# Mapping Incentive Zones for Hospital Commuters Using Mode Choice and Spatial Analysis

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A THESIS SUBMITTED TO THE FACULTY OF GRADUATE STUDIES IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF APPLIED SCIENCE IN CIVIL ENGINEERING

GRADUATE PROGRAM IN CIVIL ENGINEERING

YORK UNIVERSITY

TORONTO, ONTARIO

JULY 2026

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# Abstract

Urban hospitals in dense metropolitan regions face increasing parking congestion due to the high commuter volumes and limited parking supply. At large institutions such as hospitals in Toronto, single-occupancy vehicle (SOV) commuting remains the dominant travel pattern among the daily commuters. This creates challenges for institutions such as parking shortages, queuing, congestion and greenhouse gas (GHG) emissions. This thesis proposes a data-driven study that utilizes discrete choice modelling, spatial analysis, and budget-constrained optimization to evaluate strategies for reducing SOV commuting.

A Multinomial Logit (MNL) mode choice model was developed using survey data collected from hospital staff and volunteers at a Toronto hospital. Survey response data were grouped by Forward Sortation Areas (FSAs), defined by the first three characters of a postal code, to capture geographical difference in commuting patterns such as distance from the hospital and transit accessibility. This model estimates the probability of selecting one of three commuting alternatives: driving, public transit and carpooling. Travel time, travel cost and FSA population were included as explanatory variables. Model parameters were estimated through maximum likelihood estimation, and statistical significance was calculated using standard errors derived from the Hessian matrix of the log-likelihood function, which were used to compute z-scores and p-values.

The estimated mode choice probabilities were then incorporated into an incentive-based optimization model that applies uniform transit and carpool incentives under a fixed monthly budget. The objective of the model is to maximize the reduction in SOV commuting while remaining within the budget constraint. Sensitivity analysis was conducted for monthly budgets ranging from $5,000 to $30,000. Results indicate that larger budgets reduce predicted SOV commuting and increase transit and carpool use, although marginal benefits diminish as incentive levels increase.

Overall, the proposed framework provides a practical tool for hospital administrators and transportation planners to evaluate commuter incentive strategies and reduce parking demand. The methodology may also be adapted to other large institutions facing similar transportation and parking challenges. Future work may consider region-specific incentives, equity considerations, active transportation modes and real-time parking data.

# Acknowledgements

Throughout my academic career I have found myself to be the most successful under the supervision of Professor Mehdi Nourinejad. His wisdom and guidance have helped me grow in my career and as an individual overall. Thank you for supporting me from my bachelor's degree to now. My gratitude is dedicated to him.

I would also like to thank my colleagues, Fatemeh Sadeghi and Ali Yousefzadeh for their help and being such helpful teammates as well as all other students and faculty at Lassonde School of Engineering who helped me get to this point.

I am thankful for my family and friends for their support through this whole journey and giving me the space and support to pursue this accomplishment.

Finally, I am grateful for my husband, Ahmad, for his unlimited support and companionship during this process.

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# List of Abbreviations

CAPRI Congestion and Parking Relief Incentives

FSA Forward Sortation Area

GHG Greenhouse Gas

GIS Geographic Information System

GTA Greater Toronto Area

IIA Independence of Irrelevant Alternatives

MNL Multinomial Logit

MTC Metropolitan Transportation Commission

TOD Transit-Oriented Development

SOV Single Occupancy Vehicle

TDM Travel Demand Management

TTC Toronto Transit Commission

VMT Vehicle Miles Travelled

# Chapter 1

## 1.0 Introduction

Urban transportation systems in large metropolitan regions face ongoing challenges related to congestion, environmental sustainability, and infrastructure limitations. Hospitals are complex urban facilities because they generate significant daily travel demand from staff, patients, visitors and volunteers. Unlike many other institutions, hospitals operate continuously and must always maintain reliable accessibility. As a result, parking demand at hospitals is usually high and difficult to manage, particularly in dense urban areas where land availability is limited.

In Toronto, commuters rely heavily on private vehicles despite the availability of public transportation. Many hospital employees travel from areas across the Greater Toronto Area (GTA), resulting in variation in travel distance, travel time and access to transportation alternatives. A strong reliance on single-occupancy vehicles (SOVs) contributes to congestion surrounding hospital facilities, creating challenges related to parking availability, vehicle circulation within parking areas and accessibility for patients and emergency services. Addressing these issues requires strategies that account for travel behaviour and institutional policy practices rather than relying solely on infrastructure expansion.

This thesis proposes a data-driven framework that combines commuter behaviour modelling with incentive-based policy strategies to reduce parking congestion at hospitals and similar institutions. By integrating mode choice modelling, spatial analysis and optimization methods, the research aims to provide decision-makers with a structure for reducing parking demand and encouraging shifts toward more sustainable modes of travel.

### 1.1 Motivation

Urban hospitals in densely populated areas face significant parking congestion, much of which is linked to commuter travel behaviour. A large portion of commuters travelling to the hospitals in Toronto rely on private vehicle driving as their primary mode of travel. Effective parking management measures are therefore required to maintain accessibility and avoid operational disruptions.

Common types of parking management strategies used for addressing limited parking availability include increasing enforcement with a focus on peak periods, encouraging shared parking arrangements, promoting alternative modes, and implementing financial incentives to commuters (Litman, 2022). These strategies demonstrate that managing demand can contribute more to sustainability and cost-effectiveness compared to increasing parking supply.

According to Statistics Canada, 73.8% of people who live and work in Toronto are commuting in private vehicles, and about 85% of those commuters are driving alone (Statistics Canada, 2022). SOV commuting is usually associated with higher financial costs compared to alternative modes, especially when parking fees are required which is a common case at hospitals. Despite these costs, SOV commuting remains attractive because of its convenience, flexibility and reliability. The large number of drivers arriving daily at the hospitals contribute to congestion within and around hospital areas, causing travel delays, longer parking search times and operational inefficiencies.

Idling vehicles caused by hospital parking congestion contribute to environmental impacts including greenhouse gas (GHG) emissions. Searching for parking spaces can increase travel time and fuel exhaustion, which are additional contributing factors to emissions in urban areas. Toronto's climate change action plans include goals of decreasing GHG emissions by 2030, demonstrating the importance of promoting sustainable transportation options (City of Toronto, 2021). Major institutions like hospitals receiving high volumes of commuters have an opportunity to contribute to these goals by encouraging commuters to shift away from SOV commuting towards alternative transportation modes.

Survey data collected from a Toronto hospital indicated that SOV commuting is the dominant travel mode among staff and volunteers. This finding highlights the need for policies that encourage a shift toward more sustainable alternatives such as public transit and carpooling. Mode choice must therefore be influenced in a way that encourages commuters to shift away from driving toward more sustainable transportation options.

This project adds to current literature by combining mode choice modeling and spatial optimization with real-world commuter survey data. The survey data were categorized based on the respective Forward Sortation Areas (FSAs), representing the first three characters of postal codes, allowing commuter behaviour to be analyzed. Utility functions were developed to represent mode choice as a function of travel time, travel cost and population. Due to limited representation of active modes in the dataset, the modelling focused on driving, transit, and carpooling alternatives.

Additional data provided by the hospital lists the hospital staff population counts by FSA region. This data allowed survey-based mode choice probabilities to be applied to the broader staff populations across the

relevant regions. An optimization model was developed to maximize shift towards transit and carpooling by calculating cost incentives under fixed budget constraints. Geographic Information System (GIS) tools were used to visualize the data and outcomes for spatial decision-making.

The outcome of this study is a practical, data-driven framework for hospital administrators and policy makers. This framework can address similar parking congestion conflicts and promote sustainable transportation through targeted incentive strategies.

### 1.1.1 Urban Hospital Parking Challenges

Hospitals face specific transportation challenges compared to other institutions. They operate continuously with shift changes throughout the day, which causes parking peaks at different times of the day. In addition, hospitals provide services to a diverse range of groups with different needs. Patients and visitors may require parking spaces close to entrances if dealing with health conditions or mobility limitations, while staff represent a more stable portion of the daily demand. These different requirements cause complications in parking management and require policies that consider accessibility with efficiency.

Expanding parking supply in a vicinity is often considered the solution to parking congestion problems but this solution may not be feasible due to costly construction fees and land constraints in urban areas. Parking structures also require long-term maintenance and operational costs. Furthermore, increasing parking supply may encourage an increased reliance on private vehicles which will overtime recreate parking congestion problems. For these reasons, many institutions are focusing on managing travel demand rather than expanding parking infrastructure.

### 1.1.2 Transportation Context in Toronto

Toronto and the GTA represent one of the largest metropolitan regions in Canada. Due to population growth and commuting patterns, the region is often faced with major transportation challenges. Although the city currently has a transportation system with ongoing development, commuting behaviour varies across the regions due to differences like transit accessibility, travel times. and population density. Commuters living in suburban areas may view driving as a more convenient mode of transportation while those in areas with more transit access have more flexibility in alternatives.

Hospital employees usually hold different transportation conditions which causes variety amongst the group. Using the difference in geographical characteristics and context is essential for designing policies that are to be used to influence mode choice. FSA-specific commuter data presents the relevant differences between the regions in terms of accessibility and commuting patterns.

### 1.1.3 Importance of Behavioural Approaches

Transportation planning strategies for reducing congestion and parking demand can be categorized into supply and demand approaches. Supply-based approaches usually involve expanding infrastructure capacity. Although these approaches may solve the problem temporarily, they often require a significant financial investment and do not address the underlying behavioural causes of the problem.

Demand-based approaches, referred to as Travel Demand Management (TDM) in transportation contexts, focus on strategies that prioritize influencing travel behaviour. This includes adjusting incentives, costs or convenience associated with different modes. Examples could include transit subsidies, carpooling programs, flexible scheduling and parking pricing methods. Incentive-based strategies are evaluated to be effective since they can be implemented over time and evaluated at different budget levels. The approaches work with sustainability goals by encouraging a shift towards existing sustainable transportation systems rather than expanding infrastructure.

### 1.1.4 Impacts of Parking Congestion on Hospitals

Parking congestion at hospitals can have consequences greater than inconvenience for commuters. Limited parking availability can affect hospital operations, staff productivity, and patient experience. Employees who have trouble finding parking can result in being late to work or high stress levels that can affect work performance. Patients and visitors may also experience delays or stress when parking is unavailable or difficult to find. This is especially the case in time constraint healthcare situations like appointments and shifts. In emergencies, congestion around hospital entrances may block access for ambulances and emergency vehicles which can delay response time.

Financial impacts are also associated with parking congestion. Hospitals must contribute costs to manage parking facilities. This includes maintenance, parking enforcement and infrastructure costs. Constructing new parking structures often requires a large investment from the institution. These costs can reach millions of dollars depending on the size and location of the facility. Since healthcare institutions usually operate under cost constraints, expanding parking areas may not be the most effective solution financially. As a result, many organizations lean towards management strategies rather than increasing parking supply.

### 1.1.5 Environmental and Sustainability Considerations

Transportation networks have a large impact on environmental sustainability due to high vehicle emissions contributing to air pollution and climate change. Private vehicle commuting generates GHG emissions especially if trips involve congestion or idling situations. Hospitals located in dense urban areas usually

experience high traffic volumes near entrances and parking areas which can result in increased emissions and reduced air quality in the local areas.

Encouraging shifts toward more sustainable transportation modes such as public transit and carpooling can reduce environmental impacts associated with commuting. Institutions can contribute to larger sustainability goals by applying policies that reduce SOV commuting volumes. Sustainable transportation initiatives align with sustainability commitments at corporate level and public health goals which are both relevant to healthcare organizations.

## 1.2 Research Objectives

This research has four primary objectives:

1. To develop a Multinomial Logit (MNL) model that estimates commuter mode choice between driving, transit and carpooling.
2. To evaluate how travel time, travel cost and FSA-level characteristics influence commuter decisions.
3. To develop an optimization model that determines the transit and carpool incentives that maximize reductions in SOV commuting under fixed monthly budgets.
4. To evaluate how the effectiveness of incentive-based transportation policies varies across FSA regions.

This research contributes to transportation planning and academia by developing a MNL model based on hospital commuter data to provide a structured understanding of mode choice behaviour of healthcare workers in Toronto. The model incorporates factors influencing travel behaviour such as travel time, travel cost and region-based population characteristics to further validate their significance to the model through statistical testing.

The study introduces a budget-constrained optimization model that assigns incentives for transit and carpooling transportation modes to maximize mode shift away from driving. The purpose of these incentives is to encourage commuters to choose alternate travel modes which will improve parking conditions and reduce congestion. The results would provide estimates of projected reductions in driving and the required financial costs required to achieve the results.

The research outputs are applied across the FSA regions allowing policymakers to identify where incentives are most effective. By basing this study on a hospital setting, a framework is provided that can be applied to facilities and institutions such as universities or larger employment hubs.

### 1.2.1 Research Contributions

This research contributes to both methodology and practice. In methodological context, it utilizes discrete choice modelling with optimization and spatial analysis to evaluate incentive policies under budget constraints. It uses real commuter survey data combined with specific institutional population data to estimate impacts on a larger and more general commuter population. In practice, it provides decision-makers with results that present predicted reductions in driving under different budget scenarios which supports policy evaluation and funding guidance.

### 1.2.2 Research Gap

Although significant research has been conducted on TDM and mode choice modelling, only a minority of the studies focus specifically on transportation policies being used in healthcare facilities for behavioural and optimization approaches. Many studies research parking pricing and infrastructure strategies alone, but fewer studies combine commuter behaviour modelling with policy design under budget constraints.

Furthermore, existing research often relies on generalized travel behaviour data rather than commuter datasets collected directly from a specific institution. Hospitals represent unique environments where commuter patterns, accessibility resources and operations differ from typical workplaces. Incorporating institution-specific data can improve the relevance and accuracy for policy evaluation.

This research addresses these gaps by incorporating commuter survey data, spatial analysis and optimization methods to evaluate incentive policies specific to hospital environments. The combination of behavioural modelling and budget-constrained policy design provides a guiding framework that can be used in institutions for transportation planning decisions.

### 1.2.3 Importance for Decision Makers

Transportation policies implemented at large institutions must factor in financial requirements, operational impacts and stakeholder acceptance. Decision-makers usually use tools that provide clear projected estimates of impacts before implementing any new policies. Predictive modelling approaches allow institutions to evaluate policies and strategies that will achieve the desired outcomes efficiently.

By estimating reductions in SOV commuting under different budget constraints, this research provides valuable insights for policymakers. The ability to evaluate scenarios before implementation avoids uncertainty and is supported through evidence-based decision-making. The framework in this study can be followed at institutions facing similar parking challenges.

## 1.3 Research Questions

This thesis is aimed to address the following research questions:

- What reductions in SOV commuting can be achieved under realistic monthly incentive budgets?
- Which FSA regions experience the greatest reduction in SOV commuting when incentives are distributed uniformly?
- To what extent do regional and socio-economic characteristics influence the effectiveness of incentive policies?

The first research question examines the potential effectiveness of incentive-based transportation policies in reducing SOV commuting across hospital staff. By applying financial incentives for sustainable travel modes such as transit and carpooling, the study evaluates how commuter behaviour may change under different incentive budget scenarios. Understanding the projection of reductions in SOV trips is important for determining whether incentive programs can be effective for alleviating parking congestion in hospital facilities and similar institutions.

The second research question focuses on ranges in commuter behaviour across the different FSAs. Commuters living in different geographical regions experience different travel conditions such as transit accessibility, commuting distance and travel time. By examining the predicted mode shifts in the different regions, the study can identify which FSAs may result in having the most reductions in SOV driving.

The third research question examines if socio-economic and region-specific attributes can influence how commuters respond to transportation incentives. Factors such as population density and accessibility to public transit may affect the likelihood of commuters switching to alternative transportation modes. Evaluating these differences provides insight on how different commuter groups respond to incentive policies and supports policy adjustments that aim to use targeted demand strategies in the future.

## 1.4 Assumptions and Limitations Overview

This study includes several assumptions required for modelling and analysis. Travel times and costs were estimated using publicly available tools and assumptions specific to each mode to ensure consistency when comparing commuters. Travel times were estimated using the Google Maps Distance Matrix API for a representative weekday morning commute. Driving costs were represented by hospital parking costs, transit costs were based on the applicable transit fare for each FSA and carpool costs were assumed to equal half of the driving cost. Incentives were applied uniformly across FSA regions to provide a baseline evaluation of projected policy impacts before considering more targeted strategies. These assumptions allow the

modelling framework to focus on commuter behaviour responses to the financial incentives and maintain consistency in the data for accurate observations.

Multiple limitations are present in this study. The research uses self-reported survey data which may introduce response bias or sampling bias. Active transportation modes were excluded from the modelling process due to underrepresentation in the dataset which may impact accurate results for short-distance commuters. In addition, the MNL model assumes independent decision-making for all alternatives and may not consider complex decision factors like preferences, perceptions or institutional specifications which influence travel choices.

Despite these limitations, the modelling framework provides valuable insight into how commuter behaviour may change under different policy scenarios. Discussion on data preparation, assumptions and modelling procedures are provided in later sections of this thesis.

## 1.5 Scope of Study

This study focuses on staff commuting behaviour at a hospital in Toronto. While hospitals serve multiple groups of people, staff commuters represent a significant and consistent portion of daily parking demand, making them a good target group for studying demand management practices. The analysis considers three transportation modes: driving, public transit and carpooling. Active transportation modes were excluded from modelling due to limited representation in the dataset.

Incentives are applied uniformly across geographic regions to provide a baseline evaluation of projected impacts. Future research could study targeted incentive strategies that account for regional accessibility differences and include equity factors.

## 1.6 Thesis Organization

This thesis consists of six chapters. The first chapter, Chapter 1, introduces the research problem, motivation, objectives and research questions, putting emphasis on the challenges associated with high SOV commuting rates at large facilities in urban areas such as hospitals. Chapter 2 reviews literature relevant to the study in this thesis. This includes literature on TDM, parking pricing and management strategies, incentive-based programs, discrete choice modelling and hospital parking limitations and considerations. Chapter 3 describes the context of the specific study, reviews the survey dataset, staff population dataset, and the spatial mapping basis using FSA regions, adding discussion on limitations as well as assumptions used in the dataset to produce travel times and costs. Chapter 4 describes the modelling methodology used in this study. This includes descriptions of the MNL utility specifications, coefficient

estimation for utility functions, statistical testing, probability calculations and the incentive optimization model designed with budget constraints. Chapter 5 summarizes the outcomes of the studies and discusses the estimated mode shares and optimization outcomes based on the different budget scenarios tested. Chapter 6 concludes the study by summarizing key findings, discussing limitations and reviewing future directions for research and institutional applications.

## 1.7 Chapter 1 Summary

The chapter introduced the problem of parking congestion at urban hospitals and described the importance of reducing SOV commuting through sustainable transportation strategies. The chapter presented the motivation, objectives, research questions, assumptions and scope of the study. A data-driven framework based on mode choice modelling, spatial analysis and incentive optimization was proposed to evaluate potential reductions in parking demand. The following chapters review relevant literature, describe the study data and methodology and present the results of the proposed approach.

# Chapter 2

## 2.0 Literature Review

This chapter reviews literature relevant to transportation demand management, parking management strategies, incentive-based programs and discrete choice modelling applications in transportation planning. The purpose of this review is to study the theoretical and practical background related to the methodology used in this research. The literature also highlights the challenges related to SOV commuting and the importance of behavioural approaches for reducing parking demand at large institutions such as hospitals.

This chapter is organized into several sections. First, transportation challenges related to private vehicle dependence and mode shift are discussed. Next, parking management and TDM strategies are reviewed, including pricing approaches, land-use considerations and incentive-based programs. Examples of real-world incentive programs are discussed to demonstrate the effectiveness of such programs. The chapter then reviews discrete choice modelling theory and its application to transportation policy analysis. Finally, hospital-specific transportation considerations are discussed, including policy constraints, user characteristics and operational challenges that differentiate hospital parking from other environments.

### 2.1 Background and Motivation

#### 2.1.1 Transportation Challenges and Mode Shift

Automobile-dependent transportation modes lead to negative effects on transportation systems by causing traffic congestion, air pollution, and GHG emissions. Road transportation contributes 12-15% of global $CO_2$ emissions (U.S. Environmental Protection Agency, n.d.) and represents approximately one quarter of emissions in Canada (Canada Energy Regulator, 2016). Aside from its environmental concerns, congestion in urban areas can also create major economic costs. A study shows that 200 cities globally had productivity losses caused by congestion, with an example of an average of 97 hours per year with U.S. drivers wasting $87 billion in time and fuel yearly (Fleming, 2019). Major cities such as New York City lose billions of dollars annually from road traffic (Bloomberg, 2024). Decreasing vehicle miles traveled (VMT) and shifting mode shares from SOV to high occupancy vehicles is a major goal for sustainable growth. Mode shift strategies can also contribute to better human health by improving air quality and increasing active transportation. These impacts are important in large metropolitan areas where daily commuting demand is

high, and road space is limited. In many North American cities, certain land-use patterns and long commuting distances can motivate car dependency which makes reductions in VMT challenging with no targeting transportation and land-use strategies.

There are two main approaches used to promote mode shifts in transportation planning. The first way is using push strategies. These strategies discourage car usage by charging congestion tolls, road tolls, enforcing parking restrictions, creating low-emission zones and charging fuel taxes. These types of push strategies are usually implemented in large cities like London, Singapore, and Stockholm. The push measures are usually successful as they result in reduced traffic volumes and congestion. Pull strategies are usually used to promote alternative travel modes. These measures include promoting transit service, investing in cycling infrastructure, providing park-and-ride resources and initiating incentive programs. Pull strategies usually are publicly more accepted as they offer benefits to the users. (Rouwendal, Verhoef, & Knockaert, 2012). There is an attractive factor to be considered with pull strategies to overcome the convenience factor for car travel. A combination of both strategies is recommended to achieve a mode shift in a transportation system (Rouwendal, Verhoef, & Knockaert, 2012). While push strategies can be effective, they may face political pushback if they are viewed as consequential or inequitable. Pull strategies can amplify the influence of using sustainable alternatives by reducing out-of-pocket expenses or improving service quality. In practice, many successful programs combine both approaches by discouraging SOV usage and improving the delivery of transit and shared travel.

Travel decisions are also influenced by factors other than cost and travel time. This can include comfort, reliability, safety and flexibility. For example, commuters may value the ability to make stops on route, adjust to different shift times or have a more reliable travel time. These behavioural considerations help explain why incentives and service improvements can cause changes over time rather than immediately (Ben-Akiva & Lerman, 1985; Train, 2009).

