburg has explicitly chosen a complex route to maximize their learnings with automated buses (A. Jönsson, personal communication, April 2026). They specifically were looking at a route that had a high need and high complexity in the urban environment with higher volumes of vehicular and pedestrian traffic, as well as many intersections. They chose this approach because Sweden had already piloted ABs in low-traffic environments, so the function of this pilot was to get as much real-world experience as possible.

Despite their prior experience with AB pilots, there were organizational challenges in adoption, partly because of the large number of parties involved, including the city, the transit authority, the operator, the vehicle manufacturer, and the technology supplier. Moreover, there have been demanding requirements from EU regulators, establishing a high bar to remove the safety driver.

Like other services, one of the main challenges in terms of the drive experience is abrupt stopping; otherwise, overall feedback on the service has been limited so far. They plan to continue to expand ABs throughout the region assuming the pilot's goals are met, and are looking at ABs to add service and improve accessibility due to driver shortages.

Finally, I also received a response from Adam Laurell, owner of MobilityService consultancy in Gothenburg, who responded to the interview questions from the perspective of the region. He indicated that the scaling of ABs still is limited by technological challenges, including steering, braking, and a need for the automated systems to be more self-learning (A. Laurell, personal communication, May 2026).

Seattle's Existing Autonomous Vehicle Strategy

Neither Seattle, nor any jurisdiction in the Puget Sound Region, has any plans for autonomous public transit (beyond the existing SEA Underground in Seattle-Tacoma International Airport). However, the city does have a department that is responsible for the rollout of autonomous vehicles overall. For this thesis, I met with Armand Shahbazian, the Electric and Automated Mobility Lead at the Seattle Department of Transportation (SDOT).

SDOT has done some early research on AVs, starting by looking at rideshare and AV rollout in other cities (A. Shahbazian, personal communication, February 2026). However, AV rollouts elsewhere are still early, so there is limited data. Instead, the primary source for SDOT's understanding of the impact of AVs is from looking at what has happened with rideshare companies. The assumption is that AVs will primarily be used in shared fleets (as opposed to individually owned), and thus function like less-expensive rideshare vehicles. There is extensive research on what rideshare does to cities. From Mr. Shahbazian's perspective, there is an overall negative impact: rideshare increases VMT and decreases the usage of public transit.

Access to the rich set of data that autonomous vehicles collect is top of mind for SDOT. They would find the data useful for transportation planning purposes, but state preemption prevents the city from requiring that rideshare providers share this data except at the coarsest level: zip code. This means that they currently cannot map origins and destinations, which neighborhoods are being served, and so forth, and thus cannot verify the actual impact on VMT based on real usage in the city.

The city learned its lesson with rideshare and created regulations for micromobility (electric scooters and e-bikes) that require data to be published by the vendors. They use a standard format called the mobility data specification (MDS) that reports the full location history of every ride that happens in the city. MDS is a two-way spec, both collecting data and allowing the city to map out certain locations where micromobility should be restricted in terms of use and parking. One major focus for the city is equity, and micromobility companies are required to have 15% of their vehicles in historically underserved neighborhoods.

SDOT hopes to apply the micromobility (not rideshare) model to AVs. This would mean getting rich geographic data about each journey in the city, something that would allow the city to learn about where its gaps in transit infrastructure are. Beyond governance and data collection, however, SDOT does not have any further plans to leverage AVs for the city nor support ABs. Mr. Shahbazian indicated that labor interests may be an obstacle to adoption, and, that at the moment there are not any eligible bus manufacturers in the US investing in ABs.

METHODS

This research is broken into four distinct parts: 1) creation of a logit model predicting travel behavior in the City of Seattle, 2) creation of a model for transit priority in the city, 3) creation of new transit networks based on the characteristics of Automated Buses (ABs), and then 4) analysis of what changes in travel patterns will happen based on these different hypothetical networks. All code for these calculations is written in Python and R, and is available on GitHub at: https://github.com/ctachme/transit-priority-vision-zero.

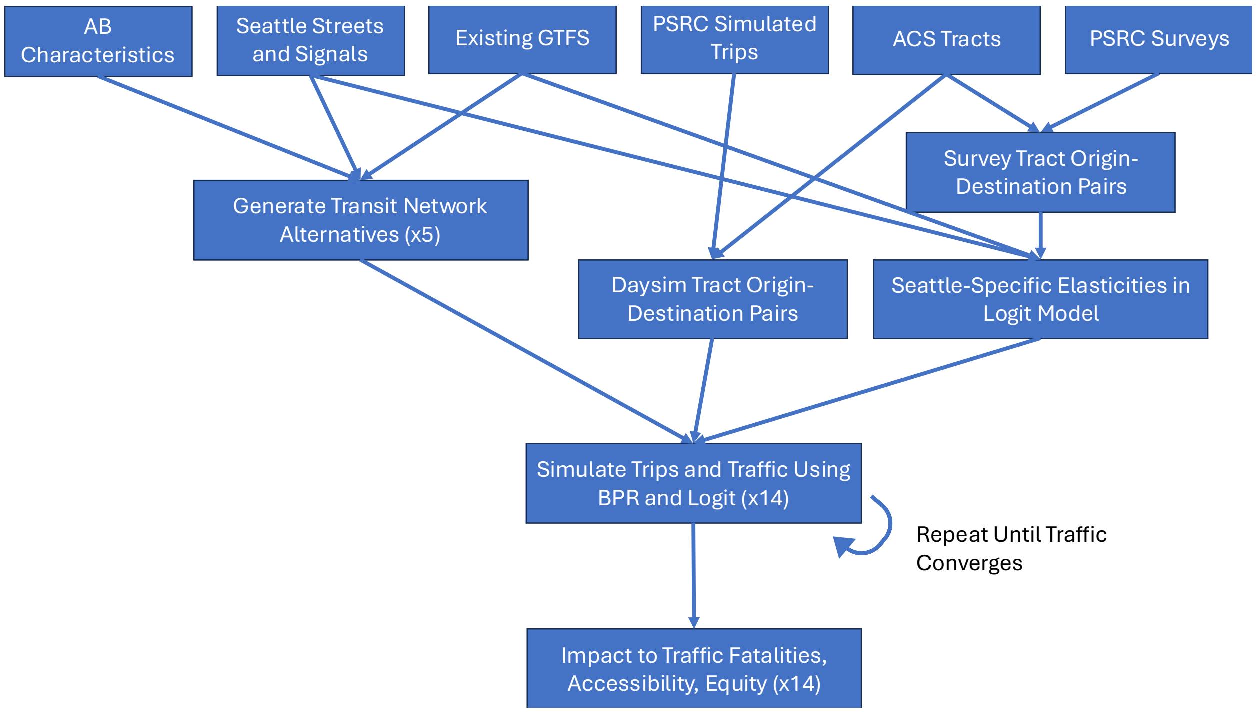

Figure 2 *Data Flow in This Thesis*

Predicting Seattle Travel Behavior

Survey Data

To understand how people move around in Seattle today, I start from the PSRC Household Travel Survey data (Puget Sound Regional Council, 2023). This dataset has 191,233 rows, each indicating a single trip that begins and ends in the four-county Puget Sound region (King, Pierce, Snohomish, and Kitsap counties). PSRC conducted surveys in four distinct years, all in the spring: 2017, 2019, 2021, and 2023. I filtered to trips that both start and end in Seattle, with complete data for all fields, resulting in 85,336 rows.

For each row the following fields were used for the analysis:

Table 1 *Fields Used From the PSRC Trips Table*

Field	Description
`trip_id`	Unique identifier for each trip
`household_id`	Unique identifier for each household

`mode_class`	Primary trip mode
`origin_tract20`	Origin 2020 census tract
`dest_tract20`	Destination 2020 census tract
`distance_miles`	Total trip distance in miles
`duration_minutes`	Total duration in minutes (the difference between start and end times)
`travel_dow`	Travel day of week
`depart_time_hour`	Departure time hour (0 to 23)
`origin_purpose_cat`	The category of the origin, such as “Home” or “Work”
`dest_purpose_cat`	The category of the destination, such as “Work” or “School”
`travelers_total`	The number of travelers on a given trip

For distances, trips recorded in the online survey are straight-line distances between origin and destination. Trips recorded in rMove are path distances via all points recorded by the app but this only constitutes 1,679 of the 6,215 household respondents in Seattle.

Once filtered, the modes noted below were visible in the dataset. This thesis treats all three Drive modes (SOV, HOV2, and HOV3+), as well as Ride Hail variants, as identical as there is no way to model the complexity of picking up or dropping off carpoolers given the limited data. Plus, we are already capturing some of this information with the `travelers_total` variable. I treat Micromobility as Bike since they have similar routing characteristics once the scooter or bike is acquired. Technically, e-scooters or e-bikes can travel faster than pedal bikes, but the volume is so low that it is not worth modeling separately. School Bus, Other, and Missing Response are excluded from the dataset.

Table 2 *Observed Mode Share for all Intra-Seattle Trips in the PSRC Trips Table*

Mode Class	Count	In Model	Mode Share
Walk	31,360	Yes	36.1%
Bike	3,365	Yes	3.9%
Micromobility	102	Yes	0.1%
Drive SOV	20,540	Yes	23.7%
Drive HOV2	12,601	Yes	14.5%
Drive HOV3+	6,350	Yes	7.3%
Ride Hail	1,496	Yes	1.7%
Transit	10,057	Yes	11.6%
School Bus	190	No	0.2%
Other	384	No	0.4%
Missing Response	363	No	0.4%

In addition to trip data, household data is available and can be joined using the `household_id`.

Table 3 *Fields Used From the PSRC Households Table*

Field	Description
`household_id`	Unique identifier for each household
`lifecycle_class`	The age buckets of the residents, for example "Household with older adults"
`vehicle_count`	Number of vehicles
`numchildren`	Number of children
`hhincome_detailed`	Buckets of income, such as "Under $10,000" or "$75,000-$99,999"

There are other fields available, such as race and income. I evaluated different models using these variables, but after exploration I was unable to use them to improve model fit.

Generating Routes

This thesis predicts trip behavior by using a multinomial logit model (MNL). There are other possible models I could have used; another could be a nested logit model, with top-level choices like drive and transit, with sub-choices like carpooling. However, because the choice of drive alone versus carpooling is not straightforward to model with the available survey data, a nested logit model would be overly complicated for this thesis. Thus, I consider only four top-level modes: driving, transit, walking, and cycling (not any sub-modes underneath these). To generate the MNL model, I need to know both the characteristics of the mode that the rider chose, and the characteristics of the modes they did not choose.

I routed trips with two different R libraries: `r5r` and `dodgr`. `r5r` is used for transit trips as well as walking and biking, because it can natively read a GTFS as well as a street network. `dodgr` is used specifically for car routing because it allows me to adjust the travel time on a link-by-link basis, which is required to run the simulation because automated vehicles adjust car demand, and transit priority reallocates street space.

The data is aggregated at census tract level but to route a trip, I need more than a census tract, I need a specific location to begin and end trips. For this thesis, I calculated the population-weighted centroid of each census tract by using census block data. For census tracts that contain substantial vacant land (or water) on one side, the point chosen is therefore most representative of the potential origins and destinations. However, this point is not necessarily on the street network. While `r5r` specifically has effective "snapping" between coordinates and the nearest accessible street, `dodgr` does not automatically do this. Thus, there is an additional step for `dodgr` routing where I find the 10 nearest vertices on the network for each origin and destination and find the closest pair that can complete a route. For the remaining points I search for any location within a mile connected to the graph. In case there is no connected point in the top 10 or within one mile and `dodgr` fails to find a path, I fall back to `r5r`. This fallback to `r5r` was required for 8.4% of the trips.

Given these points, I generated trips for different modes: driving using `dodgr`, and bike, walking, and transit using `r5r`. These networks are based on OpenStreetMap data, which I have downloaded for Washington State and clipped to the Puget Sound four-county area. The first three modes' travel times are straightforward to calculate, since they directly connect the origin and destination on one single best path. This model has a 3-hour trip limit to avoid unrealistically long commutes by walking or biking. However, transit travel time can vary depending on the exact time chosen (for example, if a bus runs only every 30 minutes, wait time can vary from 0 to 30 minutes). To mitigate this, a 20-minute window to `r5r` is provided at the top of the hour (10 minutes before and after), so 20 trips minute-by-minute are simulated, and the median trip time is chosen. The median is chosen to reduce the effect of long wait times if the user has just missed a bus. `r5r` returns not just the travel time but the different components, such as wait, in-vehicle, and transfer times.

Calibrating Travel Time

There are several limitations with this approach. First, I do not have access to existing traffic-aware routing information, so the time returned for car trips by `dodgr` is for typical free-flow conditions. Second, in many cases (especially with trips downtown) it can take time to find parking. As such, this time needs to be accounted for even if the automatic routing will not identify it. Third, the origins and destinations are approximations based on the centroid. I do have, for each trip, the known `distance_miles` and the `duration_minutes`, so I can handle these three unknowns by calibrating what `dodgr` returns with real-world survey data.

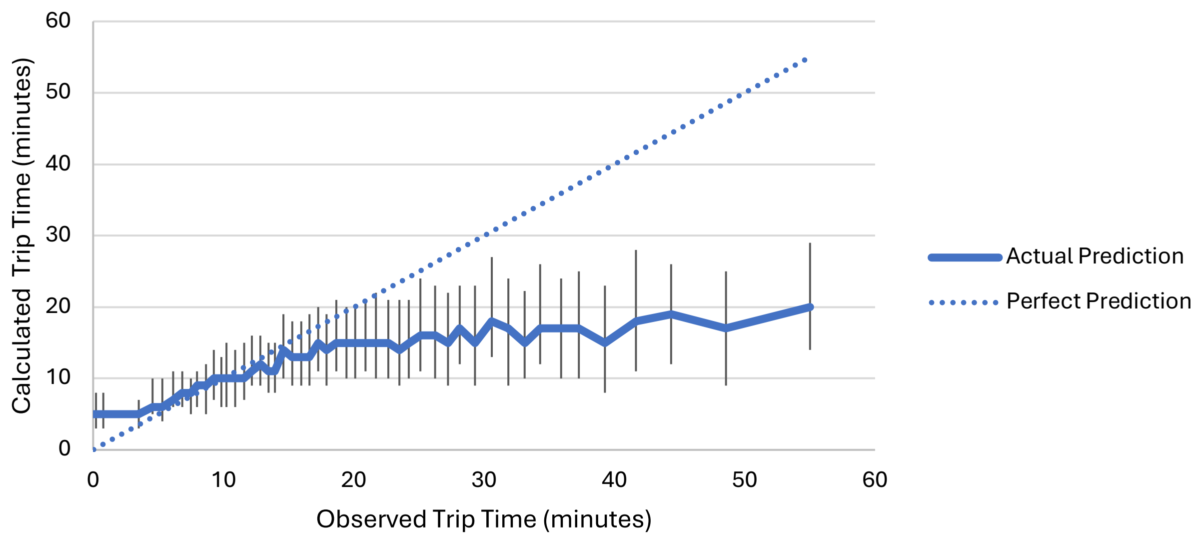

Figure 3 *Accuracy of `dodgr`-Predicted Trip Times*

Note. Vertical bars indicate the p25 to p75 range of values.

These results indicate that `dodgr` underestimates travel time for short drive journeys (those less than 10 minutes) and overestimates longer trips (over 10 minutes). This is likely because `dodgr` does not account for the final departure and arrival step (for example, to walk within the parking lot or to the appropriate part of the building at the person's destination). This effect becomes less relevant as trips get longer.

To further understand this behavior, I group trips into time-of-day buckets following the method established by PSRC (Puget Sound Regional Council, 2009):

Table 4 *Time of Day (TOD) Buckets*

Bucket	Times
AM Peak	6 a.m. to 9 a.m.
Mid-Day	10 a.m. to 3 p.m.
PM Peak	4 p.m. to 6 p.m.
Evening	7 p.m. to 10 p.m.
Night	11 p.m. to 5 a.m. (next day)

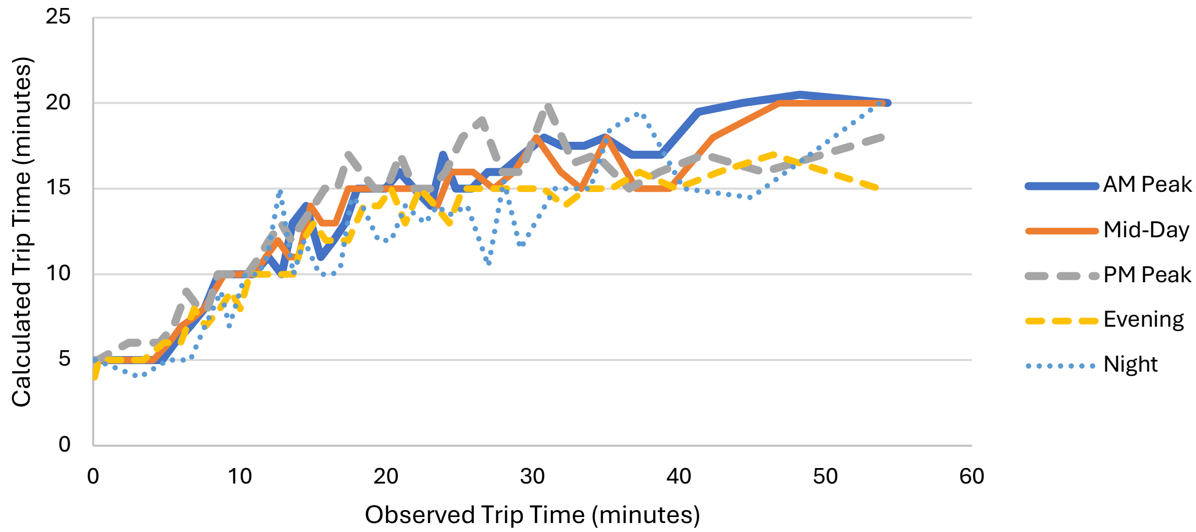

Figure 4 *Accuracy of Travel Time Prediction by Time of Day*

As expected, there does appear to be a difference between the actual and predicted data based on time-of-day bucket. The daytime has the higher numbers in terms of observed time versus predicted time, whereas night has the lowest numbers. This likely is because the libraries cannot account for congestion effects.

Now that I can see that travel time is in fact off in a consistent way, I want to adjust all the times for the trips based on the other trips in the same origin-destination (O-D) pair, with the same bucket, and the same day-of-week class (weekday versus weekend). Because I am trying to find the ratio by which the travel time is off, I use the log-ratio of the observed duration for the trip over the predicted duration (specifically that trips are 20 percent slower, rather than 20 minutes slower).

That said, it is possible to see from the above charts that the difference is not linear—it appears to be sublinear. As such, instead of just finding a raw ratio I can use a weighted generalized additive model (GAM) with restricted maximum likelihood. It is additive, meaning it can handle several different effects. Specifically, I create a function that can vary based on the distance of the trip (there are two distances—the real distance and the routed distance):

$$\log\left(\frac{t_{obs}}{t_{pred}}\right) = f_1(\log(d_{actual})) + f_2(\log(d_{routed})) + f_{1,2}(\log(d_{actual}), \log(d_{routed}))$$
$$+ f_3(peer\ log\ ratio) + tod\ offset + weekday\ offset + error$$

Then, for each trip the GAM returns a log-ratio that can be applied to the driving travel time, based on the distances, the interaction between these two distances (capturing where they disagree), what similar trips experienced, time-of-day effects, and weekday effects. The results are visible in **Figure 5**, where the numbers for travel time line up much more closely than before. It is worth noting that the calibration is only on observed trips, so there may be some bias introduced here.

