Improving Long-range Planning Models for Feasibility Analysis of Mileage-based User Fees as an Alternative Revenue Stream

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Venktesh Pandey, Ph.D., Rifa Tasnia, Ali Gorji Sefidmazgi
North Carolina Agricultural and Technical State University

Md. Sami Hasnine, PhD., and Daud Hridoy
Virginia Tech University

RESEARCH & DEVELOPMENT

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Venktesh Pandey
North Carolina Agricultural and Technical State University
1601 E Market St, McNair 434, Greensboro, North Carolina, 27411
+1-336-285-3687
vpandey@ncat.edu

North Carolina Agricultural and Technical State University

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16. Abstract

Declining motor fuel tax revenues driven by increasing fuel efficiency and zero-emission vehicle adoption have prompted North Carolina to evaluate Mileage-Based User Fees (MBUF) as a sustainable funding alternative. This study combines literature review, survey-based behavioral modeling, and statewide network analysis to assess the feasibility and potential impacts of MBUF. A comprehensive review of prior work revealed MBUF's promise as a stable, flexible revenue source, alongside persistent challenges of public acceptance, privacy, and implementation. To extend this evidence, the research team conducted the Survey to Understand the Impact of MBUF on Travelers' Choices (SUMTC) in April 2024, collecting 1,113 responses (881 valid). The survey combined revealed preference questions with stated preference experiments across seven modes using a D-efficient design. Descriptive analysis showed that cost, time, and convenience were the strongest determinants of travel, with most respondents expressing limited concern about whether charges were fuel-based or mileage-based as long as trip costs remained modest. Joint RP–SP discrete choice models revealed that higher MBUF rates reduce the likelihood of driving alone, carpooling, or using park-and-ride, with sensitivities varying by age, employment, and trip purpose. Route choice models using CatBoost achieved 87% accuracy, with toll road use frequency, age, and departure time as key predictors. A synthetic population framework fused Public Use Microdata Sample and National Household Travel Survey data to extend these insights statewide, while TransCAD simulations tested MBUF as link-level tolls. Results showed only modest increases in total system travel time, even at unrealistically high rates. Findings suggest that MBUF, implemented revenue-neutrally, is unlikely to significantly alter travel behavior. Transparency in communicating total trip costs emerges as the foremost priority for successful implementation.

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EXECUTIVE SUMMARY

North Carolina faces increasing pressure to identify sustainable transportation funding mechanisms as motor fuel tax revenues decline with the growth of fuel-efficient and zero-emission vehicles. Mileage-Based User Fees (MBUF), also referred to as Vehicle Miles Traveled taxes or road user charges, have been widely studied as a promising alternative. Nationally and within North Carolina, pilot programs demonstrate that modest rates—1.5 to 1.8 cents per mile—can generate revenue equivalent to the current gas tax, while rates in the range of 2 to 4 cents per mile could meet projected long-term infrastructure needs. Despite these advantages, challenges remain in assessing long-term behavioral impacts, fairness considerations, and public acceptance. This study responds to those gaps by systematically examining the impacts of MBUF using statewide planning models, discrete choice modeling, and behavioral surveys.

A comprehensive review of the literature highlighted three themes. First, MBUF provides stable revenues independent of fuel consumption and can be adapted to support dynamic or facility-specific pricing. Second, unresolved concerns persist around privacy, public buy-in, and fairness, particularly for rural residents and low-income groups. Third, pilot programs in multiple states—including North Carolina's participation in Eastern Transportation Coalition studies—show that public perception improves over time when transparency and context are emphasized. Beyond short-term pilots, however, there is limited understanding of how MBUF may influence long-term travel patterns, congestion, and modal choices. This report advances that understanding by embedding behavioral modeling into North Carolina's statewide planning context.

To address these gaps, the research team designed and implemented the Survey to Understand the Impact of MBUF on Travelers' Choices. Conducted in April 2024, the survey collected 1,113 responses, of which 881 were complete and valid for analysis. The survey combined revealed preference (RP) questions on demographics, household, and travel behavior with stated preference (SP) scenarios incorporating cost, time, and service attributes. Seven modes were included: drive alone, carpool, park and ride, Uber/Lyft/taxi, bike, walk, and transit. A D-efficient experimental design was used to generate six SP scenarios per respondent, capturing tradeoffs under fuel taxes, MBUF rates, and combined pricing structures.

Descriptive statistics showed that the sample was generally reflected North Carolina's demographics, with respondents distributed across income, education, and geography. Cost was the main factor in travel decisions, with time and convenience also playing a role. Most respondents relied on personal vehicles, with 62% driving almost every day and 93% holding a driver's license. Interestingly, Respondents showed little concern about whether costs came from fuel taxes or MBUF, provided total trip costs remained modest. Agreement with MBUF adoption was higher when cost differentials were small, showing that clear communication about costs matters.

The joint RP–SP mode choice models showed wide differences in how people reacted to MBUF rates. Higher MBUF rates reduced the likelihood of driving alone, carpooling, or using park-and-ride, with full-time workers especially sensitive for work trips and students more sensitive for recreational trips. Younger individuals were more responsive than older adults, while higher parking fees, tolls, and transit fares reduced the attractiveness of both motorized and shared modes. These findings confirm that mode choice under MBUF is shaped by both socio-demographics and trip purpose.

Route choice was also analyzed using machine learning (CatBoost) and regression models. The CatBoost classifier achieved 87% accuracy, with SHAP analysis identifying toll usage frequency as the strongest predictor, followed by age, departure time, and income. Older adults were less likely to choose high-cost roads, while early commuters often were willing to choose high-cost routes to save time. When total cost was shown clearly, many users switched to cheaper routes, suggesting that transparency in cost presentation is more influential than the per-mile rate itself.

To scale these insights for the state, a synthetic population framework was developed by fusing Public Use Microdata Sample socio-demographics with National Household Travel Survey behavioral data using Bayesian networks and K-Nearest Neighbors. Predictive models extended survey findings across all 76 PUMAs in North Carolina. In parallel, the statewide NCSTM TransCAD model was adapted to represent MBUF as link-level tolls ranging from \$0.05 to \$2.00 per mile, with the upper bound set deliberately high to capture variations in impacts even at rates well beyond practical implementation. Results showed that Total System Travel Time increased only slightly, even with very high rates, with variability across time periods largely driven by rerouting effects. This suggests that at the network level, MBUF is unlikely to produce significant shifts in route choice or congestion outcomes under revenue-neutral scenarios.

This study offers four key policy insights for North Carolina and other states considering MBUF. First, a simple, revenue-neutral per-mile fee remains the most practical and publicly acceptable replacement for the fuel tax. Complex differential rate structures add administrative burden without delivering substantial behavioral or congestion-management benefits. Second, transparency in costs is the primary determinant of traveler behavioral responses: clearly communicating trip-level costs and maintaining public education and pilot programs will be essential for long-term acceptance. Third, behavioral differences, especially by age group, highlight the value of targeted outreach, such as educating younger drivers on how small per-mile costs accumulate over time. Finally, effective long-term planning must integrate MBUF within broader models that account for population growth, land-use change, and technological adoption.

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Chapter 1. Introduction

1.1 Background

Transportation funding has become increasingly difficult to sustain as North Carolina—like many other states faces shrinking motor fuel tax revenues (McCaleb et al., 2021). The increased adoption of fuel-efficient vehicles and zero-emission vehicles (ZEVs) has accelerated this trend, creating a gap between available revenues and the growing costs of maintaining and improving roadway infrastructure. At the same time, the maintenance needs of aging infrastructure and the demand for new projects have continued to grow, creating a substantial funding gap (Roumboutsos et al., 2017). While most other developed or developing nations use general funds for transportation investments, the United States (US) uniquely funds transportation infrastructure primarily through the fuel tax (also referred to as gasoline or gas tax) (The Eno Center for Transportation, 2014). In the US, the pivotal Interstate Highway Act of 1956 cemented this shift to fuel taxes by creating a dedicated highway trust fund (HTF), ensuring that gas tax revenues were used solely for transportation. While other sources of funds like truck excise taxes and truck tire tax support the HTF, fuel tax comprises 90% of its current funding. However, fuel taxes, while an invisible cost in a traveler's budget, are known to be regressive and disproportionately burden lower-income households and rural residents who often drive longer distances. The transition from fuel tax funding has led to arguments favoring charging travelers based on the distance they travel rather than the amount of fuel they consume (Hensher and Mulley, 2014; The Eno Center for Transportation, 2014).

Mileage-based user fees (MBUF), also referred to as vehicle miles traveled (VMT) taxes or road user charges (RUC), have emerged as one of the most widely studied alternatives. Pilot programs across the United States, including those in North Carolina through the Eastern Transportation Coalition, have shown that even modest per-mile rates can generate revenues comparable to current fuel tax collections while offering a fairer distribution of costs among travelers with different vehicle types.

At the same time, the literature highlights several unresolved issues that extend beyond short-term revenue replacement. Concerns about fairness, public acceptance, privacy, and technology implementation persist, and there is limited understanding of how MBUF would shape long-term travel behavior and congestion patterns. Particularly for statewide planning, there remains a need to integrate behavioral responses, distributional impacts, and emerging technology considerations into models capable of evaluating future scenarios. This project responds to that gap by systematically adapting statewide travel demand tools to assess the feasibility and impacts of MBUF in North Carolina, providing evidence that can inform both ongoing pilot programs and future policy decisions.

1.2 Research Objective and Scope

This project's goal was to improve the long-range planning models used in North Carolina to assess the feasibility and impacts of MBUF as an alternative revenue source. The research objectives included (a) conducting a stated preference survey for estimating model parameters associated with MBUFs, (b) developing a methodology for explicitly incorporating MBUF in the long-term planning process, and (c) quantifying the impacts of MBUF under different implementation scenarios. Tied to these objectives, the central research questions guiding the study were: (1) how will MBUF pricing influence travel behavior and route choice at the individual and system levels; (2) what are the distributional impacts of MBUF across different traveler groups, vehicle types, and geographies; and (3) how can statewide planning models be adapted to incorporate MBUF in a way that is both methodologically rigorous and practical for policy use?

1.3 Research Approach

To answer these questions, we structured the project around five interrelated tasks: synthesizing the literature and stakeholder perspectives, conducting a stated preference survey, developing and estimating discrete choice models, quantifying system-level impacts under alternative scenarios, and synthesizing policy guidance. The following sections summarize the work completed under these tasks and the key findings that emerged.

1.4 Report Organization

The remainder of this report is organized as follows. Chapter 2 reviews the existing literature on MBUF and related funding mechanisms. Chapter 3 presents the survey of North Carolina participants along with descriptive statistics. Chapters 4 and 5 develop and estimate the mode and route choice models used to assess the long-term impacts of MBUF on individual travel behavior. Chapter 6 extends these models to the statewide scale, and Chapter 7 concludes with a synthesis of findings and accompanying policy recommendations.

Chapter 2. Literature Review

Portions of this chapter were previously published in Transportation Research Record (Tasnia et al., 2025) and are reused here with permission:

> *Tasnia, R., Pandey, V., Hridoy, D. N., & Hasnine, M. S. (2025). Review of Mileage-Based User Fees for Sustainable Transportation Funding: Challenges, Opportunities, and Research Gaps. Transportation Research Record, 03611981251352761.*

2.1 Introduction

Restructuring North Carolina's transportation funding mechanisms has been identified as a priority of the state since NCDOT has faced revenue shortfalls and there is a constant requirement for funding for maintenance and improvement of transportation infrastructure (ASCE, 2021; TRIP, 2020). North Carolina's motor fuel tax has been marked unsustainable by the NC FIRST Commission as it does not yield sufficient revenue and its usefulness is expected to fall with the increasing penetration of fuel-efficient trucks and light vehicles. Bert et al. (2020) in their report analyzing sustainable and diversified revenue streams for the state identified mileage-based user fee (MBUF) as a viable alternative for motor fuel taxes.

MBUF, also referred to as vehicle miles traveled (VMT) tax or road user charge (RUC), charges a traveler a fixed or variable rate per mile traveled on the road. In the ongoing MBUF pilot program, a rate of 1.71 cents per mile is shown to generate revenue matching the current motor fuel tax in the state of North Carolina. NC Future Investment Resources for Sustainable Transportation (FIRST) Commission (2021), in its recent report to the Secretary of Transportation, has also advised the State to adopt a permanent MBUF to fully replace the Motor Fuels Tax by 2030. In addition to the sustainable financing benefits, MBUF has shown the potential to address inequities posed by fuel taxes by distributing the infrastructure maintenance costs fairly across travelers in different geographical areas who own vehicles with varying fuel efficiencies (EBP US, Inc., 2020). While the different implementations of MBUF are being practically investigated through pilot programs and through an evaluation of public perception towards these fees (McCaleb et al., 2021), there is a need for systematic evaluation of long-term impacts of MBUF rates incorporating behavioral changes, differential impacts across population groups, and emerging technologies. The focus of this research project is to improve the long-range transportation planning models for a comprehensive feasibility analysis of MBUFs as an alternative revenue source for the state of North Carolina.

While the field of MBUF is actively being explored, several recent reviews have provided a detailed dive into the topic. Table 2.1 shows a summary of other relevant reviews on this subject. This chapter highlights from these survey articles and build upon the findings from such surveys, integrating them with other recent literature and discoveries.

The rest of the chapter is organized as follows. Section 2.2 defines MBUF and investigates its comparative performance against the gas tax in terms of performance and efficiency. It explores various MBUF implementations, discussing the rates charged and incorporating insights from recent national and statewide reports. Section 2.3 reviews the potential criteria for evaluating MBUFs, covering policy, fairness, administrative, operational, and planning issues, investigating fairness impacts in detail, and examining differential effects across various groups. Section 2.4 adopts a modeling perspective, addressing the necessary components for a detailed assessment of MBUF impacts. This includes the type of data required and the behavioral models essential for such evaluations. Section 2.5 presents lessons learned from recent MBUF pilot programs conducted in different regions. Finally, Section 2.6 provides a comprehensive summary of lessons learned, identifies research gaps, and outlines potential approaches for future investigations.

Table 2.1: Other Recent Reviews for MBUF

Citation	Citation Highlights
Aloisi et al. (2023)	Reviews the tradeoffs in replacing gas tax with other fees (such as MBUF).
Shrode et al. (2023)	Reviews the feasibility of a national-level pilot program for MBUF along with other characteristics relevant for a large-scale implementation.
Nelson and Rowangould (2023)	Analyzes rural equity and cost concerns for MBUF in Vermont, offers data-driven insights into how MBUF impacts rural areas, and addresses associated equity and cost issues.
Glaeser et al. (2023)	Reviews the regressive natures of MBUF and gasoline fees using an economic analysis arguing higher burden for top income and expenditure deciles.
Sjoquist (2023)	Studies the feasibility and implications of implementing a Vehicle Miles Traveled (VMT) tax for funding transportation in California.
Sarmiento and Zhao (2021)	Reviews and conducts economic analyses for identifying differential rates and surcharges for various MBUF implementations.
Thapa et al. (2020)	Presents a literature review of mileage-based road user fees, exploring existing knowledge and research in this area.
Beider and Austin (2019)	Examines the option of implementing a federal MBUF on commercial trucks to address imbalances in the Highway Trust Fund, covering considerations such as tax base, rate structure, and implementation methods.
Kirk and Levinson (2016)	Examines mileage-based road user charges and offers insights into the current national and international efforts regarding this funding mechanism.
Weatherford (2012)	Reviews shortcoming of gas tax and MBUF as a replacement for the state of Michigan
Larsen et al. (2012)	Evaluates the equity aspects of fees for vehicle miles traveled in Texas, examining how different charging mechanisms may impact various population segments.

2.2 Review of MBUF—Preliminaries

2.2.1 What is MBUF?

According to the Federal Highway Administration (FHWA), the United States witnessed 3.17 trillion miles of road usage in 2022, concurrently moving 12.8 billion tons of freight, constituting a 65 percent share of total freight movements (Federal Highway Administration, 2022; Bureau of Transportation Statistics, 2022). The high value of VMT has strained public infrastructure, and the deteriorating conditions, as highlighted by ASCE, highlight the need for funding solutions such as mileage-based taxes to address the $786 billion backlog (American Society of Civil Engineers, 2021).

MBUF falls within the category of road pricing designed to internalize the burden that a vehicle poses on highway infrastructure into the costs paid by the road user. MBUF charges vehicles based on their mileage rather than the gallons of gas bought. Under motor fuel taxation fuel-efficient vehicles pay less for using the highway, thus, MBUF is being investigated as a tool that ensures that vehicles pay their fair share of using the highway infrastructure. Recognizing their potential, state officials have initiated VMT-fee pilot programs, with 14 states implementing them as of July 2023. Four of these pilots have successfully transitioned into full-fledged programs including Oregon (voluntary programs), Virginia (voluntary programs), Hawaii (HI is a mandatory program affecting all EV drivers), and Utah (Shrode et al., 2023) (voluntary programs), while the state of North Carolina is currently in the final stages of its pilot program as part of the Eastern Transportation Coalition. Table A.1 shows the varying terminologies used to refer MBUF across the nation.

A report by Eastern Transportation Coalition (2021) has identified that pilot studies show promise of MBUFs as an alternate funding mechanism with features such as sustainable revenue stream, interoperability with current toll facilities, and benefits for rural drivers. Current pilot studies and survey analysis have identified that public perception towards MBUFs becomes more positive with time making it a feasible option for the long term (Thapa et al., 2020). Figure 2.1 shows the status of ongoing research, pilots, and executed programs (beyond the pilot which have limited number of participants) across the United States.

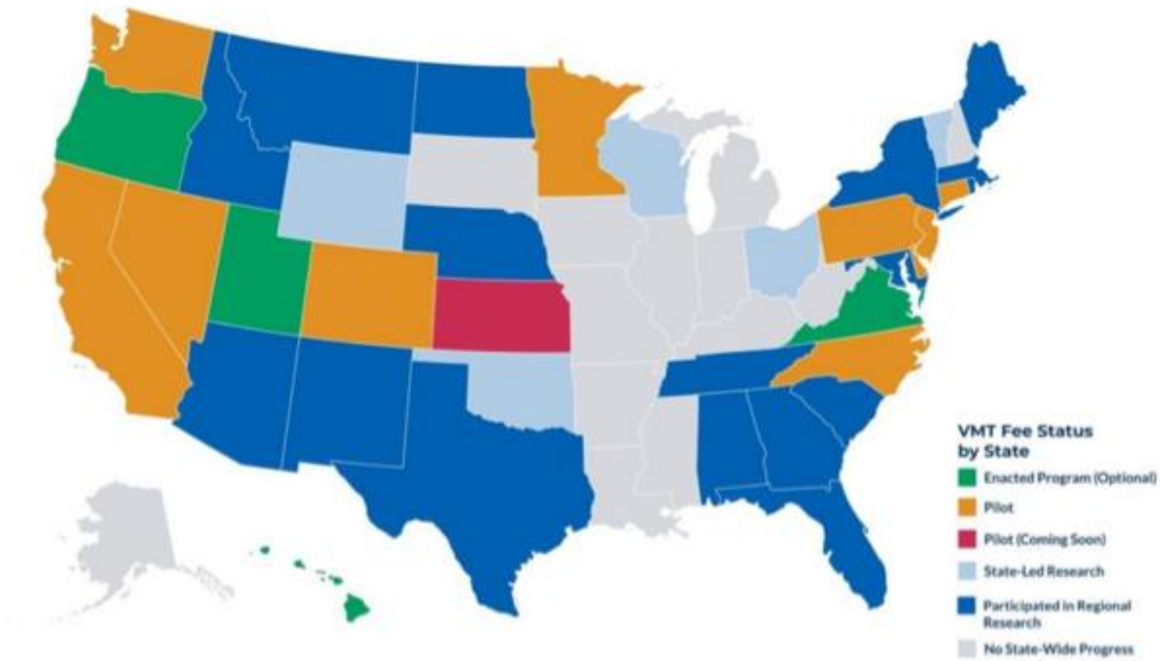


Figure 2.1: Map of State Research, Pilots, and Programs on MBUF (Shrode et al., 2023)

In addition to programs in the United States, nine EU nations, including Austria, Czechia, Germany, and Switzerland, have implemented Road Usage Charging (RUC) programs, targeting mainly heavy goods vehicles (HGVs). Another 11 EU countries are considering similar schemes, employing on-board devices for RUC administration (Malik, 2022).

2.2.2 MBUF vs Other Fees

Apart from ensuring fair charging for infrastructure impact, another motivation for utilizing MBUF is the prevailing narrative surrounding the unsustainability of funds. Chapters 2 and 3 in Shrode et al. (2023) provide an excellent overview of the history of federal excise tax as a substitute for road usage and the highway trust fund, highlighting the political system's inability to reconcile trust fund spending with revenues.

Glaeser et al. (2023) explore the impact of Pigouvian taxes and user fees, specifically focusing on the distributional consequences of the gasoline tax, bus and light rail charges, and a VMT tax. While these policies effectively address environmental externalities and fund transportation infrastructure, there is a concern about their potential burden on lower-income households. The study finds that gas taxes have become more regressive over time, partly due to environmentally oriented technological advancements. Replacing the gasoline tax with a household-level VMT tax could disproportionately affect higher-income households, especially those using hybrid-electric and battery-electric vehicles. The progressive shift in taxation would be more pronounced in the future if such vehicles become more common among wealthier households. Additionally, an expanded commercial VMT tax could place a larger burden on lower-income households, as better-off households consume more non-tradable goods not requiring transportation. User charges for airports, subways, and commuter rail are identified as progressive, while bus fees pose a significant financial challenge for lower-income households.

Furthermore, Aloisi et al. (2023) offer different dimensions for comparing the types of fees that can be considered as replacement for gas tax in the era of electric vehicles. It is argued that the effectiveness of alternative methods to replace the gas tax hinges on public and political acceptance. Viable options mirror established revenue models tied to vehicle ownership (imposed at point-of-sale or annually) and the gas tax, occasionally supplemented by toll charges. These methods, focusing on ownership, transportation use, and vehicle impact on infrastructure, address occupancy impacts (traffic congestion, pavement wear) and public health and safety impacts (vehicle weight and size externalities). Evaluating electric vehicle use within this framework involves assessing driving costs, miles driven, time, and traffic conditions. The report employs a multi-dimensional process to identify methods, revenue instruments, implementation tools, and evaluates each fee structure based on performance metrics and efficiency against vehicular mobility externalities (viz contributing to traffic congestion, pavement wear and tear, environmental impacts, and degradation of infrastructure). Table 2.2 illustrates the comparison between gas tax and MBUF along four dimensions. As observed, MBUF is found to be more stable and offers better opportunities for fairness. The reader is referred to Tables 5, 6, and 7 in Aloisi et al. (2023) for a detailed comparison with other fee structures such as standard tolling, fixed and variable fees for electric vehicle ownership, electricity taxes for home or public charging, parking pricing, and impacts-based fees.

Table 2.2: Comparing benefits and tradeoffs between Gas Tax and MBUF (adapted from Aloisi et al., 2023)

Performance	**Gas Tax**	**MBUF**
Ease of administration	✓ Payments made by wholesalers based on predetermined calculations of demand	✓ It involves using technology to track and manage vehicles' mileage; this may need additional complicated backend system (see Section 2.2.3).
Resistance to easy evasion	✓ Drivers cannot avoid payment of the tax at the gas pump	⇔ Need cutting-edge technology to guarantee precise mileage tracking, which could make evasion harder but not impossible.
Stability over time	In the pre-EV era, the gas tax has been durable over time, albeit historically volatile during an economic slowdown or disruption. X In the post-EV era, the gas tax gradually diminishes and eventually reduces to zero.	✓ Stability depends on VMTs which are reasonably stable over time. Variability may be present in the early stages, but as the system develops, stability should rise.
Fairness	⇔ The gas tax is inherently and highly regressive. However, most drivers accept the gas tax as a fair way to charge for their use of public infrastructure.	✓ Charges can be made more equitable by considering variables like vehicle type and distance traveled and basing charges on actual vehicle usage.

✓: strong or effective, ⇔ neutral, and X: low or ineffective.

2.2.3 Technology Considerations for Implementing MBUF

State pilots lack a unanimous preference for a specific data collection method, offering multiple options, up to five in some cases. These include manual odometer readings through inspections or online photo submissions, smartphone reporting via apps with or without GPS, OBD-II plug-in devices with or without GPS, and in-vehicle telematics. Manual odometer readings involve in-person reporting or online photo submissions, while smartphone reporting may or may not include GPS location information. OBD-II plug- in devices report miles traveled and other data without or with GPS. In-vehicle telematics utilizes existing integrated vehicle systems for mileage reporting, including the option to specify the locations traveled. Table A.2 summarizes the pros and cons of different approaches.

In addition to these commonly used technologies, other methods have also been explored including the “pay- at-the-pump" model. In Nevada, a transponder estimates mileage based on fuel efficiency and gas purchased, transmitting data to the pump and central office. Oregon tested similar GPS-free versions due to privacy concerns. However, it was found that coexisting a mileage charge with motor fuels tax at pay-at-the-pump systems may be complex administratively, requiring new federal collection points at retail gas stations (Kirk and Levinson, 2016).

The Infrastructure Investment and Jobs Act itself outlines tools for VMT collection such as third-party OBD-II devices, smartphone apps, automaker telemetric data, and car insurance companies’ motor vehicle data. It emphasizes the importance of steering clear of self-reporting systems, like submitting odometer readings annually during registration, to mitigate the high risk of evasion.

2.2.4 Differential Rate Implementation

Designing MBUF rates involves various considerations. Rufolo (2011) emphasizes how expensive it is to collect mileage fees for road usage compared to fuel taxes. Paz et al. (2014) go into greater detail on this, evaluating the fairness and efficacy of a VMT cost in Nevada and concluding that the current gasoline tax needs to be more equitable and effective than a 3.3 cent per mile fee. A marginal-cost VMT charge that considers pollution, deteriorating infrastructure, and traffic congestion is something that Zhang et al. (2013) and Zhang and Lu (2012) both suggest implementing. In Maryland, Zhang and Lu (2012) compute the charge based on the marginal cost of travel and internalize several externalities; Zhang et al. (2013) assesses explicitly the complete marginal cost of auto and truck traffic.

Building off the guidance in the literature, MBUF can be designed to have differential rates that vary with different characteristics including the following:

- Vary by vehicle typology (size & weight)
- Vary by location
- Vary by time
- Vary by level of service (congestion level)
- Vary by scope (limited corridors vs. system wide)

However, introducing variability in Mileage-Based User Fees (MBUF) raises two key concerns: “difficulty in explaining" and the potential creation of winners and losers (Shrode et al., 2023; Jacobs, 2022). A tiered rate structure based on vehicle fuel efficiency may be challenging to communicate and could be perceived as arbitrary, simplicity is crucial for public acceptance. Across different pilot programs, it is recommended that the initial focus should be on a straightforward, flat mileage fee as an alternative to the current fuel tax, building broad support. Over time, the technology can be adapted to address specific needs and fairness concerns.

Similarly, a revenue-neutral approach can unintentionally penalize the most fuel-efficient vehicles, creating a policy paradox (“unfairness" towards vehicles that are doing their part to protect the environment). The tiered rate system in the National Truck Pilot (NewRoad Consulting, 2023) rewarded less fuel-efficient fleets and penalized more fuel-efficient ones. Although MPG-based tiered rates don’t penalize fuel-efficient vehicles directly, they can lead to unintended winners and losers, potentially impacting lower-income households, rural drivers, and small truck fleets. Addressing significant flaws in a tiered rate structure based on MPG is crucial to avoid penalizing specific vehicles in both passenger and truck pilot programs.

In addressing the unique nature of trucks, the 2019 Congressional Budget Office report (Beider and Austin, 2019) discussed three pivotal decisions for a viable VMT fee system: determining the tax base, selecting implementation methods (excluding RFID readers due to cost constraints), and exploring an effective rate structure. Despite the challenges in replacing truck excise taxes, the recommendation emphasizes testing various rate structures, including those based on gross vehicle weight rating, gross registered weight, and vehicle class, with a focus on simplicity and minimal reporting burden for the trucking industry. Acknowledging the difficulty in full tax replacement, the suggestion is to simulate revenue-neutral rates, while states and regional coalitions are encouraged to persist in piloting VMT fees for commercial vehicles. The TETC's International Truck Pilot (NewRoad Consulting, 2023) serves as a model, using rates based on registered gross weight, providing guidance about the specific rate structures and their coding for broader applicability.

Amidst academic literature, the consensus is less clear, for pricing variability does offer the potential to address social inequities. Thapa et al. (2020) conducted a thorough literature assessment on mileage-based road user fees and highlighted the need for a more sustainable strategy. To overcome the shortcomings of the current systems, Sana et al. (2010) suggests a transparent and usage-based paradigm. Both Selmoune et al. (2020) and Munir et al. (2021) stress the significance of road network pricing in creating sustainable cities; Selmoune focuses on the elements impacting the acceptance of congestion pricing, while Munir identifies important research themes particularly. Road pricing can have favorable effects on transport and health fairness. However, there may be specific disparities in the distribution of benefits and liabilities, according to Hosford et al. (2021) deeper exploration of these topics. While in the early stages of MBUF, more complex structures can meander away from the main purpose findings sustainable transportation revenue source (Shrode et al., 2023), more research needs to be dedicated to creating effective tiered structures for MBUF that combine (a) simplicity, with (b) fair distribution of costs and benefits of MBUF.

2.3 Investigating Impacts of MBUF

2.3.1 Fairness Impacts

Like any novel system with the potential to impact people's daily lives, concerns have arisen regarding the fairness of MBUF. Surface issues become apparent in how the impacts of this system can vary based on factors such as geographical location, social considerations, and individual transportation methods. Therefore, it is crucial to scrutinize each issue and delve into the potential effects of its execution. This approach allows us to gain insights into the challenges at hand and devise strategies to mitigate their occurrence. This subsection reviews the identified fairness issues with MBUF implementation and ways it can be improved through a dive into several recent and seminal literature on the differential impacts of MBUF.

It is argued that MBUF systems can alleviate problems with gas tax revenue without improperly affecting different income groups (Aloisi et al., 2023). Sana et al. (2010) examined the income generation and social justice effects of a nationwide mileage-based user fee, which might partially or entirely replace the current gas tax. Combining data from the 2001 National Household Travel Survey with established elasticity values makes the calculation of changes in the vehicle fleet composition and miles traveled by time of day in response to pricing signals possible. These facts provide the foundation for estimating the effects of a mileage-based user fee scheme. Small mileage-based levies, ranging from 0.5 to 1.3 cents per mile, can provide income streams to supplement the current petrol tax revenue.

Rising electric vehicles, declining fuel tax, and stricter regulations demand innovative solutions, highlighting the importance of the vehicle mileage fee were discussed in Zhang and Lu (2012). The vehicle mileage fee emerges as a potent means to address and bridge the funding gap in surface transportation. This study internalizes costs such as traffic, pollution, greenhouse gas emissions, and deteriorating infrastructure to determine the car mileage tax based on marginal travel costs using data from the 2009 National Household Travel Survey. Discrete choice and regression models were used to explain the significant effect of car ownership, fuel economy, mileage driven, energy use, emissions, and fairness. The proposed fee, accounting for all costs, ranges from 7.7 to 9.1 cents per mile, more than the current fuel tax equivalent (about 1.2 cents per mile). Notably, household vehicle use is highly responsive to the fee, resulting in a substantial (27.1%) reduction in miles traveled. The price drastically decreases energy consumption and pollution or greenhouse gas emissions by around a fourth, but fuel efficiency increases marginally (up to 4.2%). While lower-income households might face more significant challenges (1.3%), the benefits, especially with rising fuel prices, underscore the sustainability advantages of the marginal-cost vehicle mileage fee.

The report Nelson and Rowangould (2023) argues the necessity of looking into alternatives to the current fuel excise tax, given the risks that high-efficiency and alternative fuel vehicles pose to revenue generation. By looking at statistics for more than 300,000 registered passenger cars, it primarily focuses on substituting a mileage-based user fee for Vermont's state fuels tax. Under the proposed mileage-based user charge, Vermont households would pay an additional $23 annually on average, with lower tax burdens for rural and low-income households than their urban and higher-income counterparts. In addition, a $180 flat charge analysis showed more significant pricing variations, with most households having to spend an additional $47 annually. The study emphasizes the equitable benefits of MBUF, especially for low-income and rural people, by eliminating cost concerns. Gaining support for this strategy through public education initiatives is recommended. The study's data clarifies public misconceptions and builds political support for mileage-based user fees, emphasizing the need for fair charge arrangements.

Yang et al. (2020) bring an international perspective on road pricing and provides the first causal assessment of the correlations between traffic density and speed, allowing for determining the best congestion charges in Beijing. The study uses fine-scale traffic data from Beijing to analyze the effects of road pricing and congestion. Fees vary from 5 to 39 cents per kilometer, which indicates an 11% rise in traffic velocity in the city center and an expected yearly welfare gain of ¥1.5 billion (relative to the current ¥10.5 billion), indicating an overall societal benefit of such taxation mechanisms. Some limitations include reliance on observational data, possible confounding variables, restricted generalizability (especially without considering multiple user groups), and the presumption of constant societal cost.

In another study by Yuan et al. (2021) the researchers used a range of data cleaning and analytical techniques to estimate the annual expenses for car owners under MBUFs at varying rates, which leveraged 119 million records from Pennsylvania's yearly vehicle inspections. They discovered that fees would be ¢2.4 to ¢3.2 per mile, the same as the current gasoline tax expenses. According to the study, automobiles in urban areas consume 10% less fuel annually and travel 10–30% fewer miles annually than the average, raising possible equality concerns. The model used to assess VMT involved odometer readings and web-scraped fuel economy data. When moving to MBUFs, it is essential to consider regional variances and equitable implications through nuanced approaches.

Similarly, Paz et al. (2014) evaluated the equity and efficacy of Nevada's vehicle miles traveled (VMT) levy for passenger cars. The influence of the fee on users' mileage and collecting capacities was considered while assessing the fee's effectiveness. Socioeconomic status, household type, geography, and ownership of fuel-efficient automobiles were all considered in the equity study. The effects of various VMT fees were calculated using the 2009 National Household Travel Survey data and a linear regression model. A 3.3 cent per mile VMT cost was shown to be more efficient than the present fuel tax and a 2.91

cent per mile VMT fee compared to the current fuel tax scheme. Its equitable distribution resulted in a modest 0.37% average cost increase per household, making it a viable revenue source without significantly burdening Nevada households.

Weatherford (2012) examined the distributional effects of using MBUF to tax vehicle kilometers traveled (VMT). The study shows the impacts across demographic groups using probable quantitative methodologies and econometric models. Econometric models, which capture connections between VMT, demographics, and MBUF impacts, are frequently used in such assessments. Fairness considerations guarantee an equitable allocation of the tax burden by addressing the fairness and the possible progressiveness of MBUF.

The switch from a state vehicle fuel tax to a road user charge (RUC) with a flat rate of 2.52 cents per mile is examined in Speroni et al. (2022). While the urban families suffer negligible cost increases across income levels, rural households typically incur slightly lower expenses due to driving longer distances in less fuel-efficient automobiles. They use data from five years ago here. The usage of a single RUC structure, and the exclusion of zero-emission cars are some of the limitations. The possible benefits and drawbacks of MBUF as an addition to or replacement for fuel taxes are examined by Zupan et al. (2012). The study finds essential but manageable problems related to MBUF deployment. MBUF might handle the significant financial obstacles associated with New York State's capital demands for transportation. The main problems here include the move away from fuel taxes, technological barriers, privacy issues, driver fairness, and higher collection expenses. The study here offers valuable insights for policymakers by highlighting the viability of MBUF while acknowledging the necessity to solve several implementation-related issues.

