SPR, Part B
MD-23-SHA/MSU/6-4

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RESEARCH REPORT

DEVELOP A MODE CHOICE MODEL TO ESTIMATE WALK AND BIKE TRIPS IN THE STATEWIDE MODEL

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FINAL REPORT

December 31, 2024

This material is based upon work supported by the Federal Highway Administration under the State Planning and Research program. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the Federal Highway Administration or the Maryland Department of Transportation. This report does not constitute a standard, specification, or regulation.

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MD-23-SHA/MSU/6-4		

4. Title and Subtitle Develop a mode choice model to estimate walk and bike trips in the statewide model	**5. Report Date** December 31, 2024 **6. Performing Organization Code:** DUNS Number: 879941318 EIN: 52-6002033
7. Author(s) Tao Tao, Ph.D. https://orcid.org/0000-0001-9865-5985 Yi Liu, D.Eng. https://orcid.org/0000-0002-6861-2914 Zhuping Sheng, Ph.D. https://orcid.org/0000-0001-8533-527X Sean Qian, Ph.D. https://orcid.org/0000-0001-8716-8989	**8. Performing Organization Report No.**
9. Performing Organization Name and Address Morgan State University 1700 E Cold Spring Lane Baltimore Maryland 21251	**10. Work Unit No.** **11. Contract or Grant No.** SHA/MSU/6-4
12. Sponsoring Agency Name and Address Maryland Department of Transportation (SPR) State Highway Administration Office of Policy & Research 707 North Calvert Street Baltimore MD 21202	**13. Type of Report and Period** SPR-B Final Report (April 2023-December 2024*) *This is the performing period. **14. Sponsoring Agency Code** (7120) STMD - MDOT/SHA

15. Supplementary Notes

16. Abstract

The walking and biking traffic environment has been challenged due to increased number of vehicles, traffic speed, safety risks, poor facilities for active travel, and fierce competition for curbside activities. Current mode choice models on biking and walking, however, have two limitations. First, the trip-level information of alternative travel modes to bike and walk trips is often in lack or limited. Second, the Level of Traffic Stress (LTS) is a critical factor influencing travelers' decisions on non-motorized modal choices but has not yet been incorporated into regional mode choice models in Maryland. LTS, which measures the traffic stress experienced by pedestrians and cyclists, has emerged as an important tool in the planning process for active travel by local transportation authorities. These limitations restrict the models' ability to accurately predict travel behavior and estimate travel demand for walking and biking. With the household travel survey and a comprehensive LTS dataset from Maryland, this study constructs a statewide mode choice model specifically considering biking and walking, along with public transit and private driving. We applied the Google Maps platform to acquire full trip-level information of all alternative travel modes for each trip, including routes, time, cost, and distance. The results showed that LTS plays an important role in improving the model performance. LTS has a significant and negative correlation with walking and biking. LTS' impact on biking and walking is heterogenous across different travelers' characteristics and infrastructure. This study highlights that transportation planners and engineers should prioritize strategies, such as complete street measures, to create a low-stress traffic environment to encourage the use of active travel modes. In addition, LTS improvement projects should be strategically prioritized in specific locations and supported by targeted policies to maximize their impact. The resultant statewide non-motorized choice model can be applied to further develop strategies, policies and infrastructure planning for active transportation.

17. Key Words	18. Distribution Statement
Level of Traffic Stress, State-wide mode choice modeling, Active travel	This document is available from the Research Division upon request.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
None	None	39	$150,000

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized.

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Executive Summary

The walking and biking traffic environment has faced significant challenges due to the increased number of vehicles, traffic speeds, and safety risks. Additionally, the infrastructure for active travels, such as sidewalks and bike lanes, is often inadequate, and there is intense competition for curbside spaces. These factors may create a hostile environment for pedestrians and cyclists, discouraging active travel and contributing to increased reliance on motor vehicles. Mode choice modeling is an important tool for transportation planners and engineers to plan and improve active travel facilities on the road network. A good mode choice model could accurately estimate the behavior of walking and biking and provide practical guides to decision makers on improving the built environment for active travel modes.

Current mode choice models on biking and walking, however, have two limitations. First, there is often a lack of information on alternative travel modes for trips. While household travel surveys and similar methods can gather data on the mode choices for people's daily trips, collecting information on the available alternative travel modes is more difficult. This limitation restricts the ability of mode choice models to comprehensively consider all potential travel options and accurately estimate the probability of individuals choosing each mode for their daily trips. Second, no mode choice models have considered the Level of Traffic Stress (LTS). LTS is an index that measures the traffic stress experienced by pedestrians and bicyclists and has emerged as an important tool in the planning process for active travels by local transportation authorities. Without incorporating LTS, mode choice models may underestimate people's preferences for walking and biking, as well as transit trips that involve walking for access and egress.

This research assessed the impact of LTS on people's mode choice for the entire Maryland state. Specifically, the research team applied a unique dataset which contains the LTS for over 140 thousand roads in Maryland. In addition, for more than 50,000 trips collected from the Maryland statewide household travel survey, the research team requested travel cost information (i.e., distance and duration) of the routes of alternative travel modes from Google Maps Application Programming Interface (API). The research team chose Google Maps because it has a large historical route choice dataset and provides multiple routes for each travel mode. The research team constructed a multinominal logit model to estimate the effects of all variables on residents' mode choice in Maryland. Furthermore, the research team carried out a sensitivity analysis to explore impacts of various LTS on mode share change of walking and biking across different contexts, such as built environment attributes and socio-demographic features.

The results showed that the inclusion of LTS could significantly improve the model performance, which demonstrates the importance of considering LTS in mode choice models with biking and walking. In addition, LTS has a significant and negative correlation with active modes and public transportation, suggesting that higher LTS would be more likely to reduce people's preference for traveling by walking, biking, and transit.

Duration is negatively associated with people's preference for traveling by all travel modes. All demographic variables considered in this research showed significant relationships with mode choice, including employment status, license, gender, age, household income, household size, and number of vehicles. This implies the important role of demographics in influencing people's mode choice. Parking cost significantly impacts travel mode choice, with higher costs leading to increased walking, transit, and biking, which decreases driving. Built environment variables of job accessibility by biking and job accessibility by car and sociodemographic variables of percentage of commuting by car and percentage of labor force have significant correlations with mode choice.

The sensitivity analysis suggested that the impacts of LTS on biking and walking mode choices change across different contexts. The LTS impact on mode share change is greater for trips starting in areas with higher job accessibility by bike and lower job accessibility by private driving, for trips ending in areas with a larger percentage of open space (e.g., parks, natural areas, and urban plazas), and for trips in regions with a lower percentage of population commuting by car and higher parking costs.

This research highlights the significant impact that LTS has on healthy and sustainable travel modes, including biking, walking, and transit. The findings underscore the importance of creating a low-stress traffic environment to encourage the use of these active travel modes. High LTS levels can discourage individuals from choosing active travel modes and transit due to perceived or real safety concerns, ultimately leading to an overreliance on motor vehicles. Transportation planners and engineers should prioritize strategies to reduce LTS in the traffic environment. This can be achieved through a variety of policies related to complete streets, such as protected bike lanes, pedestrian-focused signal timing, wider sidewalks, pedestrian crossings and traffic calming measures.

In addition, LTS improvement projects should be strategically prioritized in specific locations and supported by targeted policies to maximize their impact. For instance, reducing LTS for biking in areas with higher job accessibility, increasing availability of open space, and lowering car commuting rates, can significantly boost the positive effects of those improvement projects on walking and biking. Additionally, implementing reasonable parking costs in these areas can further amplify the benefits of LTS improvements.

This research makes two significant contributions to the existing literature. First, the research incorporates LTS into the statewide mode choice model. By considering the varying levels of comfort and safety that people experience on different roadways, the inclusion of LTS greatly enhances the model's accuracy in estimating walking and biking trips. This approach allows for a more nuanced understanding of the factors that influence active travel behavior, leading to more reliable and precise predictions. Second, the research employed Google Maps API to request the alternative travel modes of the trips and related information. This information helps further improve the mode choice model. As a result, transportation planners and policymakers can make better-informed decisions to improve infrastructure and promote safer, more appealing environments for pedestrians and cyclists.

1 Introduction

The walking and biking traffic environment has faced significant challenges due to the increased number of vehicles, traffic speeds, and safety risk. Additionally, the infrastructure for active travel, such as sidewalks and bike lanes, is often inadequate, and there is intense competition for curbside space. These factors create a hostile environment for pedestrians and cyclists, discouraging active travel and contributing to increased reliance on motor vehicles. Mode choice modeling is an important tool for transportation planners and engineers to plan and improve active travel facilities on the road network. A good mode choice model could accurately estimate the demand of walking and biking behavior and provide practical evidence to decision making on improving the traffic environment for active travel modes.

However, current mode choice models for biking and walking in the literature face two significant challenges. First, there is often a lack of information on alternative travel modes for trips. While household travel surveys and similar methods can gather data on the mode choices for people's daily trips, collecting information on the available alternative travel modes is more difficult. This limitation restricts the ability of mode choice models to comprehensively consider all potential travel options and accurately estimate the probability of individuals choosing each mode for their daily trips.

Second, no mode choice models have considered the Level of Traffic Stress (LTS). LTS is an index that measures the traffic stress experienced by pedestrians and bicyclists and has emerged as an important tool in the planning process for active travel by local transportation authorities (Faghih Imani, Miller, and Saxe 2019). Without incorporating LTS, mode choice models may underestimate people's preferences for walking and biking, as well as transit trips that involve walking for access and egress.

This research aims to address these research gaps and model the impact of LTS on people’s mode choice for the entire Maryland state. Specifically, applied is a unique dataset which contains the LTS for over 140 thousand roads in Maryland. In addition, for more than 50,000 trips collected from the Maryland statewide household travel survey, it was requested that travel cost information (i.e., distance and duration) of the routes of alternative travel modes from Google Maps API. Google Maps was chosen because it has a large historical route choice dataset and provides multiple routes for each travel mode (see Section 3.1 for more discussion about this). A multinominal logit model is constructed to estimate the effects of all variables on residents’ mode choice in Maryland. A sensitivity analysis is carried out to explore the various LTS impact on mode share change of walking and biking across different contexts.

This research makes two significant contributions to the existing literature. First, LTS is incorporated into the statewide mode choice model. By considering the varying levels of comfort and safety that people experience on different roadways, the inclusion of LTS greatly enhances the model's accuracy in estimating walking and biking trips. This approach allows for a more nuanced understanding of the factors that influence active travel behavior, leading to more reliable and precise predictions. Second, Google Maps API is applied to request the alternative travel modes of the trips and related information. This information helps further improve the mode choice model. As a result, transportation planners and policymakers can make better-informed decisions to improve infrastructure and promote safer, more appealing environments for pedestrians and cyclists.

The rest of the research report was organized as follows. The literature is reviewed on mode choice with walking and biking in the next section. The data and method is introduced in Section 3. In Section 4, the model results are presented. This report is then concluded in the last section.

2 Literature Review

2.1 Influential Factors

Current research indicates that people's decisions to walk or bicycle as modes of travel are influenced by four primary factors, including demographic and socioeconomic variables, trip characteristics, built environment attributes, and human psychological factors (Blumenberg et al. 2013; Eldeeb, Mohamed, and Páez 2021; Schultheiss et al. 2019). The variables listed are utilized in 18 selected studies.

