CPBS
Center for Pedestrian and Bicyclist Safety

A Tier-1 University Transportation Center

Exploring the Impact of Funding for Unconventional Data Collection on Vulnerable Road User (VRU) Safety Improvements, Phase I

July 2024

A Report From the
Center for Pedestrian and Bicyclist Safety

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About the Center for Pedestrian and Bicyclist Safety (CPBS)

The Center for Pedestrian and Bicyclist Safety (CPBS) is a consortium of universities committed to eliminating pedestrian and bicyclist fatalities and injuries through cutting-edge research, workforce development, technology transfer, and education. Consortium members include: The University of New Mexico; San Diego State University; The University of California Berkeley; The University of Tennessee Knoxville; and The University of Wisconsin Milwaukee. More information can be found at: https://pedbikesafety.org

Disclaimer

Acknowledgments

This study was funded, partially or entirely, by a grant from the Center for Pedestrian and Bicyclist Safety (CPBS), supported by the U.S. Department of Transportation (USDOT) through the University Transportation Centers program. The authors would like to thank CPBS and the USDOT for their support of university-based research in transportation, and especially for the funding provided in support of this project.

TECHNICAL DOCUMENTATION

1. Project No.	2. Government Accession No.	3. Recipient's Catalog No.
23UWM03		

4. Title and Subtitle	5. Report Date
Exploring the Impact of Funding for Unconventional Data Collection on Vulnerable Road User (VRU) Safety Improvements, Phase I	July 2024
	6. Performing Organization Code
	N/A
7. Author(s)	**8. Performing Organization Report No.**
Xiao Qin https://orcid.org/0000-0002-2299-1656 Robert Schneider https://orcid.org/0000-0002-6225-3615 Yang Li https://orcid.org/0000-0001-5358-7835 Mohammad Abrari Vajari https://orcid.org/0000-0001-6150-1077	N/A
9. Performing Organization Name and Address	**10. Work Unit No. (TRAIS)**
Center for Pedestrian and Bicyclist Safety Centennial Engineering Center 3020 The University of New Mexico Albuquerque, NM 87131	**11. Contract or Grant No.** 69A3552348336
12. Sponsoring Agency Name and Address	**13. Type of Report and Period Covered**
United States of America Department of Transportation Office of Research, Development, and Technology (RD&T)	Final Report – June 2023 to May 2024
	14. Sponsoring Agency Code
	USDOT OST-R

15. Supplementary Notes

Report accessible via the CPBS website https://pedbikesafety.org and DOI https://doi.org/10.21949/qbpb-xk95

16. Abstract

This study explores how funding for unconventional data collection impacts safety improvements for vulnerable road users (VRUs) through two phases: planning and implementation. This report details the efforts of the planning phase, which included a thorough review of existing literature, a national survey, and planning activities for several regional and national workshops. The literature review revealed significant gaps in the availability and utilization of unconventional data sources, such as crowdsourced data, computer vision, and IoT, for VRU safety. It also identified organizational and financial challenges in adopting these data sources. A comprehensive survey has been designed and will be distributed to transportation agencies to understand their adoption and utilization of new technologies and data sources. Additionally, plans have been developed for workshops and webinars to present the research findings and engage stakeholders in discussions about the benefits and challenges of integrating unconventional data into transportation planning. The next phase will focus on implementing the survey and conducting these workshops. By bridging the gap between funding decisions and data access, this research aims to enhance the safety of pedestrians and bicyclists through more informed and effective transportation planning and policymaking.

17. Key Words	18. Distribution Statement
Non-motorized transportation; Financing; Data management; Surveys; Workshops	No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	40	

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

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

Exploring the Impact of Funding for Unconventional Data Collection on Vulnerable Road User (VRU) Safety Improvements, Phase I

A Center for Pedestrian and Bicyclist Safety Research Report

July 2024

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Acronyms, Abbreviations, and Symbols

AIC	Akaike Information Criterion
APBP	Association of Pedestrian and Bicycle Professionals
BIC	Bayesian Information Criterion
CNN	Convolutional Neural Network
CPBS	Center for Pedestrian and Bicyclist Safety
DOT	Department of Transportation
FLC	Fuzzy Logic Controller
GIS	Geographic Information System
IoT	Internet of Things
ISTEA	Intermodal Surface Transportation Efficiency Act
KNN	k-Nearest Neighbor
MPO	Metropolitan Planning Organization
OLED	Organic Light-Emitting Diode
R-CNN	Region Convolutional Neural Network
SEM	Structural Equation Modeling
TAM	Technology Acceptance Model
TRB	Transportation Research Board
VRU	Vulnerable Road User
XGBoost	Extreme Gradient Boosting
YOLO	You Only Look Once

Abstract

This study explores how funding for unconventional data collection impacts safety improvements for vulnerable road users (VRUs) through two phases: planning and implementation. This report details the efforts of the planning phase, which included a thorough review of existing literature, a national survey, and planning activities for several regional and national workshops. The literature review revealed significant gaps in the availability and utilization of unconventional data sources, such as crowdsourced data, computer vision, and IoT, for VRU safety. It also identified organizational and financial challenges in adopting these data sources. A comprehensive survey has been designed and will be distributed to transportation agencies to understand their adoption and utilization of new technologies and data sources. Additionally, plans have been developed for workshops and webinars to present the research findings and engage stakeholders in discussions about the benefits and challenges of integrating unconventional data into transportation planning. The next phase will focus on implementing the survey and conducting these workshops. By bridging the gap between funding decisions and data access, this research aims to enhance the safety of pedestrians and bicyclists through more informed and effective transportation planning and policymaking.

Executive Summary

The study aims to address the critical need for accurate, timely, and reliable data on pedestrian and bicyclist activities and behaviors, which are essential for informed decision-making in transportation planning. This project is divided into a planning phase and an implementation phase. The planning phase, detailed in this report, lays the groundwork for the next steps of distributing surveys and conducting workshops and webinars.