### 2.1.2 Hospital Challenges and Mode Shift

Hospitals located in dense urban areas face unique transportation and parking challenges due to the diverse groups of users that access their facilities. Daily parking demand is generated by staff, patients, visitors, volunteers and service vehicles, each with different travel patterns and accessibility requirements. Effective multimodal transportation strategies, such as transit, carpooling and active modes, must be utilised to design parking policies to shift travel behavior toward more sustainable commute modes and managing parking demand (Litman, 2020). Parking must be considered as part of the overall multimodal transportation system and parking policies should be designed to consider principles like utilization, prioritization, user information and pricing (Litman, 2020). These principles are important for managing demand while encouraging sustainable modes.

Unlike many employment institutes, hospitals operate on a 24-hour basis and experience demand throughout the day due to shift changes, appointments, emergency visits and visitors. Staff commuting demand can typically be predictable, while patient and visitor demand is often not certain. As a result, hospital parking policies must balance demand management objectives with accessibility requirements, particularly for patients with mobility limitations and healthcare needs (Canadian Medical Association, 2015). Parking congestion can contribute to late arrivals, increased stress for employees and negative experiences for patients and visitors, especially when searching for parking adds travel time and causes idling.

Expanding parking capacity through new parking garages usually requires large financial amounts and physically may be difficult in dense urban areas. Parking structures require significant costs, ongoing maintenance and land that may compromise the needs at healthcare facilities. For this reason, demand-based strategies such as incentives for transit and carpooling are often considered more efficient and scalable than infrastructure expansion (Litman, 2020). They are also more reliable for targeted outcomes under budget constraints.

## 2.2 Parking Management and Pricing

### 2.2.1 Travel Demand Management

Travel Demand Management is a strategy of policies and procedures which are created to reduce travel demand. TDM does not increase transportation supply to address demand but instead manipulates the demand by refactoring space or time. Some common practices used for TDM include carpooling programs, telecommuting, flexible work hours to avoid peak travel time, transit pass discounts and promoting active transportation (Smart Commute, n.d.; York Region, n.d.; Rouwendal, Verhoef, & Knockaert, 2012). Many TDM measures aim to reduce travels during peak time since usually peak times have the highest congestion rates and parking demand. For large institutions like hospitals, small reductions in demand during peak times can make a noticeable difference in parking availability.

New mobility technology, which include transportation or parking apps, assist with reducing parking demands by providing wayfinding and with reducing parking search times. These apps can optimize trips to reduce any type of barriers and stalls on route (Shoup, 2018; Litman, 2020). Along with recent technological advances, incentive-based strategies have had a major impact on commuting behaviour. (Bauer, 2018). These types of strategies reward travellers and collect more frequent commuter data to assist with shifting commuting away from peak hours and commuter mode share shift towards more sustainable modes. These strategies show that even with a small reward, commuters' behaviour can be influenced and

shifted. Modern technology could be used to support policy implementation by verifying trips, tracking participation and allowing administrators to adjust incentives over time. This allows incentive programs to be monitored and outcomes to be evaluated for policy refinement.

### 2.2.2 Parking Pricing Strategies

One of the most effective parking demand management strategies is pricing strategies (Shoup, 2018; Marsden, 2006). Different parking pricing strategies' frameworks include fixed, hourly, progressive (increases rates by parking duration), time-of-day (peak time rate increase), permit-based and dynamic pricing (Litman, 2020). Pricing influences behaviour by increasing the costs of driving, which can reduce demand for parking and encourage shifts towards alternative modes. Pricing is usually most effective when commuters have reliability in alternatives such as reliable transit access or organized carpooling programs.

Progressive and time-of-day pricing usually targets turnover and reduces parking duration times during congestion periods. Permit-based parking structures permit access and reduce illegal parking occurrences. Additional management strategies can include enforcement at peaks, sharing parking spaces between uses, direct signage and special-event parking spaces. These strategies can be paired with pricing strategies to address parking congestion concerns (Kodransky & Hermann, 2011). Combining pricing strategies with operational strategies (e.g., enforcement and information) can improve effectiveness of the policies since commuters not only respond to price adjustments but also to reliability and convenience.

Parking management programs such as parking cash-out and transit discounts can provide a ratio of benefit to cost of 4:1. Benefits also include reduced emissions, healthy commuting from active modes, and reduced infrastructure costs (California Air Resources Board, 2025). Parking cash-out was implemented to employees by employers across California which results in a reduction in solo driving and an increase in carpooling and transit mode share (Shoup, 1997; California Air Resources Board, 2025). These results highlight that employers can increase attractiveness of alternate modes by removing the trade-offs between the two. This is especially the case if incentives are clear and consistent.

### 2.2.3 Land-Use Strategies

Land-use strategies for parking like Smart Growth, New Urbanism, Location-Efficient Development and Transit-Oriented Development (TOD) help with reducing car use and reducing parking demand. Smart Growth is an urban planning strategy that designs compact, mixed-use, walkable and transit-accessible regions. This strategy reduces sprawl, makes use of open spaces and promotes sustainable transportation (Litman, 2024). This strategy reduces trip distances and makes mode alternatives more attractive to commuters by focusing on development around transit access platforms which results in lower parking demand and reduction of vehicle storage for land-use. New Urbanism, like Smart Growth, places more

emphasis on human aesthetic for land use developments. Neighbourhoods as such are designed to be walkable between residential areas and public amenities. This makes it more feasible to get around with walking, biking and transit. Environmental characteristics on land such as density, land-use and transit accessibility influence commuting choices and can plan for long-term mode shares. Institutional travel demand can be affected by regional characteristics if it contributes to the factors that affect employee mode choices.

Location-Efficient Development refers to residential and commercial development in dense areas for lower auto reliance. Usually, developers encourage transit transportation by providing discounted transit passes (BC Office of Energy Efficiency, n.d.). TOD designs mixed-use development while focusing on pedestrian-friendly communities and limited parking. Policies that limit parking supply in TOD areas are usually aligned with transit service conditions to ensure that reduced parking availability does not create accessibility issues.

Research shows that TODs result in 58% to 84% of regular occupancy measurements, showing efficiency in this type of land-use strategy (Smart Growth America, 2015). Newman and Kenworthy's landmark international study show that cities designed through the TOD strategy result in a lower reliance on automobiles (Newman & Kenworthy, 2006). These findings support the idea that transportation policies are most successful when they align with land-use planning and when alternative modes are matched with high-quality attributes.

### 2.2.4 Incentive-Based Travel Demand Management

Incentive-based TDM include policies that target shifting commuter behaviour away from SOV by offering pricing incentives. Comparing this method to regular practices, incentives are usually accepted by the public and can be targeted and constrained for specific time periods (Xiao, et al., 2024). Typically, these incentives include transit discounts, carpooling bonuses, parking cash-outs and travel alternatives. These types of policies have been proven to be successful at various institutions with similar concerns (California Air Resources Board, 2025; Shoup, 2018). Incentive based programs can be useful for employers because they can be implemented as pilot projects with budgets and observable outcomes. This allows institutions to measure the outcomes before committing to long-term implementation.

Incentive strategies can be developed in different ways. Monetary incentives are the main strategy used where cash payments and discounts on sustainable travel modes are implemented. A point-based reward program strategy is designed for commuters to collect points based on their travel mode. The points are to be later used on rewards or benefits. Transit incentive strategies usually offer fare discounts. Free shuttle rides can sometimes be offered to shift commuters away from driving and priority parking for

carpooling is also a strategy which can be used. Incentive programs are designed to target certain ride shares and commuter behaviour to improve efficiency. These programs are used as a reward for people who alternate their commuting patterns which overall will help with reducing congestion and reducing emissions. Commuter behaviour can be consistent with the policy outcome goals when barriers for alternative commuting are perceived to be reduced. This can mean the shift in commuting becoming a habit overtime especially when incentives are consistent without going over budgets.

Researchers discuss that although charging congestion fees to drivers might be more cost-effective, incentive programs can be just as effective especially in areas where the public opposes toll policies like congestion charges (Rouwendal, Verhoef, & Knockaert, 2012). Incentive approaches need a source or base of funding whereas road charges for congestion create revenue. This means that incentives are usually implemented through pilot programs by policy makers to test effectiveness within a given budget. This trade-off is relevant in institutional environments, where employers may have more control over program budgets than over road pricing policies.

### 2.2.5 Behavioural Mechanisms and Sustained Mode Shift

Incentive-based transportation policies are known to be effective because they reduce disadvantages that commuters usually associate with switching travel behaviour. Switching from driving to alternative modes such as transit and carpooling can mean uncertainty in travel time, convenience and comfort. Financial incentives can lower this concern that commuters assume by compensating the risk of switching travel modes. Research in behavioural economics suggests that even small rewards can motivate individuals to try alternative behaviours that they usually wouldn't consider. (Bauer, 2018).

Over time, repeated action for taking new travel modes can lead to habits being formed. Studies on travel behaviour is usually based on habits rather than a constant individual revaluated decision (Verplanken & Aarts, 1999). When commuters become familiar with alternative mode attributes like daily routes, carpool partners or transit schedules, the perceived inconvenience of these modes may decrease. As a result, incentives can be places as a catalyst that can encourage experimentation and commuting patterns may persist even after incentives are reduced or removed later.

However, research also shows that incentive programs may experience diminishing returns over time if rewards remain unchanged or if commuters who are responsive to the incentives have already shifted over to alternatives. The concept is sometimes referred to as incentive fatigue or saturation, where additional rewards produce smaller amounts of behaviour changes (Bauer, 2018). For this reason, many TDM programs monitor responses to policies and procedures to constantly evaluate results and adjust incentives accordingly.

Monitoring and evaluation are important components of incentive-based programs. Data collected through commuter surveys, phone applications or parking systems can help institutions predict mode shares and monitor behaviour. These observations allow policymakers to adjust incentive structures over time and ensure that program outcomes are aligned with the policy goals such as reducing parking demand or lowering SOV commuting.

### 2.2.6 Pricing versus Reward-Based Strategies

Pricing and reward-based strategies both attempt to influence commuter behaviour, but they differ in how commuters perceive the policy. Pricing strategies increase the cost of driving or parking, while reward-based strategies reduce the cost of sustainable alternatives or provide a direct benefit for choosing them. Examples of pricing strategies include increasing parking fees, congestion charges or reducing parking subsidies. Reward-based strategies may include transit subsidies, carpool incentives, discounted transit passes or parking cash-out programs (Litman, 2022; California Air Resources Board, 2025).

Behavioural economics suggests that individuals are generally more sensitive to losses than gains, a concept known as loss aversion (Kahneman & Tversky, 1979). As a result, pricing strategies may produce larger changes in behaviour because commuters respond strongly to increased driving costs. However, pricing approaches may also face lower public acceptance because they are often viewed as penalties. In contrast, reward-based approaches are generally more acceptable to commuters because they are interpreted as benefits rather than restrictions.

Research comparing these approaches suggests that pricing measures are often more effective at reducing driving when strong transportation alternatives are available, while incentives are more politically acceptable and easier to implement (Litman, 2022; Bauer, 2018). For example, parking pricing programs have been shown to significantly reduce SOV commuting, particularly in dense urban areas where transit is available (Shoup, 2011). However, reward-based strategies such as transit subsidies and commuter benefits can also achieve meaningful shifts in travel behaviour when commuters face financial barriers to using alternative modes (Bauer, 2018).

Rather than considering pricing and rewards as separate strategies, many studies suggest that combining both approaches may be most effective. For example, an institution may increase parking costs while simultaneously providing transit or carpool incentives. This combined strategy reduces the attractiveness of driving while improving the attractiveness of sustainable modes (Litman, 2022). The present study focuses on reward-based incentives because hospitals may be more likely to implement strategies that are publicly acceptable to staff while still encouraging reductions in SOV commuting.

### 2.2.7 Equity Considerations in Transportation Policies

Equity is an important consideration in transportation policy because commuters do not experience the same travel opportunities or constraints. Commuters living farther from employment locations or from major transit corridors may have fewer feasible alternatives to driving. As a result, policies that increase the cost of driving may place a greater burden on commuters who already face limited transportation options (Lucas, 2012; Martens, 2016).

Previous research has shown that transportation pricing policies can have unequal effects across income groups and geographic areas. Lower-income commuters and those living in suburban or inaccessible transit areas may be more affected by increased parking prices because they have fewer realistic alternatives. For this reason, many researchers argue that transportation demand management policies should consider both efficiency and fairness when evaluating outcomes (Martens, 2016).

Reward-based strategies may offer a more equitable alternative because they reduce the cost of sustainable travel modes rather than imposing additional costs on driving. Transit subsidies, commuter benefits and carpool incentives can help reduce financial barriers for commuters who are willing to switch modes but may be limited by cost (Litman, 2022). However, even incentive programs may not be equally effective across all regions. Uniform incentives may benefit commuters in transit-accessible areas more than those living in regions where transit service is limited.

Several studies recommend that transportation policies account for regional accessibility and socio-demographic differences when designing incentives. Spatially targeted approaches may therefore improve both effectiveness and equity by providing larger incentives to commuters living in areas with fewer transportation alternatives (Foth et al., 2013; California Air Resources Board, 2025). The present study begins by evaluating uniform incentives across all FSA regions to provide a baseline comparison. However, the results are interpreted with recognition that future work may consider targeted or equity-based incentive strategies.

### 2.2.8 Program Design Considerations for Institutional Incentive Policies

While incentive-based transportation programs have shown effectiveness in many case studies, their success often depends on the program design and implementation details. Institutional programs usually have eligibility requirements regarding who can participate in the programs. For example, incentive programs implemented by large employers like hospitals would often specify policy for staff while organizing separate policies for visitors or patients whose travel options may not be so flexible. Clearly defining eligibility to participate helps ensure that incentives influence the right commuter group and align with objectives.

Another important consideration is the timing of incentives. Some programs focus specifically on reducing peak-period congestion by rewarding commuters who travel outside peak periods. Time-based incentives can be effective in institutions such as hospitals, where staff shift schedules vary and parking demand may range throughout the day.

Targeting incentives based on geographic commuting characteristics can make incentive programs more effective. Uniform incentives distributed across all commuter groups may not produce consistent outcomes because commuting constraints can differ across regions. For example, commuters living in areas with transit accessibility may not respond to incentives the same way as those who don't live in transit accessible areas. Designing programs that consider regional differences can improve efficiency and policy outcomes.

Equity considerations are also important for designing incentive programs. Incentives should avoid benefiting those commuters who already have easy access to sustainable commuting without considering those who have harder constraints to sustainable transportation access. Considering accessibility factors when designing such policies help institutions ensure that outcomes are balanced and fairness is provided for all commuter groups.

### 2.2.9 Examples of Incentive Programs

Many best practices globally of incentive programs have shown that incentive programs are effective and can be successful in terms of influencing shift in travel behaviour. Case studies are useful because they provide real-world evidence of the impacts of incentive policy strategies and their outcomes under different designs, budgets and commuter specifics.

One of the notable incentive-based projects is the Dutch "Spitsmijden" program. Spitsmijden is Dutch for "avoid the peak". In 2006, Spitsmijden trials offered incentives to drivers everyday they didn't drive during a morning rush (Federal Highway Administration, n.d.). The first pilot launched in Zoetermeer, Netherlands, with 340 commuters being rewarded €3 to €7 per day for not driving during 7:30-9:30AM. The results shown that a €3 reward dropped peak time trips by 46% and €7 rewards dropped the trips by 61% (Federal Highway Administration, n.d.). Some of the car trips shifted to a time period just around the peak-period window which 10%-14% of commuters switched to commuting with sustainable modes such as transit or active transportation (Federal Highway Administration, n.d.). 20%-25% of people stopped commuting during the peak completely after rewards were implemented (Federal Highway Administration, n.d.). This project shows that even small incentives can be effective for shifting mode choice. The government behind the program extended it to larger projects. For example, the Dutch Ministry of Transport implemented these incentives during the one-year long construction of the Hollandse Brug (bridge), and

3,000 drivers were rewarded €4 for avoiding peak hour driving and €6 if avoiding the route the whole day. This made the trips at peak hours decrease by 40% (Federal Highway Administration, n.d.). This project is used as a proof-of-concept for a reward-based system being successful in relieving congestion.

The Bangalore "INSTANT" program in 2008-2009 was implemented by researchers from Stanford Institute for Human-Centered Artificial Intelligence and Infosys. In Bangalore, India, congestion was heavy at the Infosys campus. The INSTANT project implemented an incentive strategy that was lottery based so employees could be influenced to arrive to work at off-peak hours (Federal Highway Administration, n.d.). Commuters who were commuting before 7:30AM earned points which were redeemed as entered ballets for a weekly draw for a reward (Federal Highway Administration, n.d.). The weekly prizes went up $240 (Federal Highway Administration, n.d.). The outcome of this program showed a demand in early buses to accommodate the mode share shift, and company buses had to reschedule their routes to be 15-30 minutes earlier (Federal Highway Administration, n.d.). The final results shown that employees that were arriving before 8:30am had increased by double, commuting times decreased from 71 to 54 minutes, and 2600 person-hours were saved per day (Prabhakar, Goel, et al., 2009). This shows an improvement in transit behaviour provided an incentive program by employers.

In the United States of America, Stanford University's Congestion and Parking Relief Incentives (CAPRI) program in 2012-2014 was funded $3 million by the federal government and targeted a reduction of peak-hour driving to campus. Stanford also offered a lottery-based incentive strategy where collected rewards are drawn for prizes. The program showed a success with 21% lower trip rates in the morning and 13% lower trip rates in the evening (Federal Highway Administration, n.d.). Commuters shifted their commute around peak hour, mostly an hour before peak (Federal Highway Administration, n.d.). Results also showed that commuters who received recent rewards were more likely to continue travelling at off-peak hours showing an influence in behaviour from the rewards (Federal Highway Administration, n.d.). Following the program, Stanford started a "Commute Club" offering up to $300 a year to commuters who don't buy a parking permit, as well as other rewards like free transit passes (Federal Highway Administration, n.d.). This shows a long-term adoption of incentive programs from employers.

Other North American cities have implemented incentive programs. Los Angeles released a "Reduce Traffic Ahead" program that offered incentives of $2 each day per commuters who drive outside peak hours. The results of this program were not direct. In 2022-2023, the San Franisco Bay Area's Metropolitan Transportation Commission (MTC) released a pilot for Incentivizing Active and Shared Travel. The pilot was able to recognize the minimum incentive amount needed to increase the probability of a mode shift. This incentive amount was $3 and incentives below this amount did not have an effect (Metropolitan Transportation Commission & Metropia, 2024). This shows behaviour economics where the

incentive has to be great enough to overcome the comfort factor of driving. A study that took place in Vancouver showed that employers who implemented transit subsidies to their employees had a reduction in auto commuting and an increase in transit commute mode share (Etezady et al., 2021). Other studies have shown that employers who provided incentives to target sustainable commuting behaviour can result in VMT reductions of 4% to 76% after employer-based commuting incentives, and SOV mode share reductions of 7% to 20% and a mode shift to transit mode share of 50% to 108% (California Air Resources Board, 2025).

In the GTA, incentive-based programs for TDM have been provided through employers and the Smart Commute program. Smart Commute is a program that partners with employers to encourage commutes away from driving towards commutes like carpooling, emergency ride home services and incentive programs (York Region, n.d.). Hatch Ltd. is an engineering firm in Toronto that offered their employees a carpool-based incentive where the drivers received a reward for every additional passenger they had in their car going to work (City of Toronto, 2008). Hatch reported that this program was a "simple economic decision" as in return they relieved parking demand and removed the need for an expensive construction project for creating extra parking spaces at their facility (City of Toronto, 2008). Another employer who also contributed to this incentive program is Enbridge Gas. The company set up vanpools for their employees who commute long distances and subsidized the van. This resulted in a decrease of 16 cars driving into work and $19,000 saved per year in parking costs (City of Toronto, 2008). These examples show that regionally, Toronto employers have found success in implementing an incentive-based TDM program.

In a hospital setting context, an example of an incentive base strategy used to relieve parking on hospital premises is at the Seattle Children's Hospital. The hospital implemented daily parking charges, removed monthly permits and offered a $4.50 daily incentive for alternative commuting. The hospital also offered transit discounts, shuttle transportation vehicles, biking accommodations and carpool parking. This policy resulted in a SOV mode share reduction from 73% in 1995 to 38% in 2015 addressing on-site parking concerns. This strategy also avoided the need of building a $20 million parking garage, which contributed to the city's sustainability goals of reducing SOV mode shares to 30% by 2030 (Commute Seattle, 2015; Tools of Change, 2021; Practice Greenhealth, 2017). This case study is evidence to show that implementing incentives can result in a mode shift in health-care facilities.

The review literature and best practices demonstrate success in incentive-based policies to reduce SOV driving. Results show that a reduction can be 5-40% or more depending on which commuter group is targeted (Federal Highway Administration, n.d.). Higher incentives usually are highly successful and feasible for pilot programs whereas moderate reward is usually more sustainable for long term results. It's

also important to note that not all commuters react uniformly to the applied incentives. Some commuters may respond positively and move away from driving while some may not react to incentives and will continue driving. Considering this limitation, incentive policy design still yields success in trying to shift users towards sustainable commuting modes.

## 2.3 Discrete Choice Modelling and Optimization Applications

Discrete choice modeling like MNL is commonly used to predict commuter behaviour. This is done by modeling the utility of travel choices based on cost, time and socio-demographics (Ben-Akiva & Lerman, 1985; Train, 2009). Ben-Akiva & Lerman (1985) provide foundational theory for random utility maximization and discrete choice modeling. Train (2009) gives guidance on estimating MNL models, understanding and interpreting results of the model that include the parameters, standard errors and p-values using Hessian-based inference. These models are crucial for policy analysis because they allow researchers to observe how commuters respond to changes in travel times and cost scenarios.

### 2.3.1 Discrete Choice Modelling Theory

In context of this research, to predict how commuters will react to implemented incentives, it is important to understand what factors cause influence on their mode choice. Transportation research for decades has shown that a travel mode choice is largely dependent on the cost of each mode option. The costs for each mode include monetary costs, travel times, comfort, convenience and other smaller factors like reliability. Classical economic theory shows that commuters want to maximize their utility when making their mode choice. This is usually demonstrated through discrete choice modeling. In transportation-based studies, MNL model is utilized (Al-Salih & Esztergar-Kiss, 2021). The random utility framework contains observed variables that represent measurable components of travel barriers (travel time and costs), while unobserved variables represent personal commuter preferences that are not directly measurable. The MNL model shows that the utility of an alternative $i$ is:

$$U_i = V_i + \varepsilon_i$$

Where:

- $U_i$ is the utility of mode $i$,
- $V_{i,j}$ is the systematic utility generated from observed variables,
- $\varepsilon_{i,j}$ is an unobserved random variable following Gumbel distribution

The choice of i will be made when Ui is the greatest compared to all other alternatives. The probability of choosing the mode is produced through a logistic function of all the utilities.