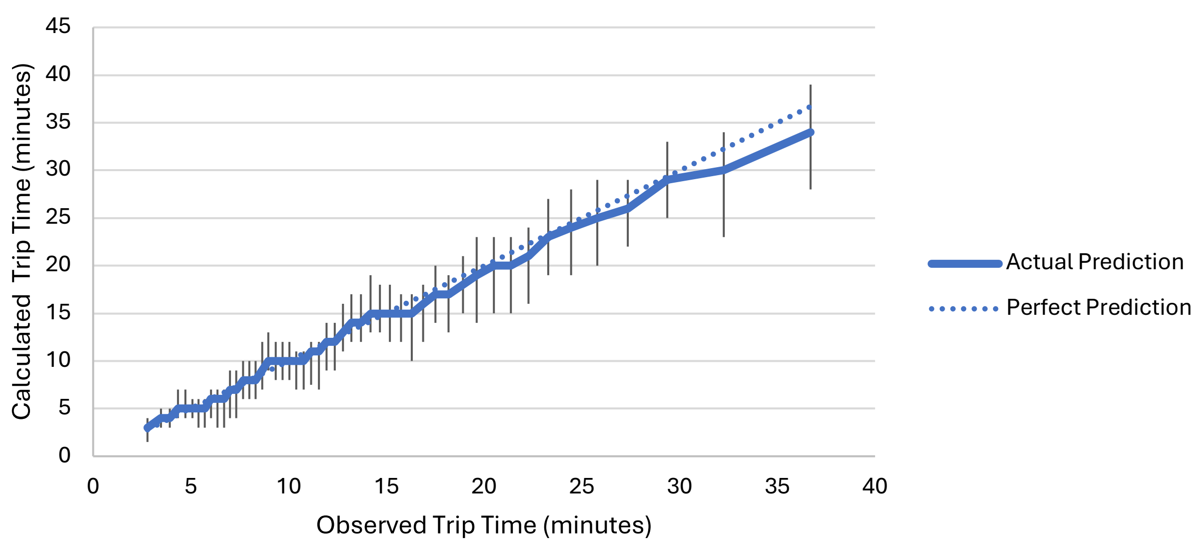

Figure 5 Actual Travel Time Versus Calibrated Travel Time

There is one more limitation in the data: in the filtered dataset there are 15,065 trips that begin and end in the same census tract. As this is 17.6% of the data, I did not want to discard it as it represents an important sample of shorter trips. However, for this dataset I have only distance and duration for the chosen mode. To deal with this, I use the median speed for each mode in each time-of-day bucket and normalize it to the distance and speed of the actual trip. I set a minimum trip distance of half the equivalent circle radius (to ensure the trip is not just someone going around the block and returning home).

Calculating the Model

The model itself receives up to four rows per trip, all with each mode's respective travel time. Technically, not every trip can be completed on each mode because of the following limits:

Table 5 Per-Mode Limitations and Resulting Rows

Mode	Limits	Count
Walk	Found path with `r5r`, > 0 min, and ≤ 180 min	80,516
Bike	Found path with `r5r`, > 0 min, and ≤ 180 min	85,327
Drive	Found path with `dodgr` or `r5r`, > 0 min and ≤ 180 min	85,336
Transit	Found path with `r5r`, total time > 0 min and ≤ 180, walk time ≤ 45 min, wait time ≤ 60 min, and number of legs ≤ 4	80,516

Once the trips are calculated, I create the model. In this model, drive is the reference and the other modes are the alternatives. Here is a snippet of R code representing the task (this uses a library called `mlogit`):

```
choice ~ cost + walking_min_alt + bike_tt_alt + drive_tt_alt +
        transit_total_diff_alt + vc_drive_alt | is_work
```

Table 6 MNL Variables

Variable	Description
`cost`	For driving, this is calculated at the AAA-published rate of $0.77/mile (AAA, 2025) plus parking costs (see below), then divided by `travelers_total` to get the per-person cost. For transit this is a range from $0 to $3 depending on the household (see below), and for walking and biking it is $0.
`walking_min_alt`	The total walking time—be it directly to a destination, or in the case of a transit journey, the walk time to and from the bus stop.

`bike_tt_alt`	The total travel time for cycling if that is the alternative.
`drive_tt_alt`	The total travel time for driving. Travel time is 0 for the rows that are not associated with that alternative.
`transit_total_diff_alt`	The transit time penalty over driving, that is, the time while the bus is taking a rider stop-to-stop as well as any time waiting for the bus to arrive or a transfer, minus the drive time. Walk time is already accounted for in the previous variable.
`vc_drive_alt`	The number of cars the household has access to if the mode is drive, 0 otherwise.
`is_work`	Whether the trip is for work or not.

As mentioned in the table above, with `mlogit`, each trip alternative only has the travel time for that mode. This allows each mode to receive its own time coefficient, since we know from literature that people value time spent walking differently from time driving. Two of the variables, `walking_min_alt` and `transit_total_diff_alt`, are pooled because the former includes walking that is a part of the transit trip and the latter represents the penalty over driving.

Expanding further on these two variables, I discovered that there are several different possible permutations in literature. For example, transit time can be composed of in-vehicle time and out-of-vehicle time. Or, number of transfers could be a separate variable as riders do not like transferring many times. Additionally, transit reliability is a factor that influences people's mode choice—more so than other modes. However, after evaluating over 60 different possible permutations of variables, I determined that the model is highly sensitive to the exact permutation of these variables. Certain variables (such as transit in-vehicle time, walk time to transit, and number of transfers), when standing alone, pick up confounding effects that distort the model. Pooling these variables together removes these confounding effects.

Transit Costs

Transit costs vary depending on the age and income of people in the household (King County Metro, 2025). The cost is $0 for students and children, $1.23 for workers (59% of employers provide ORCA Business Passport for free), and otherwise the standard $3/trip. However, if a household is low-income (gross household income less than 200% the federal poverty level) or is a senior household, adults receive a $1 reduced fare. If a household has people with different rates (for example, students and workers), the average fare is used for each trip from the household.

Parking Costs

The other field that is calculated here is the parking cost. Parking ease and availability can be a major factor that affects mode choice, so I wanted to include it with as much public information as possible.

There are three different ways that people park: in a paid parking garage or lot, paid curbside parking, or free parking (which may be time-limited in a restricted parking zone). Seattle publishes data about paid parking rates on streets and in public garages (City of Seattle, 2026a), as well as where the restricted parking zones are. I am using a logit model to calculate parking cost for each trip. There are four variables: cost, search time, walk time, and repark time. The model uses the published price for garages, or if no price is published, the average price for all paid parking within 0.5 miles (if there are still no available values, it uses the average value for either inside or outside of downtown). For curbside parking, the rates are published in the data layer. The search time is fixed at two minutes for a garage (as a lower-bound assumption) and the time it takes to find a spot at 85% occupancy (based on Seattle's Performance-Based Pricing Program) (City of Seattle, n.d.). Walk distance is distance to the lot or garage, or half the block average width (assuming the goal is to find a same-block spot). For restricted parking zones, the search time and walk distance is doubled because of the challenges of finding parking there. There is an additional repark time penalty added if there is a time limit on the street parking (most often there is a 2-hour limit). Finally, I combine the time and cost variables by applying the USDOT's guidance of estimating the value of travel time at half the median hourly household income (U.S. Department of Transportation, 2016). In the Seattle area this is $28.54 as of 2024 (U.S. Census Bureau, 2024b).

Then, I use a logit model to select among the parking candidates. I do not merely take the cheapest option because people do not have perfect knowledge and do not always choose the mathematically optimal option. The probability that a given parking option j is selected can be calculated by dividing the cost c_j by the sum of all options with cost c_k:

$$P_j = \frac{e^{-\frac{c_j}{\theta}}}{\sum_k e^{\frac{-c_k}{\theta}}}$$

This is the multinomial-logit choice rule and makes cheaper candidates more likely but allows for some variation. I select a value of θ which represents a 10-minute dispersion of the preferences between the different options. Then, the probability-weighted money costs are added to the AAA driving cost for the total drive cost.

Scaling to All Trips

For this project, I consider the household survey data to be a representative sample of the region in terms of how people choose between different modes. PSRC includes weighting coefficients associated with each household, but this weighting is not census-tract aware, so it is of limited utility. To properly quantify the impact of changes to the transportation system, however, I need more than just mode choice. I need to be able to quantify in absolute numbers how many people would choose one travel mode over another. PSRC provides exactly this in the form of simulated data. PSRC has an activity-based model called Daysim, which provide parcel-level origins and destinations for the entire four-county region. This dataset is large, with over 16M trips in it since it theoretically represents every trip taken within the region in a typical weekday. For the purposes of this project, I am not assuming that people will change any behavior other than specifically their mode choice.

I did not want to use this dataset to generate the travel model as it is simulated data, and moreover PSRC itself cautions that this data is “draft” data. That said, the simulation has been trained by PSRC to reflect the same results as the household survey data so it should be stable to use in terms of complementing the actual survey. Specifically, I am treating the survey as the training dataset for the model, and then the Daysim dataset as the runtime data.

Understanding the Seattle Street Network

The City of Seattle publishes a rich set of information about the streets in the city. To model traffic flows and transit priority, I need to understand the capacity of each street in the city. This includes the current configuration in terms of number of travel lanes, and the potential for future bus lanes. The Street Lanes Dataset identifies all street lanes in Seattle as of 2021. The city is no longer publishing this dataset, so it is five years old as of 2026. However, it provides sufficient information for this thesis.

To determine the current capacity of a street link, I look at each set of lanes and find the minimum width on the block. This lane data includes bike lanes, parking lanes, medians, turn lanes, and travel lanes. To reduce complexity, I am only looking at travel lanes per direction (logged as a cardinal direction of N, S, E, W, NE, NW, SE, SW), not cycling, parking, or turn. However, I also sum the full set of lanes (including cycling, parking, and turn) to understand the curb-to-curb width. This is useful because it indicates the potential for a bus lane.

This only contains arterial data, but Seattle is rigorous with its classification such that I can make the simplifying assumption that all non-arterials provide a single travel lane in each direction and rarely have enough street width for bus lanes.

Modeling Transit Priority

There are a variety of different transit priority methods that can be used to speed up buses. The two main aspects are traffic signals and lanes. Seattle has over 1,200 traffic signals, the vast majority of which provide no priority for traveling buses (City of Seattle, 2026c). Likewise, while

Seattle does have 54 lane-miles of transit lanes (City of Seattle, 2025), this is a small percentage of the approximately 1,750 lane-miles of the arterial street network (City of Seattle, 2026b).

The first step is to assume that 100% of intersections in the city (where there will be a bus) have transit signal priority (TSP). There are many different levels of TSP, but for this study I assume the most aggressive form is implemented: phase insertion when the bus phase is directly inserted into the signal prior to arrival of the bus. This approach models an upper-bound TSP scenario where signal delay is near-zero, unless there is another bus approaching the same intersection from a perpendicular path.

The second step is to assume that all streets wide enough to accommodate bus lanes will have bus lanes if there are any buses routed along that street. Assuming bidirectional travel, this means a minimum width of 40 feet, with 10.5 feet per transit lane and 9.5 feet per general purpose (GP) lane. This is tight but represents the minimum case and is not typical. If a street could be restricted to one direction of general-purpose traffic, then a single contra-flow bus lane is possible. However, there are performance concerns with this approach since buses cannot bypass each other at stops with only one bus lane. See **Figure 6** for a map of which arterial streets in Seattle are candidates for bus lanes. Non-arterials are excluded from this analysis as they are typically not wide enough to accommodate bus lanes.

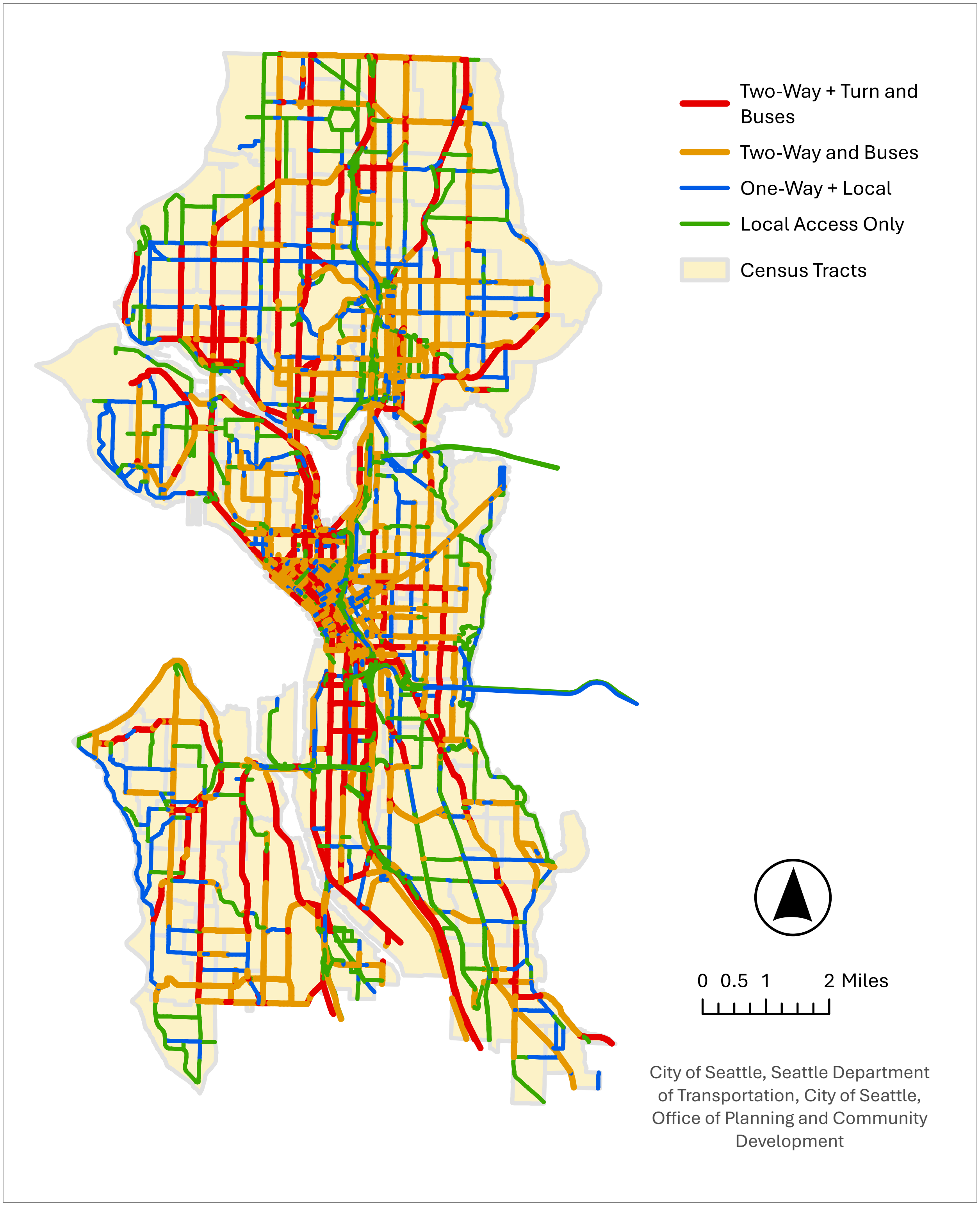

Figure 6 *Seattle Streets Wide Enough for Bus Lanes and GP Traffic*

This thesis assumes comprehensive adoption of the highest-quality bus lanes. Studies show that center-running lanes provide the best protection for buses (National Association of City Transportation Officials, 2016). Typically, center-running lanes are expensive to install because agencies want to minimize the impact that buses have on the remaining GP traffic. To accomplish this, they adopt center platforms with left-side doors (like the Rapid Ride G line), or floating and offset right-hand platforms (like at 4th and Jackson). Either way, both approaches are undesirable because they require expensive and non-standard buses with doors on both sides, and are problematic because they require riders to always cross traffic. With a typical curbside stop, riders must cross on only 50% of the trips. Yet with floating platforms, 100% of trips require waiting a light cycle to cross (and people commonly choose to walk against the light, introducing safety challenges).

TSP-Driven Intersection Approach

An alternate approach to dealing with intersections relies on the fact that buses already have TSP with dedicated signals installed. When approaching an intersection, same-direction GP traffic can be held with a red light until the approaching bus has fully cleared the intersection (see **Figure 7**).

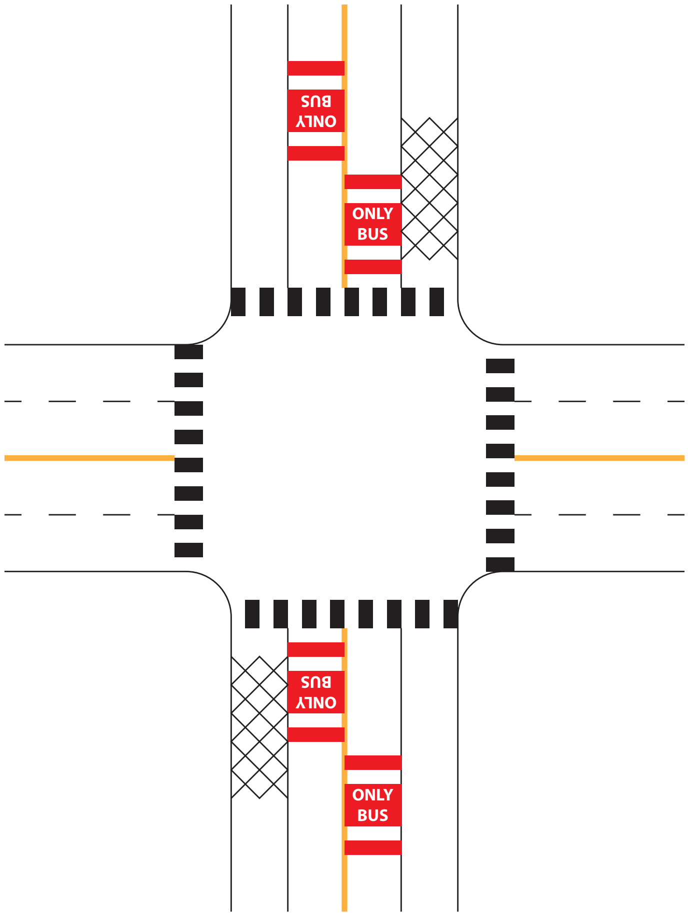

Figure 7 *Typical Modeled Intersection With Minimum 40-Foot Road Width*

This allows the bus to leave the left lane and serve a curbside stop. To prevent traffic in the subsequent block from occupying the bus stop zone, do-not-block markings can be painted on the street, signifying that cars are not permitted to advance until the bus zone is completely clear. New York City's automated camera enforcement program has yielded a reported 40% reduction in blocked bus lanes and stops since implementation (MTA, 2025). Once the bus has finished serving the stop, it can pull directly into the left lane and continue. This has the added advantage of being efficient for express services. If there is only a curbside lane, or only a left lane with floating platforms, an express bus would have to wait behind other buses serving the stop. With this proposed approach, express buses can continue at full speed through intersections.

