National Center for Sustainable Transportation
A USDOT University Transportation Center

Research Report

August 2025

Data Collection of Odometer Images via WhatsApp to Measure Vehicle Miles Traveled

Siddhartha Gulhare, University of California, Davis

Keita Makino, University of California, Davis

Ranbir Roshan, ServiceNow, Inc.

Giovanni Circella, University of California, Davis

UC DAVIS Institute of Transportation Studies

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
NCST-UCD-RR-25-19	N/A	N/A

4. Title and Subtitle	5. Report Date
Data Collection of Odometer Images via WhatsApp to Measure Vehicle Miles Traveled	August 2025
	6. Performing Organization Code N/A

7. Author(s)	8. Performing Organization Report No.
Siddhartha Gulhare, Ph.D., https://orcid.org/0000-0003-2377-5717 Keita Makino, https://orcid.org/0000-0001-5080-2843 Ranbir Roshan, ServiceNow, Inc., https://orcid.org/0009-0001-6058-5819 Giovanni Circella, Ph.D., https://orcid.org/0000-0003-1832-396X	UCD-ITS-RR-25-43

9. Performing Organization Name and Address	10. Work Unit No.
University of California, Davis Institute of Transportation Studies 1605 Tilia Street, Suite 100, Davis, CA 95616	N/A
	11. Contract or Grant No. USDOT Grant 69A3551747114 and 69A3552344814

12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE, Washington, DC 20590	Final Research Report (January 2024 – June 2025)
	14. Sponsoring Agency Code USDOT OST-R

15. Supplementary Notes

DOI: https://doi.org/10.7922/G21834VC
Dataset DOI: https://doi.org/10.5061/dryad.g79cnp62m
The code for the study can be accessed here: https://github.com/3rfm-its-davis/odometer-reading

16. Abstract

California sets ambitious climate goals that demand a sharp reduction in the per-capita vehicle miles traveled (VMT). Traditionally, researchers have relied on three types of VMT data collection methods – travel surveys, passively collected data, and simulated data – to estimate VMT or understand factors affecting VMT. However, each of these methods has disadvantages for obtaining a reliable VMT dataset. Although travel surveys are an inexpensive way to collect VMT data with rich traveler attributes, they often suffer from bias and errors in reporting or recalling. Passively collected VMT data, such as traffic count data, can provide precise VMT data, yet they often lack information about "who" and "why" of travel. Lastly, simulated VMT data is useful when making counterfactual testing, but they are after all not real data. In this study, to fulfill the gap between current data collection strategies, we introduce a WhatsApp-based VMT data collection framework. The framework deployed on the Azure cloud platform automatically lets study participants submit photos of their odometer, communicates with them for administrative events, manages submitted images and other information of the participants, and displays that data on the web UI for the study administrator. With a pilot study with 77 participants, we successfully collected 173 photos of the odometer. Although only 3 photos out of 173 were unusable, demonstrating the capability of our framework, a couple of potential improvements, such as an interface that aligns the photo timestamps over the days or better recruitment approaches, should be addressed in future work.

17. Key Words	18. Distribution Statement
Vehicle miles traveled, Travel survey, Odometer, App-based data collection, WhatsApp	No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	56	N/A

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

About the National Center for Sustainable Transportation

The National Center for Sustainable Transportation is a consortium of leading universities committed to advancing an environmentally sustainable transportation system through cutting-edge research, direct policy engagement, and education of our future leaders. Consortium members include: the University of California, Davis; California State University, Long Beach; Georgia Institute of Technology; Texas Southern University; the University of California, Riverside; the University of Southern California; and the University of Vermont. More information can be found at: ncst.ucdavis.edu.

Disclaimer

Acknowledgments

This study was funded, partially or entirely, by a grant from the National Center for Sustainable Transportation (NCST), supported by the U.S. Department of Transportation (USDOT) through the University Transportation Centers program. The authors would like to thank the NCST and the USDOT for their support of university-based research in transportation, and especially for the funding provided in support of this project. Additional funding was provided by the 3 Revolutions Future Mobility (3RFM) Program of the University of California, Davis. The authors would like to thank Basar Ozbilen, Patrick Loa, Prem Pratap Singh, Prashanth Venkataram, Grant Matson, Leon Kang, Yongsung Lee, Michael Dominick Fortunato, and all other members of 3RFM for their contributions to the research.

Data Collection of Odometer Images via WhatsApp to Measure Vehicle Miles Traveled

A National Center for Sustainable Transportation Research Report

Siddhartha Gulhare, Institute of Transportation Studies, University of California, Davis

Keita Makino, Institute of Transportation Studies, University of California, Davis

Ranbir Roshan, ServiceNow, Inc.

Giovanni Circella, Institute of Transportation Studies, University of California, Davis

Table of Contents

List of Tables

List of Figures

Data Collection of Odometer Images via WhatsApp to Measure Vehicle Miles Traveled

Executive Summary

Existing VMT Data Collection Methods

Travel surveys have played a crucial role in transportation planning and will continue to play an essential role in the California Air Resources Board's goal to reduce per capita vehicle miles traveled (VMT) by providing detailed insights into travel patterns. A well-designed travel survey can assess the impact of new policies and infrastructure investments on VMT (*1–3*) and understand the key determinants of VMT to help design more targeted policies *(4–6)*.

However, the planning and research community struggles to collect accurate VMT estimates. While self-reported VMT in travel surveys is the most common and non-invasive method, VMTs sourced by such reporting are subject to significant measurement errors for several reasons, including memory decay, unwillingness to report full travel details, carelessness, and rounding/approximate measurement of distances. The recent technological integration into survey data collection, such as Global Positioning System (GPS)-enhanced tracking tools (*7–9*), can provide better estimates of VMT. However, they can be too intrusive by tracking every movement and are too expensive to scale up.

Certainly, there are options to use passively collected VMT data provided by the Federal Highway Administration (FHWA), the Department of Transportation (DoT) of the states, traffic counts, odometer readings of state Department of Motor Vehicles (DMV) inspection data, and so on. These methods are better in providing more reliable and accurate VMT data, if processed correctly, but rarely come with travelers' characteristics that are essential for successive travel behavior analysis.

Development of the Proposed Automation Framework

In our pursuit of a more accurate, effective, and scalable solution, we developed a new automation framework for collecting odometer images, which researchers can use to estimate the VMT in a period, via the WhatsApp messaging service. WhatsApp is secure, widely trusted, and already used by more than 100 million users in the United States (*10*), eliminating the need for app installation and significantly reducing data collection costs. We have developed an automation framework hosted on an Azure server using the WhatsApp Application Programming Interface (API) to communicate, collect, and organize odometer images from the participants. We can estimate VMT over a given period by calculating the difference between consecutive odometer readings.

Pilot Study of the Automation Framework

The study then tested this approach through pilot deployment to assess its performance and determine its feasibility as an extension to large-scale travel surveys or an independent study for future VMT data collection. We recruited the study participants through convenience sampling by mainly sending invitation emails with a prescreening survey link to university listservs and personal connections. Those who filled out the survey received a follow-up instruction email with a unique access code and our WhatsApp number to participate in the study by sending odometer images. A total of 117 people completed the prescreening survey, and later, 47 of them sent at least two odometer images on WhatsApp, which was required to compute the VMT between the images.

Results of the Pilot Study

The automation framework worked flawlessly without errors and seamlessly, communicating with the participant, receiving and organizing the odometer images, and sending notifications after receiving and manually verifying the images. The team received only two invalid odometer images (one duplicate and one blurred) among 147 submitted images, dispelling the initial concerns that participants might struggle to follow the instructions or find the process too complicated. It also alleviated reservations about potential misuse of the system to claim gift card incentives.

This result demonstrates the potential of the automation framework, showing some potential to aid existing surveys or other methods in measuring VMT by collecting odometer images via a commonly used social media. However, we encountered several challenges and issues during the pilot study. First, it was found that the study participants submit odometer images at varying times of the day, for instance, one image at night and another in the morning. This may notably cause larger errors in assessing VMT in a short-term study, where the variation in VMT over one day is more significant. Additionally, we discovered that the recruitment process for the study was more challenging than we initially anticipated. Despite our efforts to distribute the invitation email through listservs and other means, our final sample size consisted of 147 images, which is not large enough for rigorous VMT analysis. Hence, we acknowledge that this study has not provided sufficient support for the proposed method as a scalable and cost-effective method of VMT data collection compared to existing ones.

As a result, this study primarily examined the proposed approach of VMT data collection via WhatsApp as one valid alternative. Future studies are expected to further enhance the method by several means, such as adopting other communication channels (e.g., short messaging services or Facebook Messenger) or using it as an add-on study of an existing large-scale survey.

Introduction

California's Goal to Reduce Per Capita VMT

The California Air Resources Board (CARB) highlights that, despite cleaner vehicles and low-carbon fuels, the path to carbon neutrality by 2045 depends on reducing per capita vehicle miles traveled (VMT) (*11*). In its latest 2022 Scoping Plan (a strategic blueprint developed every four years to guide the state toward meeting its long-term climate goals), CARB proposes reducing per capita VMT by 25% in 2030 and 30% in 2045 (both compared to 2019 levels). This implies that Metropolitan Planning Organizations (MPOs) need to devise policies to reduce per capita VMT by an average annual rate of 2.5% to 3% to meet the 2030 targets. MPOs across California are implementing Sustainable Communities Strategies (SCS) to integrate land use, housing, and transportation plans to achieve the VMT reduction targets (*12*).

Travel Surveys Can Play a Crucial Role

Travel surveys are widely employed to understand individual-level travel behavior, which plays a vital role in transportation planning. Surveys will continue to play an important role in CARB's VMT reduction goals by providing detailed insights into travel patterns. A well-designed travel survey can assess the impact of new policies and infrastructure investments on VMT (*1*–*3*) and/or understand the key determinants of VMT to help design more targeted policies (*4*–*6*).

However, the surveyors struggle to collect accurate VMT information in the surveys. Self-reported VMT is one of the most common methods to collect such information. Most travel surveys also collect sociodemographic and other influencing factors, allowing us to develop statistical models to assess the impact of policy interventions on VMT while controlling these individual factors. Yet, the self-reported VMTs are subject to significant measurement errors for several reasons: memory decay, recalling errors, unwillingness to report full travel details, carelessness, and rounding/heaping biases in the measurement of distances. The analysis of data from the California Household Travel 2001 Survey demonstrated that the VMT estimated using the travel survey in Sacramento was 30% below the actual VMT measured using a GPS device installed in the respondents' vehicles (*13*). Perhaps, the self-reported VMTs can substantially differ from the actual VMT reduction achieved through infrastructure or policy interventions. This raises alarming questions about the heavy reliance on the self-reported VMT collected for tracking progress to support CARB's reduction goals.

The recent technological integration into survey data collection, such as Global Positioning System (GPS)-enhanced (*7*, *14*–*19*) and mobile app-based surveys or tracking tools (*8*, *18*, *20*–*22*) can provide better estimates of VMT. However, they can be intrusive by tracking every movement and are too expensive to scale up. They also suffer from lower response rates, high dropout rates, or even self-selection biases resulting from hesitation in using GPS devices or installing mobile apps on personal smartphones. Therefore, the samples collected from these enhanced methods may prove problematic in terms of generalization and representativeness of the population for policy analysis.

Certainly, there are several non-survey-based methods for VMT data collection. These are usually passively collected data, either sourced from the Federal Highway Administration (FHWA), the Department of Transportation (DoT) of the states, traffic counts, or odometer readings of state Department of Motor Vehicles (DMV) inspection data. These are good options to retrieve more reliable and accurate VMT data (if processed correctly), but rarely come with travelers' characteristics that are critical for successive travel behavior analysis.

In short, through a rigorous literature review presented in a later section, we identified that current VMT data collection methods do not reconcile the capabilities of collecting both accurate VMT and travelers' characteristics in an inexpensive and non-intrusive way.

Proposed Methodology to Collect VMT Information

To satisfy certain needs of VMT data collection that current methods do not cover, this study develops a new automation framework for collecting odometer images, which researchers can use to estimate the VMT in a period, via the WhatsApp messaging service. The study then tested this approach through pilot deployment to assess its performance and determine its feasibility as an extension to large-scale travel surveys or an independent study for future VMT data collection.

Structure of the Report

The remaining paper's structure is as follows. The second chapter reviews existing methods for collecting VMT. The third chapter explains the details of the proposed methodology. The fourth chapter presents the details of the experimental simulated data collection and the pilot deployment of actual data collection, followed by the fifth chapter reviewing the results and findings. Finally, the sixth chapter concludes by briefly reviewing the summary and potential future works.

Literature Review

This chapter reviews the current literature on the VMT and discusses our contributions to it through the present project. The following sections review the characteristics of previous studies from two perspectives: study objective and VMT data collection method, to understand the trends of prior studies and existing research gaps.

Study Objective

Research on VMT encompasses diverse objectives, reflecting its multifaceted roles and needs in transportation studies and policy analysis. In this section, we classified the objective of the prior studies into three large categories: determinant effects on VMT, modeling and forecasting, and policy design and evaluation. The number of studies under each category is tabulated in Table 1.

Among the studies that we have reviewed, the most popular objective of studies was to assess the influence of various factors. We identified four smaller categories within this type of objective. Some studies examine the effect of individual behavior or propensity, such as ride-hailing use (*23*) or trip chaining (*24*) on VMT. A similar analysis with built-environment factors (e.g., urban sprawl (*25*) or housing development designs (*26*)) are also popular in the field. In addition, various types of policy interventions, mobility programs, or emerging technologies (e.g., shared autonomous vehicles) are investigated for their effects on VMT changes. Other studies certainly argue the combined effect of these factors or other effects, such as economic activity in the U.S. (*27*).

Another considerable interest in literature is to develop, identify, or verify new methods or tools to estimate VMT. This type of study includes validation of the use of vehicle safety inspection data as an estimator of VMT (*28*), development of the VMT estimation method with fuel sales data (*29*), development of an alternative VMT-estimation approach based on available data (*30*), or argument on the feasibility of the use of GPS-based survey data for VMT estimation (*7*). The number of studies focusing on factors influencing VMT and obtaining accurate VMT readings underscores the field's desire for precise recordings of this metric.

Moreover, an undeniable amount of literature focuses on policy-related topics. VMT fee/tax topics, such as evaluation of VMT fee/tax strategies of current or proposed policy implementations (*1*, *31*) takes a large share in this subfield. This intense interest in literature highlights the impact of VMT on the environment and the desire of authorities for clean and energy-efficient transportation.

Table 1. Distribution of the Study Objective of VMT Research

Study Objective Type		Count	References
Determinant effects on VMT	Behavior or propensity	13	(*5*, *23*, *24*, *32–41*)
	Built environment	26	(*3*, *25*, *26*, *42–64*)
	Policy, program, or technology	19	(*20*, *65–82*)
	Complex or other	18	(*18*, *27*, *83–98*)
Modeling and forecasting		44	(*6*, *7*, *9*, *17*, *19*, *28–30*, *99–134*)
Policy design and evaluation		27	(*1*, *8*, *16*, *31*, *135–157*)
Other		4	(*22*, *158–160*)

Data Collection Method

Table 2 summarizes the data collection method used in prior studies. There are roughly three categories of dataset types. The first one is travel-survey-based datasets that are usually obtained through asking people for their input. Survey-based VMT datasets have a clear advantage over other datasets due to the availability of travelers' characteristics, trip purposes, built environments, mode choices, or other factors associated with VMT generation. Within travel-survey-based datasets, one popular sub-category is to use the National Household Travel Survey (NHTS) data published by the Oak Ridge National Laboratory (ORNL).