Mode choice models typically include variables such as travel time, travel cost, distance, other important influential factors and some modal constants. Travel time is usually an influential factor for all mode alternatives whereas distance is usually a larger factor for transit. Travel costs are very influential, and research shows that an increase in transit fares or driving costs can cause a shift towards other modes (Al-Salih and Esztergar-Kiss, 2021). In addition, socio-demographic factors (such as income, populations etc.), service quality (such as transit frequency, access etc.) and personal preferences are all factors that can also affect a mode choice.

The model usually assumes that a commuter will choose the mode with the highest utility. Researchers have used choice models to design policies like pricing or incentives, often within budget constraints. An incentive feature add-on can manipulate the utility. This is implemented in the mode choice model where an incentive can be reduced from the total cost of a sustainable mode. The model will take this incentive factor and increase the utility of the sustainable modes. Using this modelling technique is common for designing incentive-based strategies.

Recent mode choice modelling practices consider specific sensitivities to different users in the group. Some can also consider a multimodal type of trip where a commuter can integrate different modes in on their trip. Although this may not be considered for the objective of this thesis, it is important to note that targeted groups can be diverse where some commuters may prioritize travel time and convenience over incentive amount while others can easily shift away from SOV driving if they are cost sensitive. The commuters may also differ where some commuters may consider a shift in travel mode for the reward, and some commuters may shift for the environmental aspect where sustainable commuting is a better choice to make overall (U.S. Department of Transportation, n.d.). This type of theory is a psychological theory called the Goal-Framing Theory where people have hedonic (pleasure), gain (self-interest) and normative ideologies which effect their choices (U.S. Department of Transportation, n.d.). With this theory, the incentive strategies can integrate environmental impacts to increase encouragement.

Using logit-based mode choice modeling, incentive impacts can be analyzed by comparing the current scenario of commuter behaviour to commuter behaviour after applying the incentive policies. In this study the results can compare the scenarios through numbers which will show reductions in SOV trips and any increases in sustainable transportation trips.

A notable strength in the MNL models is their ability to incorporate policy specifics directly into the utility details. For example, incentives can be represented as a discounted rate to travel costs of carpooling and transit which allows for predictions of mode choice under different budget scenarios.

### 2.3.2 Applications in Policy Analysis

Discrete choice models are commonly used in transportation planning when a new policy is proposed and the projected travel demand, mode share and policy outputs need to be evaluated. By comparing baseline scenarios to policy scenarios, the models generate results to observe potential driving reductions, transit rider increases and decreases in congestion and emissions.

When incentives are designed under budget constraints, modelling becomes useful because it can be a tool for "what-if" scenarios. This can help identify cost sensitive program designs. Optimization methods can be combined with mode choice modelling to ensure appropriate resources are used for targeted policy objectives.

### 2.3.3 Modelling Considerations and Limitations

Although MNL models are commonly used in transportation research, a common list of assumptions and limitations should be known when interpreting model results. One commonly known limitation is the Independence of Irrelevant Alternatives (IIA) assumption. This assumption states that the probability of choosing between two alternatives is not affected by the existence or characteristics of other alternatives (Train, 2009). In the transportation context, alternatives may share similar characteristics which contradicts this assumption, which can influence the model predictions.

Another limitation relates to excluded factors which influence commuter decisions. While mode choice models consider variables such as travel time, travel cost and socio-demographic characteristics, other influences such as personal preferences, convenience or unexpected travel conditions may not be captured by the model. These types of factors are represented by the random error term in the random utility framework.

Although MNL models come with these limitations, the model is still frequently used in transportation planning due to their interpretability and manageable data requirements (Ben-Akiva & Lerman, 1985; Train, 2009). The model structure allows researchers to estimate the sensitivity of commuters to changes of travel costs or travel times and to project travel behavioural responses under different policy scenarios.

For policy evaluation, the ability to simulate alternative scenarios is valuable. Incentive values, parking prices or transit costs can be incorporated directly into utility functions, allowing the model to

estimate how commuters may respond to all different policy design scenarios. As a result, discrete choice models are usually used as decision-making tools for evaluating TDM strategies before they are implemented.

## 2.4 Hospital-Specific Policies and Procedures

When designing a parking structure for a hospital, the system should consider the balance between equitable access for users in-need and demand management for staff. Ontario's 2016 hospital parking policy requires hospitals with parking fares over $10 a day to provide discounted 5-, 10- and 30-day passes with in-and-out privileges and longer permitted hours. The province estimated hundreds of thousands of visitors would benefit from this policy yearly (Ontario Newsroom, 2016). Best-practice parking management strategies at hospitals suggest that hospitals should consider accessibility, maintenance and cost considerations. This encourages hospitals to produce parking fees for those who can commute with alternative transportation modes and cross-subsidize reduces fees for patients with more needs (Canadian Medical Association, 2015). Modern technologies such as parking lot occupancy counting and signage guidance can improve the use of parking spaces and reduce search times, emissions and late arrivals (Parking Logix, n.d.). These policies highlight that parking management contributes to also being an access and affordability issue especially for patients who visit often.

### 2.4.1 Shared Parking and Hospital Demand

Shared parking strategies and park-and-ride concepts can help with matching supply with parking demand beyond on-site hospital parking without requiring large parking structure projects (Litman, 2020). Hospital parkers are diverse in factors such as time urgency, income and parking duration. This would require that parking strategies implemented at hospitals reflect the differences between different commuters (Alfonzo et al., 2014). To utilize shared parking and park-and-ride, studies suggest systems for reserving shared parking spaces and fixed time policies. This can include fixed staff schedule-based parking duration times, longer walking distances for visitors and prioritizing closer parking distances for emergency patients (Young et al., 2014). Shared parking approaches can be useful in dense urban areas where neighbouring land-uses don't share the same peak periods.

### 2.4.2 Technology and Data in Hospital Transportation

Hospitals are relying on technology more overtime to improve parking operations and reduce vehicles from idling in parking areas. Tools such as occupancy sensors, camera-based counting systems and dynamic signage can provide real-time information on parking space availability and can reduce the time spent searching for parking.

In addition, data collected through parking systems and commuter programs can be used as case studies for future planning and provide evidence of results. Combining institutional data with behavioural modelling can help decision-makers evaluate the outcomes of different pricing and incentive strategies and use the observations to adjust policies.

## 2.5 Conceptual Framework for Incentive-Based Mode Shift

The literature reviewed in this chapter highlights the importance of integrating behavioural modelling with policy design when dealing with transportation demand challenges. A conceptual framework was developed to support the methodology of this thesis which includes commuter characteristics, travel attributes and incentive policies to predict changes in transportation behaviour.

Commuter mode choice is influenced by multiple factors such as travel time, travel cost, accessibility and socio-demographic characteristics. These factors are used to create the utilities of each transportation option available to commuters. Within the random utility maximization framework, commuters are to select the alternative that provides the greatest benefit.

In this research, the conceptual framework begins with identifying baseline commuter characteristics from the survey data. These include residential locations, commuting patterns and travel preferences of hospital staff. Travel attributes such as travel time and travel cost are then calculated for each travel mode. These attributes are then used in the MNL model to estimate the utility of each transportation alternative.

Once baseline utilities are estimated, the MNL model produces probabilities representing the likelihood that a commuter from each FSA will select each travel mode. These probabilities represent the current commuting behaviour in existing scenarios. Incentive-based transportation policies are then applied to modify generalized travel costs usually associated with sustainable travel modes.

By reducing the generalized cost of these alternatives, their utilities increase. The resulting changes in utility values generate new mode choice probabilities that reflect how commuters may respond to the new policies. The new probabilities are then applied to staff populations across the FSAs to estimate the number of commuters expected to shift away from SOV travel.

Finally, the results of this process provide estimates of potential reductions in driving trips and parking demand under different incentive budget scenarios. This framework allows policymakers to evaluate transportation policies before implementing them and provides information on how behavioural responses to incentives can improve parking management at large institutions.

The conceptual framework presented in this chapter provides the foundation for the modelling methodology described in the following chapters. Chapter 3 introduces study data and spatial basis used in the analysis, while Chapter 4 represents the mode choice modelling and optimization methodology developed to evaluate transportation incentive policies.

## 2.6 Research Gap and Contribution

Existing research has examined parking pricing, commuter incentives and mode choice behaviour in a variety of transportation contexts. However, many studies consider these elements separately. Parking studies often focus only on pricing or supply expansion, while mode choice studies often estimate behavioural relationships without evaluating policy applications.

Only limited research combines institution-specific commuter survey data, spatial analysis and budget-constrained optimization within a hospital context. Hospitals are distinct from many other employment centres because they operate continuously, generate high parking demand and serve employees with diverse commuting patterns across a large geographic area.

In addition, few studies evaluate how transportation incentives vary across different geographic regions while considering the influence of accessibility and regional characteristics. This research addresses these gaps by integrating hospital commuter survey data, FSA-level analysis, MNL modelling and incentive optimization to evaluate realistic transportation policies for reducing SOV commuting.

## 2.7 Chapter 2 Summary

This chapter reviewed literature on transportation challenges associated with SOVs. This discussion touches on congestion, emissions and TDM strategies to reduce SOV commuting. It summarized parking management strategies such as pricing, regulation, land-use planning and shared parking. Incentivized strategies can be used to encourage alternative modes. The chapter also touched on discrete choice modelling theory and example practices using incentive programs. The discussion of these strategies shows the purpose of using MNL models for predicting mode choice behaviour through change of costs and times. Overall, this chapter is a summary of relevant literature for the thesis methodology and introduces the modelling and optimization processes discussed in Chapters 3 and 4. The reviewed studies support the use of incentive-based TDM policies and are a useful tool for large institutions. This review molds the modelling framework into this thesis.

# Chapter 3

## 3.0 Study Data

This chapter describes the datasets, study area and assumptions used in this research. The chapter introduces the hospital commuter survey data, the staff population data by FSA and the spatial basis used in the analysis. It also discusses the quality and representativeness of the dataset, ethical considerations, limitations and the process used to estimate generalized travel costs for each transportation mode.

### 3.1 Toronto Hospital Staff Commuter Survey Data

The primary dataset used in this study was a commuter assessment survey completed by staff and volunteers at a hospital in Toronto. The survey was distributed between March 24 and April 24, 2024, and a total of 127 responses were collected.

The survey was originally developed as part of the hospital's internal assessment of employee commuting and parking behaviour. Its purpose was to better understand how staff currently travel to work, identify barriers to sustainable transportation and evaluate opportunities for TDM initiatives aimed at reducing dependence on SOVs.

The questionnaire was designed to collect both behavioural and attitudinal information related to commuting. Respondents provided information regarding their current travel mode, commuting frequency, monthly commuting costs, residential postal code, work schedule and willingness to consider alternative transportation options. Additional questions examined perceived barriers to using sustainable transportation, willingness to participate in public transit or carpooling programs, and resources or incentives that could encourage changes in commuting behaviour.

The survey was organized into three categories: "Your Work Arrangements", "Your Commute" and "Exploring New Commute Options". The first section collected information related to respondents' employment characteristics, including work schedules and on-site attendance. The second section focused on existing commuting behaviour, including travel mode, commuting frequency, travel costs and residential location. The final section explored respondents' willingness to adopt more sustainable transportation

modes, perceived barriers to changing travel behaviour and potential transportation demand management measures that could encourage a shift away from SOV commuting.

The survey data provide the behavioural foundation for this research. In addition to representing baseline commuting patterns, the responses supplied the explanatory variables used to estimate the MNL mode choice model described in Chapter 4. The residential postal codes also enabled respondents to be spatially aggregated into FSAs, allowing the survey to be integrated with the staff population dataset and regional census data for regional analysis.

## 3.2 Study Area

The study area includes Toronto and the GTA, in Ontario, Canada, reflecting the residential locations of the hospital staff and volunteers included in the survey. The GTA is an appropriate study area because it contains a wide range of commuting conditions, including dense urban areas with high transit accessibility as well as suburban regions where automobile dependence is greater.

The GTA is one of the largest metropolitan regions in Canada and experiences significant daily commuting flows between suburban municipalities and employment centers within the City of Toronto. The regional transportation network consists of a combination of municipal transit systems such as the Toronto Transit Commission (TTC), regional commuter rail operated by GO Transit and highway infrastructure connecting surrounding municipalities. Despite the availability of transit services, commuting patterns in the GTA still depend heavily on private vehicles, particularly for commuters traveling from suburban areas with limited transit accessibility.

Travel demand within the GTA is influenced by factors such as commuting distance, employment location and transit availability. Many commuters travel long distances between their residential areas and employment locations, increasing the attractiveness of private vehicle use due to convenience and flexibility. At the same time, major institutions such as hospitals attract staff from a wide range of locations, resulting in diverse commuting patterns across the region.

This study uses FSAs as the spatial unit of analysis. FSAs are defined by the first three characters of Canadian postal codes and provide a suitable geographic scale for comparing commuter characteristics across different regions.

In Ontario, the first letter of the postal code indicates a broad geographic area. For example, M identifies Metropolitan Toronto, L identifies Central Ontario, N identifies Southwestern Ontario and K identifies Eastern Ontario, as displayed in Figure 1. The second character identifies whether the area is

urban or rural, while the third character further identifies the district geographically (Office of the Superintendent of Bankruptcy, 2015).




*Figure 1: Forward Sortation Area (FSA) regions in Canada based on the first character of postal codes.*

By categorizing commuters based on their FSA region, the analysis captures spatial variation in commuting behaviour and accessibility conditions. This allows the modelling framework to evaluate how transportation policies may affect commuters differently depending on their geographic locations. FSAs located closer to transit connections may provide greater opportunities for shifting to alternative modes, while commuters in areas with limited transit accessibility may face greater constraints in reducing reliance on private vehicles.

The use of FSAs allows commuter behaviour to be grouped spatially while maintaining privacy and avoiding identification of individual respondents. Survey responses were aggregated to FSA level and combined with additional staff population and census data. The resulting FSA-based approach allows the study to compare regional differences in mode choice, accessibility and response to transportation incentives.

## 3.3 Survey Structure and Variables

The survey collected information on both current behaviour and possible willingness to adopt alternative modes. Variables obtained directly from the survey included current transportation mode, number of days commuting to the hospital per week, monthly commuting cost, residential postal code, willingness to use transit, willingness to carpool, perceived barriers to sustainable transportation, work schedule and shift frequency.

The survey responses were used to develop the explanatory variables for the mode choice model. Travel times and estimated travel costs for each transportation mode were added to the survey data after processing. In addition, postal codes were converted to FSA regions so that regional socio-demographic characteristics could be incorporated into the analysis.

The transportation modes initially considered in the study included driving, public transit, carpooling, walking and cycling. However, because relatively few respondents reported walking or cycling commutes, the active transportation modes were later excluded from the final model estimation. The final mode choice model therefore focuses on driving, transit and carpooling.

## 3.4 Staff Population by FSA

In addition to the survey data, the hospital provided a separate dataset containing the number of staff residing within each FSA. The dataset represented the complete hospital staff population and included more than 4,000 employees. This staff population dataset was used only to scale model outputs and did not contain any personal identifying information.

The staff population dataset was used to extend the survey-based mode choice results to the broader hospital workforce. While the survey provides information on individual travel behaviour, the FSA staff counts allow the predicted mode shares to be applied to the full staff population.

For each FSA, the probabilities estimated through the mode choice model were multiplied by the corresponding number of staff residing in that FSA. This process generated estimated numbers of commuters travelling by each transportation mode under both the existing and optimized scenarios.

Using staff population data by FSA improves the practical value of the study because it allows the results to be interpreted in terms of actual numbers of commuters rather than only percentages or probabilities.

## 3.5 Data Quality and Representativeness

Although the survey provides useful information regarding commuter behaviour, the sample size and voluntary basis of the survey introduce limitations related to representation.

The survey received 127 responses from a hospital workforce of more than 4,000 employees. Because participation was voluntary, the respondents may not fully represent the characteristics of the entire staff population. Certain commuter groups may be overrepresented or underrepresented in the sample.

For example, employees who are more interested in transportation issues or more willing to consider sustainable transportation may have been more likely to respond. In contrast, some groups of commuters may be less represented, particularly those travelling long distances or those who consistently drive and do not consider alternative modes.

The survey also contained limited representation of walking and cycling commuters. As a result, these travel modes could not be accurately modelled and were excluded from the final mode choice model.

To improve representativeness of the analysis, survey responses were combined with the full staff population dataset by FSA. This allows the estimated probabilities to be scaled to the broader hospital workforce while maintaining the behavioural patterns observed in the survey.

## 3.6 Limitations of the Dataset

Several limitations of the dataset should be considered when interpreting the results.

First, the survey responses are self-reported. As a result, there may be differences between the travel behaviour respondents reported and their actual commuting behaviour. Respondents may overestimate or underestimate travel times, costs or willingness to switch transportation modes.

Second, the dataset reflects commuter conditions during a single time period. Travel behaviour may change over time due to changes in gas prices, transit service, parking costs, seasonal conditions or work schedules.

Finally, the study assumes that the behaviours observed in the survey apply to the broader hospital workforce when scaled using FSA staff populations. This approach can improve the usefulness of the analysis but, the estimated mode shares stay dependent on the quality of the original survey responses.

## 3.7 Constructing Generalized Costs

To compare transportation alternatives consistently, travel times and generalized travel costs were estimated for each transportation mode.

Travel times were estimated using the Google Maps Distance Matrix API. Travel times for driving and transit were generated using each respondent's residential postal code and the hospital location. To ensure consistency across all respondents, travel times were estimated for an 8:00AM departure on a typical weekday morning.

The generalized cost of driving was based on hospital parking charges. The hospital provided both a monthly parking pass option and a daily parking rate. For each commuter, the driving cost was calculated as the lower value between the monthly parking pass cost and the daily parking cost multiplied by the number of days worked on-site each week and then multiplied by four weeks per month.

Transit costs were estimated based on the transit system most relevant to the commuter's residential FSA. Fare values were assigned using the applicable transit agency serving the region.

Carpooling costs were estimated by assuming that two commuters share the cost of driving. Therefore, the generalized cost of carpooling was assumed to equal 50% of the driving cost.

These estimated travel times and generalized costs were later incorporated into the mode choice model described in Chapter 4. The resulting variables formed the basis of the utility functions used to estimate the probability of selecting each transportation mode.

## 3.8 Chapter 3 Summary

This chapter describes the datasets and study context used in the research. It introduced the hospital commuter survey, the staff population data by FSA and the study area within Toronto and the GTA. The chapter also discussed the quality and limitations of the dataset, as well as the ethical procedures used to maintain privacy.

Finally, the chapter described the process used to estimate travel times and generalized costs for each transportation mode. These data and assumptions form the basis of the mode choice modelling and optimization process presented in Chapter 4.

# Chapter 4

## 4.0 Modeling Methodology

This chapter describes the modelling methodology used in this study. This includes the preparation of the raw data, development of the mode choice model and implementation of the incentive-based optimization strategy. The methodology includes four aspects: data preparation, formulation of utility functions, probability estimation with MNL modelling and spatial optimization of pricing incentives with a budget constraint.

### 4.1 Data Preparation

The hospital commuter survey and staff population datasets required several preprocessing steps before model estimation. Data preparation ensured consistency across variables, generated travel attributes for travel modes and created the inputs required for the mode choice model and optimization framework.

Survey data gathered from hospital staff and volunteers was used to categorize commuter behaviour, while the staff population dataset was used to estimate commuter volumes across FSAs. Prior to model development, the survey was also explored spatially using ArcGIS dashboards to better understand regional commuting patterns across the Greater Toronto Area. This data provided information on hospital staff's commuting patterns and their stance on transitioning their commutes to work into a more sustainable mode of travel. The beginning of the data preparation required extracting only relevant information from the survey dataset to be used to generate a mode choice model.

As an initial exploratory step, the survey responses were visualized using ArcGIS Pro and ArcGIS Online. Respondents' residential postal codes were geocoded and displayed geographically to examine the spatial distribution of commuters across Toronto and the GTA. Survey attributes, including transportation mode, commuting cost, commuting frequency and willingness to consider alternative transportation modes, were linked to each location and displayed within an interactive dashboard. The dashboard allowed survey responses to be explored spatially and supported the identification of regional commuting patterns prior to model development.

The dashboard layout displayed with the map, graphs and tables is shown Figure 2, retrieved from ArcGIS Online.

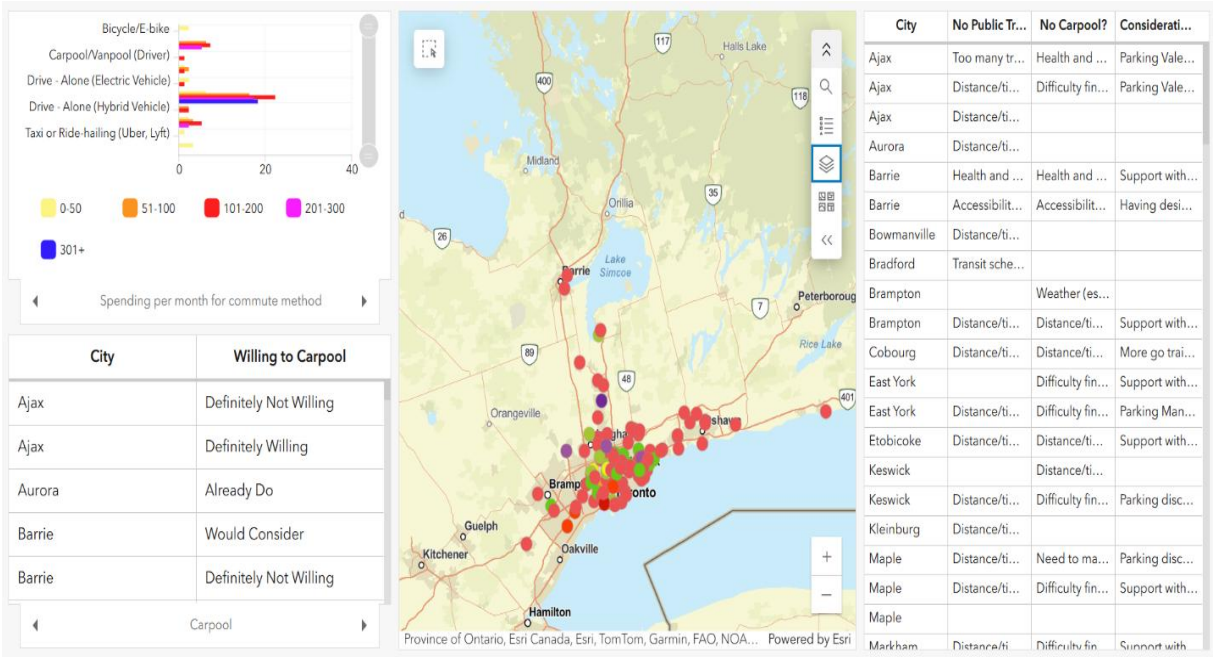


*Figure 2: Interactive ArcGIS dashboard developed to explore the spatial distribution of commuter survey responses across the Greater Toronto Area.*

The dashboard also incorporated interactive filtering capabilities that allowed subsets of respondents to be explored based on selected survey variables, showing comparisons between geographic locations and commuter characteristics during the exploratory analysis.