Demographic and socioeconomic variables refer to the data that describe the characteristics of a person or a household within the broader context of a population. For a person, the related variables could be age (Eldeeb, Mohamed, and Páez 2021), gender (De Vos et al. 2021), education (Wu, Chen, and Jiao 2019), driver license (Aziz et al. 2017), and employment status (Mo, Shen, and Zhao 2018). For a household, the related variables could be household size (Spinney, Maoh, and Millward 2019), income (Wu, Chen, and Jiao 2019), and car ownership (Ding et al. 2017). While demographics and socioeconomics are usually measured at the individual level (i.e., person or household), they could also be aggregated at the zone level, such as average household income (Khan, M. Kockelman, and Xiong 2014), car per capita (X. Zhao et al. 2020), and crime density (Singleton and Wang 2014). Studies have shown that demographics and socioeconomics play a vital role in influencing mode choice of walking and bicycling. For example, Wu et al. (2019) explored the impact of multiple factors on the mode choice associated with shopping trips in Shanghai, China. They found that males are more likely to ride bikes than to walk, and people with a higher education level are less likely to do walking and bicycling. Sun et al. (2017) studied the influence of several types of variables on the mode choice of commuting trips in Shanghai, and found that gender, age, household size, and number of kids in family are important predictors for choosing walking and bicycling. Furthermore, all the studies in Table 1 considered demographics and socioeconomics in their mode choice modeling.

Trip characteristics indicate various attributes or details associated with individual trips, such as distance (Ding et al. 2017; Faghih Imani, Miller, and Saxe 2019), duration (Ermagun, Rashidi, and Lari 2015; Whalen, Páez, and Carrasco 2013), monetary cost (Khan, M. Kockelman, and Xiong 2014), and purpose (Cheng et al. 2019; Clifton et al. 2016). One example is that Faghih Imani et al. (2019) examined the factors that affect the mode choice of home-based trips. They showed that trip distance is negatively correlated with the possibility of riding a bicycle. Most of the studies listed in Table 1 considered trip characteristics. It is worth noting that the other three studies (Martín and Páez 2019; Sun, Ermagun, and Dan 2017; Wu, Chen, and Jiao 2019), although did not consider trip characteristics directly, applied proximity variables such as distance from home to work locations or to the downtown.

Built environment attributes are the human-made surroundings that provide the setting for human activities. There are five major types of the built environment, also known as "5D" (Ewing and Cervero 2010), including density, design, diversity, distance to transit, and destination accessibility. Density variables include population density (Spinney, Maoh, and Millward 2019) and job density (Singleton and Wang 2014). Design variables include intersection density (Wu, Chen, and Jiao 2019), network density (Eldeeb, Mohamed, and Páez 2021), and facilities supply specific to walking and bicycling (Whalen, Páez, and Carrasco 2013). Diversity variables include land use entropies (Khan, M. Kockelman, and Xiong 2014) and areas/proportions of different types of land use (e.g., commercial and residential) (Aziz et al. 2017). Distance to transit includes variables such as transit stop density (Mo, Shen, and Zhao 2018) and distance to nearest transit stop/station (Cheng et al. 2019). Destination accessibility mainly refers to employment accessibility (Ding et al. 2017; Faghih Imani, Miller, and Saxe 2019) and distance to downtown/central business district (CBD) (Muñoz, Monzon, and Daziano 2016; Sun, Ermagun, and Dan 2017). Several studies focused on the impact of built environment attributes on travel mode choices. For example, Mo et al. (2018) studied the built environment effects on mode choices of first- and last-mile MRT trips while considering the built environment attributes in both origin and destination. They found that people living in areas with a higher land use mix prefer walking than other travel modes. Similar to demographics and socioeconomics, all studies in Table 1 applied built environment variables in their models.

Human psychological factors are variables related to the cognitive, emotional, and social aspects that influence travel mode decisions, such as personal preference for travel modes and residential locations (i.e., self-selection) (De Vos et al. 2021), social norms and peer influence, safety perception (Ermagun, Rashidi, and Lari 2015), and environmental concerns. These variables are usually unobservable and included as latent variables in the models (Muñoz, Monzon, and Daziano 2016). A few studies from the selected studies considered human psychological factors. For example, De Vos et al. (2021) considered the change in people's preferences for different types of travel modes when studying the influential factors on the change in mode frequency. Human psychological factors are less considered than other types of factors in the selected studies in Table 1 because most household travel surveys do not offer related questions.

Besides the four main types of factors, studies also considered some other variables that could influence people's decisions on their travel mode choices, including parking permit (Whalen, Páez, and Carrasco 2013), parking cost (Khattak et al. 2017; X. Zhao et al. 2020), transit card (Cheng et al. 2019), crash rate (Aziz et al. 2017), and weather/climate (Spinney, Maoh, and Millward 2019). For example, when estimating the mode choice model for commuting trip in New York, US, Aziz et al. (2017) considered number of pedestrian crashes and bicycle crashes in the origin and destination census tracts.

In addition to the direct impacts of these factors on mode choice, scholars have also examined the associated indirect impacts (De Vos et al. 2021; Ding et al. 2017). For example, De Vos et al. (2021) explored how shifts in residential locations directly and indirectly impact changes in mode frequency with the data from Ghent, Belgium. One of their findings suggests that change in neighborhoods has a considerable indirect effect on walking frequency through change in travel distance.

Table 1. *Summary of Selected Studies*[1] (Continued on next page)

Author Year	**Study area**	**Method**[2]	**Data**[3]	**Dependent variable**	**Travel mode choices**[4]	**Sample size**	**DG/ SE**	**TF**	**BE**	**PF**	**Other factors**
Whalen et al. (2013)	McMaster University, Canada	MNL	RP	Mode choice of trip to school	Bicycle, walk, HSR, car	1,385	×	×	×	×	Possession of a parking permit
Khan et al. (2014)	Windsor, Canada	MXL	RP	Mode choice of nonwork/shopping trip	Car/transit, walk/bicycle	Nonwork trips (448) Shopping trips (230)	×	×	×		
Singleton and Wang (2014)	Portland, US	MNL	RP	Mode choice of discretionary trip	Car, transit, bicycle, walk	3,028	×	×	×		
Ermagun et al. (2015)	Tehran, Iran	RF	RP	Mode choice of trip to school	Escorted (car, school bus, public transit, walk); unescorted (walk, public transit)		×	×	×	×	
Clifton et al. (2016)	Portland, US	Logit	RP	Mode choice of home-based nonwork trip	Walk, other		×	×	×		
Aziz et al. (2017)	New York, US	MXL	RP	Mode choice of commuting trip	Transit, car, bicycle, walk	3,357	×	×	×		Crash rate
Ding et al. (2017)	Baltimore metropolitan area, US	SEM and MNL	RP	Mode choice of home-based trip	Transit, car, walk/bicycle	4,375	×	×	×		
Khattak et al. (2017)	Pittsburgh, US	NL	SP	Mode choice of commuting trips to downtown	Public (bus, LRT); private (car, walk, bicycle); commuter pool (carpool, vanpool)	6,513	×	×	×		Parking cost
Sun et al. (2017)	Shanghai, China	MNL	RP	Mode choice of commuting trip	Transit, car, bicycle/e-bike, walk	857	×		×		

[1] DG: demographics; SE: socioeconomics; TC: trip characteristics; BE: built environment characteristics; PF: Human psychological factors
[2] MNL: multinominal logit; MXL: mixed logit; RF: random forest; SEM: structural equation model; NL: nested logit
[3] RP: revealed preference survey; SP: stated preference survey
[4] HSR: high-speed rail; LRT: light rail

Author Year	Study area	Method[2]	Data[3]	Dependent variable	Travel mode choices[4]	Sample size	DG/ SE	TF	BE	PF	Other factors
Mo et al. (2018)	Singapore	MXL	RP	Mode choice of first- and last-mile MRT trip[5]	Binary (walk, transit) Multinominal (walk, transit, LRT)	Binary (20,181) Multinominal (2,373)	×	×	×		
Cheng et al. (2019)	Nanjing, China	RF	RP	Mode choice of general trip	Walk, bicycle, E-motorcycle, transit, and car	7,276	×	×	×		Possession of a transit card
Faghih Imani et al. (2019)	Toronto, Canada	Logit	RP	Mode choice of home-based trip	Bicycle, other	83,937	×	×	×		
Martín and Páez (2019)	Vitoria-Gasteiz, Spain	MNL with spatial expansion	RP	Mode choice of general trip	Walk, bicycle, car-driver, car-passenger, transit	16,413	×		×		
Spinney et al. (2019)	Halifax, Canada	Mixed MNL	RP	Mode choice of trip to school	Car, transit, walk	1,971	×	×	×		Weather/ climate
Wu et al. (2019)	Shanghai, China	MNL	RP	Mode choice of shopping trips	Car, transit, bicycle, walk	2,838	×		×	×	
Zhao et al. (2020)	University of Michigan, US	RF	SP	Mode choice of commuting trip	Car, walk, bicycle, transit	8,141	×	×	×		Parking cost
De Vos et al. (2021)	Ghent, Belgium	SEM	RP	Change in mode frequency		1,650	×		×		
Eldeeb et al. (2021)	Hamilton, Canada	NL with a spatial expansion	RP	Mode choice of primary trip on weekdays	Non-motorized (walk, bicycle); Motorized (HSR, car-driver, car-passenger)	4,739	×		×		

[5] MRT: Mass Rapid Transit in Singapore

2.2 Data Sources

To collect the mode choices of traveling trips, scholars mainly applied two types of data sources: revealed preference (RP) survey and stated preference (SP) survey. Both surveys are two commonly used data sources to discover and analyze people's decisions for their travels (Lavasani et al. 2017).

RP survey collects data from actual behaviors observed in the daily travels. Household travel survey is one major type of RP survey. For example, Ding et al. (2017) used the 2001 National Household Travel Survey Baltimore Add-on data, and Singleton and Wang (2014) applied the Oregon Household Activity Survey data. The major advantage of RP survey is that it is based on real-world behavior, so the results are often seen as reliable and valid. In addition, the RP survey has no hypothetical bias since it is based on actual choice. One limitation of RP survey is that it cannot include conditions or scenarios that do not exist currently. Sixteen of the selected studies listed in Table 1 applied RP survey data.

SP survey, however, uses hypothetical scenarios to gather data on how individuals might behave under different conditions. SP survey applies state-choice experiment, in which respondents are presented with various choices and indicate their preferences or choices based on these scenarios. For example, Zhao et al. (2020) asked their participants about their mode choice if a change occurred in the current transit system, such as the application of high-frequency services. SP survey can incorporate scenarios that do not currently exist and is flexible in experimental design. However, responses may be affected by hypothetical bias since respondents are not making real-world decisions with actual consequences. Furthermore, the quality of the results depends on the realism and design of the scenarios. Only two of the selected studies in Table 1 used SP survey for their choice models.

Most of the studies estimated the mode choice at the trip level. One exemption is that De Vos et al. (2021) focused on the change in mode frequency at the level of individual participant.

2.3 Methods

Two major types of methods have been applied by scholars when constructing mode choice models are statistical models and machine learning models. Statistical models assume the data follow a certain probability distribution and model the relationships between the factors and mode choices based on this assumption. Statistical models provide significance levels of the factors according to statistical tests, which can be used to measure the importance of the factors. Machine learning models, however, have less restrictions on the relationships when modeling the relationships. Therefore, machine learning models can estimate more complex relationships and provide better fitness than statistical models. Machine learning models provide feature importance (e.g., relative importance or Shapley value by Chen et al. (2022)) to evaluate the contribution of factors (Molnar 2020). In addition, scholars use partial dependence plots or accumulated local effect plots (Apley and Zhu 2020) to visualize the relationships between factors and mode choice.

Among the selected studies (Table 1), several statistical models have been applied, including logit model (Clifton et al. 2016; Faghih Imani, Miller, and Saxe 2019), multinominal logit model (MNL) (Singleton and Wang 2014; Sun, Ermagun, and Dan 2017; Whalen, Páez, and Carrasco 2013), mixed logit model (MXL) (Aziz et al. 2017; Khan, M. Kockelman, and Xiong 2014; Mo, Shen, and Zhao 2018), nested logit model (NL) (Eldeeb, Mohamed, and Páez 2021; Khattak et al. 2017), and structural equation model (SEM) (De Vos et al. 2021; Ding et al. 2017). Logit and MNL models are most widely used when estimating mode choices. Logit model is used when the choice set only contains two options. For example, Clifton et al. (2016) only considered walking and other travel mode and Faghih Imani et al. (2019) only considered bicycling and other travel mode in their studies, respectively. When the choice set has more than two options, MNL is applied. For example, Wu et al. (2019) considered driving, transit, bicycling, and walking in their studies.