The primary objective is to explore how transportation agencies, including Departments of Transportation (DOTs) and Metropolitan Planning Organizations (MPOs), adopt and utilize new technologies and data sources in active transportation planning and safety improvements. Specific questions include the potential for unconventional data to become a primary source and method for non-motorist data collection, the impact of funding levels on safety improvements, and the perceived benefits and challenges of adopting these new data sources.

In this project, the main tasks include:

1. **Literature Review:** A thorough review of existing studies was conducted to understand the current state of unconventional data sources in transportation. The review highlighted significant gaps in comprehensive data on pedestrian and bicyclist activities and behaviors. It underscored the potential of unconventional data sources, such as crowdsourced data, computer vision, and IoT, to address these gaps. The review also indicated that the adoption of these new data sources faces organizational and financial challenges, necessitating further research.
2. **Survey Design:** A comprehensive survey was developed to gather insights from transportation agencies regarding their adoption and use of new technologies and data sources. The survey is designed to explore organizational attitudes and behaviors, guided by the Technology Acceptance Model (TAM). It includes questions on perceived benefits, challenges, funding mechanisms, and data management practices.
3. **Workshop/Webinar Planning:** Plans for workshop and webinar sessions were formulated to present the findings and engage stakeholders in discussions about the integration of unconventional data into transportation planning. These sessions aim to disseminate knowledge, share best practices, and gather feedback from practitioners, researchers, and policymakers.

This planning phase has established the foundation for the next phase of the project. The insights gained from the literature review have informed the design of survey and workshops, ensuring that the most pertinent questions and challenges are addressed. The next phase will focus on the distribution of the survey and execution of workshops and webinars, aiming to bridge the gap between funding decisions, data access, and safety improvements for VRUs. Ultimately, this

research seeks to assist transportation organizations in effectively incorporating unconventional data into their strategies and prioritizing safety improvements for VRUs.

Introduction

Problem Statement

The growing availability of new and emerging data sources from crowdsourcing, video analytics, and aerial images presents a promising opportunity to better understand the trend and behavior of pedestrians, bicyclists, and other non-motorists. Known for their broad geographic coverage, these unconventional data sources can be more cost-effective and efficient than conventional count stations for collecting exposure data and creating inventories for documenting infrastructure and its condition. With the increasing number of transportation agencies who are interested in this type of data, there is a need to investigate the impact of funding for acquiring unconventional data on VRU safety improvements. The specific questions are:

1. Will unconventional data become a primary method for non-motorist data collection in the future?
2. How does the level of funding for unconventional data affect safety improvements for VRUs?
3. What is the perceived impact of such investment on agencies' decision-making processes?
4. What are the major impediments to encouraging data sharing such as privacy concerns?
5. What are the agencies' data management or data governance practice of unconventional data sources?

By leveraging the power of unconventional data sources, transportation organizations can tap into valuable information on road conditions, traffic patterns, and user feedback. This study aims to bridge the gap between funding decisions, data access, and safety improvements for VRUs. By combining qualitative and quantitative analyses, this research will provide insights and guidance to transportation organizations, specifically State Departments of Transportation (DOTs), and Metropolitan Planning Organizations (MPOs), to effectively incorporate crowdsourced data into their funding strategies and prioritize safety improvements for VRUs.

Objectives and Methodology

The main objective of this study is to investigate how transportation agencies, DOTs, and MPOs adopt and use new technologies and data sources, such as crowdsourced data, in active transportation for safety and planning improvements. The study also aims to analyze how various factors, including funding mechanisms, influence this adoption process.

To achieve this objective, we employed a methodology that combines a literature review, surveys/interviews, and interactive workshops. The literature review focused on new technologies and data sources in active transportation, organizational attitudes towards these innovations, and the technology acceptance model. The first part of the review discussed various new data sources and technologies used in active transportation, emphasizing their application in improving safety and planning. The second part examined organizational attitudes towards adopting these new sources and explored the factors, including funding, that influence their adoption and usage. Then a national survey will be conducted among transportation agencies, DOTs, and MPOs to gain a deep understanding of the perceived and actual benefits, challenges, and current practices related to new technologies and data sources. The technology acceptance model (TAM) will be employed as a tool to guide the design of the survey, which will better help measure and quantify the attitudes of transportation agencies affecting their behaviors and decisions towards new data sources. As a result, the survey will explore organizational attitudes towards adopting these new technologies and data sources. Workshop sessions will be conducted at various conferences related to non-motorist activities and safety. These workshops will provide an opportunity to discuss and present our findings to the target audience. Furthermore, during the workshops, through discussions with practitioners, researchers, and other attendees, we will explore the importance of new data sources in active transportation, along with the benefits and challenges associated with them. We will engage with these stakeholders to enhance understanding of the factors that can affect the adoption and usage of these technologies.

Report Overview

Chapter 1 provides essential introductory information and motivation of the project. This chapter covers research objectives and methodology. In the end, Chapter 1 describes the overall research structure of this study.

Chapter 2 presents a comprehensive review of the existing literature on two topics: 1. organizational acceptance towards unconventional transportation data, and 2. unconventional transportation data in planning and safety improvements for VRUs.

Chapter 3 describes the design of the survey questionnaire that will be distributed for among transportation agencies, DOTs, and MPOs to gain a deep understanding of the perceived and actual benefits, challenges, and current practices related to new technologies and data sources. A brief introduction of the TAM will be provided as the method is the guide for designing the survey.

Chapter 4 introduces the design and plan of the workshop sessions that will provide an opportunity to discuss and present our findings to the target audience. A sample agenda for the first workshop session is appended for the demonstration purpose.

Chapter 5 concludes this research.