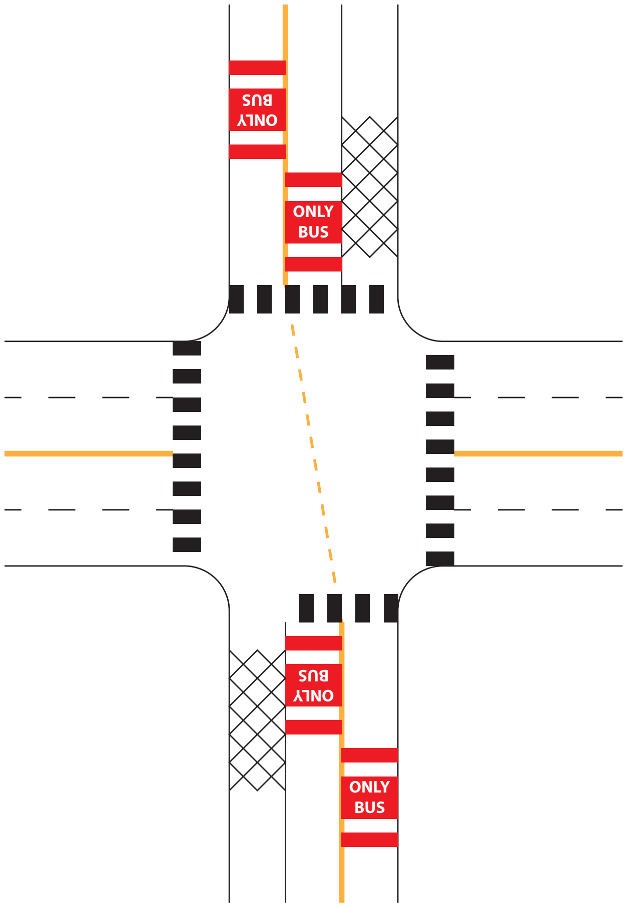

Figure 8 *Typical Modeled Intersection With One-Way GP Traffic*

It is worth noting this intersection style is not an existing practice for implementation of bus lanes. Possible reasons for this include the fact that it requires an accurate TSP system and so is only feasible with the latest cloud-based forms of TSP. Moreover, there will be significant impact to general purpose traffic. Given that traffic engineers are focused on providing the highest LOS (level of service) possible for an intersection, an intervention such as this, which explicitly reduces LOS, would typically see significant pushback. That said, like with bus lanes, my goal with this thesis is to model what would happen if street infrastructure explicitly maximized transit throughput, even at substantial reduction to GP LOS.

Moreover, given the high frequency being discussed, the risk of bus bunching is high. This approach also allows buses running behind schedule to quickly skip stops if none of the riders need to alight there.

Although far-side stops are recommended, there may be cases where they are not feasible (due to intersection or driveway geometry). In this case, if a near-side stop is required, a similar effect can be achieved by moving the stop line before the bus loading zone. As before, TSP would stop the GP traffic in the right lane and clear the bus stop for service.

The primary drawback with this approach is it relies on the presence of a traffic signal to clear the right lane for the bus. Though it would be possible to install new traffic lights, the expense of this would be high. While it is typically $15,000 to add TSP to an existing signal (U.S. Department of Transportation, 2013), new traffic lights cost between $250,000 and $500,000 (Washington State Department of Transportation, 2026). It is not feasible to consider every bus stop a candidate for a traffic signal. Thus, not all arterial corridors with left-side bus lanes can be 100% traffic-free. Wherever the gap between signals exceeds 0.5 miles (the maximum stop spacing considered acceptable), I assume there will be more stop delay as buses deal with merging across lanes.

Transit priority infrastructure is only effective if people follow the law. This thesis assumes near-perfect compliance. While this is not the case in Seattle today, technological advancements have made automated enforcement of transit lanes possible—both via static cameras mounted above intersections and on-vehicle cameras. These forms of automated enforcement tend to pay for themselves because of high initial violation rates. From an equity perspective, automated enforcement can reduce officer-discretion bias. Seattle is already piloting both styles of cameras (Seattle Police Department, n.d.), but for the purposes of this thesis I am assuming a comprehensive rollout.

Understanding Existing Bus Driver Costs

To understand the potential financial impact of switching from human-piloted buses to automated buses, I need to separate the cost of service into three components: operator labor, other costs that scale with the service like fuel and maintenance, and fixed back-office costs that do not scale, like general administration. King County Metro spends $314M in operator labor and fringe benefits annually ($310M specifically for buses) (Federal Transit Administration, 2024a). Next, I need to calculate the total cost of a revenue hour. This is the sum of the values in the below table (Federal Transit Administration, 2024b), divided by the total number of revenue hours (3.34M).

Table 7 *Cost Components of Revenue Hours*

Variable	Total	Per Revenue Hour	Type
Operator labor	$310M	$93	Marginal
Other vehicle operations	$123M	$37	Marginal
Vehicle maintenance	$159M	$47	Marginal
General administration and facility maintenance	$261M	$78	Fixed

This yields a cost of $255/hour, with $78 of fixed overhead that does not change with service being added or removed. The remaining $177 is the cost of one additional revenue hour, and drivers constitute 52% of that.

Driver cost has a secondary cost implication: it incentivizes agencies to run vehicles that are as large as possible. When agencies do not need to account for the cost of a driver, they are free to use smaller, more fuel-efficient vehicles. To model this, I looked at the hourly cost of King County Metro's demand-response vehicles (which are used for paratransit). These vehicles typically seat 20 people versus a standard 40-foot coach that seats 38 people. The vehicle maintenance cost per revenue mile for these vans is only $0.96, instead of $4.77 for a full bus (Federal Transit Administration, 2024b). This difference means a savings of $38/hour when combined with the $93/hour operator cost, and results in a marginal cost of $46/hour instead of $177/hour, or roughly one quarter.

For this thesis, I am thus modeling tripling bus service levels (see the exact numbers for different networks in the below section). This is slightly more conservative than quadrupling the number of buses because there may be other unaccounted-for costs in automated vehicle operations.

Generating Alternate Transit Networks

This thesis looks at both changes to the transit network (the routes and stops for buses), and the street network (lane allocation and speeds due to congestion). I start with a baseline network with no changes, which will be used to validate the overall approach.

After the baseline, each new transit network assumes automated bus adoption. Specifically, that means the full King County Metro fleet has transitioned to ABs. This thesis evaluates four different transit network layouts:

1. An existing as-is network with simply increased frequency on existing routes, and no changes to overall stops nor to route design.
2. A grid-like network focused on existing transit-classified streets, selecting those with transit priority. With the higher frequency of buses, this reduces the transfer penalty. Moreover, increased priority and frequency means routes can be longer without reliability issues.
3. A denser grid-like network built around providing additional, closer local service but at less-frequent headways.
4. A hub-and-spoke model with many small local shuttles providing direct service to transit hubs which have higher capacity and more direct connections.

These network approaches are not intended to be exhaustive but instead are illustrative of different possible approaches that could be used for ABs.

Network: Simple 3x

This variation is built on assuming existing vehicle costs remain fixed. That means without drivers, roughly 3x the number of service hours can be deployed to the network. To create this network, my model ingests the GTFS for King County Metro and transforms it with the following rules:

1. Any route that runs less frequently than every 10 minutes is tripled in frequency (applies to 102 routes).
2. More frequent routes are only doubled in frequency. In addition, I add an express overlay only stopping at GTFS timepoints (applies to 11 routes).
3. Peak-only routes are not impacted (applies to 23 routes).

I interpolated one or two new trips within the existing trips, and for express routes decreased the travel time by 30 seconds for each stop skipped, based on the typical time to accelerate, decelerate, and serve the stop (Kittelson & Associates, Inc. et al., 2013). There were no other adjustments to stops, layovers, or routing. Turnbacks at the beginning and end of service were ignored. Peak-only commute expresses were ignored by this analysis; they are sparse and infrequent enough that it would not make sense to simply triple their frequency.

One additional factor to consider is what happens when the number of service hours are affected by transit priority or AV-induced congestion. For this network, I assume the number of buses is constant. That means that if trips become faster, I can increase the frequency, but if trips are slower, I must decrease the frequency.

Network: Grid-Based

Rather than using the existing network as a base, this approach uses the full arterial street grid as a base, with an emphasis on those streets that have the highest-quality transit priority (left-side lanes, where possible, otherwise curbside or even single-direction lanes). For this approach I trace end-to-end pathways on parallel arterial corridors, with an emphasis on following those corridors with wide streets (≥ 40 feet curb-to-curb) on which installing new bus lanes is easiest. These types of arterials are typically spaced 0.5 to 1 mile apart, which is the best practice for transit route spacing. These routes run every 2.33 minutes during the day and every 5.67 minutes in the late night and early evening.

The geography of Seattle naturally focuses north-south routes on downtown (which means there is some interlining and reduced route spacing downtown). All these routes span nearly the full height of the city. East-west routes all go from Lake Washington to Puget Sound forming a perfect grid where every north-south route intersects every east-west route. Since most east-west corridors do not go through the downtown core, those downtown-bound trips require transfers.

In addition, to enhance intermodal connections, all east-west routes are aligned to connect to a Link Light Rail station, introducing some minor deviations from a perfectly-straight east-west path. Finally, Seattle is not perfectly rectangular, but in fact is narrower at the top and in the middle. This means it is not possible to have all north-south routes continue the full height of the city. Instead, north of 105th Street, the east-west routes fold at the corners to meet the north-south routes. There is also some folding in West Seattle and Magnolia which extends past the main body of the city. This ensures the perfect grid characteristic of all perpendicular routes intersecting.

For stops, instead of using King County Metro's stop spacing (King County Metro, 2021), I start with all traffic signals along the route but maintain an average of no more than four stops per mile. This matches the European guidance of a stop every 400–540 meters (Devunuri et al., 2024). For portions of the network where there are no traffic lights, I maintain this general stop spacing and prioritize major intersections where a light could be installed in the future.

This means, unlike in the current network, routes are not constrained in their quadrant of the city (for example, staying within Northeast Seattle as many of the 6x and 7x routes do today). The improved reliability of transit priority and increased frequency of automation makes longer routes feasible, reducing the penalty of transfers.

In addition to the grid over arterials, there is also a network of faster roads and highways that can receive enhanced express service, or that have express service today; specifically, Aurora Ave N, Interstate 5, 15th Ave NW / Elliott Ave, Lake City Way, Rainier Ave and SR 99. I add six routes on the north and south of the city that leverage these corridors (and specifically the Interstate 5 express lanes when available). These routes have limited stops—only stopping when they can connect to one of the other grid-based routes. They run every 2.25 minutes during the day and 5.5 minutes at night.

To create this network, I start with ArcGIS's Trace tool over the SND layer. I create a layer with line features to represent each route. Then I use the Seattle Signals layer as a starting place for bus stops. Each traffic signal provides TSP, and therefore allows the bus to jump in front of any other traffic and serve the stop. I manually add stops on road segments that lack traffic signals.

Finally, I use a Python script in ArcGIS to output GTFS files. This creates a near table to associate stops with each route and then queries point and distance along the routes to ensure the stops are in the correct order. This produces the below network that covers virtually all street segments that can support transit priority:

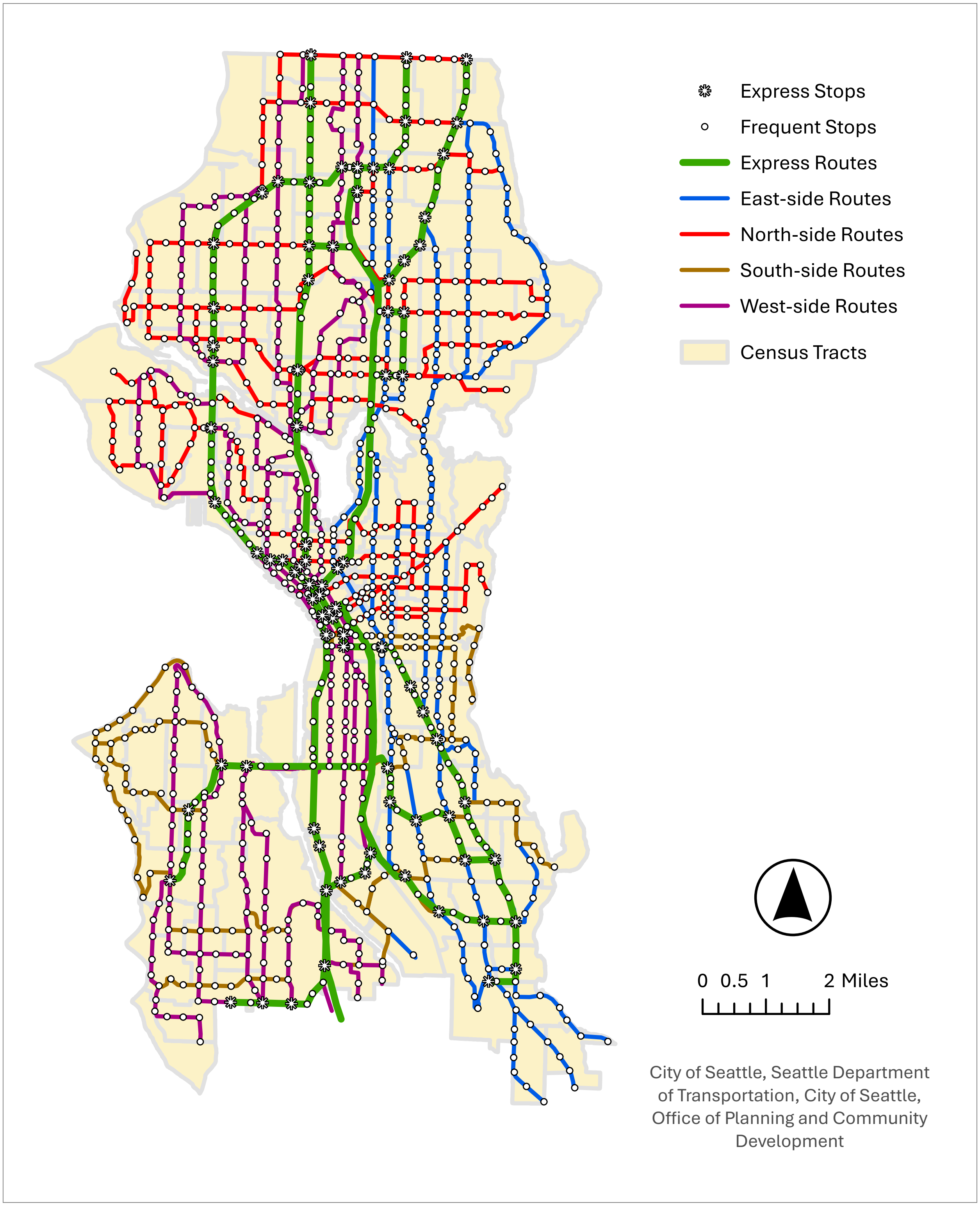

Figure 9 *Grid-Based Network Prioritizing Wide Arterials*

Network: Grid + Local

This approach builds on the grid-based network by adding a secondary layer of less frequent local routes, sometimes on non-arterial streets. These can be served by smaller shuttles, which can more easily navigate the local streets. One additional consideration is the impact to street pavement. Seattle does not currently permit Metro to run buses on non-arterial streets because of the physical impact of heavy buses on the pavement. Use of smaller vehicles mitigates this externality. To match the service levels of the Grid-Based network I decreased the frequency of the regular routes to every 3.33 minutes during the day. The local routes run every 5 minutes at day and 10 minutes at night.

The focus of this approach is to minimize the number of street segments that are more than five minutes from any bus stop. The walkshed for a given bus stop can be generated in ArcGIS Pro using the Network Analysis Service Area feature. This finds all locations on the street network (excluding freeways) that are more than 0.25 miles from at least one bus stop. This analysis yields the fact that there are substantial gaps in the existing network and the grid-based approach, especially in areas outside of the downtown core.

Thus, to build the network, I found all the locations where there were inaccessible streets and routed a local shuttle down the most significant street in that area. Unlike the grid-based frequent routes, it was not feasible to continue throughout the entire city or maintain a strong north-south or east-west bearing. Instead, these local routes connect adjacent unserved areas together and provide quick transfers to a more frequent route.

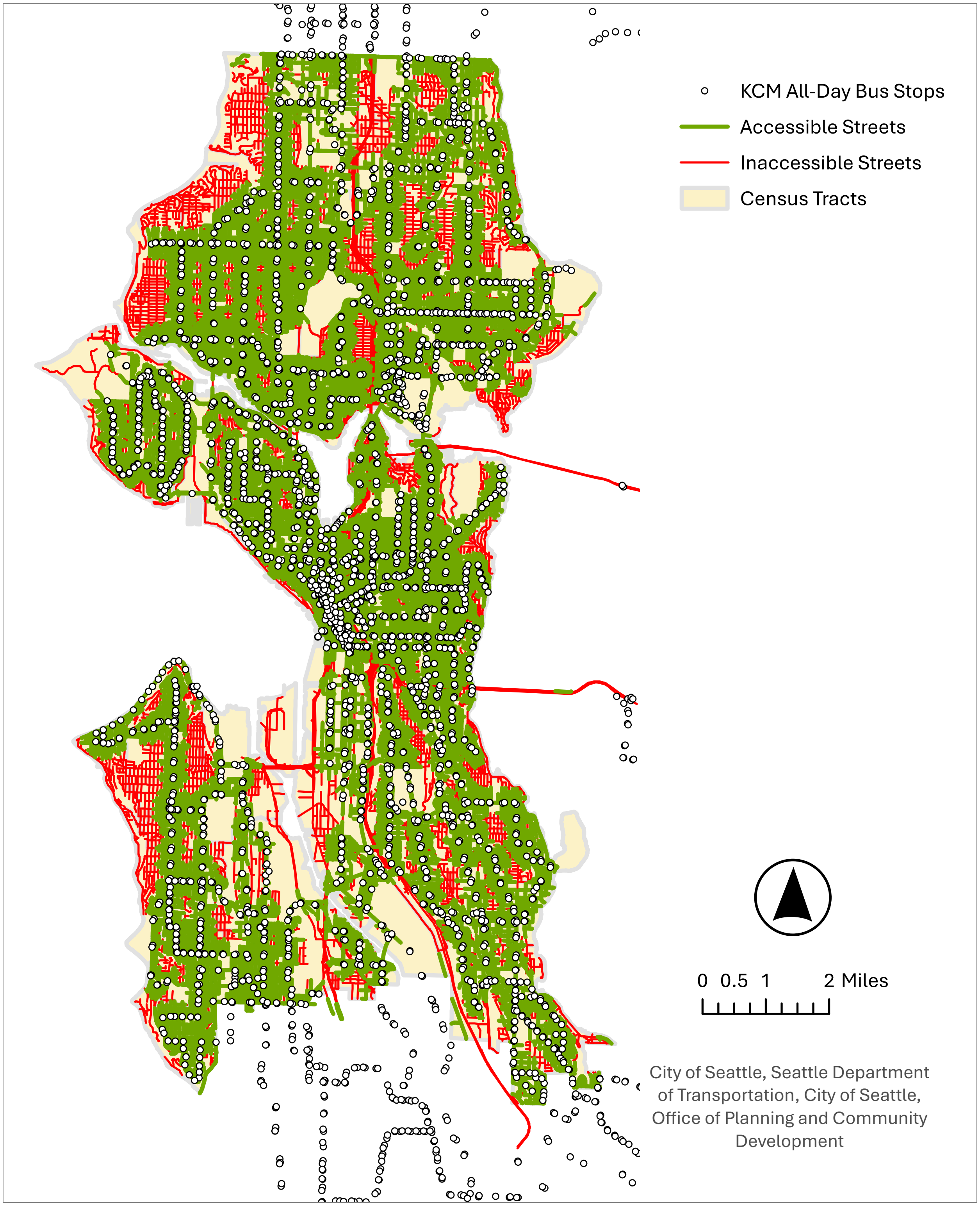

Figure 10 *Street Network Accessible Within a 5-Minute Walk to Existing Bus Stops*