The NHTS datasets are typically useful for many types of studies as they are available nationwide with a large sample size, and they consist of travelers' social demographic factors or other fundamental information for travel behavior analysis. They are available in the annualized data type and the non-annualized data type. The former type also includes the BESTMILE variable developed by ORNL, which contains the estimated annual VMT of the sample based on the combination of the odometer reading of the survey taker's car, self-reported annual VMT, the annualized value of the VMT on the day that the survey taker recorded their trip diary for the survey, and the characteristics of the primary vehicle driver (*161*). However, researchers can use a self-reported annual VMT or other, more naive data as well if needed. For instance, Wang and Chen (2014) explicitly stated that the analysis was based on the NHTS self-reported annual VMT because the use of the estimated VMT in the model leads to the problem of spurious regression (*83*).

Some studies can also use the non-annualized VMT data from the NHTS, which are usually based on the trip diary in the survey instrument. This type of dataset provides more details about the trip length, trip purpose, and/or the transportation mode used for the trip, making it useful for conducting individual-level or context-specific analyses regarding VMT. For example, Ding et al. (2017) suggested that the effects of the built environment on VMT significantly vary between the two trip purposes of commuting and non-commuting trips (*50*). Wu and MacKenzie (2021) estimated the net effect of a specific transportation mode of ridesourcing services on VMT changes in the U.S. based on the trip-level information in the NHTS data (*23*).

While NHTS datasets are conveniently available, covering the entire U.S. and having rich information about not only VMT but also travelers' characteristics or built environments, it has a few drawbacks in research usability. First, it is an infrequent snapshot of the travel behavior in the country, conducted every five to eight years. The dataset might not be outdated if a researcher desires to conduct a travel behavior analysis with an emerging transportation option (e.g., ride-hailing or autonomous taxis) or in an unprecedented situation (e.g., the COVID-19 pandemic). Also, the VMT information is available only in the annualized VMT, which could be too long and generalized to assess specific travel behaviors in a certain span, or based on one-day trip diaries, which could be too short to capture the variability in travel behaviors. Also, as it is conducted across the nation, the sample size might be too small for a researcher unless there is an NHTS add-on data in the specific area of their interest available.

Datasets based on non-NHTS surveys are useful when researchers need to obtain more context-aware travel behavior in a specific region, target population, or transportation mode. They can rely on some publicly available survey datasets or may conduct their own survey using a more diverse and tailored survey instrument for the study if there are no suitable data sources available. Questionnaires about self-reported VMT or activities that lead to estimating VMT (e.g., use of ride-hailing services or teleworking behaviors) are one of the most straightforward methods to obtain VMT information from the survey sample. Tirachini and Gomez-Lobo (2020) conducted an Uber use survey in Chile and evaluated the effect of Uber on the change in vehicle kilometers traveled (VKT) by integrating the data by building a simulation model with parameters derived from other studies (*40*). This type of questionnaire is superior to other methods as it demands a small respondent burden. Survey participants do not need to provide a full, detailed travel diary or continuous input over time. Still, researchers can ask not only about people's general travel behavior or travel activities of a specific day but also those in a specific range (e.g., the use of ride-hailing services in the last month). However, a large drawback of this method is that, as one can easily expect, it is prone to errors due to memory decay, recalling biases, rounding issues, and/or heaping biases. In short, survey takers, when they are asked to recall their activities or driving mileage, are not able to provide the true number. Also, these types of questionnaires often lack spatial and temporal granularity. If these details, for instance, when someone took the ride-hailing service from one place to another, need to be input trip-by-trip, the survey will be rather classified into a travel diary.

Still, conducting such an explicit trip diary and using the data for VMT-related analysis is also a popular approach among studies that we reviewed. Using a trip diary is more likely to yield a fine-grained dataset that is necessary for studies that require more precise information to estimate VMT based on the trip details. Zhang et al. (2025) examined the effect of the use of electric vehicles on trip frequency and VKT in the Netherlands, using a one-day-travel-diary dataset (*94*). The dataset for their analysis contained not only detailed information on socioeconomic and demographic characteristics, residential environment, and trip specifics, including trip length, mode of transport, and purpose, but also household car ownership, car fuel types, and residential locations (*94*). One clear disadvantage of using a trip diary is, however, that it significantly increases the response burden of the survey takers. Also, the advantage of a higher precision of travel data is not assured unless the survey taker is forced to input the details of every trip that the researcher targets. Survey takers may skip reporting small trips, may forget the details of the trips, or simply forget the trips themselves. After all, as far as the questionnaire depends on survey takers' self-reporting, this type of dataset is inevitably determined to have a similar drawback that we discussed earlier for the self-reported or activity-based VMT dataset.

Asking one's odometer reading in a travel survey, as NHTS conducts, resolves this issue to some extent because the survey takers do not need to rely on their memory to report the VMT. Tilov and Weber (2023) conducted an analysis of the fuel price elasticity of VMT using a rolling-panel travel survey in Switzerland with information on odometer readings reported in different survey waves (*90*). It can be a reliable and versatile source of VMT information when odometer readings are collected along with the vehicle owner's social demographic characteristics and other factors asked for in the survey. However, one critical deficit of this approach is that obtaining one odometer reading does not provide an accurate VMT. Researchers need to obtain at least two readings to compute the difference between the datetimes of the readings and then compute VMT based on it. Otherwise, VMT will be a rough estimate evaluated by dividing the odometer by the number of years elapsed since the vehicle's model year. This VMT evaluation method could be too naive in some cases, for instance, the current owner of the vehicle purchased it as a used car, and therefore, the pace of VMT accumulation changes at a certain time point.

The last survey-based VMT data collection method is to use a dedicated GPS device to collect the GPS trajectories of the travelers for a certain period, in the form of a trip diary. If the researcher can obtain travelers' information and trip information (e.g., trip purpose or transportation mode) with a separate questionnaire, this approach will provide the most precise and accurate source of VMT information for further analysis. Meanwhile, this method is inevitably expensive to conduct. The survey administrator needs to distribute a dedicated device for GPS data collection or manage software that would be installed on survey takers' mobile phones. From the survey takers' perspective, they are required to keep the dedicated device with them or have the mobile app connected all the time. This requirement could be considered a large burden, or even intrusive into privacy, which may lead to a self-selection bias in the survey participation.

Looking at non-survey-based VMT data collection methods, they mostly depend on an external data source or passively collected data. The most popular data source is from the FHWA. FHWA publishes the highway statistics series that summarizes the annual VMT by state, highway type, or vehicle type. Researchers can use this type of information to conduct relatively large-scale and long-term analyses. A similar type of dataset can be sourced from state DoTs as well. Although the Highway Statistics series is summarized by aggregating the reports from state DoTs, and thus some of the datasets that the 10 studies depend on could be from the same data source as those based on the FHWA, we classified studies into this category if they did not explicitly mention the data source to be FHWA. As a use case of this kind of dataset, Memmott (2007) argued the trend in VMT growth in the entire U.S. from 1970 to 2005 in relation to real personal income growth, using the FHWA Highway Statistics and the NHTS dataset. While the FHWA dataset provides comprehensive VMT information across the U.S., covering all the highways and other types of public roads, it lacks several important information, including the travelers' characteristics, spatial and temporal precision, or trip purposes. This type of dataset is merely for studies that only require an aggregated number of VMT.

Another type of passively collected dataset is GPS-based datasets or datasets collected through connected devices. Some private companies, such as INRIX or StreetLight Data, provide large-scale travel information based on the trajectory of mobile devices or embedded GPS trackers. Researchers can use either a disaggregated GPS trajectory of each vehicle or aggregated travel volume from point to point or region to region to estimate the VMT of their interest. However, several issues about data quality may arise. Due to privacy concerns, detailed travelers' information could be anonymized by the private data providers, or even if included, it could be processed through their proprietary "black box". Also, VMT information derived from these sources includes only drivers and vehicles with the equipment to submit the telemetry (e.g., a specific smartphone app or network-connected vehicle). This can lead to sampling bias in the eventually obtained VMT data.

The dataset of fuel sales is a simple but effective proxy to estimate the VMT. As automobiles run a certain length by a certain amount of fuel (e.g., 25 miles per gallon), knowing the total fuel consumption in a region or by an individual will be accurate enough to estimate the total VMT run by the region or the individual. Hossain and Gargett used the petrol sales by the Department of Resources, Energy and Tourism in Australia to estimate the quarterly VKT of the states/territories and their capital city in the country (*29*). Still, this data type also lacks information about the drivers. Also, the fuel efficiency of automobiles largely varies from vehicle to vehicle. Thus, the application of fuel sales data as a source of VMT estimation would be mostly limited to aggregate-level analysis in a wide region.

Datasets of odometer reporting by periodic vehicle inspection or manufacturers' service records are another source of accurate VMT information. This method provides a dataset of VMT in a similar way to surveys with odometer reporting, but on a much larger scale. Yuan et al. (2021) leveraged the vehicle inspection data provided by the Pennsylvania DoT, which contains more than 100 million odometer readings from 1999 to 2018, to estimate the difference between what drivers currently pay for fuel taxes and what they would pay for mileage-based user fees (*146*). Similar to other passively collected data types, this data type lacks drivers' characteristics, although it can include details of the vehicle itself. Also, it might be difficult for researchers to access the full dataset of authoritative inspection data or service records due to privacy concerns.

The last passively collected data source for VMT estimation features non-FHWA- or non-DoT-based traffic count data. This type of data usually targets certain segments of highways or an urban area rather than the state-level road network. For instance, Jung et al. (2017) estimated VKT based on traffic volumes and travel speeds on road links in Incheon, South Korea (*130*). This approach enables researchers to focus on a smaller area of study with precise real-world traffic counting, which cannot be done in any other form of data collection. The drawback of the method is that the travelers' information is not included. Also, since it oftentimes requires specific hardware (e.g., a loop detector) or a video recorder to count traffic, conducting a long-term experiment may result in a higher cost.

In addition to the survey-based data and passively collected data mentioned above, some studies used VMT data or estimated VMT by simulation. On one hand, there are studies based on relatively small-scale simulations, such as an estimation of VMT by simulating on-demand food-delivery orders and deliveries to them (*98*) or mathematical analysis of the sidekick routing paradigm (*128*). On the other hand, some used demand models, which are usually provided by state DoTs or MPOs. Researchers can forecast VMT based on the characteristics of the population, employment, built environments, road geometries, transit availability, and so on (*82*). These methods are useful when obtaining real-world VMT data is difficult or infeasible. Also, forecasting VMT based on available data of travelers or urban structure is versatile in testing counterfactual scenarios, hypothetical policy planning, or future infrastructure expansion. Meanwhile, one must beware of potential errors, biases, and/or overgeneralization, due to the forecasting method and/or the quality of the dataset by which they generate it, when relying on these methods. In short, simulated data should never be treated as a true reflection of the real world.

Table 2. Classification of the data types of prior studies

Dataset type			Count	References
Survey-based data	NHTS	Annual data	12	(*1*, *49*, *66*, *83*, *86*, *87*, *118*, *139–143*)
		Non-annual data	5	(*23*, *50*, *67*, *88*, *160*)
	Non-NHTS	Self-reported or activity-based	17	(*40*, *41*, *51–57*, *70–73*, *91*, *122–124*)
		Trip-diary	18	(*3*, *5*, *24*, *26*, *42*, *58–61*, *74–76*, *92–95*, *125*, *145*)
		Odometer reporting	10	(*6*, *39*, *68*, *69*, *89*, *90*, *119–121*, *144*)
		GPS-based	3	(*7–9*)
Passively collected data	FHWA		27	(*25*, *27*, *30*, *32*, *37*, *38*, *45–48*, *65*, *84*, *85*, *108–115*, *135–138*, *158*, *159*)
	State DoT		11	(*35*, *36*, *44*, *101–107*, *131*)
	GPS-based data		5	(*17*, *19*, *31*, *116*, *117*)
	Connected device		7	(*18*, *20*, *22*, *34*, *43*, *99*, *100*)
	Fuel sales		1	(*29*)
	Odometer reporting		8	(*16*, *28*, *62*, *126*, *127*, *146–148*)
	Traffic count		7	(*64*, *129*, *130*, *132*, *133*, *150*, *151*)
Simulated data			17	(*33*, *63*, *77–82*, *98*, *128*, *134*, *152–157*)
Other			3	(*96*, *97*, *149*)

Table 3. General pros and cons of the data types

Dataset type	Pros	Cons
Survey-based data	Easy to implement Can freely include questions about travelers' characteristics	Subject to errors by recalling, rounding, or other reasons Not suitable for a continuous study for a certain period (e.g. one month) rather than a one-time reporting or short-term trip diary
Survey-based data (with GPS)	Can collect very accurate VMT data along with travelers' characteristics	Can be too intrusive and cause a self-selection bias Can be too expensive with the device/application cost to scale
Passively collected data	Can collect relatively accurate VMT data	Rarely come with travelers' characteristics and trip purposes
Simulated data	Can forecast VMT in situations where researchers cannot obtain the real data	Not real VMT data after all Depending on the quality of the data for forecasting

Summary of the VMT Literature Review

In this section, we reviewed the current state of research regarding VMT by investigating 151 prior studies from the perspective of the study objective and data collection method. A few key findings in our review include:

1) Regarding the study objective, the most common approach in VMT research was to assess the effect of various factors, such as the use of ride-hailing services, the built environment, policy interventions, or mobility programs, on individual or societal VMT. Exploration of new tools or methods to estimate VMT and discussions on VMT tax/fee follow in the quantity.
2) Methods for VMT data collection have diversity. Broadly speaking, data collection methods can be categorized into survey-based methods, non-survey-based methods, and generative methods. Generally, survey-based methods are prone to errors due to recall biases or rounding and heaping biases in reporting the VMT unless the questionnaire asks for direct reporting of odometer reading. Non-survey-based methods are a good source of precise VMT information but generally lack the information about "who" travels (i.e., travelers' social demographics) for "what" (i.e., trip purposes). Generative methods are helpful when the VMT data is not readily available for the study area. However, researchers need to acknowledge that the simulated VMT data is not real after all. The pros and cons of each category are summarized in Table 3.
    a. Among the survey-based methods, using the NHTS dataset is one straightforward and reliable approach. The NHTS dataset comprises fundamental information for VMT analysis with social demographic factors,

vehicle possession, built-environment factors, and trip details of a specific day. However, due to its update frequency and availability of the temporal/spatial scale, this dataset is inconvenient for timely analysis with emerging trends or technologies, observation of long-term (e.g., one-month-length) analysis, or area-specific analysis of VMT.

b. Non-survey-based methods roughly have four sub-methods: self-reported or activity-based, trip-diary, odometer reporting, and GPS-based. In short, self-reported or activity-based VMT data is the easiest-to-collect data type, but it has a high risk of reporting biases and is not suitable for fine-grained studies with high temporal/spatial resolutions. Trip diary questionnaire provides high-resolution travel behaviors of the survey takers, but it is still prone to error, and it demands a larger response burden than other methods. While VMT data based on direct reporting of odometer readings is less prone to errors in the numbers, it requires at least two readings to be reported for better precision of VMT. Lastly, adopting a dedicated GPS device or mobile app for GPS-based VMT data collection may yield the best quality in both the travel behaviors and the travelers' characteristics. However, it is not readily scalable in terms of the sample size or study period due to its high administration cost. Additionally, a privacy concern for potential study participants due to its intrusive nature may result in self-selection biases in the obtained VMT data.

c. Non-survey-based methods of VMT data collection generally rely on external data sources of authorities (e.g., FHWA or state DoTs) or passively collected data, such as GPS-trajectory data, odometer readings, inspection data, or traffic count. Although these methods yield VMT data with superior accuracy to most survey-based methods, there is an undeniable deficit in that detailed travelers' characteristics are usually not accessible.

d. Among the generative methods, simulated VMT data is useful for disaggregate-level studies in a relatively small area of interest. Meanwhile, travel demand models are good tools for a more comprehensive analysis of travel behaviors. Both methods have a strong point in assessing VMT in hypothetical situations, such as assessing the effect of a planned mobility program or future transit-oriented development on regional VMT. However, researchers and policymakers should not consider what these generative methods suggest to be the true representation of the real VMT. Simulation models or travel demand models can make mistakes or too bold generalizations.