Literature Review

Organizational Acceptance towards Unconventional Transportation Data

Active transportation, or non-motorized transportation, refers to modes of transport that involve physical activity and are powered by human energy. Walking and cycling are the most common forms of this mode, but other activities like skateboarding, rollerblading, scootering, and using a manual wheelchair also fall under this category (Cook et al., 2022). Active transportation offers numerous benefits, not only on a personal level but also societally. For individuals, it promotes physical health, reduces stress, enhances mental well-being, and lowers transportation costs. Societally, it decreases reliance on motor vehicles, thereby reducing greenhouse gas emissions, easing traffic congestion, and lowering noise pollution. Furthermore, active transportation supports more sustainable urban development by encouraging the creation of walkable, bike-friendly communities and enhancing connectivity between segregated areas (Fishman et al., 2015). Given these benefits, active transportation has gained popularity in recent years, with many individuals choosing these modes for their commuting and leisure trips. Moreover, many cities worldwide are promoting it as a sustainable transport option by creating more supportive environments and improving infrastructure. For example, data from the National Travel Survey indicates that approximately 10% of all trips in the United States are made by walking (Buehler & Pucher, 2023), and about 5% of the working population reports using active transportation or public transit as their means of commuting to work (Stroope, 2021). However, alongside its growing popularity, there has been a concerning increase in fatalities among pedestrians and cyclists, also known as vulnerable road users. Data from the National Highway Traffic Safety Administration reveals that in 2021, there were 7,388 pedestrian fatalities in road crashes in the United States—a 12.5% increase from the 6,565 deaths in 2020, marking the highest number recorded since 1981 (National Center for Statistics and Analysis, 2023).

The growing interest in active transportation, coupled with safety concerns, underscores the critical need for accurate, timely, and reliable data on pedestrian and bicyclist activities and behaviors, such as travel patterns, crash hotspots, infrastructure usage, and their preferences for routes, types of infrastructure, amenities, safety features, and connectivity (Lee & Sener, 2020). This data is essential for transportation agencies, departments of transportation (DOTs), policymakers, and transportation planners to make informed decisions and effectively plan based on accurate information. However, there has been a significant lack of data on non-motorist activities for decades. Collecting data on non-motorist behavior and activities is notably more challenging compared to motorized traffic. These difficulties stem from the unique characteristics of non-motorist activities and behaviors. Non-motorist behaviors can be unpredictable and vary across different locations; for example, they may not always use designated pathways or might create their own routes, such as jaywalking. Additionally, their behavior is influenced by environmental factors such as weather conditions, topography, and land use patterns. Furthermore, the data collection facilities for non-motorist activities are limited compared to those available for motorized traffic (Feng et al., 2021).

As technology advances, new tools and unconventional data sources become available that enable deeper insights into non-motorist activities and behaviors. These include crowdsourced data, virtual reality, computer vision, remote sensing, and the Internet of Things (IoT), among others. When integrated with advanced analytical techniques such as machine learning and deep learning, these new sources provide information on non-motorist behaviors that was previously challenging to obtain. (Torbaghan et al., 2022). Transportation agencies and departments of transportation can utilize this information to enhance various practices within the transportation system, such as infrastructure planning, ridership monitoring, connectivity assessment, and safety improvement, all aimed at better supporting non-motorists.

The integration of new technologies, knowledge, or data sources into an organization involves four key steps: exposure to the new technology, knowledge, or data source; its adoption; exploratory implementation; and transition to routine use. When these steps are effectively managed and completed, they can lead to significant improvements and changes within the organization's programs. It's important to note that during this process, various organizational factors and characteristics can significantly influence each step. (Lehman et al., 2002). In the context of active transportation, despite the potential benefits of new data sources and technologies to transform and improve the understanding and management of non-motorist activities and infrastructure, their widespread adoption within departments of transportation (DOTs) and other transportation agencies faces significant obstacles.

Most transportation agencies and state DOTs in the U.S., which play an important role in setting policy guidelines and in the planning, design, and construction of infrastructure, have traditionally focused on highways and motorized traffic (Dill et al., 2017). Although the passage of the Intermodal Surface Transportation Efficiency Act (ISTEA) by the U.S. Congress in 1991 required DOTs to include and consider active transportation in their plans, establish new funding sources for this mode of transport, and appoint a bicycle and pedestrian coordinator (Pucher et al., 1999), the longstanding emphasis on motor vehicles still limits their interest and potential to explore and integrate unconventional data sources and technologies that provide insights into pedestrian and cyclist behavior. A survey conducted among DOTs in 2010 showed that the level of support for active transportation varied across state plans and guidance, but overall, the support and interest were not particularly encouraging and were even minimal in some aspects (Dill et al., 2017).

Moreover, many transportation agencies and DOTs, similar to other organizations, face considerable resistance to change (Miller & Lambert, 2014). In today's dynamic environment, marked by rapid technological progress and shifting market and policy trends, organizations must continually reassess their processes, strategies, and culture. However, implementing change is often difficult, and most organizations find it challenging to successfully implement change plans (Rehman et al., 2021). Previous research indicates that about two-thirds of organizational change efforts are unsuccessful (Meaney & Pung, 2008). These studies highlight that employee attitudes and responses to change are pivotal factors influencing the success of change processes. One of the primary challenges organizations face is dealing with resistance from employees. Lack of awareness about the benefits of change can lead employees to fear and view these changes as unnecessary or unjust. This often results in negative attitudes and resistant behaviors towards change, a situation referred to as resistance to change (RTC). Employees might then try to impede or completely stop the change initiatives (Hughes, 2006).

Another important factor is organizational resources. In organizational theory, these resources are defined as all assets, capabilities, processes, attributes, information, and knowledge that an organization uses to implement strategies and changes to improve its performance (Amiri et al., 2023). These resources include facilities, staffing patterns, training, and equipment, which play significant roles in shaping organizational attidues and adapting to new technologies. Adequate resources ensure the necessary infrastructure is in place to support new systems and practices. For instance, modern and well-equipped offices are essential, as inadequate office space can hinder staff from adopting new approaches. Additionally, access to necessary equipment, such as computers with adequate computing power, is crucial. Ensuring staff have access to ongoing education and opportunities also enhances their skills and adaptability. Most importantly, sufficient and well-trained staff members are essential for meeting organizational goals, as workloads and practices can be challenging without proper staffing. Currently, many organizations face a shortage of well-trained staff to handle the workload. To establish sustainable solutions, organizations should prioritize effective human resource management policies. This includes strategies such as expanding the workforce, increasing the number of qualified staff, and forming multidisciplinary teams. The staff mix and skill mix strategy, effective in various sectors including healthcare, can also be applied to improve organizational performance and adaptability (Dubois & Singh, 2009).