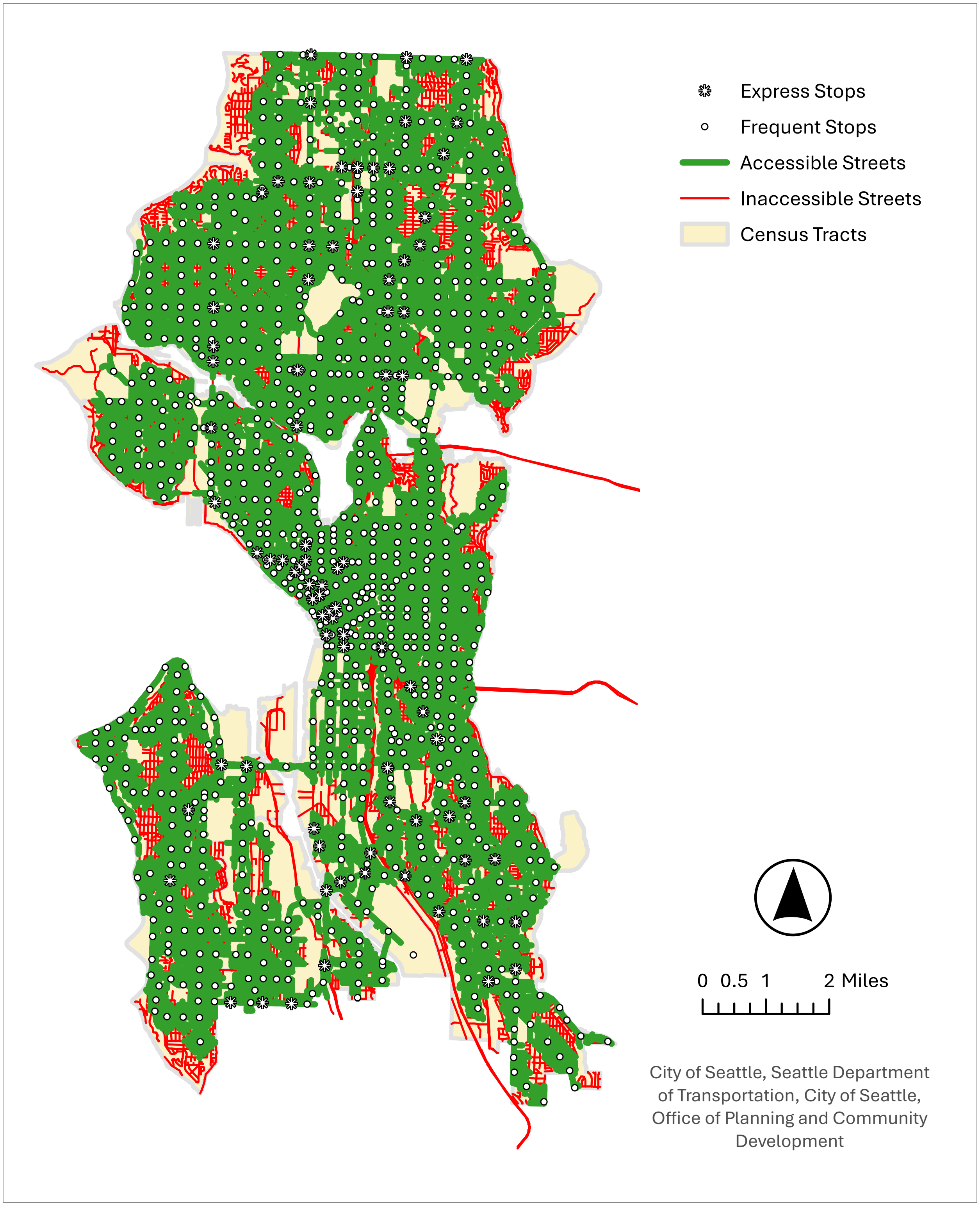

Figure 11 *Street Network Within a 5-Minute Walk to Grid-Based Bus Stops*

Here is the network with bus routes targeting those poorly-served portions of the street grid:

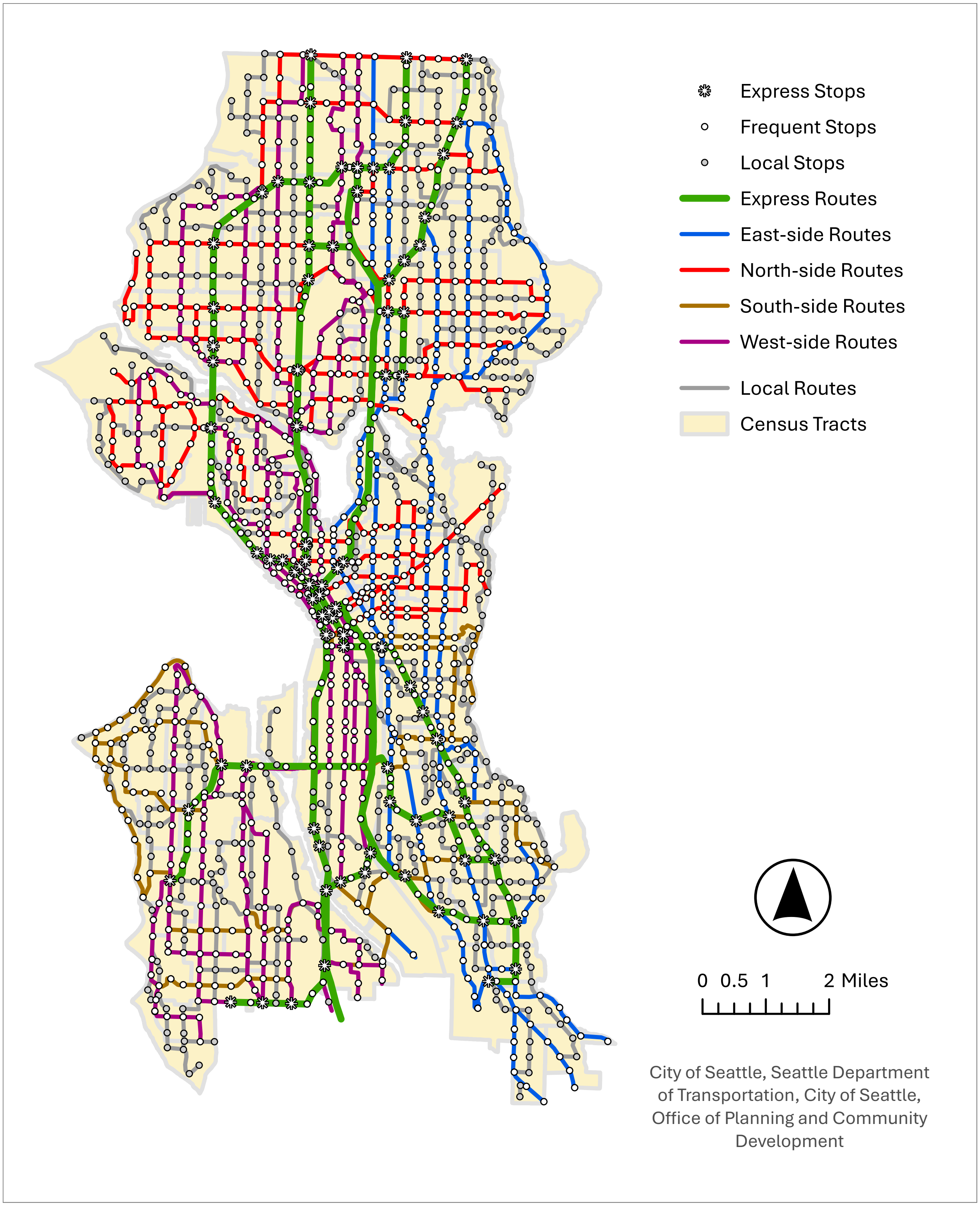

Figure 12 *Network Including All Local, Frequent, and Express Services*

This network now services virtually every street segment within a 5-minute walk:

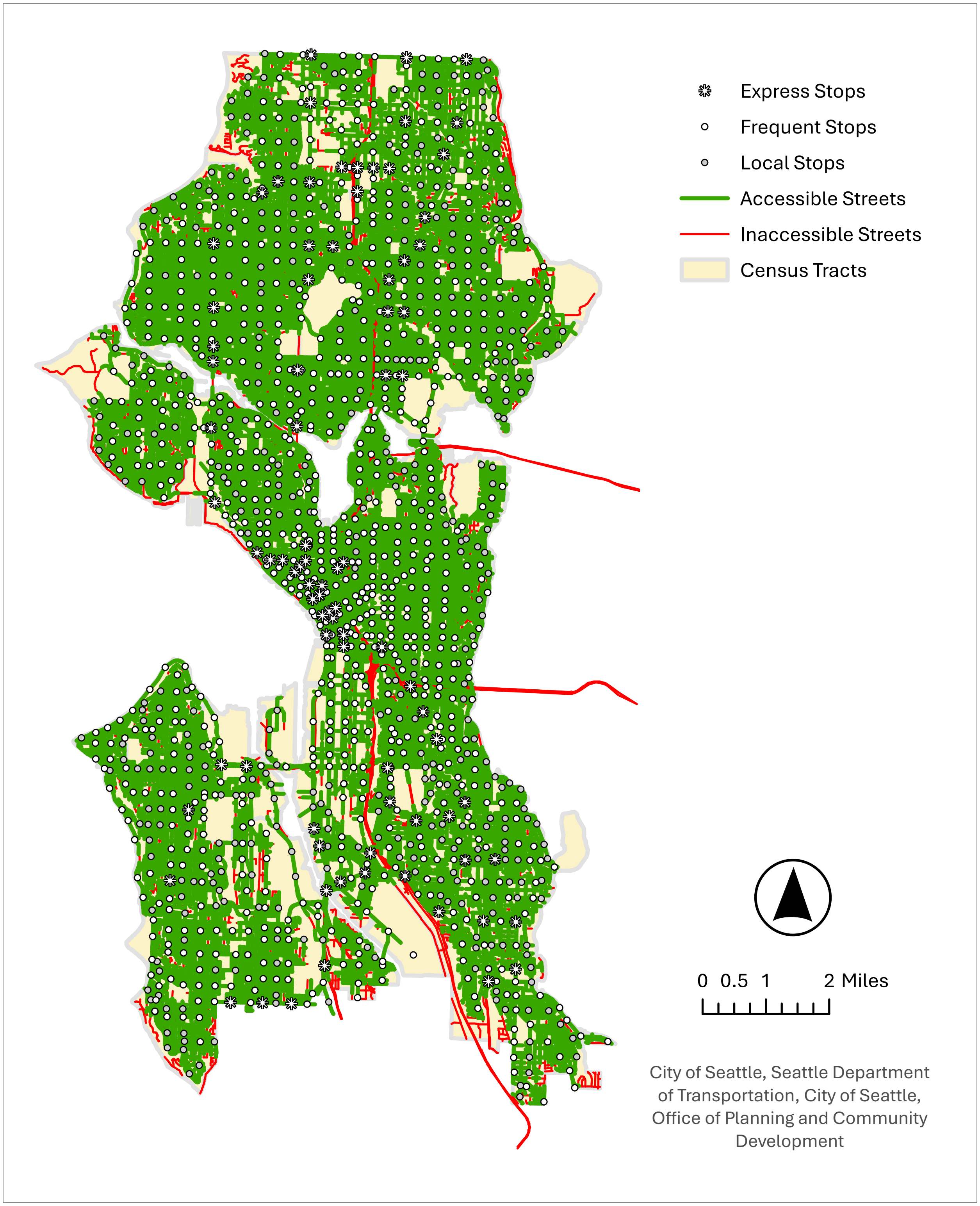

Figure 13 *Walkshed Analysis for Grid + Local Network*

Network: Node-Based

The final approach is the most different from the existing network. Instead of a grid, there is a set of core transit nodes established. Frequent express service goes node-to-node on the fastest route available. Then local shuttles (smaller vehicles) provide frequent access to each node for most people who live outside the walking distance. Whereas the grid-based network has only five express routes, this approach has 16 total.

To build this network, the first step is to create nodes throughout Seattle. I divided the city into a 0.5-mile by 0.5-mile grid and then used the PSRC parcel data to weight each cell with the number of trips that begin and end in it.

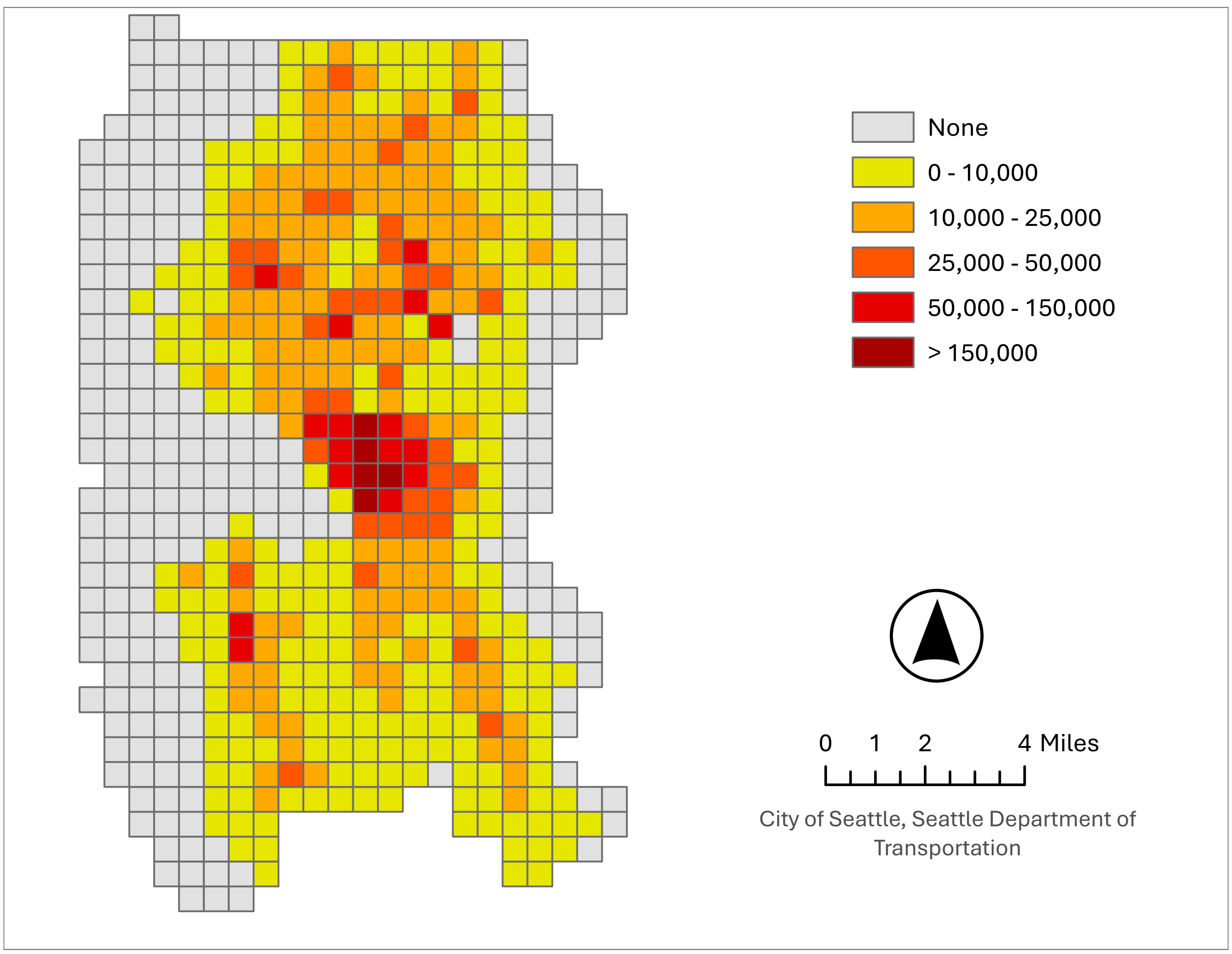

Figure 14 *Seattle With 0.5-Mile Cells Colored by Travel Demand*

Then I used the `p-median` library to minimize the value of distance times trips. I tried different counts of nodes to find the number between 6 and 16 that struck a good balance between having enough nodes for good coverage but not too many nodes to serve.

Table 8 *Coverage by Count of Nodes*

Number of Nodes	Weighted Average Miles	% Improvement	% of Parcels Within 0.25 Miles	% of Parcels Within 0.5 Miles
6	1.17	—	7.9%	23.2%
8	1.01	-13.1%	9.2%	33.7%
10	0.91	-10.5%	8.3%	35.6%
12	0.82	-10.0%	12.1%	42.8%
14	0.76	-7.8%	12.9%	45.8%
16	0.70	-7.3%	17.6%	48.6%

There is more than 10% improvement down to 12 nodes, but this improvement is less pronounced going to 14 and beyond. Thus, I selected 12 nodes as the count. Next, I identified which candidate nodes were adjacent to existing light rail or monorail stations and fixed those as specific nodes. This resulted in the Seattle Center monorail station, and Westlake, Capitol Hill, U District, Northgate, Beacon Hill, and Othello link stations as nodes. In addition to these, the algorithm identified Lake City, Greenwood, Ballard, West Seattle, and Delridge as nodes.