The research by Hasnat and Bardaka (2023) evaluates North Carolina's revenue contribution and cost-sharing for highway infrastructure. This shows that specific trucks underpay by 37% to 92%. On the other hand, lightweight vehicles generate much more money than their cost obligations. The influence of proposed tax hikes, such as the motor fuel or vehicle sales tax, on enhancing revenue and cost parity among vehicle classes is negligible. An emphasis on US tax laws and possible inefficiency in resolving fairness concerns are among the limitations.

Discussing ways to reinvest MBUF revenue towards public good, Sjoquist (2023) shows how a VMT tax might be used to pay for transit in Georgia. The study aims to evaluate the viability and ramifications of imposing a VMT Tax on Georgia's transportation financing. To assess the effects of a VMT Tax, the study uses quantitative analysis, combining information on travel trends, economic variables, and possible tax arrangements. The study should highlight the advantages and disadvantages of enacting a VMT tax in Georgia. Limitations include potential equality issues and the inherent difficulties of implementing a new tax system. The study by Zhang et al. (2009) investigated distributional issues using a $0.012/mi flat VMT tax. According to the results, the proposed fee's distributional impacts are not statistically significant over the long or short term. The study concludes that the future application of VMT fees shouldn't be hampered by these distributional concerns. The report highlights that worries over the equitable impact of the $0.012/mi flat VMT cost shouldn't prevent its implementation. The study measures outcomes including changes in customers' surplus, fee-collection agency revenue, and overall welfare changes across income and geographical groups to evaluate the distributional impact of the proposed VMT fee policy without participant interventions.

Yang et al. (2016) design and assess fair income-based mileage charges in Maryland. This research provides insights into the structure and efficacy of income-based mileage fees with the conclusion that the adoption of such fees has restrictions that may raise equality difficulties. Similarly, Larsen et al. (2012) study econometric models, taking demographics, travel habits, and income into account for evaluating equity impacts of MBUF in the state of Texas. The feasibility and sensitivity of replacing the gas tax with a mileage-based road usage charge (RUC) are also examined in Fitzroy and Schroeckenthaler (2018). With the diverse structure of statewide vehicle fleets and home driving patterns in mind, the study attempts to evaluate the factors impacting the formation of charges. Researchers assessed several aspects before concentrating on fuel type and efficiency. To stop income erosion, they suggested an annual updated parameterized RUC. The article performs comparative studies with a flat RUC and the current fuel excise tax, examining the distributional effect on households in urban, mixed, and rural areas, as well as on various fuel kinds. Compared to an excise-based gas tax, the results showed that urban households paid more on average, whereas mixed and rural households paid less. By adjusting for fuel efficiency, differences were lessened, highlighting the potential contribution of alternate fuels to future advancements.

Vermont's legislative process regarding House Bill 479, which focuses on transportation program enhancements and associated legal amendments, is progressing, with one final hurdle to clear. There is impetus to improve the state's transportation infrastructure and regulatory environment, as evidenced by the measure, which is ready for adoption pending one more legislative approval. DOT's optimism about getting the required support is noteworthy; the agency believes the bill will meet state transportation objectives.

This legislative milestone shows that Vermont is committed to tackling transportation issues and promoting sustainable mobility solutions. The state wants to update transportation programs while ensuring that laws change to meet changing needs, and it intends to do so using legislative tools. The pending approval of House Bill 479 highlights (TrackBill, 2025) a collaborative effort between stakeholders, legislators, and the public to establish practical transportation laws. The Department of Transportation (DOT) is eager to receive the final legislative sign-off, emphasizing careful consideration and stakeholder participation throughout the bill's development. Such assurance points to a fit between the goals of legislation and the interests of stakeholders, encouraging the formation of consensus and efficient government. House Bill 479's finalization process in Vermont is a prime example of how legislative processes are iterative. Policy outcomes are determined by constant consensus-building and improvement. With the bill almost finished, interested parties should expect improved transportation initiatives and legislative structures complementing the state's general socioeconomic goals.

In another related study, Munnich et al. (2012) employ a comprehensive methodology that integrates qualitative and quantitative approaches using surveys, interviews, and the examination of taxes and transportation models to assess equity impacts. In comparison to fuel taxes, the findings highlight the technical viability of MBUF implementation and suggest it as a potentially equitable and sustainable funding source for transport infrastructure. It also offers better revenue stability and also less environmental impact. The paper tackles equity problems and suggests ways for a fair distribution of the financial burden, although it also acknowledges limitations related to data and modeling assumptions. In their exploration of equity aspects in the appraisal of transport projects, Thomopoulos et al. (2009) offer a methodology built on the Multi-criteria Analytic Hierarchy Process. The study emphasizes the renewed interest in equity in transportation appraisal and presents a stakeholder-analysis paradigm that can help decision-makers.

Jacobs (2022) investigates other options for using mileage-based user fees to pay for transport infrastructure. Using quantitative analysis and policy evaluations—possibly with the aid of econometric modeling—the process most likely entails an extensive assessment. Information about the viability, efficiency, and difficulties of various mileage-based user fee schemes is included in the document. It is unspecified, but maybe economic or transportation modeling is the model that was utilized. Though they aren't explicitly mentioned, possible restrictions could include difficulties gaining broad acceptability, political concerns, and ambiguities in forecasting user behavior. A thorough account of the conversations and discoveries surrounding MBUF may also found in Baker, Taylor, and Stevens' summary of the 2013 National Symposium on Mileage-Based User Fees. The paper summarizes the symposium's presentations and debates using a qualitative methodology, providing important insights on the benefits, difficulties, and possible applications of MBUF (Baker et al., 2014).

Finally, a study conducted by Douma et al. (2021) delves into how the transportation system serves the driver that funds the benefits, offering a breakdown of horizontal and vertical equity. Through this breakdown, we can systematically categorize taxes as regressive or progressive, determining their efficacy. The study defines taxation based on the ability to pay as progressive, while other forms are considered regressive. Examples of regressive taxes include motor fuel tax and wheelage tax. The study uses the ability-to-pay and benefit- received criteria to assess distance-based fees (DBF) equity. Differences between rural and urban areas have an impact on DBF equity; potential detrimental effects on low-income people, those with disabilities, and people who depend on driving have been suggested. Variable rates and subsidies are meant to meet equitable social, mode, and geographical considerations. Shared mobility (SM) providers express apprehensions about increased operational costs and emphasize the societal benefits of their services. At the same time, modal equity concerns revolve around the potential hindrance to adopting electric vehicles. There are differences in geographic equity and recommendations for changes such as congestion charging. Overall, balancing DBF equity and various socioeconomic and geographic characteristics is argued to be difficult requiring further research and investigation.

Results for North Carolina

Primarily for the state of North Carolina, it has been found that the benefits of a revenue-neutral MBUF rate are more prominent for rural and mixed-use areas where travelers own fuel-inefficient vehicles and drive longer distances and thus pay more under given fuel tax prices (see Figure 2.2). However, there is a clear mismatch between the concerns about the unfairness of a mileage-based user fee to rural residents and the reality that it would likely cost rural residents slightly less than the current gas tax. Recent surveys have found that the strongest argument against an MBUF is that it unfairly impacts rural residents (despite the preliminary evidence in Figure 2.2) with 73% of respondents choosing this option (McCaleb et al., 2021; DHM Research, 2020). These surveys have also found that (a) public support for increased transportation taxes and fees was greatest among those with higher education levels, those living in urban areas, and those who were more knowledgeable about how transportation is funded and that (b) offering more context to the residents and making them aware about the state of transportation funding has a significant impact on their willingness to support MBUF.

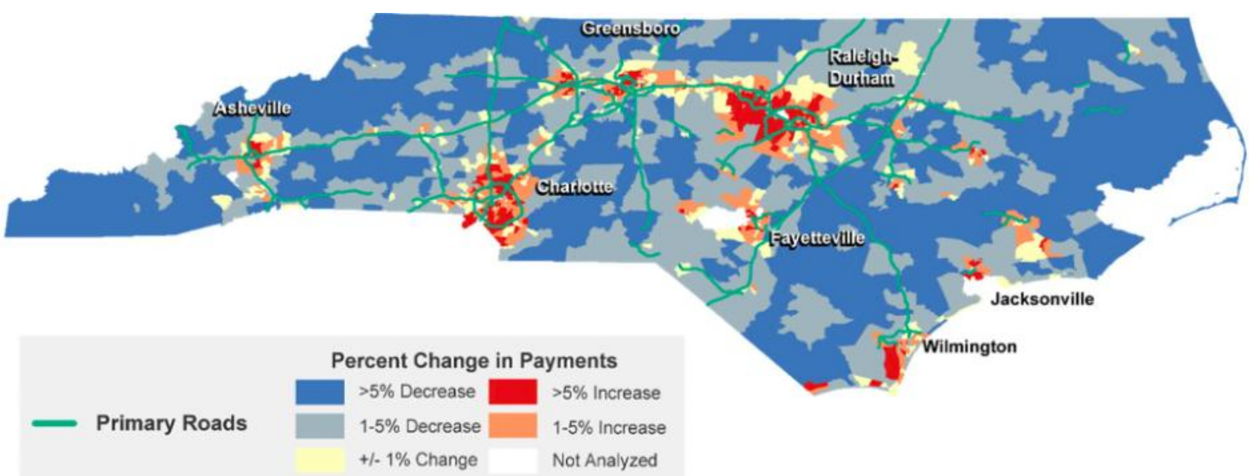


Figure 2.2: Percent change in household payments under a revenue-neutral MBUF (EBP US, Inc., 2020)

Summarizing the social and spatial equity under MBUF, it becomes evident that the main concern revolves around modal equity as how it will be influenced under the transition to MBUF. With the wide variety of cars along the market there is bound to be discrepancy between taxes paid out to the government. The main concern is light-duty cars vs trucks and doing taxation correctly. The argument that can be made is that trucks should have to pay more due to the impact their vehicles have on the infrastructure. Douma et al. (2021) research explores the idea that ESAL should be used for a vehicle-dependent surcharge due the impact vehicles have on asphalt pavement. A breakdown of rates structured according to specific vehicle type is provided and it is argued that: “all the vehicles grouped together in each category are assumed to have the same impact on the roadway system regardless of their actual occupancy/load and vehicle class". Future research should investigate such tiered structures through simulation or modeling approaches.

2.3.2 Privacy, policy, administrative, and planning issues related to MBUF

Technological costs and privacy concerns impact on public support for road mileage user fees have been studied and identified across various pilot programs. Duncan et al. (2014) investigate the relationship between privacy perceptions, technological costs, and the support for mileage fees. Some of the key findings are included below.

Georgia: Privacy concerns arise in VMT tax systems collecting location and time data in Sjoquist (2023). Over half of the survey participants expressed concern about sharing their vacation itinerary details. Some suggest handling data collected by private companies rather than the government. Notably, comparable data is already tracked by popular systems like E-ZPass, OnStar, and insurance plans.

California: Policy concerns are also discussed in Speroni et al. (2022). The fuel tax replacement with a flat rate Road Usage Charge (RUC) could negatively affect the least fortunate urban residents by driving up expenditures. The change eliminates financial incentives for fuel-efficient cars; however, it goes against state climate policy. Some policy alternatives are differentiated rates, lifeline rates for low-income households, and RUC adjustments depending on vehicle economy. It also reduces the impact of RUC on low-income families by encouraging fuel-efficient, emission-free cars or limiting the number of miles driven.

Minnesota: Privacy and administration concerns are also discussed in Douma et al. (2021). The definitions of personally Identifiable Location Information (PILI) and Personally Identifiable Information (PII) are crucial in understanding privacy concerns. Legal conditions have evolved post-2014, influenced by shifting public expectations and landmark court decisions—for example, Riley v. California and Carpenter v. United States. Federal statutes like the Privacy Act and Driver’s Privacy Protection Act are navigating the complex landscape alongside FTC rules. State privacy laws add a layer of complexity, often diverging from federal requirements. Concerns escalate when considering distance-based fees, with criteria for consent crucial in personally identifying information collection. Distinctions between public and private sector data gathering contribute to varying privacy expectations. Voluntary participation in data collection programs can reduce privacy expectations, prompting the need for stringent protective measures. Oregon and Minnesota provide examples of procedural approaches enhancing privacy in distance-based fee programs. Measures like encryption, one-way mechanisms, and third-party data acquisition safeguard anonymity in this evolving realm of transportation data privacy.

Louisiana: The public shows concern about the risks to personal privacy posed by GPS-based systems that monitor cars and handle sensitive data. Inadequate security for privacy may result in many people opposing the system. Some identified policy challenges include:

- Various mileage-based road user fees may result from different state regulations regarding tax collection.
- Issues involving intrastate and interstate jurisdiction provide difficulties, particularly regarding the effect on driving outside of the state.
- Local governments may establish charges using asset management, planning, and safety data.
- Policy demands to protect the budget, deal with possible double taxation, and consider long-distance commuters’ needs.

- To maintain equity, implementation issues must be considered, particularly for people with low incomes and those who drive electrified or less fuel-efficient cars.

Considering the implementation challenges, the study by Rufolo (2011) evaluated the feasibility and financial consequences of introducing a VMT fee system using information from Siemens, T-Systems, and Vodafone, three distinct Dutch providers. The study examined each provider's VMT pricing structure, particularly concerning Onboard Units (OBUs), communication strategies, calculation of charges, visitor management, and enforcement protocols. OBU, billing and payment, enforcement, declaration and customer care, and miscellaneous are the five categories of cost data. The investigation showed that the three suppliers differed in their annual depreciation, annual running costs, and initial setup costs. Total operational costs were lowest for Siemens and highest for T-Systems. Between $4.72 and $11 was the average yearly operational cost per 1,000 vehicle miles traveled among the providers. The study used specifications and cost estimates that Siemens, T-Systems, and Vodafone gave for installing a VMT charge system in the Netherlands. Due to differences in each provider's information, operational strategies, and technological choices, the study needed help to compare cost estimates. The interoperability specifications and privacy rules of the Dutch system also had an impact on the cost calculations. The results highlight how crucial it is to give careful consideration to interoperability, privacy requirements, and technology selections when developing and executing VMT fee schemes. The report also emphasizes the necessity of establishing methods to enable affordable implementations.

Broadly, pilot programs across the states have investigated ways to address these issues and their recommendations are discussed in Section 2.5.

2.4 Understanding MBUF using Behavioral Models

Incorporating new policy variables such as MBUF or tolls into existing travel demand models poses difficulties. The challenges arise from the necessity of acquiring the most recent data sources for the updated travel demand model, which is both costly and time-consuming. Moreover, developing the new demand model requires a contemporary traffic assignment model for accurate level-of-service calculations regarding time and cost. As a result, integrating new policy variables and assessing their impact within a comprehensive, statewide model is frequently a complex undertaking. A few studies have incorporated behavioral models in presence of MBUF which are discussed next.

Yang et al. (2016) used the Maryland Statewide Transportation model to evaluate the impact of MBUF. The statewide demand model used a nested logit model for mode choice. For the destination choice model, they adopted a multinomial logit model, and for the route choice model, they used a multi-class user equilibrium trip assignment. The authors estimated consumer surplus as a byproduct of the econometric model. Using various MBUF structures (flat, Ramsey, fixed interval, and fixed percentage), they found different consumer surpluses for different income groups. Calibrating a pre-estimated model and using it for forecasting is a standard practice in travel demand models. However, it is recommended to use a dataset that has already collected some information about individuals' perceptions towards MBUF. Therefore, artificially incorporating MBUF into a pre-existing model may not provide accurate results all the time.

Matteson et al. (2016) adopted a data fusion technique (i.e., statistical matching) for VMT estimation. The researchers used a wide range of data sources, including NHTS, to approximately calculate VMT. They calculated MBUF for the different geographical areas (rural versus urban), vehicle types (i.e., cars, SUVs, Van, or pickup trucks), Vehicle age range, and fuel usage (i.e., MPG). This study did not rely on a specific cross-sectional data; rather, it relied on various approximate data points, which may not give the exact VMT estimation.

Burris et al. (2015) used NHTS 2009 data and developed a series of predictions for urban and rural areas. In addition, they presented various comparisons of the MBUF structure. This research also used Lorenz curves and Gini coefficients to better understand the equity implications of MBUF. Similarly, Weatherford (2012) used the National Household-level Travel Survey (NHTS) 2001 and 2009 to estimate individuals' annual VMT. The researcher adopted Cobb-Douglas's demand model to estimate individuals' annual VMT. The Cobb-Douglas model uses the logarithm of both dependent and independent variables. The beauty of the Cobb-Douglas model is the elasticity values are equal to the parameter estimates, which makes elasticity comparison easier. As independent variables, the authors used household price, annual income, vehicle availability, population density, number of workers in the household, etc.

Duncan et al. (2020) used a linear regression model and tested whether we could influence people to participate in the MBUF program by better tax-rate design. The data came from four separate studies in four consecutive years. The authors tested three fare structures: weighted, fuel-economy, and flat fare. One observation regarding the model result is the goodness of fit is very close to zero.

To determine whether and how urban form characteristics relate to travel behavior changes that participants made in response to the mileage tax program, the study by Guo et al. (2011) examined two fee structures—a variable charge and a flat rate—on seven different vehicle miles traveled (VMT) scenarios. It discovered that charging a notably higher fee for driving in congested areas can effectively encourage households to drive less during those hours and locations where traffic is most a challenge. Under a charging scheme that charges a high rate for peak-hour travel, households in traditional (mixed-use, dense, transit-accessible) and suburban (single-use, low-density) neighborhoods are likely to reduce their overall and peak-hour travel. However, households in the traditional neighborhoods will likely reduce more. It also concludes that the underlying influence of urban form on travel behavior will probably be strengthened by a mileage tax program that charges a high rate during peak hours.

In chapters 4 to 6, we seek to address the modeling gap by designing behavioral models that can be integrated within the statewide demand models to enable holistic long-term impacts of various MBUF pricing scenarios.

2.5 Lessons Learned from Pilot Programs

Various states are currently evaluating the feasibility of MBUF fees as shown in Figure 2.3.

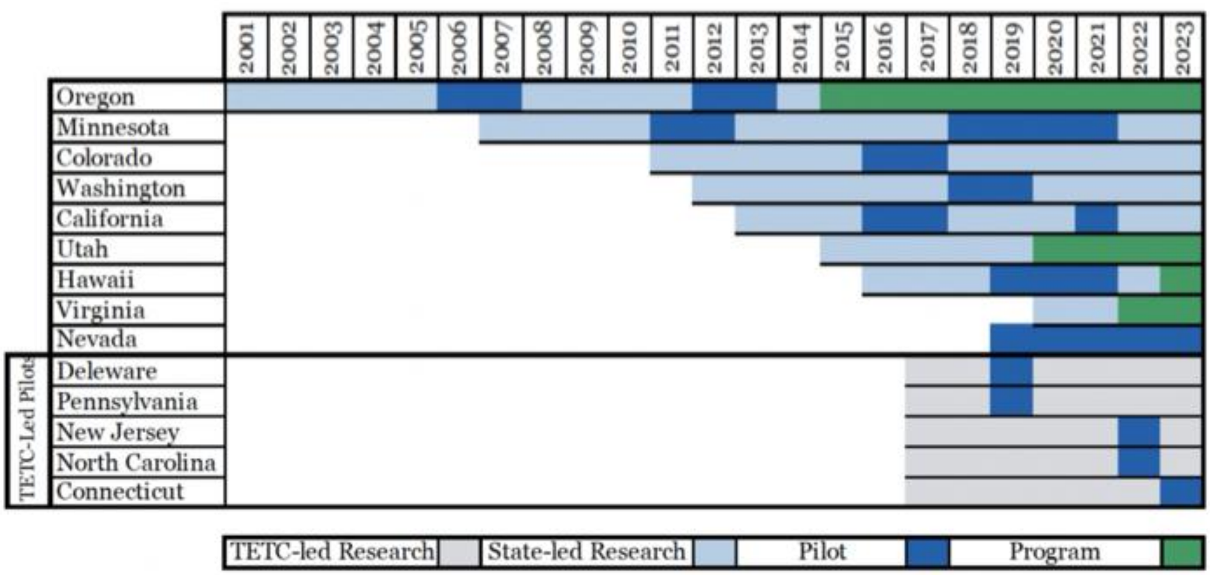


Figure 2.3: Timeline for State-led MBUF (Source: Shrode et al. (2023))

2.5.1 Oregon (Jones et al., 2017)

First, the report offers recommendation for partnerships with the private sector. Oregon's collaboration with the private sector for tax administration enhanced the system through value-added services, choices for volunteers, and innovation. Value-added services, facilitated by Senate Bill 810, included offerings like geo-fencing, car insurance partnerships, and engine diagnostics from account managers Azuga, emovis, and Verizon Telematics. The OReGO program's emphasis on choices, informed by outreach and focus groups, empowered volunteers to select account managers, devices, billing options, and more. This approach makes per-mile payments more acceptable in a mandatory program. Partnering with the private sector fostered innovation, expanded revenue potential, and introduced new technology, enhancing the overall tax experience. Second, the report discussed the importance of technology-agnostic solutions. The Road Usage Charge Administration System (RUCAS) is technology-agnostic, designed to receive and manage mileage and fuel data from different sources. RUCAS adapts to evolving technologies as long as the data is in ODOT-specified format. The road usage charge offers a credit for state fuels tax used on taxed miles, making it a potential replacement for state fuels tax. This system ensures fair payment based on actual road use, irrespective of vehicle efficiency.

Next, it was recommended that administrative costs need reduction for a fully mandatory program, with options like a flat annual usage charge and effective compliance mechanisms. Relying solely on in-vehicle devices was found to pose challenges, leading ODOT to explore alternative technologies like embedded telematics and cell phone imagery. Public opinion favored mileage-based charging as fair, ensuring everyone pays their share for road use, where the concerns about rural and low-income drivers were debunked by research showing equitable impacts (Whitty and Imholt, 2005). Oregon plans to make the program mandatory for new vehicles in 2026, with ongoing improvements and expansion of technology options through federal grants and participation in RUC West.

2.5.2 Utah (Utah Foundation, 2021)

In the 2021 Utah General Session, a "Road Usage Charge Program Special Revenue Fund" was established, allocating revenues from Utah's RUC program and other sources for administrative costs and transportation purposes. However, lawmakers recently rejected a bill proposing a reduction in the state RUC to 1.0 cent per mile, along with registration fee increases for electric and alternative fuel vehicles.

Utah's program offers similar insights into the financial unsustainability of fuel taxes amid rising vehicle efficiency. While RUC programs can address funding challenges, their implementation complexity and potential impact on fairness and privacy must be carefully considered. The report suggests a gradual approach to full implementation, using government vehicles for experimentation and modification based on program advancements.

2.5.3 Virginia (Virginia Department of Motor Vehicles, 2021)

Virginia implemented a highway use fee on alternative fuel, electric, and fuel-efficient vehicles starting July 1, 2020. Fuel-efficient vehicles, with a combined fuel economy of 25 mpg or more, incur a fee based on 85% of the taxes paid by a vehicle with a 23.7 mpg average, driven 11,600 miles annually. Electric vehicles face a similar fee calculation. Additionally, a voluntary mileage-based user fee (MBUF) program was introduced as an alternative to the flat fee, allowing vehicle owners to pay based on actual miles driven. The program's eligibility, fee structure, and collection procedures are defined in the Code of Virginia.

The conventional annual fee paid at the time of vehicle registration is replaced by an optional per-mile payment option for highway use fees for qualified drivers under Virginia's Mileage Choice Program. In order to encourage cost-effectiveness, participants pay according to the actual miles driven; fewer miles driven equals cheaper rates. The program makes sure that drivers won't have to pay more than the standard annual price even if they drive more than they had planned. The annual mileage average for Virginians is 11,600 miles. The program is managed by Emovis, the contracted operator, who also handles mileage records and client fee collections. This creative method provides flexibility and might encourage less driving by matching payments to real road usage.

The working group suggests enacting specific statutory safeguards for information gathered in the Mileage-Based User Fee (MBUF) program in Virginia. This legislation should address sharing and usage conditions, increasing customer confidence in data protection and encouraging program participation. The recommendation proposes modeling the information protection laws for MBUF data on existing statutes safeguarding information collected by toll facility operators in Virginia. Additionally, the working group advises enhancing information protection in the MBUF program by amending § 46.2-773 of the Code of Virginia to include explicit statutory safeguards for this data.

2.5.4 Hawaii (Hawaii Department of Transportation, 2022)

In 2018, Hawaii Department of Transportation (HDOT) initiated a three-year research, public outreach, and demonstration effort to explore per-mile road usage charging (called Hawaii RUC or HiRUC) as a fair and sustainable alternative to fuel taxes. The research aimed to provide recommendations for a gradual transition toward RUC to maintain usage-based funding for state road and bridge upkeep. Hawaii had set a target year of 2045 for achieving 100% renewable energy, including ground transportation.

After three years of thorough research, public outreach, and stakeholder engagement, HDOT reported the public and stakeholders sensitivities around the topic of transportation funding. Considering these sensitivities, HDOT showed interest in a straightforward pathway to implement a minimally disruptive Road Usage Charge program, aiming for a sustainable, equitable revenue for vital networks. HDOT suggested introducing RUC as an option for Electric Vehicles (EVs), replacing the $50 annual registration surcharge, with a per-mile rate similar to the average vehicle’s state gas tax payment. The recommendation aligns with Hawaii’s changing vehicle landscape, emphasizing the need for a flexible revenue system. Federal support covering 70% of RUC implementation costs strengthened the proposal. It is suggested that the initial RUC program may start small, allowing for evolution and a smoother transition. HDOT continues preparing for future policy and program adjustments, emphasizing proactive planning to meet long-term funding and clean energy goals. They plan to conduct additional work, including improving data quality, interfaces with county departments, and ongoing public engagement.

2.5.5 Ongoing Lessons from the Eastern Transportation Coalition (Jacobs, 2022)

The TETC coalition pilots and efforts contribute to a richer set of findings. The report makes five key findings. First, understanding the complexities of users is vital, especially trucks that contribute substantially to the Highway Trust Fund (HTF). Despite covering greater distances, the recurring costs exclusively borne by trucks, such as fuel taxes and fees, are significantly higher. Similarly, indicating potential benefits for rural drivers with the adoption of Mileage-Based User Fees (MBUF) is essential for its wider acceptance. Second, real-world pilots have proven effective in alleviating privacy concerns associated with MBUF. These programs provide drivers with practical experience, offering choices for mileage reporting, including non-GPS options. Establishing robust data privacy and security protections as integral components of MBUF system requirements further contributes to reducing privacy apprehensions. Third, leveraging technology has shown to provide solutions, particularly for passenger vehicle drivers using plug-in devices with GPS mileage reporting options. This approach opens opportunities for synergies between tolling, congestion management, and MBUF collection. Fourth, implementing a tiered rate based on miles per gallon (MPG) has proven ineffective (at least for the early stages), leading to significantly different charges for vehicles with similar MPGs. This approach is also challenging to explain, creating disparities and winners and losers, as detailed in the report. Finally, customized outreach efforts are essential for advancing MBUF, considering that it remains a relatively unknown concept for the general public. Public opinion surveys indicate that a significant portion of the population is unfamiliar with MBUF, emphasizing the need for increased outreach to bridge knowledge gaps and address potential concerns about this funding approach.

2.6 Summary

This chapter systematically examined the landscape of MBUF as a prospective sustainable source for transportation agencies' revenue.

Overall, MBUF holds various promises and opportunities. As a promising substitute for the gas tax, MBUF is shown to have versatile rate options, such as per-mile charges or facility-specific charges through a smart system. It can incorporate base fees or premiums tied to factors like time, location, or traffic levels. It also offers policy flexibility including the concept of a state-level "VMT budget" for drivers. Compared to fuel taxes, MBUF provides a stable revenue stream unaffected by fuel-related factors. Implementing the VMT charge at the federal level will ensure consistent funding for national transportation infrastructure, while state-level implementation allows local customization. There is exciting hope in the direction of transition towards MBUF with the current push at national and state levels. Advanced technologies will enable accurate mileage recording, reducing evasion risks.

Within the realm of investigating MBUF impacts, a key focus on fairness issues, spanning spatial and social dimensions, is present. These impacts are nuanced and depend on factors such as geographical location, social considerations, and individual transportation methods. Several studies highlight the potential benefits and drawbacks of MBUF implementation. Some argue that MBUF systems can address issues with gas tax revenue without unduly affecting different income groups, while others emphasize differential rates for creating fair benefits. Studies also stress the importance of considering regional variances and potential equality concerns when transitioning to MBUFs. However, challenges such as privacy issues, technological barriers, and concerns over equitable charge arrangements need to be addressed for successful MBUF implementation. MBUF offers the potential to address equity concerns through means testing and adjustments for unique travel patterns, particularly in rural areas with limited travel choices. Behavioral models, invoked for comprehensive understanding, will be instrumental in generalizing lessons from pilot programs conducted in diverse states toward long-term predictions.

Forthcoming research efforts should address critical questions such as the optimal approach to determining rates for trucks versus light-duty vehicles and formulating a system that incentivizes environmentally friendly cars without inadvertently diminishing the imperative of fuel efficiency. The implementation of MBUF is expected to bring about behavioral changes in individual travel patterns and freight routes. Anticipated changes include a potential reduction in individual travel demand as travelers may opt for alternative modes or shorter routes to mitigate MBUF-related costs. Carpooling and a shift to fuel-efficient vehicles are also expected outcomes. For freight routes, MBUF rates may influence logistics and lead to shifts in transportation modes to optimize costs. Accurate estimations of these long-term behavioral changes require a model-based evaluation, incorporating adjustments to existing travel demand models to assess the impacts of varying MBUF rates on travel patterns and freight movement. Furthermore, systematic evaluation of the impacts of different MBUF implementation scenarios in North Carolina are needed, aiming to identify disparities and investigate strategies to mitigate inequities across travel groups. Additionally, there is a need for incorporating the role of emerging technologies, including connected and autonomous vehicles (CAVs) and GPS-based tracking. The future success of MBUF implementations is contingent on evaluating the impacts of these technologies, especially regarding dynamic rate adjustments based on the time of day, warranting careful cost-benefit assessments.

Chapter 3. Survey Design and Statistical Analysis of Mode and Route Choices

Portions of Chapters 3 and 4 were previously published in Case Studies on Transport Policy (Hridoy et al., 2025) and are reused here with permission:

> *Hridoy, D. N., Tasnia, R., Pandey, V., & Hasnine, M. S. (2025). Towards vehicle miles traveled reduction: Impact of mileage-based user fee on travel mode choices. Case Studies on Transport Policy, 101454.*

3.1 Study Area

The study focuses on North Carolina, with survey sampling and modeling efforts designed to reflect the state's demographic and economic characteristics. The population has grown to approximately 10.4 million (a 9.5% increase over the past decade), with notable diversification driven by growth in Hispanic and Asian communities (U.S. Census Bureau, 2020). The state's economy continues to expand, particularly in metropolitan regions such as Charlotte and Raleigh, which serve as technology and financial hubs. Key socioeconomic indicators, including an employment rate of about 59.2%, a median household income of roughly $67,000, and a college attainment rate of 35.9%, were considered when ensuring that survey respondents represent North Carolina's demographic and regional diversity (U.S. Census Bureau, 2020). Figure 3.1 illustrates the spatial distribution of home and work locations reported by respondents across the state.

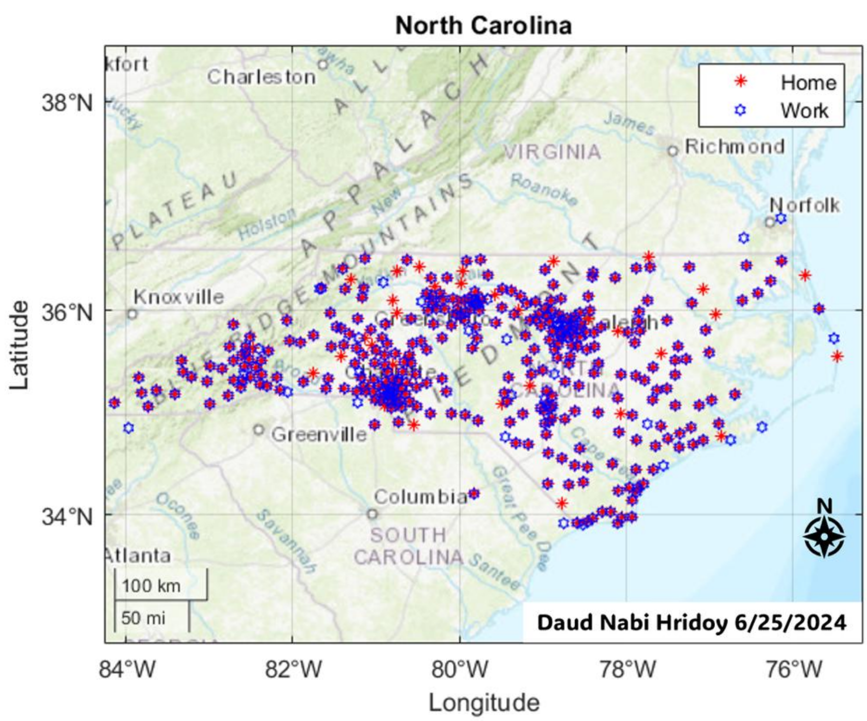


Figure 3.1 Study area (North Carolina) indicating home and work locations for the survey participants

3.2 Survey Development

"Survey to Understand the Impact of MBUF on Travelers Choices (SUMTC)" is a web-based survey (included in Appendix B). The survey design for this study considers two significant elements: revealed preference (RP) and stated preference (SP). The RP survey includes questions designed to collect data on three key categories: personal, household, and travel-related factors. To collect the data on personal attributes, questions are asked about the respondent's gender, age, race category, and whether they are of Hispanic or Latino origin. Moreover, SUMTC asked about their employment, education level, and driver's license status. Regarding household attributes, SUMTC asked about the dwelling type, number of members in the household, number of individuals living in the household over the age of 12, annual income of the household, bike, and car ownership of the household and their home location. Additionally, for travel-related attributes, questions are asked about their primary mode choice for trips in the last week, departure time, fuel category for the vehicle they use most frequently, and total miles traveled in the past year. Additionally, they are asked whether they own an EzToll/NC quick pass toll transponder or smartphone-based public transportation fare apps. Additionally, a question is asked to understand the usage frequency of different modes and toll roads by the respondents. Figure 3.2 summarizes the attributes of the RP survey.