Given these points, we identified that a methodological gap exists between the previously reviewed methods for VMT data collection. Existing methods fail to reconcile the capability of collecting disaggregate-level and precise/accurate VMT along with travelers' characteristics, a non-intrusive data collection approach, easy-to-follow VMT reporting, low administration cost for the researcher, and long-term data collection for one week or more. In this study, we aim to introduce an innovative method to collect odometer data from the public by utilizing the WhatsApp application. It enables a cost-effective, fast, non-intrusive yet accurate data collection of odometer information by asking people to send odometer photos via WhatsApp. To facilitate smooth participation, we developed a dedicated web application system whose details are presented in the next chapter. The application automates user registration, photo handling, communications, and so on with the study participants. We believe that the introduction of this system, presented in the following chapter, and the results of the pilot study will contribute to a more comprehensive understanding of VMT and its applications in various fields, including Road User Charging programs.

Development of the Proposed Framework

The Central Idea Behind Collecting Odometer Images

The central idea behind the development of an automation framework is to collect multiple odometer images over time from participants and calculate the difference between the two odometer readings to estimate VMT, with a lot of human work. It would be very tedious, time-consuming, and prone to errors for a researcher to collect such odometer images and evaluate the VMT manually.

Our automation framework (or simply, system) has three components to achieve this goal:

1) The WhatsApp endpoint to which study participants submit the odometer images and/or other queries ("WhatsApp endpoint" henceforth),
2) The central web application ("webapp" henceforth) that handles queries and communications, and
3) The database that stores binary data of the odometer images ("database" henceforth).

Combined together, the automation framework is expected to perform the following duties:

1) Managing the status of the study participants ("user" henceforth),
2) Receiving and systematically organizing all the odometer images submitted by users,
3) Sending a confirmation message both after receiving and verifying the images to reassure the users, and
4) Handling queries from the users, such as requests to delete some accidentally sent images, to stop further communication, or any other unforeseen requests.

In the following subsections, we will review the details of the automation framework. Also, we made the code used for the study on GitHub (https://github.com/3rfm-its-davis/odometer-reading), which can be reviewed and scaffolded for future studies.

Overview of Automation Framework for Odometer Image Collection

Figure 1 illustrates the overall structure of our system, and the following subsection will explain its technical details, including the WhatsApp endpoint, web app, and database.

1) WhatsApp endpoint: For the first component of the system, we chose WhatsApp for all back-and-forth communication with users because it is a widely used, free messaging service primarily installed on smartphones. By using an already widely accepted smartphone application, potential participants in our study are not required to download an additional survey app or repeatedly access survey links to send images. Additionally, its service is end-to-end encrypted and user-friendly, allowing for the efficient and convenient collection of multiple odometer images from users without increasing the response burden. We set up a WhatsApp business account on the WhatsApp Developer Hub and registered a WhatsApp app that relays incoming messages from study participants to our web app via a webhook.

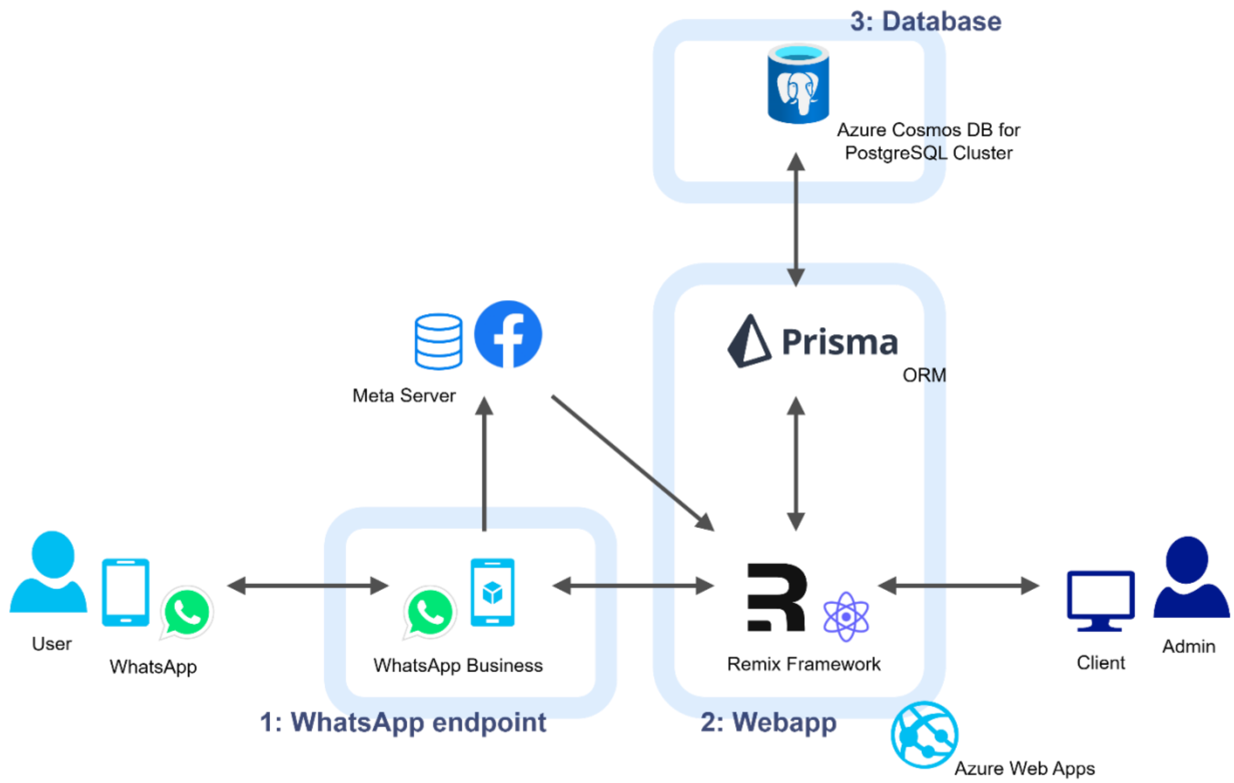

Figure 1. Overall diagram of the system architecture.

2-3) Webapp and database: Secondly, to handle various requests from the users, data transfer between the Meta server and our database, and administrative events by study admins (i.e., ourselves), we have built a Node.js full-stack application with the Remix framework (*162*) and hosted it on the Microsoft Azure cloud server. Also, to store the user status, binary data of the odometer images, and other information, we chose PostgreSQL (Azure Cosmos DB for PostgreSQL) as the database. To let the webapp efficiently communicate with the database, we also adopted the Prisma object-relational mapper (ORM) (*163*). The web app has the following key features.

First, it receives the previously mentioned webhooks from the WhatsApp endpoint and executes appropriate program(s) based on the input. In other words, users can run several programs of our webapp by sending a command through a WhatsApp message. Examples of the commands that study participants can execute include user registration, adding image(s), or deleting image(s).

Additionally, when an odometer image is submitted to our WhatsApp endpoint, it relays the notification to our web application. As it receives such a notification, it requests the image binary from the Meta database, on which the odometer image has been stored. After retrieving the image binary, the webapp posts it to our PostgreSQL database on Azure for later use.

Additionally, our webapp provides the frontend web UI for the study admins with the React framework (*164*). It offers the following functionalities:

1. Add or edit the odometer reading associated with each submitted image.
2. Approve the odometer reading that another admin has added.
3. Reject an image (i.e., if the odometer image is blurred).
4. Display the tabulation of image properties (e.g., image size or approval/rejection status).
5. Display the tabulation of user statistics (e.g., number of submitted images or number of approved images).
6. Display the list of submitted non-image messages from study participants (e.g., “Help, I want to delete the last image”).
7. Display the list of emails of the participants who completed the study and are eligible for a gift card.

Lastly, the webapp, if needed, can send messages to the study participants via the WhatsApp endpoint. For instance, when a study admin approves the odometer reading of an image, it sends a confirmation message to the participant (or a rejection message if it is rejected).

Regarding the security perspective, as participants’ email addresses are considered personally identifiable information (PII), we have coded the webapp to automatically encrypt them using the bcrypt function. Study admins can decrypt them on the web UI using a pre-defined decryption key. Also, the frontend web user interface (UI) requires admins to log in with their email address and password, which were encrypted in the same way.

Illustration of Automated Data Collection

This section illustrates the automated communication, receiving, and organizing of odometer images. Figure 2 displays an example of the communication process on WhatsApp. A person registers using a unique access code shared with them via email, which enables the research team to create the user’s account on the system, linking their phone number with their email ID and other relevant information. The web app immediately verifies the registration key and responds to the participants. After the registration, each time a participant sends an image, they receive a message notifying them that the image has been received. Participants also have the option to delete the image directly from our database using a predefined command, “DELETE IMG.” Once the image is verified for quality and the VMT reading has been manually extracted by the research team, the participants will receive an automated notification message confirming the image verification. This notification serves the vital purpose of reassuring the participants that their images are being verified, motivating them to continue sending images.

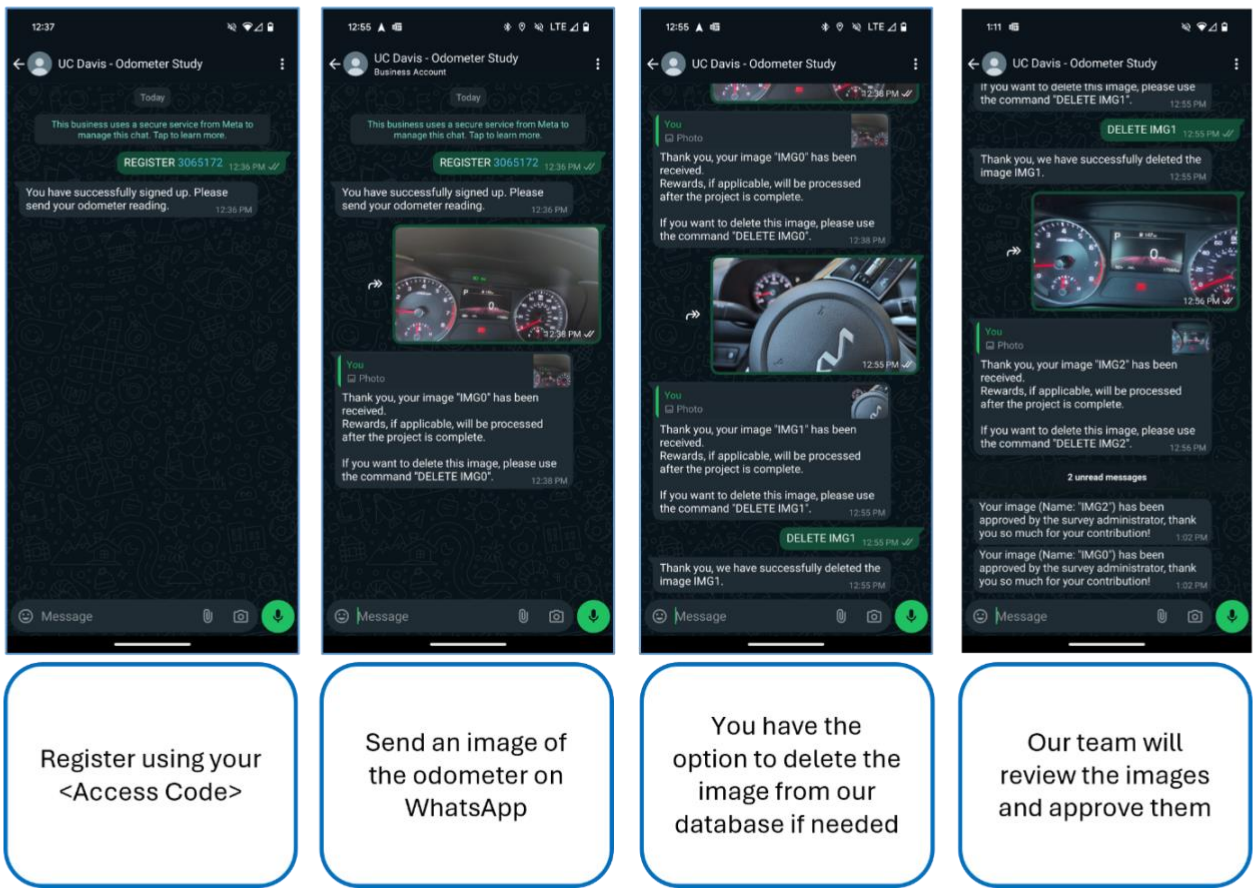

Figure 2. Illustration of communication on WhatsApp

Figure 3 illustrates the frontend web UI developed to aid administrators in verifying the quality of odometer images and manually extracting odometer readings. The left-hand panel shows the access code of the registered users. Blue represents the number of images that require an action of the admin, green represents the number of approved images from which odometer readings have been extracted, and red represents the number of rejected images. The UI in Figure 3 represents the user profile of one of the participants for whom readings from three images were extracted, and one image was rejected. Admins can also access other pages from the top panel to check the users’ statistics or check if any messages have been received from the participants.

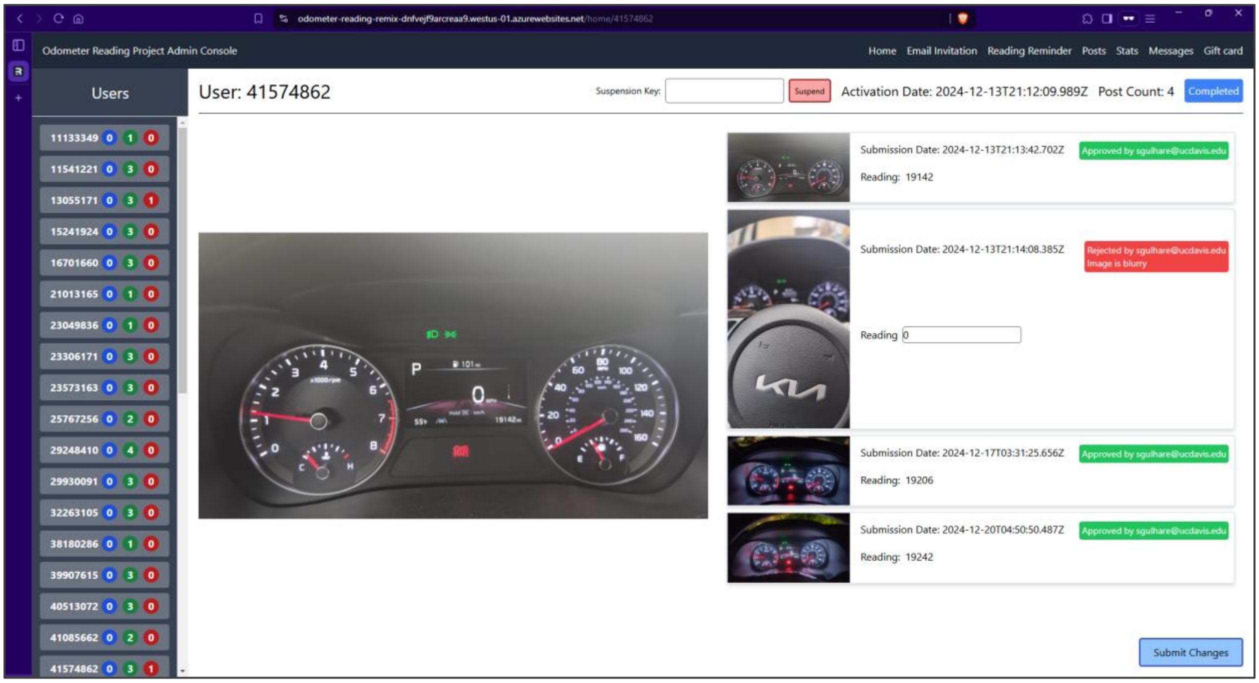

Figure 3. Example window of the web dashboard where administrators add odometer readings to the photo or reject it

Data Format

Through the study participation illustrated in the previous subsection, the web app enables us to collect images and the odometer reading attached to each of them. Table 4 illustrates the example of the user-specific odometer reading data. In the Table 4, the user has submitted three odometer images. The team has approved and extracted reading from the first, third, and fourth images, but the second image was rejected due to its low quality. Consequently, the VMT is estimated by calculating the difference between the two adjacent readings, i.e., the VMT between 12-13-2024 and 12-17-2024 is computed to be 64 miles.