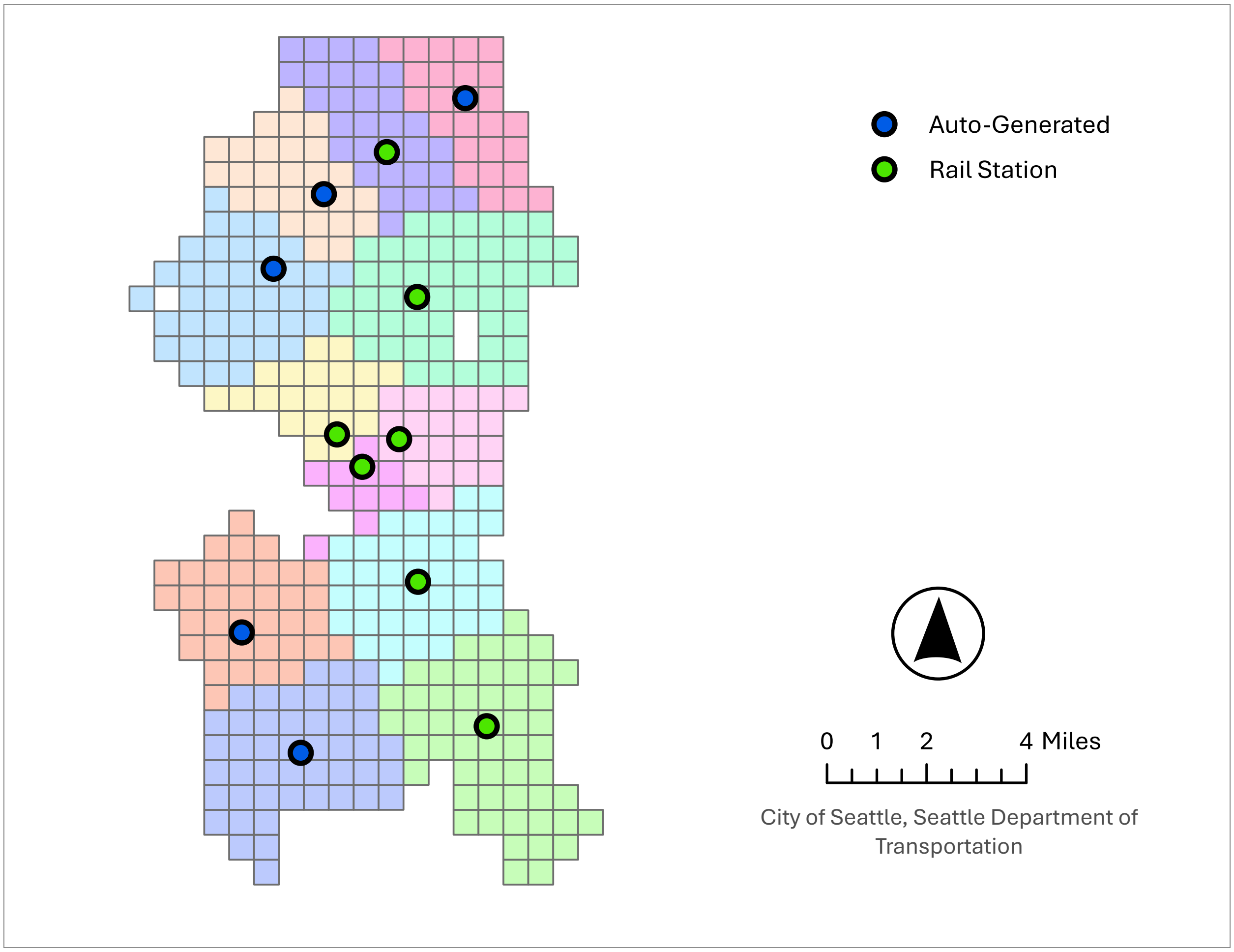

Figure 15 *All 12 Nodes in Seattle*

The second step is to create express routes that connect all these nodes together. To create this network, I established a policy that no two nodes could have a journey between them that was greater than 33% slower than a direct car trip. I also established a limit on distance traveled, specifically, no pair of nodes on a given route may have a detour greater than 50% of the direct distance. Given these constraints, I generated 1,093 possible corridors:

Table 9 *Number of Nodes in Each Generated Corridor Candidate*

Number of Nodes	**2**	**3**	**4**	**5**	**6**	**7**
Number of Routes	66	226	362	306	121	12

I then used an Integer Linear Program (ILP) to calculate the set of corridors that most effectively served all the nodes. In addition, I limited the number of routes serving a given node to be no more than 4x the relative demand of that node, and removed any routes that are subsets of other routes. This results in 17 different routes (all running every 2 minutes during the day and every 4 minutes at night) that look like this:

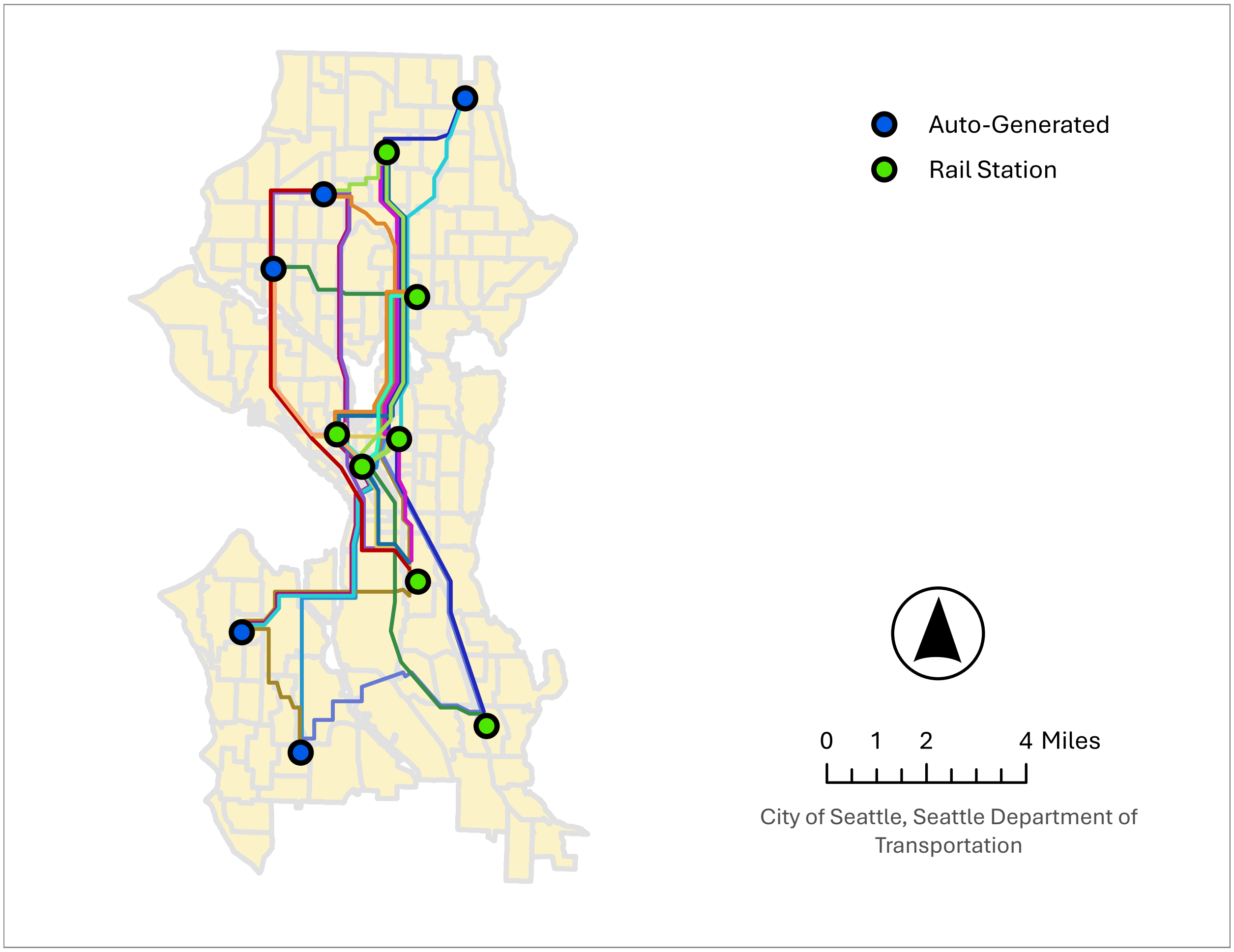

Figure 16 *Diagram of a Possible Set of Node-to-Node Routes*

The third step is to create local shuttle routes that serve each of the nodes. To do this, I started with the set of stops from the Grid + Local network, since those stops effectively served the entire city within a 5-minute walk. I then programmatically extended routes out from each node in different directions, attempting to hit as many nodes as possible. I continued until all stops from the Grid network were served.

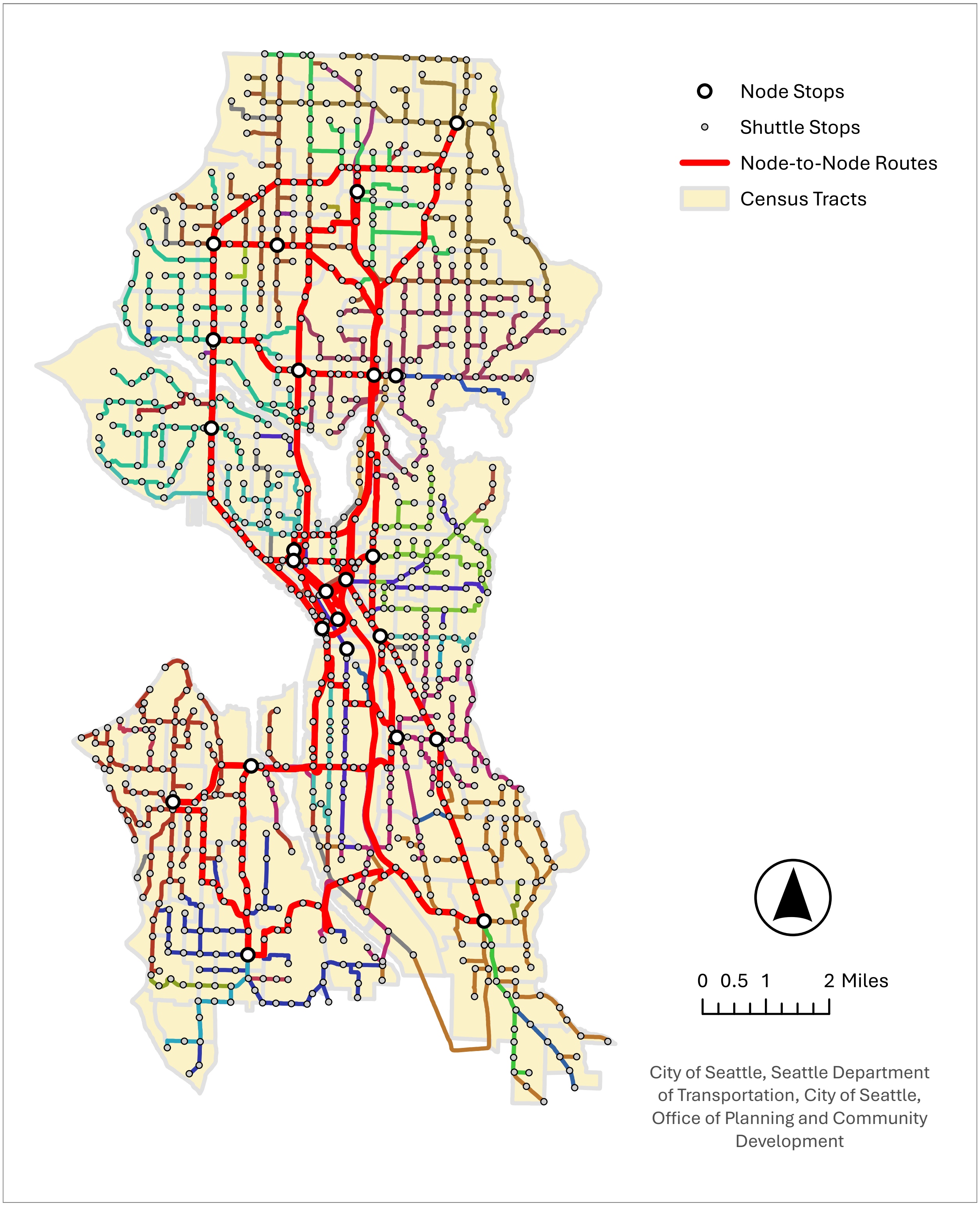

Figure 17 *All Feeder Routes for the Node-Based Network*

Note. Shuttle routes to nodes are the thinner lines colored differently depending on what node(s) they connect to.

This process started with 350 possible local routes, of which 284 only connected to one node. I used ILP to optimize the number of routes and ended up with 136 routes that serve all frequent stops and 83.6% of local stops with a route within one-sixth of a mile. These buses run every 5 minutes during the day and 10 minutes at night.

Summary

The goal is that all proposed interventions roughly triple the number of vehicles serving the city at peak times.

Table 10 *Summary Characteristics of All Transit Networks*

Transit Network	Peak Hour Vehicles	Median Speed (mph)	Median Headway (min)	Median Route Length (mi)
Baseline	453	14.8	19	10
Baseline + Transit Priority	361	18.5	19	10
Simple 3x	1,263	14.5	9.2	10.5
Simple 3x + Transit Priority	1,262	18.8	7.3	10.5
Grid-Based	1,245	18.2	2.3	12.5
Grid + Local	1,250	19	3.3	9.2
Node-Based	1,244	17.6	5	4.4

All networks except baseline have approximately three-times the vehicles currently required at peak (ranging from 1,244 to 1,263). The median speed for the new grid-based network is like the speed for the Baseline and Simple 3x networks. This indicates that the travel times are well-calibrated in that they match actual observed free-flow times for existing bus routes.

The data confirms that the grid-based network indeed has longer routes, and the effect of adding local routes is visible through the lower average in the Grid + Local row. The Node-Based network has slower speeds because of the large number of local shuttle routes that primarily serve residential streets. This network has very short routes since it is mostly made up of short feeder routes to the 12 nodes, served by smaller, more nimble vehicles.

The most dramatic changes are in headways, with the new networks all showing much more frequent buses.

Generating Alternate Street Networks

For each of the transit networks, there are many possible street networks on which to run these buses. There are two sets of variations to consider: whether transit priority is fully implemented, and what happens if there were ubiquitous personal automated vehicle adoption.

The first set of variations is to model ubiquitous transit priority. This impacts both transit and car drive travel time. For existing transit routes, I approximate full priority by using free-flow transit travel time. Free-flow here refers to travel time when there is the least amount of traffic interfering with the bus. Typically, this is a late night or early morning trip. This is an approximation that eliminates congestion effects, though there are some simplifying assumptions with this approach—signal timing may still not be optimized, and dwell time may be artificially reduced since there are few boardings and alightings in the early morning. That said, these effects are likely to be small and in opposite directions and so cancel each other out. The net-new networks I am creating have these savings built-in already.

Adding a bus lane not only makes buses go faster, but by reallocating space away from general purpose traffic, it can slow down other vehicles. While reducing lanes does not necessarily make traffic worse in the long run due to traffic evaporation and network rebalancing, this effect may be meaningful with many bus lanes added. This is particularly critical in the segments that are no longer wide enough for two throughlanes of traffic. These road segments are limited to local access only, and may have a more substantial impact on traffic.

To account for this, I adjust travel time per travel link as traffic increases using the Bureau of Public Roads (BPR) traffic model, and the traditionally published coefficient of β=4 (Federal Highway Administration, 2022), with α varying by street classification. This is a static assignment model, not a simulation. The model is:

$$t = t_0(1 + \alpha\left(\frac{v}{c}\right)^{\beta})$$

To calculate the capacity of each road link, I need the number of lanes. There are two possible sources: the Seattle Street Network (for arterials only), and OpenStreetMap. Capacity varies depending on the classification of the street—a lane of highway provides different capacity than a lane on a residential street. To prevent extreme overloading, I am capping v/c at 2.0, as truly saturated roads do not behave like BPR suggests at values much greater than 1.0. These capacity numbers are based on the Highway Capacity Manual (Sampson, 2018).

Table 11 *Modeled Per-Lane Capacity and α Based on Classification Type*

Classification	Peak VPH / Lane	α Value
Freeway	2,200	0.15
State Route	1,900	0.20
Principal Arterial	850	0.71
Minor Arterial	750	0.71
County Arterial	700	0.50
Collector Arterial	600	0.50
Residential / Non-Arterial	150	0.50
Local Access Only (for transit lanes)	0	0.50

Note. I reduced the traditional residential value of 250 to the living street value of 150 to reduce cut-through traffic and in accordance with Seattle's plans for livable streets. Local access only set to 0 means that through traffic will not be routed on that street, but local access is preserved.

Next, I parse the total volume of traffic that is currently on each link by using Seattle's vehicular counts (City of Seattle, 2026d). Seattle conducts regular traffic studies on a subset of major road segments—these are typically week-long studies of all the traffic that passes a certain point. In addition, they have several control points where they collect data monthly. This allows me to control for seasonal trends. To use this data, I filter to segments with data collected in the past five years to exclude effects of the pandemic and calibrate these by summing the traffic for the control points over those 60 months. I then multiply the traffic for the given segment by the calibration to get a seasonally-adjusted traffic volume on a given segment.

I then run the simulation multiple times until it converges at a new set of travel times. The specific process is:

1. Find the fastest path for every pair using default link times.
2. Count the drivers along each path.
3. Plug these volumes into BPR to get new link times.
4. Average the new times with the previous iteration(s)' times.
5. Check if the relative change is below 1% or at the limit of iterations.

This is called the Method of Successive Averages (MSA) and re-runs until this tolerance is reached. The routing is all-or-nothing, meaning I am not introducing any randomness into the routing choices that would often be done in more advanced models. This is an approximate method, but it is commonly used in academic analyses (Boyles et al., 2025).

These simulations all model the traffic for the five distinct time of day (TOD) periods distinctly (AM peak, midday, PM peak, evening, and night). I then aggregate the results based on the weighted traffic for that TOD.

Dealing with External Traffic

Not all people who drive in Seattle start and end their trips within the city. Looking at the full matrix of in- and out-of-city trips in the PSRC model, I see that there are substantial inbound and outbound flows:

Table 12 *Percentages of Trips Based on Whether They Cross the City's Limits*

% of Trips in PSRC	**Ending in Seattle**	**Ending Outside Seattle**
Starting in Seattle	18.3%	3.7%
Starting outside Seattle	3.7%	74.2%

Moreover, the generated bus networks do not apply outside of the city, so I could not reasonably get transit times for such trips either. To avoid having to route every trip in the region, I identify the specific freeway and arterial gateways as Seattle's sole entry and exit points as a simplifying assumption. I then route all trips through one of these gateways, and hold these trips fixed throughout the different simulations. This capacity continues to load the roads but does not play into the mode choice calculations.

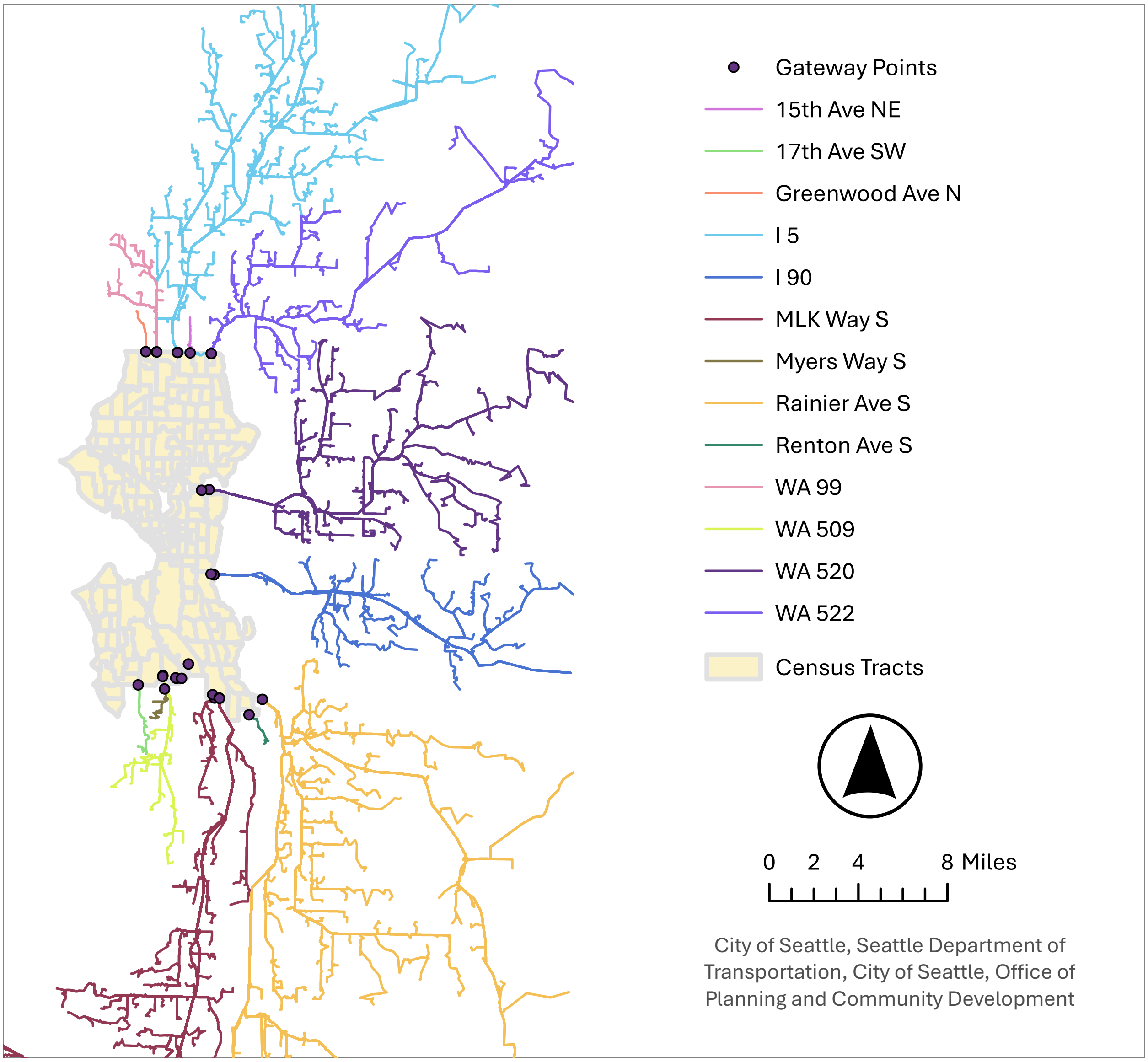

Figure 18 *AM Peak Gateway Flows*

Modeling Automated Vehicles

The second set of variations is to model environment with ubiquitous AV adoption. To model this, I reduce the value of time cost for driving by 59% based on literature review. Specifically, in the MNL model I multiply `β_tt` by 0.41. This increases the amount of traffic and thus the travel time on the road network for cars. To model the impact to transit, I then perform a spatial join of each GTFS route against this congested network. I use a weighted average of travel time increases to slow the bus down. I do not model the fact that this would mean a corresponding decrease in frequency and/or an increase in the number of buses.