MXL model is an improvement of logit and MNL models. MXL can include random terms in the model to account for the unobserved heterogeneity in the travel decision making process of individuals (Train 2009). Instead of assuming the coefficients are fixed across individuals, MXL allows one or more of the coefficients to vary, which usually provides a good fitness to the data. For example, Khan et al. (2014) estimated both MNL and MXL models in their study and found that MXL has a better fitness to the sample than MNL.

Nested logit extends the MNL by grouping alternatives into "nests." MNL assumes that the relative odds of choosing between two alternatives are unaffected by the presence or absence of other alternatives, which is known as independence of irrelevant alternatives (IIA) assumption. In many cases, IIA is not valid. For example, driving and taking transit are similar in terms of that they are both motorized travel modes. Nested logit addresses this issue by putting similar options into groups, such as that driving and transit could be grouped into motorized travel mode and walking and bicycling could be grouped into non-motorized groups. Eldeeb et al. (2021) used a similar typology (i.e., motorized and non-motorized travel modes) in their study.

Structural equation model (SEM) advances simple statistical models by incorporating more complex structures of the relationships among factors and travel behavior outcome. Simple statistical models can only account for the direct relationships between factors and outcome. SEM, however, can also estimate indirect relationships through factors. For example, De Vos et al. (2021) applied a SEM model to examine the indirect effect of change in neighborhood on change in mode frequency through car ownership, travel distance, and mode-specific attitude.

While most of the research has emphasized the overarching effects of certain factors, scholars have argued that these effects can differ across the locations in the study region (Nkeki and Asikhia 2019; Páez 2006). Some scholars have utilized specific methodologies to highlight these potential local disparities (Eldeeb, Mohamed, and Páez 2021; Martín and Páez 2019). For example, Eldeeb et al. (2021) considered spatial variability of the built environment attributes in their MNL and NL models by using a quadratic polynomial trend surface. The model result indicates a significant spatial variation of the correlations between different types of factors and mode choices across the study region.

In Table 1, three studies applied machine learning approaches (Cheng et al. 2019; Ermagun, Rashidi, and Lari 2015; X. Zhao et al. 2020). While all these studies used random forest as their final modeling approach, scholars also tested other machine learning methods. For example, Zhao et al. (2020) considered classification and regression trees, random forest, boosting trees, bagging trees, and neural networks. Machine learning approaches outperform traditional statistical models in terms of their strong capability of fitting the data. For example, Ermagun et al. (2015) compared the performance of random forest and nested logit. They found that random forest has a better accuracy than nested logit when predicting the mode choices (62.3% vs. 38.1%).

2.4 Integration to Regional or Statewide Models

Integration of walking and bicycling travel modes to the regional travel demand models provides many benefits. They include enhancing model responsiveness to variables closely related to active travel, producing outcomes that adapt better to socio-demographic shifts and policy initiatives, offering more precise predictions of mode transitions and the total count of non- motorized trips, and delivering more valuable model data for active travel route planning, safety evaluations, health impact studies, and greenhouse gas reduction assessments (Clifton et al. 2016).

However, there are several challenges when modeling pedestrian and bicyclist trips in the regional travel demand models. First, walking and bicycling activities have been underreported in regional household travel surveys with the traditional self-reported approach (Singleton, Park, and Lee 2021). Second, the analysis spatial resolution applied in regional models has been too coarse to model walking and bicycling trips (Liu, Evans, and Rossi 2012) that are generally in short distances or time. Most regional models use census tract or traffic analysis zone as analysis spatial units which are suitable for motorized travel modes, such as car and transit. However, pedestrian and bicyclist trips are usually short and need a more granular analysis spatial unit. Third, data sources for modeling pedestrian and bicyclist behavior were not widely available at the regional level. For example, built environment attributes such as pedestrian and bicycle facilities have been only available for metropolitan areas but not for the entire region.

Fortunately, these research gaps have been gradually addressed. With the application of GPS devices and smartphones in the household travel survey, participants can report their travel diaries more accurately (C. Chen et al. 2010; F. Zhao et al. 2019). Furthermore, computing devices have become more powerful to estimate the regional models with smaller analysis areas. Finally, regional available datasets have been offered to scholars. For example, the smart location database (EPA 2021) hosted by the Environmental Protection Agency provide multiple built environment attributes across the US. These developments make it more possible to integrate pedestrians and bicyclists into the regional models. Based on the survey on 48 largest metropolitan planning organizations (MPOs) by Singleton et al. (2018), 75% of these MPOs consider non-motorized travel modes in their models.

2.5 Summary of Literature Review

Overall, the existing literature has considered multiple types of factors that affect walking and bicycling mode choices, including demographic and socioeconomic variables, trip characteristics, built environment characteristics, and human psychological factors. Two major data types are employed, which are RP and SP surveys. The scholars applied statistical and machine learning models to assess the relationships between multiple factors and mode choices. While challenges have persisted in integrating walking and bicycling into regional travel demand models—due to issues like the underrepresentation of walking and bicycling trips, large analysis zones, and the unavailability of regional datasets—scholars and practitioners have progressively tackled these obstacles. Consequently, an increasing number of regional models now incorporate walking and bicycling considerations.

However, several major research gaps have been identified in the literature. First, LTS is seldom considered in the choice modeling for walking and bicycling trips. One exemption is that Faghih Imani et al. (2019) considered job accessibility through facilities with different LTSs. No studies considered the LTS of the trip route directly in their models. Second, very few of these studies applied the real estimate of trip distance and duration. Instead, most of them used reported values which are not accurate. Third, none of the studies included travel modes of walking + transit and bicycling + transit. Simply considering transit trips for all transit related trips may underestimate the walking and bicycling trips and negatively impact the model results (Goughnour et al. 2022). Fourth, studies seldom evaluate the impact of complete street on mode choices.

3 Methodology

3.1 Data

The trip information applied in this research was extracted from the Maryland statewide household travel survey data from the Maryland Department of Transportation (MDOT). The survey was carried out from April 2018 to August 2019, covering 18 counties in the Baltimore Metropolitan Region, the Eastern Shore, and Western Maryland (Figure 1). The participants have three options to finish the survey, including online, smartphone application, and telephone interview. Totally, 6,828 households completed one-workday (i.e., Monday to Friday) survey (Westat 2020). The survey collected the demographic information and one-day travel diary. The trip information contains the origination and destination at the census block level, the starting and ending time, travel mode, trip purpose, travel time, distance, and duration.

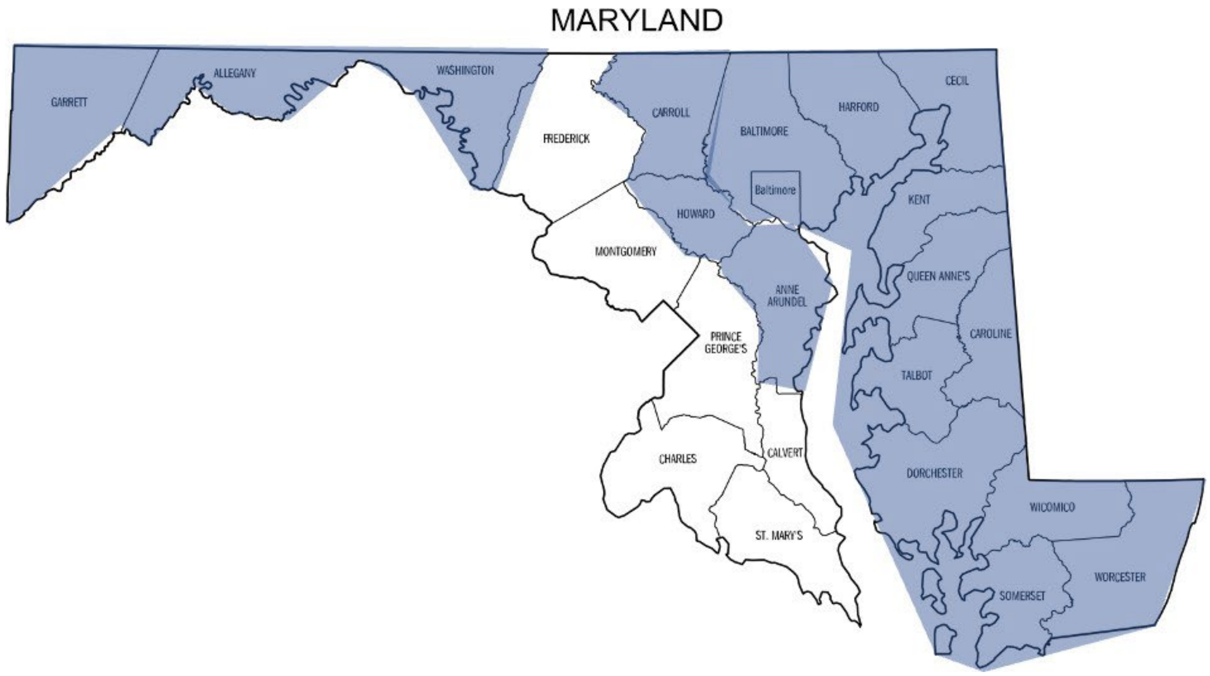

Figure 1. *Counties in Color are Covered by the Maryland Statewide Household Travel Survey*

For choice modeling, the data was augmented with the distance and duration of four travel modes (i.e., walking, biking, transit, and driving) for each trip through the Google Maps API. Commercial platforms such as Google Maps over other approaches were selecected for several main reasons. First, commercial platforms adjust their recommendations to adapt to their customers' real-world choice to help them gain a larger share in the market. Their recommended routes are very close to people's selected routes for their daily travel. Second, viable route choices in most areas (e.g., downtown and urban areas) are extremely limited. Although viable routes may differ slightly from local connectors, the main segment of each route is limited. This implies that the main part of each recommended route does not change as much and does not have too many alternatives. The recommended routes by the commercial platform are mostly within this route choice set. Third, the platform recommends routes based on the choice from its large-number public customers. In other words, their recommendations are based on aggregated perception from the general public. Finally, commercial platform provides their data in a relatively low cost.

Google Maps provided reasonably valid information for the alternative travel modes of the trips and stand out in this task over other platforms (e.g., Apple and Bing) for mainly two reasons. First, Google Maps is the largest navigation platform and accounts for over 1 billion monthly users (Auwerx 2023). This large number of users provide a huge database of route choices to Google Maps to train their own route recommendation system. With that said, the routes recommended by Google Maps could be those closest to people's route choices in their daily life. Second, Google Maps also provides multiple routes between one origination-destination pair for each travel mode whenever they are available. Specifically, Google Maps provides the distance, duration, and polyline of at most three routes by driving, three routes by walking, three routes by biking, and six routes by transit. The average duration and distance generated from these routes are more robust than that of single route.

For each trip, one point was randomly selected from the starting and ending census block as the starting and ending points of the trip (Figure 2). Census block is sufficiently small to avoid the case where originations and destinations of walking and biking trips are located in the same area. The distribution of all starting and ending points are presented in Figure A1-A2 in the appendix. Note that, although the survey only covered part of Maryland, the destinations of the trips may be located over Maryland, Washington DC, and the entire US. In this research, only trips within Maryland and Washington DC areas were focused on. It was then requested the potential routes by different travel modes between the selected starting and ending points from Google Maps through its 'googlemaps' Python package. The distance and duration of the requested routes for each travel mode was then averaged.