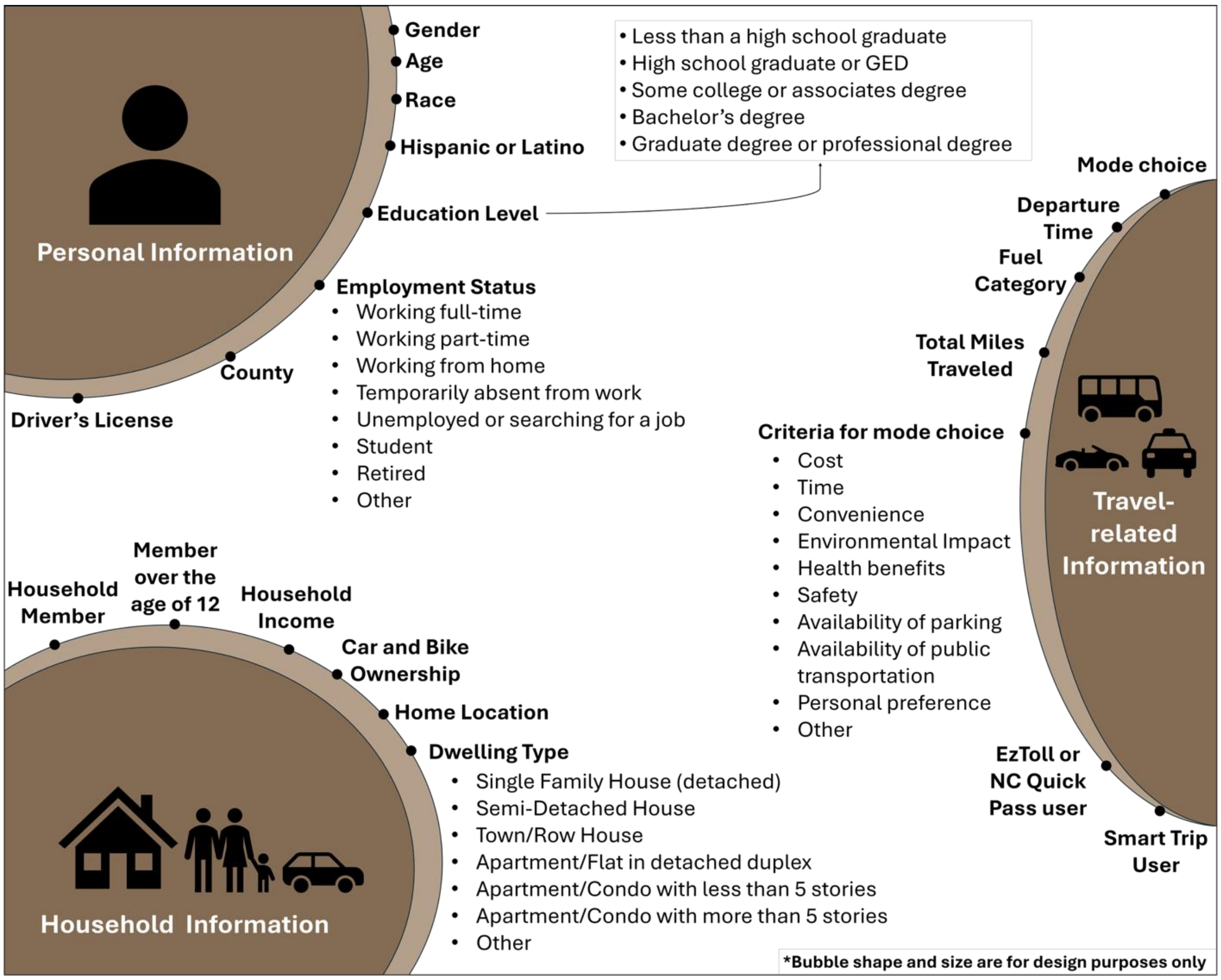


Figure 3.2: RP attributes summary in SUMTC

The main focus of this study's SP survey is to understand the impact of MBUF on travelers' mode and route choices. Several travel demand management (TDM) strategies such as fuel cost, parking/toll/admin cost, additional wait time, and state tax (i.e., fuel tax, MBUF, combination of both) along with level of service attributes (i.e., time, cost, distance) are considered in this study to evaluate their influence on travelers' choices. The distance values were estimated using the representative values from the North Carolina statewide demand model. The range for other values were derived by assuming specific values for the parameters as follows: The NC fuel cost excluding state tax was $3.4 per gallon as of April 2024, with a fuel cost share for a passenger in carpool mode at 60%. The fuel tax base rate was $0.43 per gallon, and the maximum MBUF rate, if the fuel tax was replaced by MBUF, was 2 cents per mile (considering the rates in the ongoing state MBUF pilots). The average speed values for different transportation modes were: Drive and Uber/Lyft at 40 mph, Auto Passenger at 35 mph, Transit at 25 mph, Bike at 20 mph, and Walking at 4 mph, which were used to derive the travel times. The base hiring cost for a taxi was $10, with an additional cost per mile of $2. The bus cost per mile was set at $0.2, and the proportion of the park and ride trip involving driving was assumed to be 20%. Finally, other variables such as wait times for buses and park and ride, were assumed to take a range of reasonable values between 4 to 15 minutes.

A D-efficient experimental design method was then adopted to design the SP choices for this study. A total of six mode-choice scenarios were generated using a D-efficient experimental design. More details about the SP survey design have been discussed in the next section. SUMTC considers a total of seven modes in the SP survey: 1. Drive Alone, 2. Passenger in a Carpool, 3. Park and Ride, 4. Uber/Lyft/Taxi, 5. Bike, 6. Walk, 7. Transit. The modes, along with corresponding attributes and values associated with the attributes, are presented in Table A.3.

3.3 Experimental Design and Data Collection

3.3.1 Mode Choice Experimental Design

The scenarios of this study are designed using "Ngene" software (ChoiceMetrics, 2021). This approach is proven to be providing significantly improved results than the typical orthogonal design (Hensher et al., 2009; Rose and Bliemer, 2009; Rose et al., 2008). Alternative-specific utility equations are written in the Ngene software to design the scenarios, and the coefficient values are obtained from previous studies. Once the RP and SP components are developed, they are added to a survey platform called Qualtrics. Then, the survey link is shared with the hired market research company, which collects the data from a random set of panel members living in North Carolina. Also, we don't provide any direct incentive to the respondents for taking part in the survey. The data collection is done in two steps: pilot survey and final survey. The pilot survey took place on April 4, 2024. An SP-only model is estimated based on the complete and valid 54 responses. The estimated parameter values from the model are then used to re-design the SP scenarios for the final survey. The D-error and S-estimate were significantly higher in the initial design. D-error captures the accuracy of an experimental design. A low D-error suggests a better design. The S-estimate indicates the desired sample size to achieve the desired efficiency in an experimental design. The estimated parameters from the pilot study ensure that the D-error is low with a reasonable sample estimation in the final design. The comparison between the before and after pilot study design is shown in Table 3.1.

Table 3.1: Efficiency Measurement Comparison

	Initial Design (Before Pilot)	**Final Design (After Pilot)**
D-error	8.03	1.31
S-estimates	7436.94	886.21

A total of six SP scenarios are presented to the respondents. After each scenario, the respondents selected their preferred mode for different activities such as work, grocery/shopping, and recreational. A sample mode-choice SP scenario presented to the respondents is provided in Figure 3.3.

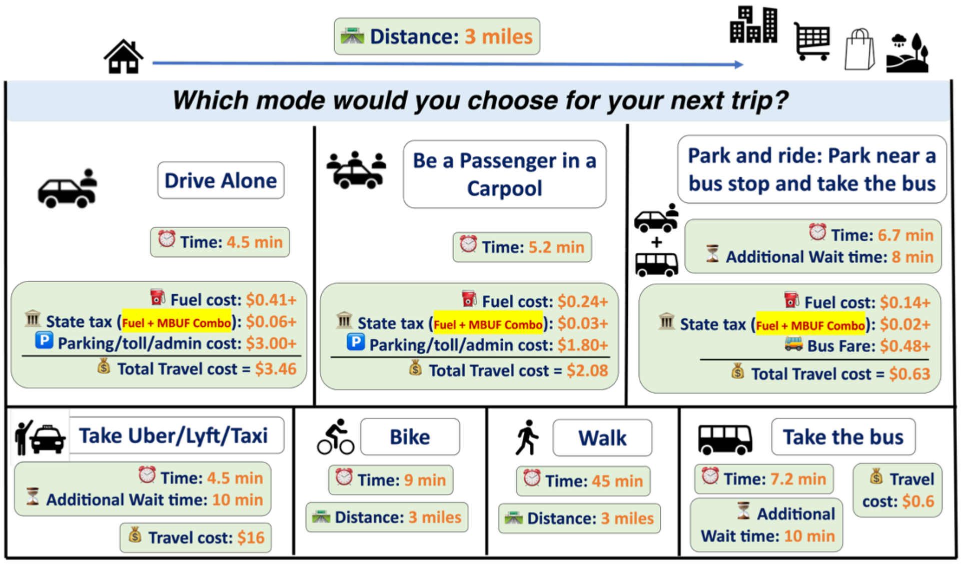


Figure 3.3: Example SP Scenario

3.3.2 Route Choice Experimental Design

Similar to the mode choice experiments, the route choice experiments incorporate attributes such as travel time, distance, fuel costs, tolls, parking fees, and administrative charges.

Participants were presented with two alternative routes—one subject to a MBUF and one without—for the same origin-destination pair. The routes differed in attributes such as travel time, total travel cost, vehicle fuel efficiency (set at either 15 or 35 miles per gallon), and MBUF rate (set at 2, 8, or 15 cents per mile). Each participant evaluated twelve scenarios in total, evenly split between short-distance (SD) and long-distance (LD) trips. For each scenario, participants first made a route choice based on basic time and cost information, then reconsidered their decision after viewing a detailed cost breakdown that included fuel, MBUF, and toll costs. After making their final selection, they rated their confidence in the decision. Figure 3.4 shows a sample stated-preference question, illustrating how respondents compared route options under varying pricing and service conditions. Respondents then re-evaluated their choice after cost visibility, followed by a confidence rating.

Table 3.2 presents both short- and long-distance scenarios to evaluate how varying MBUF rates (2¢–15¢/mile), vehicle efficiency, and toll costs influence total travel expenses and route decisions. For the same trip, low- MPG vehicles incur higher total costs not due to the MBUF itself, but because they continue to pay fuel taxes and consume more fuel per mile. We kept fuel tax constant across all scenarios to isolate the im- pact of MBUF. Despite consistent time savings on toll routes (10–20 minutes), the additional cost burden varies—ranging from under $2 to nearly $8 depending on the scenario.

Table 3.2: Summary of Short-Distance (SD) and Long-Distance (LD) Scenarios

Variable	SD1	SD2	SD3	SD4	SD5	SD6	LD1	LD2	LD3	LD4	LD5	LD6
MBUF (¢/mi)	2	8	15	2	8	15	2	8	15	2	8	15
Vehicle Fuel Efficiency (MPG)	15	15	15	35	35	35	15	15	15	35	35	35
Time on Toll Road (min)	10	10	10	10	10	10	50	50	50	50	50	50
Time on Non-Toll Road (min)	20	20	20	20	20	20	70	70	70	70	70	70
Miles Traveled on Toll Road	5	5	5	5	5	5	50	50	50	50	50	50
Flat Toll Cost ($)	5.00	5.00	5.00	5.00	5.00	5.00	10.00	10.00	10.00	10.00	10.00	10.00
Gas Tax (¢/gal)	43	43	43	43	43	43	43	43	43	43	43	43
Fuel Price ($/gal)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Trip Cost (Non-Toll, $)	2.49	3.09	3.79	1.18	1.78	2.48	14.92	18.52	22.72	7.08	10.68	14.88
Trip Cost (Toll, $)	6.24	6.54	6.89	5.59	5.89	6.24	22.43	25.43	28.93	15.90	18.90	22.40
Net Additional Cost ($)	3.76	3.46	3.11	4.41	4.11	3.76	7.51	6.91	6.21	8.82	8.22	7.52
Time Saved by Toll Road (min)	10	10	10	10	10	10	20	20	20	20	20	20

The final data collection took place on April 17 and April 18, 2024. A total of 1113 invitations were sent, and 1005 completed the survey. However, among them, there were some missing and invalid responses. In the complete responses, the respondents answered all the questions asked. After cleaning the data for incomplete and invalid responses, 881 samples are used for the model estimation, which is close to the sample size mentioned in Table 3.1.

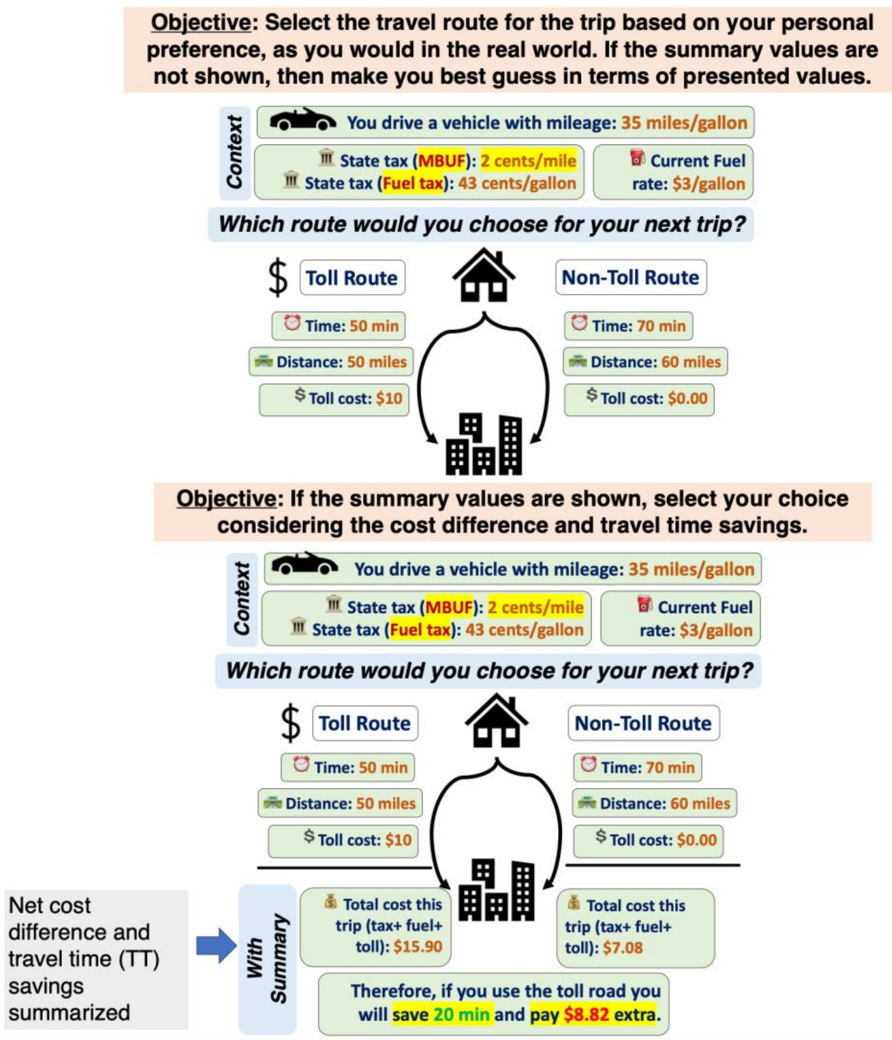


Figure 3.4: Sample Question for MBUF Route Choice Scenario

3.4 Mode Choice Data Analysis

Figure 3.5 shows the distribution of several attributes of the sample of this study. In this survey, the number of female respondents is higher than that of male respondents. Regarding race, a significant portion of the respondents are White or Caucasian (76.05%), followed by Black or African American (18.27%). The observation shows that in terms of education level, 26.11% of the respondents have a Bachelor's degree, while 15.10% hold a graduate or professional degree. Moreover, a significant proportion (35.87%) have some college or associates degree, and 20.89% have at least a high school degree. This is a good representation of the education level of the residents of North Carolina state. Interestingly, most of the respondents are either working full-time (36.10%) or retired (30.42%), while 9.53% are unemployed or searching for a job.

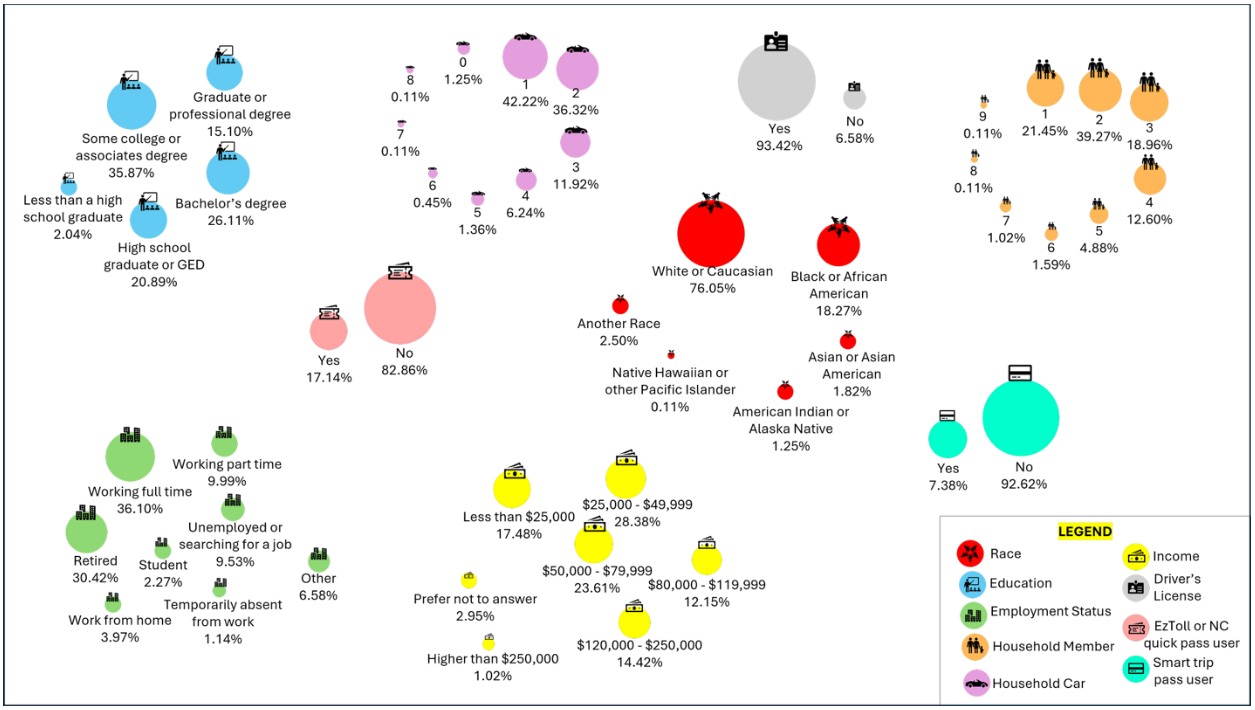


Figure 3.5: Descriptive statistics of the sample

Regarding income, 28.38% of respondents earn between $25,000 and $49,999, and 23.61% earn between $50,000 and $79,999. Moreover, only 1.02% of respondents earn more than $250,000 annually. In terms of members of the household, 39.27% of the respondents have at least two people in their household, whereas a single-person household is not far behind at 21.45%. Also, 18.96% and 12.60% of the respondents have three and four family members, respectively. For car ownership, respondents with at least one (42.22%) are the highest, followed by two vehicles (36.32%). Furthermore, 93.42% of respondents possess a driver's license. Besides, 17.14% of respondents own an EzToll or NC quick pass toll transponder. Lastly, 7.38% of respondents use a Smart Trip or other pass for public transportation on their average trip.

As part of SUMTC, respondents are asked about the criteria they typically consider when choosing a mode of travel. The survey results show that respondents prioritize "Cost" the most when selecting a travel mode, as shown in Figure 3.6a. Moreover, they are also sensitive to "Time" and "Convenience". Regarding daily trips, the survey tries to understand the frequency of modes and toll roads used by the respondents. The findings indicate that about 62% of the respondents use personal cars everyday/almost everyday, as shown in Figure 3.6b. Moreover, 32.35% rarely use toll roads, and a significant portion (48.13%) never used them for their trip purposes. Additionally, few respondents rely on public transportation, ride-share, and vehicle rental services for their daily trips. The results show that only 3.63% of the respondents use public transportation everyday/almost everyday and 68.90% have never used it for daily trips. This similar trend is observed for ride-share and vehicle rental services.

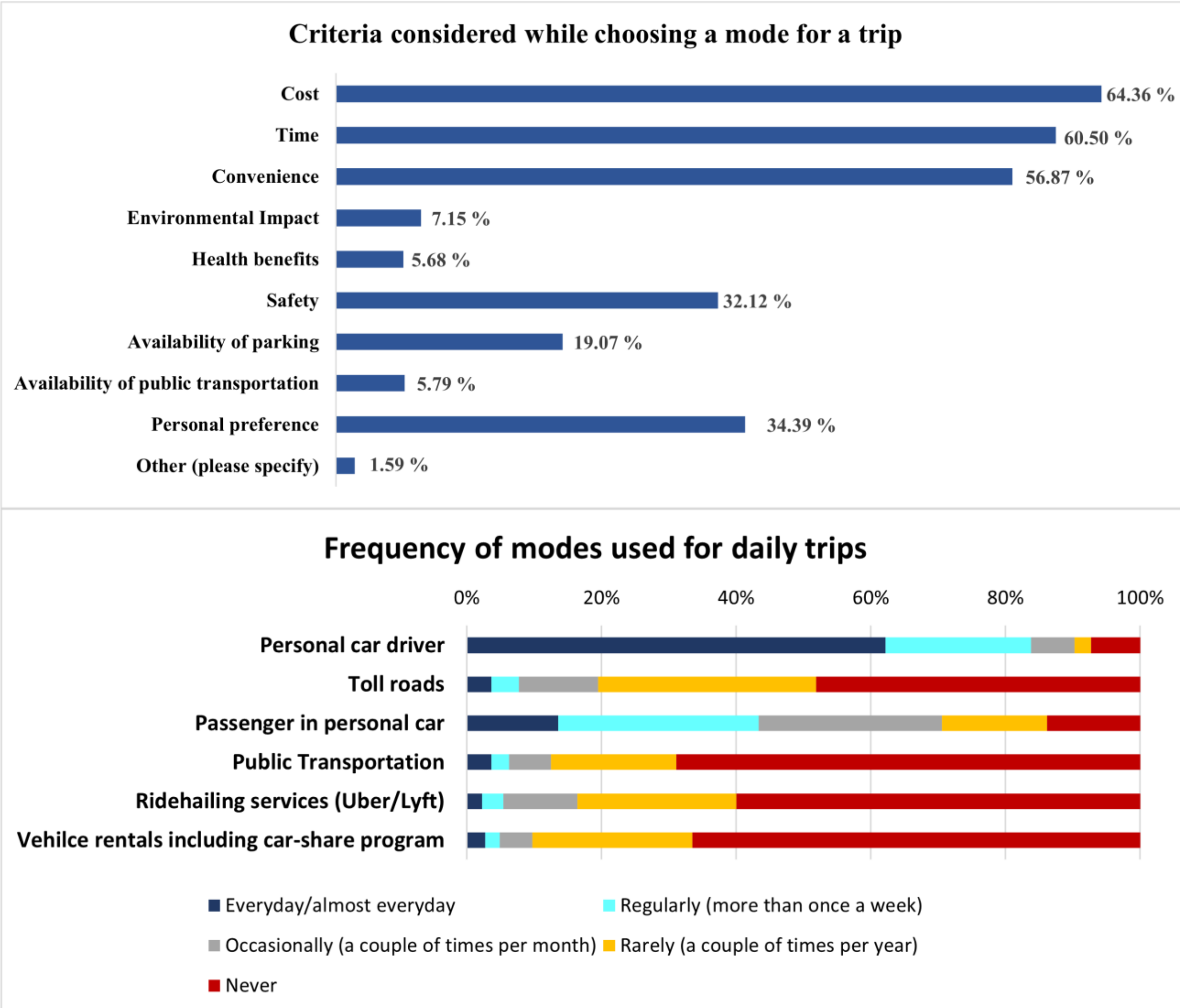
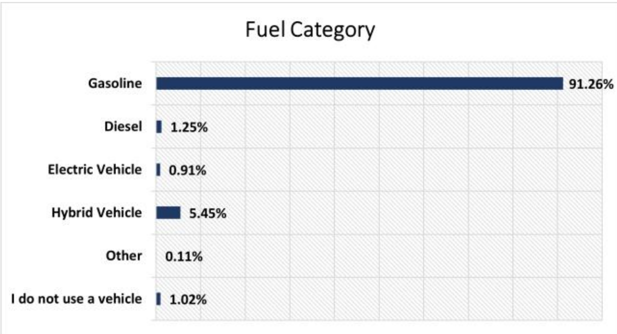


Figure 3.6: (a) Criteria for mode choice (Top), (b) Distribution of mode choice frequency (Bottom)

To learn more about respondents' travel behavior, they are asked about the fuel type of the vehicle they use most frequently and their average monthly fuel cost. Moreover, they are also asked about the total miles they traveled in the past year. It is observed from the result that "Gasoline" is the most used fuel category while using "Electric" vehicles is not that common among the respondents (Figure 3.7a). Also, about 47% of the respondents spent \$10 to \$100, and 31.13% spent \$100 to \$200 for fuel costs monthly (Figure 3.7b).

Furthermore, the average miles traveled by the respondents in the past year is about 13,388 miles, and the median is about 10,361 miles. Furthermore, 75% of the respondents traveled less than about 18,414 miles in the past year (Figure 3.8).

After the SP mode choice scenarios, to understand the perception of respondents on MBUF, they are asked to exhibit their agreement and disagreement on a set of statements. The five-point Likert scale is used to collect the responses to these statements. Figure 3.9 shows a summary of the responses by the respondents. The responses to these statements demonstrate that the proportion of respondents agreeing to shift to MBUF from fuel tax is relatively higher than disagreeing. Also, as long as the change in cost per trip is not that significant, they are not worried whether the tax is fuel-based or MBUF. Moreover, they prioritize the travel mode with the shortest travel time over the mode with the lowest costs.



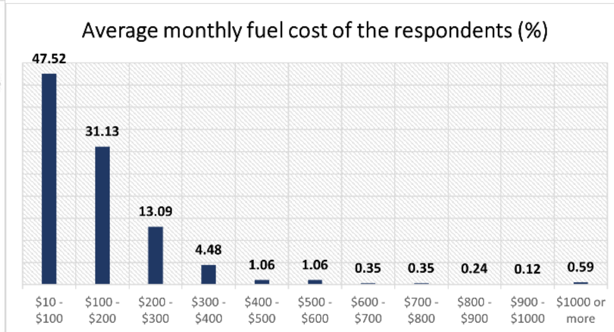


Figure 3.7: (a) Fuel category of the most frequently used vehicle. (b) Average monthly fuel cost.

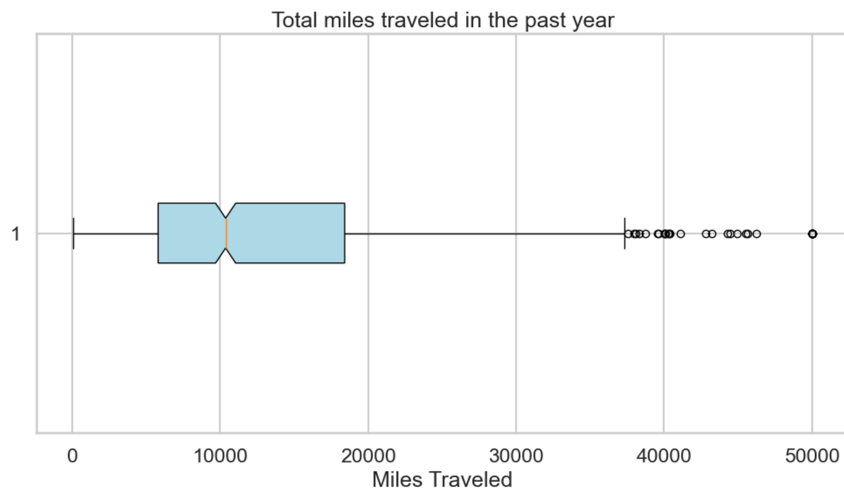


Figure 3.8 Vehicle miles traveled by the respondents (box-plot distribution)

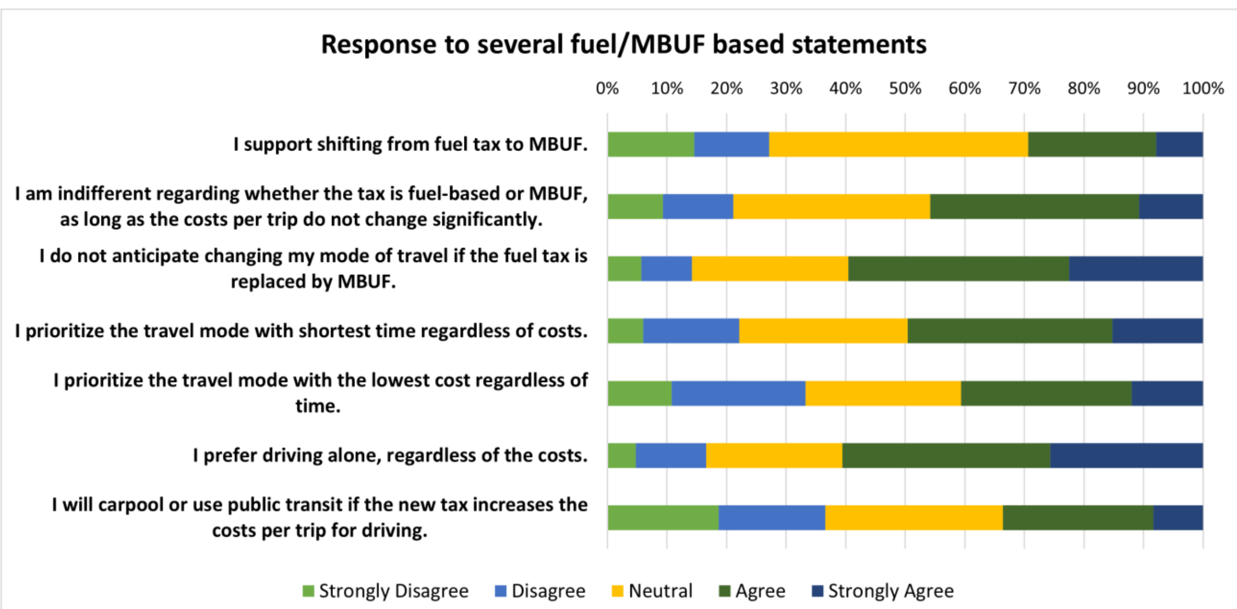


Figure 3.9 Stacked horizontal bar chart showing the percentage distribution across various MBUF-related mode choice statements

3.5 Route Choice Data Analysis

Distribution of Route Preferences Across MBUF Levels

Figure 3.10 illustrates respondents' attitudes toward MBUF-related route choice statements. A majority agree or strongly agree that cost and time influence their decisions, though concern increases under MBUF for longer trips.

The figure illustrates respondent agreement levels with the statement that a MBUF is a fair way to pay for road use, across eight different scenarios. Support is generally moderate to high, with the majority selecting "Agree" or "Strongly Agree," especially in costlier scenarios (e.g., Scenario 6), where 60%+ express positive sentiment. However, a non-negligible share still selects "Disagree" or "Neutral," highlighting lingering skepticism, possibly tied to income, fuel efficiency, or policy unfamiliarity.

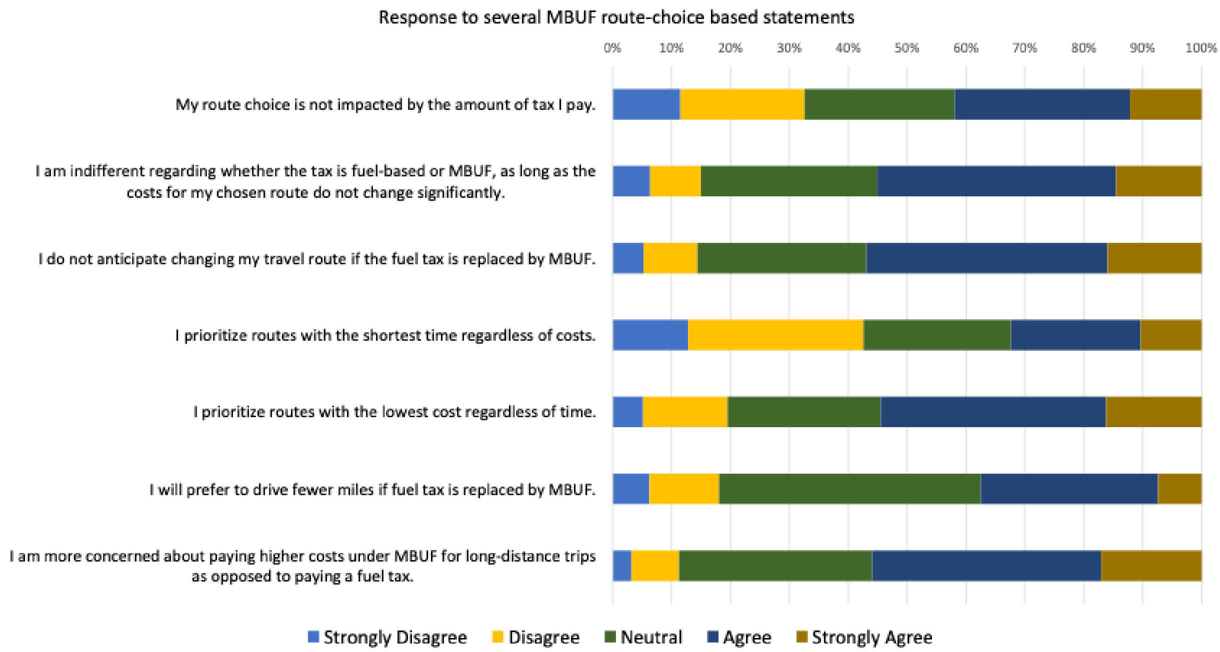


Figure 3.10: Stacked horizontal bar chart showing the percentage distribution across various MBUF-related route choice statements

MBUF vs Non-MBUF: Route Switching Behavior Under MBUF Policies

Studying whether providing an information summary, as shown in Figure 3.4, impacts route choices in both SD and LD scenarios (see Figure 3.11), we find limited behavioral change. The majority of users consistently remained on their original route (Toll → Toll or Non-Toll → Non-Toll), with stability rates averaging 82%. However, route switching (especially from Toll → Non-Toll) increased in higher MBUF cases (e.g., SD5, LD5, SD6, LD6), likely due to rising per-mile MBUF rates (up to 15¢/mile), which raised total trip cost by up to \$4–\$6 in SD and \$7–\$9 in LD scenarios. Scenarios where the user had access to a vehicle with lower fuel efficiency (15 MPG) faced greater fuel-related expenses (\$2.49–\$22.72) compared to 35 MPG vehicles, amplifying sensitivity to overall travel cost. This heightened price sensitivity likely prompted a shift away from toll routes, especially in longer trips where toll, fuel, and MBUF charges accumulate more substantially.

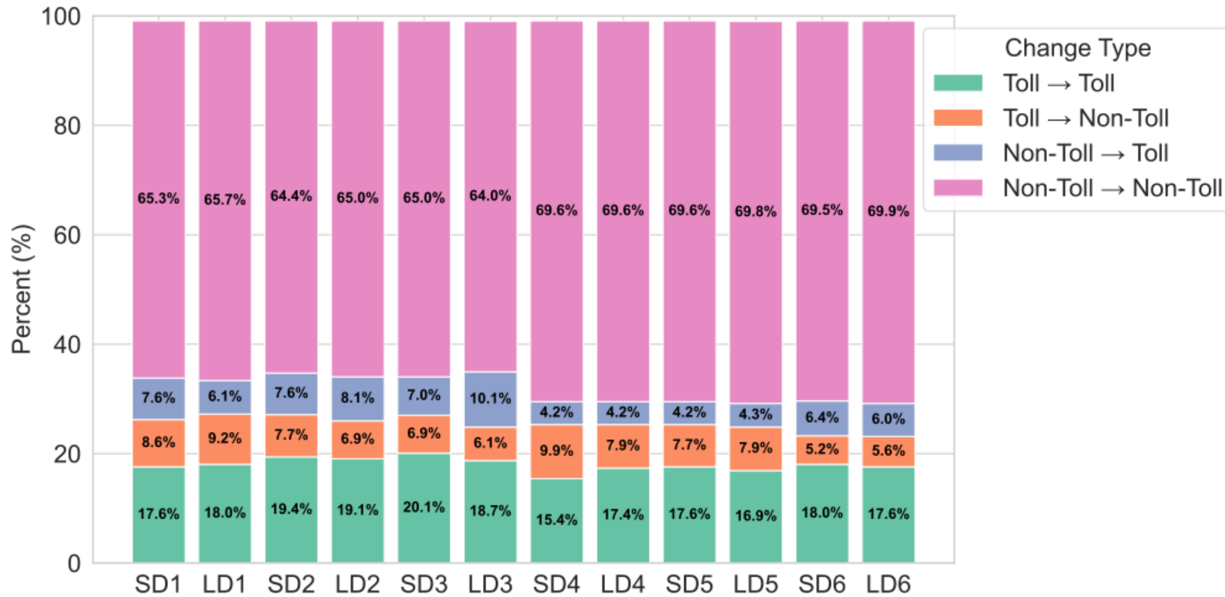


Figure 3.11: Short and Long-distance route choice transitions under scenarios outlined in Table 3.2

Distribution of Toll Preference Confidence level Scores Analysis

Figure 3.12 shows the distribution of Toll Preference Scores, ranging from 1 (strong confidence in choosing the non-toll route) to 10 (strong confidence in choosing the toll route), across all SD and LD scenarios, both with and without summary information. Across both SD and LD groups, a large share of respondents fall within low to mid confidence scores (1–5), indicating a general leaning toward non-toll routes. This tendency becomes more prominent in higher MBUF scenarios (SD5–SD6, LD5–LD6), where more respondents report low confidence in selecting toll options.