The exploratory analysis revealed several patterns that informed the subsequent modelling framework. Driving alone was identified as the dominant commuting mode. Furthermore, commuters reporting monthly commuting costs exceeding $301 were exclusively SOV users. Many of these respondents also reported travelling to the hospital five days per week, indicating consistent parking demand among full-time staff. The dashboard further showed that respondents from the same municipalities frequently expressed a willingness to participate in carpooling, suggesting that geographic clustering may support the implementation of employer-sponsored carpool matching programs. Similarly, the spatial distribution of respondents willing to use public transit indicated that willingness varied across residential locations, highlighting the potential influence of commute distance and transit accessibility on mode choice. Responses regarding barriers to sustainable transportation further indicated that many commuters would consider alternatives such as transit or carpooling if additional resources, incentives or organizational

support were available. Together, these observations provided valuable context for selecting explanatory variables and supported the development of the mode choice model and incentive optimization framework.

The ArcGIS dashboard was not only used as a visualization tool, but also as an exploratory analysis tool to identify spatial commuting patterns across the GTA. By integrating commuter locations, transportation modes and survey responses into an interactive tool, the dashboard supported the interpretation of regional travel behaviour and helped identify areas with stronger dependence on SOV commuting. These observations provided additional context for the development of the mode choice model and incentive optimization framework.

Following the exploratory analysis, the survey dataset was filtered and prepared for model estimation. Variables considered most relevant to transportation mode choice were selected based on transportation theory, previous literature and data availability. These included travel time, generalized travel cost and selected socioeconomic variables.

To begin, using Google Distance Matrix API, each commuter's postal code location was used to generate travel times for the mode options of driving, public transit and carpooling from their departure to the hospital. For consistency in the data, the travel time of the commutes were estimated for 8:00 AM on a typical Monday morning. All travel times were added to the existing dataset to be used for further modeling.

Another feature which was generated was the estimated costs for each travel mode. All commuters from the survey reported their monthly costs for their commute choice. Since the commuters reported their spendings per month only for the modes they use, costs for the remaining travel modes were generated to allow comparison across alternatives in the mode choice model. The cost for driving was calculated based on the parking costs at hospitals. Since hospitals offer a monthly parking pass option for those who are commuting to the hospital frequently and also have a daily parking cost for those who commute less frequently, the two costs were calculated and compared to determine the lower cost option for each commuter. For example, a comparison can be made for a hospital offering a monthly pass reported at $330 for staff, but daily passes at $25. To calculate the respective driving monthly cost for a commuter using the daily passes, the number of workdays on-site per week reported in the survey was multiplied by the daily cost and multiplied by 4 to reflect four weeks in a month. This calculated monthly cost was then compared to the cost of a monthly parking pass of $330, and the lower value between the two options was selected as the driving cost used in the dataset.

The next travel cost calculated was transit cost. Through the reported postal codes, the residential regions were identified and matched with the public transit system used in the region. Depending on which

form of public transportation was the most optimal for the route, the corresponding transit system's fare was considered for the public transit commute cost.

The carpooling cost was considered assuming two people share the driving cost, which was calculated as half of the driving cost.

The data was then categorized into FSA locations (first three characters of the postal codes) to enable spatial analysis and integration with regional socio-demographic data. The FSA identifiers were matched with socio-demographic data from a 2021 Statistics Canada census retrieved from the Statistics Canada open data portal (Statistics Canada, 2022). The relevant data retrieved from the census data included:

- Average income per household in each FSA
- Private dwellings per household
- Average age of women and men
- Population per FSA

These socio-demographic features were tested to evaluate which variables were most significant for predicting commuter mode choice.

### 4.1.1 Variable Selection

The variables included in the final mode choice model were selected based on transportation theory, statistical performance and available data in the dataset. Travel cost and travel time were included because they are commonly identified as major determinants of commuter mode choice. Population was included as a regional characteristic representing differences between commuter origin areas while also reflecting the scale of urban activity within each FSA. Although population density is commonly used as an indicator of transit accessibility, total population was selected because it was readily available at the FSA level and provides a practical measure of regional context. In the GTA, FSAs with larger populations generally correspond to more urbanized areas that offer greater access to public transportation and employment opportunities.

## 4.2 Survey Characteristics

Before estimating the mode choice model, the survey responses were examined to better understand existing commuting behaviour and identify characteristics that may influence transportation mode choice.

### 4.2.1 Existing Travel Behaviour

The survey indicated that driving alone was the dominant travel among respondents, accounting for approximately 62% of completed responses. Public transit represented the second most common travel

option, while carpooling accounted for only a small portion of existing commuting behaviour. These findings demonstrate the hospital's strong dependence on SOV commuting and provide justification for investigating transportation demand management strategies aimed at encouraging shifts toward more sustainable travel modes.

### 4.2.2 Carpooling

Although relatively few respondents currently carpooled, many indicated that they would consider doing so under appropriate conditions. Several respondents also commented that the hospital no longer maintained an active carpool matching program following the COVID-19 pandemic. These observations suggest that low carpool participation may reflect institutional barriers, suggesting that employer-supported carpool matching programs may represent an effective transportation demand management strategy.

### 4.2.3 Transit

Survey responses also indicated that transit represented an existing alternative for many commuters, although willingness to switch was influenced by travel time, convenience and service availability. These observations support the inclusion of travel time and travel cost as explanatory variables within the MNL model.

The exploratory survey analysis confirmed the hospital's strong reliance on SOV commuting while also identifying opportunities for increasing transit and carpool use through targeted transportation demand management initiatives. These observations informed both the selection of explanatory variables and the development of the MNL model described in the following sections.

## 4.3 Mode Choice Modelling and Utility Functions

### 4.3.1 Random Utility Framework

Utility functions are used in discrete choice modeling to represent the associated satisfaction or preference an individual associates to a set list of alternatives. Discrete choice modeling is a method used to analyze decisions where individuals choose from a set number of alternatives. The random utility maximization theory assumes individuals choose the alternative that maximizes their utility. These utility functions are used in MNL models, where the likelihood of choosing an alternative increases with the corresponding utility. All utility functions are linear functions that display variables with coefficients that quantify the effect of each influential variable. These utility functions produce probabilities representing the likelihood of selecting each transportation mode. This framework is established and retrieved from (Ben-Akiva & Lerman, 1985; Train, 2009).

Each utility function, Ui,j for mode I and region j, follows the following format:

$$U_{i,j} = V_{i,j} + \varepsilon_{i,j}$$

Where:

- $U_{i,j}$ is the total utility of mode i and region j,
- $V_{i,j}$ is the systematic utility generated from observed variables,
- $\varepsilon_{i,j}$ is an unobserved random variable following Gumbel distribution

### 4.3.2 Utility Function Specification

The initial utility functions contained five mode choices – drive, transit and carpool. The utility functions contained influential features from the data which affect the factors of selecting each mode choice. A manual feature selection process was utilized for the mode choice modeling aspect of this project. Variables which are typically significant in mode choice literature including travel cost, travel time and sociodemographic variables were considered for the significant feature selection process. Driving utility consisted of the driving travel cost, transit utility consisted of the transit travel time, transit travel cost and population of region features and the carpooling utility consisted of the travel cost of carpooling feature.

### 4.3.3 Parameter Estimation and Statistical Testing

The model runs a parameter estimation, and the coefficients are evaluated with the Hessian matrix to generate the standard errors of the estimated coefficients. These are the equations used to calculate z-scores and p-values for statistical significance testing:

z-scores:

$$\mathrm{Z}_i = \frac{\beta_i}{SE_i}$$

- $\mathrm{Z}_i$ is the z-score being calculated
- $\beta_i$ is the parameter estimate
- $SE_i$ is the standard error of the variable

p-values:

$$p_i = 2 \times (1 - \varphi(|Z_i|))$$

- $p_i$ is the p-value being calculated
- $\varphi$ is the cumulative distribution function of the standard normal distribution
- $Z_i$ is the z-score of the variable

### 4.3.4 Final Model Specification

Utility functions were created for three mode choices: driving, transit and carpooling. The purpose of these functions is to represent how desirable each mode is based on different factors. The final factors considered were determined to be the most significant for influencing commuter mode choice. Due to the under representation of the active modes in the data set and their statistical insignificance (high p-values), the two modes were removed from the modeling process to achieve accurate results. Retaining statistically insignificant alternatives may reduce overall model stability and weaken predictive performance. Therefore, walking and cycling were excluded from the final calibrated model, and the final specification focused on driving, transit and carpooling. $V_{i,j}$ is a linear combination of features which have been normalized along with their corresponding estimated coefficients. The calibrated model used the following utility specifications:

Drive Utility

$$U_{Drive,j} = \beta_0^{Drive} + \beta_1^{Drive} \times COST_{Drive,j}$$

Transit Utility

$$U_{Transit,j} = \beta_1^{Transit} \times TIME_{Transit,j} + \beta_2^{Transit} \times COST_{Transit,j} + \beta_3^{Transit} \times Population_j$$

Carpool Utility

$$U_{Carpool,j} = \beta_1^{Carpool} \times COST_{Carpool,j}$$

Each variable incorporated into the utility functions were normalized prior to the estimation process:

- $COST_{Drive,j}$: Normalized cost of driving from survey or calculated parking fee
- $TIME_{Transit,j}$: Normalized estimated travel time by public transit
- $COST_{Transit,j}$: Normalized public transit fare based on available public transit system for route
- $COST_{Carpool,j}$: Normalized carpool cost (half the value of the driving cost)
- $Population_j$: Normalized total population of the commuter's FSA

Due to the large differences in magnitude between the variables, all explanatory variables were standardized prior to model estimation using z-score normalization. Standardization converted every variable to have a mean of zero and a standard deviation of one, preventing variables with large numerical scales from causing the coefficient estimation process to be disproportionate.

$$X_{norm} = \frac{X - \mu}{\sigma}$$

Where:

- $X$ is the original variable value
- $\mu$ is the mean of the variable
- $\sigma$ is the standard deviation of the variable

Variable normalization was conducted to place all explanatory variables on comparable numerical scales before coefficient estimation. This improves model stability during optimization and allows variables measured in different units, such as dollars, minutes and population counts, to be compared more consistently.

The presented variables are represented with corresponding units. Cost is in dollars per month. Travel time is in minutes per one way commute. Population is based on the specific population in the FSA collected from the 2022 Stats Canada census data.

The $\beta$ coefficients are estimated using maximum likelihood estimation method. The function used in python for this is scipy.optimize.minimize(). The number and sign of each coefficient reflect the effectiveness of each corresponding variable in the utility. The coefficient values are interpreted based on

the generated number and sign. A positive value on a parameter estimate means the feature will increase utility and this feature increases the probability of choosing the corresponding mode. A negative value on a parameter estimate means the feature will decrease the utility and this feature decreases the probability of choosing the corresponding mode.

The dataset is randomly divided in two sets, 70% training data and 30% testing data to evaluate the accuracy of the model's predictions. The purpose of the training division of the dataset is to estimate the parameters. This process teaches the model the correlation between each variable and the corresponding mode choice. The 30% of the data used for testing validates the new observed data by comparing the predictions on the test data with the actual mode choices made. This results in a measurement of accuracy for the model's ability to predict. This method is widely used in discrete choice modelling.

After running the model, the final utility functions with the coefficients were as following:

Drive Utility

$$U_{Drive,j} = 2.923 - 3.2138 \times COST_{Drive,j}$$

Transit Utility

$$U_{Transit,j} = -1.3102 \times TIME_{Transit,j} - 1.5201 \times COST_{Transit,j} + 0.5586 \times Population_j$$

Carpool Utility

$$U_{Carpool,j} = -1.4623 \times COST_{Carpool,j}$$

The initial coefficient for the drive utility is a positive number, 2.923, which indicates that driving is initially desirable for commuters. The coefficient for the driving cost in the driving utility is -3.2138, a larger number but negative, meaning the higher the cost of driving is the less desirable the mode becomes. For transit utility, the transit time coefficient is -1.3102 meaning a longer commuting time for public transit results in the commuter having less of a desire to choose transit for their travel mode. The transit cost coefficient is also a negative number, -1.5201, indicating that a higher transit cost will also result in less of a desire for a commuter to choose transit for their travel mode. The population coefficient is positive, 0.5586, suggesting that commuters residing in higher-population FSAs are more likely to choose transit. Within the study area, higher-population FSAs generally represent more urbanized areas with greater transit availability, making population an appropriate regional contextual variable in the model. The carpool utility is a negative number, -1.4623, indicating a higher carpooling cost will make the mode less desirable.

The following table indicates the statistical testing results for the model's estimated utility parameters:

*Table 1: Table indicating the statistical testing results for the model's estimated utility parameters.*

| Parameter | Estimate | Standard Error | Z-Score | P-Value |
|---|---|---|---|---|
| $\beta_0^{Drive}$ | 2.923048 | 0.599511 | 4.875721 | 1.00E-06 |
| $\beta_1^{Drive}$ | -3.21385 | 0.767803 | -4.185774 | 2.80E-05 |
| $\beta_1^{Transit}$ | -1.310196 | 0.56751 | -2.308675 | 0.020962 |
| $\beta_2^{Transit}$ | -1.5202126 | 0.669612 | -2.27016 | 0.023198 |
| $\beta_3^{Transit}$ | 0.558611 | 0.406314 | 1.374825 | 0.169186 |
| $\beta_1^{Carpool}$ | -1.462326 | 0.69158 | -2.114472 | 0.034475 |

The standard error values measure how precise the parameter estimate is. A smaller standard error means the estimate is more precise while a larger standard error means the estimate is less certain. The z-score values measure how many standard deviations the estimate is away from zero. A larger z-score means the coefficient is more statistically significant while a smaller absolute z-score means the coefficient is less statistically significant. Higher absolute z-scores results in smaller p-values. P-values smaller than 0.05 means the coefficient is statistically significant. Most model parameters were statistically significant at conventional confidence levels. The population variable was not statistically significant at the 95% confidence level; however, it was retained because it represents an important spatial characteristic of commuter origins and improved the behavioural interpretation of the model.

The population coefficient $\beta_3^{Transit}$, produced a p-value of 0.169, which exceeds the 0.05 threshold. This indicates that the population was not statistically significant in explaining transit mode choice within the sample used for this study. However, the variable was retained in the model because it represents an important spatial characteristic of commuter origin regions and is used as an explanatory variable representing regional differences.

All cost-related variables were negative and statistically significant ($p < 0.05$), which is consistent with transportation and economic theory, as increasing travel costs reduce the attractiveness of a transportation mode. Transit travel time was also negative and statistically significant ($p = 0.021$), indicating that longer transit travel times reduce the likelihood of commuters choosing transit.

Overall, the model demonstrated a good fit, with McFadden's $R^2$ value of 0.581. The 70/30 training and testing validation method produced an accuracy of 83.5% on the training dataset and 86.5% on the testing dataset, suggesting that the model provides reliable predictions of commuter mode choice behaviour.

## 4.4 Mode Choice Probability Estimation

After the utility functions are generated, each probability of choosing mode i for region j is generated through MNL probability expression with k being the set of all possible alternative modes j:

$$P_{i,j} = \frac{e^{U_{i,j}}}{\sum_{k\epsilon\{Drive,Transit,Carpool\}} e^{U_{k,j}}}$$

Where:

- $P_{i,j}$ is the probability of selecting mode $i$ from region j
- $U_{i,j}$ is the utility of mode $i$ from region j
- The denominator is the sum of the exponent of the utilities for all modes: driving, transit and carpooling.

These probabilities were generated for all FSAs using the respective utility functions. Higher utility values correspond to higher probabilities of selecting a transportation mode relative to the competing alternatives.

## 4.5 Incentive Based Optimization

To influence a shift in commuter behavior to reduce parking congestion, incentive strategies are designed with a fixed budget constraint. The optimization modelling process consists of producing the most optimal transit and carpooling incentives to maximize commuting away from driving and into more sustainable modes (transit and carpooling), given a monthly hospital budget. An optimization model was created to maximize the shift from driving alone to sustainable modes (transit and carpooling) by creating mode-specific cost incentives that provide discounts to each specific sustainable mode. The incentives are assigned uniformly to all staff regardless of which FSA they reside in. Using a constrained optimization approach, incentives were determined subject to the available monthly budget constraint and applied uniformly across all FSAs.

Sensitivity analysis was conducted through different fixed monthly budgets for incentives. The different budgets used to be optimized were $5,000, $10,000, $15,000, $20,000 and $30,000. The monthly budget range of $5,000 to $30,000 was selected to represent a plausible set of institutional pilot scenarios rather than an unrealistically large funding range. This range is consistent with the scale of commuter benefits reported in employer-based TDM programs. For example, Stranford University offers up to $300 per year in commuter benefits through its Commute Club program (Stanford University, 2025), while Seattle Children's Hospital implemented a $4.50 daily incentive for alternative commuting (Seattle Children's Hospital, 2018). In addition, California's parking cash-out framework provides commuter benefits in a higher range depending on the market value for employee parking (California Air Resources Board, 2025). These examples suggest that commuter incentives in the range of tens of dollars per month are realistic in practice. Relative to the high costs of expanding parking supply, the monthly incentive budgets tested in this study may also be viewed as a modest TDM expense (Litman, 2022). For an institution with approximately 4,000 staff members, the tested range corresponds to approximately $1.25 to $7.50 per employee per month if distributed across full staff population. Therefore, the selected budget range is appropriate for evaluating pilot incentive scenarios for hospitals and large institutions.

The optimization model was developed to determine the incentive values for transit and carpooling that maximize reductions in expected SOV commuting while remaining within a fixed monthly budget. The optimization framework allows transportation policies to be evaluated under realistic financial constraints and provides decision-makers with estimates of expected behavioural responses.

Using a specific dataset which presents staff population commuting to the hospital from each FSA, new probabilities for each FSA were calculated and applied to the provided staff populations. The optimization objective was to minimize the expected number of SOV commuters across all FSAs while satisfying the monthly budget constraint. The optimization problem can be expressed as:

$$\min\left(\sum_{i=1}^{n}(D_i)\right)$$

Where:

- $D_i$ is the optimized number of SOV commuters from FSA $i$
- $n$ is the total number of FSAs included in the analysis

With the budget contraint being expressed as:

$$x_T N_T + x_C N_C \leq B$$

Where:

- $x_T$ is the transit incentive
- $x_C$ is the carpool incentive
- $N_T$ is the number of transit users
- $N_C$ is the number of carpool users
- $B$ is the monthly incentive budget

The monthly budgets evaluated in the sentivity anlysis were:

$$B \in \{5000, 10000, 15000, 20000, 30000\}$$

Once the optimal incentive values were determined, they were incorporated into the mode choice model by reducing the transit and carpool travel costs. The equations used for the new calculated costs for transit and carpooling modes are:

$$Cost_{Transit} = Original\ Cost - \ Incentive_{Transit}$$

$$Cost_{Carpool} = Original\ Cost - \ Incentive_{Carpool}$$

With the new probabilities generated from the new costs, the updated mode choices from each FSA were determined and the new scenario is compared to the original scenario. The new scenario demonstrates the effect of the applied incentives. Incentives were applied only to transit and carpooling alternatives because the objective of the study is to encourage shifts away from SOV commuting. Driving was therefore treated as the reference alternative and did not receive any incentive adjustments.

## 4.6 Chapter 4 Summary

This chapter presented the modelling and optimization methodology used in this study to estimate the commuter mode choice and design incentive strategies. It described the data preparation process, the

Random Utility Maximization framework and the utility functions formulation for driving, transit and carpooling using travel time, travel cost and FSA level populations. The chapter explained the process of estimating parameters through maximum likelihood methods and statistical testing of coefficients using standard errors, z-scores and p-values. The chapter used estimated utilities to provide details on the calculation of the MNL mode choice probabilities for all regions. Finally, it introduced the budget-constrained incentive optimization approach and sensitivity analysis conducted across multiple monthly budget amounts. The models show how the new costs generated through the applied incentives produce new probabilities and cause mode shifts that are discussed in Chapter 5.

# Chapter 5

## 5.0 Results and Discussion

The results and findings from the mode choice model, spatial optimization model and visualization processes will be presented in this section. Understanding current commuting patterns is important for evaluating how incentives could affect travel behaviour towards more sustainable transportation.

### 5.1 Mode Choice Results

With the MNL model and utility functions, mode choice probabilities were generated for each FSA region and applied to the staff population of that region. In the current scenario, the probability of someone driving as a mode choice was the highest. Drive alone commuting sums up to 1,652 daily trips. The second highest mode choice was transit, with 686 daily trips and the smallest probability of mode choice was carpooling with 146 trips. This means that 66% of commuters at the hospital are commuting by driving alone, 28% are commuting via transit and 6% are commuting via carpool. These results were expected since most staff reported to drive SOV and are expected at highly populated North American cities like Toronto. More precisely, those who lived further from the hospital were driving to the hospital while transit was usually chosen in areas with more transit access. Carpooling at 6% is a low percentage of mode choice, representing the decline in carpool rates in U.S. commuters from 20% in 1980 to around 10% more recently (Nelson, 2025) similar to rates in Canada. Carpooling may also not be popular at Toronto hospitals if there are no carpooling programs available to commuters.

The estimated baseline mode shares are consistent with commuting patterns observed in similar institutional settings. Previous studies examining employee travel behaviour in North American cities report that SOV commuting rates for large institutions often range between 60% to 75%, depending on the availability of public transit and any implemented parking policies in place by the organization (Litman, 2020). The predicted SOV share of approximately 66% in this study which aligns with the expected numbers for cities where employees travel from suburban areas with different levels of access to transit.

The estimated coefficients generally align with expected commuter behaviour. Higher travel costs and travel times reduce attractiveness of transportation alternatives, while regional characteristics influence

the likelihood of selecting sustainable modes. These findings support the suitability of the model for evaluating transportation policy scenarios.

Similarly, the low share of carpooling that are shown in the results is consistent with usual commuting behaviour. Over recent years, carpooling rates in North America have decreased significantly due to increased vehicle ownerships and the convenience that comes from driving alone. The results of this study therefore reflect expectations in typical commuting trends and support the validity of the modelling approach used.