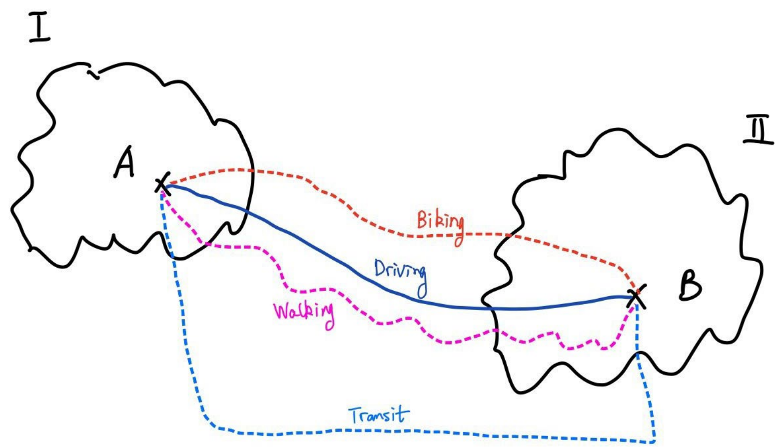

Figure 2. *Four Travel Modes are Considered for Each Trip*

Reliability indicates the variance of the speed along the route. Larger variance suggests the travel time along the route is not reliable. The historical hourly speed for the road segments in Maryland in 2019 from INRIX was requested. The variance of the speed for each road segment was calculated. Then, a calculation of the length-weighted speed variance for each route and averaged the value for each travel mode of each trip. For transit, only the road segments travelled by transit was considered. For walking and biking, the reliability is zero, which indicates that they are very reliable.

The parking cost was obtained by data MDOT. The parking cost is estimated based on the household travel survey conducted in Maryland in 1993 (Livewire Data Platform, n.d.). This survey provides parking costs in cents per hour for each traffic analysis zone across the state. It's the most recent state-wide parking cost data was included in the research.

The data was also augmented with sociodemographic information and built environment attributes at the origination and destination census block for each trip. The sociodemographic information was extracted from the National Historical Geographic Information System (NHGIS) database. The sociodemographic variables include average household income and percentage of labors.

The built environment attributes include job accessibility, land use, and LTS (level of traffic stress). Job accessibility variables were extracted from the Accessibility Observatory, including job accessibility by biking, transit, and driving, respectively. The observatory, however, does not provide job accessibility by walking in the study area. Land use data was requested from Replica, which is a transportation-focused data platform. Land use related variables include percentage of commercial area, percentage of residential area, percentage of open space, and percentage of industrial area in the corresponding census block.

The LTS data was obtained from MDOT and the District Department of Transportation (DDOT). The data contains the LTS index that evaluates the travel experience during biking. LTS is estimated based on multiple factors such as speed limit, bike facilities, and number of lanes (Andrew Bernish 2024). The LTS index is applied for both walking and biking trips. LTS is measured for each road segment (Figure 3), with an integer ranging from 1 to 4, with a larger value indicates a higher level of stress. Note that in Maryland, LTS is measured on a scale from 1 to 5, while in Washington DC, it is measured from 1 to 4. To ensure consistency, road segments in Maryland with an LTS of 4 or 5 were combined into a single category of 4, aligning them with the Washington DC scale. For each travel mode of the trip, the length-weighted mean LTS of the road segments along the requested routes was first measured and then averaged the LTS of the routes. Although LTS is measured for biking, in this research, it was assumed that pedestrians have the same LTS with cyclists on the same road segment. For transit trips, it was only considered LTS for road segment travelled by walking if there is any. Car trips have no LTS value.

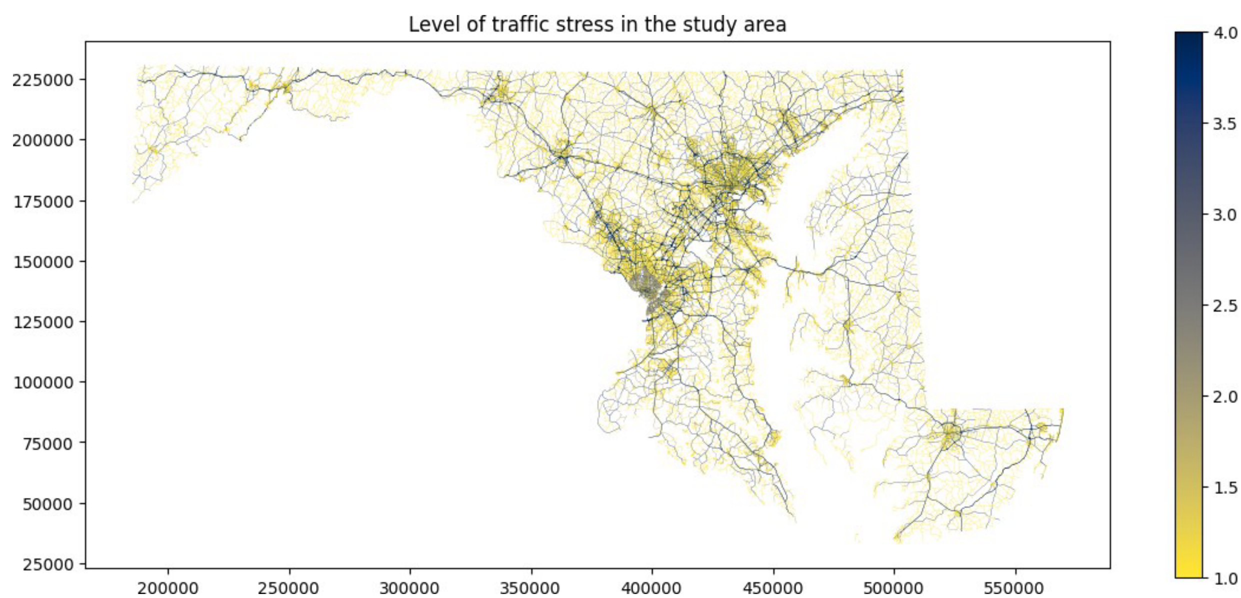

Figure 3. *Distribution of LTS in the Study Area*

Table 2 provides a comprehensive overview of the variables considered in this research. It includes detailed descriptions, data sources, and the respective years for each variable. Table 3 presents the descriptive statistics of all variables considered in the research for each travel mode.

Table 2. *Variable Description, Data Source, and Year* (Continued on next page)

Variable	Description	Data source	Year
Travel mode	The travel mode the trip, including walking, biking, transit, and driving	Travel survey	2019
	Trip patterns		
LTS	Average level of traffic stress of the road segments along the trip	MDOT	
Distance	Network distance in mile of the trip by travel mode	Google Maps API	2024
Duration	Duration in minutes of the trip by travel mode		
Reliability	Variance of travel time along the route in 2019	INRIX	2019
Parking cost at origination	Parking cost in cent per hour of the starting traffic analysis zone	MDOT	1993
Parking cost at destination	Parking cost in cent per hour of the ending traffic analysis zone		1993
	Built environment attributes		
Job accessibility by driving at origination	Number of job opportunities within 20-minute driving from the centroid of the starting census block of the trip	Accessibility observatory	2019
Job accessibility by driving at destination	Number of job opportunities within 20-minute driving from the centroid of the ending census block of the trip		
Job accessibility by transit at origination	Number of job opportunities within 30-minute travel by transit from the centroid of the starting census block of the trip		
Job accessibility by transit at destination	Number of job opportunities within 30-minute travel by transit from the centroid of the ending census block of the trip		
Job accessibility by biking at origination	Number of job opportunities within 30-minute biking from the centroid of the starting census block of the trip		
Job accessibility by biking at destination	Number of job opportunities within 30-minute biking from the centroid of the ending census block of the trip		
Percentage of residential area at origination	Percentage of residential area of the starting census block group of the trip	Replica	2023
Percentage of residential area at destination	Percentage of residential area of the ending census block group of the trip		
Percentage of commercial area at origination	Percentage of commercial area of the starting census block group of the trip		
Percentage of commercial area at destination	Percentage of commercial area of the ending census block group of the trip		
Percentage of open space at origination	Percentage of open space (e.g., parks, natural areas, and urban plazas) of the starting census block group of the trip		
Percentage of open space area at destination	Percentage of open space (e.g., parks, natural areas, and urban plazas) of the ending census block group of the trip		
Percentage of industrial area at origination	Percentage of industrial area of the starting census block group of the trip		
Percentage of industrial area at destination	Percentage of industrial area of the ending census block group of the trip		
	Sociodemographic variables (at census block group level)		
Median household income at origination	Median household income of the starting census block group of the trip	NHGIS	2019

Median household income at destination	Median household income of the ending census block group of the trip		
Percentage of labor force at origination	Percentage of population in labor force of the starting census block group of the trip		
Percentage of labor force at destination	Percentage of population in labor force of the ending census block group of the trip		
Percentage of commuting by car at origination	Percentage of population who commute by car of the starting census block group of the trip		
Percentage of commuting by car at destination	Percentage of population who commute by car of the ending census block group of the trip		
Demographic variables			
Age	Age group of the participant 1 = 0-4 years old 2 = 5-17 years old 3 = 18-44 years old 4 = 45-64 years old 5 = 65 years old or older		
Gender	A dummy variable indicating that the participant is male		
License	A dummy variable indicating that the participant holds a driving license		
Employment status	A dummy variable indicating that participant is employed		
Household size	Number of members in the household of the participant 1 = 1 2 = 2 3 = 3 4 = 4 5 = 5 6 = 6 7 = 7 8 = 8 or more	Travel survey	2019
Household income	Income of the household of the participant 1 = Less than $50,000 2 = $50,000 to $99,999 3 = $100,000 or more		
Number of vehicles	Number of vehicles in the household of the participant 0 = 0 1 = 1 2 = 2 3 = 3 4 = 4 5 = 5 6 = 6 7 = 7 8 = 8 or more		

Table 3. *Descriptive Statistics of all Variables (N=37,338)* (Continued on next page)

Variable	Driving		Transit		Walking		Biking	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
LTS	0	0	2.31	0.77	2.60	0.68	2.64	0.67
Distance	11492	16265	19013	24014	11526	24098	11545	19912
Duration	808	742	6229	6477	9512	19218	2457	3952
Reliability	22	19	11	10	0	0	0	0
Parking cost at origination	5.40	13.88	5.40	13.88	5.40	13.88	5.40	13.88
Parking cost at destination	5.33	13.83	5.33	13.83	5.33	13.83	5.33	13.83
Job accessibility by driving at origination	297122	272694	297122	272694	297122	272694	297122	272694
Job accessibility by driving at destination	297382	272983	297382	272983	297382	272983	297382	272983
Job accessibility by transit at origination	17445	47142	17445	47142	17445	47142	17445	47142
Job accessibility by transit at destination	17431	47328	17431	47328	17431	47328	17431	47328
Job accessibility by biking at origination	10754	29182	10754	29182	10754	29182	10754	29182
Job accessibility by biking at destination	10744	29197	10744	29197	10744	29197	10744	29197
Percentage of residential area at origination	0.52	0.27	0.52	0.27	0.52	0.27	0.52	0.27
Percentage of residential area at destination	0.52	0.27	0.52	0.27	0.52	0.27	0.52	0.27
Percentage of commercial area at origination	0.21	0.18	0.21	0.18	0.21	0.18	0.21	0.18
Percentage of commercial area at destination	0.21	0.18	0.21	0.18	0.21	0.18	0.21	0.18
Percentage of open space at origination	0.02	0.06	0.02	0.06	0.02	0.06	0.02	0.06
Percentage of open space area at destination	0.02	0.06	0.02	0.06	0.02	0.06	0.02	0.06
Percentage of industrial area at origination	0.04	0.09	0.04	0.09	0.04	0.09	0.04	0.09
Percentage of industrial area at destination	0.04	0.09	0.04	0.09	0.04	0.09	0.04	0.09
Median household income at origination	80583	35591	80583	35591	80583	35591	80583	35591
Median household income at destination	80764	35581	80764	35581	80764	35581	80764	35581
Percentage of labor force at origination	0.67	0.13	0.67	0.13	0.67	0.13	0.67	0.13
Percentage of labor force at destination	0.67	0.13	0.67	0.13	0.67	0.13	0.67	0.13
Percentage of commuting by car at origination	0.82	0.17	0.82	0.17	0.82	0.17	0.82	0.17
Percentage of commuting by car at destination	0.82	0.17	0.82	0.17	0.82	0.17	0.82	0.17
Age	3.91	0.81	3.91	0.81	3.91	0.81	3.91	0.81
Gender	0.44	0.50	0.44	0.50	0.44	0.50	0.44	0.50

Variable	Driving		Transit		Walking		Biking	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
License	0.94	0.24	0.94	0.24	0.94	0.24	0.94	0.24
Employment status	0.65	0.48	0.65	0.48	0.65	0.48	0.65	0.48
Household size	2.46	1.27	2.46	1.27	2.46	1.27	2.46	1.27
Household income	2.14	0.79	2.14	0.79	2.14	0.79	2.14	0.79
Number of vehicles	1.99	1.09	1.99	1.09	1.99	1.09	1.99	1.09

3.2 Method

In this research, the multinominal logit model (MNL) was applied to estimate the model choice. MNL is a statistical model used to predict the probability of a particular outcome when there are more than two possible choices. As shown in Table 1, many studies have applied this method to estimate their mode choice model. Equation (1) below lists the variables considered in the modeling process.

$$\begin{gathered} \textit{Mode Choice} = f\,(\textit{LTS, trip patterns,} \\ \textit{built environment variables, sociodemographic variables,} \\ \textit{demographic variables}) \end{gathered} \tag{1}$$

LTS, reliability, duration, and distance are alternative-specific variables related to trip patterns. All built environment attributes and demographic variables were treated as individual-specific variables in this research. After variable correlation test, variables that are highly correlated were removed, including distance, job accessibility by transit at origination, job accessibility by transit at destination, percentage of commercial area at origination, and percentage of commercial area at destination. Trips with missing values in the variables were also removed.