Table 4. Example of user-specific odometer reading data

Anonymized User ID	Date	Status	Odometer reading	VMT
41574862	12-13-2024	Approved	19142	-
41574862	12-13-2024	Rejected	NA	-
41574862	12-17-2024	Approved	19206	64
41574862	12-20-2024	Approved	19242	36

Cost of Data Collection

For this project, we host the whole application on the Azure cloud platform with the following specifications listed in Table 5. Notably, we have built a comprehensive application for odometer-reading data collection with a running cost of less than 100 U.S. dollars per month.

Table 5. Monthly cost of data collection

Purpose	Service name	Monthly cost (USD, January 2025)
Webapp	Azure App Service (S1 plan)	74.40
Database	Azure Database for PostgreSQL	22.94
Phone number	Azure Communication Service	2.00

Data Collection

In this chapter, we present how the data collection presented earlier has been deployed in a real-world study, including details of the recruitment flow, participation flow, experimental simulated data collection, and pilot data collection.

Recruitment Process

First, Figure 4 illustrates the overview of our recruitment process. In this study, we employed a two-step recruitment process: 1) sending an invitation email to the listservs, and 2) sending a follow-up instruction email to the personal email address of those who had shown interest in the invitation email. The detailed process is presented below in steps.

1. Invitation

1.1 Sending invitation email via email listservs

We adopted the convenience sampling method for the present study, where we sent invitation emails to potential participants via listservs and to some personal connections of the project administrators. The invitation email provided a brief description of the background, procedure, and incentive criteria. However, in the pilot deployment of the data collection process, we encountered difficulties in sending invitation emails to the listservs. We requested that the administrators of listservs within and outside the university forward our email, but many declined our request for unknown reasons. Therefore, we also recruited participants through physical fliers posted in various bulletin boards on the campus resident halls.

1.2 Prescreening survey

The invitation email contains a link to the prescreening survey on the Qualtrics platform, where the potential participants would provide the following information:

1. Age
2. Gender
3. Household income level
4. Educational attainment
5. Possession of a driver’s license
6. Number of household vehicles

If the person responds that they do not have a license or a household vehicle, the survey is terminated, preventing further participation. If they qualified, a few additional questions were asked.

7. Number of people who will drive the vehicle for which the participant will report the odometer reading
8. Estimated VMT of the vehicle in the last seven days
9. Anticipated VMT of the vehicle for the next seven days (including today)
10. Confidence level on the ordinal scale of the previous estimations
11. Email address to receive the instruction email for participation

2. Instruction

2.1. Notification of prescreening survey completion

Upon completing the prescreening survey, the results, along with the email addresses, are automatically sent to our system, allowing the webapp to send further instructions to those who have completed the survey.

2.2 Distribution of instruction emails

Our server scans for new survey responses every ten minutes. Suppose there are one or more new responses, an additional instruction email is sent to the email address provided by the survey respondent for study participation. The email instruction contains a unique access code and our WhatsApp phone number, which the potential participant will use to become a user (i.e., start actual study participation, simply "user" henceforth) described in the following section.

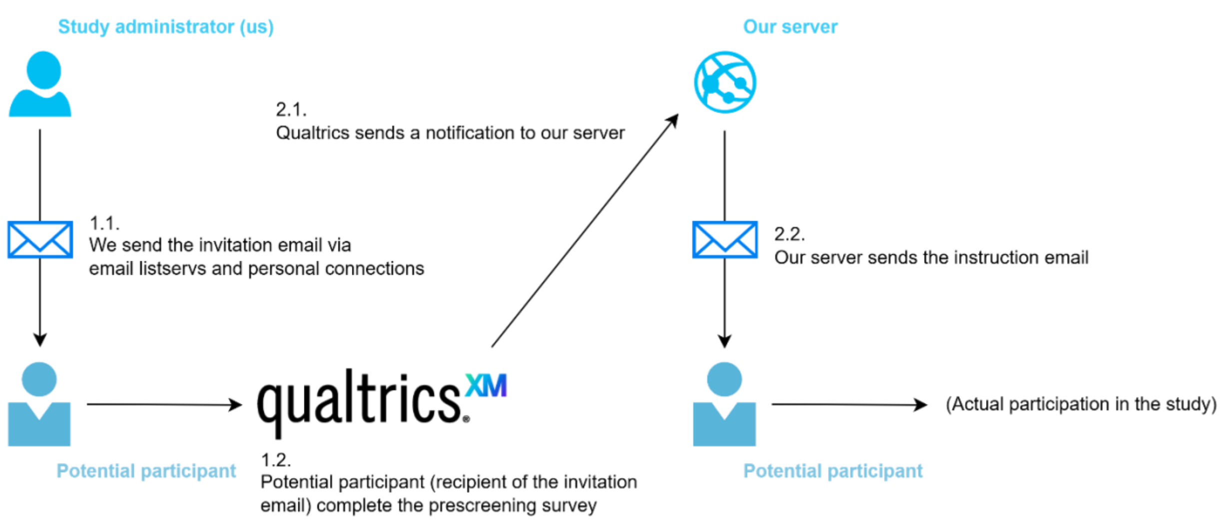

Figure 4. Illustration of the recruitment method of the present project

Participation Process

The detailed participation steps are illustrated in Figure 5. First, when the potential study participant receives the instruction email, they can now register themselves as a user by submitting the access code to our WhatsApp number. Then, our server registers the user in the database for further identification.

After that, the user can submit several photos of their odometer to our WhatsApp number. Once the image is received by our WhatsApp number, it will be transmitted to our database and stored there. We, as the study administrator, can review each image on the web UI (shown earlier in Figure 3). If the submitted image is good (i.e., odometer reading is clearly visible), we add a mileage reading to the image on the UI. Meanwhile, if the image is bad (e.g., blurry, the odometer reading is blocked, or a duplicate of an image previously submitted), we select the rejection reason on the web UI and mark it as a rejected image. Either way, the participant will receive a notification message of image confirmation or rejection from our server when we take action on the web UI.

By repeating this process, if three images are approved within 14 days from the registration date, the user is considered to have completed the study. They will receive a confirmation message upon study completion and are entitled to a $5 gift card. The gift card is later manually distributed by us through Giftbit.com to the email address of the user. If 14 days elapse since the user opened their account (i.e., they registered as a user) with less than three images approved by us, their account will automatically be closed.

Also, the user can request to delete the image(s) or close their account if needed during the participation period. These options are prepared for the user's privacy concerns. When the user closes their account, they can even select whether to keep the binary data of the images that they have submitted to our database or delete them all.

If the user completes the study by having three images approved by us or their account has been closed, they can no longer communicate with us via WhatsApp to reduce the communication burden.

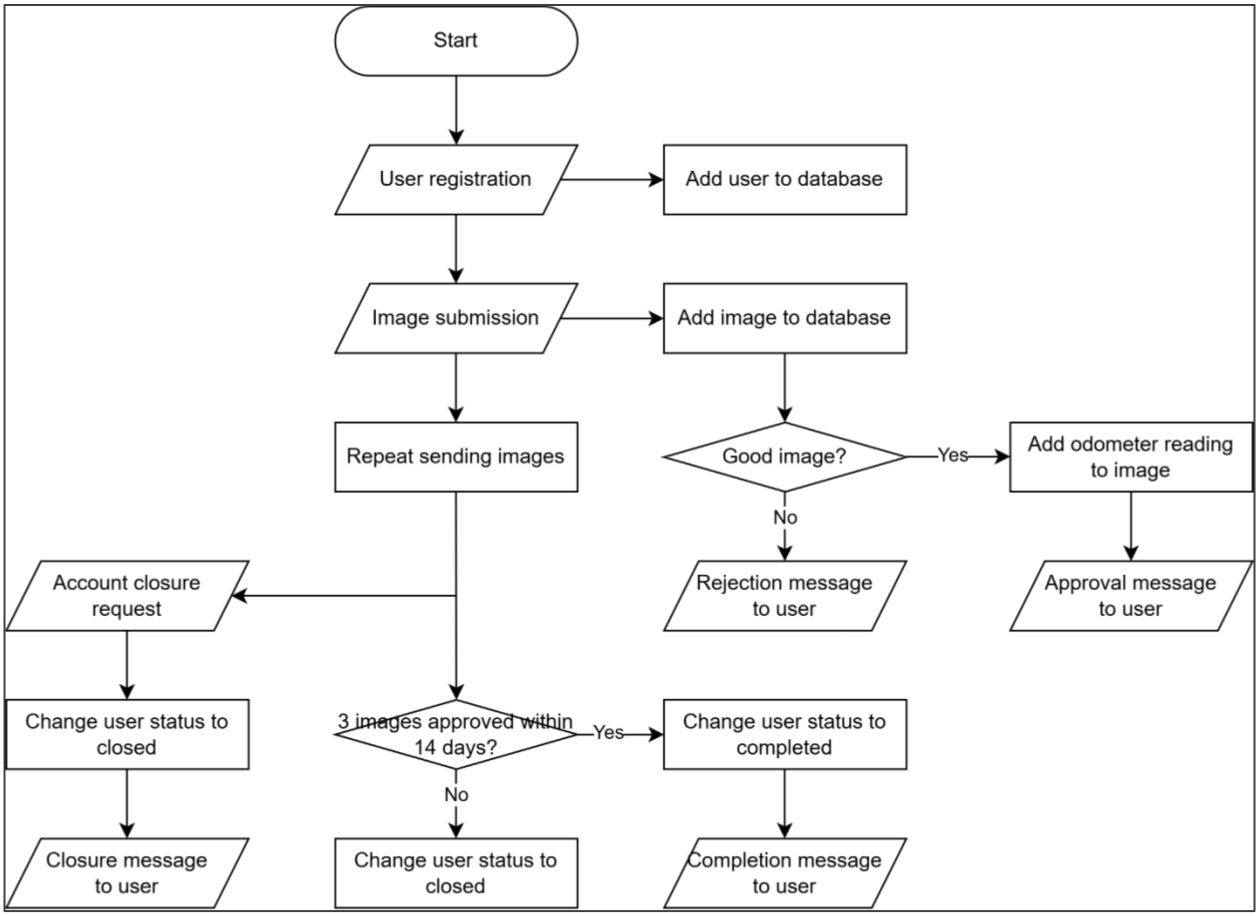

Figure 5. Participation logic on WhatsApp

Simulated Data Collection

Before reviewing the real-world data collection, we will review the details of an experimental simulated data collection. Since our webapp autonomously communicates with the database, accesses the Meta server, and/or sends text messages to the users, a misspecification in the programming code may result in a critical failure, such as spamming messages to users or posting a lot of irrelevant and invalid images to the database. Therefore, before launching the actual data collection trial, we rigorously tested our system for debugging purposes.

To test the system's functionality, we simulated data collection after building the core components using a mock dataset. First, as an initial step, we prepared 58 dummy odometer images and set 12:00 AM on December 1, 2024, as the reference datetime. Then, we ran a program that generated 30 mock users. The mock datetime of the completion of the prescreening survey was randomly set seven days later than the reference datetime for each user. Also, the mock activation datetime (i.e., when the user submitted the access code to the WhatsApp endpoint) was set from the prescreening completion time of the user to 3 days later than it.

Consequently, the program added dummy images picked from the 58 mock images, which contain 46 odometer images and 12 non-odometer images, at random. The number of images per user was set to seven for a part of the sample and 10 for the other. The mock image submission datetime was assigned 14 days later than the activation datetime for each image, with a truncated normal distribution (mean of zero and standard deviation of two for part of the sample and three for the other). Finally, we assigned a mock email address and phone number to each user, encrypted the email address using the bcrypt algorithm, and posted the users with the image data to the database.

After that, we and an undergraduate student assistant verified that each user has correctly owned image data in the database and added the odometer reading to each image using the web UI. We added a reading to 461 images in total, with 370 approvals and 91 rejections. The share of approved images (370/461=80.3%) was roughly equal to that in the valid images in the mock images (46/58=79.3%). We made a few minor adjustments based on their feedback, but the system generally performed as smoothly as we had expected. However, it should be noted that we tested only the webapp and the database in this process, excluding the WhatsApp endpoint. Although it was technically possible, due to the development cost, we decided not to purchase many phone numbers on Azure or other platforms. Instead, we registered them all as a mock WhatsApp user and tested sending and receiving messages to and from them during the development phase.

Pilot Study Deployment and Its Results

In this section and the following, we review the details of the pilot study deployment, its results, and notable experiences that we encountered during the data collection.

We launched a pilot study of the VMT data collection using the presented system schema in mid-December 2024 and ended it at the end of May 2025. Table 6 shows the summary statistics of the study participation. By the end of the study, 159 people started the Qualtrics prescreening survey, and 117 of them (73.6%) completed it. 40.3% of the initial sample started study participation (i.e., activated as a user by sending the unique access code to our WhatsApp number), and 25.8% of them completed the study (i.e., had three valid odometer-reading photos approved by us). The completion rate might look even though these numbers are not very good for performing any rigorous statistical analysis, we believe it is enough to examine and demonstrate the capability of our automation framework for collecting people’s VMT efficiently and with ease.

Table 6. Statistics of the study sample

Category	Sample size	Ratio to the sample size compared to prescreening completed
Prescreening survey started	159	(100.0%)
Prescreening survey completed	117	73.6%
Activated the account	64	40.3%
Submitted at least one valid image	53	33.3%
Submitted at least two valid images	47	29.6%
Submitted at least three valid images	41	25.8%

Survey participants

Table 7 displays the sociodemographics of participants in our pilot deployment who completed the prescreening survey (n=117) and those who sent two or more valid odometer images (n=47). As mentioned in the previous chapter, we employed a convenience sampling method for this study, primarily within the University of California, Davis. Consequently, our sample is largely skewed towards younger, low-income, and highly educated individuals compared to the standard population of California. Looking at the difference between the distribution among the prescreening survey participants and those who completed the study by submitting three valid odometer images, there are slightly more older and low-income people in the final sample, but overall, the distributions remain similar between the samples.

We also asked the participants to estimate the VMT in the last seven days and for each of the forthcoming six days, including the day when they took the survey. Table 7 also includes the distribution of self-reported confidence in the VMT estimations. Overall, people were not very confident in estimating how many miles they drove when asked to recall the most recent week. Only 20% of respondents in the prescreening survey reported very high confidence. Interestingly, however, people were slightly more confident in estimating their expected mileage in the forthcoming week. The share of “very confident” and “completely confident” increased to about 30% while estimating VMT for the coming week.