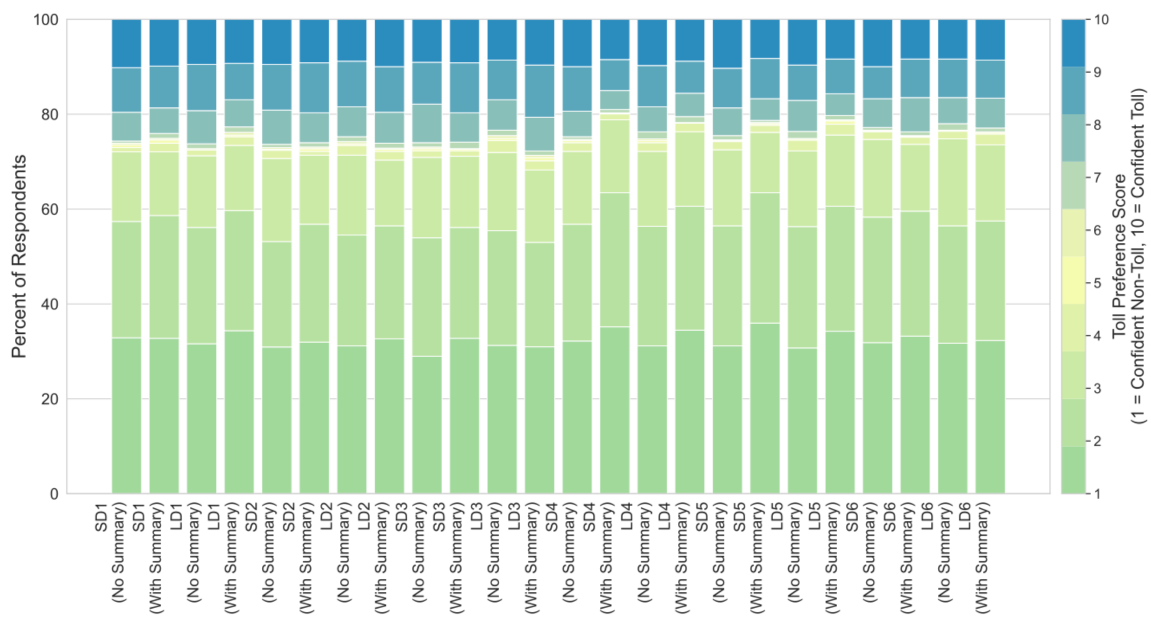


Figure 3.12 Distribution of Toll Preference Confidence level Scores Across Scenarios (With and Without Summary Information)

Scenarios with summary information consistently show a slight upward shift in preference scores, especially in LD scenarios, suggesting that presenting cost-time trade-offs can help improve confidence in toll route selection. However, in costlier conditions (e.g., SD6 and LD6), while the summary effect does lead to a modest increase in high toll preference scores (8-10), the overall distribution still remains concentrated in lower scores. This suggests that economic burden tends to outweigh informational nudges when toll, fuel, and MBUF costs are high.

Across the short-distance scenarios, we observe that users generally maintain stable route preferences, with modest shifts influenced by cost transparency and perceived trip value. Lower-income and low-MPG drivers tend to exhibit greater sensitivity to changes in MBUF rates, adjusting their route choices more frequently when detailed cost information is provided. However, overall route stability remains high, suggesting that many users perceive toll routes as worthwhile even with added per-mile charges. Gender distribution across scenarios remains relatively consistent, with small variations indicating that cost awareness affects both groups similarly. The next two chapters build discrete choice models that quantify how variables such as income, age, gender, and vehicle characteristics shape individual mode and route decisions under varying MBUF conditions.

Chapter 4. Mode Choice Modeling and Insights

4.1 Model Description

In this chapter, the collected RP-SP data from SUMTC is used to estimate joint RP-SP discrete choice models: (i) multinomial logit (MNL) model (ii) mixed logit model with error components. The model estimated using joint RP-SP data can overcome the drawbacks and provide improved results compared to the standalone RP-only or SP-only model (Hensher, 1994; Hensher et al., 1998; Cherchi and Ortúzar, 2006). The model formulation is briefly described next.

4.1.1 Joint RP-SP discrete model: Multinomial Logit (MNL)

Regarding joint RP-SP model, RP and SP data have their own utility equations (Cherchi and Ortúzar, 2006). The total utility of an individual (r) of choosing an alternative (d) can be described as:

$$U_{dr}^{RP} = \beta x_{dr}^{RP} + \sigma P_{dr}^{RP} + \epsilon_{dr}^{RP} = V_{dr}^{RP} + \epsilon_{dr}^{RP}$$

and

$$U_{dr}^{SP} = \beta x_{dr}^{SP} + \delta Q_{dr}^{SP} + \epsilon_{dr}^{SP} = V_{dr}^{SP} + \epsilon_{dr}^{SP}$$

Here:

$r =$ individual, $d =$ alternatives, U_{dr}^{RP} and U_{dr}^{SP} represent total utility for RP and SP data respectively, β is the parameter vector, σ and δ are the parameter set of alternative specific variables, x_{dr}^{RP} and x_{dr}^{SP} are the common attributes (available modes), P_{dr}^{RP} and Q_{dr}^{SP} are the alternative mode-specific attributes, ϵ_{dr}^{RP} and ϵ_{dr}^{SP} represent the random components of RP and SP utilities, and V_{dr}^{RP} and V_{dr}^{SP} represent the systematic utility terms for RP and SP data, respectively.

The variance of the RP and SP datasets is different. As a result, the scale parameter in RP and SP is not the same, and scaling is necessary. The scale parameter for RP is considered 1, and the scale parameter for SP is scaled based on it (Brownstone et al., 2000; Cherchi and de Dios Ortúzar, 2006). The loglikelihood function for the joint RP-SP multinomial logit model can be expressed as:

$$\mathrm{LL}(\beta) = \sum_{r=1}^{S} y_{dr} \ln\left(\frac{e^{V_{dr}}}{\sum_{d'=1}^{7} e^{V_{dr}}}\right) + \sum_{r=1}^{S}\sum_{n=1}^{N} y_{drn} \ln\left(\frac{e^{\phi^{SP} V_{dr}^{SP}}}{\sum_{d'=1}^{7} e^{\phi^{SP} V_{d'r}^{SP}}}\right)$$

where, S is the sample of individuals, d is the options of alternatives, N is the number of SP choice tasks, n is one out of the six scenarios, ϕ^{SP} is the scale parameter of the SP data, and $y_{dr} = 1$ if respondent r chooses mode d otherwise 0. Similarly, $y_{drn} = 1$ if mode d is chosen by respondent r in scenario n, or 0 otherwise.

4.1.2 Joint RP-SP discrete model: mixed logit with error components

A similar approach to the multinomial logit model is taken to model the RP mode choices. The utility and probability of an individual (r) choosing an alternative (d) is:

$$U_{dr}^{RP} = \beta' x_{dr}^{RP} + \sigma P_{dr}^{RP} + \epsilon_{dr}^{RP} = V_{dr} + \epsilon_{dr}^{RP}$$

$$P_{dr}^{RP} = \sum_{r=1}^{S} y_{dr} \ln\left(\frac{e^{V_{dr}}}{\sum_{d'=1}^{7} e^{V_{dr}}}\right)$$

The mixed logit with error components is employed for the SP mode choice model. The total utility of an individual (r) choosing an alternative (d) can be expressed as (Train, 2009):

$$U_{dr}^{SP} = V_{dr}^{SP} + \eta_{dr}^{SP}$$

$$V_{dr}^{SP} = \zeta' \nu + \omega_h \Lambda_{rh} y_{dh} + \epsilon_{dr}^{SP},$$

Where ζ represents vector of parameter values, ν represents vector of independent variables associated with SP scenarios, ω_h represents error components associated with nest h, Λ_{rh} represents variable that is normally distributed associated with individual r and nest h, and $y_{dh} = 1$ if alternative d is in the nest h otherwise 0.

For RP and SP, the assumption for the distribution of the random component is that it is independent and identically distributed (iid) type I extreme value (Train, 2009). The probability of an individual (r) choosing an alternative (d) in the choice scenarios (n) can be expressed as:

$$P_{rn}^{SP}(d) = \int \frac{e^{\phi^{SP} V_{dr}}}{\sum_{d' \in E_r^{SP}} e^{\phi^{SP} V_{d'r}}} f(\theta) d\theta$$

Here, ϕ^{SP} is the scale parameter of the SP data, E_r^{SP} are the SP scenarios choice set for individual r, and $f(\theta)$ is the probability density function of θ.

In SUMTC, respondents completed a total of six SP choice scenarios, so the probability of individuals choosing different alternatives in these choice scenarios can be expressed as:

$$P_r^{SP}(d_1, d_2, d_3, d_4, d_5, d_6) = \prod_{n=1}^{6} P_{rn}^{SP}(d_n)$$

The loglikelihood for the joint RP-SP mixed logit model can be expressed as:

$$LL(\beta, \eta, \omega, \theta, x, \nu, y) = \prod_{r=1}^{S} \left(P_r^{RP}(d)^{y_{rd}^{RP}} \times \left(\prod_{n=1}^{6} \left(P_{rn}^{SP}(d) \right)^{y_{drn}^{SP}} \right) \right)$$

The models are estimated using the classical maximum likelihood method and by writing codes in the “GAUSS” programming language (GAUSS, 2024). For the mixed logit model error components simulation, the Halton sequence technique is used.

4.2 Model Results

The detailed results of the estimated multinomial logit (MNL) models are provided in Table A.4, Table A.5, and Table A.6 and the mixed logit model results are detailed in Table A.7, Table A.8, and Table A.9. These tables correspond to different trip purposes, specifically work, grocery/shopping, and recreational trips. The t-statistics of the parameters were computed at a 95% confidence level, with most parameters demonstrating statistical significance. Although some parameters did not achieve statistical significance at the 95% confidence level, they have been retained in the model results due to their valuable insights into mode choice modeling.

The $\rho 2$ value for the mixed logit model generally exceeds that of the traditional MNL model, as it captures individual-specific variations and random preference heterogeneity. This results in a more precise and accurate representation of choice behavior, leading to a significantly improved model fit. The findings from this study align with these theoretical expectations emphasizing the mixed logit model’s effectiveness. The $\rho 2$ values obtained from the mixed logit model for work trips (0.48), grocery trips (0.59), and recreational trips (0.46) indicate an improved model fit compared to the corresponding values from the MNL model, which are 0.44, 0.57, and 0.38, respectively. It is worth mentioning that the t-statistics for the error components in the mixed logit models are tested against a value of 1, and they are statistically significant.

Initially, the level of service attributes such as travel time, trip cost, and travel distance are estimated in both MNL and mixed logit models. The results from these models exhibit the anticipated negative sign for these parameters. In terms of travel time, the findings indicate that for mode choice individuals exhibit greater sensitivity to work trips compared to grocery or recreational trips. One potential rationale is that individuals are required to arrive at their workplace promptly, following a specific schedule. Regarding travel distance, the findings exhibit that individuals are least sensitive to travel distance for recreational trips, potentially due to the willingness to travel far for enjoyable activities and fewer time constraints. It is important to note that the travel distance parameter is only considered for bike and walk modes when estimating the models.

Furthermore, parameters related to motorized vehicles and transit, such as fuel cost, parking/toll/admin cost/bus fare, and additional wait time, are tested in the models. The model findings indicate that individuals are less likely to prefer drive-alone or carpool modes with increased fuel costs. Also, individuals are less likely to prefer drive-alone, carpool, and park-and-ride modes for their trip purposes, with increased parking/toll/admin cost/bus fare. The model result also reveals that increased wait time reduces the attractiveness of the park-and-ride and transit modes. This is consistent with the intuitive understanding that people generally dislike waiting. This trend is observed in both MNL and mixed logit models.

Lastly, the study examines the interaction between several explanatory variables (e.g., employment, age, education level) and strategies like MBUF and fuel tax to understand their influence on travelers' mode choices. The results show that full-time workers are less inclined to opt for drive-alone, carpool, and park-and-ride modes with higher MBUF or fuel tax. For full-time workers who travel to work every day, MBUF will impose a visible incremental cost to their travel. This could be the inherent reason why full-time workers are less inclined to opt for modes where there is an effect of MBUF.

Similarly, part-time or full-time college/university students are less likely to prefer carpool and park-and-ride modes with increased MBUF and fuel tax. Furthermore, the result reveals that full-time workers are more sensitive to MBUF for work trips and more sensitive to fuel tax for grocery/shopping-related trips. Since this analysis did not investigate distance-specific shopping trips and their sensitivity towards the cost of fuel, it is difficult to comment on this specific finding. However, one possible reason is that fuel tax could be very high for long-distance shopping trips. Unlike big cities like Chicago and New York City, some cities in North Carolina do not have a centralized shopping mall where people can do all types of shopping. For example, many individuals who live in Greensboro (NC) may need to drive to High Point (NC) for organic poultry and meat. So, this finding regarding fuel tax could be more applicable to transportation in spread-out locations.

Conversely, part-time or full-time students are more sensitive to MBUF for recreational trips and show higher sensitivity to fuel tax for grocery/shopping trips. As for age, young individuals are less likely to prefer drive- alone, carpool, and park-and-ride options with increased MBUF or fuel tax, and this trend is also observed for older adults. Additionally, young individuals are more sensitive to MBUF for work and grocery/shopping trips and also more sensitive to fuel tax for recreational trips. Conversely, elderly individuals show more sensitivity to MBUF for work-related trips and are more responsive to fuel tax for grocery/shopping trips. The model results also reveal that young individuals are more sensitive to MBUF than older adults. The difference can be explained by the fact that younger individuals typically have lower incomes than older adults. Consequently, the direct cost per mile might be more visible to them than the relatively less visible cost of fuel taxes. Some other parameters are also tested in the model but are not added to the final model as they did not show statistical significance within 95% confidence interval.

Overall, the mode choice models reveal the following findings:

- Travelers show higher sensitivity to travel time and cost during work trips than for grocery or recreational trips, indicating that commuting decisions are less flexible but still responsive to cost changes.

- Higher MBUF or fuel tax rates reduce the likelihood of choosing drive-alone, carpool, and park-and- ride modes, with the strongest response observed among full-time workers and college students.
- Sensitivity to MBUF is greater in regions with longer commuting distances or dispersed destinations, such as areas where shopping or employment opportunities are spread across multiple cities.
- While MBUF-related cost coefficients are statistically significant, their magnitudes are small, indicating that moderate MBUF rates would not cause large shifts in mode choice. This suggests that traveler behavior is more influenced by cost transparency and perceived fairness than by the absolute rate level.

4.3 Conclusion

This chapter presented a mathematical modeling framework to understand the impact of MBUF on travelers' mode choice behavior. It investigated how MBUF affects different socioeconomic groups for different trip purposes, such as work, grocery, and recreational trips.

The findings from the descriptive analysis indicated that "Cost", "Time", and "Convenience" influence the most when choosing a travel mode for daily trips in rural and urban parts of North Carolina. The results reveal that respondents are most likely to use a personal car for daily travel, where they rely on "Gasoline" as the fuel type for their vehicles and spend around $10 to $100 monthly on fuel. It is found that, a majority of the respondents are likely to adapt to MBUF if it is implemented. Additionally, as long as the cost per trip is not significantly high, they are not concerned whether the tax is fuel-based or MBUF.

The joint RP-SP model results reveal that, in general, individuals are less likely to opt for driving, be a passenger in a carpool, or use park and ride mode if the MBUF rate is high. Additionally, full-time workers are more sensitive to MBUF for work trips, whereas part-time or full-time college students are for recreational trips. The results also reveal that young individuals show more sensitivity towards MBUF than older adults. Regarding trip purpose, young individuals are more responsive to MBUF for work or grocery shopping trips than recreational trips. Lastly, increased parking, toll costs, bus fares, and delays make drive alone, carpool, transit, ride-share, and park and ride modes less attractive to individuals.

The results show that individuals' sensitivity towards MBUF varies for trip purposes and socio-demographic groups. Based on these results, some policies can be recommended:

- Adaptable MBUF rates could be applied based on the purpose of the trip. As people are more sensitive to MBUF for work trips, the rate of MBUF could be higher for work trips than for grocery or recreational trips to reduce congestion and Greenhouse Gas (GHG) emission in busy cities like Greensboro or Raleigh. This might encourage individuals to switch to public transit or other sustainable modes of transportation (if present). This could help in reducing the dependency on personal car and MBUF could work as an effective and low-cost transportation demand management (TDM) strategy.
- Higher MBUF rates for work trips and increased parking or admin costs at workplaces could discourage individuals from driving and encourage them to switch to carpool, transit, and park and ride modes. This will help in reducing traffic congestion and emissions.

Regarding future work, one suggestion would be to evaluate the impact of MBUF on individuals' departure time choice behavior. This could help understand individuals' travel behavior, specifically during peak hours. Moreover, it could provide information on the impact of time-varying MBUF rates on travelers' departure time choices. Another extension of this work would be to look at the influence of MBUF on individuals' tour-based mode choice behavior, specifically whether MBUF will influence the mode choices individuals make sequentially throughout the day.

Chapter 5. Route Choice Modeling and Insights

A portion of this chapter is based on a manuscript currently under review at the Transportation Research Record and accepted for presentation at the 2026 Transportation Research Board Annual Meeting:

> *Gorji-Sefidmazgi, A., Tasnia, R., Pandey, V., Hridoy, D. N., & Hasnine, M. S. (2025). Evaluating the impact of mileage-based user fees on travel route choices. Manuscript under review, Transportation Research Record.*

This chapter proposes an approach to evaluate how MBUF tax influences driver route choices, particularly between high cost and low-cost options. Unlike prior studies, our research integrates (i) controlled variation in MBUF levels within a stated-preference survey, (ii) machine learning techniques that maintain behavioral monotonicity, and (iii) observation-level interpretability through model explainability. While MBUF has been broadly debated from policy and revenue perspectives, its direct impact on individual route choice behavior remains underexplored. To address this gap, we designed a stated-preference experiment involving 881 individuals, each evaluating 12 travel scenarios characterized by varying MBUF rates and trip features. See Chapter 3 for details on survey design.

We applied CatBoost (Dorogush et al., 2018), a gradient-boosted decision tree algorithm well-suited for categorical data and complex interactions, to predict toll road usage based on scenario attributes and individual socio-demographics. To interpret the model, we used SHAP values, which quantify the marginal contribution of each variable to each individual prediction. This approach enables observation-level transparency and supports integration of machine learning with behavioral modeling frameworks for policy analysis.

5.1 Model Development and SHAP-Based Interpretation

5.1.1 Feature selection

To improve model efficiency and reduce complexity, we applied feature selection to exclude variables with low predictive value. This process helps streamline training, improve generalization, and enhance interpretability by focusing on the most relevant inputs. We used CatBoost's built-in SHAP-based feature selection method to identify key features. Table A.10 presents all input variables and highlights those retained after selection. Note that while the "Student" variable includes a K–12 category, no respondents in our dataset fell into this group, as the survey was limited to individuals aged 18 and older.

5.1.2 CatBoost

A key challenge in our dataset was the prevalence of high-cardinality categorical variables, which limited model choices. Traditional approaches like one-hot encoding would have led to a sparse, memory-intensive feature space and increased risk of overfitting. To address this, we used CatBoost (Dorogush et al., 2018), which natively handles categorical features without explicit encoding, making it well-suited for our data structure.

To assess model performance, we report the following standard classification metrics:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1} - \text{Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Macro Avg} = \frac{1}{N}\sum_{i=1}^{N}\text{Metric}_\text{i}$$

$$\text{Weighted Avg} = \frac{\sum_{i=1}^{N}\text{Support}_\text{i}\cdot\text{Metric}_\text{i}}{\sum_{\text{i}=1}^{\text{N}}\text{Support}_\text{i}}$$

Here, TP (true positives) refers to correctly predicted positive cases, FP (false positives) to incorrect predictions of positive cases, FN (false negatives) to missed positive cases, and TN (true negatives) to correctly predicted negatives. Precision captures how many predicted positives are actually correct, while recall measures the proportion of true positives that were successfully identified. F1-score balances these two, offering a single metric that penalizes imbalanced performance, which is particularly useful in our case for assessing how well the model handles the uneven distribution of positive and negative outcomes. Accuracy represents the share of correct predictions overall, but in our dataset, where positive cases are less frequent, it can overstate performance. To address this, we also compute the macro average, which treats each class equally, and the weighted average, which adjusts for class imbalance by weighting metrics by the number of true instances per class.

5.1.3 Monotonic constraints

To ensure the model reflects realistic behavioral patterns, we imposed monotonic constraints on selected features using CatBoost's built-in functionality and hyperparameter changes. Monotonicity was applied where prior literature and domain knowledge suggest directional effects on route choice. Specifically, time on non-toll roads and time saved were constrained positively, indicating that increased delays or greater time savings should increase the likelihood of choosing toll routes (Kim and Bansal, 2024). Conversely, distance on non-toll roads, toll road time, toll cost, and total cost paid were constrained negatively, reflecting that increases in these variables are expected to reduce toll route preference. These constraints guide the model to produce consistent, interpretable responses aligned with established behavioral theory.

5.1.4 SHAP analysis for interpretation

SHAP (Lundberg and Lee, 2017) is a model-agnostic method based on cooperative game theory that explains individual predictions by assigning each feature a contribution value. When applied to complex models like CatBoost, SHAP helps interpret both global feature importance and the direction of their influence (positive or negative) on predictions.

5.2 Results and SHAP Analysis

5.2.1 Performance

The CatBoost model demonstrated strong predictive performance on the test set, achieving an overall accuracy of 87 percent. Class 0 (non-toll or lower-cost route) showed high precision at 0.88 and recall at 0.96, resulting in an F1 score of 0.92. Class 1 (toll or higher-cost route), though less frequent, had a precision of 0.84 and a recall of 0.63, leading to an F1 score of 0.72. These results indicate that the model performs well in identifying non-toll choices, with some underprediction of toll route selections.

The macro average F1 score, which gives equal weight to each class, was 0.82. The weighted average, which accounts for the distribution of samples across classes, reflected similar performance. Broadly, these metrics suggest that the model maintains good overall accuracy while reasonably capturing behavior in both majority and minority classes.

Although predictive metrics were significant, the credibility of route choice models also depends on the inclusion of behaviorally relevant variables. Results around incorporating key attributes such as travel time and cost, combined with monotonic constraints and SHAP-based interpretation, are discussed next.

5.2.2 SHAP analysis

Figure 5.1 presents a SHAP Beeswarm plot, which visualizes the contribution of each feature to the model's predictions. The vertical axis lists features in order of their overall importance, while the horizontal axis shows the magnitude and direction of their impact on the model output. Positive SHAP values indicate a push toward selecting the toll route (coded as 1), while negative values push the prediction toward the non-toll route (coded as 0). Each point represents a single prediction, and its color reflects the feature value—red for high and blue for low, while categorical variables are marked as gray.

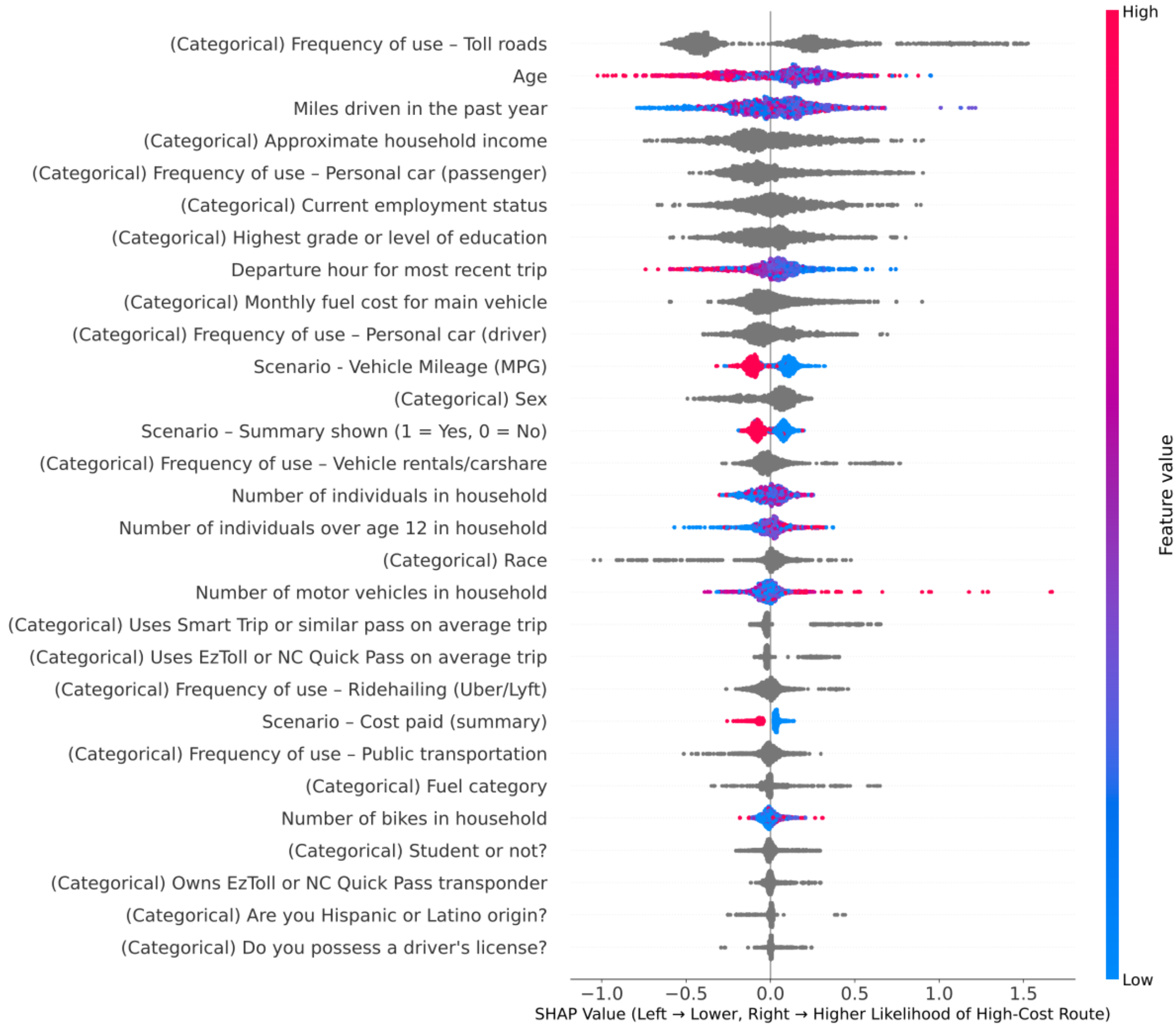


Figure 5.1 SHAP Beeswarm Plot Showing Feature Importance and Direction (Categorical features are grayed out; however, the variables are presented in the order of importance from top to bottom)

Interpretation of the plot reveals that toll road usage frequency and age are the most influential predictors in traveler's route choices. Older individuals are more likely to choose non-toll roads, while cost-related variables tend to reduce the likelihood of toll road selection. Since several influential features are categorical, we further examine how their specific values impact the model's output in the following analysis.

Figure 5.2 presents mean SHAP values indicating the influence of categorical variables on the likelihood of choosing high-cost (toll) routes. As expected, the most important predictor is the frequency of toll road use: individuals who use tolls every day or regularly show strong positive SHAP values (+1.19, +1.09), significantly increasing the probability of selecting high-cost routes. In contrast, users who never use toll roads have a negative SHAP (–0.43), pulling preference toward low-cost routes.

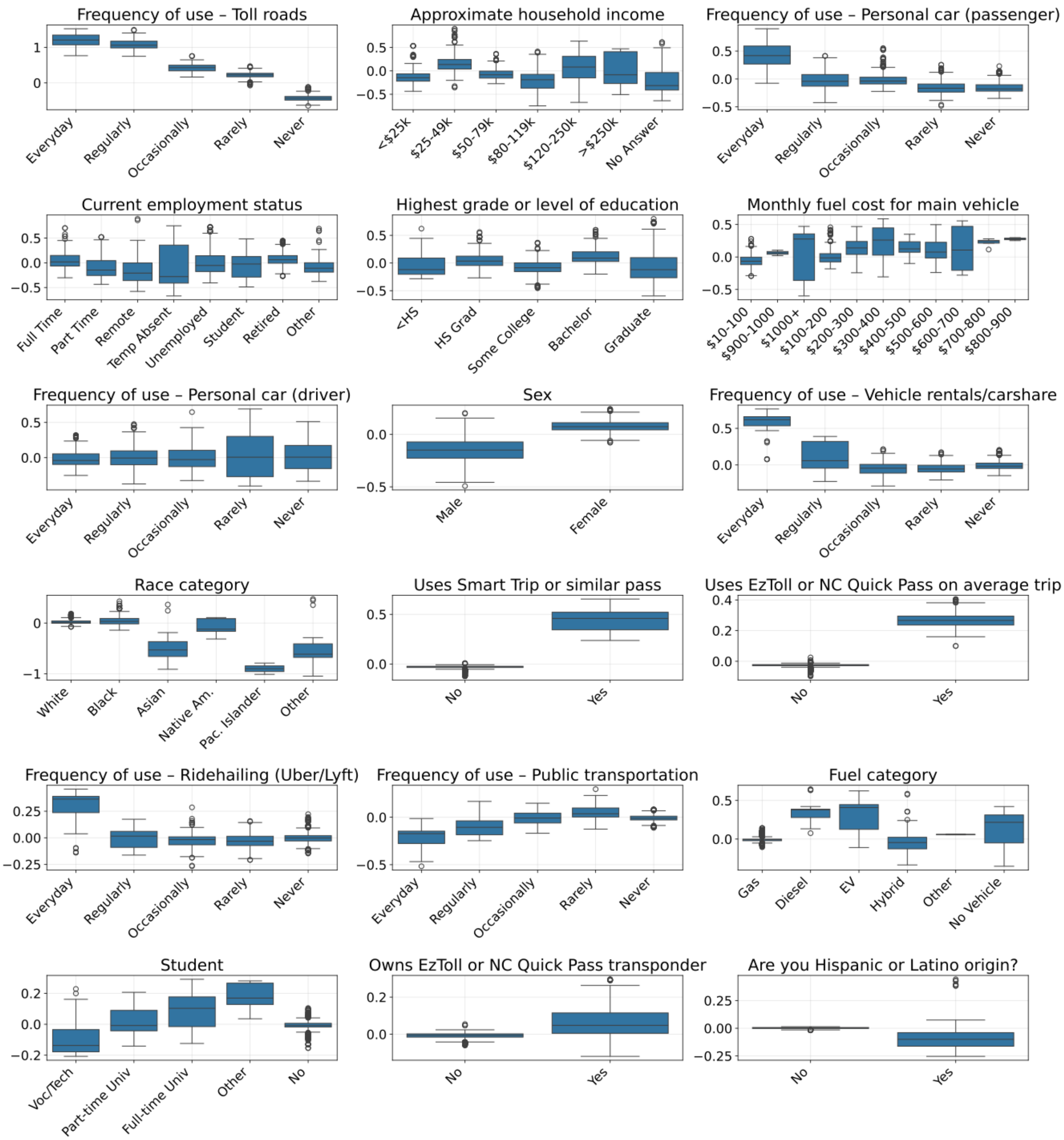


Figure 5.2 SHAP values for categorical variables. Positive values indicate the feature increases prediction toward high-cost route (1), while negative values indicate the feature decreases prediction toward low-cost route (0). Box plots show the distribution of SHAP values for each category within each variable.

Household income shows a nuanced pattern. Middle-income groups (e.g., $25–49k) lean toward usage of high-cost routes, but the lowest (<$25k) and highest (>$250k) income brackets show negative SHAP values, suggesting cost sensitivity at the bottom and potential avoidance at the top. Respondents who did not report income also lean against toll use. Mobility behavior further influences preference: Smart Trip and EzToll users show strong positive SHAP values (+0.43 and +0.27), indicating ease of payment facilitates toll choice. Frequent vehicle rental and ridehailing users also lean toward high-cost routes, while public transit users, especially everyday riders, are less likely to choose tolls (SHAP –0.21).

Similarly, remote workers and students lean toward low-cost routes, while full-time and retired individuals are more open to high-cost options. Gender and race show systematic effects: females lean toward tolls, while males do not. White and Black respondents have mild positive SHAPs, while Asian, Other, and Pacific Islander groups exhibit aversion to tolls (however, due to small sample size for these groups, the findings may not be generalizable). Fuel cost and fuel type (e.g., diesel, EV) correlate positively with high-cost preference, indicating travel intensity and vehicle type play roles in toll adoption.

5.2.3 Comparison with binary logit and probit models

We also trained the model to compare with binary logit and probit models using the selected explanatory variables for interpretability. As shown in Table A.11, the logit and probit regression models demonstrated poor overall fit, with pseudo $R2$ values below 0.15, indicating that the included variables explain only a small fraction of the variance in toll road choice behavior (worse fit than the Catboost model discussed earlier).

Notably, variables we expected to be significant predictors, such as fuel tax rates and vehicle fuel efficiency (MPG), showed weak or non-significant effects, contrary to economic theory suggesting that fuel costs should influence route choice decisions. The MPG variable was only marginally significant ($p \approx 0.056$), implying that fuel economy considerations play a limited role in toll road usage decisions among our sample respondents.

Despite the poor overall model fit, both models converged on similar results, with coefficients maintaining consistent signs and relative magnitudes across specifications. The key finding was the strong age effect, with each additional year reducing toll road usage odds by 1.3% (Odds Ratio (OR) = 0.987), suggesting younger drivers place a higher value on time savings relative to toll costs. Income effects revealed a non-linear pattern, where middle-upper income groups ($120k-$250k range) showed the strongest preference for toll roads (OR= 2.49), indicating an optimal income threshold for toll road adoption. Interestingly, student status variables produced contradictory effects: full-time university students were nearly three times more likely to use toll roads (OR = 2.86), while individuals identifying employment status as "student" were significantly less likely to use tolls (OR = 0.36), possibly reflecting different financial circumstances or travel patterns between these groups.

The consistency between logit and probit models, as well as their alignment with earlier machine learning approaches, provides confidence in the robustness of these demographic relationships despite the low explanatory power. The odds ratios reveal economically meaningful effect sizes: high-income groups' 2.5x higher odds of toll usage suggests strong income elasticity of demand for time savings, while the education level effects (some categories showing 43% lower odds) indicate that educational attainment may proxy for unmeasured preferences or risk attitudes toward toll roads.

5.3 Discussion and Conclusion

This chapter discussed a predictive modeling framework to evaluate how MBUF influence travelers' route choice behavior. Using a combination of descriptive analysis, machine learning (CatBoost), and traditional regression models, we examined behavioral responses to MBUF under varying vehicle efficiencies, toll rates, and cost transparency levels. The findings suggest that travelers' sensitivity to MBUF is strongly moderated by how cost information is presented. While MBUF rates alone had limited impact on route preferences, clearly communicating the total monetary burden significantly influenced switching behavior. This suggests that successful MBUF implementation may depend less on the specific pricing structure and more on transparent cost communication. Rather than centering policy debates on

MBUF versus fuel tax models, emphasis should be placed on improving user awareness of total travel costs, which appears to be a stronger driver of behavioral change than the fee mechanism itself.