This scenario is at 100% AV adoption. AVs will constitute a subset of vehicles for decades to come, but this makes it possible to understand the hypothetical full impact of automating not just the buses, but personal vehicles as well.

Calculating Impact of Network Alternatives

In sum, the different networks above create several possible configurations because we apply the cross-product of street and transit network alternatives. That said, not all possible configurations were evaluated because the net-new transit networks are predicated on transit priority.

Table 13 *Configurations to Be Evaluated*

Transit Network Configuration	**Street Network Configuration**			
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority	Transit Priority and Automated Vehicles
Baseline	Yes	Yes	Yes	Yes
Simple 3x	Yes	Yes	Yes	Yes
Grid-Based	No	No	Yes	Yes
Grid + Local	No	No	Yes	Yes
Node-based	No	No	Yes	Yes

For each configuration I evaluate several factors, including the final mode shares, VMT, and average speeds of each. I look at the mode shares on a tract-by-tract basis, which makes it possible to apply an equity lens to the changes in travel behavior by comparing the results such as accessibility to each census tract's Race and Social Equity Index.

A core question of this thesis is the impact on serious injuries or fatalities. There are two lenses: the amount of exposure to cars, and the danger represented by those cars. To measure exposure, I reference Hughes who found unit elasticity (a 1% reduction in VMT caused a 1% reduction in fatalities). The danger of a vehicle is affected by several factors, including weight and height, but the sole factor this thesis varies in the model is speed (due to increased congestion). To calculate this, I use Nilsson's Power Model which says that fatalities scale like an exponent of speed, specifically v^4, and serious injuries scale like v^3. More recent research has found slightly different values depending on road and environment type—since urban roads (as opposed to freeways) dominate the injury sites in Seattle, this thesis uses those numbers: 3.0 for fatalities and 2.0 for serious injuries (Cameron & Elvik, 2010).

To calculate the absolute impact, I retrieved the past five-year count of serious injuries and fatalities from the City of Seattle (Seattle Department of Transportation, 2026h):

Table 14 *Seattle Vision Zero Statistics, 2021–2025*

	2021	**2022**	**2023**	**2024**	**2025**
Serious injuries	189	225	268	213	219
Fatalities	31	30	28	31	27

This thesis uses an average of 29.4 fatalities per year and 222.8 serious injuries per year. Note that 2025 data is preliminary as of April 2026. The Vision Zero report also shows that pedestrians and cyclists are especially at risk.

These numbers are low in absolute magnitude, and the published research is based on a variety of cities across many different years. Thus, I expect the results to be directional and order-of-magnitude but would not be able to predict specific outcomes.

RESULTS

Model Fitting

Running the MNL model provides the following results. This calculates the ASC (Alternative Specific Constants) and β values for each variable:

Table 15 *MNL Model Coefficients*

Variable	β	SE	z	p	Signif
(Intercept):walk	2.43914	0.02319	105.2	< 0.001	***
(Intercept):bike	−1.33198	0.03372	−39.50	< 0.001	***
(Intercept):transit	−0.28468	0.02525	−11.27	< 0.001	***
cost	−0.05127	0.00163	−31.40	< 0.001	***
walking_min_alt	−0.05975	0.00049	−121.18	< 0.001	***
bike_tt_alt	−0.02874	0.001	−28.83	< 0.001	***
drive_tt_alt	−0.02822	0.00126	−22.40	< 0.001	***
transit_total_diff_alt	−0.00771	0.00113	−6.83	< 0.001	***
vc_drive_alt	0.99236	0.0122	81.32	< 0.001	***
is_work:walk	0.14367	0.02974	4.83	< 0.001	***
is_work:bike	0.59679	0.04536	13.16	< 0.001	***
is_work:transit	0.86878	0.02888	30.08	< 0.001	***

Note. All the values are highly significant (***).

One standard way to understand the β values is in value of travel time (VOTT), which is β time / β cost:

Table 16 *Values of Travel Time for Different Variables*

Variable	VOTT in $ / Hour
`walking_min_alt`	$69.90
`bike_tt_alt`	$33.60
`drive_tt_alt`	$33.00
`transit_total_diff_alt`	$9.00

In this model, the `walking_min_alt` is higher than what literature would suggest, which is possibly because it is serving the purpose of capturing utility for two different modes. As such, this cannot be interpreted as a pure wage-like value of walking time.

The overall model has fitted log-likelihood of –69,255 (selecting the chosen mode with a 45% probability) versus the null log-likelihood of –115,640 (26%: the chance one might randomly select the correct mode). The model has a McFadden R^2 of 0.4011 (values over 0.4 are considered to represent a strong fit). The likelihood-ratio test against null—χ^2—is 92,771 (with 12 degrees of freedom, $p < 0.0001$), confirming that this model is statistically significant.

Baseline Network

The baseline model results in mode shares that are indistinguishable from the Daysim numbers. As expected, transit is the mode where people must spend the most time, and walking is the mode with the shortest distance traveled:

Table 17 *Basic Trip Characteristics by Mode Based on Daysim Weights*

Mode	% of Trips	Total Trips	Average Travel Time (min)	Median Travel Time (min)	Average Trip Length (miles)
Walk	39.3%	820,454	14.3	11.4	0.7
Bike	2.3%	65,156	21.7	19.7	3.8
Drive	53.7%	1,621,447	23.8	19.8	10.7
Transit	4.5%	166,800	44.7	39.5	9.3

Note that these numbers are different from the values in **Table 2** because that is unweighted data from the survey, whereas **Table 17** has the actual predicted mode shares based on weighting in the Daysim model. One additional point of comparison is the American Community Survey data. This data is not filtered to intra-Seattle trips so cannot be compared 1-to-1 with the above results; however, it can be used to check that the underlying PSRC survey data is aligned with actual mode share:

Table 18 *Comparison to American Community Survey Commute Shares*

Mode	% of PSRC Work Trips	Total Trips	ACS Mode Share
Walk	12%	203,366	12%
Drive	64%	486,846	66%
Bike	6%	21,214	3%
Transit	19%	39,693	20%

Travel Time Impacts

Overall, all the new networks demonstrate a clear reduction in travel time, although it is not proportional to network investment. Using the existing network layout and tripling service results in the median trip time dropping from 31.2 minutes to 27.6 minutes. Here are the aggregate median transit travel times for intra-Seattle trips:

Table 19 *Transit Travel Time Changes for Different Configurations*

Transit Network Configuration	Street Network Configuration		
	Current Traffic and Transit Priority (min)	Automated Vehicle-Induced Traffic (min)	Full Transit Priority (min)
Baseline	31.2	38.9	29.4
Simple 3x	27.6	38.4	25.1
Grid-Based	—	—	20.5
Grid + Local	—	—	20.7
Node-Based	—	—	22.8

Note. Travel times are identical to Full Transit Priority when AV-Induced Traffic is introduced since buses are protected from congestion with bus lanes and TSP.

When transit priority is implemented, the median travel time drops to 29.4 minutes on the existing network. The optimizations to the other transit networks further improve travel time savings, with the best possible outcome being 20.5 minutes (a 34% time-savings).

Transit Accessibility Impacts

There are two different ways to look at access via transit. The first, from a transit perspective, is simply the percent of residents that can easily walk to a transit stop. In 2015, the City of Seattle established a goal of maximizing the number of residents served by buses that are within a 10-minute walk, and stop every 10 minutes or better, over the following decade. As of 2025, the goal was 72% of residents (City of Seattle, 2015), but only 53% of residents were within a 10-minute walk of very frequent transit (Seattle Department of Transportation, n.d.). That said, a 10-

minute goal is a low bar—looking at the 5-minute walksheds, there is a substantial difference between the different networks:

Table 20 *Percent of Area Within a 5-Minute Walk of 10-Minute or Better Transit*

Transit Network Configuration	Street Network Configuration		
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority
Baseline	25.4%	3.9%	25.4%
Simple 3x	69.0%	13.9%	70.0%
Grid-Based	—	—	71.6%
Grid + Local	—	—	83.3%
Node-Based	—	—	80.1%

Note: This is area-based not network or population-based values. Those values would be higher as more people cluster around dense transit.

The other way to evaluate accessibility is the percent of jobs within a 30-minute commute of a home (Owen & Levinson, 2015). This is aggregated into a population-weighted average:

Table 21 *30-Minute Employment Accessibility by Configuration*

Street Network Configuration	Transit Network Configuration	Jobs Accessible by Car (k)	Jobs Accessible by Transit (k)	Drive % Change	Transit % Change
Current Traffic and Transit Priority	Baseline	395	117	—	—
	Simple 3x	394	144	−0.1%	22.40%
Automated Vehicle-Induced Traffic	Baseline	395	84	−0.1%	−28.4%
	Simple 3x	395	84	−0.1%	−28.3%
Full Transit Priority and Current Traffic	Baseline	384	134	−2.9%	14.00%
	Simple 3x	383	188	−3.1%	60.30%
	Grid-Based	383	409	−3.2%	249.00%
	Grid + Local	384	381	−2.8%	224.80%
	Node-Based	383	286	−2.9%	143.70%
Full Transit Priority and AV-Induced Traffic	Baseline	383	134	−2.9%	14.00%
	Simple 3x	382	188	−3.3%	60.30%
	Grid-Based	383	409	−3.0%	249.00%
	Grid + Local	383	381	−3.1%	224.80%
	Node-Based	383	286	−2.9%	143.70%

Although there were overall improvements in transit travel times and transit mode share, changes are not evenly distributed—for 30-minute accessibility, there was anywhere between no improvement to a more than 100-fold gains across different census tracts. While that seems high, this approach uses a hard cutoff of 30 minutes. In this case, that means that once the central business district is less than 30 minutes away, riders suddenly have access to a much larger job market than employment opportunities local to their neighborhood.

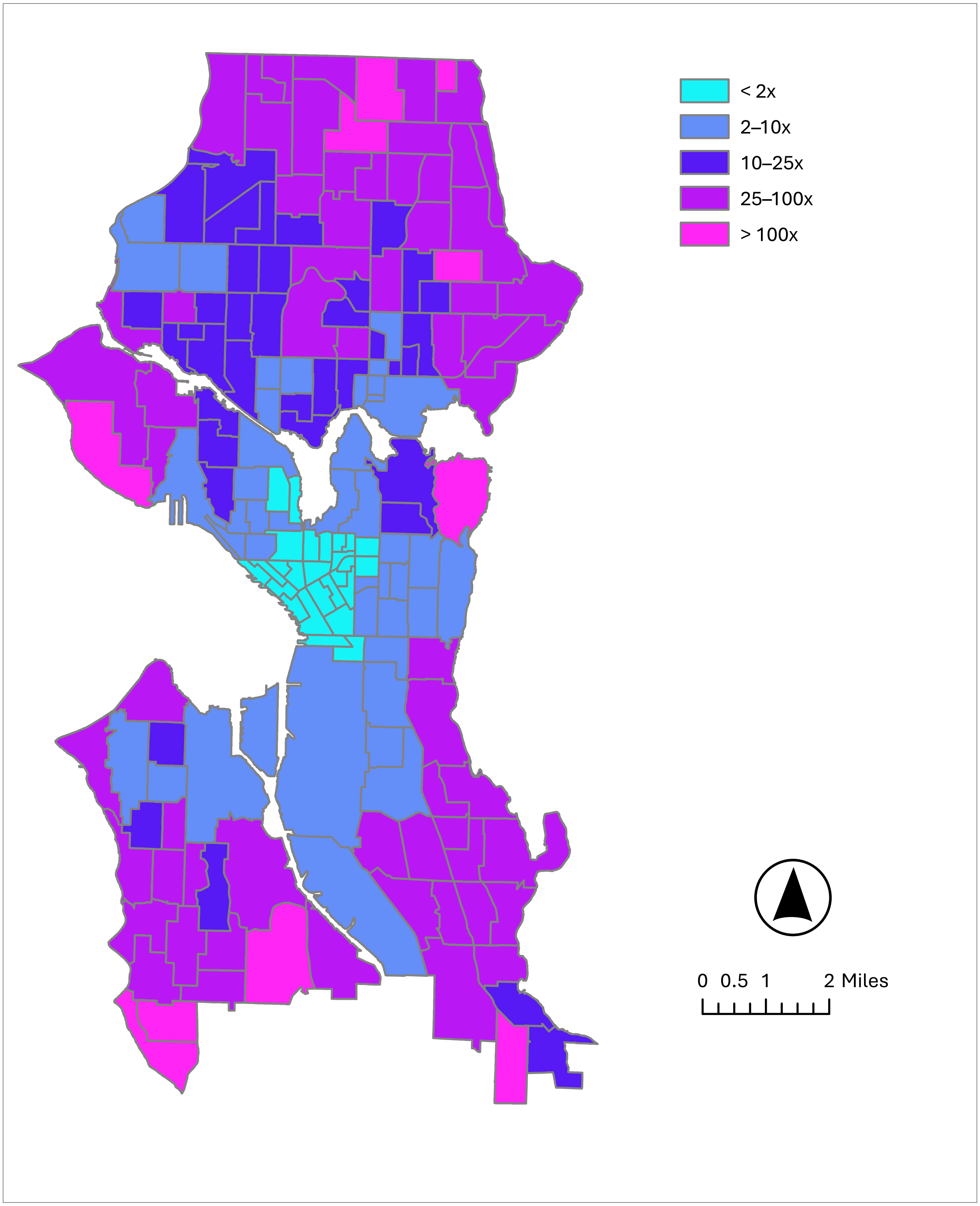

***Figure 19** Change in Transit Accessibility for the Grid-Based Network With AV Traffic*

The downtown area saw the smallest improvement in transit accessibility. This is likely because that portion of the city is already well-served by transit. The greatest improvement tends to be in the perimeter of the city that has poor transit access today. Contrasting this with drive accessibility it has the opposite effect where there are perimeter areas that have a greater decline in accessibility.

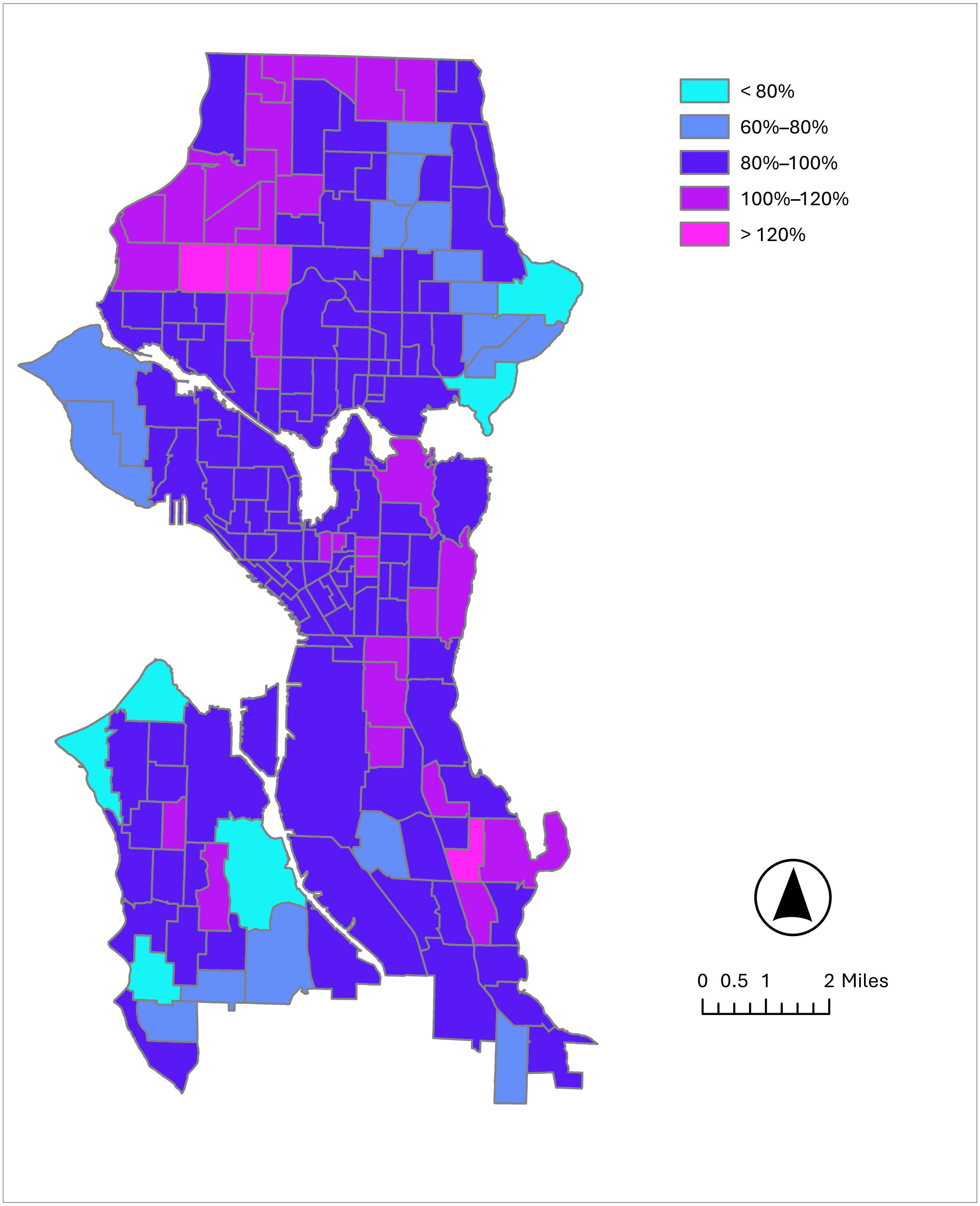

Figure 20 Change in Drive Accessibility for Grid-Based Network With AV Traffic

Mode Share Impact

The two factors that pull in opposite directions are the reduced cost of automated vehicles, and the myriad of improvements to transit networks. The below table shows the delta in mode share for both drive / transit (walk and bike mode shares did shift as well, but that is less relevant to this thesis):

Table 22 *Drive / Transit Mode Share Changes From Baseline*

Transit Network Configuration	Street Network Configuration			
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority Current Traffic	Full Transit Priority and AV-Induced Traffic
Baseline	—	+4.2pp / −3.6pp	−0.5pp / +0.5pp	+2.1pp / −0.8pp
Simple 3x	−0.6pp / +0.9pp	+4.1pp / −3.4pp	−1.2pp / +1.6pp	+1.5pp / +0.1pp
Grid-Based	—	—	−1.9pp / +2.4pp	+0.9pp / +0.9pp
Grid + Local	—	—	−1.9pp / +2.5pp	+0.9pp / +0.9pp
Node-Based	—	—	−1.7pp / +2.2pp	+1.0pp / +0.6pp

In total, AV-induced congestion effects are stronger than any possible improvements to public transit. That said, increasing service can mitigate some of this effect, as observed by the slight 0.9pp increase in transit mode with the Grid + Local network.