Table 7. Distribution of the social demographic factors and difficulty with recalling and confidence in the estimation of VMT

Factor	Level	Share with those who...	
		completed the prescreening survey	submitted two or more valid images
(Sample size)		117	47
Age	Under 25	25.6%	34.0%
	25-39	56.4%	40.4%
	40 or older	17.9%	25.5%
Gender	Man	38.5%	40.4%
	Woman	61.5%	59.6%
Income	Less than $50,000	17.1%	21.3%
	$50,000 -99,999	16.2%	8.5%
	$100,000-149,999	29.1%	27.7%
	$150,000 or more	35.0%	40.4%
	Prefer not to say	2.6%	2.1%
Education	Bachelor's or less	52.1%	55.3%
	Graduate/Professional	47.9%	44.7%
Number of Household Vehicles	1	43.6%	40.4%
	2 or more	56.4%	59.6%
Difficulty in recalling last week's VMT	It's very hard to recall it	2.6%	0.0%
	I struggled a bit to estimate it	18.8%	17.0%
	I think I remembered it okay	32.5%	42.6%
	I'm pretty sure I got it right	35.0%	27.7%
	Yes, I remember it exactly	11.1%	12.8%
Confidence in the estimation of next week's VMT	Not confident at all	5.1%	4.3%
	Slightly confident	26.5%	29.8%
	Moderately confident	39.3%	44.7%
	Very confident	23.9%	14.9%
	Completely confident	5.1%	6.4%

During the study, we obtained 147 odometer images from 53 users in total. Next, Table 8 shows the distribution of the number of images submitted in different hours of the day. Although it is not required in the study, one straightforward assumption is that users would submit an odometer image immediately after they took it, rather than saving the image and submitting it a while later. Generally, users tend to submit an odometer image at midday rather than morning or night. It is inferred that since our study collects images of odometers, people would notice that they can take an image and send it when they start or finish driving during the day. However, obtaining an odometer image during the day is not ideal in terms of following VMT analysis, since it is difficult to determine if the odometer image was taken before they drive or after they finish driving. For instance, when people complete their work at the office at 6:00 PM, they can take an image either before leaving the office or after arriving home. It is more likely that the image was taken before or after the trip if the image was sent in morning or at night respectively, but this does not go beyond a naive assumption and should be noted as one drawback of our data collection method.

Table 8. Number of images submitted in different hours of the day (n=144)

	Morning (6 AM-9 AM)	Midday (10 AM-6 PM)	Night (7 PM-11 PM)	Late night (12 AM-5 AM)
Number of images	23	85	32	4
Share	15.6%	59.0%	22.2%	2.8%
(Hourly average)	5.75	9.44	6.40	0.67

The numbers in the header show the range of hours in the day on the 24-hour scale. Rejected images (n=3) have been removed.

Next, with 47 participants submitting more than one valid image, Figure 6 illustrates the difference in time of the day between the consecutive odometer images. Here we include only the first, second, and third images approved for VMT analysis. Users could send multiple images on the same day or beyond the third approval but those have been removed. Every point in the plot is placed at the X coordinate of the image submission time of the earlier image and the Y coordinate of that of the later image. It is desirable that a user submits images at the same time of the day for every image as it makes easier to compute and examine the daily VMT of the person. However, the image indicates a large variation in the image submission time for the same user. For instance, if a user submits one image at 7:00 AM in one day and 9:00 PM on the next day, it is likely that they had VMT of two days instead of one. Unless we can obtain odometer images of the person large enough to assess their daily driving behavior, this variation could be a notable obstacle to computing a good estimate of VMT.

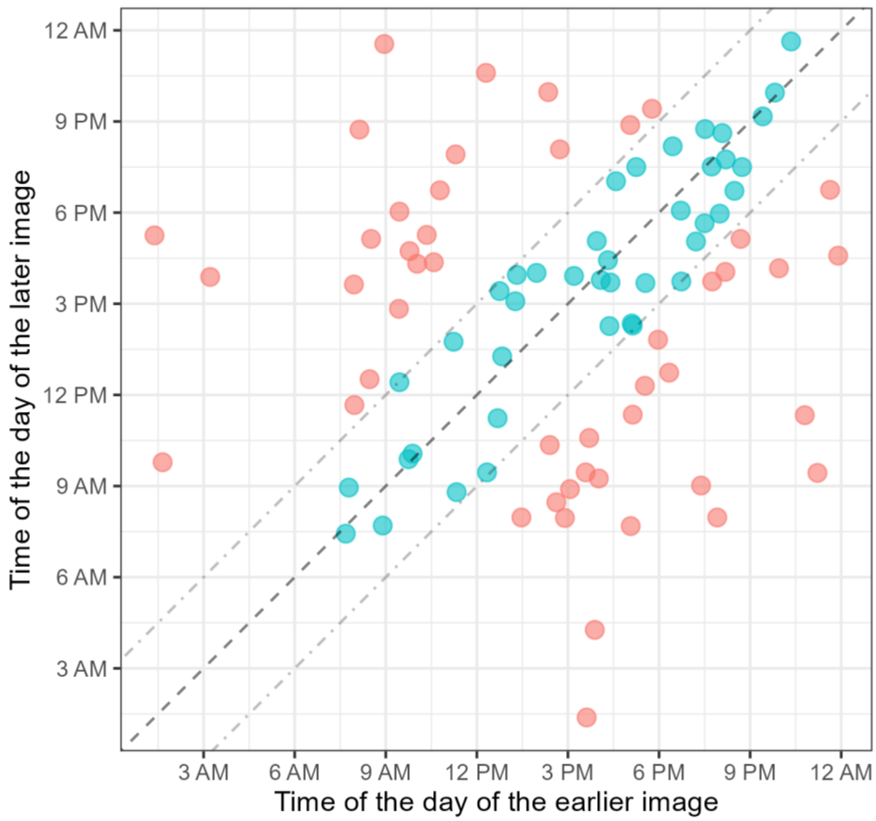

Figure 6. Distribution of the difference in time of the day between consecutive images (n=83). Blue points represent those with the time difference smaller than three hours.

Although there are generalizations and assumptions mentioned above, we still computed the cumulative VMT from the odometer reading of the first image and that of the second/third images. Calling this VMT actual VMT ($aVMT$), we also computed the expected VMT ($eVMT$) by adding up the expectation of VMT answered in the prescreening survey. For instance, assume a user submitted the first image 1.8 days later than when the user completed the prescreening survey and the second one 4.5 days later than the prescreening. Then, defining $sVMT_n$ as the expectation of VMT for the nth day, counting from the day when they took the prescreening survey (i.e., n =1 stands for the day of the prescreening survey participation), we compute the $eVMT$ as

$$eVMT = \sum_{n=1}^{4} sVMTn + 0.5 \times sVMT_5 - \sum_{n=1}^{2} sVMTn + 0.8 \times sVMT_3$$

which stands for an interpolated expectation of VMT that the user would make between the date of the first and second image submission. Because we asked the expectation of VMT up to six days after the date of the prescreening survey participation, we removed images which were submitted seven or more days later than the prescreening survey participation date (n=73).

Figure 7 displays the scattered plot of the expected VMT and the actual VMT extracted from the odometer image(s) in the log scale. While we made a very naive VMT estimation, the plot still indicates uncertainty of a driver's VMT estimation to some extent. The plot suggests that participants tend to underestimate their VMT for the forthcoming days in this study.

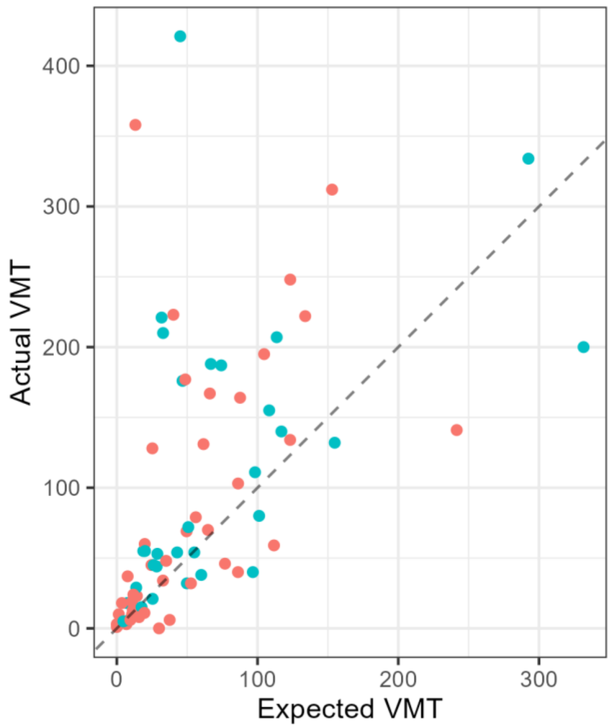

Figure 7. Distribution of the expected VMT estimated by the participant and the actual VMT reported by the odometer images. Red dots show the VMT computed by the first and second odometer image (n=42), and blue dots show that by the first and third odometer image (n=31).

Finally, Table 9 shows the summary statistics of the computed expected VMT ($eVMT$) and actual VMT ($aVMT$). It is expected that the mean and standard deviation of $eVMT$ and $aVMT$ becomes larger for the third image because the cumulative VMT becomes larger as time elapses. As we reviewed with the previous scatterplot, the expected VMT is generally smaller than actual VMT, implying the users' tendency to underestimate their driving range. As the magnitude of VMT gets larger, the mean absolute error (MAE) and root mean squared error (RMSE) become larger accordingly. However, a smaller number of those statistics on the %-scale (MAE% and RMSE%) suggest that the expectation of VMT is relatively closer to what they drive for the VMT computed by the third image. This result could be an implication that people are better at estimating their driving range in a longer time by thinking of the weekly routines rather than estimating the range of a specific forthcoming day or two. The RMSE-MAE ratio at 1.68 and correlation at 0.553 and 0.504 suggest that there are some outliers in the data, but it is far better than at random. In other words, some people might have a very long drive that they did not expect when taking the prescreening survey or vice versa.

Table 9. Summary statistics of the expected VMT, actual VMT, and its difference

Statistics	VMT by the second image (n=42)		VMT by the third image (n=31)	
	Expected	**Actual**	**Expected**	**Actual**
Mean	50.5	83.0	70.0	109.6
S.D.	51.2	91.0	75.1	100.5
MAE (MAE%)	48.6 (68.6%*)		57.9 (46.6%)	
RMSE (RMSE%)	81.7 (98.4%)		97.2 (88.7%)	
RMSE-MAE ratio	1.68		1.68	
Correlation	0.553		0.504	

The unit is miles except for the %-scale statistics, RMSE-MAE ratio, and the correlation.
*: the MAE% was computed by removing the observations whose actual VMT is zero.

Pilot Study Experience

In this section, we will share some experience and challenges that we encountered during the pilot study from a few perspectives: system, participants, and researchers.

Performance of the system

First, most of the functions and features of the developed system worked smoothly and without flaws beyond our expectation. The Remix framework made it easy for us to control various types of data, including odometer images, odometer reading added to them, user status, post summary, and other tables in one convenient place of integrated web UI. As long as we observed, there was no downtime of the system or WhatsApp API, suggesting that the combination of the solutions will be encouraged for future studies with a similar data collection trial as well.

Experience of the participants

The system was well-accepted from the user's side too. As we adopted a convenience sampling method, we had a chance to discuss the experience of the study participation with some of our research colleagues and friends. Their impression and review were positive overall, highlighting the seamless participation using the WhatsApp interface and easy-to-follow instructions.

One note about this positive review is, however, that our colleagues and friends were a WhatsApp user already when we launched the study and therefore there was no obstacle for them to using the software (or even to installing the software). We do not have an interview or hear feedback from non-WhatsApp users, but certainly it might make potential participants stay away to try a new phone app just for this kind of study.

Inquiries from participants

As reviewed in the system specification, during the system development, we built a component to handle non-command WhatsApp messages. This functionality was supposed to be a help center in case users needed help for registration, deletion of images, gift card, discontinuation of participation, and so on. However, we had only one message in the whole study, contrary to our initial expectation.

Manual extraction of odometer readings from images

Contrary to our initial concerns, only two invalid images (one duplicate image and one blurred image) were submitted by a study participant. There seemed to be no spamming images or attempts to cheat to get a gift card by submitting artificial intelligence (AI)-generated images or similar, as far as we verified. Also, the image quality (e.g., brightness, contrast, or clarity) was overall excellent, probably thanks to recent rapid improvement in the quality of smartphone cameras. Consequently, the extraction of odometer readings was much easier than we initially thought, and it was done in a short time. These results are important hints for future studies that may attempt a similar data collection method for VMT or other objectives.

Challenges in the recruitment of participants

While we enumerated positive aspects of our system and user experience with it, there was a significant challenge with the recruitment process. For the present study, we did not use an online opinion panel. One of the reasons for the decision was insufficient funding to request data collection through an opinion panel. Meanwhile, the other is due to the nature of this study. Although an online opinion panel can let a certain number of people complete the prescreening survey with questions about social demographic factors and driving behaviors, it is not guaranteed that those people would participate in the later phase of our study by submitting the odometer images. Since we had not known the ratio between those who complete the prescreening survey and those who complete the study by submitting three images (that is, 35% as reviewed in Table 6), it was a risk for us to fully account for an online opinion panel for data collection.

Even with the convenience sampling method that we eventually adopted, there were several issues that we did not initially expect. When we asked universities' email listservs to circulate the invitation email for the study, many of them were not willing to do so due to irrelevance with their agenda/theme. Even when the email is distributed through some listservs, the response rate is significantly smaller than our expectations. Also, we initially desired to distribute physical flyers with a quick response (QR) code to the prescreening survey and other necessary information to the residential halls of the university, but it was restricted by their policy, and we were only able to display a copy of the flyer on some bulletin boards of the halls. Consequently, we made additional recruitment efforts through our personal connections, yet the sample size ended up smaller than our initial plan. Future studies are encouraged to further examine the concept of the data collection method presented in this study in an environment that enables a larger sample size.

Summary, Conclusion, and Future Works

In this study, we developed a brand-new methodology for VMT data collection using WhatsApp and examined its capabilities and challenges through a pilot study. Lastly, we conclude this study by discussing the summary of the findings and potential future work.

Summary of the Findings

Despite the emerging need for accurate VMT data to develop policies and countermeasures for sustainable transportation options, researchers and other stakeholders are facing several challenges in the current methods for collecting VMT data. Travel-survey-based VMT data are relatively easy and cheap to collect, but are almost always subject to recall errors, rounding, and/or heaping biases. Adopting GPS-based data collection during a travel survey significantly increases the accuracy of the collected VMT data, but it can be expensive to scale the study or may be too intrusive. Passively collected VMT data is relatively more accurate but usually does not include information about the travelers or trip purposes, which can be a critical flaw in travel behavior analysis. Simulated VMT data, such as those generated through travel demand models, can be a good source for analysis of the potential impact of hypothetical situations or plans. However, those are, after all, not a real representation of the true VMT and depend on the quality and availability of the data by which the forecast was generated.

To address the limitations of such existing VMT data collection methods, we developed a novel system that collects images of odometer readings submitted via WhatsApp. Our full-stack web application automatically communicates with study participants and organizes the images in the database. By using a commonly used social media platform and the automation framework, we aim to achieve VMT data collection that is more accurate, low-cost, less intrusive, and suitable for longer-term or large-scale studies.

Consequently, we evaluated the feasibility of the system with a pilot VMT data collection trial. We conveniently sampled participants by sending invitation emails to listservs and our personal connections and distributing flyers in several locations. The invitation email contains information about the study along with a link for a prescreening survey. The prescreening survey collected information on sociodemographics, about VMT, and their email address. Those who completed the pre-screening survey received an instruction email with detailed participation instructions and a unique registration key. The participants were asked to send up to three odometer images within seven days to qualify for the gift card of $5.

The data collection through pilot deployment demonstrates that the automation framework worked smoothly for users and us as the administrators without critical errors. The team received only two invalid images (one duplicate image and one blurred image) among all the 147 submitted images, dispelling the team's initial concerns that participants might struggle to follow the instructions or find the process too complicated. It also alleviated worries about potential misuse of the system to claim gift card incentives. Hence, this study, to some extent, supports the capability and feasibility of the presented system as a method of alternative VMT data collection.

However, our pilot study indicated a few caveats and challenges with the proposed method. First, it was found that the study participants submit odometer images at varying times of the day, for instance, one image at night and another in the morning. This observed behavior of the study participants implied that the proposed method might not be suitable for a short-term study, in which the variation of VMT in one day is more important.