In addition to employee support, organizational attitudes and change heavily rely on the decisions and actions of top managers (TMs) and middle managers (MMs). Changing procedures are typically viewed through either 'top-down' or 'bottom-up' approaches. In both frameworks, managers play a central role in initiating change. Bottom-up perspectives emphasize the crucial role of middle managers in starting change processes, while top-down perspectives see top managers as the primary initiators. Regardless of the approach, both top and middle managers are important in effectively carrying out these changes. TMs and MMs each possess unique strengths and weaknesses that prove most effective when strategically combined. Research has shown that changes initiated by middle managers often receive robust support from employees, particularly when these changes are executed by top managers (Heyden et al., 2017). Leveraging the strengths of middle managers such as their proximity to daily operations and their understanding of new technologies along with the ability of top managers to efficiently manage resources, typically results in strong employee support for change initiatives. In the context of active transportation, effective management support and strategic leadership are crucial within transportation agencies and Departments of Transportation (DOTs). Consequently, the level of managerial support in these organizations for active transportation and related programs is important for successfully advancing these initiatives. Previous research indicated that support for pedestrian and bicycle projects and policies among top management in state DOTs stands at approximately 50%. While this level of support surpasses that among employees, which is about 30%, it still shows a significant gap. This result indicates the need for increased managerial support to transition from traditional sources to innovative technologies and data sources in active transportation (Dill et al., 2017). The same research also revealed that safety was the primary reason for state DOT bicycle and pedestrian coordinators to adopt statewide plans, policies, and programs, while climate change was considered the least significant factor.

Funding and funding strategies are also crucial in shaping organizational attitudes and their capacity to adopt new technologies and data sources. Research on state Department of Transportation (DOT) sustainability plans has revealed a significant positive correlation between the availability of external funding and plan coordination. This research indicates that external funding empowers agencies to implement more effective outreach methods (Mansfield & Hartell, 2012). Similarly, a study by Aytur et al. examining the spatial and temporal patterns of North Carolina's pedestrian and bicycle plans found a notable increase in the number of these plans over time, particularly after 2006 when a state grant funding program was introduced (Aytur et al., 2013). In another study, Dill et al. examined the promotion of active transportation within U.S. state departments of transportation. They found that funding was the primary barrier coordinators faced when attempting to implementing more bicycle and pedestrian projects (Dill et al., 2017).

Unconventional Transportation Data in Planning and Safety Improvements for VRUs

Traditional methods for collecting data on non-motorist activities, behaviors, and attitudes include a variety of approaches. For example, traffic counting equipment (temporary and permanent) and manual counts (field or video-based) are utilized to collect data on traffic volume and travel patterns. For safety studies involving non-motorists, data typically come from police reports, hospitals, and insurance records. Open data portals also serve as primary sources for information about infrastructure conditions. Additionally, surveys and public consultations are used to understand the attitudes and preferences of non-motorists (Nelson et al., 2021).

While these data collection methods provide useful information about non-motorists, they have several limitations related to their scope and the data gathered through them. First, data collected with traditional approaches often have limited spatial and temporal coverage. For example, bicycle or pedestrian volume data are typically available for a limited number of locations and time periods (Roy et al., 2019). Furthermore, data collected using these approaches are not always comprehensive and may be biased. For instance, official statistics might over represent severe crashes involving non-motorists while underrepresenting non-fatal incidents involving them (Medury et al., 2019). Moreover, these data collection methods are typically resource-intensive, time-consuming, and susceptible to human error and device malfunctions.

Nowadays, transportation and mobility data are being generated at an unprecedented rate and volume, significantly surpassing what was previously available. Advances in technologies such as the Internet of Things (IoT), wireless technologies, and crowdsourced data collection, combined with low-cost sensors, widespread smartphone use, enhanced connectivity, and reduced data storage and processing costs, have all driven this surge in data generation (Torre-Bastida et al., 2018). These unconventional data sources have enabled transportation agencies and planners to access more detailed information about transportation networks, users, and their behaviors. This is particularly crucial in the field of active transportation (i.e. walking and biking), which has historically suffered from a lack of sufficient and adequate data on non-motorist activities and behavior. The shortage of data in this field has limited the ability of transportation policymakers and practitioners to research and implement effective transportation policies and plans, as well as to enhance the safety of users (DiGioia et al., 2017). The following section will explore new data collection methods and unconventional data sources for non-motorists that have been made available by recent technological advancements.

Crowdsourced Data

Crowdsourced data refers to information collected from a large group of people, volunteers or contributors from the general public, who willingly share their data (Xu & Nyerges, 2017). This method uses the collective intelligence and capabilities of a dispersed crowd to quickly and cost-effectively gather diverse data points. The widespread adoption of smartphones, affordable electronic devices equipped with GPS, and improved internet and Wi-Fi connectivity have made crowdsourcing even more accessible and economical. For instance, in 2024, approximately 90 percent of individuals in the United States have internet access, a significant increase from about 75 percent in 2015. Additionally, more than 90 percent of adults owned a smartphone in 2023 (*Internet Penetration United States 2024*, n.d.; *US Smartphone Ownership 2023*, n.d.). This trend provides opportunities to connect with and collect data from communities and groups of people that were previously challenging to reach using conventional methods.

Crowdsourcing is highly beneficial in the transportation sector for collecting data across all modes. Specifically, in active transportation, crowdsourced data from bike-sharing programs, GPS, accelerometry data, and fitness apps can be used to gather detailed information about non-motorist behaviors. Data collected from these sources can effectively mitigate the limitations of traditional methods of non-motorist data collection by providing continuous spatial and temporal coverage (Nelson et al., 2021). Among all sources of crowdsourced data in active transportation, data from fitness apps such as Strava, Replica, and StreetLight are considered one of the main sources. In this approach, individuals use GPS-enabled smartphones and mobile applications, websites, or other platforms to record their walking or cycling activities, including trip locations, times, and other relevant characteristics. The recorded data from individuals is then aggregated to generate broader data sets, including traffic counts for larger geographic areas. This aggregated data can be used to study non-motorist activities and behaviors in different geographical areas and across various time periods. Leveraging the benefits of these data sources, several studies have explored the use of crowdsourced data from fitness apps for non-motorist volume estimation, safety analysis, equity studies, and infrastructure assessment and management (Nelson et al., 2021; Sanguinetti & Alston-Stepnitz, 2023).