The CatBoost classifier achieved an overall accuracy of 87%, indicating robust predictive performance. The F1-score was 0.92 for non-toll users and 0.72 for toll users, reflecting class imbalance. Both logit and probit regression models corroborated these machines learning findings, demonstrating consistent demographic effects despite poor overall model fit (pseudo $R^2 < 0.15$).

The SHAP analysis revealed that the most influential predictor is self-reported toll road usage frequency, indicating behavioral consistency. Age emerged as the second most significant variable older individuals were less likely to choose high-cost roads, likely due to fixed incomes or risk aversion. Departure time was also important early commuters favored toll routes to avoid peak-hour congestion, supporting the economic principle of time-value tradeoffs. Other notable factors included:

- Income, education, and employment showed variable effects, suggesting that demographic responses to toll pricing are context dependent.
- A larger cost difference between toll and non-toll options discouraged toll use.

When a cost summary was provided, users often switched to lower cost roads, implying that people underestimate the impact of MBUF when only shown the rate. Seeing the full financial burden prompted route reassessment. SmartTrip users and those using shared rides tended to prefer high-cost roads, possibly because cost-sharing reduces individual toll burden. In contrast, Uber/Lyft users and transit riders were more open to toll options. Those with higher education levels were also more inclined to select toll roads. Importantly, while explicit MBUF rate values showed minimal direct impact on choice behavior, the total cost implications significantly influenced decisions—highlighting the importance of perceived financial burden over fee structure.

One limitation of this study is the relatively narrow range of MBUF rates tested (2 to 15 cents per mile as shown in Table 3.2) which may not have been sufficient to capture the full spectrum of behavioral responses, as the next chapter shows that these rates do not raise costs enough to induce major changes in route choice. Beyond pricing, the stated preference scenarios did not fully incorporate real-time traffic conditions, which could also influence route preferences under higher cost scenarios—although such dynamic modeling would only be meaningful if MBUF rates themselves were varied in real time, which is difficult to implement administratively. Future research should explore multimodal contexts, integrate real-time information dynamics, and test higher toll scenarios to assess nonlinear responses. Despite these limitations, the current findings still offer actionable policy insights: even modest MBUF levels influence route decisions, particularly when supported by summary information, indicating that transparent communication of cost–time tradeoffs can enhance user acceptance.

Chapter 6. Deriving State-Level Insights

6.1 Overview of Explored Methodologies

In order to evaluate the statewide impacts of Mileage-Based User Fees, our team explored multiple methodological directions that connect individual-level behavioral insights from Chapter 4 and 5 with network-level travel outcomes. At the core, the challenge lay in how to meaningfully apply machine learning and choice models in an already trained statewide framework. Initial efforts discussed in Chapters 4 and 5 focused on using our collected survey and behavioral data to train ML models, exploring variations such as panel effects and monotonicity constraints. These models provided insights into variable importance and traveler preferences. However, key limitations emerged, especially in the restricted scope of applying such models directly to statewide prediction (since commonly an origin-destination pair is connected by more than two routes or the mode set available between an origin-destination pair may not include transit or park-and-ride as modes). We also recognized gaps in the state of the art, particularly the difficulty of scaling detailed behavioral models to the level of a statewide travel demand model.

We also considered extrapolating ML-based predictions to larger populations through synthetic population generation. While this offered a pathway to apply attitudinal responses across geographies, it required careful reconciliation of survey data with public datasets like Public Use Microdata Sample (PUMS) and National Household Travel Survey (NHTS), raising issues of spatial mismatch (PUMAs vs. TAZs) and error propagation in synthetic estimation. In parallel, we examined direct use of the North Carolina Statewide Travel Demand Model (NCSTM) in TransCAD. This allowed us to vary per-mile charges by adjusting link- level tolls but had limitations: the model does not explicitly incorporate fuel tax variability by vehicle type, and it does not draw on our observed survey data. Finally, we explored hybrid back-of-the-envelope estimates that attempted to approximate route utilities by combining TransCAD flows with routing models, though these approaches mimic traffic equilibrium considerations.

From these explorations, we converged on three complementary strategies that balance feasibility with analytical rigor: (a) analyzing non-overlapping routes between representative origin–destination pairs to evaluate how generalized travel costs change under varying MBUF rates implemented as link-level tolls, (b) running the NCSTM/TransCAD model with varying MBUF rates implemented as link-level tolls, (c) extrapolating survey agree/disagree statements to the statewide scale through synthetic population generation, and (d) framing policy guidance primarily from the comparative insights across these analyses. These details are discussed next.

6.2 Route Choice Impact Analysis

Let G denote the finite set of all traveler groups between an origin-destination pair, where each group $g \in G$ is characterized by their vehicle's mileage and value of time (VOT), the latter being proportional to the income bracket of the traveler. For each group g, let α_g denote the traveler's value of time (in \$/hour), and γ_g denote the vehicle's mileage (in miles per gallon). Reasonably, α_g varies between \$10/hr and \$50/hr (NCSTM), while γ_g ranges between 15 and 75 miles per gallon (for reasonable mileage values).

Cost structure under fuel tax and MBUF regimes

Under the current fuel tax regime, the effective fuel-related cost per mile depends on both the total distance traveled and the vehicle's fuel economy. If β_{fuel} and $\beta_{\text{fuel-tax}}$ represent the base fuel price and the fuel tax (both in \$/gallon), respectively, then the effective per-trip cost for a group g traveling along link (i, j) of length l_{ij} (in miles) is given by:

$$\tau_{ij}^{\text{fuel}} = (\beta_{\text{fuel}} + \beta_{\text{fuel-tax}}) \cdot \frac{l_{ij}}{\gamma_g}$$

Under a mileage-based user fee (MBUF) regime, the cost per mile is independent of fuel efficiency and depends only on total distance driven. Let β_{MBUF} denote the MBUF rate (in \$/mile). Then:

$$\tau_{ij}^{\text{MBUF}} = (\beta_{\text{fuel}}) \cdot \frac{l_{ij}}{\gamma_g} + \beta_{\text{MBUF}} \cdot l_{ij}$$

Approximate Equilibrium Representation

At equilibrium, the set of used paths between an origin–destination (OD) pair have equal and minimal generalized costs. Formally solving for a full stochastic user equilibrium with heterogeneous travelers and path-specific cost functions on a statewide network is analytically intractable (Boyles et al., 2020). Therefore, we employ an approximate procedure to demonstrate the potential magnitude of route cost changes under a uniform MBUF implementation.

We identify up to four non-overlapping shortest paths between a representative OD pair (from the Charlotte region to the north of Raleigh) using the ESX algorithm; See Figure 6.1. Recent advancements, such as those by Chondrogiannis et al. (2020), improve upon dissimilar path construction by generating k-non-overlapping shortest paths, moving beyond the limitations of candidate path sets (Liu et al., 2017).

We consider shortest non-overlapping routes with less than 10% spatial similarity to ensure that all routes are realistically feasible between the OD pair while still allowing for meaningful variation in travel length and time. If overlapping segments were allowed, path lengths would be even more similar, implying smaller differences after MBUF implementation. Hence, our analysis represents a conservative upper bound on potential variation in route costs.

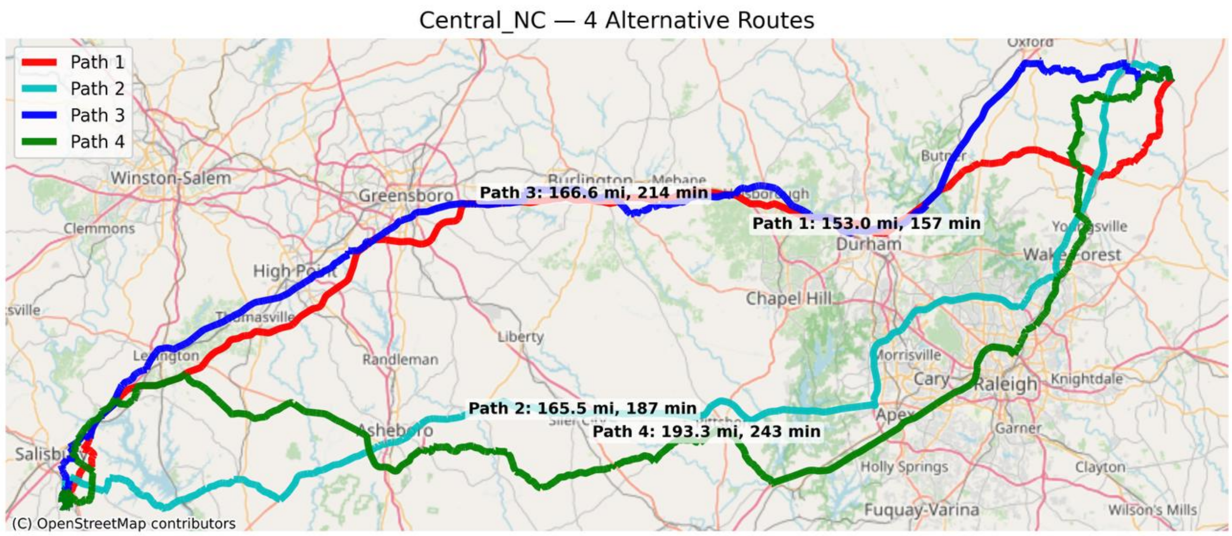


Figure 6.1 Four non-overlapping shortest routes for a traveler from Charlotte, NC, to a north-west location near Wake Forest, NC

Generalized Cost Formulation

We assume that these four paths $\pi \in \{\pi_1, \pi_2, \pi_3, \pi_4\}$ are the equilibrium-used routes prior to MBUF implementation. Each path π is associated with travel time t_π and length l_π. The generalized cost for a traveler group g before MBUF is given by:

$$C_{\pi,g}^{\text{before}} = \alpha_g t_\pi + \frac{\beta_{\text{fuel}} l_\pi}{\gamma_g} + \frac{\boldsymbol{\beta_{\text{fuel-tax}} l_\pi}}{\boldsymbol{\gamma_g}}$$

After MBUF implementation, the generalized cost becomes:

$$C_{\pi,g}^{\text{after}} = \alpha_g t_\pi + \frac{\beta_{\text{fuel}} l_\pi}{\gamma_g} + \boldsymbol{\beta}_{\mathbf{MBUF}} \boldsymbol{l_\pi}$$

If travel behavior and route choice remain unchanged immediately after implementation, the only difference between these two expressions lies in the bolded tax-related terms.

We next adjust travel times t_π across the four paths so that, under the 'before' scenario, their generalized costs are equal, reflecting the equilibrium condition that all used paths have equal and minimal generalized cost (that is, $C_{\pi,g}^{\text{before}}$ is identical for all paths π, represented by C_g^{before}). We then recompute the generalized costs after introducing the MBUF and measure the relative deviation among the four path costs for each $(\alpha_g, \gamma_g, \beta_{\text{MBUF}})$ combination assuming the fuel-tax and total fuel cost were set at approximately 43 cents/gallon and \$3.04 per gallon, respectively (representative of the state average in 2024).

Specifically, for each combination of VOT, MPG, and MBUF rate, we compute:

$$\text{Spread}_{(\alpha_g,\gamma_g,\beta_{\text{MBUF}})} = 100 \times \frac{\max_\pi(C_{\pi,g}^{\text{after}}) - \min_\pi(C_{\pi,g}^{\text{after}})}{C_g^{\text{before}}}$$

This metric quantifies how much the generalized cost across the four non-overlapping routes diverges after MBUF implementation relative to the baseline.

Results and Interpretation

Figure 6.2 presents the resulting heatmaps of cost spread (%) across all combinations of VOT and MPG for six representative MBUF rates ranging from \$0.015 to \$0.04 per mile. Even for the most vulnerable traveler groups—those with low value of time and owning car with high fuel efficiency—the maximum cost spread across routes is less than 1.5%. Because such groups typically represent a small share of the total driving population and often do not own the highest-efficiency vehicles, the practical impacts are expected to be even smaller.

These findings suggest that a uniform MBUF rate within the studied range will not significantly alter route choice behavior, as the differences in generalized cost across feasible paths remain negligible relative to overall trip cost and time. However, if MBUF rates were differentiated by traveler type, vehicle class, or roadway category, the resulting disparities could be larger. Previous studies, however, note that such differential rate structures are administratively complex and challenging to implement and sustain from a policy and public-acceptance standpoint. When combined with the findings from the previous chapter (showing that cost transparency itself influences behavior more strongly than marginal price changes), it becomes evident that day-to-day route costs for individuals are unlikely to change meaningfully under MBUF. This is because current fuel expenditures already reflect distance-driven differences, meaning that longer routes naturally incur higher gasoline costs even without an additional per-mile fee.

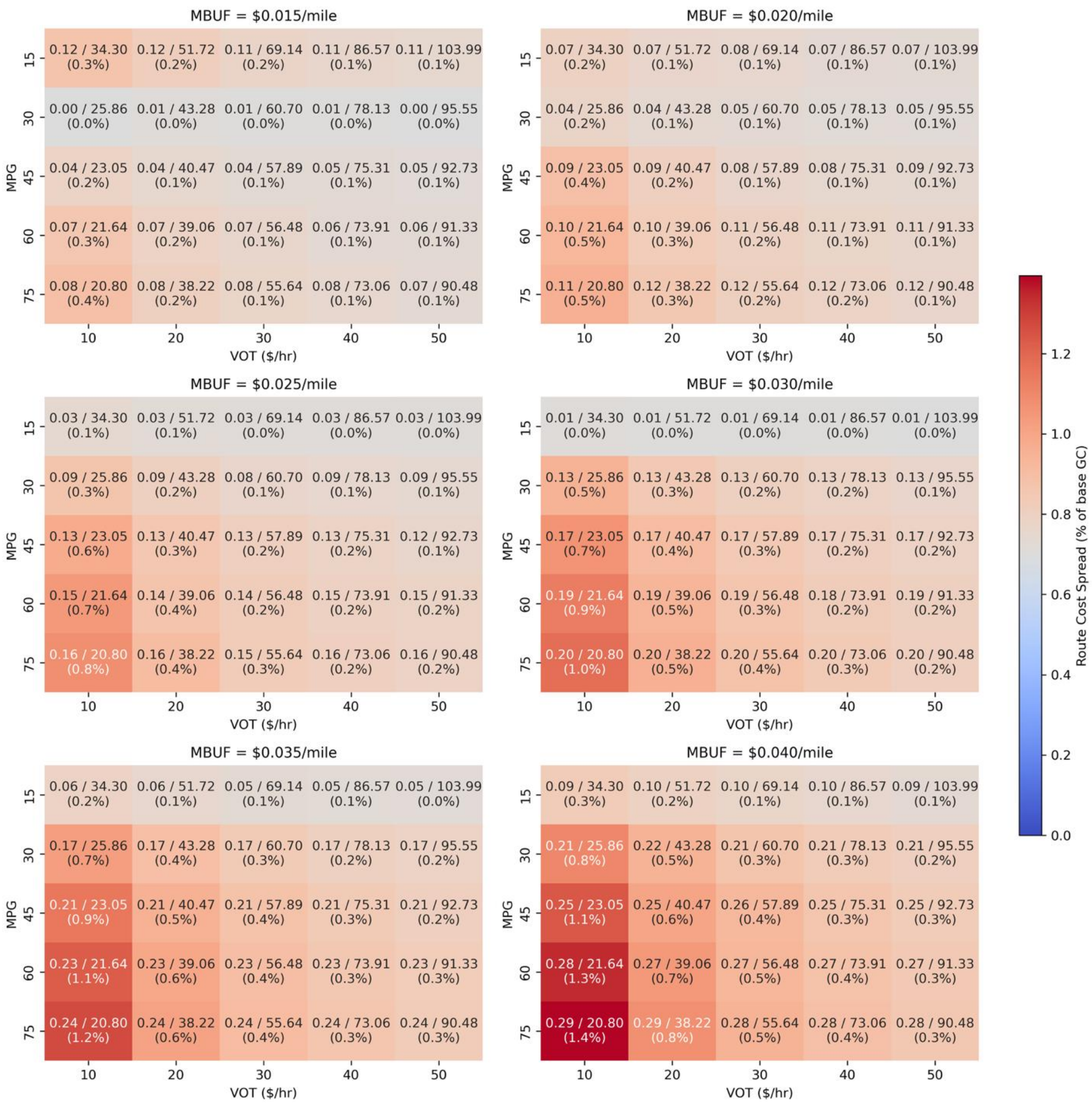


Figure 6.2 Heatmap of $\text{Spread}_{(\alpha_g,\gamma_g,\beta_{\text{MBUF}})}$ in generalized costs expressed as a percentage, computed across the four routes shown in Figure 6.1. Each cell reports the absolute spread in generalized cost (in $), that is, the difference between the maximum and minimum $C_{\pi,g}^{\text{after}}$ values, divided by the baseline generalized cost C_g^{before} for the corresponding group's MPG (miles per gallon) and VOT (value of time).

6.3 NCSTM Model and Toll-induced Behavioral Change

This section analyzes the second methodological approach, using the North Carolina Statewide Travel Model (NCSTM Gen4.5) to simulate MBUF as a mileage-proportional toll. The NCSTM Gen4.5 is a multimodal, time-of-day-sensitive travel demand model developed in TransCAD to assess highway and freight system performance across the state. The model comprises both person and freight travel modules and distinguishes between short-distance and long-distance trip purposes. It incorporates household-level socio-economic characteristics and land use data to simulate base and future year scenarios (2017 to 2045) under multiple pricing, infrastructure, and policy configurations.

From a network perspective, the NCSTM integrates regionally significant and statewide roadway networks, including enhancements in urban centers to reflect finer connectivity. The model contains traffic assignment algorithms, centroid connectors, interchange detail, and topographic corrections. Scenario-specific networks, housed in the model's Scenarios/ directory, are built upon a master highway network and include customizable project and toll configurations.

A core feature of Gen4.5 is its implementation of a toll choice model to estimate traveler responses under alternative pricing regimes. The toll model uses a Mixed Multinomial Logit (MMNL) specification, calibrated using stated preference (SP) surveys from the Triangle Expressway, Monroe Connector, and Metrolina regions. This approach enables simulation of differentiated willingness-to-pay for time savings across market segments (e.g., income groups, trip purposes, time-of-day), allowing for behavioral elasticity in route choice.

6.3.1 Highway assignment and toll modeling in NCSTM Gen4.5

The NCSTM Gen4.5 employs a multi-class user equilibrium (UE) traffic assignment procedure to allocate vehicle flows across the statewide highway network. The model utilizes the Tri-Conjugate Frank- Wolfe algorithm implemented in TransCAD, which is optimized for convergence performance and employs feedback loops to iteratively update impedance skims and travel demand.

During each assignment iteration, vehicle demand generated from the trip distribution and mode choice steps is assigned to the network using impedance skims representing travel time and generalized cost for each origin-destination (O-D) pair. The highway network is segmented by facility type, area type, and travel direction (AB/BA), with centroid connectors providing access between Traffic Analysis Zones (TAZs) and the road network. Travel times are dynamically updated using Bureau of Public Roads (BPR) volume- delay functions (VDFs) that have been calibrated to North Carolina-specific traffic conditions. Assignment iterations proceed until a convergence threshold, typically a relative gap of $10{-}4$ to $10{-}5$, is achieved.

Toll modeling is embedded within the assignment process through the incorporation of additional cost components in the generalized cost function. Auto and truck vehicle classes are assigned toll values based on direction-specific link attributes (such as columns AB_AUTOTOLL_PK and BA_AUTOTOLL_OP). These tolls are converted into equivalent time costs using market-segment-specific Value of Time (VOT) parameters. The VOTs vary by income group, trip purpose, and time-of-day, and are derived from coefficients estimated via MMNL models using data from multiple Stated Preference (SP) surveys. For example, peak-period commuters exhibit higher sensitivity to time savings and are thus more likely to opt for tolled facilities, whereas off-peak travelers may divert to untolled routes.

To simulate behavioral responses to toll changes, modified network scenarios were developed wherein toll values (e.g., \$0.05, \$0.70 per mile) were applied to selected highway segments or the entire network. Each modified scenario was subjected to the same UE assignment procedure as the base case. This approach allows for controlled evaluation of the influence of toll visibility on traveler route choice and system-wide performance metrics.

The model's TollChoice step incorporates the computed generalized costs of toll and non-toll paths to update utility values in both mode choice and route selection stages. These updated utilities influence a reallocation of trips across the network. The feedback mechanism ensures consistency between assigned flows and utility-based route preferences across successive iterations, thereby capturing the dynamic equilibrium of user route choice under varying pricing scenarios.

6.3.2 Assignment output metrics

For each toll scenario and time period, TransCAD generates a comprehensive set of network performance metrics to evaluate changes in traffic conditions under different pricing and demand settings. The primary flow metrics include directional link flows (AB and BA), total flow on each link, and flow adjusted by passenger car equivalents to account for truck impacts. System efficiency is represented by total vehicle miles traveled (VMT), total vehicle hours traveled (VHT), maximum congested travel time, and the highest volume-delay function (VDF) ratio, which identifies oversaturated links.

Toll and cost metrics are derived from direction-specific toll charges by vehicle class and time of day, along with the generalized cost combining tolls, travel time (converted using value of time), and operating costs. Cumulative toll revenue is computed as the product of assigned flows and toll values across tolled segments.

The key performance indicator, Total System Travel Time (TSTT), aggregates the time spent by all vehicles across the network, computed as the sum of flow multiplied by congested travel time on each link. Higher TSTT reflects greater congestion and delay, making it a useful measure to compare the efficiency of alternative tolling strategies. While tolling can reduce VMT through route or mode shifts, it may also increase TSTT when traffic diverts to slower, lower-capacity corridors. Evaluating TSTT across toll levels helps reveal whether MBUF implementation improves network throughput or creates localized inefficiencies.

The NCSTM assignment is performed across four distinct time-of-day segments to capture fluctuations in travel demand and congestion as shown in Table 6.1.

Table 6.1: Time period definitions in NCSTM

Time Period	Hours	Description
AM	6:00 AM – 9:00 AM	Morning peak (commute to work/school)
MD	9:00 AM – 3:00 PM	Midday (shopping, services, school trips)
PM	3:00 PM – 6:00 PM	Evening peak (commute home)
NT	6:00 PM – 6:00 AM	Night (freight, discretionary, overnight trips)

6.3.3 Base Model: baselines TSTT before MBUF

To compare the baseline and policy scenario outputs, Model A presents the TSTT before implementing the MBUF. Table 6.2 summarizes the baseline TSTT prior to implementing any MBUF scenarios. As shown, the midday (MD) period exhibits the largest baseline travel time burden, with over 106,000 hours of TSTT, compared to approximately 38,000 in the morning peak (AM) and 53,000 in the evening peak (PM). Interstate contributions are relatively small in magnitude compared to regional roadways, which account for the bulk of system-wide travel time in every period. The nighttime (NT) period, while lower than midday, still reflects significant system use with nearly 88,000 hours of travel.

Table 6.2 Model A: Baseline TSTT values across time periods and network types before applying MBUF scenarios

Period	TSTT (Before) Hours	Interstate TSTT Before (Hours)	Regional Road TSTT Before (Hours)
AM	38,020.25	46.93	581.80
MD	106,582.52	119.26	1,641.73
PM	53,436.31	59.76	820.63
NT	88,064.17	103.73	1,348.39

6.3.4 Model with MBUF: changes after MBUF application

Model B applies a fixed MBUF rate by multiplying the length of each road segment with the corresponding per-mile charge, which is represented in the model as a toll. This framework allows us to evaluate how system-wide travel outcomes shift under different per-mile fees.

This section analyzes how TSTT and VMT respond to varying MBUF rates across four time periods: AM, MD, PM, and NT. TSTT and VMT are evaluated both before and after the application of tolls ranging from $0.05 to $2.00 per mile. We deliberately tested values as high as $2.00 per mile—well beyond practical implementation levels—in order to assess the thresholds at which MBUF rates begin to produce significant impacts on route choice and travel outcomes. A summary of these results is presented in Table 6.3 and discussed next.

Table 6.3 Model B: TSTT percentage changes for full, interstate, and non-interstate networks under varying MBUF toll levels (units are dollars per mile)

Time	MBUF	Full Network TSTT (Hours)		Full Network TSTT % Change	Interstate TSTT (Hours)		% Change (Interstate TSTT)	Non-Interstate TSTT (Hours)		% Change (Non-Interstate TSTT)
		Before	After		Before	After		Before	After	
AM	$0.05	38,020.25	38,041.68	0.01%	46.93	46.63	-0.65%	581.8	582.1443	0.06%
	$0.08		38,041.68	0.06%		46.52	-0.87%		582.4916	0.12%
	$0.15		38,104.52	0.11%		46.3	-1.34%		582.9448	0.20%
	$0.30		38,104.52	0.22%		45.79	-2.43%		584.0765	0.39%
	$0.70		38,212.24	0.50%		44.7	-4.75%		586.7685	0.85%
	$2		38,556.98	1.41%		41.56	-11.44%		594.6808	2.21%
MD	$0.05	106,582.52	106,664.81	0.08%	119.26	118.87	-0.33%	1,641.73	1643.325	0.10%
	$0.08		106,691.66	0.10%		118.6	-0.55%		1643.935	0.13%
	$0.15		106,783.06	0.19%		117.97	-1.08%		1646.104	0.27%
	$0.30		107,015.00	0.41%		116.91	-1.98%		1650.453	0.53%
	$0.70		107,587.52	0.94%		114	-4.42%		1662.2	1.25%
	$2		109,430.04	2.67%		106.29	-10.88%		1698.117	3.43%
PM	$0.05	53,436.31	53,472.74	0.07%	59.76	59.56	-0.34%	820.63	821.2928	0.08%
	$0.08		53,479.19	0.08%		59.46	-0.51%		821.5183	0.11%
	$0.15		53,521.35	0.16%		59.15	-1.03%		822.3426	0.21%
	$0.30		53,591.01	0.29%		58.6	-1.95%		824.0391	0.42%
	$0.70		53,795.00	0.67%		57.18	-4.32%		828.3395	0.94%
	$2		54,456.63	1.91%		53.26	-10.87%		841.5299	2.55%
NT	$0.05	88,064.17	88,114.54	0.06%	103.73	103.42	-0.30%	1,348.39	1349.472	0.08%
	$0.08		88,137.49	0.08%		103.17	-0.54%		1349.952	0.12%
	$0.15		88,260.93	0.22%		102.71	-0.98%		1352.193	0.28%
	$0.30		88,429.91	0.41%		101.96	-1.71%		1355.823	0.55%
	$0.70		88,896.62	0.95%		99.62	-3.96%		1364.892	1.22%
	$2		90,406.56	2.66%		92.91	-10.43%		1394.258	3.40%

Across all time periods, the rise in TSTT with increasing MBUF rates is minimal, even at very high toll levels. For instance, TSTT increases only about 1.4% during the AM, 2.7% during midday, 1.9% during PM, and 2.7% during nighttime when the toll reaches an extreme rate of $2.00 per mile, far exceeding any realistic policy scenario. These marginal changes indicate that MBUF has limited influence on network-wide congestion. Most travelers maintain their original routes, especially during peak hours when alternatives are constrained, while off-peak increases stem from minor rerouting to avoid tolled links. Overall, the results imply that even large MBUF rates are unlikely to trigger significant behavioral or system-level changes, underscoring that route choice impacts remain negligible under realistic, revenue-neutral implementations.

Figure 6.3 shows the percentage change in TSTT across different toll levels and time periods. A consistent upward trend is visible as toll rates increase, with more substantial changes occurring at higher toll levels. The night and midday periods show the highest TSTT increases, reaching 2.66% and 2.67% respectively under the $2.00 scenario. The AM and PM periods show relatively smaller increases of 1.41% and 1.91%, which may reflect limited rerouting options or more stable commuting behavior. The lower TSTT growth during peak periods implies that many users continue to travel on preferred routes despite the minor changes in costs, whereas midday and nighttime travelers show greater sensitivity.

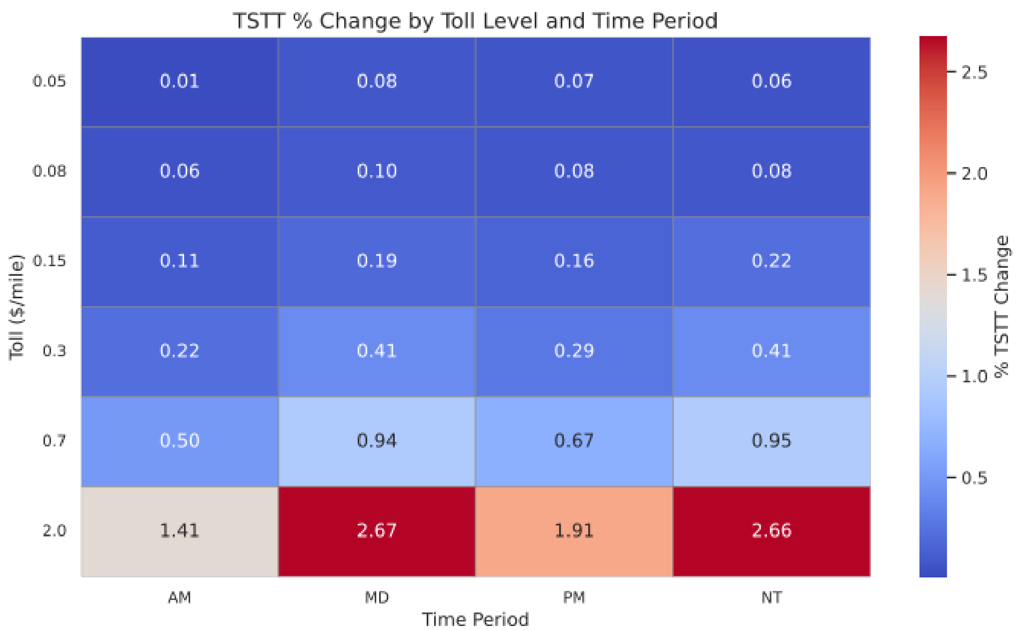


Figure 6.3 Percentage change in TSTT by MBUF level ($/mile) and time period

6.3.5 Model with MBUF: VMT Analysis across time-periods

As shown in Table 6.4, the implementation of MBUF scenarios reveals a consistent downward trend in VMT across all time periods as toll rates increase. This pattern reflects the sensitivity of travel demand to cost increments, especially in discretionary or non-commute trips. A comparative analysis was conducted for AM, MD, PM, and NT periods across six toll levels ($0.05, $0.08, $0.15, $0.30, $0.70, and $2.00 per mile).

VMT is consistently lower under MBUF scenarios, indicating that longer routes become less attractive as drivers adjust toward shorter or more direct paths. Across all time periods, VMT declines modestly with increasing MBUF rates, confirming that overall travel behavior is only mildly sensitive to per-mile cost changes.

During the AM period, VMT decreases by about 0.79% (from 108.76 to 107.90 million miles), suggesting minor route optimization or trip consolidation among commuters. The midday (MD) period shows the highest sensitivity, with VMT dropping by 0.87% (from 278.97 to 276.55 million miles), likely due to the more discretionary nature of mid-day trips such as errands, deliveries, and appointments. The PM period exhibits slightly smaller reductions of around 0.81%, reflecting a blend of inelastic work-related travel and elastic discretionary movement. During the night (NT) period, VMT declines by about 0.87% (from 233.48 to 231.45 million miles), suggesting that even lower-demand periods—often involving freight or flexible logistics—adjust modestly in response to pricing.

Table 6.4 Summary of Vehicle Miles Traveled (VMT) by Period and MBUF Rate

Period and MBUF rate ($/mile)		**VMT (Before) (miles)**	**VMT (After) (miles)**	**Abs. Reduction (miles)**	**VMT % Change**
AM	$0.05	108,758,027	108,721,896	36,131	-0.03%
	$0.08		108,699,861	58,166	-0.05%
	$0.15		108,661,018	97,009	-0.09%
	$0.30		108,559,695	198,332	-0.18%
	$0.70		108,332,678	425,349	-0.39%
	$2.00		107,897,354	860,673	-0.79%
MD	$0.05	278,973,947	278,893,885	80,062	-0.03%
	$0.08		278,838,863	135,085	-0.05%
	$0.15		278,729,489	244,458	-0.09%
	$0.30		278,448,068	525,879	-0.19%
	$0.70		277,848,492	1,125,455	-0.40%
	$2.00		276,549,633	2,424,314	-0.87%
PM	$0.05	142,581,225	142,535,836	45,389	-0.03%
	$0.08		142,511,174	70,051	-0.05%
	$0.15		142,456,641	124,584	-0.09%
	$0.30		142,330,595	250,630	-0.18%
	$0.70		142,030,918	550,308	-0.39%
	$2.00		141,420,654	1,160,571	-0.81%
NT	$0.05	233,482,841	233,407,340	75,501	-0.03%
	$0.08		233,366,481	116,360	-0.05%
	$0.15		233,260,537	222,304	-0.10%
	$0.30		233,028,328	454,513	-0.19%
	$0.70		232,528,676	954,165	-0.41%

$2.00	231,448,352	2,034,489	-0.87%

Overall, reductions remain below 1% even at the extreme $2.00 per-mile rate, implying that MBUF has limited impact on aggregate travel demand. These consistent yet small decreases across all time periods suggest that travelers are optimizing routes and marginally reducing mileage, but large-scale shifts in total travel behavior are unlikely under realistic or revenue-neutral MBUF implementations.

6.3.6 Model with MBUF: analysis of links with greater than 10% flow change across time periods

The percentage of network links experiencing greater than 10% change in flow is a key indicator of how toll pricing affects route choice behavior and system stability. A high percentage signals significant route switching, while lower percentages suggest more stable travel patterns. This section presents a time-period- wise evaluation based on observed simulation results under MBUF toll scenarios.

Across the AM period, the proportion of roadway links experiencing more than 10% flow change provides insight into how tolls disrupt usual travel patterns (See Figure 6.4). At a $0.05 toll, only 0.51% of links undergo significant change, showing minimal network disturbance. As the toll increases to $0.08 and $0.15, the proportion rises to 1.84% and 3.12%, respectively. At $0.30, over 6.49% of links exhibit large flow deviations, indicating more widespread behavioral adjustment. The impact becomes more pronounced at $0.70, with 12.78% of links affected. The $2.00 toll results in a substantial 26.42% of links experiencing over 10% flow change—implying system-wide rerouting, likely from high-cost avoidance. These values show a nonlinear response, where medium-to-high tolls significantly alter route choices and load distribution across the network.

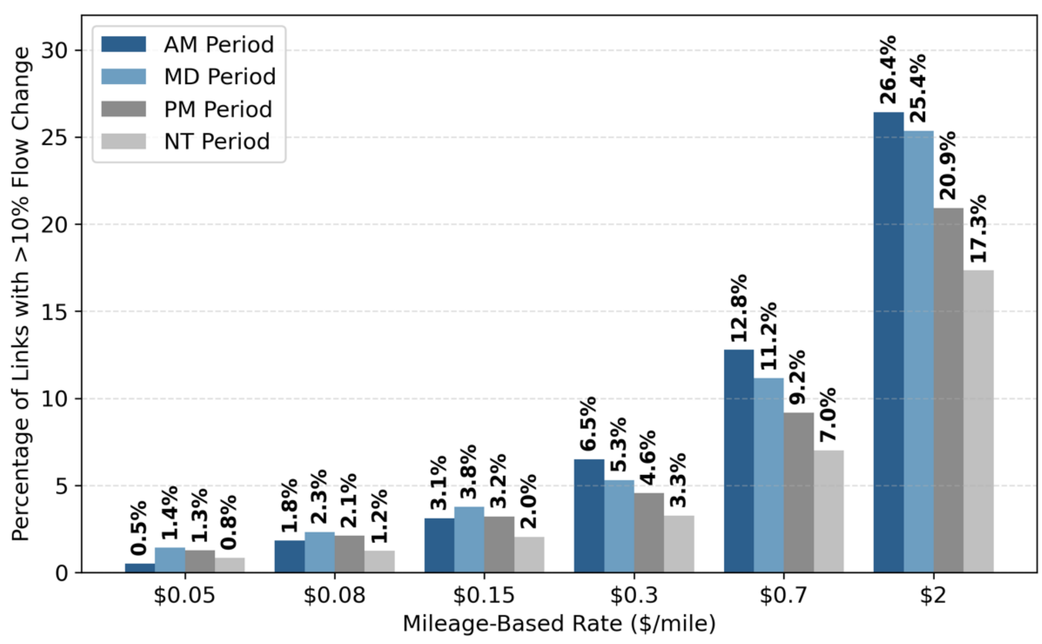


Figure 6.4 All periods – Percentage of Links with >10% Flow Change

Across all periods, the share of roadway links experiencing more than 10% flow change rises sharply as MBUF rates increase. During the midday period, affected links grow from just 0.5% at a $0.05 toll to 24.4% at $2.00, reflecting substantial rerouting at higher rates. The evening period shows a similar pattern, with affected links increasing from 0.9% to 23.8%, while nighttime flows shift from 1.5% to 25.2% across the same toll range. These results indicate that mid- to high-level MBUF rates can trigger widespread rerouting across the network, with notable shifts concentrated on alternative corridors as travelers seek to avoid tolled segments.