## 5.2 Optimization Results

Five different budgets scenarios were used for the optimization model. The input budget is a per month budget. It's to be used to calculate the appropriate incentives applied across the FSAs. The incentives were used to calculate updated travel costs for transit and carpooling and were used for generating new mode choice probabilities. With the first inputted budget of $5,000 equating to a $2.77 incentive for transit users and a $15.18 incentive for carpool users would drop drive alone trips from 1,652 to 1,593 (a 3.5% reduction), would not change transit commuting but would increase carpooling trips from 145 to 204. With the next inputted budget of $10,000 equating to a $5.18 incentive for transit users and a $25.56 incentive for carpool users would drop drive alone trips from 1,652 to 1,545 (a 6.47% reduction), would not change transit commuting but would increase carpooling trips from 145 to 252. With the next inputted budget of $15,000 equating to an $8.64 incentive for transit users and $31.96 incentive for carpool users would drop drive alone trips from 1,652 to 1,502 (a 9.07% reduction), would increase transit commuting from 685 to 700 and would increase carpooling trips from 145 to 279. With the next inputted budget of $20,000 equating to a $12.38 incentive for transit users and $36.97 incentive for carpool users would drop drive alone trips from 1,652 to 1,463 (a 11.44% reduction), would increase transit commuting from 685 to 720 and would increase carpooling trips from 145 to 299. With the next inputted budget of $30,000 equating to a $19.18 incentive for transit users and $46.07 incentive for carpool users would drop drive alone trips from 1,652

to 1,390 (a 15.86% reduction), would increase transit commuting from 685 to 755 and would increase carpooling trips from 145 to 337. The results are represented in the following table:

*Table 2: Results of sensitivity analysis*

| Budget ($/month) | Transit Incentive | Carpool Incentive | Number of Driving Users | Number of Transit Users | Number of Carpooling Users | Driving Reduction |
|---|---|---|---|---|---|---|
| 0 (Base) | $0 | $0 | 1652 | 685 | 145 | 0 |
| 5000 | $2.77 | $15.18 | 1593 | 685 | 204 | 59 |
| 10000 | $5.18 | $25.56 | 1545 | 685 | 252 | 107 |
| 15000 | $8.64 | $31.96 | 1502 | 700 | 279 | 150 |
| 20000 | $12.38 | $36.97 | 1463 | 720 | 299 | 189 |
| 30000 | $19.18 | $46.07 | 1390 | 755 | 337 | 262 |

The incentives resulted in a reduction in driving as the monthly budget increases. Transit and carpooling commuters increase in mode choice. A $5,000 monthly budget towards incentives gives an optimized incentive of $2.77 per month per transit user and $15.18 per month per carpooling user. This scenario results in a decrease of driving users by 59 people.

Figure 3 compares the base scenario to the optimized scenario given a $5,000 budget.

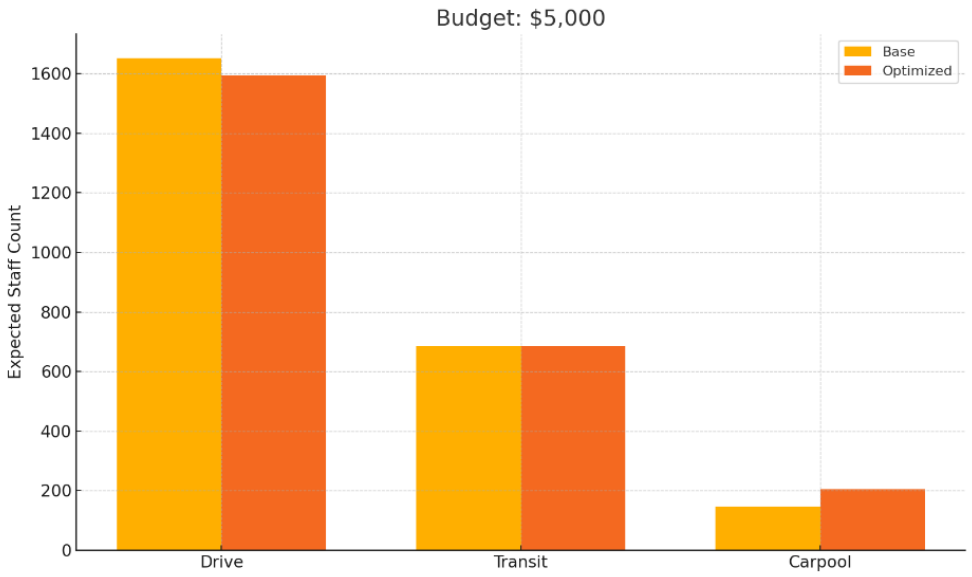


*Figure 3: Chart comparing the base scenario to the optimized scenario given a $5,000 budget.*

Although this causes a reduction in drivers, there is only an increase in carpooling users rather than transit users. Transit users stay the same in this scenario.

A $10,000 monthly budget towards incentives gives an optimized incentive of $5.18 per month per transit user and $25.56 per month per carpooling user. This scenario results in a decrease of driving users by 107 people. Figure 4 compares the base scenario to the optimized scenario given a $10,000 budget.

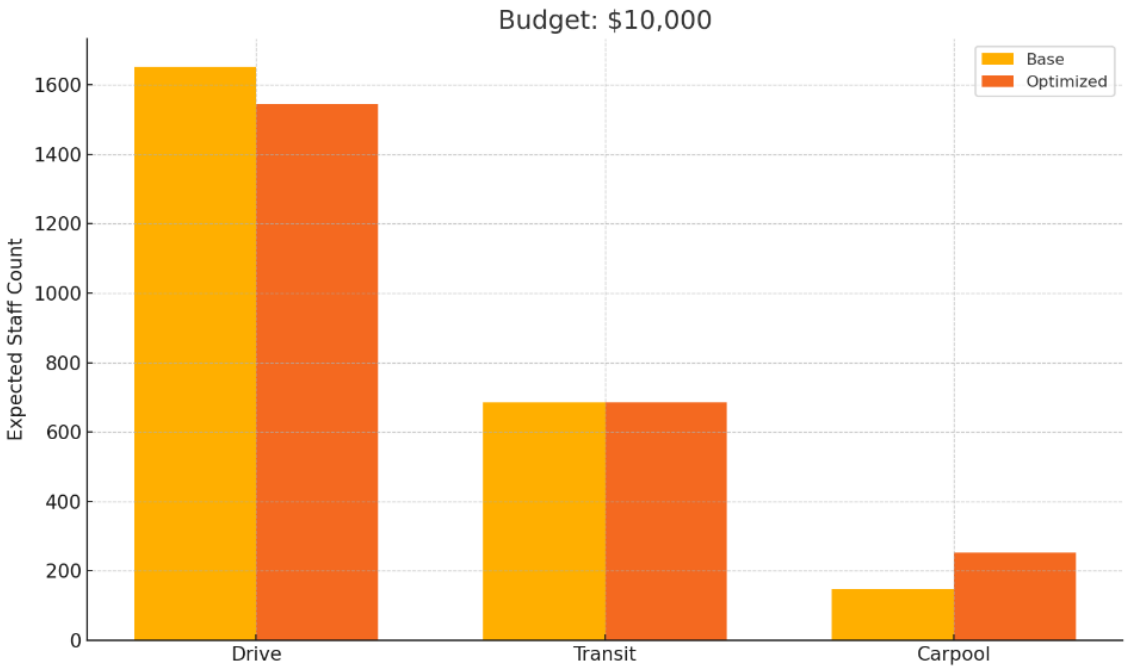


*Figure 4: Chart comparing the base scenario to the optimized scenario given a $10,000 budget.*

Although this causes a reduction in drivers, there is only an increase in carpooling users rather than transit users.

A $15,000 monthly budget towards incentives gives an optimized incentive of $8.64 per month per transit user and $31.96 per month per carpooling user. This scenario results in a decrease of driving users by 150 people. Figure 5 compares the base scenario to the optimized scenario given a $15,000 budget.

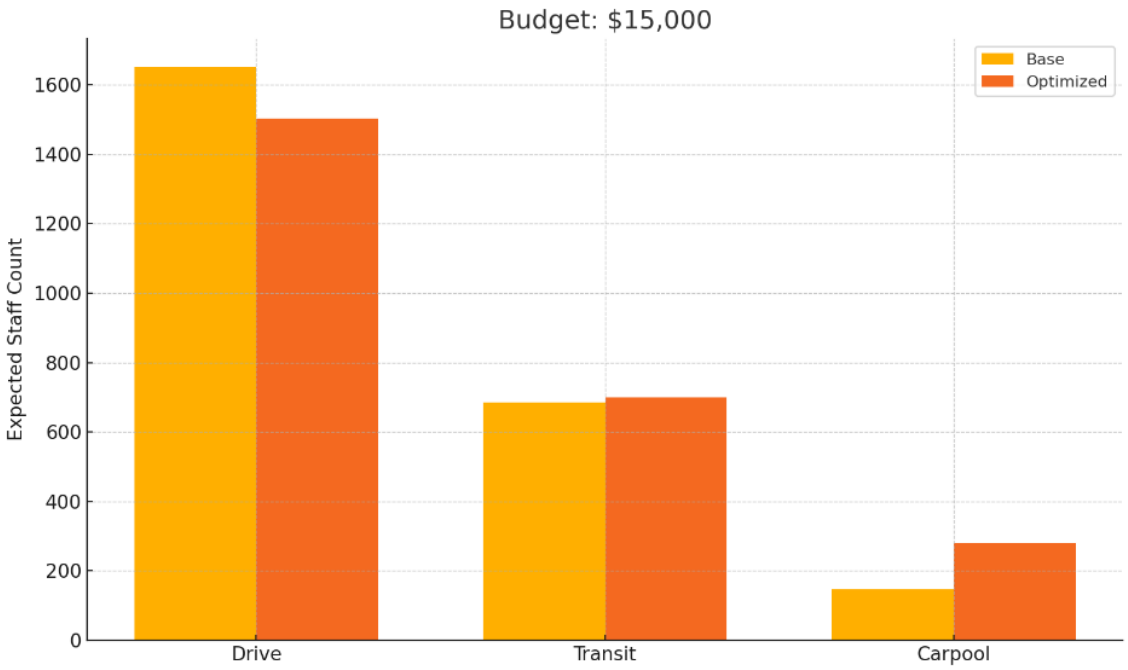


*Figure 5: Chart comparing the base scenario to the optimized scenario given a $15,000 budget.*

A $20,000 monthly budget towards incentives gives an optimized incentive of $12.38 per month per transit user and $36.97 per month per carpooling user. This scenario results in a decrease of driving users by 189 people. Figure 6 compares the base scenario to the optimized scenario given a $20,000 budget.

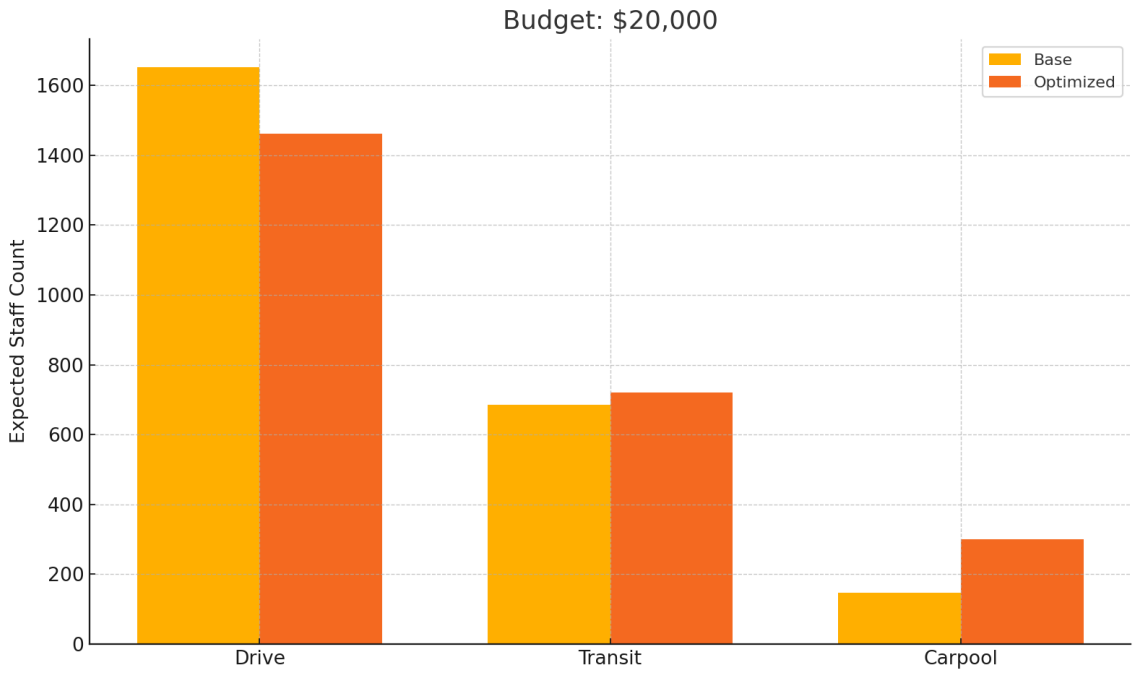


*Figure 6: Chart comparing the base scenario to the optimized scenario given a $20,000 budget.*

A $30,000 monthly budget towards incentives gives an optimized incentive of $19.18 per month per transit user and $46.07 per month per carpooling user. This scenario results in a decrease of driving users by 262 people. Figure 7 compares the base scenario to the optimized scenario given a $30,000 budget.

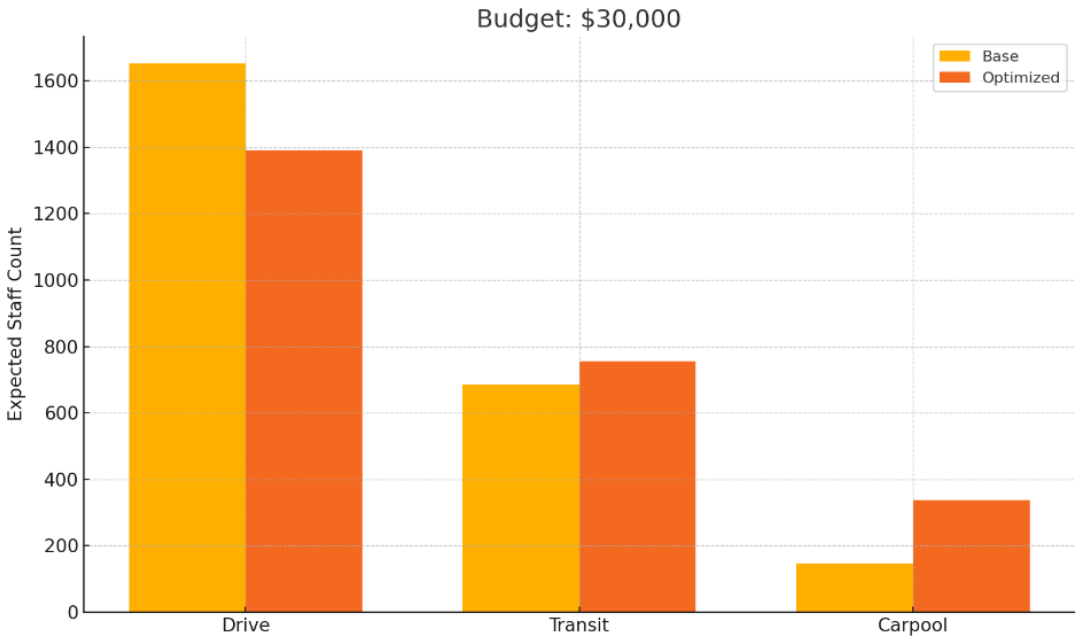


*Figure 7: Chart comparing the base scenario to the optimized scenario given a $30,000 budget.*

Carpooling probabilities were increased in areas with higher SOV commuters and lower populations while transit probabilities increased in areas with higher populations.

Due to applying incentives evenly across all regions and a limited budget, the effect of the incentives in some cases were not very impactful. Future work could target incentives for specific regions or focus on one sustainable mode choice for a greater effect.

The overall effect of the sensitivity analysis for all given budgets is shown in Figure 8 presenting the relationship between budget spent on incentives versus the reduction in drivers.

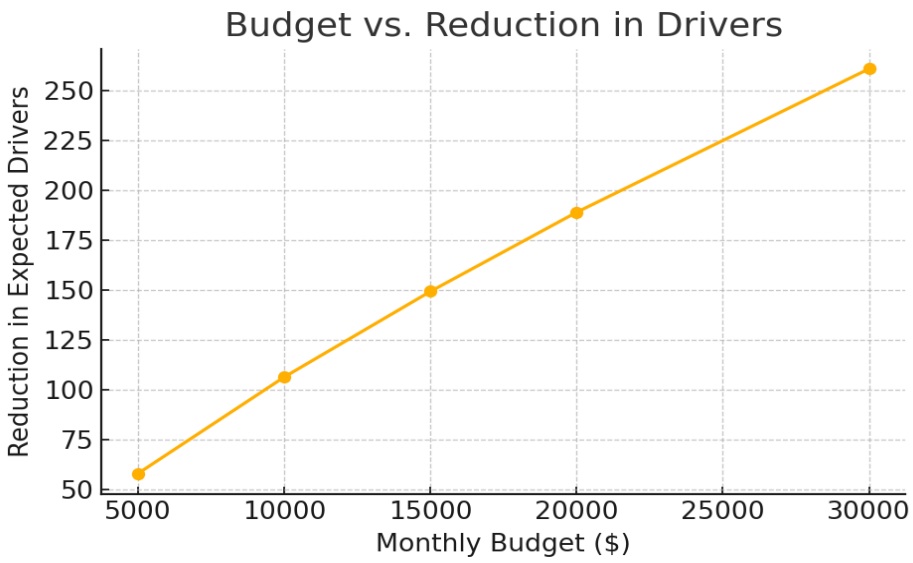


*Figure 8: Chart showing the relationship between budget spent on incentives versus the reduction in drivers.*

The sensitivity analysis demonstrates that larger budgets generally produce greater reductions in SOV commuting. However, the rate of improvement decreases at higher budget levels, indicating diminishing marginal returns. This finding suggests that beyond a certain threshold, additional incentive spending may generate progressively smaller behavioural changes.

The budget starting at $5,000 results in a reduction of 59 drivers whereas the jump from $20,000 to $30,000 produces a reduction of 73 drivers. This shows that the marginal impact per dollar reduces at higher budgets. This means that doubling the budget towards incentives may not double the decrease in SOV transportation. After a certain budget point the influenced commuters have already shifted away from driving and shifting the remainder of the drivers may not be easy at a higher incentive amount. The largest rate of reduction in driving is from the $5,000 budget scenario, and as the budget increases, the rate of commuters shifting away from driving decreases, although the number of drivers shifting away is increasing.

The incentives for carpooling in the results are higher than transit incentives for all given budget constraints. This is because the model considers the original prices of each mode choice cost. The original costs coming from either the original survey data or the calculated mode choice costs. The carpooling original costs were calculated to be half of the driving cost whereas the transit cost was calculated based on the corresponding transit fares. In the original baseline case, the cost of carpooling was higher than the average transit fare. Since the model is designed to shift commuters away from driving and towards transit and carpooling, it provides higher incentives for those modes that need higher cost reductions to be an alternative competitor to driving. Since the hospital did not have an existing carpooling program, the

hospital policy would have to introduce a carpooling program and make the incentive high enough to gain attractiveness from commuters. Transit had already had a relatively lower cost. This caused the model to apply lower incentives to public transit fares to either maintain the mode choice or slightly increase it as higher budgets are given. This explains the balance between the distribution of incentives between both mode shares.

When producing results for both scenarios, the probabilities of each mode choice at each FSA was calculated. The results for each budget can be found displayed in the table found in the Appendix showing each FSA, the base probabilities of choosing each mode versus the optimized probability. In each budget-constrained scenario, the probability of driving as a mode choice decreases at every FSA. At first, the probability difference in reductions in driving at each FSA is a small amount. As the budget increases, the driving probability reduces at a higher rate at each FSA.

## 5.3 Spatial Distribution of Mode Choice Probabilities

To further examine the spatial impacts of the optimization framework, ArcGIS Pro was used to visualize the predicted mode choice probabilities across all FSAs. The maps compare the baseline mode choice probabilities with the optimized probabilities generated using the $20,000 monthly incentive scenario. This scenario was selected because it represents a realistic balance between implementation cost and reductions in SOV commuting while demonstrating meaningful changes in travel behaviour. The complete probability tables for all budget scenarios are provided in Appendix A.

### 5.3.1 Driving Maps

Figures 9 and 10 compare the predicted probability of driving before and after optimization. Under the baseline scenario, driving is dominant travel mode throughout the study area, with most FSAs exhibiting probabilities above 85%. Following the optimization, driving probabilities decrease consistently across nearly all FSAs, demonstrating that the incentive program successfully reduces the attractiveness of SOV commuting throughout the region. Although driving remains the most likely travel mode in many suburban FSAs, the reduction in probability illustrates the effectiveness of the optimized incentive strategy. Some regions show a larger drop in SOV commuting compared to other regions.