Several studies have been conducted to explore the potential of using Strava data to estimate bicycle volumes. Kwigizile et al. utilized bicycle counts from 19 different locations in two cities in Michigan, collected via video cameras and/or pneumatic tubes as ground truth data. Alongside Strava, other features such as socio-demographic data, land use, weather, and bike facility types were also incorporated in the modeling process. To evaluate the impact of factors on hourly cyclist volume, a Negative Binomial regression and five Machine Learning models (Random Forest, Bagged Regression Tree, K-Nearest Neighbor, Support Vector Machines, and Neural Network) were employed. Based on the study results, the Random Forest model demonstrated the best predictive performance and was chosen to create a tool for estimating bicycle counts. Furthermore, the study underscored the significance of Strava data as a predictor variable, noting that when its penetration rate was around 10 percent, it was the most important predictor variable in all models (Kwigizile et al., 2022). In another study, Dadashova and Griffin aimed to estimate daily bicycle counts using Strava data. The research utilized a variety of contributing factors, including Strava counts, facility type, roadway characteristics, household income, Average Daily Traffic (ADT), posted speed limits, pavement type, gender, and weather conditions. The study incorporated bicycle count data from 34 counting stations, including both permanent and temporary locations in Texas, to develop daily direct-demand models. A regression tree with random effects (REEM) method was used to identify the most influential factors. Based on the results, Strava data was identified as the most significant factor in explaining the observed variability in daily bicycle counts. Additionally, the inclusion of meteorological, socio-demographic, and economic factors significantly enhanced the predictive power of these models (Dadashova & Griffin, 2020).

Crowdsourced data can significantly enhance safety studies for non-motorists by providing more comprehensive data. Saad et al. used crowdsourced Strava data to estimate safety performance functions for bicycle crashes at intersections. They analyzed both crash data and Strava data from intersections in Orange County, Florida, over a four-year period (2013-2016), developing their crash prediction models using a negative binomial model. To address biases in the Strava data, the researchers made adjustments based on population distribution and direct field observations. The study showed that the most accurate crash prediction models were those that incorporated Strava data along with adjustments based on both population and field observations (Saad et al., 2019). In addition to data from fitness apps, other sources of crowdsourced data, such as incident reporting apps or websites, can also help address limitations related to non-motorist safety data. These platforms allow non-motorists to report more detailed data on incidents or near misses through self-reporting, thereby enhancing the understanding of these events. Fischer et al. conducted a study to explore bicycle crash data from BikeMaps.org, a global crowdsourced website for reporting bicycling incidents, in British Columbia, Canada. The study analyzed 281 crash reports from 2005 to 2019, along with 21 other features, to model the severity of bike crashes. The findings underscored the significant value of the detailed descriptions provided in BikeMaps.org reports for the modeling process (Fischer et al., 2020).

Bike share programs are another source of crowdsourced data for studying non-motorist activities. These programs provide bicycles that users can pick up and return at self-service docking stations located in various areas. Many of these bicycles are equipped with technology that records and monitors their location at these stations, and some even include GPS for tracking bicycle trajectories. The popularity of bike share programs has increased significantly, expanding from just a few in the late 1990s to over 800 by 2014 worldwide (Kabra et al., 2020). This expansion has provided a rich source of detailed data on cyclist ridership. A key resource for bike share data is Bike Share Research, which collects data from hundreds of bike share programs globally. Given the richness and accessibility of this data, it has become a favored tool among researchers for their studies. For example, Sylwia et al. utilized data from bike share systems to estimate bicycle traffic volumes, incorporating weather-related variables into their analysis. The study involved data from 13 locations that had both bicycle count and bike share data available over a two-year period. The results of the regression analysis demonstrated that data from bike share systems could effectively be used to assess the impact of weather conditions on bicycle volumes (Pazdan et al., 2021). In another study, Ding et al. utilized data from bike share programs to examine the effects of various risk factors on bicycle crashes. Their research employed bike share data as a proxy for bicycle exposure, incorporating it along with other features as an independent variable in random parameter negative binomial models. The results indicated that models using bike share data as the exposure measure outperformed others, achieving the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Ding et al., 2020).

Computer Vision

Computer vision (CV) is a branch of artificial intelligence (AI) that enables computers and systems to derive information from digital images, videos, and other visual inputs. Utilizing machine learning (ML) and deep learning (DL) techniques, CV applications can detect and classify objects, recognize patterns, and make decisions based on visual data (Sharma et al., 2021).

Recently, the field of object detection in computer vision has advanced significantly, attracting considerable attention. The evolution of object detection techniques can be broadly split into two main phases. Initially, researchers relied on traditional algorithms that used basic image processing methods like edge detection, corner detection, and image segmentation to identify objects. However, the introduction of deep learning-based algorithms marked a major shift, particularly with the introduction of Convolutional Neural Networks (CNN) in 2012 and Region Convolutional Neural Networks (R-CNN) in 2014. These advancements have substantially enhanced image recognition and object detection tasks, outperforming older methods (Wu et al., 2020). Deep learning-driven object detection algorithms fall into two categories: one-stage and two-stage detectors. Two-stage detectors, which are more complex, first generate proposals and then classify regions. On the other hand, one-stage detectors, such as the You Only Look Once (YOLO) series, simplify the process by eliminating the proposal generation phase, allowing for quick and accurate detections in one step. Although two-stage detectors often deliver better performance, they may not be suitable for devices with limited computational capabilities. Among one-stage detectors, the YOLO series is particularly notable for its effective balance of speed and accuracy, making it ideal for real-time applications (Bacea & Oniga, 2023).