Also, one of the most difficult issues that we encountered was in the recruitment process. In spite of our efforts to distribute the invitation email through listservs and other means, our final sample size was 147 images, which is not large enough for rigorous VMT analysis. We expected that our method is relatively cheap and scalable for large data collection, but we admit that this concept was not supported by this study. As one of the proposed advantages of our system is that the cost of data collection remains the same as long as the webapp can handle queries, the method may become more effective when integrated as an add-on study to existing travel surveys or other experiments that can ensure a relatively large sample to be studied.

Future Works

Finally, we enumerate a few potential improvements or new features that can be added to the proposed data collection for future studies.

First, the integration of non-WhatsApp communication methods will be essential to improve the study participation rate. In the U.S., it is reported that WhatsApp has 100 million users (*10*) As of 2024, however, this implies that more than one third of U.S. residents will automatically be excluded from our study. Including opportunities for people to participate in this type of VMT data collection via other means, such as short message services (SMS) or Facebook Messenger, will be helpful to increase the sample size.

Secondly, better navigation for users will also help with a higher retention rate in the study. In our study, our webapp did not send messages more than confirmation/rejection notifications or replies to other user commands. This would be good for some users who did not want to be disrupted by WhatsApp notifications, but at the same time, it could be a reason for them to forget about the study. A daily reminder or snoozing for image submission, as they request in advance, will keep them more informed and engaged in the study. Also, this type of reminder may be great to control image submission time. For instance, when someone submits one image, the webapp could send a message to them, asking whether they desire to receive a reminder at the same time on the next day. This approach can yield more consistency in the image submission time of the day for the same user.

Other potential improvements in the participation flow include the integration of the API of Giftbit, which we used to distribute the gift cards in this study, into the program to automate the instant distribution of gift cards to the participants after the verification of odometer photos. In the current project, the team manually distributed the gift cards after the completion of participation in the study. If there is an instant distribution of smaller-amount gift cards (e.g., $1) to the participants after verification of an odometer image, it will keep the users more motivated during the study.

Also, the integration of a follow-up survey into our WhatsApp communication could be a great enhancement in data collection. WhatsApp provides features to administer surveys (e.g., simple multiple-choice questions) within its application. This feature can be utilized to collect information on the travel after the submission of each odometer image. For example, the teams can collect additional information about the trip purpose for the day, work arrangements (i.e., remote work vs. commuting), or shopping behavior (i.e., e-shopping vs. in-store shopping) to understand how activities affect VMT.

As we have made the program we developed for this study publicly available on GitHub (https://github.com/3rfm-its-davis/odometer-reading) under the Massachusetts Institute of Technology (MIT) license, we hope that future studies will build upon the source code and develop further work on it.

References

1. Larsen, L., M. Burris, D. Pearson, and P. Ellis. Equity Evaluation of Fees for Vehicle Miles Traveled in Texas. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2297, No. 1, 2012, pp. 11–20. https://doi.org/10.3141/2297-02.
2. Polzin, S. E., X. Chu, and L. Toole-Holt. Forecasts of Future Vehicle Miles of Travel in the United States. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1895, No. 1, 2004, pp. 147–155. https://doi.org/10.3141/1895-19.
3. Sadek, A. W., Q. Wang, P. Su, A. Tracy, and others. *Reducing Vehicle Miles Traveled through Smart Land-Use Design.* New York State Energy Research and Development Authority, 2011.
4. Akar, G., and J.-M. Guldmann. Another Look at Vehicle Miles Traveled: Determinants of Vehicle Use in Two-Vehicle Households. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2322, No. 1, 2012, pp. 110–118. https://doi.org/10.3141/2322-12.
5. Jamal, S., M. A. Habib, and N. A. Khan. Does the Use of Smartphone Influence Travel Outcome? An Investigation on the Determinants of the Impact of Smartphone Use on Vehicle Kilometres Travelled. *Transportation Research Procedia*, Vol. 25, 2017, pp. 2690–2704. https://doi.org/10.1016/j.trpro.2017.05.201.
6. Spissu, E., A. R. Pinjari, R. M. Pendyala, and C. R. Bhat. A Copula-Based Joint Multinomial Discrete–Continuous Model of Vehicle Type Choice and Miles of Travel. *Transportation*, Vol. 36, No. 4, 2009, pp. 403–422. https://doi.org/10.1007/s11116-009-9208-x.
7. Zhang, L., and X. He. Feasibility and Advantages of Estimating Local Road Vehicle Miles Traveled on Basis of Global Positioning System Travel Data. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2399, No. 1, 2013, pp. 94–102. https://doi.org/10.3141/2399-10.
8. Li, M., Y. Jia, Z. Shen, and F. He. Improving the Electrification Rate of the Vehicle Miles Traveled in Beijing: A Data-Driven Approach. *Transportation Research Part A: Policy and Practice*, Vol. 97, 2017, pp. 106–120. https://doi.org/10.1016/j.tra.2017.01.005.
9. Blei, A., K. Kawamura, M. Javanmardi, and A. Mohammadian. Evaluation Methods for Estimating Vehicle Miles Traveled with GPS Travel Survey Data. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2495, No. 1, 2015, pp. 112–120. https://doi.org/10.3141/2495-12.
10. WhatsApp LLC. 100 Million Using WhatsApp across the United States. https://blog.whatsapp.com/100-million-using-whatsapp-across-the-united-states. Accessed Feb. 8, 2025.
11. California Air Resources Board. *Appendix E - Sustainable and Equitable Communities*. 2022, pp. 1–30.

12. California Air Resources Board. What Are Sustainable Communities Strategies? *What are Sustainable Communities Strategies?*. https://ww2.arb.ca.gov/our-work/programs/sustainable-communities-program/what-are-sustainable-communities-strategies.
13. Wolf, J., M. Oliveira, and M. Thompson. Impact of Underreporting on Mileage and Travel Time Estimates: Results from Global Positioning System-Enhanced Household Travel Survey. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1854, No. 1, 2003, pp. 189–198. https://doi.org/10.3141/1854-21.
14. Wolf, J., S. Bricka, T. Ashby, and C. Gorugantua. *Advances in the Application of GPS to Household Travel Surveys*. 2004.
15. Henao, A., W. E. Marshall, and B. Janson. Impacts of Ridesourcing on VMT, Parking Demand, Transportation Equity, and Travel Behavior (MPC-19-379).
16. Porter, J. D., D. S. Kim, H. A. Vergara, J. Whitty, J. Svadlenak, N. C. Larsen, C. B. Sexton, and D. F. Capps. Development and Performance Evaluation of a Revenue Collection System Based on Vehicle Miles Traveled. *Transportation research record*, Vol. 1932, No. 1, 2005, pp. 9–15.
17. Nasri, A., L. Zhang, J. Fan, K. Stewart, H. Younes, C. Fu, and S. Jessberger. Advanced Vehicle Miles Traveled Estimation Methods for Non-Federal Aid System Roadways Using GPS Vehicle Trajectory Data and Statistical Power Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2673, No. 11, 2019, pp. 296–308. https://doi.org/10.1177/0361198119850790.
18. Gehrke, S. R., and M. P. Huff. Spatial Equity Implications and Neighborhood Indicators of Ridehailing Trip Frequency and Vehicle Miles Traveled in the Phoenix Metro Region. *Transportation*, Vol. 51, No. 1, 2024, pp. 271–295. https://doi.org/10.1007/s11116-022-10327-3.
19. Liu, W., L. Hao, and F. Li. *Estimation of Vehicle Miles Traveled Based on Improved Ant Colony Algorithm*. SAE Technical Paper, 2020.
20. Chandra, S., R. Vyas, and R. Mazin. *Evaluating Crowdsourcing as a VMT Reduction Tool to Support Smart Cities Initiatives*. Mineta Transportation Institute, 2020.
21. Patterson, Z., K. Fitzsimmons, S. Jackson, and T. Mukai. Itinerum: The Open Smartphone Travel Survey Platform. *SoftwareX*, Vol. 10, 2019, p. 100230. https://doi.org/10.1016/j.softx.2019.04.002.
22. Ahmed, N. K., and J. Kapadia. Seasonality Effect on Electric Vehicle Miles Traveled in Electrified Vehicles. *SAE International Journal of Alternative Powertrains*, Vol. 6, No. 1, 2017, pp. 47–53. https://doi.org/10.4271/2017-01-1146.
23. Wu, X., and D. MacKenzie. Assessing the VMT Effect of Ridesourcing Services in the US. *Transportation Research Part D: Transport and Environment*, Vol. 94, 2021, p. 102816. https://doi.org/10.1016/j.trd.2021.102816.
24. Duncan, M. How Much Can Trip Chaining Reduce VMT? A Simplified Method. *Transportation*, Vol. 43, No. 4, 2016, pp. 643–659. https://doi.org/10.1007/s11116-015-9610-5.

25. Yeo, J., S. Park, and K. Jang. Effects of Urban Sprawl and Vehicle Miles Traveled on Traffic Fatalities. *Traffic Injury Prevention*, Vol. 16, No. 4, 2015, pp. 397–403. https://doi.org/10.1080/15389588.2014.948616.
26. Majid, M. R., A. N. Nordin, and I. N. Medugu. Influence of Housing Development Designs on Household Vehicle Miles Traveled: A Case of Iskandar Malaysia. *Transportation Research Part D: Transport and Environment*, Vol. 33, 2014, pp. 63–73. https://doi.org/10.1016/j.trd.2014.09.001.
27. McMullen, B. S., and N. Eckstein. Relationship between Vehicle Miles Traveled and Economic Activity. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2297, No. 1, 2012, pp. 21–28. https://doi.org/10.3141/2297-03.
28. Kirley, B., Y. Wang, R. Foss, S. Harrell, and A. Goodwin. *Estimating Motorcycle Miles Traveled From State Vehicle Inspection Records*. Publication DOT HS 813 288. 2022.
29. Hossain, A., and D. Gargett. Road Vehicle-Kilometres Travelled Estimated from State/Territory Fuel Sales. 2011.
30. Vadlamani, S. *Development of an Alternative Approach to Estimate Vehicle Miles Traveled Using a Classification Procedure*. Master of Science in Civil Engineering. Louisiana State University and Agricultural and Mechanical College, 2005.
31. Kim, D. S., J. D. Porter, J. Whitty, J. Svadlenak, N. C. Larsen, D. F. Capps, B. Imholt, J. L. Pearson, and D. D. Hall. Technology Evaluation of Oregon's Vehicle-Miles-Traveled Revenue Collection System: Lessons Learned. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2079, No. 1, 2008, pp. 37–44. https://doi.org/10.3141/2079-06.
32. United States. Dept. Of Transportation. Research And Innovative Technology Administration, and J. Memmott. Trends in Personal Income and Passenger Vehicle Miles. 2007. https://doi.org/10.21949/1501499.
33. Ma, J., Y. He, Q. Jiang, M. T. Center, and others. *Evaluating Policies and Incentives to Reduce Vehicle-Miles-Traveled and Air Pollutant Emissions through the Promotion of Telework and Remote Services*. METRANS Transportation Center (Calif.), 2022.
34. Bekka, A., N. Louvet, and F. Adoue. Impact of a Ridesourcing Service on Car Ownership and Resulting Effects on Vehicle Kilometers Travelled in the Paris Region. *Case Studies on Transport Policy*, Vol. 8, No. 3, 2020, pp. 1010–1018. https://doi.org/10.1016/j.cstp.2020.04.005.
35. Ward, J. W., J. J. Michalek, I. L. Azevedo, C. Samaras, and P. Ferreira. Effects of On-Demand Ridesourcing on Vehicle Ownership, Fuel Consumption, Vehicle Miles Traveled, and Emissions per Capita in U.S. States. *Transportation Research Part C: Emerging Technologies*, Vol. 108, 2019, pp. 289–301. https://doi.org/10.1016/j.trc.2019.07.026.
36. Lopez-Zetina, J., H. Lee, and R. Friis. The Link between Obesity and the Built Environment. Evidence from an Ecological Analysis of Obesity and Vehicle Miles of Travel in California. *Health & Place*, Vol. 12, No. 4, 2006, pp. 656–664. https://doi.org/10.1016/j.healthplace.2005.09.001.
37. Choo, S., P. L. Mokhtarian, and I. Salomon. Does Telecommuting Reduce Vehicle-Miles Traveled? An Aggregate Time Series Analysis for the U.S. *Transportation*, Vol. 32, No. 1, 2005, pp. 37–64. https://doi.org/10.1007/s11116-004-3046-7.

38. Choo, S., P. L. Mokhtarian, and I. Salomon. Impacts of Home-Based Telecommuting on Vehicle-Miles Traveled: A Nationwide Time Series Analysis. 2002.
39. Tal, G., M. A. Nicholas, J. Davies, and J. Woodjack. Charging Behavior Impacts on Electric Vehicle Miles Traveled: Who Is Not Plugging In? *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2454, No. 1, 2014, pp. 53–60. https://doi.org/10.3141/2454-07.
40. Tirachini, A., and A. Gomez-Lobo. Does Ride-Hailing Increase or Decrease Vehicle Kilometers Traveled (VKT)? A Simulation Approach for Santiago de Chile. *International Journal of Sustainable Transportation*, Vol. 14, No. 3, 2020, pp. 187–204. https://doi.org/10.1080/15568318.2018.1539146.
41. Núñez-Córdoba, J. M., M. Bes-Rastrollo, K. M. Pollack, M. Seguí-Gómez, J. J. Beunza, C. Sayón-Orea, and M. A. Martínez-González. Annual Motor Vehicle Travel Distance and Incident Obesity: A Prospective Cohort Study. *American journal of preventive medicine*, Vol. 44, No. 3, 2013, pp. 254–259.
42. Zhang, L., A. Nasri, J. H. Hong, and Q. Shen. How Built Environment Affects Travel Behavior: A Comparative Analysis of the Connections between Land Use and Vehicle Miles Traveled in US Cities. *Journal of Transport and Land Use*, Vol. 5, No. 3, 2012. https://doi.org/10.5198/jtlu.v5i3.266.
43. Ngo, N. S., Z. Zou, Y. Yang, and E. Wei. The Impact of Urban Form on the Relationship between Vehicle Miles Traveled and Air Pollution. *Transportation Research Interdisciplinary Perspectives*, Vol. 28, 2024, p. 101288. https://doi.org/10.1016/j.trip.2024.101288.
44. Hankey, S., and J. D. Marshall. Impacts of Urban Form on Future US Passenger-Vehicle Greenhouse Gas Emissions. *Energy Policy*, Vol. 38, No. 9, 2010, pp. 4880–4887. https://doi.org/10.1016/j.enpol.2009.07.005.
45. Cervero, R., and J. Murakami. Effects of Built Environments on Vehicle Miles Traveled: Evidence from 370 US Urbanized Areas. *Environment and Planning A: Economy and Space*, Vol. 42, No. 2, 2010, pp. 400–418. https://doi.org/10.1068/a4236.
46. Noland, R. B., and W. A. Cowart. Analysis of Metropolitan Highway Capacity and the Growth in Vehicle Miles of Travel.
47. Clark, D. E., and B. M. Cushing. Rural and Urban Traffic Fatalities, Vehicle Miles, and Population Density. *Accident Analysis & Prevention*, Vol. 36, No. 6, 2004, pp. 967–972. https://doi.org/10.1016/j.aap.2003.10.006.
48. Ewing, R., S. Hamidi, F. Gallivan, A. C. Nelson, and J. B. Grace. Combined Effects of Compact Development, Transportation Investments, and Road User Pricing on Vehicle Miles Traveled in Urbanized Areas. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2397, No. 1, 2013, pp. 117–124. https://doi.org/10.3141/2397-14.
49. Lee, S., and B. Lee. Comparing the Impacts of Local Land Use and Urban Spatial Structure on Household VMT and GHG Emissions. *Journal of Transport Geography*, Vol. 84, 2020, p. 102694. https://doi.org/10.1016/j.jtrangeo.2020.102694.
50. Ding, C., C. Liu, Y. Zhang, J. Yang, and Y. Wang. Investigating the Impacts of Built Environment on Vehicle Miles Traveled and Energy Consumption: Differences