Congestion and Speed

The addition of bus lanes will increase congestion, at least in the short term. Longer-term, people adjust their travel patterns and so this traffic may evaporate, but for this thesis I am looking at short-term effects. The below table includes the average speed across the network and the percent of flow on links that are over capacity.

Table 23 *Average Network Driving Speeds and Percent Over Capacity*

Transit Network Configuration	Street Network Configuration			
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority Current Traffic	Full Transit Priority and AV-Induced Traffic
Baseline	24.6 mph / 23.3%	24.0 mph / 24.3%	20.7 mph / 26.4%	20.2 mph / 27.3%
Simple 3x	24.6 mph / 23.1%	24.0 mph / 24.2%	20.8 mph / 26.2%	20.3 mph / 27.1%
Grid-Based	—	—	20.9 mph / 26.0%	20.4 mph / 27.0%

Grid + Local	—	—	20.9 mph / 25.9%	20.4 mph / 27.0%
Node-Based	—	—	20.8 mph / 26.0%	20.4 mph / 27.0%

Although average driving speeds decline by about 4 mph (a 17% slowdown), some corridors experience larger reductions—especially Interstate 5 and many of Seattle's arterials (see Figure 20). Another limitation of the centroid-based approach is that it concentrates all demand from each census tract at a single point, often on a residential street. As a result, that street can become overloaded because it must carry all traffic generated by the tract.

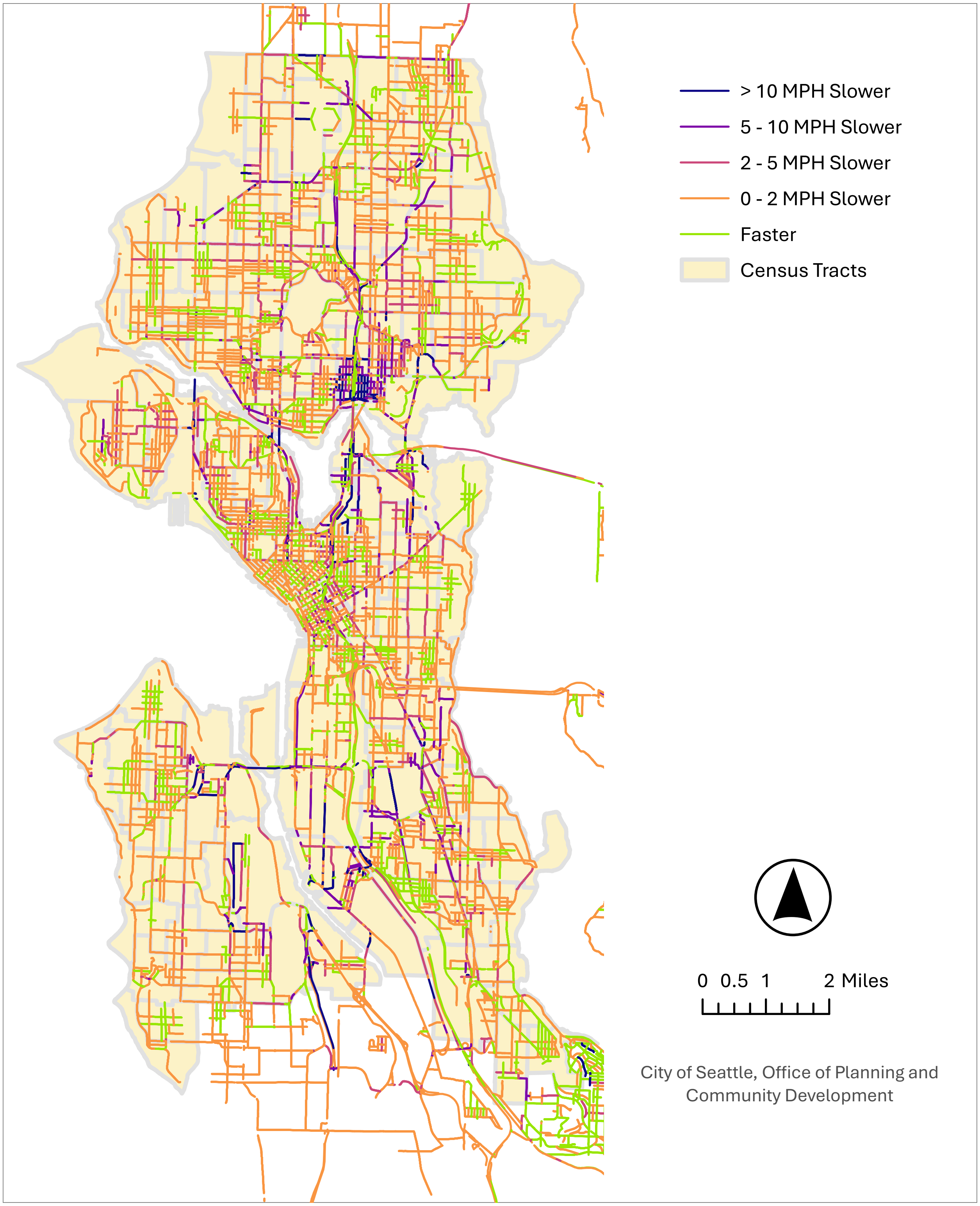

Figure 21 *Distribution of Speed Impacts to the Street Network for the Grid-Based Network*

Sensitivity Analysis

There are several assumption-driven parameters called out in the methods section including constants around factors for congestion, and assumptions around the impact of AVs. I validated several different values for each of these before running the full final model to see its sensitivity to different inputs. Instead of running all time periods and all the networks, I selected the Grid + Local network as the main one to validate and chose just the AM time period. There are several different output metrics that are worth examining:

Table 24 *Output Metrics for Two Different Models at AM Peak*

Metric	Baseline Networks	Grid + Local and AV-Induced Traffic
Drive mode share	72.70%	73.70%
Transit mode share	8.80%	9.70%
Network-avg speed (mph)	21.9	17.6
Transit jobs reachable / 30 min	82,684	414,244
Drive jobs reachable / 30 min	331,450	309,742
Projected fatalities / yr	29.4	16.5 (−44%)

I ran a one-factor-at-a-time (OFAT) sensitivity analysis for the following five factors:

Table 25 *Factors Used in Sensitivity Analysis*

Factor	Description	Base Value	Other Values to Evaluate
`av_drive_tt_shrink`	The reduction in perceived value of travel time for automated vehicles	0.41	0.25, 0.60, 0.80
`bpr_vc_cap`	The cap on the amount of traffic where we stop applying additional time penalty	2	1.5, 3.0
`auto_occupancy`	The average number of people per vehicular trip	1.10	1.00, 1.25
`vz_nilsson_exp_fatal`	The exponential factor used to calculate fatalities	3.0	2.0, 4.0, 4.5
`vz_hughes_elasticity`	The elasticity of fatality with respect to VMT	1.0	0.5, 1.2

The first three impact the actual equilibrium loop, whereas the latter two are just changing the final calculation. The results were that irrespective of the values chosen, transit mode share remains close to the original values.

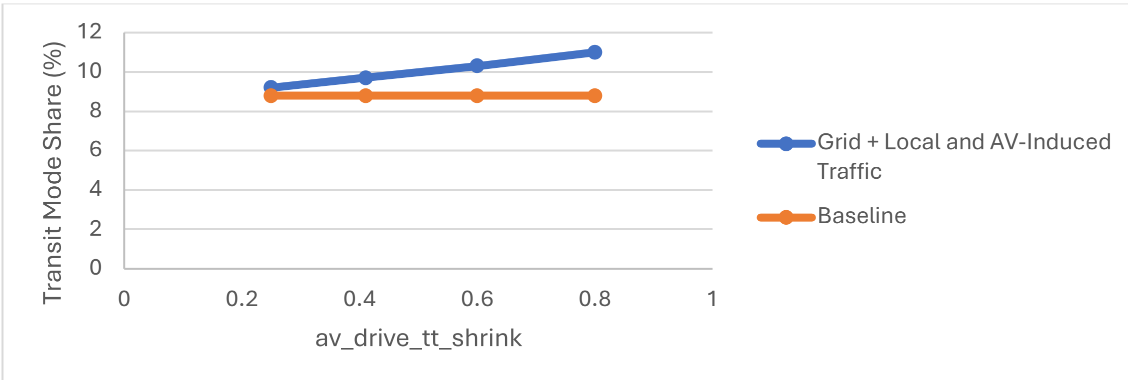

Figure 22 *Transit Mode Share Changes by AV Perceived Travel Cost*

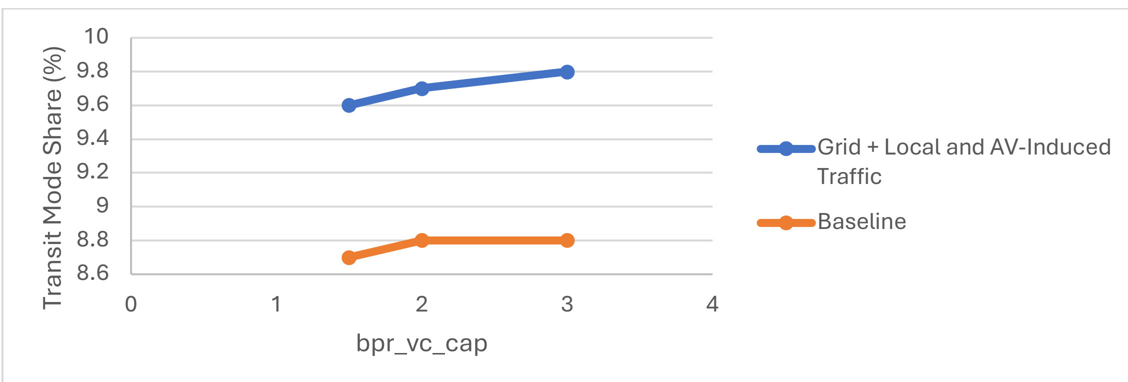

Figure 23 *Transit Mode Share Changes by the Cap on Time Penalty*

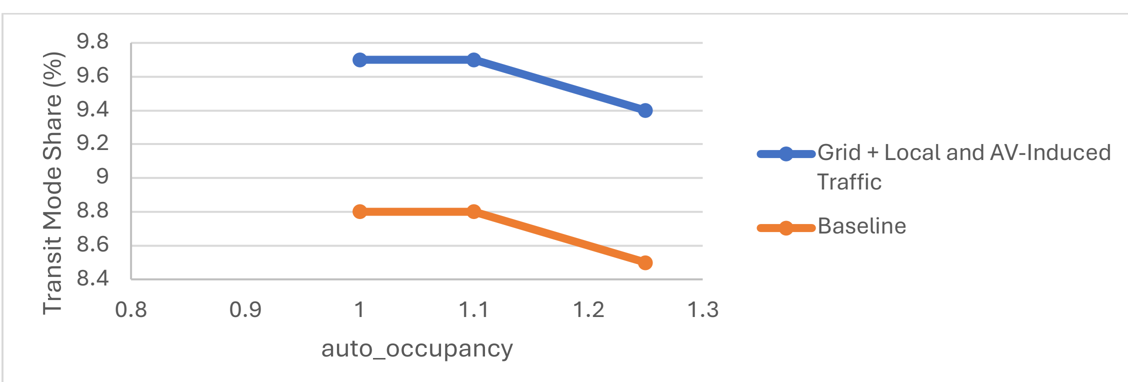

Figure 24 *Transit Mode Share Changes by Auto Occupancy*

The most significant impact of these changes was by `bpr_vc_cap` on average network speed, with a higher cap resulting in traffic, on average, halving speeds. These lower speeds resulted in lower projected fatalities.

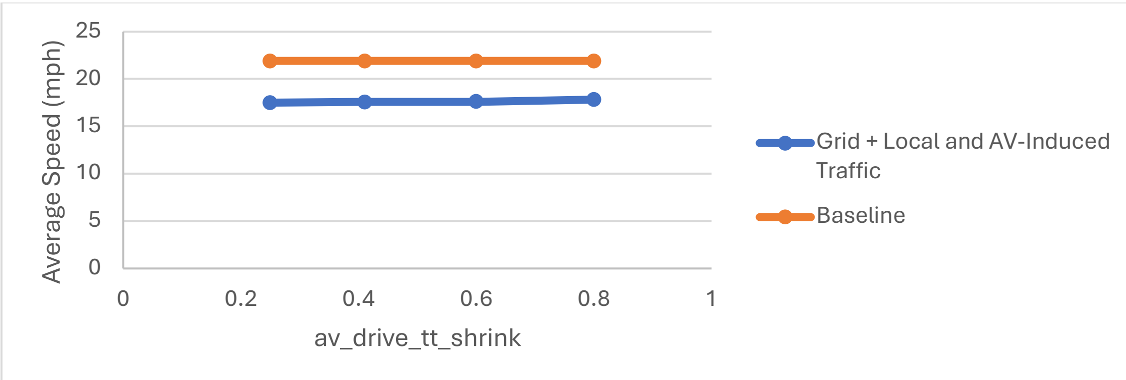

***Figure 25** Network Average Speed Changes by AV Perceived Travel Cost*

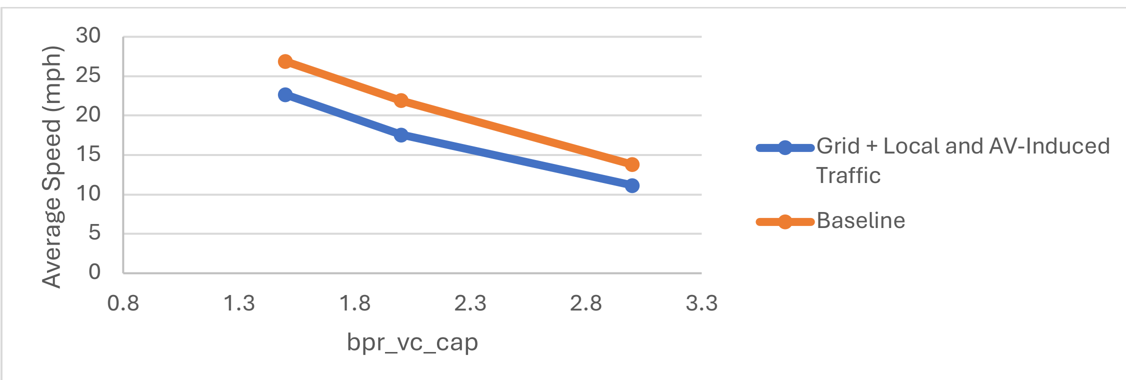

***Figure 26** Network Average Speed by Cap on Time Penalty*

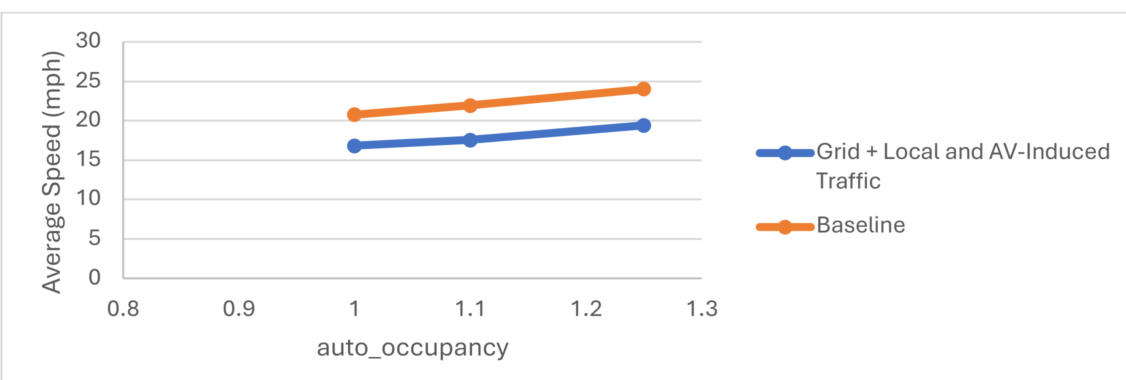

***Figure 27** Network Average Speed by Auto Occupancy*

Finally, looking at the Vision Zero metrics, because VMT moves so little, changing the elasticity does not have a significant impact. As the speed exponent is varied, the number of fatalities does change significantly, indicating that the results should be considered to represent a broad range.

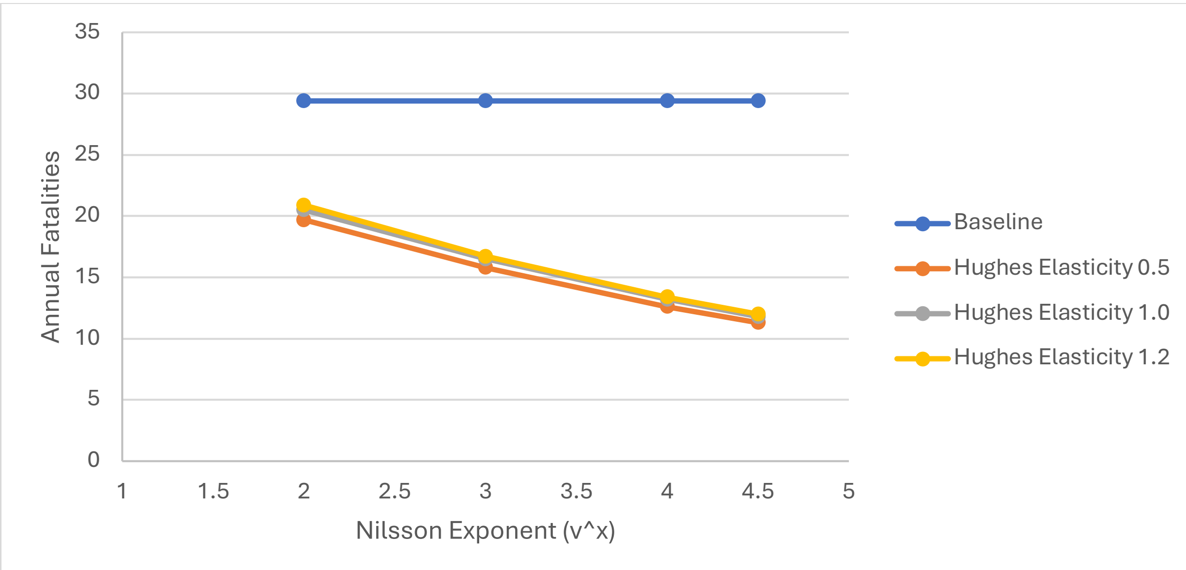

***Figure 28** Vision Zero Metrics Regarding Varied Factors*

Equity Considerations

Next, I evaluate whether these changes will increase equity in any way. The City of Seattle defines the RSE Index as a combination of race, language, nationality, and socioeconomic level (City of Seattle Office of Planning & Community Development, 2017). Below is the statistical correlation (Spearman's ρ) between the change in the number of jobs within 30 minutes and the RSE Index:

***Table 26** Correlation Between Change in Job Accessibility and RSE Index*

Transit Network Configuration	**Street Network Configuration**			
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority Current Traffic	Full Transit Priority and AV-Induced Traffic
Baseline	—	0.147	−0.215	−0.215
Simple 3x	−0.259	0.12	−0.160	−0.160

Grid-Based	—	—	0.037	0.037
Grid + Local	—	—	0.03	0.03
Node-Based	—	—	−0.242	−0.242

Overall, there is not a strong correlation between equity and any of these networks. When designing the bus networks, I did not look at an equity lens. I assumed that serving the harder-to-reach portions of the city would be agnostic to equity.