We estimated five models were estimated. The first model is the full model, which including all trips from the sample. The sample size of the model is 149,352, which indicates that 37,338 trips were included in the model estimation[6]. We only keep variables with significant results (i.e., p-value smaller than 0.05) during the model estimation.

In addition, four sub-models based on trip purpose were estimated (Tables A1-A4 in the appendix). According to the activity type of the trip in its origination and destination, six trip purposes were initially considered, including home-based work (HBW), home-based school (HBSc), home-based shopping (HBS), home-based other (HBO), non-home-based work (NHBW), and non-home- based other (NHBO) trips. This typology is consistent with the practice of (Maryland Statewide Transportation Model (MTSM). Each sub-model with the trips of the same trip purpose was then estimated. During the model estimation, HBSc and HBS models cannot converge due to their relatively small sample size (289 and 1576 trips). HBSc and HBS trips was then combined into HBO trips and estimated one model. All models used the same set of independent variables.

[6] Each trip contains four travel mode, so the trip number is 149,352÷4=37,338 trips.

Note that HBW removed open space at destination and NHBW model removed employment status and license to make these models converge.

4 Research Findings

In this section, the comprehensive results of the full model were presented. The outcomes of the four sub-models are detailed in the appendix (Tables A1-A4).

4.1 Model Results

The results of the full model are listed in Table 4. The overall model performance is satisfactory, as evidenced by the McFadden R-squared value of 0.4031.

Two alternative-specific variables are significantly correlated with mode choice. LTS has a negative correlation with mode choice of walking, biking, and transit. This result suggests that higher level of traffic stress could more likely prohibit people from choosing active travel and transit. Note that LTS has not been considered for car trips. In addition, a likelihood ratio test was carried out between the models with and without LTS (Table A5 in the appendix). The result suggests that the model with LTS is significantly better than the model without LTS based on the estimated likelihood, which shows the importance of LTS in estimating mode choice. Moreover, duration has a negative relationship with people's preference for traveling. When the trip is longer, people will be less likely choose all travel modes.

Table 4. *Full Model Results* (Continued on next page)

Variable		**Estimate**	**P-value**	**Significance level**
LTS		-0.58	0.000	***
Duration		-4.10E-04	0.000	***
Parking cost at origination	**Walk**	0.02	0.000	***
	Bike	0.01	0.371	
	Transit	0.02	0.000	***
Parking cost at destination	**Walk**	0.02	0.000	***
	Bike	0.02	0.007	**
	Transit	0.01	0.000	***
Employment status	**Walk**	-0.15	0.011	*
	Bike	0.11	0.628	
	Transit	0.13	0.122	
License	**Walk**	-1.79	0.000	***
	Bike	-1.24	0.000	***
	Transit	-2.40	0.000	***
Gender	**Walk**	0.21	0.000	***
	Bike	1.62	0.000	***
	Transit	0.10	0.162	
Age	**Walk**	-0.21	0.000	***

Variable		**Estimate**	**P-value**	**Significance level**
	Bike	-0.69	0.000	***
	Transit	-0.15	0.003	**
Household income	**Walk**	0.25	0.000	***
	Bike	0.18	0.160	
	Transit	0.06	0.259	
Household size	**Walk**	0.01	0.749	
	Bike	-0.28	0.003	**
	Transit	0.13	0.000	***
Number of vehicles	**Walk**	-0.45	0.000	***
	Bike	-0.53	0.000	***
	Transit	-1.34	0.000	***
Job accessibility by biking at origination	**Walk**	1.08E-06	0.235	
	Bike	1.11E-05	0.000	***
	Transit	-4.47E-06	0.000	***
Job accessibility by car at origination	**Walk**	3.73E-08	0.728	
	Bike	-1.74E-06	0.000	***
	Transit	6.28E-07	0.000	***
Percentage of open space at destination	**Walk**	0.76	0.067	
	Bike	0.89	0.558	
	Transit	1.84	0.000	***
Percentage of labor force at origination	**Walk**	0.45	0.027	*
	Bike	0.04	0.952	
	Transit	1.60	0.000	***
Percentage of labor force at destination	**Walk**	0.42	0.036	*
	Bike	0.35	0.592	
	Transit	1.24	0.000	***
Percentage of commuting by car at origination	**Walk**	-1.58	0.000	***
	Bike	-1.42	0.008	**
	Transit	-2.99	0.000	***
Percentage of commuting by car at destination	**Walk**	-1.63	0.000	***
	Bike	-1.71	0.002	**
	Transit	-2.78	0.000	***
Intercept	**Walk**	4.32	0.000	***
	Bike	2.57	0.002	**
	Transit	5.20	0.000	***
Sample size		149,325		
McFadden R^2		0.4031		

For all individual-specific variables, the car was chosen as the reference point and estimated coefficients for all travel modes. Among sociodemographic variables, employment status, license, gender, age, household income, household size, and number of vehicles have significant relationships with mode choice. People who are employed would be more likely to choose driving over walking. This result makes sense as the major travel mode for commuting is driving in the US. People with driving licenses are more likely to travel by car than walking, biking, and transit. Compared with female participants, male participants would be more likely to choose walking and biking over driving. This might be because of two reasons. First, walking and biking generally needs more physical effort, and males perform better than females in such physical activities. Second, walking and biking are less safe than driving and transit. The results of age suggest that seniors are more likely to choose private driving over walking, biking, or transit.

People living in households with higher income are more likely to choose walking over driving. It might be inferred that wealthy people prefer healthy travel modes. Larger households would like to choose driving over biking. Households with more members need more of the convenience of cars when traveling. However, the result indicates that larger households are more likely to choose transit over driving. The reason for this choice is not clear. Compared with vehicle trips, the number of vehicles have negative relationships with the other three travel modes. This implies that people living in households with more vehicles prefer to choose driving over walking, biking, and transit.

Both parking cost in the origination and destinations are significantly correlated with travel mode choice. Specifically, when parking cost increases in originations, people prefer walking and transit over driving. In addition, when parking cost increases in destinations, people are more likely to choose walking, biking, and transit, compared with driving. The results show the negative impact of parking cost on driving.

Three built environment variables have significant relationships with mode choice, including job accessibility by biking at origination, job accessibility by car at origination, and percentage of open space at destination. When leaving areas with higher job accessibility by biking, people prefer biking over driving. At the same time, people prefer driving over transit. On the contrary, when leaving areas with higher job accessibility by driving, people would be more likely to choose driving over biking. At the same time, people prefer transit over driving. In addition, when going to areas with more open space in percentage, people may choose transit over driving. This is probably because open space provides a good environment for walking and biking, which makes it easier for people to connect their destinations with transit.

Lastly, four sociodemographic variables have significant relationships with mode choice. They are percentage of labor force and percentage of commuting by car at both origination and destination. When leaving from or heading to areas with more people in the labor market, people would be more likely to choose transit and walking over driving. This might be because transit routes usually connect major employment centers, and some employment centers prefer to be located near labor markets. Furthermore, when leaving from or heading to areas with more people commuting by car, people are more likely to choose driving over walking, biking, and transit.

As to the sub-models, LTS and duration are negatively correlated with active mode choices and public transportation. For other variables considered, their significance levels vary across models because of different sample sizes. Gender, household income, number of vehicles, parking cost at destination, percentage of labor force at destination, and percentage of commuting by car at origination and destination are significant in all four models. Both employment status and percentage of open space at destination are only significant in the HBO model, but not in other sub-models. Percentage of labor force at origination is significant only in the NHBO model. License, age, and job accessibility by car at origination are insignificant only in the NHBW model. Both household size and parking cost at origination are insignificant only in the HBO model. Job accessibility by biking at origination is insignificant only in the HBW model.

4.2 Model Validation

The model's performance was validated based on the predicted probability of travel modes. 80% of the trips were randomly sampled to estimate a model (with the setting of the full model) and used the model to predict the model choice of the rest 20% of the trips. This process was ran 100 times and averaged the predicted mode share for all travel modes (Figure 4). In general, the average predicted mode share is consistent with that observed in the original sample, demonstrating a good prediction performance. In the original sample, driving accounts for 88.6%, biking for 0.4%, transit for 4.0%, and walking for 7%. According to Figure 4, the predicted share of biking fluctuates around 0.37%, driving around 88.7%, transit around 4.0%, and walking around 7.1%.

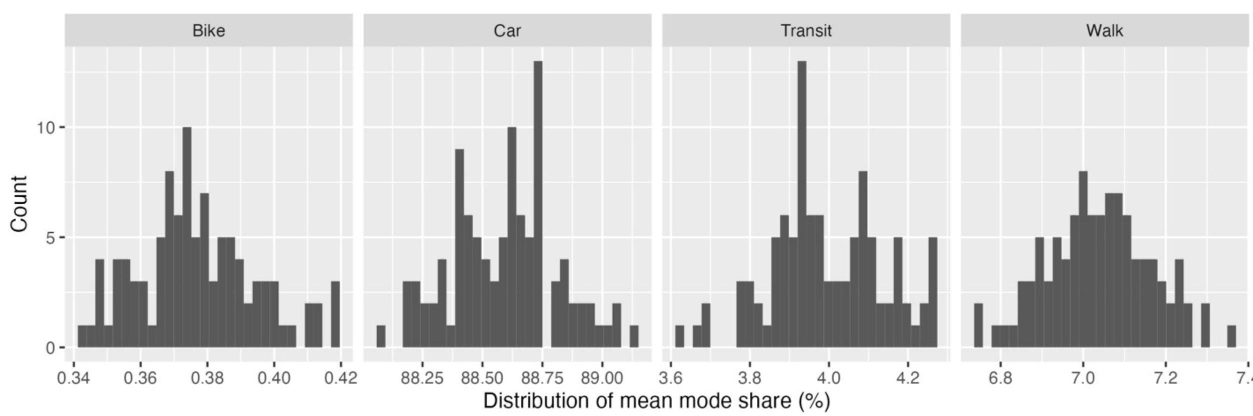

Figure 4. *Distribution of the Predicted Mode Share*

4.3 Sensitivity Analysis

It is expected that the impact of LTS on travel mode choice varies by infrastructure and travelers' characteristics. A sensitivity analysis was carried out with the estimated model to explore how LTS changes mode choice of walking and biking and how this change is related to different factors.