between Commuting and Non-Commuting Trips. *Cities*, Vol. 68, 2017, pp. 25–36. https://doi.org/10.1016/j.cities.2017.05.005.
51. Reid Ewing, Keunhyun Park, Sadegh Sabouri, Torrey Lyons, Keuntae Kim, Dong-ah Choi, Katherine Daly, and Roya Ghasrodashtiy. *Reducing Vehicle Miles Traveled, Encouraging Walk Trips, and Facilitating Efficient Trip Chains Through Polycentric Development*. Transportation Research and Education Center (TREC), 2020.
52. Xi, Y. (Luna), J. Allen, E. J. Miller, S. Farber, and R. Keel. Importance of Automobile Mode Share in Understanding the Full Impact of Urban Form on Work-Based Vehicle Distance Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2674, No. 4, 2020, pp. 222–234. https://doi.org/10.1177/0361198120911053.
53. Loder, A., R. Tanner, and K. W. Axhausen. The Impact of Local Work and Residential Balance on Vehicle Miles Traveled: A New Direct Approach. *Journal of Transport Geography*, Vol. 64, 2017, pp. 139–149. https://doi.org/10.1016/j.jtrangeo.2017.08.016.
54. Chen, F., J. Wu, X. Chen, and J. Wang. Vehicle Kilometers Traveled Reduction Impacts of Transit-Oriented Development: Evidence from Shanghai City. *Transportation Research Part D: Transport and Environment*, Vol. 55, 2017, pp. 227–245. https://doi.org/10.1016/j.trd.2017.07.006.
55. Duncan, M., and D. Cook. Is the Provision of Park-and-Ride Facilities at Light Rail Stations an Effective Approach to Reducing Vehicle Kilometers Traveled in a US Context? *Transportation Research Part A: Policy and Practice*, Vol. 66, 2014, pp. 65–74. https://doi.org/10.1016/j.tra.2014.04.014.
56. Lovejoy, K., G.-C. Sciara, D. Salon, S. L. Handy, and P. Mokhtarian. Measuring the Impacts of Local Land-Use Policies on Vehicle Miles of Travel: The Case of the First Big-Box Store in Davis, California. *Journal of Transport and Land Use*, Vol. 6, No. 1, 2013, pp. 25–39. https://doi.org/10.5198/jtlu.v6i1.336.
57. Van Herick, D., P. L. Mokhtarian, and X. He. Calculation of Changes in Drive-Alone Commute, Vehicle Miles Traveled, during Temporary Freeway Closure: The Fix I-5 Project in Sacramento, California. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2319, No. 1, 2012, pp. 67–76. https://doi.org/10.3141/2319-08.
58. Ding, C., Y. Wang, B. Xie, and C. Liu. Understanding the Role of Built Environment in Reducing Vehicle Miles Traveled Accounting for Spatial Heterogeneity. *Sustainability*, Vol. 6, No. 2, 2014, pp. 589–601. https://doi.org/10.3390/su6020589.
59. Xiao, Z., Q. Liu, and J. Wang. How Do the Effects of Local Built Environment on Household Vehicle Kilometers Traveled Vary across Urban Structural Zones? *International Journal of Sustainable Transportation*, Vol. 12, No. 9, 2018, pp. 637–647. https://doi.org/10.1080/15568318.2017.1422576.
60. Boarnet, M. G., K. S. Nesamani, and C. S. Smith. Comparing the Influence of Land Use on Nonwork Trip Generation and Vehicle Distance Traveled: An Analysis Using Travel Diary Datat.
61. Salon, D., M. G. Boarnet, and P. Mokhtarian. Quantifying the Effect of Local Government Actions on VMT. 2014.

62. Diao, M. I., and J. Ferreira. Vehicle Miles Traveled and the Built Environment: Evidence from Vehicle Safety Inspection Data. *Environment and Planning A: Economy and Space*, Vol. 46, No. 12, 2014, pp. 2991–3009. https://doi.org/10.1068/a140039p.
63. Wygonik, E., and A. V. Goodchild. Urban Form and Last-Mile Goods Movement: Factors Affecting Vehicle Miles Travelled and Emissions. *Transportation Research Part D: Transport and Environment*, Vol. 61, 2018, pp. 217–229. https://doi.org/10.1016/j.trd.2016.09.015.
64. Chen, W., and H. A. Klaiber. Does Road Expansion Induce Traffic? An Evaluation of Vehicle-Kilometers Traveled in China. *Journal of Environmental Economics and Management*, Vol. 104, 2020, p. 102387. https://doi.org/10.1016/j.jeem.2020.102387.
65. Concas, S., A. Kolpakov, A. M. Sipiora, and B. R. Sneath. *Autonomous Vehicle (AV) and Alternative Fuel Vehicle (AFV) Florida Market Penetration Rate and VMT Assessment Study*. 2019.
66. Munyon, V. V., W. M. Bowen, and J. Holcombe. Vehicle Fuel Economy and Vehicle Miles Traveled: An Empirical Investigation of Jevon's Paradox. *Energy Research & Social Science*, Vol. 38, 2018, pp. 19–27. https://doi.org/10.1016/j.erss.2018.01.007.
67. Weinberger, R., M. Seaman, and C. Johnson. Residential Off-Street Parking Impacts on Car Ownership, Vehicle Miles Traveled, and Related Carbon Emissions: New York City Case Study. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2118, No. 1, 2009, pp. 24–30. https://doi.org/10.3141/2118-04.
68. Seethaler, R., and G. Rose. Using Odometer Readings to Assess VKT Changes Associated with a Voluntary Travel Behaviour Change Program. *Transport Policy*, Vol. 16, No. 6, 2009, pp. 325–334. https://doi.org/10.1016/j.tranpol.2009.10.006.
69. Hardman, Scott, Chakraborty, Debapriya, and Kohn, Eben. A Quantitative Investigation into the Impact of Partially Automated Vehicles on Vehicle Miles Travelled in California. 2021. https://doi.org/10.7922/G2XK8CVB.
70. Asmussen, K. E., A. Mondal, and C. R. Bhat. Adoption of Partially Automated Vehicle Technology Features and Impacts on Vehicle Miles of Travel (VMT). *Transportation Research Part A: Policy and Practice*, Vol. 158, 2022, pp. 156–179. https://doi.org/10.1016/j.tra.2022.02.010.
71. Duncan, M. Would the Replacement of Park-and-Ride Facilities with Transit-Oriented Development Reduce Vehicle Kilometers Traveled in an Auto-Oriented US Region? *Transport Policy*, Vol. 81, 2019, pp. 293–301. https://doi.org/10.1016/j.tranpol.2017.12.005.
72. Fromm, H., L. Ewald, D. Frankenhauser, A. Ensslen, and P. Jochem. *A Study on Free-Floating Carsharing in Europe : Impacts of Car2go and DriveNow on Modal Shift, Vehicle Ownership, Vehicle Kilometers Traveled, and CO$_{2}$ Emissions in 11 European Cities*. Karlsruhe, 2019.
73. Fukushige, T., D. T. Fitch, and S. Handy. Estimating Vehicle-Miles Traveled Reduced from Dock-Less E-Bike-Share: Evidence from Sacramento, California. *Transportation Research Part D: Transport and Environment*, Vol. 117, 2023, p. 103671. https://doi.org/10.1016/j.trd.2023.103671.

74. Rodier, C., F. Alemi, and D. Smith. Dynamic Ridesharing: Exploration of Potential for Reduction in Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2542, No. 1, 2016, pp. 120–126. https://doi.org/10.3141/2542-15.
75. Zhang, W., S. Guhathakurta, and E. B. Khalil. The Impact of Private Autonomous Vehicles on Vehicle Ownership and Unoccupied VMT Generation. *Transportation Research Part C: Emerging Technologies*, Vol. 90, 2018, pp. 156–165. https://doi.org/10.1016/j.trc.2018.03.005.
76. Shin, E. J. Commuter Benefits Programs: Impacts on Mode Choice, VMT, and Spillover Effects. *Transport Policy*, Vol. 94, 2020, pp. 11–22. https://doi.org/10.1016/j.tranpol.2020.05.001.
77. Rasoldier, A., A. Girault, S. Quinton, J. Combaz, and K. Marquet. Assessing the Potential of Carpooling for Reducing Vehicle Kilometers Traveled. Presented at the 2023 International Conference on ICT for Sustainability (ICT4S), Rennes, France, 2023.
78. Zhao, Y., and K. M. Kockelman. Anticipating the Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas. *Journal of Urban Planning and Development*, Vol. 144, No. 4, 2018, p. 04018032. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000463.
79. Haghighi, N., R. Chamberlin, K. Fayyaz, C. Liu, and others. *Impact of Shared Autonomous Vehicles (SAVs) on Vehicle Miles Traveled (VMT) in Utah*. Utah. Dept. of Transportation, 2019.
80. Moreno, A. T., A. Michalski, C. Llorca, and R. Moeckel. Shared Autonomous Vehicles Effect on Vehicle-Km Traveled and Average Trip Duration. *Journal of Advanced Transportation*, Vol. 2018, 2018, pp. 1–10. https://doi.org/10.1155/2018/8969353.
81. Jiang, Q., B. Yueshuai He, and J. Ma. Connected Automated Vehicle Impacts in Southern California Part-II: VMT, Emissions, and Equity. *Transportation Research Part D: Transport and Environment*, Vol. 109, 2022, p. 103381. https://doi.org/10.1016/j.trd.2022.103381.
82. Rodier, Caroline, Alemi, Farzad, and Smith, Dylan. Synergistic Integration of Transportation Demand Management Strategies (Land Use, Transit, and Auto Pricing) with New Technologies and Services (Battery Electric Vehicles and Dynamic Ridesharing) to Enhance Reductions in VMT and GHG. , 2015.
83. Wang, T., and C. Chen. Impact of Fuel Price on Vehicle Miles Traveled (VMT): Do the Poor Respond in the Same Way as the Rich? *Transportation*, Vol. 41, No. 1, 2014, pp. 91–105. https://doi.org/10.1007/s11116-013-9478-1.
84. Leard, B., J. Linn, and C. Munnings. Explaining the Evolution of Passenger Vehicle Miles Traveled in the United States. *The Energy Journal*, Vol. 40, No. 1, 2019, pp. 25–54. https://doi.org/10.5547/01956574.40.1.blea.
85. Polzin, S. E., and X. Chu. Peak Vehicle Miles Traveled and Postpeak Consequences? *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2453, No. 1, 2014, pp. 22–29. https://doi.org/10.3141/2453-03.
86. Pathomsiri, S., A. Haghani, and P. M. Schonfeld. Vehicle Miles Traveled in Multivehicle Households.

87. Woldeamanuel, M., and A. Kent. Determinants of per Capita Vehicle Miles Traveled (VMT): The Case of California. No. 53, 2014, pp. 35–46.
88. Sardari, R., S. Hamidi, and R. Pouladi. Effects of Traffic Congestion on Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2672, No. 47, 2018, pp. 92–102. https://doi.org/10.1177/0361198118791865.
89. Kalinowska, D., and H. Kuhfeld. Motor Vehicle Use and Travel Behaviour in Germany: Determinants of Car Mileage.
90. Tilov, I., and S. Weber. Heterogeneity in Price Elasticity of Vehicle Kilometers Traveled: Evidence from Micro-Level Panel Data. *Energy Economics*, Vol. 127, 2023, p. 107078. https://doi.org/10.1016/j.eneco.2023.107078.
91. Zhao, P., and P. Li. Rethinking the Determinants of Vehicle Kilometers Traveled (VKT) in an Auto-Dependent City: Transport Policies, Socioeconomic Factors and the Built Environment. *Transportation Planning and Technology*, Vol. 44, No. 3, 2021, pp. 273–302. https://doi.org/10.1080/03081060.2021.1883228.
92. Sun, X., C. G. Wilmot, and T. Kasturi. Household Travel, Household Characteristics, and Land Use: An Empirical Study from the 1994 Portland Activity-Based Travel Survey. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1617, No. 1, 1998, pp. 10–17. https://doi.org/10.3141/1617-02.
93. Singh, A. C., S. Astroza, V. M. Garikapati, R. M. Pendyala, C. R. Bhat, and P. L. Mokhtarian. Quantifying the Relative Contribution of Factors to Household Vehicle Miles of Travel. *Transportation Research Part D: Transport and Environment*, Vol. 63, 2018, pp. 23–36. https://doi.org/10.1016/j.trd.2018.04.004.
94. Zhang, L., D. Van Lierop, and D. Ettema. The Effect of Electric Vehicle Use on Trip Frequency and Vehicle Kilometers Traveled (VKT) in the Netherlands. *Transportation Research Part A: Policy and Practice*, Vol. 192, 2025, p. 104325. https://doi.org/10.1016/j.tra.2024.104325.
95. Ke, Y., and B. S. McMullen. Regional Differences in the Determinants of Oregon VMT. *Research in Transportation Economics*, Vol. 62, 2017, pp. 2–10. https://doi.org/10.1016/j.retrec.2017.03.002.
96. Chung, S., J. Kwon, and Y. Ahn. *Forecasting Commercial Vehicle Miles Traveled (VMT) in Urban California Areas*. Mineta Transportation Institute, 2024.
97. Barla, P., B. Lamonde, L. F. Miranda-Moreno, and N. Boucher. Traveled Distance, Stock and Fuel Efficiency of Private Vehicles in Canada: Price Elasticities and Rebound Effect. *Transportation*, Vol. 36, No. 4, 2009, pp. 389–402. https://doi.org/10.1007/s11116-009-9211-2.
98. Liu, H., P. Hao, Y. Liao, K. Boriboonsomsin, and M. Barth. Model-Based Vehicle-Miles Traveled and Emission Evaluation of On-Demand Food Delivery Considering the Impact of COVID-19 Pandemic. *Transportation Research Record: Journal of the Transportation Research Board*, 2023, p. 03611981231169276. https://doi.org/10.1177/03611981231169276.
99. Voulgaris, C. T., G. S. Macfarlane, and J. C. Kaylor. Whose Miles Are These Anyway?: Estimating Site-Generated Vehicle Miles Traveled. *Journal of the American Planning*

Association, Vol. 90, No. 4, 2024, pp. 593–609. https://doi.org/10.1080/01944363.2023.2298962.
100. Meroux, D., A. Broaddus, C. Telenko, and H. Wen Chan. How Should Vehicle Miles Traveled Displaced by E-Scooter Trips Be Calculated? *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2677, No. 1, 2023, pp. 356–368. https://doi.org/10.1177/03611981221099506.
101. Methodologies Used to Estimate and Forecast Vehicle Miles Traveled (VMT).
102. Teng, H., and N. Wang. Estimating Vehicle Miles Traveled Combined with ITS Data. *Transportation Planning and Technology*, Vol. 34, No. 8, 2011, pp. 777–794. https://doi.org/10.1080/03081060.2011.613587.
103. Pulugurtha, S. S., S. Mathew, and M. Tech. Develop Local Functional Classification VMT and AADT Estimation Method.
104. Klatko, T. J., T. U. Saeed, M. Volovski, S. Labi, J. D. Fricker, and K. C. Sinha. Addressing the Local-Road VMT Estimation Problem Using Spatial Interpolation Techniques. *Journal of Transportation Engineering, Part A: Systems*, Vol. 143, No. 8, 2017, p. 04017038. https://doi.org/10.1061/JTEPBS.0000064.
105. Smith, B. L., Y. Qi, H. Park, M. A. Perfater, and others. *A Methodology to Estimate Vehicle Miles Traveled (VMT) Fractions as an Input to the Mobile Emission Model*. Virginia Transportation Research Council (VTRC), 2006.
106. Benekohal, R. F., and M. Girianna. Technologies for Truck Classification and Methodologies for Estimating Truck Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1855, No. 1, 2003, pp. 1–13. https://doi.org/10.3141/1855-01.
107. Bhat, C. R., and H. S. Nair. VMT-Mix Modeling for Mobile Source Emissions Forecasting: Formulation and Empirical Application. *Transportation research record*, Vol. 1738, No. 1, 2000, pp. 39–48.
108. Ewing, R., S. Hamidi, F. Gallivan, A. C. Nelson, and J. B. Grace. Structural Equation Models of VMT Growth in US Urbanised Areas. *Urban Studies*, Vol. 51, No. 14, 2014, pp. 3079–3096. https://doi.org/10.1177/0042098013516521.
109. Mamkhezri, J., and M. Khezri. Vehicle Miles Traveled Induced Demand, Rebound Effect, and Price and Income Elasticities: A US Spatial Econometric Analysis. *Transport Policy*, Vol. 158, 2024, pp. 224–240. https://doi.org/10.1016/j.tranpol.2024.09.023.
110. He, X., and L. Zhang. Statistical Modeling of Spatial and Temporal Variation in Vehicle Kilometers Traveled. Presented at the 11th International Conference of Chinese Transportation Professionals (ICCTP), Nanjing, China, 2011.
111. Vasudevan, V., and S. Nambisan. A Model to Estimate Passenger Vehicle Fleet Composition, Vehicle Miles Traveled, and Fuel Consumption. *Public Works Management & Policy*, Vol. 18, No. 1, 2013, pp. 56–81. https://doi.org/10.1177/1087724X12438408.
112. Pickrell, D., D. Pace, J. Wishart, and others. FHWA Travel Analysis Framework: Development of VMT Forecasting Models for Use by the Federal Highway Administration. 2014.