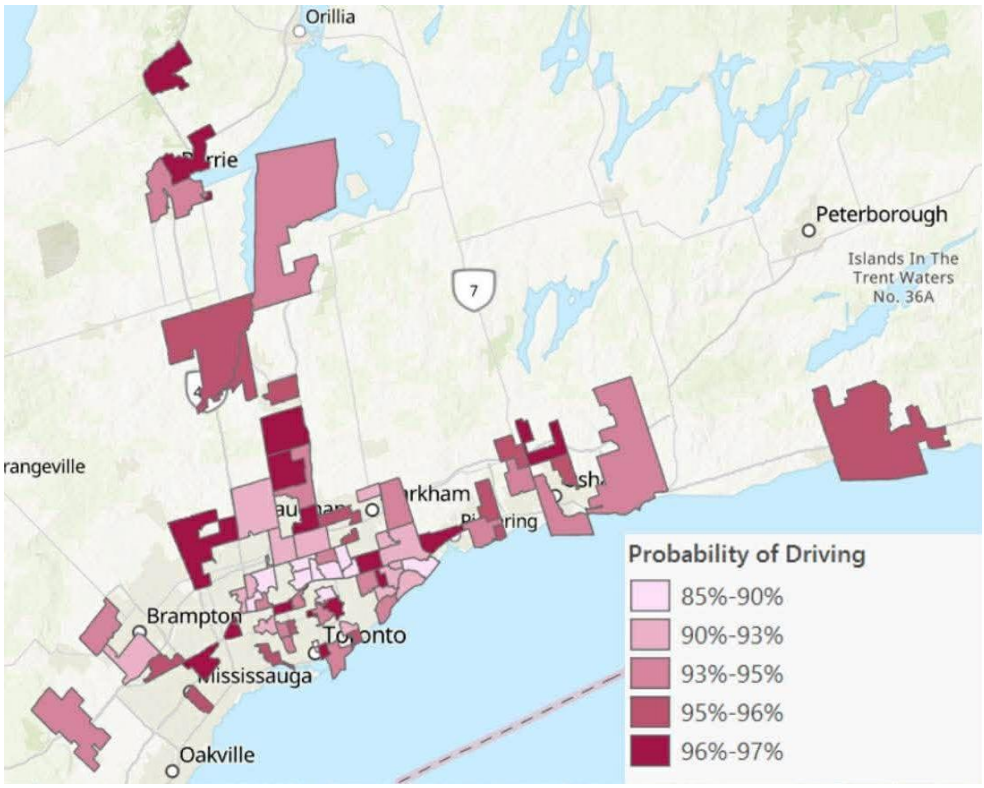


*Figure 9: Baseline probabilities of driving across the region*

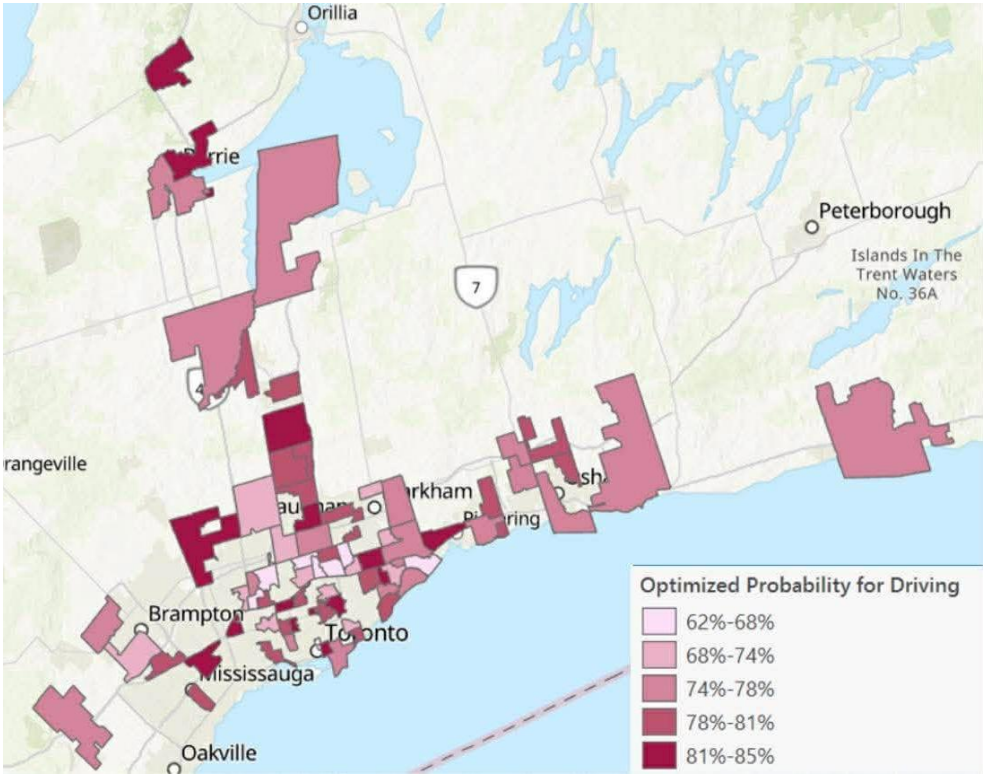


*Figure 10: Optimized probabilities of driving across the region*

### 5.3.2 Transit Maps

Figures 11 and 12 illustrate probability of selecting transit before and after optimization. Prior to optimization, the highest transit probabilities are concentrated in FSAs with greater transit accessibility, particularly those closer to the City of Toronto. Following optimization, transit probabilities increase throughout the study area, with the largest improvements occurring in areas where transit was already a competitive travel alternative. These results demonstrate that reducing transit costs through financial incentives can further increase transit attractiveness without altering the existing transportation network.

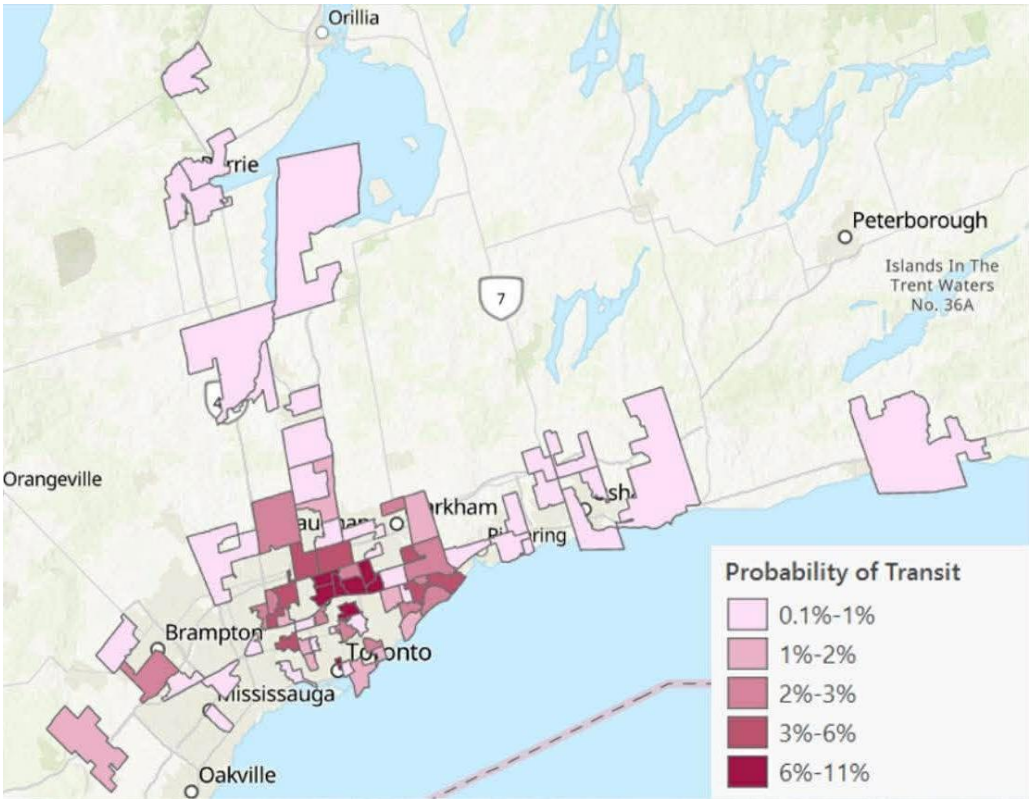


*Figure 11: Baseline probabilities of transit across the region*

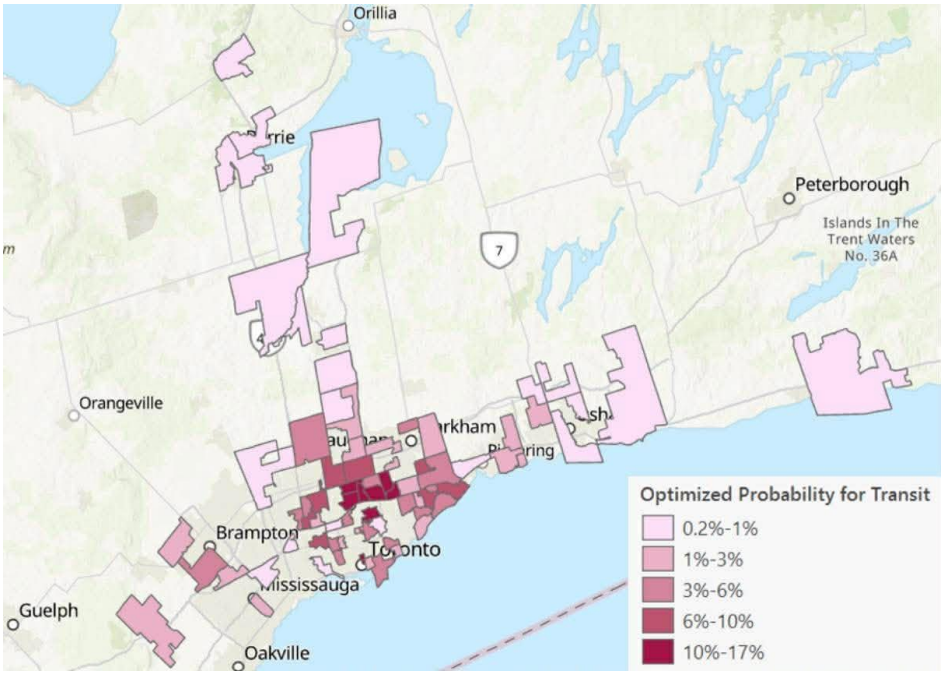


*Figure 12: Optimized probabilities of transit across the region*

### 5.3.3 Carpool Maps

Figures 13 and 14 present the predicted probability of carpooling before and after optimization. The baseline scenario indicates relatively low probabilities across most FSAs. After optimization, carpool probabilities increase substantially throughout the study area, reflecting the larger incentive allocated to carpooling by the optimization model. Compared with transit, the optimization assigned higher financial incentives to carpooling because its generalized travel cost was initially less competitive relative to driving. Consequently, the greatest proportional increases in sustainable travel were observed through increased carpool participation. For this mode, the general trend of regions more likely to carpool in the baseline scenario stays somewhat consistent in the optimized scenario.

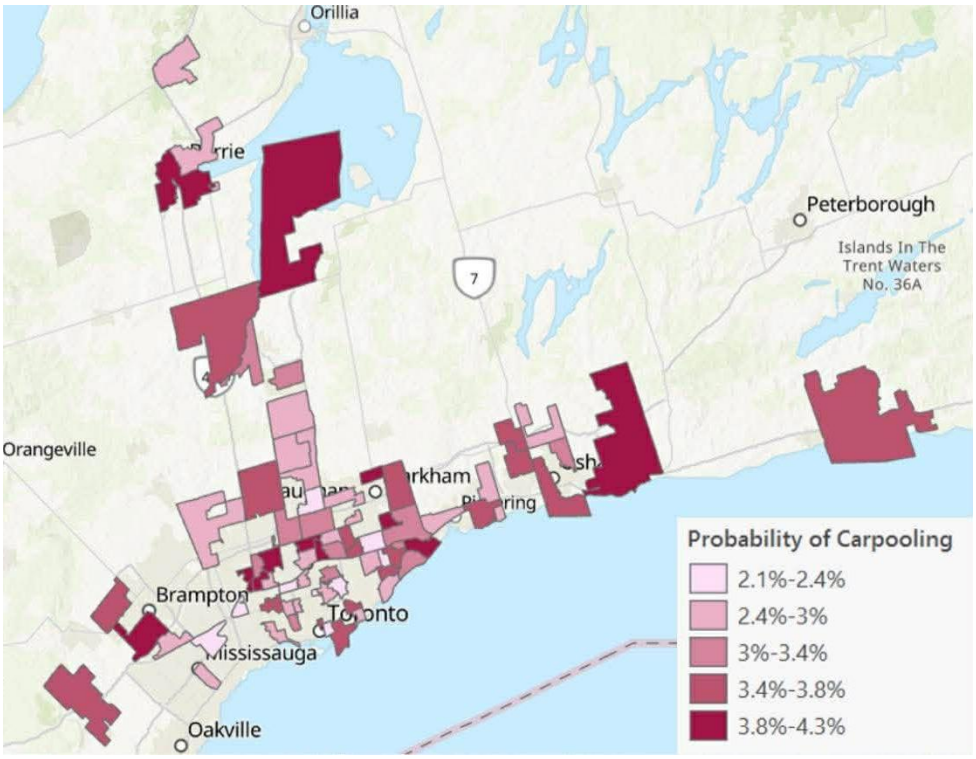


*Figure 13: Baseline probabilities of carpool across the region*

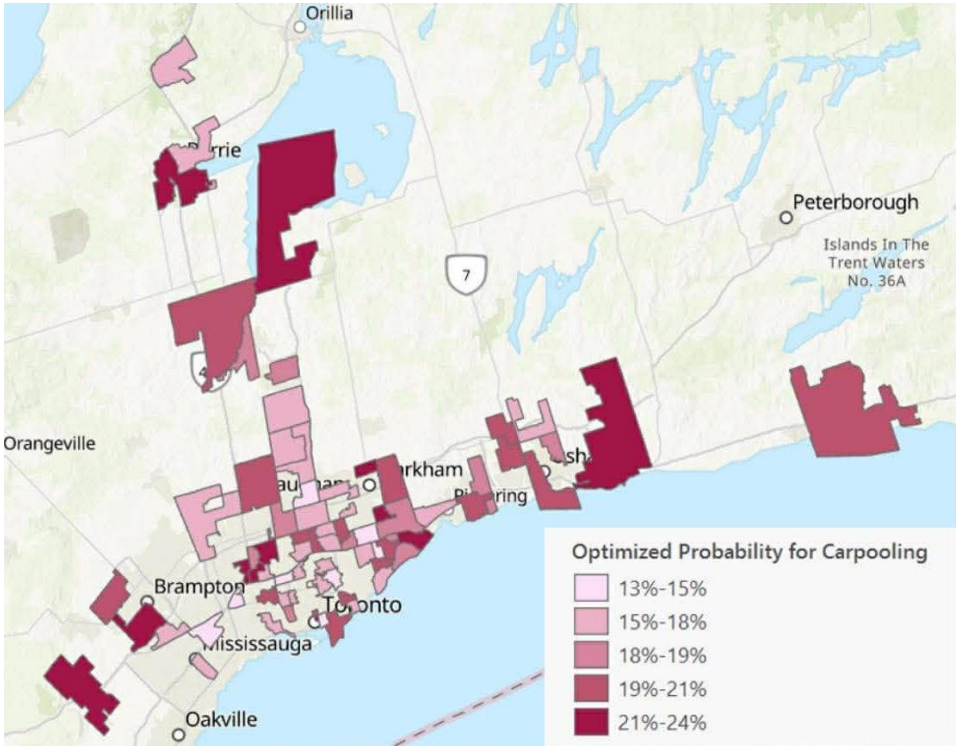


*Figure 14: Optimized probabilities of carpool across the region*

Overall, the spatial probability maps demonstrate that the optimization framework produces consistent reductions in driving probability while increasing the attractiveness of both transit and carpooling across the study area. The maps provide geographic representation of the optimization results and illustrate how the integration of mode choice modelling with spatial analysis can support transportation planning by identifying regional differences in predicted behavioural responses to incentive-based policies.

## 5.4 Discussion

The results of this project demonstrate that a strategically designed incentive program can result in a shift in commuter behaviour. Although after incentivizing a policy that will shift commuters away from driving, most of the commuters are still choosing SOV mode-shares and can not fully eliminate SOV mode choices. The reduction in SOV commutes will still have a significant impact on a reduction of congestion at the hospital facility, with a reduction of around 3-15% depending on the budget constraint. This reflects real world incentive policy shift compared to the best practices mentioned earlier like CAPRI with a 13-21% reduction of peak trips with a large incentive budget (Federal Highway Administration, n.d.).

One of the clearest findings from this research is the strong potential for employer-supported carpooling programs within the hospital. Several independent results support this conclusion. The survey indicated that many respondents were willing to participate in carpooling under appropriate conditions, while the exploratory spatial analysis identified groups of commuters residing within the same municipalities who could potentially be matched into employer-supported carpooling programs. Furthermore, the optimization model consistently assigned larger financial incentives to carpooling than to transit across all budget scenarios, resulting in substantial increases in predicted carpool participation. Together, these findings suggest that introducing or re-establishing a hospital carpool matching program, combined with modest financial incentives, may provide one of the most practical and cost-effective strategies for reducing parking demand.

A larger consideration as to why most commuters will still commute through SOV modes are factors which effect the structure of the transportation mode, for example if transit is too slow or transit is unavailable, or if the staff require a car for their jobs such as site visits or the need to carry equipment. No incentive that is realistic will influence those commuters to switch to a sustainable mode. So, the first policy goal is to target travel which realistically has available travel alternatives. The optimization model done so by considering factors which indicate more transit access. This can be further implemented by considering which specific areas can match carpooling commuters and target under utilized transit.

### 5.4.1 Policy Implications for Hospital Transportation Planning

The results of this study provide several insights for transportation planning and transportation policy design at healthcare institutions. Hospitals located in densely populated areas often are constrained when wanting to expand parking infrastructure due to high construction costs and land limitations. As a result, TDM strategies that don't require increasing parking supply can provide a more cost-effective solution for addressing congestion.

The incentive-based policy scenarios explored in this research show that moderate monthly budgets can result in reductions in SOV commuting. Although the results show that driving remains the dominant travel mode even after incentives are implemented, the reduction of 3-15 percent in SOV trips across the scenarios tested represent an impactful improvement for parking availability and traffic conditions around the hospitals.

For hospital management, these results suggest that targeted commuter incentive programs could be utilized as a tool for managing parking demand. Programs encouraging both transit use and carpooling can help reduce parking demand. However, the findings of this study suggest that carpooling may provide the greatest immediate opportunity for reducing SOV commuting. The survey demonstrated a willingness among staff to participate in carpooling, the exploratory analysis identified potential geographic groupings of commuters from similar municipalities, and the optimization consistently allocated larger incentives to carpooling than to transit. Together, these findings support the implementation of employer-sponsored carpool matching programs alongside financial incentives as a practical transportation demand management strategy for hospitals.

The results also show the importance of considering geographic differences in commuter behaviour when designing transportation policies. Employees living in regions with greater transit accessibility may be more responsive to incentives for transit use, while those living farther from transit hubs may benefit more from carpooling programs. Future institutional policies could consider combining financial incentives with additional strategies such as carpool matching programs, transit pass discounts and improved commuter information resources.

### 5.4.2 Implementation Considerations

While the modelling results show the potential effectiveness of incentive-based transportation policies, practical implementation of such programs requires consideration of operational factors. Hospitals must determine how incentives will be distributed, monitored and evaluated overtime. For example, incentive programs may require systems to verify the accuracy of the usage of travel modes and ensure that the rewards are given fairly to participants.

Another consideration is the long-term financial sustainability of incentive programs. Unlike pricing-based policies such as parking charges or congestion tolls, incentive programs require funding sources to support the incentive amounts. Institutions must evaluate how incentive budgets are suitable for the existing operations taking place and whether the reductions in parking demand justify the required expenses.

In addition, the success of incentive programs can depend on employee awareness and their participation. Communication strategies and commuter outreach programs can be utilized to further encourage staff to consider alternative commuting options. Providing information about transit routes, carpooling matching programs and program eligibility requirements can help increase participation rates and improve the effectiveness of the policies.

Finally, incentive programs should be monitored and evaluated regularly to ensure that policy objectives are being reached. Data collected through parking systems, commuter surveys or virtual applications can provide valuable feedback that can be used to adjust the policy design. By consistently evaluating program results, institutions can adjust incentive structures and maximize the effectiveness of TDM strategies.

## 5.5 Limitations

The results of this project present that price incentives can influence commuter behaviour and mode choice. These types of policies are generated based on cost sensitivity, mode access and all conditions given in base scenario. Although results present accurate predictions, some limitations exist. Active transportation modes were removed from predictions due to limited representation in initial survey data, incentives are uniform across all FSAs rather than consideration of factors such as demand per region or income and the MNL model may not reflect perfect real-life behaviour.

## 5.6 Chapter 5 Summary

This chapter reported the estimated mode choice results and the outcomes of the incentive-based optimization model scenarios. It presented predicted trip counts and mode shares across the mode choices, driving, transit and carpooling. The results showed that SOV commuting remains dominant in the output of the scenarios. Results from the sensitivity analysis demonstrate that increasing monthly incentive budgets consistently reduces predicted demand for driving SOV while increasing sustainable mode counts but had diminishing marginal returns at higher budgets. The chapter presented why optimized carpool incentives were much larger than transit incentives. This was connected to baseline generalized cost. Noticeable

patterns through the different FSAs were discussed to demonstrate how region-specific characteristics influence community responses to incentives. Overall, the findings provide policy related guidelines on budget levels and expected reductions in driving for institutional parking demand management.

# Chapter 6

## 6.0 Conclusion

This project presented a solution to a presented parking congestion conflict at a hospital located in Toronto. This was done by a spatial data-driven process which analyzed and optimized commuter mode choice. Using survey data from hospital staff, a MNL model was created to estimate mode choice probabilities across FSAs around the hospital. The model used travel times, travel costs and population.

A spatial optimization model was created to generate appropriate pricing incentives for sustainable travel modes using given budgets. The optimization model targeted the objective to maximize the change from driving mode choice to sustainable mode choices which were public transit and carpooling. The results showed financial incentives can impact commuter behaviour when calculated appropriately.

The research contributes to transportation planning literature by integrating commuter survey data, MNL mode choice modelling, spatial analysis and budget-constrained optimization within a hospital context. The proposed framework demonstrates how commuter incentives can be evaluated before implementation and provides a practical decision-support tool for institutional transportation planning.

Beyond demonstrating that incentive-based policies can reduce SOV commuting, this research identifies employer-supported carpooling as a particularly promising strategy for hospitals. The survey responses indicated a willingness among many staff members to carpool if institutional support were available, while the optimization model consistently allocated the largest financial incentives to carpooling, resulting in substantial increases in predicted participation. These findings suggest that hospitals may achieve meaningful reductions in parking demand through the implementation of coordinated carpool matching programs combined with targeted financial incentives, rather than relying solely on parking expansion or transit subsidies.

Future work should consider a few elements. Incentives can be calculated through prioritizing FSAs which would be strongly impacted by these policies by considering demand, mode access and equity. Active mode data can be incorporated into the project data to incorporate active transportation for those who it's feasible for. Real-time parking data from the hospital could be incorporated for dynamic pricing strategies and more accurate results. These models and policies could be applied to other hospitals or institutions to address similar conflicts.

Using technical transportation modeling with spatial analysis and policymaking, this project reflects sustainable, accessible and data-driven solutions for managing parking congestion issues at hospitals.

The findings of this research highlight the potential for behavioural transportation policies to address parking congestion challenges in institutional settings. Rather than turning to infrastructure expansion solutions, hospitals can implement TDM strategies that can influence commuter travel behaviour. By combining commuter survey data, discrete choice modelling and spatial analysis, this study demonstrates how data-driven methods can support transportation planning decisions.

The modelling framework used in this research provides a structured approach for evaluating transportation policies before implementation. Administrators can use similar modelling strategies to test alternative policy scenarios and evaluate potential outcomes. As healthcare institutions continue to face increasing transportation and parking challenges, the utilization of behavioural modelling and TDM policy design become important for sustainable transportation planning.

## 6.1 Chapter 6 Summary

This chapter summarized the thesis contributions and key findings from the study of a combined mode choice and incentive optimization framework. It revisits how the MNL model was used to estimate commuter preferences and how incentive strategies under fixed budgets were evaluated to reduce SOV commuting and reduce parking pressure. The chapter highlighted real-world applications for hospital administrators, including the effectiveness of moderate incentive budgets and the diminishing returns shown during budget increase. Limitations were acknowledged, including reliance on self-reported survey data, uniform incentive allocation for all FSAs used in the study and the exclusion of active modes due to underrepresentation in the data. The chapter finished off by outlining future research directions such as targeted incentive allocation, improved representation of active travel, incorporating transit service quality factors and integration of real-time parking data to potentially include more dynamic policy design.