First, it was assumed that the LTS of the biking routes of all trips becomes 1 and used the estimated model to predict the probability of biking mode choice. All other variables of the biking routes and all variables of other routes remained the same during this process. Then, the same LTS value was set to be 4 and predicted the probability of the biking mode choice again. The change in the probability of biking mode when LTS changes from 1 to 4 was calculated (i.e., from lowest stress to highest stress). The same analysis was used for walking mode and calculated the probability change of walking mode when LTS changes from 1 to 4. The distribution of these probability changes was shown in Figure 5. In general, the probability change of mode trip is mostly small but has a wide range. The probability change of walking mode (0.081) is larger than biking mode (0.007). However, the probability changes also exhibit a wide range of variation, suggesting the heterogenous impact of LTS improvement on mode choices. The probability increase is ranging from 0 to 0.23 for biking and from 0 to 0.41 for walking.

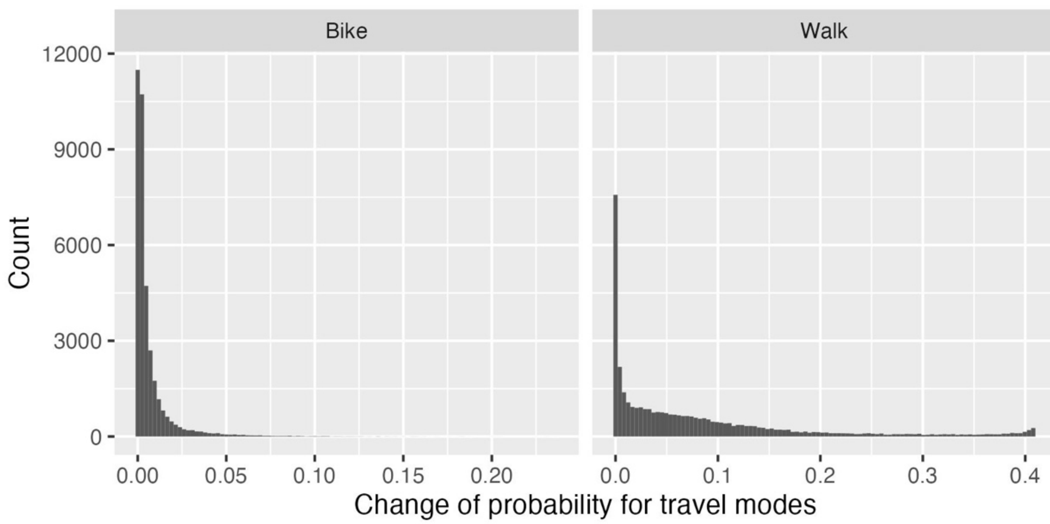

Figure 5. *Distribution of Probability Change for Bike and Walking Travel Modes*

Furthermore, out a linear regression analysis with to study the relationships between change of probability and other important independent variables was carried out. The variables considered in this analysis are those presented in Table 4 (except for LTS) as they have been shown significantly correlated with mode choices. The results of the biking and walking models are listed in Table 5 below. The R-squared are 0.513 for biking model and 0.612 for walking model.

Overall, the results of biking and walking modes are consistent. As to the original travel mode of the trip, the probability change is greater for biking, transit, and walking trips compared to driving trips. Probability change is smaller for longer-duration trips. This indicates that LTS improvement is more impactful to walking and biking use for short-distance trips. Additionally, probability change is greater for trips originating from areas with higher job accessibility by biking and lower job accessibility by driving. The probability change is greater for trips destined for areas with a larger share of open space. These results suggest that LTS improvement works better in encouraging walking and biking trips starting and ending in areas with specific attributes. Furthermore, probability change is higher for trips commencing and concluding in areas with a lower percentage of commuting by car and higher parking costs. This result implies that parking policy may help strengthening the impact of LTS improvement.

For trips destined for areas with a larger percentage of the labor force, both walking and biking probability changes are greater. However, for trips originating from areas with a larger share of the labor force, biking probability change is smaller, while walking probability change is larger. The reason for this disparity remains unknown.

Table 5. *Results of Mode Choice Probability Change Models*

Variable	Biking			Walking		
	Estimate	P-value	Significance level	Estimate	P-value	Significance level
Original travel mode of the trip (Car as reference level)						
Bike	0.014	0.000	***	0.079	0.000	***
Transit	0.002	0.000	***	0.058	0.000	***
Walk	0.005	0.000	***	0.116	0.000	***
Duration	-1.97E-06	0.000	***	-3.38E-05	0.000	***
Job accessibility by biking at origination	1.06E-07	0.000	***	3.35E-07	0.000	***
Job accessibility by car at origination	-9.91E-09	0.000	***	-1.27E-08	0.000	***
Percentage of open space at destination	0.002	0.063		0.016	0.004	**
Percentage of labor force at origination	-0.001	0.001	**	0.019	0.000	***
Percentage of labor force at destination	0.002	0.000	***	0.025	0.000	***
Percentage of commuting by car at origination	-0.007	0.000	***	-0.060	0.000	***
Percentage of commuting by car at destination	-0.009	0.000	***	-0.069	0.000	***
Parking cost at origination	4.59E-05	0.000	***	0.001	0.000	***
Parking cost at destination	1.36E-04	0.000	***	0.001	0.000	***
Demographics	Yes			Yes		
Constant	4.56E-02	0.000	***	0.305	0.000	***
Sample size	37,338			37,338		
R squared	0.513			0.612		

Note: Demographic variables are controlled in the models, but their results are not presented in the table.

4.4 Integration into the Regional Maryland Statewide Transportation Model (MSTM)

Integrating the calibrated active mode choice model into the MSTM involves several key steps. First, trip patterns including travel time, travel distance and trip-level LTS need to be calculated for all trips between the origin and destination traffic analysis zones (TAZ) included in the MSTM. Second, built environment attributes and sociodemographic variables are generated for each TAZ. Table 4 provides a full list of those attributes and variables. Finally, the calibrated active mode choice model can be applied to calculate the mode shares for walking, biking, transit, and driving for each TAZ pair. These results can then be used to disaggregate the total number of trips into mode-specific trips for each TAZ pair. This process can be done for each trip purpose, e.g. HBO and HBW. This process can also be applied for baseline year or forecast years as long as trip patterns, built environment attributes, and sociodemographic variables are estimated consistently for the same year.

One potential challenge is estimating trip distances and times between TAZ pairs. With over 1,600 TAZs in the MSTM, this could result in more than 1 million TAZ pairs. Using Google Maps API for this purpose may be prohibitively expensive. An alternative approach could involve leveraging the state-level travel demand model to estimate trip distances and times by travel mode for each TAZ pair. MSTM could be expanded to a multi-mode network with a complete set of transit, walking and biking facilities. In this expanded MSTM, trip distances and times can be estimated for various travel modes and for each O-D pair.

5 Conclusions and Policy Implications

In this research, a set of state-wide mode choice models was estimated, specifically considering walking and biking with the household survey data from Maryland. The Google Maps platform was utilized to acquire information of alternative travel modes for each trip. LTS was explicitly considered in the model and explored the impact of LTS on mode choice in Maryland. Furthermore, built environment attributes and socio-demographic variables of the originations and destinations, and demographic variables of the travelers were also considered. A multinominal logit model was constructed to estimate the mode choice model considering walking, biking, transit, and driving. Sub-models for different trip purposes, including home-based work, home-based other, non-home-based work, and non-home-based other trips were also estimated.

The results showed that the inclusion of LTS could significantly improve the model performance, which demonstrates the importance of considering LTS in mode choice models with biking and walking. In addition, LTS has a significant and negative correlation with all mode choices except for driving, suggesting that higher LTS would be more likely to reduce people's preference for traveling by walking, biking, and transit.

Duration is negatively associated with people's preference for traveling by all travel modes. All demographic variables considered in this research showed significant relationships with mode choice, including employment status, license, gender, age, household income, household size, and number of vehicles. This implies the important role of demographics in influencing people's mode choice. Parking cost significantly impacts travel mode choice, with higher costs leading to increased walking, transit, and biking, and decreased driving. Built environment variables of job accessibility by biking and job accessibility by car and sociodemographic variables of percentage of commuting by car and percentage of labor force have significant correlations with the mode choice.

Model performance validation was achieved by predicting travel mode shares for 20% of trips, with an average of over 100 runs. Predicted mode share generally aligned with the observed sample, with automobiles dominating the transportation modes and other modes accounting for a relatively small percentage. The overall performance is reasonable and satisfactory.

The sensitivity analysis suggested that the impacts of LTS on biking and walking mode choices change across different contexts. The LTS impact on mode share change is greater for trips starting in areas with higher biking job accessibility and lower driving job accessibility. for trips ending in areas with a larger percentage of open space, and for trips in regions with a lower percentage of population commuting by car and higher parking costs.

This research highlights the significant impact that LTS has on healthy and sustainable travel modes, including biking, walking, and transit. The findings underscore the importance of creating low-stress traffic conditions to encourage the use of these active travel modes. High LTS levels can deter individuals from choosing active travel modes and transit due to perceived or real safety concerns, ultimately leading to an overreliance on motor vehicles. Transportation planners and engineers should prioritize strategies to reduce LTS in traffic environments. This can be achieved through a variety of complete streets policies, such as protected bike lanes, pedestrian-focused signal timing, wider sidewalks, improved pedestrian crossings, and traffic calming measures.

In addition, LTS improvement projects should be strategically prioritized in specific locations and supported by targeted policies to maximize their impact. For instance, enhancing LTS in areas with higher job accessibility by biking, greater availability of open space, and lower car commuting rates can significantly boost the positive effects on walking and biking. Additionally, implementing reasonable parking costs in these areas can further amplify the benefits of LTS improvements.

References

Andrew Bernish. 2024. "Maryland Bicycle Level of Traffic Stress (LTS)." December 18, 2024. https://data.imap.maryland.gov/datasets/maryland::maryland-bicycle-level-of-traffic-stress-lts/about.

Apley, Daniel W., and Jingyu Zhu. 2020. "Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 82 (4): 1059–86. https://doi.org/10.1111/rssb.12377.

Auwerx, Peter. 2023. "Google Maps Leads the Way with Over 1 Billion Monthly Users." 2023. https://www.linkedin.com/pulse/google-maps-leads-way-over-1-billion-monthly-users-peter-h-j-auwerx-43sve/.

Aziz, H. M. Abdul, Nicholas N. Nagle, April M. Morton, Michael R. Hilliard, Devin A. White, and Robert N. Stewart. 2017. "Exploring the Impact of Walk–Bike Infrastructure, Safety Perception, and Built-Environment on Active Transportation Mode Choice: A Random Parameter Model Using New York City Commuter Data." *Transportation* 45 (5): 1207–29. https://doi.org/10.1007/s11116-017-9760-8.

Blumenberg, Evelyn, Brian D. Taylor, Michael J. Smart, Kelcie Ralph, Madeline Wander, and Stephen Brumbaugh. 2013. "The Next Generation of Travel Statistical Analysis."

Chen, Cynthia, Hongmian Gong, Catherine Lawson, and Evan Bialostozky. 2010. "Evaluating the Feasibility of a Passive Travel Survey Collection in a Complex Urban Environment: Lessons Learned from the New York City Case Study." *Transportation Research Part A: Policy and Practice* 44 (10): 830–40. https://doi.org/10.1016/j.tra.2010.08.004.

Chen, Hugh, Scott M. Lundberg, and Su-In Lee. 2022. "Explaining a Series of Models by Propagating Shapley Values." *Nature Communications* 13 (1): 4512. https://doi.org/10.1038/s41467-022-31384-3.

Cheng, Long, Xuewu Chen, Jonas De Vos, Xinjun Lai, and Frank Witlox. 2019. "Applying a Random Forest Method Approach to Model Travel Mode Choice Behavior." *Travel Behaviour and Society* 14:1–10. https://doi.org/10.1016/j.tbs.2018.09.002.

Clifton, Kelly J., Patrick A. Singleton, Christopher D. Muhs, and Robert J. Schneider. 2016. "Representing Pedestrian Activity in Travel Demand Models: Framework and Application." *Journal of Transport Geography* 52 (April):111–22. https://doi.org/10.1016/j.jtrangeo.2016.03.009.