6.3.7 Flow Change Visualization

Figure 6.5 highlights links with over 20% increase in traffic flow. Analysis reveals that major increases in flow are concentrated near urban centers and along interstate corridors in central and eastern North Carolina. These white-hued links indicate potential congestion or rerouting impacts and may represent critical infrastructure under increased demand. The interactive tooltips further aid interpretation by displaying before and after volumes and percent change for each segment. This aligns with the intuition that MBUF can encourage preference for shorter distance routes over shortest time routes; however, we note that these differences are fairly minor and only show up at very high MBUF rates ($2 per mile).

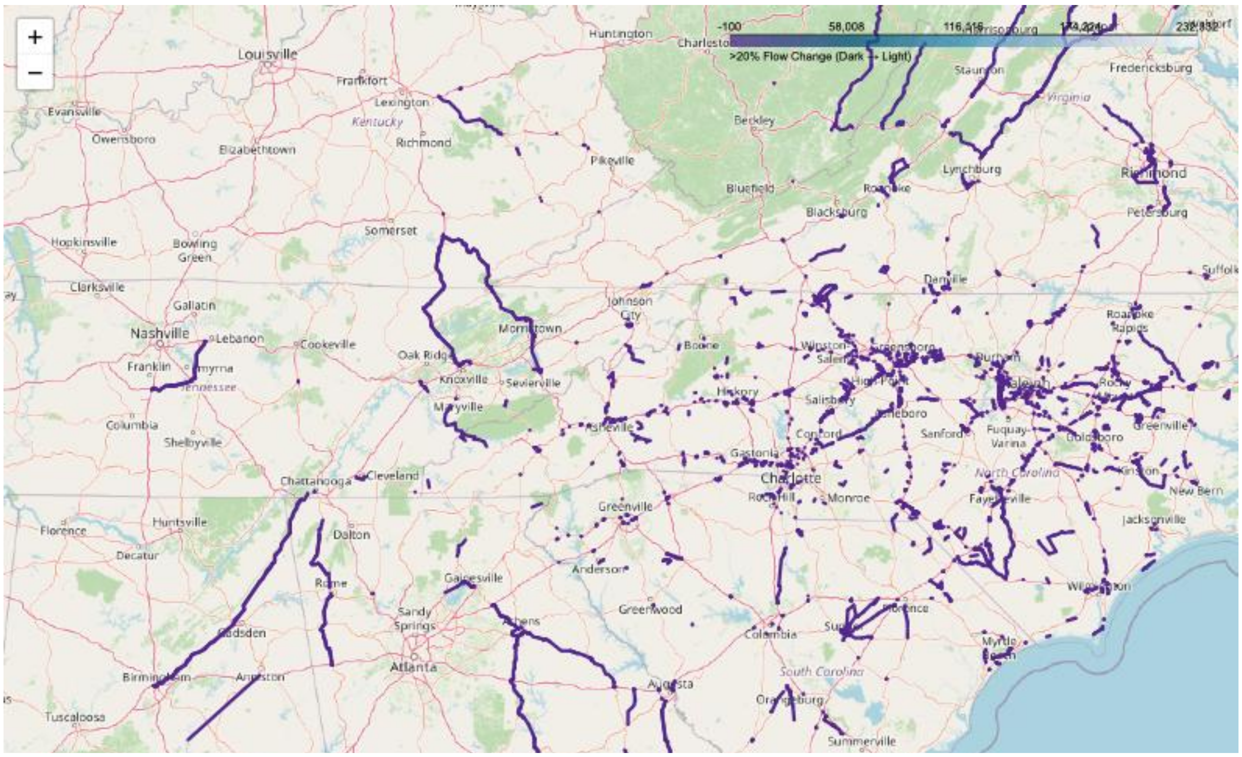


Figure 6.5 Flow change visualization for links with >20% flow increase

6.3.8 Model with MBUF on interstates only

A comparative case was tested applying MBUF exclusively to interstate facilities at $0.70/mi. In this scenario, TSTT on interstate segments decreased by up to 6% due to traffic diversion, while non-interstate routes experienced up to 5% higher travel times and localized congestion. Flow changes concentrated on parallel arterials near urban centers, demonstrating that partial-network pricing can shift congestion spatially rather than reducing it system-wide.

Table 6.5 highlights the top 10 links with the highest relative increase in traffic flow under the non-interstate tolling scenario during the MD period. Notably, links such as 65390 and 65403 experienced dramatic increases due to extremely low baseline flows (near zero), which amplify percentage changes. This pattern suggests previously underutilized links are now absorbing significant rerouted traffic. Mid-tier links like 55184 and 50442 also saw major shifts, indicating redistribution from tolled interstates to alternative local routes.

Table 6.5 Top 10 Links with Highest Flow Changes (MD, Non-Interstate Scenario)

Link ID	Flow Before (veh)	Flow After (veh)	Change
65390	0.000040	35.156183	35.156143
65403	0.000040	35.156183	35.156143
55184	0.012030	4523.043986	4523.031956
50442	0.012030	4523.043986	4523.031956
55136	0.012030	4046.356633	4046.344603
15269	0.002678	374.854691	374.852013
15283	0.002678	374.854691	374.852013
15401	0.002678	374.854691	374.852013
15258	0.002678	374.854691	374.852013
15399	0.002678	374.854691	374.852013

6.3.9 Limitations of NCSTM Analysis

While the NCSTM framework provides a useful statewide view of network-level impacts under varying MBUF rates, several limitations constrain the precision of behavioral inference. (a) The model does not explicitly incorporate fuel tax parameters in its cost formulation, meaning that MBUF is applied as an additional toll rather than as a replacement for existing fuel taxes. (b) The simulation relies on embedded statewide calibration parameters and does not directly integrate our observed survey data, which capture user perceptions and preferences. (c) The model treats travelers as homogeneous with respect to vehicle fuel economy and income, omitting heterogeneity in utility and sensitivity to pricing. Moreover, the current version of NCSTM does not dynamically model freight route changes under tolling scenarios, limiting insights into commercial vehicle behavior.

Despite these limitations, the analysis remains valuable for understanding how systemwide VMT and TSTT respond across different MBUF levels. The marginal variations observed suggest that while statewide impacts are modest, localized effects could emerge under differential rate structures—such as higher rates on interstates or income-sensitive pricing schemes.

6.4 Synthetic Population Analysis

To overcome the limitations of TransCAD modeling, we developed a synthetic population framework to estimate individual-level travel behavior across North Carolina where the choice model can be applied. As shown in Figure 6.6, we began with the Public Use Microdata Sample (PUMS) to generate socio-demographic profiles for each Public Use Microdata Area (PUMA), and the National Household Travel Survey (NHTS) to capture travel behavior variables. Because census data does not provide conditional distributions, both datasets were expanded using Bayesian networks to approximate dependencies across attributes.

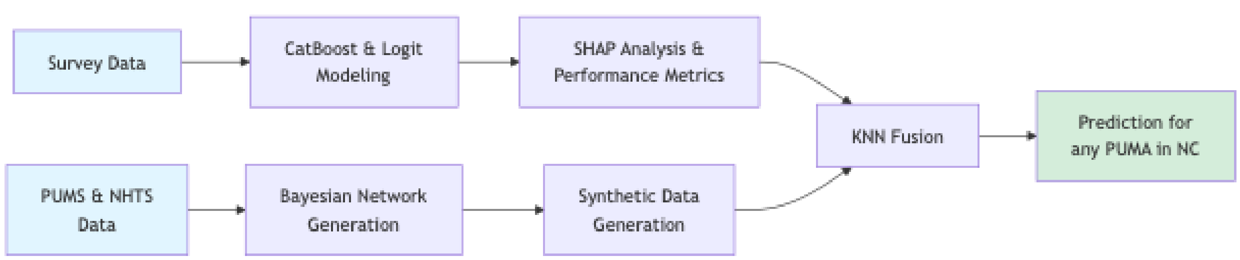


Figure 6.6 Synthetic population generator used for extending the model to statewide analysis

A Bayesian network (Barbrook-Johnson and Penn, 2022) is a model that learns probabilistic relationships between variables in a dataset and generates synthetic data consistent with those relationships. A Bayesian network is represented as a directed acyclic graph (DAG), where each node corresponds to a variable and each edge represents a conditional dependency. In other words, the network encodes how each variable probabilistically depends on its parent nodes.

These synthetic datasets were then statistically matched through K-Nearest Neighbors (KNN) on common variables, producing a fused dataset that realistically combines socio-demographic and travel behavior information.

With this fused synthetic survey dataset, we trained predictive models—specifically CatBoost and logit models—to estimate responses to seven attitudinal survey questions. Performance metrics were compared across models, and SHAP (SHapley Additive exPlanations) analysis was used to explain prediction drivers. The final framework allows us to generate behavioral predictions for any PUMA in North Carolina, effectively extending survey insights to regions where direct data collection is infeasible. The flowchart illustrates the end-to-end process: from raw data, Bayesian expansion, and fusion, to modeling, prediction, and interpretability.

Figures 6.7 shows a sample analysis for key questions on a scale of 1 to 5 (1 = strongly disagree and 5 = strongly agree). Overall, responses to the statement “My route choice is not impacted by the amount of tax I pay" were fairly neutral across the state, with many respondents neither agreeing nor disagreeing; however, regression modeling revealed slightly higher agreement levels in some eastern counties. For the question “I will prefer to drive fewer miles if the fuel tax is replaced by MBUF," similar trends were observed, with slightly higher agreement in the western region of North Carolina. It is important to note that these differences are relatively minor, suggesting that impacts may not be highly region-specific. We refer the reader to EBP US, Inc. (2020) for additional analysis on region-wide impacts of MBUF.

While the model provides a useful framework for state-level extrapolation, some limitations remain, particularly the scarcity of detailed datasets (e.g., type of vehicle ownership). The trained machine learning models primarily rely on age and toll-use frequency as key predictors, which reduces variability across counties or PUMA regions since people of all ages reside in each area. Consequently, regional differences should be interpreted as indicative rather than statistically significant. Additionally, a Bayesian network assumes conditional independence of variables given their parents, which may not hold for complex or nonlinear relationships. It can also converge to local optima when datasets are small or noisy.

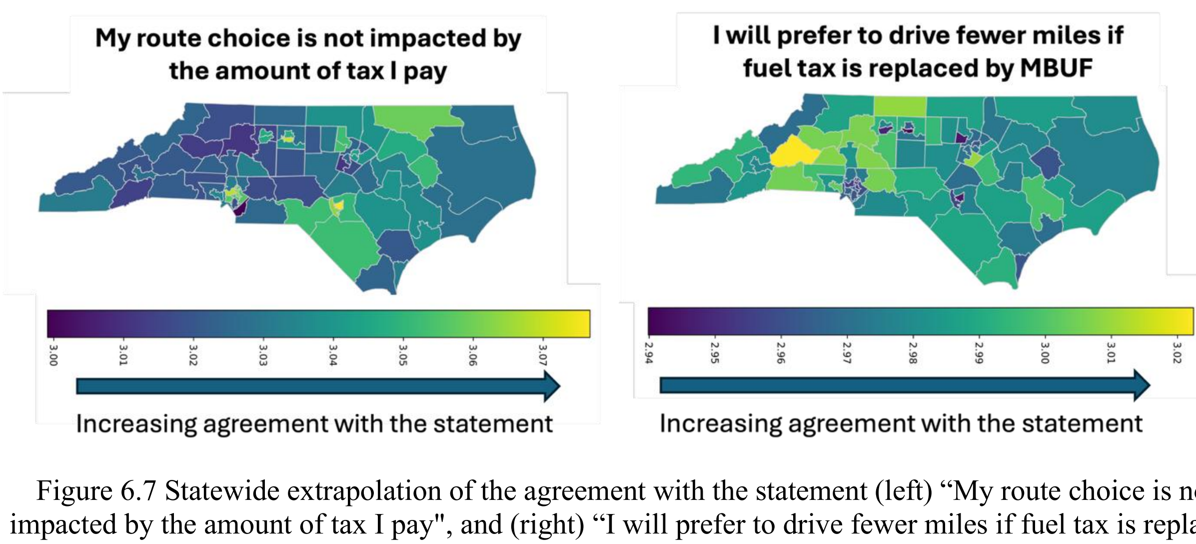


Figure 6.7 Statewide extrapolation of the agreement with the statement (left) “My route choice is not impacted by the amount of tax I pay", and (right) “I will prefer to drive fewer miles if fuel tax is replaced by MBUF”

An additional limitation throughout this chapter lies in the assumption that only mode and route choices are affected by the transition from a fuel tax to an MBUF system. In practice, broader economic, demographic, and political factors are likely to influence long-term travel behavior and VMT in North Carolina. Several urban centers in the state rank among the fastest growing in the nation, driven by shifts in land use, real estate development, and demographic change. As such, future VMT patterns will depend not only on pricing mechanisms but also on the evolving spatial and economic structure of the state. While this study provides reasonable analytical and back-of-the-envelope numerical estimates, a more detailed, adaptive modeling framework, integrating land-use, demographic, and economic feedback, will be necessary for robust long-term MBUF planning and implementation.

Chapter 7. Findings, Recommendations, and Implementation Plan

7.1 Summary of Findings

This study evaluated the long-term feasibility and impacts of MBUF as an alternative revenue mechanism for North Carolina's transportation system. The motivation comes from well-documented limitations of the fuel tax, especially as vehicles become more efficient and zero-emission models grow in number. The literature review showed that while MBUF offers the potential for a more sustainable and equitable funding model, its adoption faces hurdles related to fairness, privacy, technology implementation, and public acceptance. Importantly, previous pilot programs have shown that even small per-mile rates can match or exceed current fuel tax revenue streams, but there is limited understanding of behavioral and distributional effects at the statewide scale.

Building on this foundation, we developed and deployed the Survey to Understand the Impact of MBUF on Travelers' Choices (SUMTC) across North Carolina. The survey included both revealed preference (RP) and stated preference (SP) components, collecting detailed demographic, household, and travel behavior information. More than 800 valid responses were analyzed to evaluate how people balance time, cost, and convenience when faced with MBUF scenarios. The descriptive statistics showed that cost, time, and convenience are the dominant criteria shaping mode and route choice, with the majority of respondents continuing to rely on personal cars powered by gasoline. Many respondents expressed willingness to shift from fuel taxes to MBUF provided that the cost per trip remained reasonable, indicating that user acceptance may depend more on perceived burden than on the fee mechanism itself.

The analysis of joint RP–SP discrete choice models offered insights into the factors that influence mode choice. Results showed that higher MBUF rates lowered the likelihood of choosing to drive alone, carpool, or use park-and-ride facilities, with sensitivities varying across socio-demographic groups and trip purposes. Full-time workers reacted more to MBUF for work trips, while students exhibited greater sensitivity for recreational travel. Younger individuals reacted more strongly to MBUF changes in terms of their mode choice compared to older adults. In addition, higher parking fees, tolls, and transit fares further reduced the attractiveness of both motorized and shared modes. These findings showed that mode choice is shaped both by travel costs and by demographic and trip-purpose characteristics, emphasizing the need to consider differences across groups in policy design.

In contrast, the route choice analysis highlighted different behavioral factors. Using machine learning models and regression approaches, we found that self-reported toll road usage frequency was the strongest predictor of route preference, reflecting behavioral consistency. Age again emerged as a key factor, with older individuals less likely to select high-cost or toll routes, while early commuters showed a greater likelihood of paying for toll roads to save time. Cost differences between tolled and non-tolled alternatives discouraged the use of higher cost routes, and providing a total trip cost summary often prompted travelers to switch away from tolled routes. Together, these results indicate that route choice is primarily influenced by habitual toll use, cost transparency, and time-of-day considerations, while mode choice decisions are more strongly tied to demographic attributes, trip purposes, and generalized travel costs.

Building on these findings, we developed a synthetic population framework combining the Public Use Microdata Sample (PUMS) with the National Household Travel Survey (NHTS). Using Bayesian networks and K-Nearest Neighbors (KNN) matching, we generated a statewide synthetic dataset with socio-demographic and behavioral attributes. Predictive models, including CatBoost classifiers and logit regressions—were trained on this dataset to extrapolate attitudinal survey responses across all Public Use Microdata Areas (PUMAs) in North Carolina. The models performed well overall, with CatBoost achieving 87% accuracy. SHAP analysis revealed that toll usage frequency, age, departure time, and income were the most influential predictors of route choice under MBUF. These statewide extensions confirmed that while direct MBUF rates showed limited impact on route choice, the perception of total trip cost strongly influenced decisions, highlighting the importance of transparent cost communication.

At the statewide scale, we also adapted the North Carolina Statewide Travel Demand Model (NCSTM) to simulate traffic assignment under varying per-mile charges. Model A established baseline travel times across periods and network types, while Model B introduced MBUF rates represented as link-level tolls ranging from $0.05 to $2.00 per mile. Results showed modest increases in Total System Travel Time (TSTT), primarily driven by rerouting effects as drivers avoided tolled links. Even under extreme MBUF rates well beyond practical implementation, overall increases in TSTT remained small, suggesting that significant network-level route shifts are unlikely under realistic MBUF scenarios. The variability was observed across time periods, with midday and nighttime showing the highest sensitivity, although the magnitudes were still minor.

Together, these analyses converge on several core findings. First, MBUF is financially viable and can be calibrated to replace or exceed fuel tax revenues, but behavioral responses are nuanced and uneven across groups. Second, public acceptance depends on perceived fairness and transparency of costs rather than the technical mechanism, which the pilot studies have achieved in many ways. Third, large-scale rerouting effects are unlikely, meaning that network performance will remain stable under plausible MBUF scenarios. Finally, while advanced modeling can improve estimates, pilot programs and surveys remain essential to ground-truth behavioral assumptions.

7.2 Policy Guidance and Recommendations

The findings of this study support several policy directions for North Carolina and other states considering MBUF adoption. Foremost, the modest impact of MBUF on network-level performance suggests that policymakers should prioritize simple, uniform per-mile rates rather than complex time-of-day or trip-specific tolling structures. In our analysis, a constant per-mile MBUF produced minimal behavioral or system-level changes, suggesting that differential rate structures (e.g., by time of day, roadway type, or vehicle class) may be needed to elicit stronger mode and route choice changes. However, such complexity runs counter to earlier policy guidance favoring simplicity, transparency, and administrative ease. Prior studies, including Shrode et al. (2023), have emphasized that time-of-day or trip-specific differentiation offers limited congestion benefits while introducing operational and fairness challenges. A more pragmatic outlook is that simpler, uniform MBUF structures—though unlikely to induce major behavioral shifts—are still preferable for ensuring public trust, policy stability, and long-term feasibility.

A second key policy direction concerns the importance of cost transparency. Our findings indicate that it is not the mechanism of per-mile charging but the perceived cost that drives behavioral response. When MBUF is implemented in a revenue-neutral manner—designed to replace rather than add to existing fuel taxes—it does not substantially change travel costs and, therefore, is unlikely to alter behavior. Clear communication of how MBUF translates into trip-level costs can enhance user understanding and trust far more effectively than rate design alone. Continued pilot programs and public education initiatives are essential for demonstrating fairness, clarifying misconceptions, and maintaining public confidence during transition.

Age also emerged as an important behavioral factor: younger travelers and students showed greater sensitivity to MBUF-related cost changes, particularly for recreational and non-work trips, whereas older individuals tended to be more stable in their route and mode preferences, preferring lower cost modes or routes. Targeted outreach, such as educational campaigns helping younger drivers recognize how small per-mile charges aggregate into meaningful costs, can help improve acceptance while reinforcing the value of transparent, fair pricing.

Finally, future planning efforts should integrate MBUF into statewide and regional models to evaluate long- term impacts alongside emerging technologies such as connected and autonomous vehicles (CAVs), land-use change, and evolving demographics. Investments in data collection, behavioral modeling, and technology pilots are warranted to ensure that North Carolina remains at the forefront of sustainable transportation finance.

The study has a few limitations: the statewide analysis, in particular, proved challenging to scale due to constraints in data resolution and the difficulty of aligning survey-based behavioral insights with network-level assignment models. While the synthetic population approach allowed extrapolation of attitudinal responses across PUMAs, the results remain approximate and may not fully capture local or regional variability. A more refined extrapolation strategy—potentially leveraging Census tract-level integration or region-wide surveys—would improve the robustness of statewide forecasts. Furthermore, the survey sample, though representative of North Carolina demographics, cannot capture the full heterogeneity of travel behavior across all user groups, especially freight operators. Future research should aim to address these limitations through larger-scale data collection, finer spatial resolution, and more detailed integration of freight and emerging mobility technologies into long-term planning models.

7.3 Implementation Plan and Technology Transfer

The results of this study are immediately implementable within NCDOT's existing modeling and planning framework. NCSTM already includes the necessary functionality to simulate link-level tolling. Since the MBUF does not induce large-scale changes in route choice at revenue-neutral rates, its implementation can be modeled by adding an additional toll attribute on selected roadway segments proportional to the MBUF rate. This capability allows future MBUF policy analyses to be integrated directly within NCDOT's established statewide and regional models without additional software investments (especially as part of the current strategic prioritization process).

The mode choice models developed under this project can also be used to support planning decisions by quantifying sensitivity to cost, time, and convenience. These results highlight that traveler behavior is more responsive to perceived total trip costs than to the rate structure itself, emphasizing that transparency and communication are more critical than complex pricing strategies. Accordingly, we recommend that any future deployment of MBUF or related pricing mechanisms prioritize cost transparency and clear reporting tools to enhance public acceptance and trust. To facilitate adoption, the research team will conduct a closeout and implementation meeting with NCDOT's Steering Committee. This session will be recorded and will demonstrate how MBUF rates can be embedded into the NCSTM framework, provide documentation of the Python-based data fusion and behavioral modeling tools, and ensure that model updates can be replicated by agency analysts and MPO partners.

Beyond the immediate application, the research findings provide a foundation for continued collaboration with NCDOT's Research and Development Unit and the Eastern Transportation Coalition. The developed synthetic population framework and statewide mapping of behavioral tendencies can be extended for other applications such as dynamic tolling, fairness analysis, or environmental impact evaluation. These tools can also serve as templates for regional adaptation in metropolitan models. Finally, the project team will provide a detailed documentation package and technical summary to be archived in NCDOT's Research Library and shared with other DOTs through the Transportation Research Board's networks.

REFERENCES

Aloisi, J., B. Atluri, J. Zhao, Y. Zheng, and S. Joyce-Johnson (2023, July). Replacing the Gas Tax: Leveraging the Electric Vehicle Transition to Build a Stronger Transportation Funding System in the United States. Technical report, MIT Mobility Initiative and JTL Transit Lab. URL: https://www.mmi.mit.edu/_files/ugd/29d096_eb9d66f3b2394eb29e1a76ae9c8be156.pdf.

American Society of Civil Engineers (2021, March). 2021 Report Card for America's Infrastructure: Roads. Technical report, American Society of Civil Engineers. https://infrastructurereportcard.org/wpcontent/uploads/2017/01/Roads-2021.pdf.

ASCE (2021, Oct). North Carolina Report card: North Carolina Infrastructure: ASCE's 2021 infrastructure report card.

Baker, R. T., M. R. Taylor, and E. Stevens (2014). Summary of 2013 National Symposium on Mileage-Based User Fees. Technical report, Texas Transportation Institute. URL: https://static.tti.tamu.edu/conferences/mbuf13/proceedings/proceedings.pdf. Last Accessed: January 2024.

Barbrook-Johnson, P. and A. S. Penn (2022). Bayesian Belief Networks, pp. 97–112. Cham: Springer International Publishing.

Beider, P. and D. Austin (2019). Issues and Options for a Tax on Vehicle Miles Traveled by Commercial Trucks. Technical report, Congressional Budget Office. Congressional Budget Office Report. URL: https://trid.trb.org/view/1661270. Last Accessed: January 2024.

Bert, S., W. Head, N. Norboge, S. Odom, L. Dorn, and D. Findley (2020). Modernizing North Carolina's Infrastructure Through Sustainable and Diversified Revenue Streams. Technical report, Institute of Transportation Research and Education. Report to NC Chambers Foundation. URL: https://ncchamber.com/wp-content/uploads/NC-Chamber-Foundation-Study_Modernizing-NCs-Infrastructure-Through-Diversified-and-Sustainable-Revenue-Streams.pdf. Last Accessed: January 2024.

Boyles, S. D., N. E. Lownes, and A. Unnikrishnan (2020). Transportation Network Analysis (0.85 ed.), Volume 1.

Brownstone, D., D. S. Bunch, and K. Train (2000). Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transportation Research Part B: Methodological 34(5), 315–338.

Bureau of Transportation Statistics (2022, December). Moving Goods in the United States: Weight of Shipments by Transportation Mode. Technical report, U.S. Department of Transportation. URL: https://data.bts.gov/stories/s/Moving-Goods-in-the-United-States/bcyt-rqmu/. Last Accessed: January 2024.

Burris, M., S. Lee, T. Geiselbrecht, R. Baker, and B. Weatherford (2015). Equity Evaluation of Sustainable Mileage-based User Fee Scenarios. In Journal of the Transportation Research Forum, Volume 54.

Cherchi, E. and J. de Dios Ortúzar (2006). On fitting mode specific constants in the presence of new options in RP/SP models. Transportation Research Part A: Policy and Practice 40(1), 1–18.

Cherchi, E. and J. d. D. Ortúzar (2006). Use of mixed revealed-preference and stated-preference models with nonlinear effects in forecasting. Transportation Research Record 1977(1), 27–34.

ChoiceMetrics (2021). Ngene 1.3 user manual and reference guide. https://www.choice-metrics.com/NgeneManual130.pdf.

Chondrogiannis, T., P. Bouros, J. Gamper, U. Leser, and D. B. Blumenthal (2020). Finding k-shortest paths with limited overlap. The VLDB Journal 29(5), 1023–1047.

DHM Research (2020, 7). I-95 MBUF North Carolina Baseline Survey. Report submitted to Eastern Transportation Coalition.

Dorogush, A. V., V. Ershov, and A. Gulin (2018). Catboost: gradient boosting with categorical features support.

Douma, F., J. Zhao, C. Fonseca, R. Zeerak, A. Lari, L. Munnich, M. Benesh, and J. Love- land (2021). Minnesota user based fee demonstration. Technical report, Center for Transportation Studies, University of Minnesota. URL: https://www.cts.umn.edu/publications/report/minnesota-user-based-fee-demonstration. Last Accessed: January 2024.

Duncan, D., D. Li, and J. D. Graham (2020). Tax rate design and support for mileage user-fees. Transport Policy 93, 17–26.

Duncan, D., V. Nadella, A. Bowers, S. Giroux, and J. D. Graham (2014). Bumpy designs: Impact of privacy and technology costs on support for road mileage user fees. National Tax Journal 67(3), 505–530.

Eastern Transportation Coalition (2021). Six Things to Know About Mileage-Based User Fees. URL: https://tetcoalitionmbuf.org/wp-content/uploads/2021/03/TETC-March-2021-Fact-Sheet.pdf. Last Accessed: January 2024.

EBP US, Inc. (2020). Financial impact of shifting from fuel tax to mileage-based user fees in North Carolina. URL: https://tetcoalitionmbuf.org/wp-content/uploads/2021/04/Financial-Impact-of-Shifting-from-Fuel-Tax-to-Mileage-Based-User-Fees-in-North-Carolina-1.pdf. Last Accessed: January 2024.

Federal Highway Administration (2022, December). December 2022 Traffic Volume Trends. Techni- cal report, U.S. Department of Transportation. https://www.fhwa.dot.gov/policyinformation/travel_monitoring/22dectvt/figure1.cfm. Last Accessed: January 2024.

Fitzroy, S. S. and K. Schroeckenthaler (2018). Estimating revenue-neutral mileage-based fees for urban and rural households in eight western states. Transportation Research Record 2672(4), 23–31.

GAUSS (2024). Aptech systems, inc. https://www.aptech.com/.

Glaeser, E. L., C. S. Gorback, and J. M. Poterba (2023). How regressive are mobility-related user fees and gasoline taxes? Tax Policy and the Economy 37(1), 1–56. URL: https://www.journals.uchicago.edu/doi/abs/10.1086/724352.

Guo, Z., A. Weinstein Agrawal, J. Dill, M. Quirk, M. Reese, et al. (2011). The Intersection of Ur- ban Form and Mileage Fees: Findings from the Oregon Road User Fee Pilot Program. Technical re- port, Mineta Transportation Institute. URL: https://ssti.us/wp-content/uploads/sites/1303/ 2012/03/Mineta-Urban-form-and-VMT-fees.pdf. Last Accessed: January 2024.

Hasnat, M. M. and E. Bardaka (2023). Distribution of highway infrastructure cost responsibility and revenue contribution shares among highway users in North Carolina: Present conditions and future alternatives. Transportation Research Record 2677(2), 1082–1102.

Hawaii Department of Transportation (2022, August). Hawaii Road Usage Charge Demonstration Final Report. Technical report, Hawaii Department of Transportation.

Hensher, D., J. Louviere, and J. Swait (1998). Combining sources of preference data. Journal of Econometrics 89(1-2), 197–221.

Hensher, D. A. (1994). Stated preference analysis of travel choices: the state of practice. Transportation 21, 107–133.

Hensher, D. A. and C. Mulley (2014). Complementing distance-based charges with discounted registration fees in the reform of road user charges: the impact for motorists and government revenue. Transportation 41, 697–715. URL: https://link.springer.com/article/10.1007/s11116-013-9473-6.

Hensher, D. A., J. M. Rose, J. de Dios Ortuzar, and L. I. Rizzi (2009). Estimating the willingness to pay and value of risk reduction for car occupants in the road environment. Transportation research part A: policy and practice 43(7), 692–707.

Hosford, K., C. Firth, M. Brauer, and M. Winters (2021). The effects of road pricing on transportation and health equity: a scoping review. Transport reviews 41(6), 766–787.

Hridoy, D. N., Tasnia, R., Pandey, V., & Hasnine, M. S. (2025). Towards vehicle miles traveled reduction: Impact of mileage-based user fee on travel mode choices. *Case Studies on Transport Policy*, 101454

Jacobs (2022). Exploration of Mileage-Based User Fee Approaches for All Users. URL: https://tetcoalitionmbuf.org/wp-content/uploads/2022/02/ Exploration-of-Mileage-Based-User-Fee-Approaches-for-All-Users_Condensed-1.pdf. Last Accessed: January 2024.

Jones, K., M. Bock, and Oregon Department of Transportation (2017, April). Oregon's Road Usage Charge: The OReGO Program | Final Report. Technical report, Oregon Department of Transportation. URL: https://www.oregon.gov/odot/Programs/RUF/IP-Road%20Usage%20Evaluation%20Book%20WEB_4-26.pdf.

Kim, E.-J. and P. Bansal (2024). A new flexible and partially monotonic discrete choice model. Transportation research part B: methodological 183, 102947.

Kirk, R. S. and M. Levinson (2016). Mileage-based road user charges. In Proceedings of the Conference Name. Library of Congress, Congressional Research Service. URL: https://sgp.fas.org/crs/misc/R44540.pdf. Last Accessed: January 2024.

Larsen, L., M. Burris, D. Pearson, and P. Ellis (2012). Equity evaluation of fees for vehicle miles traveled in Texas. Transportation research record 2297(1), 11–20.

Liu, H., C. Jin, B. Yang, and A. Zhou (2017). Finding top-k shortest paths with diversity. IEEE Transactions on Knowledge and Data Engineering 30(3), 488–502.

Lundberg, S. and S.-I. Lee (2017). A unified approach to interpreting model predictions.

Malik, S. (2022, August). RUC: Learning from the European experience. Technical report, Ptolemus Consulting Group. https://www.ptolemus.com/insight/ruc-learning-from-the-european-experience.

Matteson, M., N. Crocker, L. Martin-Mahar, and C. See (2016). Development of a fuel consumption and mileage allocation model to support mileage-based user fee research in Washington state. Transportation Research Record 2597(1), 11–19.

McCaleb, E., N. D. Norboge, W. Head, D. Findley, M. Cobb, L. Goode, and E. Bardaka (2021). Public Perceptions of Transportation Fees and Taxes in North Carolina 2020. Technical Report FHWA/NC/2020- 55, North Carolina Department of Transportation. URL: https://connect.ncdot.gov/projects/ research/RNAProjDocs/2020-55_FinalReport.pdf. Last Accessed: January 2024.

Munir, T., H. Dia, and H. Ghaderi (2021). A Systematic Review of the Role of Road Network Pricing in Shaping Sustainable Cities: Lessons Learned and Opportunities for a Post-Pandemic World. Sustainability 13(21), 12048.

Munnich, L., J. Doan, and M. Schmit (2012). Mileage-based user fee policy study: Supporting technical information. Minnesota Department of Transportation, Research Services. URL: https://www.cts.umn.edu/publications/report/ mileage-based-user-fee-policy-study-supporting-technical-information. Last Accessed: January 2024.

National Highway Traffic Safety Administration (2019, October). Odometer disclosure requirements. Federal Register. URL: https://www.federalregister.gov/documents/2019/10/02/2019-20360/ odometer-disclosure-requirements, note = Document ID: 2019-20360.

NC Future Investment Resources for Sustainable Transportation (FIRST) Commission (2021, Jan). Final Com- mission Report. URL: https://www.ncdot.gov/about-us/how-we-operate/finance-budget/ nc-first/Documents/2021-01-08-final-report.pdf. Last Accessed: January 2024.

Nelson, C. and G. Rowangould (2023). A Data-Driven Analysis of Rural Equity and Cost Concerns for Mileage-Based User Fees in Vermont. Transportation Research Record.

NewRoad Consulting (2023, September 12). Mileage-Based User Fees: 2022 International Truck Pi- lot Final Report. Technical report, NewRoad Consulting. URL: https://tetcoalitionmbuf.org/ wp-content/uploads/2023/09/TETC_Phase-IV_Final-Report_91123_FINAL.pdf.

Paz, A., A. Nordland, N. Veeramisti, A. Khan, and J. Sanchez-Medina (2014). Assessment of Economic Impacts of Vehicle Miles Traveled Fee for Passenger Vehicles in Nevada. Transportation Research Record 2450(1), 26–35.

Rose, J. M. and M. C. Bliemer (2009). Constructing efficient stated choice experimental designs. Transport reviews 29(5), 587–617.

Rose, J. M., M. C. Bliemer, D. A. Hensher, and A. T. Collins (2008). Designing efficient stated choice experiments in the presence of reference alternatives. Transportation research part B: Methodological 42(4), 395–406.