Computer vision techniques, particularly object detection, are applied across various industries including healthcare, retail, manufacturing, agriculture, and transportation. In transportation, computer vision significantly enhances the automation of transport systems and improves traffic safety. For example, it is employed in various areas such as detecting and classifying vehicles, automatic license plate recognition, pedestrian detection, vehicle speed assessment, front car detection, distance measurement between vehicles, obstacle and anomaly detection, lane recognition, traffic sign identification, facilitating road toll collection, and supporting the development of autonomous vehicles. These applications contribute to smarter, safer, and more efficient transportation systems (Dilek & Dener, 2023). For example, Menon et al. developed a computer vision model for pedestrian counting using YOLOv3. Given that the process of pedestrian detection and counting requires a comprehensive collection of images and videos for training, the study utilized two image datasets: the INRIA dataset and the ShanghaiTech-B Dataset. The study demonstrated that person detection using YOLOv3 is among the best compared to previous models. Moreover, the results indicated that this system operates significantly faster than its predecessors. The model's three-layer structure also enhances the identification of very small objects compared to earlier versions of YOLO. The model achieved an accuracy of more than 95% in less crowded images and approximately 80% accuracy in images with more crowded scenes (Menon et al., 2021).

Several other studies have also employed computer vision technologies to detect objects such as crosswalks, traffic signs, and more. One potential application of these studies is that the models can be used to automate the process of creating pedestrian and bicycle inventories or to extract useful information about the quality and condition of bike and pedestrian facilities. For example, Chen et al. used remote sensing images to automatically detect crosswalks. They developed a three-stage process for detecting crosswalks: First, they used CNN models (YOLOv3, Faster R-CNN, and DenseNet-based YOLOv3) for crosswalk detection. Next, they discarded detections with low confidence levels. Finally, they used U-Net to extract potential road areas with crosswalks. The results indicated that all models were able to detect crosswalks with an accuracy of more than 80 percent. The results showed that all models could detect crosswalks with an accuracy of more than 80 percent (Chen et al., 2021). Li et al. developed a novel approach using a CNN model to monitor changes in marked crosswalks at intersections, utilizing Google Street View images from 2007 to 2020. The dataset, comprising 4,925 images, was divided into a training set (approximately 55% of all images) for learning model parameters, a validation set (25%) for tuning hyperparameters, and a test set (20%). The study revealed an overall increase in the number of marked crosswalks at intersections. Notably, there was a decrease in traditional parallel-line crosswalks, while high-visibility crosswalks became more prevalent. The research also explored crosswalks near transit stations in New York City and San Francisco to demonstrate their geographic distribution and relationship with other characteristics of the built environment. Based on the results, areas characterized by high-density residential populations and a higher proportion of zero-vehicle households experienced significant increases in high-visibility crosswalks (Li et al., 2023).

Internet of Things (IoT)

The term Internet of Things (IoT) describes a scenario where a network of interconnected devices, including electronic devices, sensors, and everyday items not typically recognized as computers, are connected and capable of generating, processing exchanging, and exchanging data with other IoT devices and the cloud with minimal human involvement [42]. This concept can be further extended to smart cities, where all elements, including vehicles and citizens, demonstrate high levels of intelligence and interactivity. In transportation, IoT significantly enhances the smart transportation system concept by providing tools to monitor vehicle performance, as well as driver and pedestrian behavior in real time. This capability enhances safer driving practices and helps reduce crash rates. Additionally, IoT applications in transportation cover monitoring traffic congestion, predicting road and weather conditions, providing smart parking solutions, and controlling smart traffic lights, all contributing to improved urban mobility.

Using IoT-based methods, several studies have focused on improving safety for non-motorists. Pau et al. developed a fuzzy logic-based model to dynamically adjust the phases of traffic lights at signalized intersections. The proposed Fuzzy Logic Controller (FLC) is designed simply, with the number of pedestrians waiting to cross and the time of day as its main inputs. For collecting pedestrian data, the study utilized advanced computer vision techniques and video surveillance to accurately count pedestrians, including those in groups. The approach enables modifications to the traffic light phases based on pedestrian volume and the time of day, allowing the duration of the green light to be extended beyond the traditional setting to better manage pedestrian congestion (Pau et al., 2018). In another study, Kodali et al. developed a low-cost weather monitoring system that collects weather data from a cloud database and displays the information on an OLED screen for road users. The results indicate that using an OLED sensor significantly reduces costs compared to traditional sensors such as the DHT (Kodali & Sahu, 2016).

Geographic Information System (GIS)

A Geographic Information System (GIS) is a technology designed for collecting, managing, and analyzing data that has a geographic component. This system integrates various types of data to examine spatial locations and organize information layers into visual representations, such as maps and 3D models. GIS is widely used in several sectors, including urban planning, environmental management, public safety, transportation, and resource management. A specialized branch of GIS that focuses on transportation issues is commonly known as GIS-T (Geographic Information Systems - Transportation). GIS-T has a wide range of applications, including pavement management systems, safety analysis, crash analysis, environmental impact assessments, and travel demand forecasting (Olba & Al-Ramadan, 2006).

Many studies have incorporated GIS alongside statistical models, machine learning techniques, and other data sources to enhance the depth and accuracy of their research. For example, Ding et al. proposed a GIS-based data mining method to investigate different contributing factors related to fatal crashess, including factors related to non-motorists. In their approach, the first step involved building an XGBoost model to classify crashes as fatal or non-fatal. After identifying important factors using XGBoost models, grid-based analysis (or area analysis) was employed to perform spatial analysis on fatality rates. A case study in Los Angeles County was conducted to validate the method. The results revealed that eight factors, including the involvement of pedestrians in crashes, were the most contributing factors to crash outcome (Ma et al., 2019). In another study, Hassan et al. developed a spatial multivariate clustering method utilizing the k-nearest neighbor (KNN) algorithm for traffic pattern recognition. They analyzed a total of 15 variables, encompassing 11 seasonal, three weekly, four hourly, and four spatial factors. Initially, they calculated the optimal number of clusters, categorizing the traffic patterns into 12 distinct groups within the study area. Following the implementation of the model, semantic meanings were assigned to each cluster based on their features. The results demonstrated that their model consistently delivered reliable outcomes across different time periods and outperformed traditional methods, including the conventional Michigan DOT clustering approach (Hasan & Oh, 2020).