De Vos, Jonas, Long Cheng, Md Kamruzzaman, and Frank Witlox. 2021. “The Indirect Effect of the Built Environment on Travel Mode Choice: A Focus on Recent Movers.” *Journal of Transport Geography* 91. https://doi.org/10.1016/j.jtrangeo.2021.102983.

Ding, Chuan, Donggen Wang, Chao Liu, Yi Zhang, and Jiawen Yang. 2017. “Exploring the Influence of Built Environment on Travel Mode Choice Considering the Mediating Effects of Car Ownership and Travel Distance.” *Transportation Research Part A: Policy and Practice* 100 (June):65–80. https://doi.org/10.1016/j.tra.2017.04.008.

Eldeeb, Gamal, Moataz Mohamed, and Antonio Páez. 2021. “Built for Active Travel? Investigating the Contextual Effects of the Built Environment on Transportation Mode Choice.” *Journal of Transport Geography* 96. https://doi.org/10.1016/j.jtrangeo.2021.103158.

EPA. 2021. “Smart Location Database.” 2021.

Ermagun, Alireza, Taha Hossein Rashidi, and Zahra Ansari Lari. 2015. “Mode Choice for School Trips.” *Transportation Research Record: Journal of the Transportation Research Board* 2513 (1): 97–105. https://doi.org/10.3141/2513-12.

Ewing, Reid, and Robert Cervero. 2010. “Travel and the Built Environment.” *Journal of the American Planning Association* 76 (3): 265–94. https://doi.org/10.1080/01944361003766766.

Faghih Imani, Ahmadreza, Eric J. Miller, and Shoshanna Saxe. 2019. “Cycle Accessibility and Level of Traffic Stress: A Case Study of Toronto.” *Journal of Transport Geography* 80. https://doi.org/10.1016/j.jtrangeo.2019.102496.

Goughnour, Elissa, Taylor Bonner, Eben Sweetser, and Darrell Smith. 2022. “Improving Safety for Pedestrians and Bicyclists Accessing Transit.”

Khan, Mobashwir, Kara M. Kockelman, and Xiaoxia Xiong. 2014. “Models for Anticipating Non-Motorized Travel Choices, and the Role of the Built Environment.” *Transport Policy* 35 (September):117–26. https://doi.org/10.1016/j.tranpol.2014.05.008.

Khattak, Zulqarnain, Mark Magalotti, John Miller, and Michael Fontaine. 2017. “Using New Mode Choice Model Nesting Structures to Address Emerging Policy Questions: A Case Study of the Pittsburgh Central Business District.” *Sustainability* 9 (11). https://doi.org/10.3390/su9112120.

Lavasani, Mohammad, Md Sakoat Hossan, Hamidreza Asgari, and Xia Jin. 2017. “Examining Methodological Issues on Combined RP and SP Data.” *Transportation Research Procedia* 25:2330–43. https://doi.org/10.1016/j.trpro.2017.05.218.

Liu, Feng, John E. (Jay) Evans, and Thomas Rossi. 2012. “Recent Practices in Regional Modeling of Nonmotorized Travel.” *Transportation Research Record* 2303 (1): 1–8. https://doi.org/10.3141/2303-01.

Livewire Data Platform,. n.d. “1993 Baltimore Household Travel Survey.” Accessed January 27, 2025. https://livewire.energy.gov/ds/tsdc/ds94.

Martín, Belén, and Antonio Páez. 2019. “Individual and Geographic Variations in the Propensity to Travel by Active Modes in Vitoria-Gasteiz, Spain.” *Journal of Transport Geography* 76:103–13. https://doi.org/10.1016/j.jtrangeo.2019.03.005.

Mo, Baichuan, Yu Shen, and Jinhua Zhao. 2018. “Impact of Built Environment on First- and Last-Mile Travel Mode Choice.” *Transportation Research Record: Journal of the Transportation Research Board* 2672 (6): 40–51. https://doi.org/10.1177/0361198118788423.

Molnar, Christoph. 2020. *Interpretable Machine Learning*. https://christophm.github.io/interpretable-ml-book/.

Muñoz, Begoña, Andres Monzon, and Ricardo A. Daziano. 2016. “The Increasing Role of Latent Variables in Modelling Bicycle Mode Choice.” *Transport Reviews* 36 (6): 737–71. https://doi.org/10.1080/01441647.2016.1162874.

Nkeki, Felix Ndidi, and Monday Ohi Asikhia. 2019. “Geographically Weighted Logistic Regression Approach to Explore the Spatial Variability in Travel Behaviour and Built Environment Interactions: Accounting Simultaneously for Demographic and Socioeconomic Characteristics.” *Applied Geography* 108:47–63. https://doi.org/10.1016/j.apgeog.2019.05.008.

Páez, Antonio. 2006. “Exploring Contextual Variations in Land Use and Transport Analysis Using a Probit Model with Geographical Weights.” *Journal of Transport Geography* 14 (3): 167–76. https://doi.org/10.1016/j.jtrangeo.2005.11.002.

Schultheiss, Bil, Dan Goodman, Lauren Blackburn, Adam Wood, Dan Reed, and Mary Elbech. 2019. “Bikeway Selection Guide.”

Singleton, Patrick A., Keunhyun Park, and Doo Hong Lee. 2021. "Varying Influences of the Built Environment on Daily and Hourly Pedestrian Crossing Volumes at Signalized Intersections Estimated from Traffic Signal Controller Event Data." *Journal of Transport Geography* 93 (May):103067. https://doi.org/10.1016/j.jtrangeo.2021.103067.

Singleton, Patrick A., Joseph C. Totten, Jaime P. Orrego-Oñate, Robert J. Schneider, and Kelly J. Clifton. 2018. "Making Strides: State of the Practice of Pedestrian Forecasting in Regional Travel Models." *Transportation Research Record: Journal of the Transportation Research Board* 2672 (35): 58–68. https://doi.org/10.1177/0361198118773555.

Singleton, Patrick A., and Liming Wang. 2014. "Safety and Security in Discretionary Travel Decision Making." *Transportation Research Record: Journal of the Transportation Research Board* 2430 (1): 47–58. https://doi.org/10.3141/2430-06.

Spinney, Jamie E. L., Hanna Maoh, and Hugh Millward. 2019. "Factors Affecting Mode Choice for the Home–Elementary School Journey: Evidence from Halifax, Canada." *Canadian Geographies / Géographies Canadiennes* 63 (2): 254–66. https://doi.org/10.1111/cag.12494.

Sun, Bindong, Alireza Ermagun, and Bo Dan. 2017. "Built Environmental Impacts on Commuting Mode Choice and Distance: Evidence from Shanghai." *Transportation Research Part D: Transport and Environment* 52 (May):441–53. https://doi.org/10.1016/j.trd.2016.06.001.

Train, K. E. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press.

Westat. 2020. "Maryland Statewide Household Travel Survey Final Report." Maryland, US.

Whalen, Kate E., Antonio Páez, and Juan A. Carrasco. 2013. "Mode Choice of University Students Commuting to School and the Role of Active Travel." *Journal of Transport Geography* 31:132–42. https://doi.org/10.1016/j.jtrangeo.2013.06.008.

Wu, Hao, Yong Chen, and Junfeng Jiao. 2019. "Impact of Neighborhood Built Environments on Shopping Travel Modes in Shanghai, China." *Transportation Research Record: Journal of the Transportation Research Board* 2673 (8): 669–81. https://doi.org/10.1177/0361198119844969.

Zhao, Fang, Francisco Câmara Pereira, Rudi Ball, Youngsung Kim, Yafei Han, Christopher Zegras, and Moshe Ben-Akiva. 2019. "Exploratory Analysis of a Smartphone-Based

Travel Survey in Singapore.” *Transportation Research Record: Journal of the Transportation Research Board* 2494 (1): 45–56. https://doi.org/10.3141/2494-06.

Zhao, Xilei, Xiang Yan, Alan Yu, and Pascal Van Hentenryck. 2020. “Prediction and Behavioral Analysis of Travel Mode Choice: A Comparison of Machine Learning and Logit Models.” *Travel Behaviour and Society* 20:22–35. https://doi.org/10.1016/j.tbs.2020.02.003.

Appendix

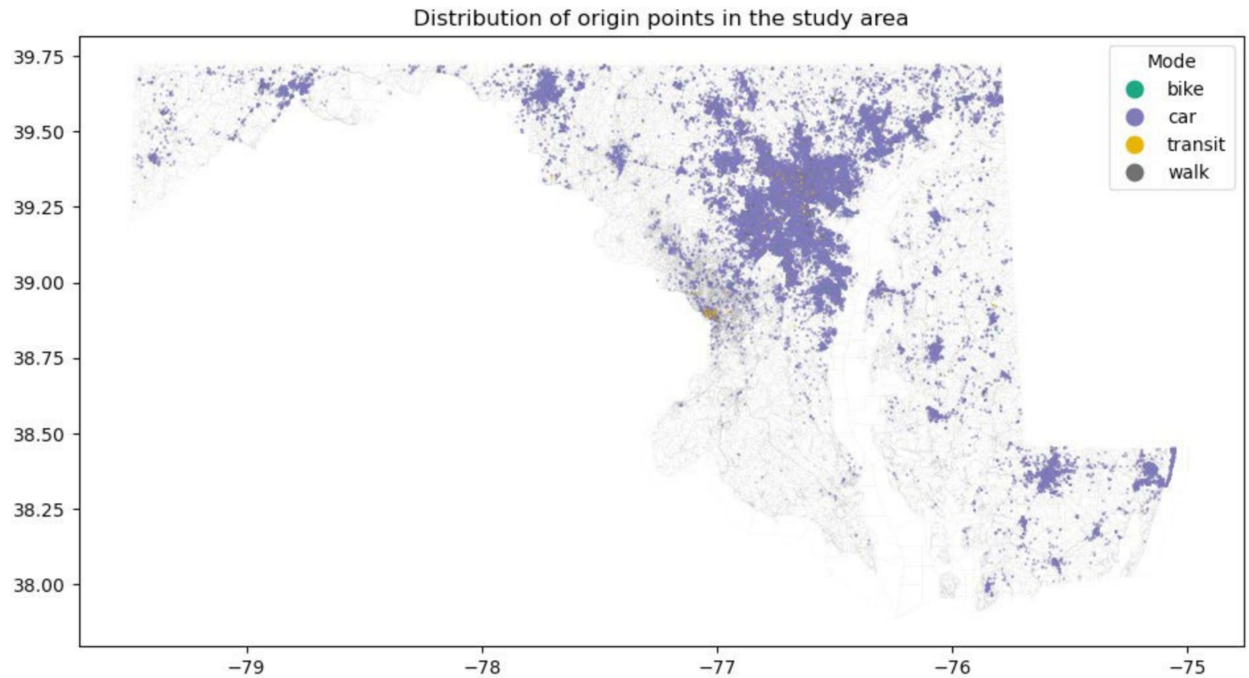

Figure A1. Distribution of origin points in the study area

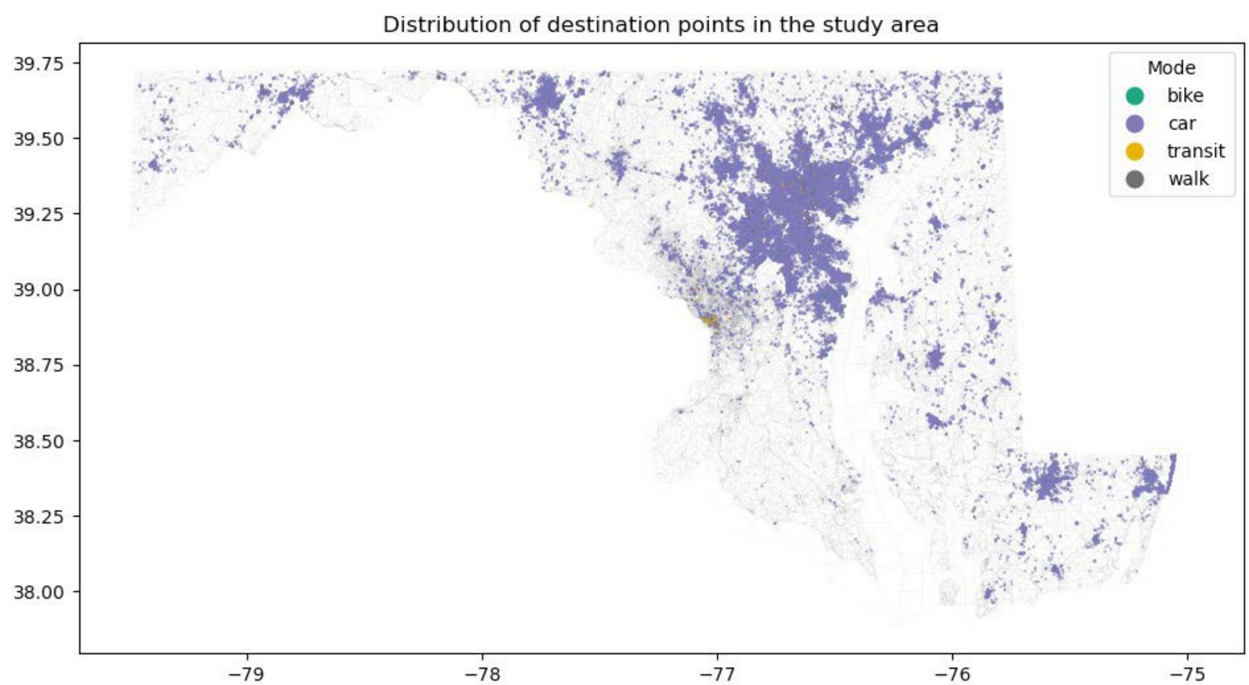

Figure A2. Distribution of destination points in the study area

Table A1. HBW model results (Continued on next page)