Roumboutsos, A., H. Voordijk, and A. Pantelias (2017). Funding and financing transport infrastructure: business models to enhance and enable financing of infrastructure in transport. Routledge.

Rufolo, A. M. (2011). Cost estimates for collecting fees for vehicle miles traveled. Transportation research record 2221(1), 39–45.

Sana, B., K. C. Konduri, and R. M. Pendyala (2010). Quantitative Analysis of Impacts of Moving Toward a Vehicle Mileage-based User Fee. Transportation Research Record 2187(1), 29–35.

Sarmiento, C. F. and J. Z. Zhao (2021). Distance-Based User Fee: Financial Analysis and Rate Setting. A Technical Report to Minnesota Department of Transportation. URL: https://dbf.dot.state.mn.us/ media/rjad1wgf/financial-analysis-and-rate-setting-1014.pdf. Last Accessed: January 2024.

Selmoune, A., Q. Cheng, L. Wang, Z. Liu, et al. (2020). Influencing Factors in Congestion Pricing Acceptability: a Literature Review. Journal of Advanced Transportation 2020.

Shrode, G., J. Davis, and R. Puentes (2023). Driving Change: Advice for the National VMT-Fee Pilot. Technical report, Eno Center for Transportation. URL: https://enotrans.org/eno-resources/ driving-change-advice-for-the-national-vmt-fee-pilot/. Last Accessed: January 2024.

Sjoquist, D. L. (2023). Funding Transportation in Georgia: Vehicle Miles Traveled Tax. Center for State and Local Finance Working Paper. URL: https://cslf.gsu.edu/files/2023/07/cslf2301.pdf. Last Accessed: January, 2024.

Speroni, S., A. W. Agrawal, M. Manville, and B. D. Taylor (2022). Charging Drivers by the Gallon vs. the Mile: An Equity Analysis by Geography and Income in California. Technical Report by the Mineta Institute.

Tasnia, R., Pandey, V., Hridoy, D. N., & Hasnine, M. S. (2025). Review of Mileage-Based User Fees for Sustainable Transportation Funding: Challenges, Opportunities, and Research Gaps. *Transportation Research Record*, 03611981251352761

Thapa, R., K. Zeringue, and J. Codjoe (2020). Literature Review of Mileage-Based Road User Fees. Technical Report 20-02TA-SS, Louisiana Transportation Research Center. Technical Assistance Report– LTRC Project Number: 20-02TA-SS. URL: https://www.ltrc.lsu.edu/pdf/2020/20-02TA-SS. pdf. Last Accessed: January 2024.

The Eno Center for Transportation (2014, December). How we Pay for Transportation: The Life and Death Highway Trust Fund of the. Technical report, The Eno Center for Transportation. URL: https://www.ibtta.org/sites/default/files/documents/MAF/ENO%20How%20We% 20Pay%20for%20Transportation.pdf".

Thomopoulos, N., S. Grant-Muller, and M. Tight (2009). Incorporating Equity Considerations in Transport Infrastructure Evaluation: Current Practice and a Proposed Methodology. Evaluation and program planning 32(4), 351–359.

TrackBill (2025). Vermont house bill 479: An act relating to the transportation program and miscellaneous changes to laws related to transportation. https://legislature.vermont.gov/bill/status/2024/H.479. Accessed on: July 2025.

Train, K. E. (2009). Discrete choice methods with simulation. Cambridge university press.

TRIP (2020, July). Restoring the Interstate Highway System: Meeting America’s Transportation Needs with a Reliable, Safe And Well-Maintained National Highway Network. URL: https://tripnet. org/wp-content/uploads/2020/06/TRIP_Interstate_Report_2020.pdf. Last Accessed: Jan- uary 2024.

U.S. Census Bureau (2020). State profile: North Carolina. https://data.census.gov/profile/North_ Carolina?g=040XX00US37. Accessed July, 2024.

Utah Foundation (2021, March). Measuring the Miles: Road User Charges in Utah. Technical Report Re- search Report 786, n/a. URL: https://www.utahfoundation.org/wp-content/uploads/rr786. pdf.

Virginia Department of Motor Vehicles (2021, July). Mileage-Based User Fee Program Interim Report. Technical report, Virginia Department of Motor Vehicles. URL: https://rga.lis.virginia.gov/Published/2021/RD255/PDF.

Weatherford, B. A. (2012). Mileage-based user fee winners and losers: An analysis of the distributional implications of taxing vehicle miles traveled, with projections, 2010–2030. Ph. D. thesis, The Pardee RAND Graduate School.

Whitty, J. M. and B. Imholt (2005). Oregon's mileage fee concept and road user fee pilot program. Report to the 73rd Oregon Legislative Assembly On the Proposed Alternatives to the Current Sys- tem of Taxing Highway Use Through Motor Vehicle Fuel Taxes, Salem, OR: Oregon Department of Transportation. URL: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=a9dc98a5a5f06270ad00ff4a55cad4d2bbd0d00c. Last Accessed: January 2024.

Yang, D., E. Kastrouni, and L. Zhang (2016). Equitable and progressive distance-based user charges design and evaluation of income-based mileage fees in Maryland. Transport Policy 47, 169–177.

Yang, J., A.-O. Purevjav, and S. Li (2020). The marginal cost of traffic congestion and road pricing: evidence from a natural experiment in Beijing. American Economic Journal: Economic Policy 12(1), 418–453.

Yuan, C., Z. Fan, L. Lyu, P. S. Acharya, and H. S. Matthews (2021). Leveraging inspection records for vehicle miles traveled estimates and analysis of mileage-based user fees in Pennsylvania. In Annual Meeting of the Transportation Research Board, Washington, DC.

Zhang, L. and Y. Lu (2012). Marginal-cost Vehicle Mileage Fee. Transportation Research Record 2297(1), 1–10.

Zhang, L., B. S. McMullen, D. Valluri, and K. Nakahara (2009). Vehicle mileage fee on income and spatial equity: Short-and long-run impacts. Transportation research record 2115(1), 110–118.

Zhang, Z., K. Spansel, and B. Wolshon (2013). Megaregion network simulation for evacuation analysis. Transportation Research Record 2397(1), 161–170.

Zupan, J., R. Barone, J. Whitmore, R. P. Association, et al. (2012). Mileage-Based User Fees: Prospects and Challenges. Published by the New York State Energy Research and Development Authority.

Appendix A. Supplementary Tables and Figures

Table A.1 presents the terminologies for MBUF used in the literature.

Table A.1: Terminologies for MBUF Used in the Literature

State	MBUF Terminology Used
California	Road Charge, Mileage Fee
Oregon	OReGO
Utah	Road Usage Charge (RUC)
Washington, Hawaii, Texas, Colorado Minnesota	Mileage-Based User Fee, Road Usage Charge
Virginia	Road Usage Charge, Mileage Fee
Arizona	Road Usage Charge
New York, Florida, Illinois, Michigan North Carolina Georgia, Massachusetts, Ohio, Pennsylvania, Wisconsin	Mileage-Based User Fee, Road Usage Charge

Table A.2 shows the technologies for reporting and monitoring MBUF. 'Ease of administration' might mean different things in different situations. 'Low' indicates simpler administration, 'medium' denotes moderate complexity, and 'high' denotes more challenging or resource-intensive tasks discussed in National Highway Traffic Safety Administration (2019) and Shrode et al. (2023). Regarding costs, numerical figures can be more precise than qualitative words like "high cost" or "low cost," however, such costs are not always available. One can estimate costs by considering many elements, including purchasing, installing, maintaining, and operating equipment. These values are usually given in ranges to allow for fluctuation.

Table A.2: Technologies for Reporting and Monitoring MBUF (Adapted from Shrode et al., 2023)

Reporting Method	Ease of Administration	Administrative Cost	Evasion
Manual Odometer Reading **<u>Pros</u>**: -Cost effective -No expensive technology needed -Allow GPS tracking -Accessible for participants without smartphones -Lower privacy concerns **<u>Cons</u>**: -Requires participant intentionality -Lack of GPS capability makes interoperability difficult.	(Medium): Online odometer photo submissions ease administration, but in-person inspections need state coordination.	(Low to Medium): Costs may range from \$100 to \$300, including expenses related to workforce for inspections or online data entry systems.	(Low): Vehicle owners' direct odometer readings reduce evasion risk.

Smart phone Reporting via Mobile App **Pros**: - Registered smartphone must be in the vehicle - Low maintenance after installation -High potential for privacy breaches. **Cons**: -Limiting flexibility if multiple drivers share the same vehicle -Challenging initial installation for drivers	(Low to Medium): Relatively easy for users to submit odometer photos. Administrative resources needed for backend.	(Low to Medium): App development, maintenance, and backend data processing may cost between \$200 and \$500.	(Medium): Without GPS verification, users may manipulate their records.
OBD-II Plug-in Device (No GPS) **Pros**: -High expense; may require replacement and upgrades -Low maintenance after installation. **Cons**: -Challenging initial installation for drivers -Limited success with OEMs in state pilot programs	(Medium to High): Plug-and-play device installation is relatively easy, but backend data processing may require resources.	(Medium): Costs may range from \$250 to \$600, including device purchase, installation, and backend data processing.	(Low to Medium): Possibility of device tampering exists
OBD-II Plug-in Device (GPS-Enabled) **Pros**: -Most expensive technology -Low maintenance after installation -Data generated by the vehicle is historically routed through OEMs leading to complex data access. **Cons**: -Challenging initial installation for drivers -Privacy concerns due to detailed location information	(Medium to High): Similar to the non-GPS option, but with added GPS data processing.	(High): Costs may range from \$350 to \$800, including additional GPS integration and data processing costs.	(Low to Medium): GPS verification reduces manipulation but does not eliminate it.
In-Vehicle Telematics **Pros**: Advanced technology for automation **Cons**: -The current cost is not substantially cheaper than using devices for VMT fee collection. -Limited success with OEMs in the state pilot programs.	(High): Integrated system requires minimal user interaction.	(High): The costs, including initial setup and integration costs, may range from \$500 to \$1000.	(Low): Integrated system reduces the risk of manipulation

Table A.3 Overview of Modes and Attributes of the SP Scenarios

Attributes	Modes	Levels
Trip Distance (miles)	All modes	3, 10, 40
Travel Time (mins.)	Drive Alone	4.5, 15, 60
	Carpool	5.2, 17.2, 68.6
	Park and Ride	6.7, 22.2, 89
	Uber/Lyft/Taxi	4.5, 15, 60
	Bike	9, 30, 120
	Walk	45, 150, 600
	Transit	7.2, 24, 96
Fuel Cost (\$)	Drive Alone	0.41, 0.68, 0.97, 2.27, 3.89, 5.44
	Carpool	0.24, 0.41, 0.58, 1.36, 2.33, 3.26
	Park and Ride	0.14, 0.14, 0.19, 0.45, 0.78, 1.09
*Parking/toll/admin/bus fare (\$)	Drive Alone	0, 3, 6
	Carpool	0, 1.8, 3.6
	Park and Ride	0.48, 1.6, 6.4

Total Travel Cost ($)	Drive Alone	1.14, 3.46, 3.77, 4.69, 8.47, 12.13
	Carpool	0.68, 2.08, 2.26, 2.81, 5.08, 7.28
	Park and Ride	0.63, 0.63, 1.83, 2.09, 7.34, 7.63
	Uber/Lyft/Taxi	16, 30, 90
	Transit	0.6, 2, 8
Additional Waiting Time (min)	Park and Ride	4, 8, 12
	Uber/Lyft/Taxi	5, 10, 15
	Transit	5, 10, 15
State Tax: Fuel ($)	Drive Alone	0.09, 0.69
	Carpool	0.05, 0.41
	Park and Ride	0.02, 0.14
MBUF ($)	Drive Alone	0.20, 0.8
	Carpool	0.12, 0.48
	Park and Ride	0.04, 0.16
Combination of both (Fuel + MBUF) ($)	Drive Alone	0.06, 0.16
	Carpool	0.03, 0.10
	Park and Ride	0.02, 0.03

**Note: Parking/toll/admin cost is associated with Drive Alone and Carpool and bus fare is associated with Park and Ride.*

Table A.4 Joint RP-SP MNL Model Result for Work Trip

Joint RP-SP MNL (Work)	
Loglikelihood of full model	-6581.4
Loglikelihood of null model	-11641.5
rho^2 against null model	0.44
Observations	881

Variable	**Mode**	**RP Coefficient**		**SP Coefficient**	
		Estimate	**t-stat**	**Estimate**	**t-stat**
ASC	Drive Alone	1.745	16.47	2.325	18.848
	Carpool	0	0	0	0
	Park and Ride	-2.984	-5.722	-2.216	-13.641
	Uber/Lyft/Taxi	-1.702	-3.263	-5.496	-23.405
	Bike	-1.015	-2.937	-3.674	-16.163
	Walk	-0.688	-1.086	-6.211	-17.507
	Transit	-2.545	-7.345	-2.629	-7.776
Travel Time	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.019	-6.495	-0.019	-6.495

Travel Cost	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.141	-4.077	-0.141	-4.077
Travel Distance	Bike, Walk	-0.163	-11.307	-0.163	-11.307
Fuel Cost	Drive Alone, Carpool	---	---	-0.172	-2.903
Parking/toll/admin cost/Bus fare	Carpool, Park and Ride	---	---	-0.053	-1.171
Additional Wait Time	Transit	---	---	-0.075	-2.404
State Tax: MBUF*Working Full Time	Drive Alone, Carpool	---	---	-0.387	-0.83
State Tax: Fuel*Working Full Time	Carpool, Park and Ride	---	---	-1.575	-2.185
State Tax: MBUF*Age (20-24)	Drive Alone, Carpool	---	---	-1.334	-2.159
State Tax: Fuel*Age (20-24)	Drive Alone, Carpool	---	---	-1.132	-1.945
State Tax: MBUF*Age (60-74)	Drive Alone, Carpool	---	---	-0.531	-2.103
State Tax: Fuel*Age (60-74)	Carpool, Park and Ride	---	---	-0.354	-1.737
State Tax: MBUF*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.669	-1.557
State Tax: Fuel*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.749	-1.454
Scale Parameter:					
RP		1	---	---	---
(Gender: Male)		---	---	-0.179	-4.675

Table A.5 Joint RP-SP MNL Model Result for Grocery/Shopping Trip

Joint RP-SP MNL (Grocery/Shopping)	
Loglikelihood of full model	-5041.04
Loglikelihood of null model	-11641.5
rho^2 against null model	0.57
Observations	881

Variable	Mode	RP Coefficient		SP Coefficient	
		Estimate	t-stat	Estimate	t-stat
ASC	Drive Alone	1.78	16.259	4.349	32.137
	Carpool	0	0	0	0
	Park and Ride	-3.063	-5.947	-2.441	-9.61
	Uber/Lyft/Taxi	-2.479	-4.492	-4.754	-18.559
	Bike	-1.218	-3.585	-3.838	-13.09
	Walk	-0.759	-1.181	-4.712	-15.909
	Transit	-2.622	-7.539	-2.558	-6.092
Travel Time	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.009	-2.176	-0.009	-2.176
Travel Cost	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.056	-1.469	-0.056	-1.469
Travel Distance	Bike, Walk	-0.096	-6.481	-0.096	-6.481
Fuel Cost	Drive Alone	---	---	-0.289	-4.743
Parking/toll/admin cost/Bus fare	Drive Alone, Carpool, Park and Ride	---	---	-0.094	-2.041
Additional Wait Time	Transit	---	---	-0.126	-3.312
State Tax: MBUF*Working Full Time	Drive alone, Carpool, Park and Ride	---	---	-1.279	-1.469
State Tax: Fuel*Working Full Time	Carpool	---	---	-2.243	-2.367
State Tax: MBUF*Age (20-24)	Drive alone, Park and Ride	---	---	-1.688	-2.696
State Tax: Fuel*Age (20-24)	Drive alone, Park and Ride	---	---	-1.089	-1.824
State Tax: MBUF*Age (60-74)	Carpool, Park and Ride	---	---	-1.049	-3.145
State Tax: Fuel*Age (60-74)	Carpool, Park and Ride	---	---	-1.406	-3.832
State Tax: MBUF*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.813	-1.304

State Tax: Fuel*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-1.303	-1.784
Scale Parameter:					
RP		1	---	---	---
(Employment Status: Working Full Time)		---	---	0.084	1.977

Table A.6 Joint RP-SP MNL Model Result for Recreational Trip

Joint RP-SP MNL (Recreational)	
Loglikelihood of full model	-7196.2
Loglikelihood of null model	-11641.5
rho^2 against null model	0.38
Observations	881

Variable	**Mode**	**RP Coefficient**		**SP Coefficient**	
		Estimate	**t-stat**	**Estimate**	**t-stat**
ASC	Drive Alone	1.889	17.673	1.208	14.142
	Carpool	0	0	0	0
	Park and Ride	-3.039	-5.923	-1.793	-6.591
	Uber/Lyft/Taxi	-2.197	-4.153	-4.589	-29.531
	Bike	-1.278	-3.678	-4.055	-21.407
	Walk	-0.786	-1.223	-5.177	-24.717
	Transit	-2.729	-8.187	-2.649	-11.522
Travel Time	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi	-0.015	-4.164	-0.015	-4.164
Travel Cost	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.074	-2.189	-0.074	-2.189
Travel Distance	Bike, Walk	-0.082	-7.543	-0.082	-7.543
Additional Wait Time	Park and Ride, Transit	---	---	-0.114	-4.305
State Tax: MBUF*Working Full Time	Drive Alone, Carpool	---	---	-1.5417	-3.171
State Tax: Fuel*Working Full Time	Drive Alone, Carpool	---	---	-0.816	-1.43

State Tax: MBUF*Age (20-24)	Drive alone, Park and Ride	---	---	-0.994	-2.488
State Tax: Fuel*Age (20-24)	Drive alone, Carpool	---	---	-1.097	-2.491
State Tax: MBUF*Age (60-74)	Carpool, Park and Ride	---	---	-0.768	-2.723
State Tax: Fuel*Age (60-74)	Carpool, Park and Ride	---	---	-0.729	-2.582
State Tax: MBUF*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.99	-2.133
State Tax: Fuel*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.962	-1.956
Scale Parameter:					
RP	RP	1	---	---	---
(Gender: Male)		---	---	-0.189	-5.183

Table A.7 Joint RP-SP Mixed Logit Model Result for Work Trip

Joint RP-SP Mixed Logit (Work)					
Loglikelihood of full model	-6090.48				
Loglikelihood of null model	-11641.5				
rho^2 against null model	0.48				
Observations	881				
Variable	**Mode**	**RP Coefficient**		**SP Coefficient**	
		Estimate	**t-stat**	**Estimate**	**t-stat**
ASC	Drive Alone	1.7185	16.353	1.974	17.947
	Carpool	0	0	0	0
	Park and Ride	-2.946	-5.663	-10.278	-15.726
	Uber/Lyft/Taxi	-1.337	-2.748	-14.355	-16.096
	Bike	-1.025	-2.952	-14.771	-13.285
	Walk	-0.694	-1.102	-16.814	-15.273
	Transit	-2.517	-7.307	-10.739	-15.36

Travel Time	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.017	-6.376	-0.017	-6.376
Travel Cost	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.186	-6.328	-0.186	-6.328
Travel Distance	Bike, Walk	-0.169	-12.95	-0.169	-12.95
Fuel Cost	Drive Alone, Carpool	---	---	-0.15	-3.05
Parking/toll/admin cost/Bus fare	Carpool, Park and Ride	---	---	-0.122	-3.038
Additional Wait Time	Transit	---	---	-0.064	-2.314
State Tax: MBUF*Working Full Time	Carpool	---	---	-1.657	-2.951
State Tax: Fuel*Working Full Time	Carpool	---	---	-1.516	-2.249
State Tax: MBUF*Age (60-74)	Drive Alone, Carpool	---	---	-1.171	-2.932
State Tax: Fuel*Age (60-74)	Carpool, Park and Ride	---	---	-0.394	-2.277
State Tax: MBUF*Part or Full Time College/University Student	Carpool	---	---	-0.512	-1.124
State Tax: Fuel*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.787	-1.632
Scale Parameter:					
RP	RP	1	---	---	---
(Gender: Male)		---	---	-1.404	-7.457
Error Components					
	Mode	---	---	**Estimate**	**t-stat**
	Drive Alone, Carpool	---	---	8.748	12.462
	Park and Ride, Transit	---	---	5.957	15.548
	Bike, Walk	---	---	6.366	7.981
	Uber/Lyft/Taxi	---	---	1	---

Table A.8 Joint RP-SP mixed logit Model Result for Grocery/Shopping Trip

Joint RP-SP mixed logit (Grocery/Shopping)					
Loglikelihood of full model	-4663.06				
Loglikelihood of null model	-11641.5				
rho^2 against null model	0.59				
Observations	881				
Variable	**Mode**	**RP Coefficient**		**SP Coefficient**	
		Estimate	**t-stat**	**Estimate**	**t-stat**
ASC	Drive Alone	1.775	16.246	4.232	33.619
	Carpool	0	0	0	0
	Park and Ride	-3.039	-5.903	-11.458	-14.34
	Uber/Lyft/Taxi	-2.186	-3.936	-12.968	-15.805
	Bike	-1.163	-3.415	-11.832	-14.876
	Walk	-0.748	-1.165	-12.632	-15.053
	Transit	-2.601	-7.504	-11.607	-13.809
Travel Time	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.015	-4.378	-0.015	-4.378
Travel Cost	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.089	-2.317	-0.089	-2.317
Travel Distance	Bike, Walk	-0.115	-7.961	-0.115	-7.961
Fuel Cost	Drive Alone, Carpool	---	---	-0.379	-5.129
Parking/toll/admin cost/Bus fare	Drive Alone, Carpool, Park and Ride	---	---	-0.164	-3.593
Additional Wait Time	Transit	---	---	-0.123	-3.32
State Tax: MBUF*Working Full Time	Drive Alone, Carpool, Park and Ride	---	---	-1.561	-2.063
State Tax: Fuel*Working Full Time	Carpool, Park and Ride	---	---	-1.726	-1.843

State Tax: MBUF*Age (20-24)	Drvie Alone, Park and Ride	---	---	-1.605	-2.674
State Tax: Fuel*Age (20-24)	Drive Alone, Park and Ride	---	---	-0.941	-1.554
State Tax: MBUF*Age (60-74)	Carpool, Park and Ride	---	---	-1.073	-3.295
State Tax: Fuel*Age (60-74)	Carpool, Park and Ride	---	---	-1.431	-4.011
State Tax: MBUF*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.768	-1.296
State Tax: Fuel*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-1.112	-1.609
Scale Parameter:					
RP	RP	1	---	---	---
	(Gender: Male)	---	---	-0.167	-2.997
Error Components					
	Mode			**Estimate**	**t-stat**
	Drive Alone, Carpool	---	---	7.83	12.011
	Park and Ride, Transit	---	---	6.83	11.911
	Bike, Walk, Uber/Lyft/Taxi	---	---	1	---

Table A.9 Joint RP-SP mixed logit Model Result for Recreational Trip

Joint RP-SP mixed logit (Recreational)					
Loglikelihood of full model	-6335.96				
Loglikelihood of null model	-11641.5				
rho^2 against null model	0.46				
Observations	881				
Variable	**Mode**	**RP Coefficient**		**SP Coefficient**	
		Estimate	**t-stat**	**Estimate**	**t-stat**
ASC	Drive Alone	1.713	16.102	1.307	16.33
	Carpool	0	0	0	0
	Park and Ride	-2.947	-5.703	-11.682	-15.668

	Uber/Lyft/Taxi	-3.177	-8.555	-15.419	-16.351
	Bike	-1.267	-3.657	-17.027	-16.89
	Walk	-0.827	-1.295	-17.882	-17.681
	Transit	-2.511	-7.561	-12.729	-17.79
Travel Time	Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.021	-6.419	-0.021	-6.419
Travel Cost	Drive Alone, Carpool, Park and Ride, Uber/Lyft/Taxi, Transit	-0.194	-6.628	-0.194	-6.628
Travel Distance	Bike, Walk	-0.104	-11.521	-0.104	-11.521
Additional Wait Time	Transit	---	---	-0.061	-2.236
State Tax: MBUF*Working Full Time	Drive Alone, Carpool	---	---	-1.156	-2.892
State Tax: MBUF*Age (20-24)	Drvie Alone, Park and Ride	---	---	-0.721	-1.656
State Tax: Fuel*Age (20-24)	Drive Alone	---	---	-1.123	-2.332
State Tax: MBUF*Age (60-74)	Carpool, Park and Ride	---	---	-0.75	-3.312
State Tax: Fuel*Age (60-74)	Carpool, Park and Ride	---	---	-0.763	-3.303
State Tax: MBUF*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-0.852	-2.284
State Tax: Fuel*Part or Full Time College/University Student	Carpool, Park and Ride	---	---	-1.066	-2.608
Scale Parameter:					
RP	RP	1	---	---	---
	(Gender: Male)	---	---	-2.097	-5.562
Error Components					
	Mode			**Estimate**	**t-stat**
	Drive Alone, Carpool	---	---	10.906	13.409
	Park and Ride, Transit	---	---	6.915	17.776
	Bike, Walk	---	---	6.866	15.596
	Uber/Lyft/Taxi	---	---	1	---

Table A.10 Summary of features used in the CatBoost analysis

Feature Name	Type	Categories/Range
Approximate household income	Categorical	1: <25k; 2 :25-49k; 3: 50 − 79k; 4 :80-119k; 5: 120 − 250k; 6 :>250k; 7: No Answer
Sex	Categorical	0: Male; 1: Female
Age	Continuous	Range: 15 to 94
Race category	Categorical	1: White; 2: Black; 3: Asian; 4: Native Am.; 5: Pac. Islander; 6: Other
Are you Hispanic or Latino origin?	Categorical	0: No; 1: Yes
Current employment status	Categorical	1: Full Time; 2: Part Time; 3: Remote; 4: Temp Absent; 5: Unemployed; 6: Student; 7: Retired; 8: Other
Highest grade or level of education	Categorical	1: <HS; 2: HS Grad; 3: Some College; 4: Bachelor; 5: Graduate
Student	Categorical	1: K-12; 2: Voc/Tech; 3: Part-time Univ; 4: Full-time Univ; 5: Other; 6: No
Number of individuals in household	Continuous	Range: 1.000 to 9.000
Number of individuals over age 12 in household	Continuous	Range: 1.000 to 8.000
Do you possess a driver's license?	Categorical	0: No; 1: Yes
Number of motor vehicles in household	Continuous	Range: 0.000 to 8.000
Number of bikes in household	Continuous	Range: 0.000 to 9.000
Departure hour for most recent trip	Continuous	Range: 0.000 to 2300.000
Fuel category	Categorical	1: Gas; 2: Diesel; 3: EV; 4: Hybrid; 5: Other; 6: No Vehicle
Miles driven in the past year	Continuous	Range: 0.000 to 50000.000
Owns EzToll or NC Quick Pass transponder	Categorical	0: No; 1: Yes
Uses EzToll or NC Quick Pass on average trip	Categorical	0: No; 1: Yes
Uses Smart Trip or similar pass on average trip	Categorical	0: No; 1: Yes
Frequency of use – Personal car (driver) or Personal car (passenger) or Public transportation or Ridehailing (Uber/Lyft) or Vehicle rentals/carshare or Toll Roads	Categorical	1: Everyday; 2: Regularly; 3: Occasionally; 4: Rarely; 5: Never
Monthly fuel cost for main vehicle	Categorical	1: $10-100; 2: $100-200; 3: $200-300; 4: $300-400; 5: $400-500; 6: $500-600; 7: $600-700; 8: $700-800; 9: $800-900 10: $900-1000; 11: $1000+; 12; Do not know
Scenario – MPG of vehicle	Continuous	Range: 15.000 to 35.000
Scenario – Time on toll or non-toll road (min)	Continuous	Range: 10.000 to 20.000
Scenario – Distance on toll or non-toll road (miles)	Continuous	Range: 5.000 to 10.000
Scenario – Cost on toll road	Continuous	Range: 5.000 to 5.000
Scenario – State gas tax (¢/gallon)	Continuous	Range: 43.000 to 43.000
Scenario – Fuel rate ($/gallon)	Continuous	Range: 3.000 to 3.000
Scenario – Cost paid (summary)	Continuous	Range: 3.000 to 4.000
Scenario – Time saved (summary, min)	Continuous	Range: 10.000 to 10.000
Scenario – Summary shown (1 = Yes, 0 = No)	Continuous	Range: 0.000 to 1.000

Table A. 11 Logit and Probit Regression Results with Model Comparison

Variable	Logit Coef.	Std. Error	Odds Ratio	Probit Coef.	Std. Error
Male	0.074	(0.060)	1.076	0.046	(0.035)
Age	-0.013***	(0.002)	0.987	-0.008***	(0.001)
Vehicle MPG	-0.007.	(0.004)	0.993	-0.004.	(0.002)
Total Cost	-0.067	(0.080)	0.935	-0.038	(0.047)
Time Saved	0.026	(0.043)	1.026	0.010	(0.025)
Summary Shown	-0.097.	(0.053)	0.907	-0.060*	(0.031)
Approximate_household_income_25-49k	0.317***	(0.087)	1.373	0.188***	(0.050)
Approximate_household_income_50-79k	0.039	(0.095)	1.039	0.031	(0.054)
Approximate_household_income_80-119k	0.092	(0.111)	1.096	0.049	(0.064)
Approximate_household_income_120-250k	0.913***	(0.106)	2.493	0.548***	(0.063)
Approximate_household_income_250k	-0.061	(0.288)	0.941	-0.056	(0.171)
Approximate_household_income_No Answer	0.096	(0.172)	1.101	0.069	(0.098)
Employment Status: Part Time	-0.261*	(0.102)	0.770	-0.144*	(0.059)
Employment Status: Remote	0.264*	(0.131)	1.302	0.150.	(0.079)
Employment Status: Temporarily absent from work	-0.305	(0.271)	0.737	-0.168	(0.153)
Employment Status: Unemployed or searching for job	0.030	(0.099)	1.031	0.014	(0.058)
Employment Status: Student	-1.026***	(0.196)	0.358	-0.597***	(0.114)
Employment Status: Retired	-0.044	(0.090)	0.957	-0.025	(0.052)
Employment Status: Other	-0.067	(0.120)	0.935	-0.036	(0.069)
Education: HS Grad	-0.319	(0.197)	0.727	-0.186	(0.118)
Education: Some college or associates degree	-0.567**	(0.197)	0.567	-0.327**	(0.118)
Education: Bachelor's Degree	-0.220	(0.201)	0.803	-0.124	(0.121)
Education: Graduate degree or professional degree	-0.066	(0.206)	0.936	-0.040	(0.124)
Student_Part-Time college/University	0.347	(0.326)	1.415	0.228	(0.189)
Student_Full-Time college/University	1.050***	(0.315)	2.858	0.658***	(0.184)
Student_Other	0.880*	(0.442)	2.410	0.549*	(0.267)
Student_No	-0.291	(0.298)	0.748	-0.159	(0.172)
Model Comparison Statistics					
Log-Likelihood	−4412.39			−4414.26	
AIC	8878.77			8882.52	
BIC	9068.62			9072.37	
Pseudo R^2	0.0600			0.0596	
Accuracy	0.7451			0.7441	
N	881			881	

Notes: Standard errors in parentheses.

Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1 Odds ratios shown for logit model only.

Model comparison statistics: Logit model in column 2, Probit model in column 5.

Appendix B. Survey

The survey was conducted online using Qualtrics. The JPG format of the asked questions is included below. The PDF survey can found on this permanent link for easier access (33.9 MB): https://drive.google.com/file/d/1o9DU1MvQNjX1xebFN63gPJzDy8NNygG6/view?usp=drive_link

NORTH CAROLINA A&T
STATE UNIVERSITY

Consent Form

Dear Survey Respondent,
You've been randomly selected to take part in a cutting-edge research study that aims to explore **transportation choices in the era of mileage-based user fees (MBUF)**. This page contains all the information you need to make an informed decision about joining the study. Additionally, you'll get a chance to learn about mileage-based user fees before we dive into the questions on next pages.

Purpose of the Study
Mileage-based user fee (MBUF), also referred to as vehicle miles traveled tax or road user charge, charges a traveler a fixed or variable rate per mile traveled on the road and is being considered by the state of North Carolina to serve as a replacement for the fuel tax. The purpose of this study is to **understand the impact of MBUF on travelers choices and develop models predicting long-term travel patterns accounting for those choices**. We wish to study whether shift to mileage-based user fees may trigger changes in the ways travelers behave in their choices of modes and routes to their destination. For example, it may be possible that travelers like you will switch to other modes (such as transit, biking, etc.) or other routes with a shorter distance to circumvent the new costs posed by MBUFs. Carpooling and a shift towards fuel-efficient vehicles are also expected.

You have been asked to participate in this study because you are an active transportation user; however, your participation is voluntary. If you choose to participate, you will be asked to complete an online survey based on your best understanding of transportation systems under the presence of mileage-based user fees. This will take approximately 20 minutes of time.

Procedure
You will be asked simple questions based on the choices you make in a day-to-day transportation system under various scenarios. Each scenario is independent, and you may choose to participate in any, all, or none of them at any time without penalty.

Voluntary Participation
Your participation in this research study is voluntary and you may end your participation at any time. You may choose not to participate in any survey activity or choose not to be a part of the survey program overall at any time for any reason. Refusing to participate or leaving the study will not result in any penalty or loss of benefits to which you are entitled.

Risks
We do not anticipate any risks from your participation in this research study.

Benefits
This research will effectively develop more accurate and robust transportation planning models, which will provide us accurate forecasting and better plan the infrastructure management across the state of North Carolina. Eventually, we will be able perform better short-term and long-term transportation planning, which will have a substantial societal impact in terms of reduced travel times, travel costs, and efficient operations of traffic.

Compensation
There is no direct compensation to participants in this study apart from the benefits obtained from completing the survey with the market research company.

Confidentiality
Your privacy is important to us. **This survey is anonymous, and no personal identifying information, such as your name, address, phone number, or email address, will be collected.** All other information collected in this study will be kept strictly confidential to the extent permitted by law. Only authorized research staff will have access to the data, which will be stored securely in a locked file cabinet or on a password-protected computer.

To protect your confidentiality, personal identifiers will be removed from all data collected, and the data will be coded and/or aggregated prior to analysis. This means that your individual responses will be combined with those of other participants to produce group averages, and no one will be able to link your responses to you personally.

Identifiable data will be disposed of upon completion of the study or after 5 years, whichever occurs later. This will be done by securely shredding any paper documents or deleting any electronic files containing personal identifiers. The research team will be responsible for ensuring that all identifiable data is disposed of properly.

Questions About the Study
If you have questions or concerns about this research later, please contact Dr. Venktesh Pandey at (336) 285-3687 or vpandey@ncat.edu.

If you have any study-related concerns or any questions about your rights as a research subject, you may call the Office of Research Compliance and Ethics at North Carolina A&T State University at (336) 285-3179 or email irb@ncat.edu. (**Study Protocol #HS23-0145**)

Voluntary Participation/Withdrawal
Your participation is voluntary, and you may end your participation at any time. Refusing to participate or leaving the study at a later time will not result in any penalty or loss of benefits to which you are entitled.

Statement of Consent
I have read the above information and have received answers to all

my questions. I am at least 18 years old and voluntarily consent to take part in this research study.

Yes
No

Screening Questions

What is your approximate household income? (considering annual income from all sources)

Less than $25,000
$25,000 - $49,999
$50,000 - $79,999
$80,000 - $119,999
$120,000 - $250,000
Higher than $250,000
Prefer not to answer

Which state do you reside in?

Texas
California
North Carolina
Florida
Georgia
New York
None of the above

Verify that you are not a robot

I'm not a robot

Introduction to MBUF

Are you already familiar with the Mileage-based User Fees? If yes, proceed to the next page; else, read below.