Additionally, data from mapping companies like Google, Apple, TomTom, Baidu, HERE, and platforms such as OpenStreetMap (OSM) can be leveraged to develop networks for non-motorists and to continuously update and standardize infrastructure information. For instance, Yang et al. proposed a methodology for creating a pedestrian network. In their method, initially, they segmented the tracking data into two behavioral types: "walking with a clear destination" and "walking without a clear destination." They then applied clustering techniques to extract pedestrian pathways and regions from this categorized data (Yang et al., 2020).

Design of the Survey Questionnaire

Brief Introduction of Technology Acceptance Model (TAM)

Given the benefits of new technologies and data in active transportation, it is important to examine the factors that drive the adoption of new technology and data sources within transportation agencies and DOTs. As previously mentioned, while the technology and data themselves—along with related features such as the type and quality of new data sources—are crucial, other factors including funding, staffing, management strategies, policies, and guidelines also play significant roles. Additionally, readiness for change within organizations, the alignment of new technologies with existing infrastructure, legal and regulatory compliance, training and development programs, and organizational culture can significantly impact this adoption process (Verma et al., 2018). Overall, these elements collectively shape organizational attitudes towards new data sources.

The importance of adopting and utilizing new technologies and data sources in various organizations has been highlighted by many researchers. Bouwman et al. investigated how organizations adopt new technologies, highlighting a two-part process that includes both organizational and individual levels. In the first stage, executives or managers within the organization decide to adopt a new technology or data source. Following this, in the second stage, individual members must accept and begin to use the new technology. Based on their findings, successful implementation and utilization of new technologies require strategic decisions at the organizational level, which are then complemented by operational decisions made by individual users (van de Wijngaert et al., 2005).

Several models and theories have been proposed by researchers to explain new technology adoption and usage in organizations, which also involve individual adoption decisions within these organizations. These include the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI) theory, the Technology-Organization-Environment (TOE) framework, and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Jokonya, 2015). Among these, the Technology Acceptance Model (TAM) is the most commonly used to explain the adoption and implementation of new technologies (Intan Salwani et al., 2009).

TAM, originally proposed by Davis in 1989, is based on the theories of reasoned action and planned behavior. It provides a framework, as illustrated in Figure 1, for understanding how external factors shape beliefs, attitudes, and intentions related to the adoption of new technologies and data sources. The Technology Acceptance Model (TAM) contends that the adoption of new technology depends on users' attitudes toward it. It highlights two measures: perceived ease of use and perceived usefulness, which are crucial in shaping attitudes towards the adoption of new technology. According to TAM, if individuals believe that a particular technology will enhance performance or benefit the company, they are more likely to adopt it. Additionally, if the technology is seen as easy to implement, this perception further promotes its acceptance (Davis, 1989; Matikiti et al., 2018).

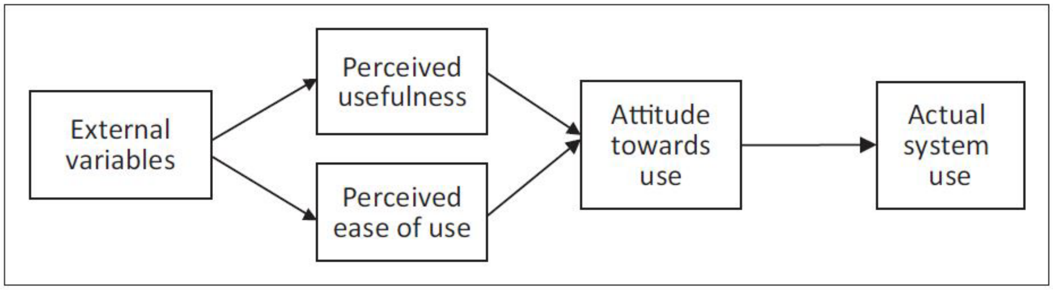

Figure 1. Technology Acceptance Model[1]

The Technology Acceptance Model (TAM) has been extensively utilized in research across various sectors including health, education, transportation, tourism, and banking. Numerous researchers have expanded upon the original constructs of TAM by incorporating additional factors such as perceived enjoyment, output quality, managerial support, competitive pressure, time constraints, and cognitive instruments (Verma et al., 2018). For example, Matikiti et al. developed an extended version of TAM to investigate social media marketing in the South African tourism industry. Their modified version of the model included new factors related to organizational, technical, and external elements that influence attitudes toward adopting social media marketing. They created a questionnaire based on this modified model and distributed it to 150 travel agencies and tour operators. The findings highlighted that managerial support and the educational level of managers are the most important organizational factors. Pressure from competitors, perceived benefits, and perceived ease of use were identified as the most significant external factors influencing the use of social media marketing. Additionally, the results showed that technical knowledge plays a significant role in determining the level of social media marketing usage (Matikiti et al., 2018).

Vanpetch et al conducted research to explore technology acceptance and willingness to invest in Transportation Management Systems (TMS) among small and mid-sized companies. They developed a questionnaire with 25 questions addressing various aspects of TMS usage, including subjective norms toward the system, based on the TAM framework. This questionnaire was distributed to individuals actively involved in business operations. The findings revealed that most of the respondents strongly acknowledged the benefits of TMS technology. However, the age and working experience of the respondents did not significantly influence their willingness to invest in the TMS. Interestingly, users who understood the benefits of a TMS and found the system user-friendly were not necessarily more inclined to invest further in the system. Furthermore, the results

[1] Source: "Perceived usefulness, perceived ease of use, and user acceptance of information technology" (Davis, 1989) and "Application of the Technology Acceptance Model and the Technology–Organization–Environment Model to examine social media marketing use in the South African tourism industry" (Matikiti et al., 2018)

indicated that respondents who considered their technical skills to be less advanced expressed moderate concerns about the benefits of TMS and reported moderate enjoyment in working with the system (Vanpetch & Sattayathamrongthian, 2022).