Variable		Estimate	P-value	Significance level
LTS		-0.45	0.000	***
Duration		-2.36E-04	0.000	***
Employment status	**Walk**	-0.32	0.554	
	Bike	-0.28	0.810	
	Transit	0.65	0.207	
License	**Walk**	-1.46	0.000	***
	Bike	-0.22	0.809	
	Transit	-2.67	0.000	***
Gender	**Walk**	0.74	0.003	**
	Bike	1.90	0.000	***
	Transit	0.11	0.520	
Age	**Walk**	-0.21	0.273	
	Bike	-0.26	0.470	
	Transit	0.28	0.043	*
Household income	**Walk**	0.53	0.007	**
	Bike	0.44	0.208	
	Transit	0.12	0.369	
Household size	**Walk**	0.27	0.010	*
	Bike	0.15	0.480	
	Transit	0.34	0.000	***
Number of vehicles	**Walk**	-1.11	0.000	***
	Bike	-1.65	0.000	***
	Transit	-1.27	0.000	***
Parking cost at origination	**Walk**	0.04	0.001	***
	Bike	-0.01	0.619	
	Transit	1.32E-03	0.885	
Parking cost at destination	**Walk**	3.88E-03	0.708	
	Bike	0.05	0.003	**
	Transit	0.04	0.000	***
Job accessibility by biking at origination	**Walk**	-2.47E-06	0.597	
	Bike	1.38E-05	0.060	
	Transit	-6.28E-06	0.103	
Job accessibility by car at origination	**Walk**	-1.75E-06	0.004	**
	Bike	-1.94E-06	0.131	
	Transit	4.82E-07	0.316	
Percentage of labor force at origination	**Walk**	0.07	0.944	

Variable		Estimate	P-value	Significance level
	Bike	2.85	0.168	
	Transit	-0.05	0.945	
Percentage of labor force at destination	**Walk**	-0.53	0.503	
	Bike	1.27	0.392	
	Transit	2.97	0.000	***
Percentage of commuting by car at origination	**Walk**	-2.11	0.012	*
	Bike	-2.99	0.046	*
	Transit	-1.36	0.039	*
Percentage of commuting by car at destination	**Walk**	-0.79	0.261	
	Bike	1.06	0.409	
	Transit	-3.13	0.000	***
Intercept	**Walk**	4.21	0.002	**
	Bike	-3.03	0.256	
	Transit	1.46	0.183	
Sample size		13,144		
McFadden R^2		0.4291		

Table A2. HBO model results (Continued on next two pages)

Variable		Estimate	P-value	Significance level
LTS		-0.50	0.000	***
Duration		-7.32E-04	0.000	***
Employment status	**Walk**	-0.23	0.040	*
	Bike	-0.43	0.380	
	Transit	-0.59	0.004	**
License	**Walk**	-1.85	0.000	***
	Bike	-1.83	0.003	**
	Transit	-1.73	0.000	***
Gender	**Walk**	0.18	0.059	
	Bike	1.24	0.011	*
	Transit	-0.12	0.503	
Age	**Walk**	-0.22	0.001	**
	Bike	-0.61	0.041	*
	Transit	-0.46	0.000	***
Household income	**Walk**	0.19	0.009	**
	Bike	0.21	0.518	

Variable		Estimate	P-value	Significance level
	Transit	-0.18	0.254	
Household size	**Walk**	-0.02	0.729	
	Bike	-0.35	0.153	
	Transit	0.00	0.967	
Number of vehicles	**Walk**	-0.42	0.000	***
	Bike	-0.05	0.849	
	Transit	-2.15	0.000	***
Parking cost at origination	**Walk**	0.01	0.303	
	Bike	-0.02	0.400	
	Transit	-4.98E-03	0.551	
Parking cost at destination	**Walk**	0.01	0.056	
	Bike	0.03	0.043	*
	Transit	0.02	0.000	***
Job accessibility by biking at origination	**Walk**	4.96E-06	0.026	*
	Bike	8.67E-06	0.353	
	Transit	-5.10E-06	0.158	
Job accessibility by car at origination	**Walk**	-2.65E-07	0.232	
	Bike	-2.24E-06	0.043	*
	Transit	2.38E-07	0.587	
Percentage of open space at destination	**Walk**	1.29	0.134	
	Bike	4.77	0.053	
	Transit	4.66	0.000	***
Percentage of labor force at origination	**Walk**	0.39	0.402	
	Bike	0.88	0.643	
	Transit	-0.64	0.334	
Percentage of labor force at destination	**Walk**	0.54	0.204	
	Bike	-1.54	0.315	
	Transit	1.75	0.005	**
Percentage of commuting by car at origination	**Walk**	-1.19	0.004	**
	Bike	-1.48	0.362	
	Transit	-1.92	0.000	***
Percentage of commuting by car at destination	**Walk**	-1.20	0.003	**
	Bike	-1.82	0.207	
	Transit	-2.16	0.000	***
Intercept	**Walk**	4.55	0.000	***
	Bike	3.37	0.113	
	Transit	7.77	0.000	***

Variable		Estimate	P-value	Significance level
Sample size		32,052		
McFadden R^2		0.4577		

Table A3. NHBO model results (Continued on next page)

Variable		Estimate	P-value	Significance level
LTS		-0.60	0.000	***
Duration		-4.46E-04	< 2.2e-16	***
Gender	**Walk**	-0.17	0.330	
	Bike	1.81	0.108	
	Transit	-0.63	0.023	*
Age	**Walk**	-0.19	0.167	
	Bike	-0.22	0.731	
	Transit	0.05	0.790	
Household income	**Walk**	0.18	0.168	
	Bike	-0.14	0.814	
	Transit	-0.60	0.003	**
Household size	**Walk**	-0.06	0.473	
	Bike	0.02	0.963	
	Transit	0.40	0.000	***
Number of vehicles	**Walk**	-0.20	0.039	*
	Bike	-0.62	0.251	
	Transit	-1.04	0.000	***
Parking cost at origination	**Walk**	0.02	0.000	***
	Bike	-0.05	0.239	
	Transit	0.01	0.503	
Parking cost at destination	**Walk**	0.04	0.000	***
	Bike	0.02	0.558	
	Transit	0.03	0.001	***
Job accessibility by biking at origination	**Walk**	1.19E-06	0.689	
	Bike	4.10E-05	0.044	*
	Transit	-3.79E-06	0.397	
Job accessibility by car at origination	**Walk**	-2.15E-07	0.612	
	Bike	-4.66E-06	0.129	
	Transit	3.73E-07	0.517	
Percentage of open space at destination	**Walk**	0.42	0.748	
	Bike	3.62	0.269	

Variable		Estimate	P-value	Significance level
	Transit	0.71	0.693	
Percentage of labor force at origination	**Walk**	-0.27	0.701	
	Bike	-2.78	0.428	
	Transit	0.96	0.327	
Percentage of labor force at destination	**Walk**	0.96	0.149	
	Bike	2.36	0.486	
	Transit	2.12	0.015	*
Percentage of commuting by car at origination	**Walk**	-1.23	0.029	*
	Bike	0.89	0.756	
	Transit	-0.93	0.233	
Percentage of commuting by car at destination	**Walk**	-1.07	0.062	
	Bike	-1.18	0.675	
	Transit	-3.44	0.000	***
Intercept	**Walk**	1.71	0.056	
	Bike	-2.37	0.601	
	Transit	1.56	0.224	
Sample size		11,860		
McFadden R^2		0.4344		

Table A4. NHBO model results (Continued on next two pages)

Variable		Estimate	P-value	Significance level
LTS		-0.54	0.000	***
Duration		-4.36E-04	0.000	***
Employment status	**Walk**	-0.13	0.078	
	Bike	0.13	0.645	
	Transit	-0.03	0.822	
License	**Walk**	-1.80	0.000	***
	Bike	-1.31	0.000	***
	Transit	-2.50	0.000	***
Gender	**Walk**	0.24	0.000	***
	Bike	1.66	0.000	***
	Transit	0.13	0.164	
Age	**Walk**	-0.23	0.000	***
	Bike	-0.73	0.000	***
	Transit	-0.24	0.001	***

Variable		Estimate	P-value	Significance level
Household income	**Walk**	0.27	0.000	***
	Bike	0.15	0.367	
	Transit	0.03	0.707	
Household size	**Walk**	0.00	0.914	
	Bike	-0.36	0.005	**
	Transit	0.12	0.004	**
Number of vehicles	**Walk**	-0.45	0.000	***
	Bike	-0.45	0.004	**
	Transit	-1.46	0.000	***
Parking cost at origination	**Walk**	0.01	0.000	***
	Bike	0.02	0.027	*
	Transit	0.03	0.000	***
Parking cost at destination	**Walk**	0.02	0.000	***
	Bike	3.56E-03	0.617	
	Transit	-4.04E-03	0.178	
Job accessibility by biking at origination	**Walk**	1.71E-06	0.146	
	Bike	1.13E-05	0.003	**
	Transit	-2.27E-06	0.118	
Job accessibility by car at origination	**Walk**	1.25E-07	0.362	
	Bike	-1.90E-06	0.002	**
	Transit	3.85E-07	0.063	
Percentage of open space at destination	**Walk**	0.27	0.629	
	Bike	-0.89	0.718	
	Transit	-0.15	0.826	
Percentage of labor force at origination	**Walk**	0.50	0.051	
	Bike	-0.36	0.636	
	Transit	2.68	0.000	***
Percentage of labor force at destination	**Walk**	-0.04	0.879	
	Bike	0.51	0.556	
	Transit	-0.73	0.042	*
Percentage of commuting by car at origination	**Walk**	-1.62	0.000	***
	Bike	-1.33	0.042	*
	Transit	-4.35	0.000	***
Percentage of commuting by car at destination	**Walk**	-1.60	0.000	***
	Bike	-2.10	0.003	**
	Transit	-0.97	0.001	***
Intercept	**Walk**	4.51	0.000	***

Variable		Estimate	P-value	Significance level
	Bike	3.13	0.002	**
	Transit	5.95	0.000	***
Sample size		92,296		
McFadden R^2		0.4136		

Table A5. Comparison between models with and without LTS

Model	Log Likelihood	Chi square	P-value
Full model with LTS	-9900.5		
Full model without LTS	-10118.1	435.29	0.000