113. Rentziou, A., K. Gkritza, and R. R. Souleyrette. VMT, Energy Consumption, and GHG Emissions Forecasting for Passenger Transportation. *Transportation Research Part A: Policy and Practice*, Vol. 46, No. 3, 2012, pp. 487–500. https://doi.org/10.1016/j.tra.2011.11.009.
114. Brown, C., N. Kennedy, D. Wright, and W. Zak. Methodology for Estimating Vehicle Miles Traveled for Commercial Motor Vehicles at the State Level. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1830, No. 1, 2003, pp. 72–76. https://doi.org/10.3141/1830-10.
115. Kuzmyak, R. USEFULNESS OF EXISTING TRAVEL DATA SETS FOR IMPROVED VMT FORECASTING. *Transportation Research Record*.
116. Fan, J., C. Fu, K. Stewart, and L. Zhang. Using Big GPS Trajectory Data Analytics for Vehicle Miles Traveled Estimation. *Transportation Research Part C: Emerging Technologies*, Vol. 103, 2019, pp. 298–307. https://doi.org/10.1016/j.trc.2019.04.019.
117. Li, R., and K. M. Kockelman. Predicting a Vehicle's Distance Traveled from Short-Duration Data. *Transport Findings*, 2019. https://doi.org/10.32866/10110.
118. Alberini, A., L. Teja Burra, C. Cirillo, and C. Shen. Counting Vehicle Miles Traveled: What Can We Learn from the NHTS? *Transportation Research Part D: Transport and Environment*, Vol. 98, 2021, p. 102984. https://doi.org/10.1016/j.trd.2021.102984.
119. Limanond, T., J. Pongthanaisawan, D. Watthanaklang, and O. Sangphong. An Analysis of Vehicle Kilometers of Travel of Major Cities in Thailand. *ATRANS Final Report 2009*, 2009.
120. Nurulhuda, J., A. Sharifah M. R., R. Azzuhana, H. NurZarifah, and A. Khairil A. K. Vehicle Kilometer Travelled by Online Survey. *International Journal of Academic Research in Business and Social Sciences*, Vol. 10, No. 10, 2020, p. Pages 1131-1136. https://doi.org/10.6007/IJARBSS/v10-i10/8274.
121. Fukuda, A., T. Satiennam, H. Ito, D. Imura, and S. Kedsadayurat. Study on Estimation of VKT and Fuel Consumption in Khon Kaen City, Thailand. 2013.
122. Yamamoto, T., J.-L. Madre, M. De Lapparent, and R. Collet. A Random Heaping Model of Annual Vehicle Kilometres Travelled Considering Heterogeneous Approximation in Reporting. *Transportation*, Vol. 47, No. 3, 2020, pp. 1027–1045. https://doi.org/10.1007/s11116-018-9933-0.
123. Gunathilaka, S., N. Amarasingha, S. Dissanayake, and M. Lakmali. Household Travel Survey Method for Vehicle Kilometers Travel Estimations: A Case Study in a Developing Country. *Transactions on Transport Sciences*, Vol. 12, No. 2, 2021, pp. 5–15. https://doi.org/10.5507/tots.2021.016.
124. Ishak, S. Z., N. A. S. Ibrahim, N. A. Kamaluddin, and Y. Dhokhikah. Vehicle Kilometers Traveled (VKT) for Campus Population: Case Study of UiTM Main Campus. *Environment-Behaviour Proceedings Journal*, Vol. 7, No. SI9, 2022, pp. 619–624. https://doi.org/10.21834/ebpj.v7iSI9.4315.
125. Mulley, C., and M. Tanner. THE VEHICLE KILOMETRES TRAVELLED (VKT) BY PRIVATE CAR: A SPATIAL ANALYSIS USING GEOGRAPHICALLY WEIGHTED REGRESSION.
126. Shabadin, A., N. M. Johari, and H. M. Jamil. Car Annual Vehicle Kilometer Travelled Estimated from Car Manufacturer Data – An Improved Method. 2014.

127. Narváez-Villa, P., B. Arenas-Ramírez, J. Mira, and F. Aparicio-Izquierdo. Analysis and Prediction of Vehicle Kilometers Traveled: A Case Study in Spain. *International Journal of Environmental Research and Public Health*, Vol. 18, No. 16, 2021, p. 8327. https://doi.org/10.3390/ijerph18168327.
128. Carlsson, J. G., B. Jones, M. T. Center, P. S. Region, and others. *The "Sidekick" Routing Paradigm for VMT Reduction and Improved Accessibility*. Pacific Southwest Region 9 UTC, University of Southern California, 2021.
129. Kim, S., D. Park, T. Heo, H. Kim, and D. Hong. Estimating Vehicle Miles Traveled (VMT) in Urban Areas Using Regression Kriging. *Journal of Advanced Transportation*, Vol. 50, No. 5, 2016, pp. 769–785. https://doi.org/10.1002/atr.1374.
130. Jung, S., J. Kim, J. Kim, D. Hong, and D. Park. An Estimation of Vehicle Kilometer Traveled and On-Road Emissions Using the Traffic Volume and Travel Speed on Road Links in Incheon City. *Journal of Environmental Sciences*, Vol. 54, 2017, pp. 90–100. https://doi.org/10.1016/j.jes.2015.12.040.
131. Mahmud, A., I. Hamilton, V. V. Gayah, and R. J. Porter. Estimation of VMT Using Heteroskedastic Log-Linear Regression Models. *Transportation Letters*, Vol. 16, No. 4, 2024, pp. 320–329. https://doi.org/10.1080/19427867.2023.2189802.
132. Hu, P. S., T. Wright, S.-P. Miaou, D. J. Beal, and S. C. Davis. Estimating Commercial Truck VMT of Interstate Motor Carriers: Data Evaluation.
133. Frawley, W. E. Random Count Site Selection Process for Statistically Valid Estimations of Local Street Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1993, No. 1, 2007, pp. 43–50. https://doi.org/10.3141/1993-07.
134. Ito, D. T., D. Niemeier, and G. Garry. Conformity: How VMT-Speed Distributions Can Affect Mobile Emission Inventories. *Transportation*, Vol. 28, 2001, pp. 409–425.
135. Beider, P., and D. Austin. *Issues and Options for a Tax on Vehicle Miles Traveled by Commercial Trucks*. 2019.
136. Verma, P., H. Yang, P. Kachroo, and S. Agarwal. Modeling and Estimation of the Vehicle-Miles Traveled Tax Rate Using Stochastic Differential Equations. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 46, No. 6, 2016, pp. 818–828. https://doi.org/10.1109/TSMC.2015.2465297.
137. Tan, X., J. Song, N. Wang, and Y. Cao. Revelation of America's VMT Charging Mode to Chinese Highway Financing. Presented at the Fifth International Conference on Transportation Engineering, Dailan, China, 2015.
138. Bedsworth, L., and E. Hank. *Driving Change: Reducing Vehicle Miles Traveled in California*. Public Policy Instit. of CA, 2011.
139. Ju, H., M. Rahman, M. Khan, and M. Burris. Distributional Impact of a Vehicle Miles Traveled Fee. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2678, No. 7, 2024, pp. 405–412. https://doi.org/10.1177/03611981231206157.
140. Wang, Y., and Q. Miao. Implication of Replacing the Federal and State Fuel Taxes with a National Vehicle Miles Traveled Tax. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2672, No. 4, 2018, pp. 32–42. https://doi.org/10.1177/0361198118796737.

141. Kastrouni, E., K. Gkritza, S. L. Hallmark, and W. R. Stephenson. Fuel Tax versus Vehicle-Miles-Traveled Fee: Identifying Vulnerable Households by Three-Stage Least Squares Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2531, No. 1, 2015, pp. 161–169. https://doi.org/10.3141/2531-19.
142. Paz, A., A. Nordland, N. Veeramisti, A. Khan, and J. Sanchez-Medina. Assessment of Economic Impacts of Vehicle Miles Traveled Fee for Passenger Vehicles in Nevada. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2450, No. 1, 2014, pp. 26–35. https://doi.org/10.3141/2450-04.
143. Paz, A., A. Nordland, and A. Khan. Assessing Economic Impacts of Implementing a Vehicle Miles Traveled Fee in Nevada. Presented at the 2012 15th International IEEE Conference on Intelligent Transportation Systems - (ITSC 2012), Anchorage, AK, USA, 2012.
144. Feng, Y., D. Fullerton, and L. Gan. Vehicle Choices, Miles Driven, and Pollution Policies. *Journal of Regulatory Economics*, Vol. 44, No. 1, 2013, pp. 4–29. https://doi.org/10.1007/s11149-013-9221-z.
145. Alexander, S. E., M. Alfonzo, and K. Lee. *Safeguarding Equity in Off-Site Vehicle Miles Traveled (VMT) Mitigation in California*. Mineta Transportation Institute, 2021.
146. Yuan, C., Z. Fan, L. Lyu, P. S. Acharya, and H. S. Matthews. Leveraging Inspection Records for Vehicle Miles Traveled Estimates and Analysis of Mileage-Based User Fees in Pennsylvania. 2021.
147. Ferreira Jr, J., M. Diao, and J. Xu. Estimating the Vehicle-Miles-Traveled Implications of Alternative Metropolitan Growth Scenarios: AB Oston Example. *Transactions in GIS*, Vol. 17, No. 5, 2013, pp. 645–660.
148. Rodriguez, A., and S. Pulugurtha. Vehicle Miles Traveled Fee to Complement the Gas Tax and Mitigate the Local Transportation Finance Deficit. *Urban, Planning and Transport Research*, Vol. 9, No. 1, 2021, pp. 18–35. https://doi.org/10.1080/21650020.2020.1850334.
149. Sun, Y., and L. Zhang. Potential of Taxi-Pooling to Reduce Vehicle Miles Traveled in Washington, D.C. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2672, No. 8, 2018, pp. 775–784. https://doi.org/10.1177/0361198118801352.
150. Zhang, L., X. He, Y. Lu, C. Krause, and N. Ferrari. Are We Successful in Reducing Vehicle Miles Traveled in Air Quality Nonattainment Areas? *Transportation Research Part A: Policy and Practice*, Vol. 66, 2014, pp. 280–291. https://doi.org/10.1016/j.tra.2014.05.016.
151. Hallenbeck, M., O. Stewart, and A. V. Moudon. A Framework for Monitoring the Performance of Demand Management and Vehicle Miles Traveled (VMT) Reduction Activities.
152. Alexander, S., L. Chen, and M. Belote-Broussard. *Exploring Equity Frameworks for a Cross-Jurisdictional Vehicle Miles Traveled Mitigation Program in Santa Clara County*. Mineta Transportation Institute, 2024.
153. Hosseinzade, R., J. M. B. Volker, and M. Evans. Swapping Level of Service for Vehicle Miles Traveled in Project-Level Environmental Impact Analysis: Trends and

Challenges in California. *Transportation Research Record: Journal of the Transportation Research Board*, 2024, p. 03611981241275533. https://doi.org/10.1177/03611981241275533.
154. Caroline Rodier, Ihab Kaddoura, and Huajun Chai. How Can Automated Vehicles Increase Access to Marginalized Populations and Reduce Congestion, Vehicle Miles Traveled, and Greenhouse Gas Emissions? A Case Study in the City of Los Angeles. 2022. https://doi.org/10.7922/G2SB441H.
155. Jae Hong Kim, Ph. D. Assessing the Potential for Densification and Vehicle Miles Traveled Reduction in Areas without Rail Transit Access. 2024. https://doi.org/10.7922/G22V2DGJ.
156. Volker, J. M. B. *Exploring the Changing Faces of Housing Development and Demand in California: Millennials, Casitas, and Reducing VMT*. University of California, Davis, 2020.
157. Seggerman, K. E., K. M. Williams, P.-S. Lin, A. Fabregas, A. C. Nelson, and J. C. Nicholas. Methodology of Impact Fees Emphasizing Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2187, No. 1, 2010, pp. 36–43. https://doi.org/10.3141/2187-06.
158. Cohen, J., S. Vadali, M. F. Lawrence, S. Dave, and C. Clark. Peer Review: The Volpe/Federal Highway Administration National Vehicle Miles Traveled Forecasting Models. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2675, No. 10, 2021, pp. 616–628. https://doi.org/10.1177/03611981211011997.
159. Kahane, C. J. *Comparison of 2013 VMT Fatality Rates in US States and in High-Income Countries*. 2016.
160. Polzin, S. E. and others. The Case for Moderate Growth in Vehicle Miles of Travel: A Critical Juncture in US Travel Behavior Trends. 2006.
161. Oak Ridge National Laboratory. Best Estimate of Annual Vehicle Mileage for 2017 NHTS Vehicles. .
162. remix-run. Remix-Run/Remix. https://github.com/remix-run/remix.
163. Prisma Data, Inc. Prisma. https://www.prisma.io/. Accessed Jun. 6, 2025.
164. Meta Platforms, Inc. React. https://react.dev/.

Data Summary

Products of Research

By this research project, we obtained a survey dataset about 1) people's social demographic factors, including age, gender, household income, educational attainment, and number of household vehicles, 2) self-reported last-week VMT and estimate of next-week VMT for the vehicle that the person primarily drives, and 3) email address. The email address will be encrypted by the bcrypt algorithm. Also, through the WhatsApp platform, we will collect a dataset of images of people's vehicle dashboard, which we will add several metadata such as odometer reading, submission date, or image size. These datasets will be combined for further data analysis.

Data Format and Content

The survey data will be downloaded from Qualtrics in the Statistical Package for Social Sciences (SPSS) file format (.sav). The dataset of odometer photos and their metadata will be stored on a PostgreSQL database on the Azure platform and can be retrieved as JavaScript Object Notation (JSON) / Comma Separated Values (CSV) data as needed.

Data Access and Sharing

Access to the raw data is limited to the research team members. Anonymized data without people's email address, phone number, or photo binary data is published on the Dryad data repository platform in a CSV file: https://doi.org/10.5061/dryad.g79cnp62m.

Reuse and Redistribution

The anonymized data will be publicly available for reuse and redistribution with the public domain (CC0) license.