The strongest signal is a negative correlation between RSE and the accessibility changes in the simple 3x network and baseline network (-0.26). This may reflect that historical networks have inequitable spatial coverage, unlike a net-new grid-based network. My recommendation from this is that any efforts to design a network need to explicitly reach all parts of the city and be aware that if improving equity is a goal, it will not automatically happen by creating a comprehensive network.

Vision Zero

The final step is to understand the impact of these networks on Vision Zero. First, measuring exposure to vehicles, I found that VMT moved due to three factors. First, induced demand from AVs increases the amount of traffic. Second, when there is transit priority, some vehicles must take longer paths to re-route off streets that are either inaccessible to GP traffic or more congested. Third, the increase in transit accessibility in the new networks did shift some people away from driving.

Table 27 *Daily VMT Changes for Different Configurations*

Transit Network Configuration	**Street Network Configuration**			
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority Current Traffic	Full Transit Priority and AV-Induced Traffic
Baseline	—	+5.4%	+2.5%	+6.8%
Simple 3x	–0.9%	+5.1%	+1.6%	+5.9%
Grid-Based	—	—	+0.8%	+5.2%
Grid + Local	—	—	+0.7%	+5.2%
Node-Based	—	—	+1.2%	+5.5%

These new VMT numbers mean that aggregate exposure to cars goes up. That said, this effect is more than outweighed by the substantial differences in speed (see Congestion and Speed):

***Table 28** Fatalities and Serious Injuries for Different Configurations*

Transit Network Configuration	Street Network Configuration			
	Current Traffic and Transit Priority	Automated Vehicle-Induced Traffic	Full Transit Priority Current Traffic	Full Transit Priority and AV-Induced Traffic
Baseline	—	+0.3% / +1.7%	–35.1% / –25.0%	–35.7% / –24.8%
Simple 3x	+0.1% / –0.2%	+0.0% / +1.4%	–34.7% / –24.9%	–35.2% / –24.6%
Grid-Based	—	—	–34.5% / –24.8%	–35.1% / –24.5%
Grid + Local	—	—	–34.2% / –24.7%	–35.1% / –24.6%
Node-Based	—	—	–34.8% / –25.1%	–35.0% / –24.5%

In the most optimistic case, this constitutes a 35% reduction in fatalities and a 25% reduction in serious injuries. These numbers are less than a 17% reduction in speed would imply because traffic fatalities are not evenly distributed throughout the day (Seattle Department of Transportation, 2026e). See the below table for the breakdown by time of day.

***Table 29** Projections by TOD for the Grid + Local Network and AV-Induced Traffic*

Time of Day	Speed Change	VMT Ratio	Fatalities (baseline)	Fatalities (projected)	Serious Injuries (baseline)	Serious Injuries (projected)
AM peak	–19.9%	1.088	2.62	1.46	21.8	15.3
Midday	–15.5%	1.05	6.41	4.06	59.7	44.8
PM peak	–17.8%	1.057	5.5	3.23	49.7	35.5
Evening	–9.1%	1.007	6.47	4.89	44.1	36.7
Night	–14.3%	1.025	8.41	5.42	47.5	35.7

Ultimately, bus network design—despite being a key aspect of this thesis—did not have a significant impact on the Vision Zero results. This is because the primary cause for improvement is the decrease in vehicle speeds (not VMT) which the different bus networks do not meaningfully modify. As called out in the methods section, the impact to fatalities is an approximation—but it still demonstrates the possibility for significantly-reduced fatality risk.

DISCUSSION

Overall Magnitude of Transit Improvements

The most surprising result was the modest nature of outcomes in the transit system. Although the Simple 3x network triples the number of available buses, trips are only 11% faster. This is likely because there are significant fixed costs for any transit journey, such as walking time at both ends and transfers, and so there are diminishing returns from increased frequency. My expectation was that by simply increasing the frequency of buses, the network would benefit because wait time (both at the beginning of the trip and to transfer) is a large contributor to overall journey length. Moreover, I was expecting that a prioritized network that did not have to deal with traffic would see significantly greater improvements because of faster running times, but separating the buses from traffic in the baseline network yielded only a 5.8% time savings.

While these expectations were correct directionally, the magnitude of these changes was less than expected. In particular, the fact that even with 33% faster transit journeys in the Grid + Local network and Transit Priority, the finding that only 2.5pp of riders would switch modes was surprising. I believe this is partly because there is still a substantial time penalty for transit. If transit journeys can often be two or three times slower than driving, a 33% improvement is still small compared to the overall time penalty for taking the bus.

Likewise, there are substantial built-in preferences that riders have. Many people find transit uncomfortable or have trips that would be inconvenient on transit (such as grocery shopping). The model captures, through its mode-specific constants, that there are considerations other than what I trained it on (travel time and cost), and thus selects against transit for many possible trips.

Ultimately, this thesis does not indicate whether these are true preferences or a limitation of the model.

Vision Zero Results

Although the bulk of this thesis is focused on modeling transit networks, the strongest result identified is the impact of speed on fatalities and serious injuries (which does not inherently require improved transit). Reallocating street space away from cars adds to congestion, resulting in somewhat slower vehicle trips. Since fatalities scale by v^3, even a modest reduction in speed can have a huge impact on safety. From a policy perspective, this means that similar Vision Zero results could be achieved by reallocating street space for other purposes, such as bike lanes, outdoor dining, or parklets. Ultimately, transit remains the most efficient way to move people, so reallocating that space to transit furthers the mobility goals of the city while simultaneously helping the city achieve Vision Zero.

It is worth noting that these results are based on the network-average speed. There are many factors that go into making a street dangerous, and this thesis did not model any of those additional factors. This makes the results a directional proxy for what is conceivable, not a specific guaranteed number.

Automation Versus Priority Impacts

Both automated buses and transit priority infrastructure cause people to select transit options more frequently. When isolating each, they represent between a +0.5pp and +0.9pp shift in mode share towards transit respectively (see **Table 22**). However, these interventions differ significantly in terms of their impact on the built environment and the experience of city residents. Automating buses requires King County Metro to change its fleet, but would have little-to-no impact otherwise on the daily experience of the average Seattleite. On the other hand, a network of bus lanes would be highly visible to nearly every Seattleite on a daily basis. As a result, it may behoove policymakers to sequence these changes to build momentum for more impactful transformations.

Limitations

Data

This thesis relies heavily on the PSRC Household Travel Survey which extrapolates to Puget Sound-wide trips from a small sample (there are 12,118 households in the sample, of which only 6,215 are in Seattle). The small sample size reduces the predictive power of subtler elements of the model (for example, the relationship between different demographic characteristics). There are non-public datasets available with much richer O-D info, for example, collected from cell phone usage. If funding were available, using these datasets would have enabled a more reliable set of trip calculations. Use of the survey data also has the potential to introduce a temporal mismatch: the street and transit networks are based on what is on the ground in 2026, whereas the PSRC data goes back several years.

Another data gap is route-level reliability data for King County Metro (and other local transit agencies). Poor reliability is a reason why people select against transit, and priority infrastructure makes trips more reliable (and faster). However, because of the limited reliability data available, the predictive power of this factor in the model was weak.

Ultimately, the MNL model had to be tuned to mitigate unknown confounding factors. This is part of the reason why the overall mode shift was low. With more diverse datasets, it would be possible to create a model with stronger predictive power.

Congestion

The congestion model is basic. Although BPR is straightforward to implement and fast to run for this thesis, there are much richer traffic models available that could have more accurately predicted the congestion effects of different interventions. Moreover, services like Google provide access to observed congestion information, but use of those APIs are cost-prohibitive for use in this thesis.

The approach I use in this thesis also does not iteratively adjust transit times as congestion evolves. Instead, I use a simple two-pass approach: model congestion's impact to transit, then use those updated transit times as the solution converges. It would be more mathematically sound to regenerate the whole transit network after each iteration of the network in the congestion calculation.

Finally, this model assumes that the traffic that enters or exits Seattle is fixed in both its entry and exit point, and its mode. In reality, people from outside Seattle would update their routes due to changing traffic and transit inside the city. However, it was not computationally feasible to model all O-D pairs in the region.

Geographic Granularity

The unit of analysis in this thesis was the census tract. This allows me to join ACS demographic information to trip data but has a major drawback in that it is a very coarse geographic representation. Ideally, O-D pairs would be far more granular, such as to the census block level instead of tract. This would generate more diverse routes, which in turn could assist in making the congestion calculations more realistic. One of the least robust parts of the analysis is the way that intra-tract trips are modeled. A more granular unit would mostly eliminate this problem.

However, there is a basic compute challenge: as it stands, running the model with only 131 census tracts still takes many hours. There are over 11k census blocks and time to run the model scales like $O(n^2)$. There may be computational shortcuts available to optimize this problem, but with the resources and time scales available for this thesis, I cannot tackle that problem (there is also another potential intermediate aggregation unit at block group level—about 400). Finally, Seattle is highly integrated with the rest of the region, so the fact that I was only able to model these interventions within the city limits ignored the potential impact to millions of daily trips.

Car Ownership

One of the factors that has the strongest impact on the choice to drive or not in the MNL model is the number of cars a household has access to. For this thesis, I assume that number is static; specifically, even as transit becomes more attractive, people do not reduce their number of cars. This means, however, that the thesis is missing out on a potential positive feedback loop where better transit results in lower car ownership, thus resulting in more transit, and so forth. This consideration was excluded from this analysis because I do not have a model to predict car purchase (or sale) behavior. If such a model did exist, it could amplify the effect of transit improvements.

Network Design

The potential impact of a transit network can vary depending on specific choices during route alignment and stop placement. The four networks considered in this thesis are not canonical; they follow a set of transit planning principles, but other planners might generate a different network even with the same guidance. Even the simple 3x network that uses existing routing has subjective planning decisions. For example, which routes should get an express overlay, and where should the stops for such expresses be?

This thesis does not explore that further. Theoretically, I could have individually created several different grid-based networks to understand the magnitude of this effect, but that is the type of task that would be best achieved with multiple people bringing their expertise and diverse choices to the problem.

When initially ideating, I had planned on algorithmic network generation as the primary alternative. This has the advantage of reproducibility, and eliminates human decision-making. However, I discovered that at this point there is not any public tooling available for algorithmic transit network creation and optimization, possibly because this is a computationally-challenging NP-hard problem.

These network designs are predicated on the assumption of roughly tripling the number of vehicles. This intentionally ignores the up-front capital costs of automated buses (which, as I learned in the Seoul interview, are currently more expensive than human-driven buses). Instead, the focus is on ongoing operational expenses. That said, it may be beneficial to model the capital impacts in addition to the regular costs.

Safety of Automated Vehicles

This thesis assumes that on average, automated vehicles will be as safe as human-driven vehicles. This assumption is baked into calculations for fatalities and injuries. If AVs prove to be substantially safer than human-driven vehicles, these numbers could be substantially different. Congestion and accessibility impacts are real, irrespective of the safety performance of AVs.

Further Research

Policy Acceptance of Transit Priority

The most significant conclusion from this thesis is that reallocating street space to public transit makes streets safer by increasing congestion and reducing vehicle speeds. It is an open question whether or not the typical Seattleite would accept this tradeoff. I would suggest public outreach to ask the question: “Would you accept slower drive times if it made our streets safer and resulted in much faster transit times?” The numbers are powerful and most people know at least one person affected by traffic violence. However, when confronted with a real tradeoff, enthusiasm may wane. Understanding people's sensitivity to the tradeoff could help policymakers understand the boundaries of what an acceptable intervention would be.

Next Steps with Modeling

Given additional time and resources, the first thing I would suggest is to expand the robustness of the model to address the limitations mentioned in the previous section. This could be accomplished by acquiring more O-D data, using more granular geographic units, and running a more advanced congestion model. Additionally, the model should be run at the Puget Sound level, not solely at the City of Seattle level. With these changes, there could be higher confidence associated with these findings.

Sources of Anti-Transit Bias

The model suggests that people's mode choice is driven by factors beyond time and cost alone; in fact, travel time only predicts a small part of the decision to drive. Yet at the same time, there are places in the world where transit mode share is much higher than driving mode share, so these biases are not fixed. Additional research should be done comparing the Puget Sound to other worldwide locations with higher transit mode share to understand what is missing from an analysis like the one in this thesis.

Other Policy Interventions

As I mentioned in the background, the City of Seattle is thinking about what interventions are going to be required for automated vehicles. This thesis demonstrates that under the modeled assumptions, AV adoption will make traffic worse. However, the literature is clear that the introduction of congestion pricing could eliminate this externality. Congestion pricing could more effectively shape demand on the roads, so it would be good to run a model with per-mile variable congestion pricing for AVs.

I excluded it from this thesis because congestion pricing often has popular pushback, and there are enough challenging assumptions built into this thesis already. The assumptions around aggressive transit priority are difficult politically. In fact, another potential avenue for future research is how to make full transit priority politically palatable. I initially considered modeling freight and bus lanes (FAB lanes) as a less divisive approach. Freight is interesting because it is the high-capacity equivalent of movement for goods. Yet, by raw vehicle count, freight is a very small percentage of overall traffic on city streets. Moreover, the companies that move freight tend to have significant political influence. An alliance between freight and public transit for a comprehensive citywide network of FAB lanes may be more achievable than a transit-only approach and still have similar performance characteristics in terms of outcomes. This would have to be validated by future research and modeling.

The other policy intervention to research is what the regulations need to be for the adoption of ABs in the first place. The interviews indicated that the technology is not yet ready for wide-scale rollout, meaning that government has a role to play to enable this technology in a predictable and safe way. This thesis leaves how exactly this will happen as an open question.

CONCLUSION

The streets of Seattle are not safe today—in 2025 alone, 27 people lost their lives due to traffic violence. This is the impetus for Vision Zero, and yet progress has been slow. A wholesale reimagining of our transportation system could be the solution. This thesis presents several options on how to transform our streets, with a focus on autonomy both for personal vehicles and for public transit, and physical street priority.

This thesis found that reallocating street space to purposes other than cars is the primary modeled pathway that reduces fatalities and serious injuries in the transportation network. I evaluated 14 different scenarios, looking at the presence or absence of personal AVs, whether there are transit lanes, and four different layouts for the bus routes in the city. These layouts have roughly equal vehicle requirements, so there is no expectation of a funding influx here. The best models saw a 35% reduction in fatalities and a 25% reduction in serious injuries. This meant that cars would get around more slowly, with a 17% reduction in vehicular speeds. On the other hand, transit could reach much more of the city more quickly: the median transit trip could be 33% faster and people could access 249% more jobs in 30 minutes or less.

Ultimately, this thesis does not investigate whether the people of Seattle would accept such a change, but it does provide a quantitative representation of one possible path: a future in which people can be much safer on the city's streets and can get around quickly and easily with high-quality public transportation. Returning to the original research question, I found that allocating street space to buses does advance Vision Zero, while automating transit improves mobility but does not directly help improve safety in the city.

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APPENDIX A

AI Statement

Several AI tools were used in this thesis. ChatGPT (https://chatgpt.com/) was used in the initial brainstorming phase of the thesis to discuss possible research ideas. Elicit (https://elicit.com) and ChatGPT were used for literature review to discover and analyze sources. ChatGPT and Claude Code (https://claude.ai/) were used to write much of the Python and R code that I used in this project. ChatGPT, Claude, and Microsoft Word's built-in AI capabilities were used for editing feedback on the written content of the thesis document. However, all text present in the document was written by me, aside from suggested autocorrections in Microsoft Word.

APPENDIX B

Interview Questions

1. Why did you consider driverless buses for this route? Were other routes considered before this decision? What factors led to this route being selected?
2. Was there institutional or organizational pushback within your agency or from other agencies? How was this addressed?
3. How long did the process take to determine moving forward with this route? What was the most time-consuming aspect?
4. What feedback have you received from riders since the service began? Please include both positive and negative responses.
5. What are the primary operational issues (if any) with this bus service?
6. Does the bus utilize any transit priority measures such as bus lanes or signal priority? If so, how have these affected performance?
7. Do you anticipate expanding driverless buses to other routes? What factors are limiting expansion?
8. Has the bus been involved in any traffic collisions with vehicles, cyclists, or pedestrians? If so, how many and how severe were they?
9. Do you anticipate using driverless buses to replace existing fixed-route service? If so, how do you anticipate changing route design, if at all? For example, with smaller vehicles, routes can be more frequent and serve more locations; is that a consideration?
10. Do you anticipate running a mixture of driverless and driver-based buses in the future? If so, what are your considerations for which service types will have drivers or not?
11. What policies or regulations most influenced the deployment of driverless buses in your region?
12. What lessons from your city could be applied to other international cities?
13. Do you have any additional experiences you would like to share?

APPENDIX C

External Data Sources

Dataset	Citation
Household Travel Survey, 2017-2023	(Puget Sound Regional Council, 2023)
SoundCast / DaySim activity-based model outputs	(Puget Sound Regional Council, n.d.)
TIGER/Line 2020: census tracts, blocks, places	(U.S. Census Bureau, 2021)
SDOT Paid Parking Rate Tiers	(Seattle Department of Transportation, 2026c)
Restricted Parking Zone Areas	(Seattle Department of Transportation, 2026d)
Blockface	(Seattle Department of Transportation, 2026a)
Neighborhood Map Atlas districts	(Seattle Department of Transportation, 2026b)
Racial and Social Equity Composite Index	(City of Seattle, 2024)
Seattle Streets	(City of Seattle, 2026b)
Traffic Lanes	(Seattle Department of Transportation, 2026f)
Traffic Signals	(Seattle Department of Transportation, 2026g)
Traffic Flow Count	(City of Seattle, 2026d)
SDOT Collisions	(Seattle Department of Transportation, 2026e)
WSDOT traffic count data	(Washington State Department of Transportation, n.d.)
Public Garages and Parking Lots	(City of Seattle, 2026a)
OpenStreetMap, Washington extract	(OpenStreetMap contributors, 2026)
Puget Sound consolidated GTFS feed, Spring 2026	(Sound Transit, 2026)
American Community Survey estimates	(U.S. Census Bureau, 2024a)
LEHD LODES (version 8) workplace area characteristics, WA, 2022	(U.S. Census Bureau, n.d.)