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# APPENDIX A

$5000 Budget

| FSA | Population | Base Drive Probability | Base Transit Probability | Base Carpool Probability | Optimized Drive Probability | Optimized Transit Probability | Optimized Carpool Probability |
|---|---|---|---|---|---|---|---|
| K9A | 1 | 0.961659 | 0.001397 | 0.036944 | 0.863266 | 4.57E-07 | 0.136733 |
| L1C | 21 | 0.9523 | 0.006932 | 0.040768 | 0.686418 | 0.060313 | 0.253269 |
| L1J | 12 | 0.955121 | 0.008317 | 0.036562 | 0.830435 | 0.038031 | 0.131533 |
| L1K | 20 | 0.963008 | 0.004305 | 0.032687 | 0.915519 | 0.002221 | 0.082261 |
| L1L | 14 | 0.965849 | 0.004695 | 0.029456 | 0.971282 | 0.000369 | 0.02835 |
| L1M | 13 | 0.956603 | 0.006623 | 0.036773 | 0.860413 | 0.003306 | 0.136281 |
| L1R | 34 | 0.953083 | 0.010798 | 0.036119 | 0.838284 | 0.02894 | 0.132776 |
| L1S | 48 | 0.954394 | 0.009227 | 0.036379 | 0.845978 | 0.020026 | 0.133995 |
| L1V | 44 | 0.967345 | 0.006579 | 0.026076 | 0.979061 | 0.00273 | 0.018209 |
| L1Z | 37 | 0.95942 | 0.010262 | 0.030318 | 0.832196 | 0.110468 | 0.057336 |
| L3R | 51 | 0.962427 | 0.009515 | 0.028058 | 0.969057 | 0.002658 | 0.028285 |
| L3T | 74 | 0.920448 | 0.047949 | 0.031604 | 0.629371 | 0.284655 | 0.085973 |
| L3Y | 14 | 0.961381 | 0.006179 | 0.03244 | 0.855895 | 0.007073 | 0.137032 |
| L3Z | 11 | 0.959037 | 0.004342 | 0.03662 | 0.861239 | 0.002349 | 0.136412 |
| L4B | 28 | 0.966133 | 0.00906 | 0.024807 | 0.610695 | 0.328657 | 0.060649 |
| L4E | 27 | 0.964868 | 0.006801 | 0.028331 | 0.964708 | 0.007134 | 0.028158 |
| L4G | 35 | 0.968162 | 0.003907 | 0.02793 | 0.552283 | 0.109251 | 0.338465 |
| L4H | 42 | 0.966147 | 0.00606 | 0.027793 | 0.741393 | 0.087166 | 0.171442 |
| L4J | 91 | 0.913528 | 0.053703 | 0.032768 | 0.382477 | 0.583826 | 0.033697 |
| L4M | 6 | 0.966928 | 0.004308 | 0.028764 | 0.965651 | 0.006164 | 0.028185 |
| L4N | 10 | 0.955309 | 0.005139 | 0.039552 | 0.71489 | 0.021335 | 0.263775 |
| L4P | 16 | 0.949454 | 0.00767 | 0.042876 | 0.65071 | 0.034645 | 0.314645 |
| L4S | 40 | 0.955105 | 0.016359 | 0.028536 | 0.922234 | 0.050848 | 0.026918 |
| L4W | 5 | 0.970933 | 0.004667 | 0.0244 | 0.990784 | 0.001082 | 0.008134 |

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|---|---|---|---|---|---|---|---|
| L5B | 7 | 0.962455 | 0.009236 | 0.028309 | 0.954406 | 0.017737 | 0.027857 |
| L5W | 3 | 0.96217 | 0.008809 | 0.02902 | 0.965268 | 0.006558 | 0.028174 |
| L6A | 70 | 0.933311 | 0.028754 | 0.037935 | 0.495607 | 0.318217 | 0.186175 |
| L6B | 40 | 0.948403 | 0.016883 | 0.034714 | 0.797127 | 0.073417 | 0.129456 |
| L6E | 27 | 0.931446 | 0.028282 | 0.040272 | 0.645783 | 0.115941 | 0.238276 |
| L6Y | 19 | 0.933129 | 0.025042 | 0.041829 | 0.428959 | 0.308154 | 0.262887 |
| L7A | 22 | 0.953874 | 0.011011 | 0.035115 | 0.825311 | 0.043968 | 0.130722 |
| L9T | 8 | 0.944395 | 0.016974 | 0.038631 | 0.598452 | 0.180736 | 0.220812 |
| M1B | 137 | 0.935138 | 0.031381 | 0.03348 | 0.493127 | 0.42327 | 0.083604 |
| M1C | 47 | 0.901734 | 0.056453 | 0.041813 | 0.232528 | 0.624968 | 0.142504 |
| M1E | 64 | 0.938298 | 0.02761 | 0.034092 | 0.605653 | 0.334986 | 0.059362 |
| M1G | 42 | 0.920854 | 0.043322 | 0.035824 | 0.439454 | 0.493635 | 0.06691 |
| M1H | 30 | 0.965695 | 0.009947 | 0.024358 | 0.990329 | 0.001542 | 0.00813 |
| M1J | 48 | 0.936403 | 0.027495 | 0.036102 | 0.796079 | 0.07783 | 0.126092 |
| M1M | 14 | 0.955163 | 0.015987 | 0.02885 | 0.879478 | 0.094852 | 0.02567 |
| M1P | 72 | 0.94798 | 0.023578 | 0.028442 | 0.955134 | 0.016988 | 0.027878 |
| M1S | 55 | 0.966266 | 0.009584 | 0.02415 | 0.990935 | 0.00093 | 0.008135 |
| M1T | 56 | 0.894707 | 0.070146 | 0.035146 | 0.405644 | 0.509243 | 0.085113 |
| M1W | 91 | 0.88907 | 0.073629 | 0.037302 | 0.374448 | 0.535688 | 0.089864 |
| M1X | 28 | 0.916033 | 0.043647 | 0.040319 | 0.365782 | 0.499254 | 0.134963 |
| M2H | 56 | 0.944367 | 0.027846 | 0.027787 | 0.629481 | 0.289171 | 0.081348 |
| M2J | 249 | 0.878242 | 0.089066 | 0.032691 | 0.474089 | 0.494061 | 0.03185 |
| M2M | 54 | 0.849859 | 0.110535 | 0.039606 | 0.172553 | 0.721699 | 0.105748 |
| M2N | 118 | 0.89474 | 0.075395 | 0.029865 | 0.463176 | 0.520611 | 0.016213 |
| M3B | 24 | 0.890161 | 0.078855 | 0.030984 | 0.537268 | 0.433106 | 0.029626 |
| M3C | 53 | 0.970645 | 0.00798 | 0.021375 | 0.995544 | 0.000947 | 0.003508 |
| M3L | 25 | 0.9046 | 0.052604 | 0.042796 | 0.417652 | 0.326391 | 0.255957 |
| M3M | 23 | 0.954834 | 0.016227 | 0.028939 | 0.950809 | 0.021439 | 0.027752 |
| M3N | 39 | 0.933874 | 0.034324 | 0.031801 | 0.591674 | 0.34928 | 0.059046 |
| M4C | 25 | 0.930514 | 0.034146 | 0.035341 | 0.515396 | 0.40297 | 0.081634 |
| M4E | 11 | 0.956882 | 0.0147 | 0.028418 | 0.950451 | 0.021807 | 0.027742 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| M4G | 13 | 0.945972 | 0.026055 | 0.027973 | 0.959632 | 0.012359 | 0.02801 |
| M4M | 6 | 0.942385 | 0.021529 | 0.036085 | 0.827432 | 0.04151 | 0.131058 |
| M4P | 22 | 0.96476 | 0.011202 | 0.024039 | 0.990917 | 0.000948 | 0.008135 |
| M4Y | 10 | 0.875101 | 0.087157 | 0.037742 | 0.108309 | 0.851728 | 0.039963 |
| M5A | 12 | 0.967967 | 0.009677 | 0.022355 | 0.986337 | 0.007876 | 0.005787 |
| M5B | 7 | 0.881952 | 0.07641 | 0.041639 | 0.320752 | 0.482675 | 0.196572 |
| M5M | 27 | 0.946409 | 0.025975 | 0.027617 | 0.866004 | 0.073977 | 0.060019 |
| M6A | 23 | 0.972941 | 0.005387 | 0.021672 | 0.792294 | 0.153835 | 0.053871 |
| M6C | 12 | 0.963763 | 0.009881 | 0.026356 | 0.979515 | 0.002289 | 0.018196 |
| M6E | 22 | 0.952185 | 0.019252 | 0.028563 | 0.887682 | 0.086408 | 0.02591 |
| M6H | 8 | 0.94627 | 0.021754 | 0.031975 | 0.868084 | 0.056222 | 0.075695 |
| M6M | 25 | 0.921842 | 0.041106 | 0.037052 | 0.470337 | 0.440974 | 0.088689 |
| M6S | 4 | 0.963237 | 0.008479 | 0.028285 | 0.966855 | 0.004925 | 0.02822 |
| M9M | 31 | 0.922125 | 0.037459 | 0.040416 | 0.602802 | 0.174781 | 0.222417 |
| M9R | 10 | 0.971156 | 0.004546 | 0.024298 | 0.991372 | 0.000489 | 0.008138 |

10,000 Budget

| FSA | Population | Base Drive Probability | Base Transit Probability | Base Carpool Probability | Optimized Drive Probability | Optimized Transit Probability | Optimized Carpool Probability |
|---|---|---|---|---|---|---|---|
| K9A | 1 | 0.961659 | 0.001397 | 0.036944 | 0.824852 | 4.77E-07 | 0.175148 |
| L1C | 21 | 0.9523 | 0.006932 | 0.040768 | 0.628707 | 0.060307 | 0.310986 |
| L1J | 12 | 0.955121 | 0.008317 | 0.036562 | 0.792183 | 0.039606 | 0.168211 |
| L1K | 20 | 0.963008 | 0.004305 | 0.032687 | 0.891659 | 0.002322 | 0.106019 |
| L1L | 14 | 0.965849 | 0.004695 | 0.029456 | 0.96196 | 0.000399 | 0.037641 |
| L1M | 13 | 0.956603 | 0.006623 | 0.036773 | 0.822008 | 0.003448 | 0.174544 |
| L1R | 34 | 0.953083 | 0.010798 | 0.036119 | 0.799983 | 0.03015 | 0.169867 |
| L1S | 48 | 0.954394 | 0.009227 | 0.036379 | 0.807636 | 0.020872 | 0.171492 |
| L1V | 44 | 0.967345 | 0.006579 | 0.026076 | 0.972826 | 0.002964 | 0.02421 |
| L1Z | 37 | 0.95942 | 0.010262 | 0.030318 | 0.812826 | 0.114145 | 0.073029 |
| L3R | 51 | 0.962427 | 0.009515 | 0.028058 | 0.959579 | 0.002873 | 0.037547 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| L3T | 74 | 0.920448 | 0.047949 | 0.031604 | 0.614961 | 0.280498 | 0.104542 |
| L3Y | 14 | 0.961381 | 0.006179 | 0.03244 | 0.82419 | 0.007108 | 0.168702 |
| L3Z | 11 | 0.959037 | 0.004342 | 0.03662 | 0.822832 | 0.00245 | 0.174719 |
| L4B | 28 | 0.966133 | 0.00906 | 0.024807 | 0.595375 | 0.328742 | 0.075882 |
| L4E | 27 | 0.964868 | 0.006801 | 0.028331 | 0.954925 | 0.007709 | 0.037365 |
| L4G | 35 | 0.968162 | 0.003907 | 0.02793 | 0.490789 | 0.105989 | 0.403223 |
| L4H | 42 | 0.966147 | 0.00606 | 0.027793 | 0.708571 | 0.084863 | 0.206566 |
| L4J | 91 | 0.913528 | 0.053703 | 0.032768 | 0.37676 | 0.58185 | 0.04139 |
| L4M | 6 | 0.966928 | 0.004308 | 0.028764 | 0.955934 | 0.006661 | 0.037405 |
| L4N | 10 | 0.955309 | 0.005139 | 0.039552 | 0.654783 | 0.021333 | 0.323884 |
| L4P | 16 | 0.949454 | 0.00767 | 0.042876 | 0.586799 | 0.034413 | 0.378788 |
| L4S | 40 | 0.955105 | 0.016359 | 0.028536 | 0.909653 | 0.054754 | 0.035594 |
| L4W | 5 | 0.970933 | 0.004667 | 0.0244 | 0.987949 | 0.001178 | 0.010873 |
| L5B | 7 | 0.962455 | 0.009236 | 0.028309 | 0.943915 | 0.01915 | 0.036935 |
| L5W | 3 | 0.96217 | 0.008809 | 0.02902 | 0.955524 | 0.007087 | 0.037389 |
| L6A | 70 | 0.933311 | 0.028754 | 0.037935 | 0.453981 | 0.319513 | 0.226507 |
| L6B | 40 | 0.948403 | 0.016883 | 0.034714 | 0.76612 | 0.073512 | 0.160367 |
| L6E | 27 | 0.931446 | 0.028282 | 0.040272 | 0.591491 | 0.115932 | 0.292577 |
| L6Y | 19 | 0.933129 | 0.025042 | 0.041829 | 0.383755 | 0.300959 | 0.315286 |
| L7A | 22 | 0.953874 | 0.011011 | 0.035115 | 0.787093 | 0.045777 | 0.16713 |
| L9T | 8 | 0.944395 | 0.016974 | 0.038631 | 0.548143 | 0.180721 | 0.271135 |
| M1B | 137 | 0.935138 | 0.031381 | 0.03348 | 0.471945 | 0.424657 | 0.103398 |
| M1C | 47 | 0.901734 | 0.056453 | 0.041813 | 0.210273 | 0.616971 | 0.172756 |
| M1E | 64 | 0.938298 | 0.02761 | 0.034092 | 0.590497 | 0.335211 | 0.074292 |
| M1G | 42 | 0.920854 | 0.043322 | 0.035824 | 0.415672 | 0.500967 | 0.083361 |
| M1H | 30 | 0.965695 | 0.009947 | 0.024358 | 0.987455 | 0.001678 | 0.010867 |
| M1J | 48 | 0.936403 | 0.027495 | 0.036102 | 0.758111 | 0.080914 | 0.160976 |
| M1M | 14 | 0.955163 | 0.015987 | 0.02885 | 0.864403 | 0.101774 | 0.033823 |
| M1P | 72 | 0.94798 | 0.023578 | 0.028442 | 0.944692 | 0.018343 | 0.036965 |
| M1S | 55 | 0.966266 | 0.009584 | 0.02415 | 0.988113 | 0.001013 | 0.010875 |
| M1T | 56 | 0.894707 | 0.070146 | 0.035146 | 0.390984 | 0.505389 | 0.103627 |

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|---|---|---|---|---|---|---|---|
| M1W | 91 | 0.88907 | 0.073629 | 0.037302 | 0.359266 | 0.530716 | 0.110019 |
| M1X | 28 | 0.916033 | 0.043647 | 0.040319 | 0.335043 | 0.49923 | 0.165727 |
| M2H | 56 | 0.944367 | 0.027846 | 0.027787 | 0.609918 | 0.288945 | 0.101137 |
| M2J | 249 | 0.878242 | 0.089066 | 0.032691 | 0.468656 | 0.492121 | 0.039223 |
| M2M | 54 | 0.849859 | 0.110535 | 0.039606 | 0.156554 | 0.714824 | 0.128622 |
| M2N | 118 | 0.89474 | 0.075395 | 0.029865 | 0.451654 | 0.528203 | 0.020143 |
| M3B | 24 | 0.890161 | 0.078855 | 0.030984 | 0.532186 | 0.431136 | 0.036678 |
| M3C | 53 | 0.970645 | 0.00798 | 0.021375 | 0.99427 | 0.001033 | 0.004697 |
| M3L | 25 | 0.9046 | 0.052604 | 0.042796 | 0.37387 | 0.318966 | 0.307164 |
| M3M | 23 | 0.954834 | 0.016227 | 0.028939 | 0.940104 | 0.02311 | 0.036785 |
| M3N | 39 | 0.933874 | 0.034324 | 0.031801 | 0.582339 | 0.345683 | 0.071978 |
| M4C | 25 | 0.930514 | 0.034146 | 0.035341 | 0.484051 | 0.413166 | 0.102783 |
| M4E | 11 | 0.956882 | 0.0147 | 0.028418 | 0.939694 | 0.023537 | 0.036769 |
| M4G | 13 | 0.945972 | 0.026055 | 0.027973 | 0.949498 | 0.013349 | 0.037153 |
| M4M | 6 | 0.942385 | 0.021529 | 0.036085 | 0.7892 | 0.043223 | 0.167577 |
| M4P | 22 | 0.96476 | 0.011202 | 0.024039 | 0.988093 | 0.001032 | 0.010874 |
| M4Y | 10 | 0.875101 | 0.087157 | 0.037742 | 0.09921 | 0.851716 | 0.049074 |
| M5A | 12 | 0.967967 | 0.009677 | 0.022355 | 0.983688 | 0.008577 | 0.007735 |
| M5B | 7 | 0.881952 | 0.07641 | 0.041639 | 0.288651 | 0.474198 | 0.237151 |
| M5M | 27 | 0.946409 | 0.025975 | 0.027617 | 0.846807 | 0.076683 | 0.07651 |
| M6A | 23 | 0.972941 | 0.005387 | 0.021672 | 0.76739 | 0.162662 | 0.069949 |
| M6C | 12 | 0.963763 | 0.009881 | 0.026356 | 0.973331 | 0.002478 | 0.024191 |
| M6E | 22 | 0.952185 | 0.019252 | 0.028563 | 0.873061 | 0.092777 | 0.034162 |
| M6H | 8 | 0.94627 | 0.021754 | 0.031975 | 0.84402 | 0.058718 | 0.097262 |
| M6M | 25 | 0.921842 | 0.041106 | 0.037052 | 0.447459 | 0.442914 | 0.109627 |
| M6S | 4 | 0.963237 | 0.008479 | 0.028285 | 0.957222 | 0.005323 | 0.037455 |
| M9M | 31 | 0.922125 | 0.037459 | 0.040416 | 0.552127 | 0.174767 | 0.273106 |
| M9R | 10 | 0.971156 | 0.004546 | 0.024298 | 0.988588 | 0.000533 | 0.01088 |

15,000 Budget

| FSA | Population | Base Drive Probability | Base Transit Probability | Base Carpool Probability | Optimized Drive Probability | Optimized Transit Probability | Optimized Carpool Probability |
|---|---|---|---|---|---|---|---|
| K9A | 1 | 0.961659 | 0.001397 | 0.036944 | 0.797209 | 5.23E-07 | 0.20279 |
| L1C | 21 | 0.9523 | 0.006932 | 0.040768 | 0.587756 | 0.063959 | 0.348286 |
| L1J | 12 | 0.955121 | 0.008317 | 0.036562 | 0.762722 | 0.04326 | 0.194018 |
| L1K | 20 | 0.963008 | 0.004305 | 0.032687 | 0.874153 | 0.00255 | 0.123297 |
| L1L | 14 | 0.965849 | 0.004695 | 0.029456 | 0.954794 | 0.000449 | 0.044757 |
| L1M | 13 | 0.956603 | 0.006623 | 0.036773 | 0.794197 | 0.003779 | 0.202024 |
| L1R | 34 | 0.953083 | 0.010798 | 0.036119 | 0.770932 | 0.032961 | 0.196106 |
| L1S | 48 | 0.954394 | 0.009227 | 0.036379 | 0.779003 | 0.022838 | 0.198159 |
| L1V | 44 | 0.967345 | 0.006579 | 0.026076 | 0.967839 | 0.003347 | 0.028813 |
| L1Z | 37 | 0.95942 | 0.010262 | 0.030318 | 0.794468 | 0.122458 | 0.083074 |
| L3R | 51 | 0.962427 | 0.009515 | 0.028058 | 0.952134 | 0.003234 | 0.044632 |
| L3T | 74 | 0.920448 | 0.047949 | 0.031604 | 0.601467 | 0.285517 | 0.113017 |
| L3Y | 14 | 0.961381 | 0.006179 | 0.03244 | 0.802508 | 0.007591 | 0.189901 |
| L3Z | 11 | 0.959037 | 0.004342 | 0.03662 | 0.795069 | 0.002685 | 0.202246 |
| L4B | 28 | 0.966133 | 0.00906 | 0.024807 | 0.580168 | 0.335917 | 0.083915 |
| L4E | 27 | 0.964868 | 0.006801 | 0.028331 | 0.946939 | 0.008673 | 0.044388 |
| L4G | 35 | 0.968162 | 0.003907 | 0.02793 | 0.448587 | 0.109899 | 0.441514 |
| L4H | 42 | 0.966147 | 0.00606 | 0.027793 | 0.684693 | 0.087883 | 0.227424 |
| L4J | 91 | 0.913528 | 0.053703 | 0.032768 | 0.370681 | 0.584746 | 0.044572 |
| L4M | 6 | 0.966928 | 0.004308 | 0.028764 | 0.948065 | 0.007494 | 0.044441 |
| L4N | 10 | 0.955309 | 0.005139 | 0.039552 | 0.613674 | 0.022681 | 0.363644 |
| L4P | 16 | 0.949454 | 0.00767 | 0.042876 | 0.543974 | 0.036373 | 0.419652 |
| L4S | 40 | 0.955105 | 0.016359 | 0.028536 | 0.896733 | 0.061233 | 0.042035 |
| L4W | 5 | 0.970933 | 0.004667 | 0.0244 | 0.985672 | 0.001333 | 0.012995 |
| L5B | 7 | 0.962455 | 0.009236 | 0.028309 | 0.934675 | 0.021512 | 0.043813 |
| L5W | 3 | 0.96217 | 0.008809 | 0.02902 | 0.947607 | 0.007973 | 0.04442 |
| L6A | 70 | 0.933311 | 0.028754 | 0.037935 | 0.417598 | 0.333731 | 0.248671 |
| L6B | 40 | 0.948403 | 0.016883 | 0.034714 | 0.742321 | 0.077639 | 0.180039 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| L6E | 27 | 0.931446 | 0.028282 | 0.040272 | 0.551006 | 0.122484 | 0.326509 |
| L6Y | 19 | 0.933129 | 0.025042 | 0.041829 | 0.347957 | 0.309572 | 0.342471 |
| L7A | 22 | 0.953874 | 0.011011 | 0.035115 | 0.757373 | 0.04997 | 0.192657 |
| L9T | 8 | 0.944395 | 0.016974 | 0.038631 | 0.508494 | 0.190188 | 0.301318 |
| M1B | 137 | 0.935138 | 0.031381 | 0.03348 | 0.451417 | 0.434746 | 0.113836 |
| M1C | 47 | 0.901734 | 0.056453 | 0.041813 | 0.188223 | 0.626523 | 0.185255 |
| M1E | 64 | 0.938298 | 0.02761 | 0.034092 | 0.575327 | 0.342525 | 0.082148 |
| M1G | 42 | 0.920854 | 0.043322 | 0.035824 | 0.388193 | 0.520396 | 0.091411 |
| M1H | 30 | 0.965695 | 0.009947 | 0.024358 | 0.985113 | 0.001899 | 0.012988 |
| M1J | 48 | 0.936403 | 0.027495 | 0.036102 | 0.727032 | 0.088029 | 0.184939 |
| M1M | 14 | 0.955163 | 0.015987 | 0.02885 | 0.847139 | 0.113151 | 0.03971 |
| M1P | 72 | 0.94798 | 0.023578 | 0.028442 | 0.935539 | 0.020607 | 0.043854 |
| M1S | 55 | 0.966266 | 0.009584 | 0.02415 | 0.985856 | 0.001146 | 0.012998 |
| M1T | 56 | 0.894707 | 0.070146 | 0.035146 | 0.375783 | 0.513001 | 0.111216 |
| M1W | 91 | 0.88907 | 0.073629 | 0.037302 | 0.3438 | 0.537525 | 0.118675 |
| M1X | 28 | 0.916033 | 0.043647 | 0.040319 | 0.304605 | 0.514896 | 0.180499 |
| M2H | 56 | 0.944367 | 0.027846 | 0.027787 | 0.59111 | 0.297168 | 0.111722 |
| M2J | 249 | 0.878242 | 0.089066 | 0.032691 | 0.462695 | 0.495107 | 0.042198 |
| M2M | 54 | 0.849859 | 0.110535 | 0.039606 | 0.139585 | 0.723031 | 0.137384 |
| M2N | 118 | 0.89474 | 0.075395 | 0.029865 | 0.435746 | 0.542461 | 0.021793 |
| M3B | 24 | 0.890161 | 0.078855 | 0.030984 | 0.526751 | 0.433576 | 0.039672 |
| M3C | 53 | 0.970645 | 0.00798 | 0.021375 | 0.993208 | 0.00117 | 0.005621 |
| M3L | 25 | 0.9046 | 0.052604 | 0.042796 | 0.338744 | 0.327853 | 0.333403 |
| M3M | 23 | 0.954834 | 0.016227 | 0.028939 | 0.930491 | 0.025892 | 0.043617 |
| M3N | 39 | 0.933874 | 0.034324 | 0.031801 | 0.572754 | 0.349991 | 0.077255 |
| M4C | 25 | 0.930514 | 0.034146 | 0.035341 | 0.449906 | 0.435649 | 0.114445 |
| M4E | 11 | 0.956882 | 0.0147 | 0.028418 | 0.929981 | 0.026425 | 0.043593 |
| M4G | 13 | 0.945972 | 0.026055 | 0.027973 | 0.940889 | 0.015007 | 0.044105 |
| M4M | 6 | 0.942385 | 0.021529 | 0.036085 | 0.759586 | 0.047194 | 0.19322 |
| M4P | 22 | 0.96476 | 0.011202 | 0.024039 | 0.985834 | 0.001169 | 0.012997 |
| M4Y | 10 | 0.875101 | 0.087157 | 0.037742 | 0.088248 | 0.859459 | 0.052293 |