(Image credit: The Eastern Transportation Coalition)

Mileage-based user fee (MBUF), referred to as vehicle miles traveled (VMT) tax or road user charge, charges a traveler a fixed or variable rate per mile traveled on the road. The investigation of MBUF shows that it can ensure vehicle users pay for using the highway infrastructure. Through the pilot program, analyses have shown that **1.8 cents per mile** will generate enough revenue to match the current motor fuel tax in North Carolina. With a higher range of cents per mile, the state would make a higher revenue to maintain and improve transportation infrastructure.

You may also watch this short 3-minute video.

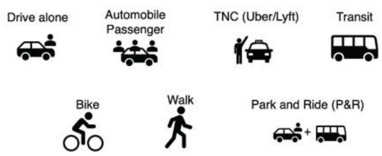
Over the next few pages, you will be presented with options on transportation choices for mode and routes under different scenarios of implementation. Proceed to the next page to begin the survey.

Revised Mode Choice

Mode Choice Experiments (1/2)

First set of experiments will **focus on mode choice**. Here you will be presented with option on available modes for a typical trip.

Mode options include:



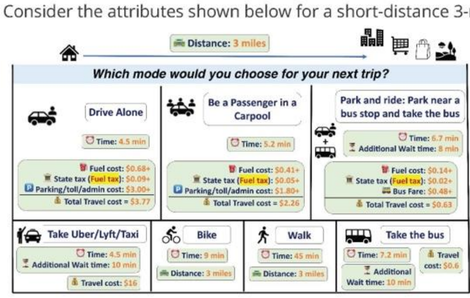
Your goal is to **choose your preferred mode for a specific trip** after reviewing the mode attributes (travel time and costs) in the trip scenarios provided for each sequence. Following figure shows a schematic for how the options will be presented.

- Your vehicle mileage, travel distance, and tax rates will be sampled at random so your costs may change.

Your primary goal is to **choose your preferred mode for a specific trip** after reviewing the mode attributes.

I understand the instructions

Consider the attributes shown below for a short-distance 3-mile trip.



While some of the modes are self-explanatory, please note the following:

- **Drive alone**: This mode indicates that you choose to drive alone using your vehicle.
- **Be a Passenger in a Carpool**: This mode signifies that you opt to be a passenger in a vehicle driven by someone in your household. **If you select 'Carpool', please ensure that someone in your household holds a valid driver's license and is available to pick you up as a passenger for your desired trip and time.**
- **Park and Ride**: This mode involves driving to a transit station stop, parking your vehicle, and primarily using public transit for the remainder of the journey.

Also note that:

- The **"Total Travel Cost" is the total out-of-pocket cost** associated with traveling including fares, tolls, fuel costs, and tax/fees. A detailed split of the cost is provided in rows for driving or automobile passenger modes, which includes:
  - Fuel cost excluding the state tax
  - State tax can be charged as a **Fuel Tax**, mileage-based user fees (**MBUF**), or a combination of both (**Fuel tax + MBUF combo**).
  - Parking/toll/admin costs
  - bus fare (if applicable).

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **work trip**?	○	○	○	○	○	○
Which mode will you pick for a **shopping or grocery** trip?	○	○	○	○	○	○
Which mode will you pick for a **recreational** trip?	○	○	○	○	○	○

How confident are you in your response?

	Very low confidence	Low confidence	Medium confidence	High confidence
For work trip	○	○	○	○
For shopping/grocery trip	○	○	○	○

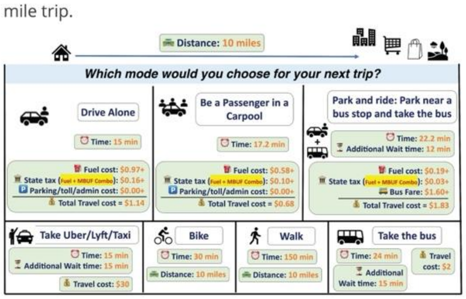
	Very low confidence	Low confidence	Medium confidence	High confidence
For recreational trip	○	○	○	○

Consider the attributes shown below for the same 3-mile trip, though the tax structure and costs have changed.

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **work trip**?	○	○	○	○	○	○

	Very low confidence	Low confidence	Medium confidence	High confidence
For recreational trip	○	○	○	○

Now consider the attributes shown below for a slightly longer 10-mile trip.



	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **work trip**?	○	○	○	○	○	○

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **shopping or grocery** trip?	○	○	○	○	○	○
Which mode will you pick for a **recreational** trip?	○	○	○	○	○	○

How confident are you in your response?

	Very low confidence	Low confidence	Medium confidence	High confidence
For work trip	○	○	○	○
For shopping/grocery trip	○	○	○	○

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **shopping or grocery** trip?	○	○	○	○	○	○
Which mode will you pick for a **recreational** trip?	○	○	○	○	○	○

How confident are you in your response?

	Very low confidence	Low confidence	Medium confidence	High confidence
For work trip	○	○	○	○
For shopping/grocery trip	○	○	○	○

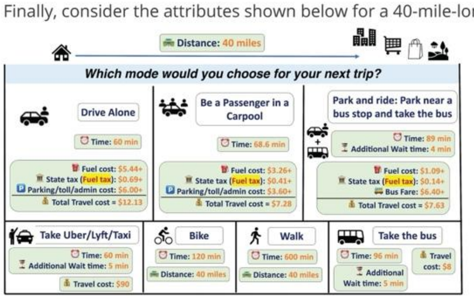
	Very low confidence	Low confidence	Medium confidence	High confidence
For recreational trip	○	○	○	○

Consider the attributes shown below for the same 10-mile trip, though the tax structure and costs have changed.

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **work trip**?	○	○	○	○	○	○

	Very low confidence	Low confidence	Medium confidence	High confidence
For recreational trip	○	○	○	○

Finally, consider the attributes shown below for a 40-mile-long trip.



	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **shopping or grocery** trip?	○	○	○	○	○	○
Which mode will you pick for a **recreational** trip?	○	○	○	○	○	○

How confident are you in your response?

	Very low confidence	Low confidence	Medium confidence	High confidence
For work trip	○	○	○	○
For shopping/grocery trip	○	○	○	○

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **work trip** if the 40-mile trip is part of your daily commute?	○	○	○	○	○	○
Which mode will you pick for an **occasional work trip**?	○	○	○	○	○	○
Which mode will you pick for an occasional **shopping or grocery** trip? (occasional)	○	○	○	○	○	○
Which mode will you pick for an occasional **recreational** trip?	○	○	○	○	○	○

How confident are you in your response?

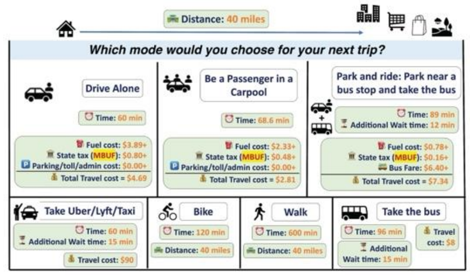
	Very low confidence	Low confidence	Medium confidence	High confidence
For daily work trip	○	○	○	○
For occasional work trip	○	○	○	○
For shopping/grocery trip	○	○	○	○
For recreational trip	○	○	○	○

	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for an occasional **shopping or grocery** trip? (occasional)	○	○	○	○	○	○
Which mode will you pick for an occasional **recreational** trip?	○	○	○	○	○	○

How confident are you in your response?

	Very low confidence	Low confidence	Medium confidence	High confidence
For daily work trip	○	○	○	○
For occasional work trip	○	○	○	○

Consider the revised attributes for the same 40-mile trip.



	Drive Alone	Carpool	Park and Ride	Taxi/Uber/Lyft	Bike	Walk
Which mode will you pick for a **work trip** if the 40-mile trip is part of your daily commute?	○	○	○	○	○	○
Which mode will you pick for an **occasional work trip**?	○	○	○	○	○	○

	Very low confidence	Low confidence	Medium confidence	High confidence
For shopping/grocery trip	○	○	○	○
For recreational trip	○	○	○	○

Based on your responses to the mode choice questions, **please indicate the extent to which you agree or disagree with the following statements:**

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I support shifting from fuel tax to MBUF.	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am indifferent regarding whether the tax is fuel-based or MBUF, as long as the costs per trip do not change significantly.	○	○	○	○	○
I do not anticipate changing my mode of travel if the fuel tax is replaced by MBUF.	○	○	○	○	○
I prioritize the travel mode with shortest time regardless of costs.	○	○	○	○	○
I prioritize the travel mode with the lowest cost regardless of time.	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I prefer driving alone, regardless of the costs.	○	○	○	○	○
I will carpool or use public transit if the new tax increases the costs per trip for driving.	○	○	○	○	○

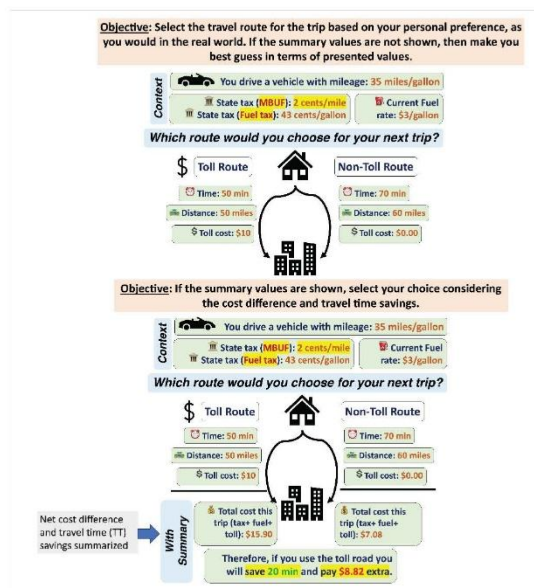
Short Distance Route Choice Part 1

Route Choice (2/2)

The survey is now 50% complete! The next few sets of experiments will focus on **route choice**. Here you will be presented with options for two routes going from origin "a" to destination "b" of your typical trip.

For these choices, assume you are the person making decisions as a driver/passenger.

Similar to the previous experiment, we will provide you with some information about each route, such as the travel time and travel cost.



You will use this information to decide which route (toll route or non-toll route) you prefer to take for this trip.

Three levers with change in the questions asked:
(1) **mileage of your car** (low mileage of 15 miles/gallon vs high

mileage of 35 miles/gallon),
(2) **the MBUF rate** (2 cents per mile, 8 cents per mile, or 15 cents per mile)
(3) **Average distance driven** (short distance or long distance)

We will also ask your level of confidence in the provided responses on a scale of 1--5.

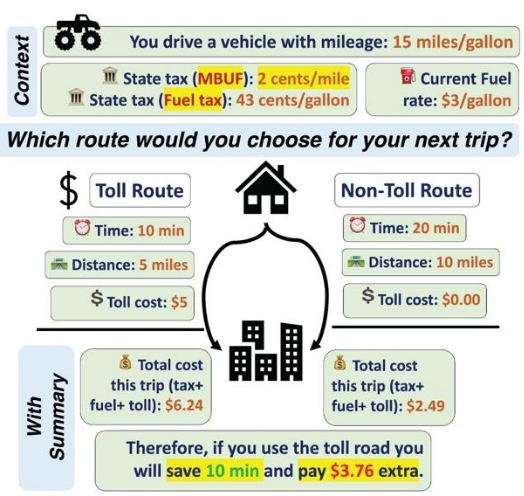
Confirm the following

I understand the instructions

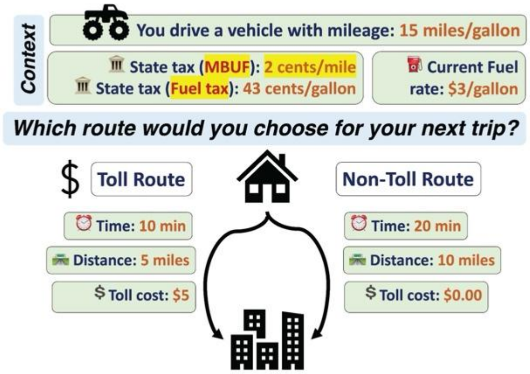
Scenario 1

Based on the attribute options shown below, which route would you choose?

Now, knowing the cost summary below, which route will you choose?



Toll
Non-toll



Toll
Non-toll

How confident are you in your response?

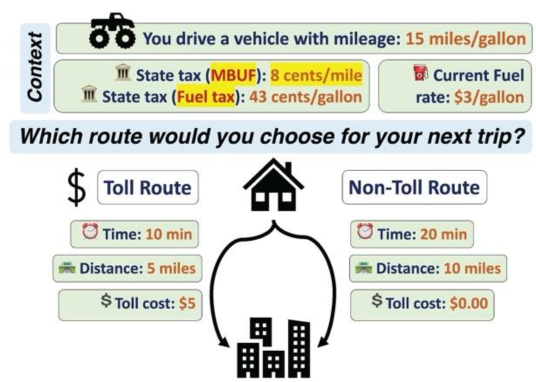
Very high confidence	High confidence	Medium confidence	Low confidence	Very low confidence
○	○	○	○	○

How confident are you in your response?

Very high confidence	High confidence	Medium confidence	Low confidence	Very low confidence
○	○	○	○	○

Scenario 2

Based on the attribute options shown below, which route would you choose? **The MBUF rate has gone up to 8 cents/mile.**



Toll
Non-toll

How confident are you in your response?

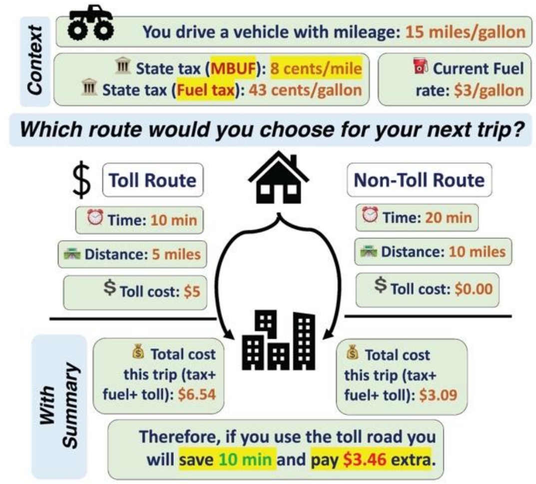
Very high confidence ○ High confidence ○ Medium confidence ○ Low confidence ○ Very low confidence ○

Now knowing the cost summary below, which route will you choose?

Scenario 3

Based on the attribute options shown below, which route would you choose? **The MBUF rate has further increased to 15 cents/mile.**

Toll
Non-toll



Toll
Non-toll

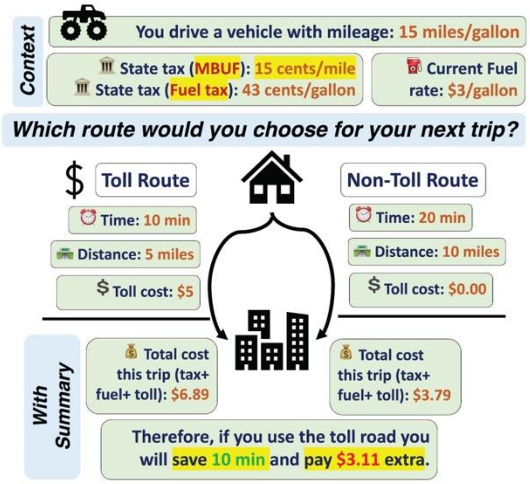
How confident are you in your response?

Very high confidence ○ High confidence ○ Medium confidence ○ Low confidence ○ Very low confidence ○

How confident are you in your response?

Very high confidence ○ High confidence ○ Medium confidence ○ Low confidence ○ Very low confidence ○

Now knowing the cost summary below, which route will you choose?



Toll

Non-toll

How confident are you in your response?

Very high confidence ◯ High confidence ◯ Medium confidence ◯ Low confidence ◯ Very low confidence ◯

Non-toll

How confident are you in your response?

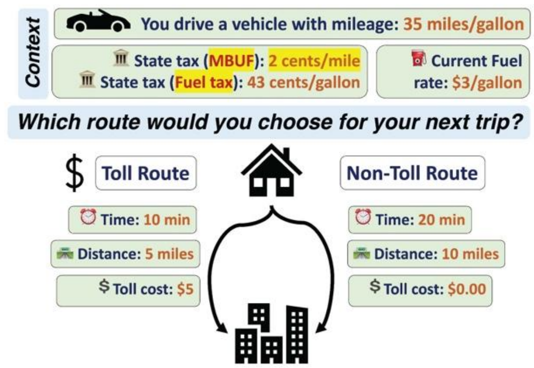
Very high confidence ◯ High confidence ◯ Medium confidence ◯ Low confidence ◯ Very low confidence ◯

Now knowing the cost summary below, which route will you choose?

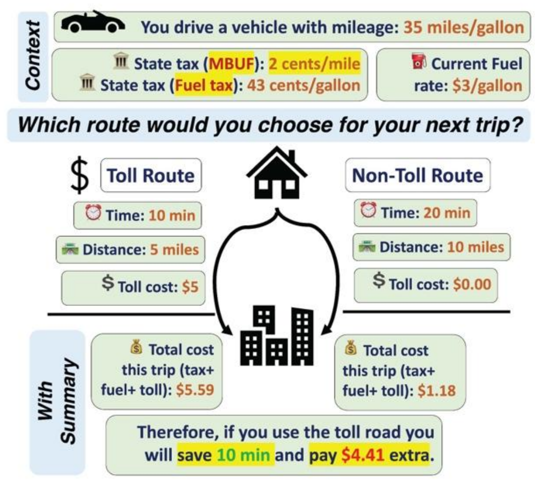
Short Distance Route Choice part 2

Scenario 4

You now own a fuel-efficient car (average mileage of 35 miles per gallon) and the MBUF rate is back to 2 cents per mile. Based on the attribute options shown below, which route would you choose?



Toll



Toll

Non-toll

How confident are you in your response?

Very high confidence ◯ High confidence ◯ Medium confidence ◯ Low confidence ◯ Strongly Negative ◯

Scenario 5

Based on the attribute options shown below, which route would you choose? Relative to Scenario 4, the MBUF rate has increased to 8 cents/mile.

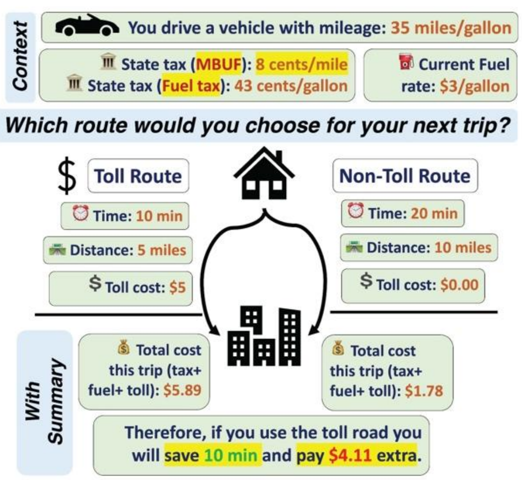
Toll

Non-toll

How confident are you in your response?

Very high confidence ○ High confidence ○ Medium confidence ○ Low confidence ○ Very low confidence ○

Now knowing the cost summary below, which route will you choose?



Toll

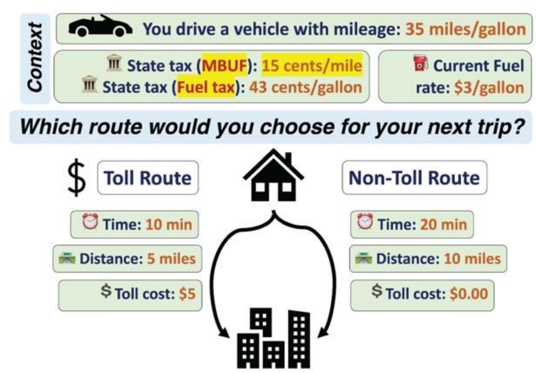
Non-toll

How confident are you in your response?

Very high confidence ○ High confidence ○ Medium confidence ○ Low confidence ○ Very low confidence ○

Scenario 6

Based on the attribute options shown below, which route would you choose? The MBUF rate has further increased to 15 cents/mile.



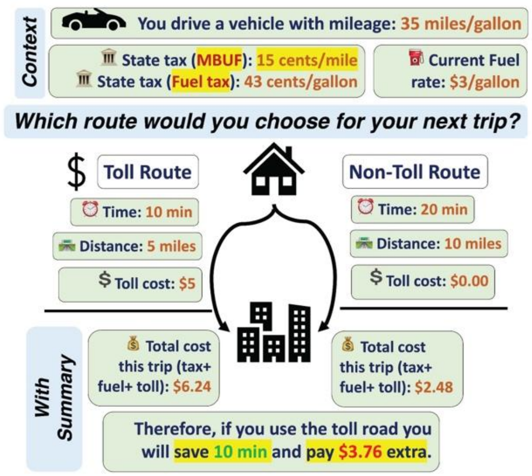
Toll

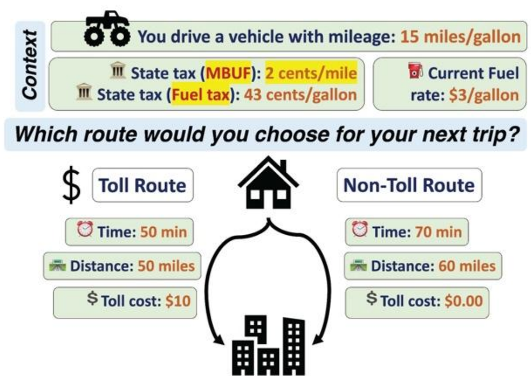
Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Now knowing the cost summary below, which route will you choose?





Toll

Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Toll

Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

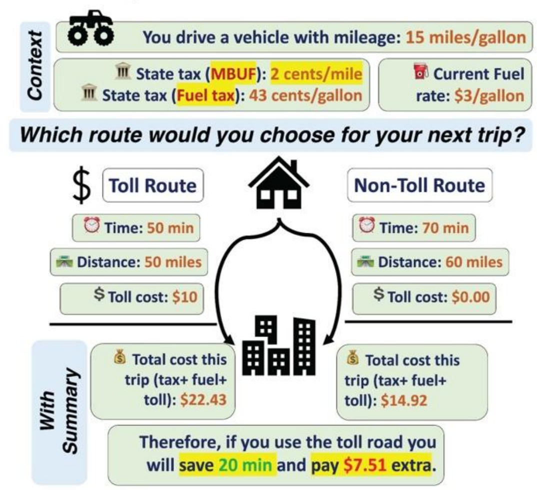
Long Distance Route Choice

Long Distance Scenario 1

Now, we will present the same scenarios, but this time, the trip distance is longer (likely resulting in higher time, costs, and taxes).

Based on the attribute options shown below, which route would you choose?

For the same scenario, now knowing the cost summary below, which route will you choose?



Toll

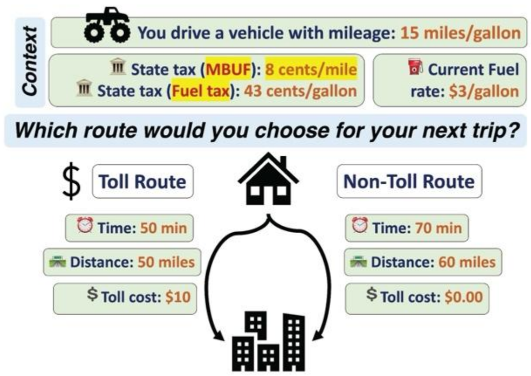
Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Long Distance Scenario 2

Based on the attribute options shown below, which route would you choose?



Toll

Non-toll

Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

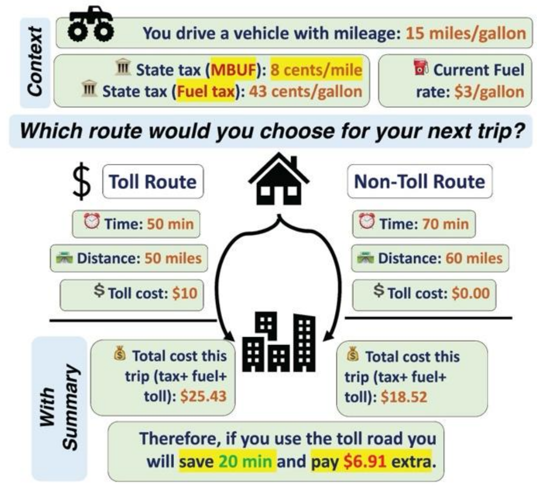
Long Distance Scenario 3

Based on the attribute options shown below, which route would you choose?

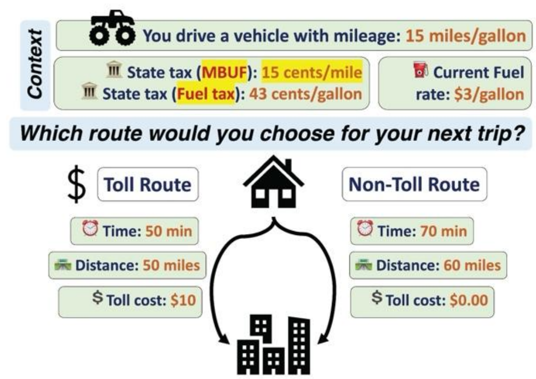
How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Now knowing the cost summary below, which route will you choose?



Toll



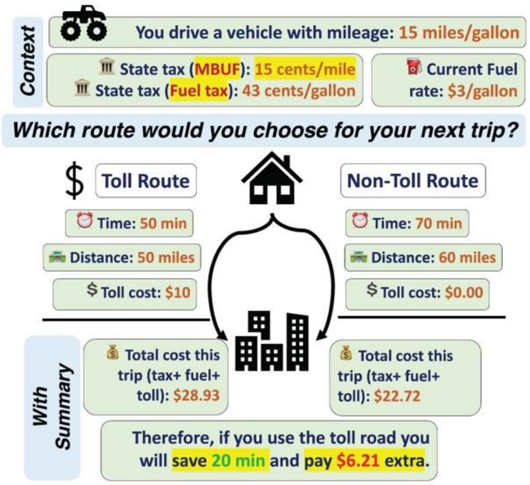
Toll

Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Now knowing the cost summary below, which route will you choose?



Toll

Non-toll

How confident are you in your response?

How confident are you in your response?

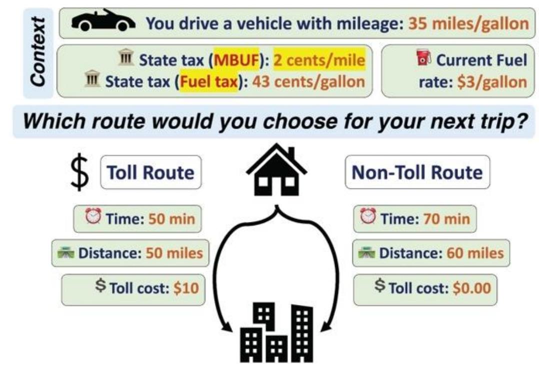
Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Now knowing the cost summary below, which route will you choose?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

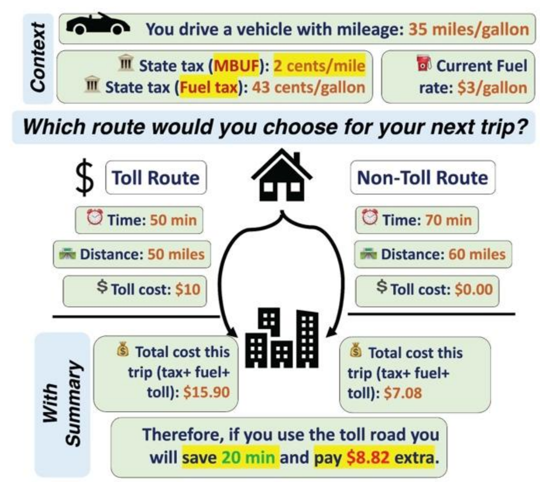
Long Distance Scenario 4

Based on the attribute options shown below, which route would you choose?



Toll

Non-toll



Toll

Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Long Distance Scenario 5

Based on the attribute options shown below, which route would you choose?

Toll

Non-toll

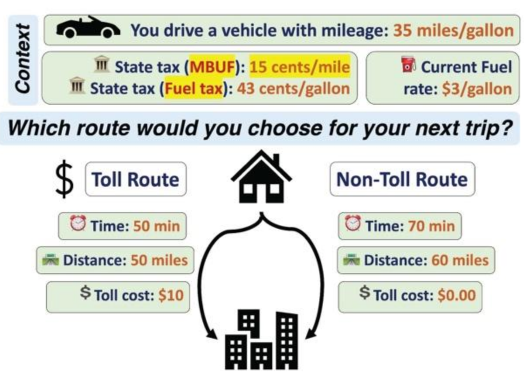
Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Long Distance Scenario 6

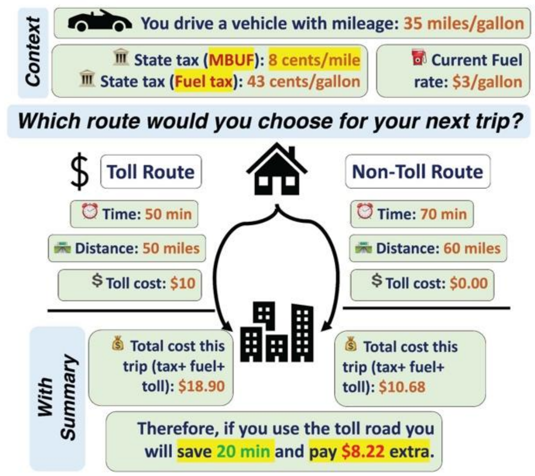
Based on the attribute options shown below, which route would you choose?



How confident are you in your response?

Very high confidence | High confidence | Medium Confidence | Low confidence | Very low confidence

Now knowing the cost summary below, which route will you choose?



Toll

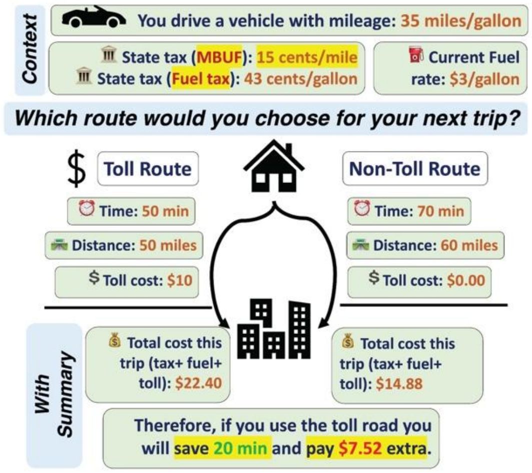
Toll

Non-toll

How confident are you in your response?

Very high confidence | High confidence | Medium confidence | Low confidence | Very low confidence

Now knowing the cost summary below, which route will you choose?



Toll

Non-toll

How confident are you in your response?

Very high confidence ○ High confidence ○ Medium confidence ○ Low confidence ○ Very low confidence ○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I am indifferent regarding whether the tax is fuel-based or MBUF, as long as the costs for my chosen route do not change significantly.	○	○	○	○	○
I do not anticipate changing my travel route if the fuel tax is replaced by MBUF.	○	○	○	○	○
I prioritize routes with the shortest time regardless of costs.	○	○	○	○	○
I prioritize routes with the lowest cost regardless of time.	○	○	○	○	○

Considering your route choices, **on average, how much money (in $)** would you be comfortable paying to

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

Save 5 minutes of travel time

Save 20 minutes of travel time

Based on your responses to the route choice questions, **please indicate the extent to which you agree or disagree with the following statements:**

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
My route choice is not impacted by the amount of tax I pay.	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I will prefer to drive fewer miles if fuel tax is replaced by MBUF.	○	○	○	○	○
I am more concerned about paying higher costs under MBUF for long-distance trips as opposed to paying a fuel tax.	○	○	○	○	○
	○	○	○	○	○

Revealed preference questions

Anonymized Personal Information

Thank you for completing the two parts. The survey is 90% complete.

Now we just need some basic anonymous information about your background. All information collected in this study will be kept strictly confidential and no personal identifier information is used.

What is your sex assigned at birth?

Male
Female

What is your age?

0 10 20 30 40 50 60 70 80 90 100

Your Age

Are you Hispanic or Latino origin?

Yes
No

Select your Race category:

Are you a student?

Yes, K-12th Grade
Yes, Vocation/Technical/Trade School
Yes- Part-Time college/University
Yes- Full Time college/University
Yes- Other
No

What is your approximate household income?

What is the zip code of your **HOME location**? (If you do not know please visit this website: https://tools.usps.com/zip-code-lookup.htm?byaddress or another website that provides your zip code)? (A sample zip code is shown)

27358

White or Caucasian
Black or African American
Asian or Asian American
American Indian or Alaska Native
Native Hawaiian or other Pacific Islander
Another Race

What is the highest grade or level of education you have earned?

Less than a high school graduate
High school graduate or GED
Some college or associates degree
Bachelor's Degree
Graduate degree or professional degree

What is your current employment status (if you are working and a student please select the working option closest to you)?

Working Full Time
Working Part Time
Working from home
Temporarily absent from work
Unemployed or searching for job
Student
Retired
Other

What is the zip code of your **WORK location**? (If you do not know please visit this website: https://tools.usps.com/zip-code-lookup.htm?byaddress or another website that provides your zip code)? (A sample zip code is shown)

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Which dwelling type best describes your current home?

Singe Family House (detached)
Semi-Detached House
Town/ Row House
Apartment/ Flat in detached duplex
Apartment/ Condo with less than 5 stories
Apartment/ Condo with more than 5 stories
Other

How many individuals (including yourself) live in your household?

How many individuals (including yourself) live in your household over the age of 12?

Which county in North Carolina do you currently live in?

Do you possess a driver's license?

Yes
No

How many functioning motor vehicles does your household have?

How many functioning bikes does your household have?

What is the **closest departure hour for your most recent trip**?

What was your **primary mode choice** for trips in the last week?

Auto (driver)
Auto (passenger)
Public transportation
Ride-hailing services (Uber/Lyft)
Park and ride (with transit)
Bike
Walk
Other (please specify)

What fuel category best describes the vehicle you use most frequently?

Gasoline
Diesel
Electric Vehicle
Hybrid Vehicle
Other
I do not use a vehicle

For the vehicle you used most frequently, about how many total miles did you drive in the past year? (0-50,000) (Report 0 if you do not own a vehicle)

	0	5000	10000	15000	20000	25000	30000	35000	40000	45000	50000
Approximate Miles Driven Last Year											

Do you own an EzToll or NC Quick Pass toll transponder?

Yes
No

Do you use the EzToll or NC Quick Pass on your average trip?

Yes
No

Do you use the Smart Trip or other pass for public transportation on your average trip?

Yes
No

How frequently do you use the following modes for your daily trip?

	Everyday/ almost everyday	Regularly (more than once a week)	Occasionally (a couple of times per month)	Rarely (a couple of times per year)	Never
Personal car driver	○	○	○	○	○
Toll roads	○	○	○	○	○
Passenger in personal car	○	○	○	○	○

	Everyday/ almost everyday	Regularly (more than once a week)	Occasionally (a couple of times per month)	Rarely (a couple of times per year)	Never
Public Transportation	○	○	○	○	○
Ridehailing services (Uber/Lyft)	○	○	○	○	○
Vehicle rentals including car-share program	○	○	○	○	○

What is the estimated average monthly cost of fuel for the vehicle you use most often?

$10 - $100
$100 - $200
$200 - $300
$300 - $400
$400 - $500
$500 - $600
$600 - $700
$700 - $800
$800 - $900
$900 - $1000
$1000 or more
Do not know or Not applicable

What criteria do you typically consider when choosing a mode of travel for a trip? Please select all that apply.

Cost
Time
Convenience
Environmental impact
Health benefits
Safety
Availability of parking
Availability of public transportation
Personal preference
Other (please specify)

What criteria do you typically consider when choosing a route to a destination? Please select all that apply.

Travel time
Distance
Cost (tolls and fuel cost)
Road quality
Traffic congestion
Scenic route
Safety
Personal preferences
Other (please specify)

(Optional) Final question: What additional thoughts, suggestions, or comments would you like to share with us about your experience with the survey or any other topic not covered in this survey?

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