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|---|---|---|---|---|---|---|---|
| M5A | 12 | 0.967967 | 0.009677 | 0.022355 | 0.981055 | 0.009705 | 0.009241 |
| M5B | 7 | 0.881952 | 0.07641 | 0.041639 | 0.259882 | 0.484334 | 0.255784 |
| M5M | 27 | 0.946409 | 0.025975 | 0.027617 | 0.829714 | 0.082859 | 0.087427 |
| M6A | 23 | 0.972941 | 0.005387 | 0.021672 | 0.740926 | 0.178167 | 0.080907 |
| M6C | 12 | 0.963763 | 0.009881 | 0.026356 | 0.96842 | 0.002792 | 0.028788 |
| M6E | 22 | 0.952185 | 0.019252 | 0.028563 | 0.856583 | 0.103264 | 0.040153 |
| M6H | 8 | 0.94627 | 0.021754 | 0.031975 | 0.823657 | 0.064075 | 0.112268 |
| M6M | 25 | 0.921842 | 0.041106 | 0.037052 | 0.422698 | 0.457442 | 0.11986 |
| M6S | 4 | 0.963237 | 0.008479 | 0.028285 | 0.949502 | 0.00599 | 0.044508 |
| M9M | 31 | 0.922125 | 0.037459 | 0.040416 | 0.512385 | 0.183992 | 0.303623 |
| M9R | 10 | 0.971156 | 0.004546 | 0.024298 | 0.986392 | 0.000603 | 0.013005 |

20,000 budget

| FSA | Population | Base Drive Probability | Base Transit Probability | Base Carpool Probability | Optimized Drive Probability | Optimized Transit Probability | Optimized Carpool Probability |
|---|---|---|---|---|---|---|---|
| K9A | 1 | 0.961659 | 0.001397 | 0.036944 | 0.781001 | 0.002474 | 0.216526 |
| L1C | 21 | 0.9523 | 0.006932 | 0.040768 | 0.754823 | 0.01198 | 0.233198 |
| L1J | 12 | 0.955121 | 0.008317 | 0.036562 | 0.77206 | 0.014658 | 0.213282 |
| L1K | 20 | 0.963008 | 0.004305 | 0.032687 | 0.797436 | 0.007729 | 0.194835 |
| L1L | 14 | 0.965849 | 0.004695 | 0.029456 | 0.812557 | 0.008612 | 0.178831 |
| L1M | 13 | 0.956603 | 0.006623 | 0.036773 | 0.773687 | 0.01168 | 0.214633 |
| L1R | 34 | 0.953083 | 0.010798 | 0.036119 | 0.770305 | 0.019029 | 0.210665 |
| L1S | 48 | 0.954394 | 0.009227 | 0.036379 | 0.77151 | 0.016264 | 0.212226 |
| L1V | 44 | 0.967345 | 0.006579 | 0.026076 | 0.827077 | 0.012231 | 0.160692 |
| L1Z | 37 | 0.95942 | 0.010262 | 0.030318 | 0.800786 | 0.018101 | 0.181113 |
| L3R | 51 | 0.962427 | 0.009515 | 0.028058 | 0.811724 | 0.017498 | 0.170778 |
| L3T | 74 | 0.920448 | 0.047949 | 0.031604 | 0.742113 | 0.078396 | 0.179492 |
| L3Y | 14 | 0.961381 | 0.006179 | 0.03244 | 0.797379 | 0.01088 | 0.191741 |
| L3Z | 11 | 0.959037 | 0.004342 | 0.03662 | 0.777948 | 0.00768 | 0.214371 |
| L4B | 28 | 0.966133 | 0.00906 | 0.024807 | 0.829915 | 0.016829 | 0.153256 |
| L4E | 27 | 0.964868 | 0.006801 | 0.028331 | 0.81482 | 0.012523 | 0.172658 |

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|---|---|---|---|---|---|---|---|
| L4G | 35 | 0.968162 | 0.003907 | 0.02793 | 0.821699 | 0.007231 | 0.17107 |
| L4H | 42 | 0.966147 | 0.00606 | 0.027793 | 0.81882 | 0.011197 | 0.169983 |
| L4J | 91 | 0.913528 | 0.053703 | 0.032768 | 0.726144 | 0.089113 | 0.184742 |
| L4M | 6 | 0.966928 | 0.004308 | 0.028764 | 0.816734 | 0.007935 | 0.175331 |
| L4N | 10 | 0.955309 | 0.005139 | 0.039552 | 0.763062 | 0.00895 | 0.227988 |
| L4P | 16 | 0.949454 | 0.00767 | 0.042876 | 0.744379 | 0.013107 | 0.242514 |
| L4S | 40 | 0.955105 | 0.016359 | 0.028536 | 0.798111 | 0.029807 | 0.172083 |
| L4W | 5 | 0.970933 | 0.004667 | 0.0244 | 0.839044 | 0.008793 | 0.152162 |
| L5B | 7 | 0.962455 | 0.009236 | 0.028309 | 0.810908 | 0.016968 | 0.172125 |
| L5W | 3 | 0.96217 | 0.008809 | 0.02902 | 0.807999 | 0.01613 | 0.175871 |
| L6A | 70 | 0.933311 | 0.028754 | 0.037935 | 0.735217 | 0.049378 | 0.215405 |
| L6B | 40 | 0.948403 | 0.016883 | 0.034714 | 0.769029 | 0.029235 | 0.201736 |
| L6E | 27 | 0.931446 | 0.028282 | 0.040272 | 0.72558 | 0.048028 | 0.226392 |
| L6Y | 19 | 0.933129 | 0.025042 | 0.041829 | 0.723585 | 0.042342 | 0.234073 |
| L7A | 22 | 0.953874 | 0.011011 | 0.035115 | 0.774695 | 0.019499 | 0.205806 |
| L9T | 8 | 0.944395 | 0.016974 | 0.038631 | 0.749408 | 0.02937 | 0.221222 |
| M1B | 137 | 0.935138 | 0.031381 | 0.03348 | 0.753888 | 0.053474 | 0.192638 |
| M1C | 47 | 0.901734 | 0.056453 | 0.041813 | 0.679748 | 0.09279 | 0.227462 |
| M1E | 64 | 0.938298 | 0.02761 | 0.034092 | 0.75596 | 0.047334 | 0.196705 |
| M1G | 42 | 0.920854 | 0.043322 | 0.035824 | 0.723726 | 0.073774 | 0.2025 |
| M1H | 30 | 0.965695 | 0.009947 | 0.024358 | 0.830231 | 0.018646 | 0.151123 |
| M1J | 48 | 0.936403 | 0.027495 | 0.036102 | 0.745018 | 0.047698 | 0.207284 |
| M1M | 14 | 0.955163 | 0.015987 | 0.02885 | 0.79715 | 0.029092 | 0.173758 |
| M1P | 72 | 0.94798 | 0.023578 | 0.028442 | 0.786939 | 0.042676 | 0.170385 |
| M1S | 55 | 0.966266 | 0.009584 | 0.02415 | 0.831954 | 0.017992 | 0.150054 |
| M1T | 56 | 0.894707 | 0.070146 | 0.035146 | 0.693884 | 0.113531 | 0.192585 |
| M1W | 91 | 0.88907 | 0.073629 | 0.037302 | 0.677519 | 0.119333 | 0.203148 |
| M1X | 28 | 0.916033 | 0.043647 | 0.040319 | 0.703466 | 0.073086 | 0.223447 |
| M2H | 56 | 0.944367 | 0.027846 | 0.027787 | 0.786037 | 0.048671 | 0.165292 |
| M2J | 249 | 0.878242 | 0.089066 | 0.032691 | 0.6804 | 0.141386 | 0.178213 |
| M2M | 54 | 0.849859 | 0.110535 | 0.039606 | 0.617321 | 0.175068 | 0.207611 |

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|---|---|---|---|---|---|---|---|
| M2N | 118 | 0.89474 | 0.075395 | 0.029865 | 0.710027 | 0.12319 | 0.166784 |
| M3B | 24 | 0.890161 | 0.078855 | 0.030984 | 0.70439 | 0.123866 | 0.171744 |
| M3C | 53 | 0.970645 | 0.00798 | 0.021375 | 0.849729 | 0.015231 | 0.13504 |
| M3L | 25 | 0.9046 | 0.052604 | 0.042796 | 0.681103 | 0.086361 | 0.232536 |
| M3M | 23 | 0.954834 | 0.016227 | 0.028939 | 0.796357 | 0.029467 | 0.174175 |
| M3N | 39 | 0.933874 | 0.034324 | 0.031801 | 0.761636 | 0.05658 | 0.181784 |
| M4C | 25 | 0.930514 | 0.034146 | 0.035341 | 0.7385 | 0.059089 | 0.20241 |
| M4E | 11 | 0.956882 | 0.0147 | 0.028418 | 0.801397 | 0.026844 | 0.171758 |
| M4G | 13 | 0.945972 | 0.026055 | 0.027973 | 0.785265 | 0.047161 | 0.167574 |
| M4M | 6 | 0.942385 | 0.021529 | 0.036085 | 0.754064 | 0.037562 | 0.208373 |
| M4P | 22 | 0.96476 | 0.011202 | 0.024039 | 0.829787 | 0.021008 | 0.149205 |
| M4Y | 10 | 0.875101 | 0.087157 | 0.037742 | 0.654277 | 0.142086 | 0.203637 |
| M5A | 12 | 0.967967 | 0.009677 | 0.022355 | 0.841475 | 0.018341 | 0.140184 |
| M5B | 7 | 0.881952 | 0.07641 | 0.041639 | 0.65376 | 0.1235 | 0.22274 |
| M5M | 27 | 0.946409 | 0.025975 | 0.027617 | 0.790604 | 0.045334 | 0.164062 |
| M6A | 23 | 0.972941 | 0.005387 | 0.021672 | 0.852646 | 0.010293 | 0.13706 |
| M6C | 12 | 0.963763 | 0.009881 | 0.026356 | 0.820108 | 0.018263 | 0.161629 |
| M6E | 22 | 0.952185 | 0.019252 | 0.028563 | 0.793298 | 0.034973 | 0.171728 |
| M6H | 8 | 0.94627 | 0.021754 | 0.031975 | 0.773495 | 0.038455 | 0.18805 |
| M6M | 25 | 0.921842 | 0.041106 | 0.037052 | 0.722668 | 0.069043 | 0.208289 |
| M6S | 4 | 0.963237 | 0.008479 | 0.028285 | 0.812281 | 0.01559 | 0.172129 |
| M9M | 31 | 0.922125 | 0.037459 | 0.040416 | 0.711809 | 0.063049 | 0.225142 |
| M9R | 10 | 0.971156 | 0.004546 | 0.024298 | 0.839798 | 0.008571 | 0.151631 |

30,000 budget

| FSA | Population | Base Drive Probability | Base Transit Probability | Base Carpool Probability | Optimized Drive Probability | Optimized Transit Probability | Optimized Carpool Probability |
|---|---|---|---|---|---|---|---|
| K9A | 1 | 0.961659 | 0.001397 | 0.036944 | 0.725183 | 6.99E-07 | 0.274816 |
| L1C | 21 | 0.9523 | 0.006932 | 0.040768 | 0.489559 | 0.078262 | 0.43218 |
| L1J | 12 | 0.955121 | 0.008317 | 0.036562 | 0.683862 | 0.056981 | 0.259157 |
| L1K | 20 | 0.963008 | 0.004305 | 0.032687 | 0.827413 | 0.003423 | 0.169164 |

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|---|---|---|---|---|---|---|---|
| L1L | 14 | 0.965849 | 0.004695 | 0.029456 | 0.934121 | 0.000645 | 0.065233 |
| L1M | 13 | 0.956603 | 0.006623 | 0.036773 | 0.721526 | 0.005044 | 0.273431 |
| L1R | 34 | 0.953083 | 0.010798 | 0.036119 | 0.693591 | 0.043565 | 0.262844 |
| L1S | 48 | 0.954394 | 0.009227 | 0.036379 | 0.70322 | 0.030287 | 0.266493 |
| L1V | 44 | 0.967345 | 0.006579 | 0.026076 | 0.953051 | 0.004852 | 0.042097 |
| L1Z | 37 | 0.95942 | 0.010262 | 0.030318 | 0.743301 | 0.151201 | 0.105498 |
| L3R | 51 | 0.962427 | 0.009515 | 0.028058 | 0.930385 | 0.004643 | 0.064972 |
| L3T | 74 | 0.920448 | 0.047949 | 0.031604 | 0.56889 | 0.305824 | 0.125286 |
| L3Y | 14 | 0.961381 | 0.006179 | 0.03244 | 0.750556 | 0.009509 | 0.239935 |
| L3Z | 11 | 0.959037 | 0.004342 | 0.03662 | 0.722584 | 0.003585 | 0.273831 |
| L4B | 28 | 0.966133 | 0.00906 | 0.024807 | 0.541059 | 0.359662 | 0.099279 |
| L4E | 27 | 0.964868 | 0.006801 | 0.028331 | 0.923115 | 0.01242 | 0.064465 |
| L4G | 35 | 0.968162 | 0.003907 | 0.02793 | 0.353834 | 0.127347 | 0.51882 |
| L4H | 42 | 0.966147 | 0.00606 | 0.027793 | 0.628071 | 0.101096 | 0.270834 |
| L4J | 91 | 0.913528 | 0.053703 | 0.032768 | 0.355695 | 0.595674 | 0.048631 |
| L4M | 6 | 0.966928 | 0.004308 | 0.028764 | 0.924687 | 0.010738 | 0.064575 |
| L4N | 10 | 0.955309 | 0.005139 | 0.039552 | 0.516238 | 0.02803 | 0.455732 |
| L4P | 16 | 0.949454 | 0.00767 | 0.042876 | 0.445839 | 0.044239 | 0.509922 |
| L4S | 40 | 0.955105 | 0.016359 | 0.028536 | 0.854593 | 0.085727 | 0.05968 |
| L4W | 5 | 0.970933 | 0.004667 | 0.0244 | 0.97883 | 0.001945 | 0.019226 |
| L5B | 7 | 0.962455 | 0.009236 | 0.028309 | 0.906088 | 0.030636 | 0.063276 |
| L5W | 3 | 0.96217 | 0.008809 | 0.02902 | 0.924048 | 0.011422 | 0.06453 |
| L6A | 70 | 0.933311 | 0.028754 | 0.037935 | 0.327166 | 0.383802 | 0.289032 |
| L6B | 40 | 0.948403 | 0.016883 | 0.034714 | 0.682437 | 0.0934 | 0.224163 |
| L6E | 27 | 0.931446 | 0.028282 | 0.040272 | 0.452688 | 0.147682 | 0.39963 |
| L6Y | 19 | 0.933129 | 0.025042 | 0.041829 | 0.265021 | 0.346383 | 0.388596 |
| L7A | 22 | 0.953874 | 0.011011 | 0.035115 | 0.677558 | 0.065673 | 0.256768 |
| L9T | 8 | 0.944395 | 0.016974 | 0.038631 | 0.411141 | 0.225907 | 0.362953 |
| M1B | 137 | 0.935138 | 0.031381 | 0.03348 | 0.399186 | 0.468426 | 0.132388 |
| M1C | 47 | 0.901734 | 0.056453 | 0.041813 | 0.135939 | 0.664737 | 0.199325 |
| M1E | 64 | 0.938298 | 0.02761 | 0.034092 | 0.536042 | 0.366813 | 0.097145 |

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|---|---|---|---|---|---|---|---|
| M1G | 42 | 0.920854 | 0.043322 | 0.035824 | 0.312399 | 0.583722 | 0.103879 |
| M1H | 30 | 0.965695 | 0.009947 | 0.024358 | 0.978021 | 0.00277 | 0.01921 |
| M1J | 48 | 0.936403 | 0.027495 | 0.036102 | 0.642328 | 0.114254 | 0.243418 |
| M1M | 14 | 0.955163 | 0.015987 | 0.02885 | 0.789856 | 0.154986 | 0.055159 |
| M1P | 72 | 0.94798 | 0.023578 | 0.028442 | 0.907282 | 0.029359 | 0.063359 |
| M1S | 55 | 0.966266 | 0.009584 | 0.02415 | 0.979097 | 0.001672 | 0.019231 |
| M1T | 56 | 0.894707 | 0.070146 | 0.035146 | 0.339242 | 0.541047 | 0.119711 |
| M1W | 91 | 0.88907 | 0.073629 | 0.037302 | 0.305493 | 0.564281 | 0.130226 |
| M1X | 28 | 0.916033 | 0.043647 | 0.040319 | 0.229039 | 0.568766 | 0.202194 |
| M2H | 56 | 0.944367 | 0.027846 | 0.027787 | 0.541371 | 0.327326 | 0.131303 |
| M2J | 249 | 0.878242 | 0.089066 | 0.032691 | 0.447859 | 0.50627 | 0.045871 |
| M2M | 54 | 0.849859 | 0.110535 | 0.039606 | 0.099247 | 0.755228 | 0.145525 |
| M2N | 118 | 0.89474 | 0.075395 | 0.029865 | 0.386804 | 0.5893 | 0.023896 |
| M3B | 24 | 0.890161 | 0.078855 | 0.030984 | 0.513146 | 0.442888 | 0.043966 |
| M3C | 53 | 0.970645 | 0.00798 | 0.021375 | 0.98994 | 0.001713 | 0.008347 |
| M3L | 25 | 0.9046 | 0.052604 | 0.042796 | 0.257194 | 0.365687 | 0.377119 |
| M3M | 23 | 0.954834 | 0.016227 | 0.028939 | 0.900608 | 0.036499 | 0.062893 |
| M3N | 39 | 0.933874 | 0.034324 | 0.031801 | 0.549702 | 0.366971 | 0.083327 |
| M4C | 25 | 0.930514 | 0.034146 | 0.035341 | 0.356955 | 0.507773 | 0.135272 |
| M4E | 11 | 0.956882 | 0.0147 | 0.028418 | 0.899622 | 0.037553 | 0.062824 |
| M4G | 13 | 0.945972 | 0.026055 | 0.027973 | 0.914691 | 0.021432 | 0.063877 |
| M4M | 6 | 0.942385 | 0.021529 | 0.036085 | 0.680163 | 0.062081 | 0.257756 |
| M4P | 22 | 0.96476 | 0.011202 | 0.024039 | 0.979065 | 0.001705 | 0.01923 |
| M4Y | 10 | 0.875101 | 0.087157 | 0.037742 | 0.061766 | 0.883708 | 0.054526 |
| M5A | 12 | 0.967967 | 0.009677 | 0.022355 | 0.972229 | 0.01413 | 0.01364 |
| M5B | 7 | 0.881952 | 0.07641 | 0.041639 | 0.192155 | 0.526092 | 0.281754 |
| M5M | 27 | 0.946409 | 0.025975 | 0.027617 | 0.78229 | 0.10491 | 0.1128 |
| M6A | 23 | 0.972941 | 0.005387 | 0.021672 | 0.659658 | 0.23303 | 0.107312 |
| M6C | 12 | 0.963763 | 0.009881 | 0.026356 | 0.953935 | 0.00402 | 0.042045 |
| M6E | 22 | 0.952185 | 0.019252 | 0.028563 | 0.801966 | 0.142029 | 0.056005 |
| M6H | 8 | 0.94627 | 0.021754 | 0.031975 | 0.76634 | 0.083867 | 0.149793 |

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|---|---|---|---|---|---|---|---|
| M6M | 25 | 0.921842 | 0.041106 | 0.037052 | 0.353983 | 0.509636 | 0.136381 |
| M6S | 4 | 0.963237 | 0.008479 | 0.028285 | 0.926697 | 0.008588 | 0.064715 |
| M9M | 31 | 0.922125 | 0.037459 | 0.040416 | 0.414883 | 0.218861 | 0.366256 |
| M9R | 10 | 0.971156 | 0.004546 | 0.024298 | 0.979874 | 0.00088 | 0.019246 |