Main Structure and Distribution Plan

To gain insights and information directly from agencies and institutions, a survey has been designed to explore various aspects of adopting and using new technologies and data sources in active transportation. The questionnaire is divided into two parts and includes open-ended, Likert scale, and multiple-choice questions.

- The first part collects basic information about the respondents, such as their roles and work experience, and poses questions related to the application, benefits, and challenges of using new data sources.
- The second part of the questionnaire designed based on the technology acceptance model addresses eight different factors that can influence the attitudes of transportation agencies towards new technologies and data sources.

The factors include:

1) managerial support, which assesses the role of leadership in technology integration;
2) time commitment, focusing on the resources and time required to adopt new technologies;
3) perceived benefits, outlining the anticipated advantages of new technologies and data sources, such as cost savings and improved efficiencies;
4) technical knowledge and expertise, evaluating the impact of existing skills within the organization on technology adoption;
5) perceived ease of use, assessing how user-friendly the new technology is;
6) pressure from competitors/customers, examining external pressures that may drive technological changes;
7) funding, investigating the effect of financial strategies on acquiring and implementing new technologies; and
8) data quality, assessing the reliability and accuracy of the data provided by new technologies and their impact on adoption decisions.

This section also aims to explore how the attitudes of organizations towards new technologies and data sources influence their adoption and the extent of usage within these organizations. The structure of the TAM model designed for the second part can be seen in Figure 2.

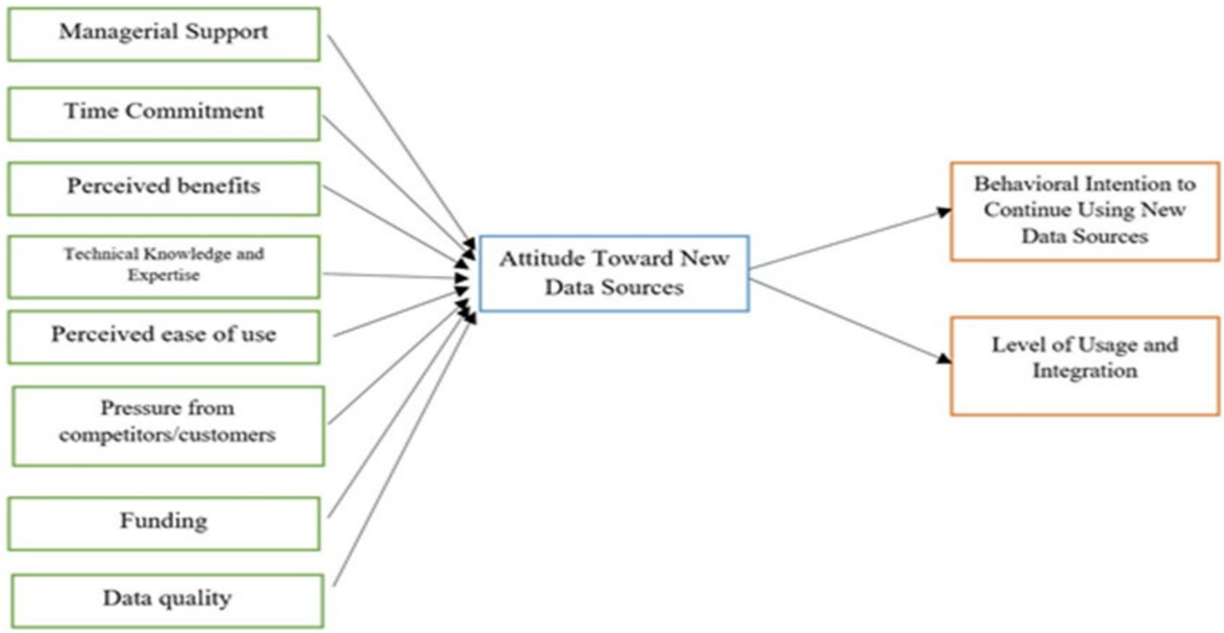

Figure 2. Key Factors Influencing Technology Adoption in Transportation Agencies

The survey will be implemented using Qualtrics, a web-based platform specifically designed for creating and distributing surveys. Before distribution, a pilot study with expert review will be conducted to ensure the validity and effectiveness of the questionnaire.

The survey will target transportation agencies, MPOs, and DOTs, focusing on staff, managers, and coordinators involved in pedestrian and bicycle initiatives. Additionally, the survey will be distributed to key organizations actively involved in pedestrian and bicycle transportation, including the Transportation Research Board (TRB) Pedestrian Committee (ACH10), Bicycle Committee (ACH20), the Association of Pedestrian and Bicycle Professionals (APBP), and the Center for Pedestrian and Bicyclist Safety (CPBS). The survey will be released in mid-July and will remain open for 30 days, providing enough time for potential respondents to complete it.

When the survey is completed and the results are collected, the valid responses will be analyzed. The primary goal of this analysis is to understand how various factors influence attitudes towards, and the adoption and usage of, new data sources in active transportation. Statistical methods will be employed, including regression analysis and structural equation modeling (SEM), to explore these relationships. Moreover, through this questionnaire, current practices, benefits, and challenges related to different new technologies and data sources will be examined. This examination will provide a comprehensive overview of how these technologies are currently being implemented and utilized within transportation agencies, MPOs, and DOTs.

Design of the Workshop Session(s)

To present our findings and engage with stakeholders in the field of active transportation, workshops will be conducted at selected conferences. The length of the workshop is designed to be under two hours. Initially, a comprehensive list of potential conferences focusing on active transportation, transportation, and urban planning was compiled. After contacting the organizers and assessing the feasibility of holding sessions, we selected three conferences: Texas Trails and Active Transportation Conference, the Association of Pedestrian and Bicycle Professionals (APBP) Webinar, and the Transportation Research Board (TRB) Annual Meeting.

- The Texas Trails and Active Transportation Conference, which will be held in Austin, Texas, from September 4-6, 2024, is a biennial conference that brings together professionals involved in bicycle, pedestrian, and other active transportation and recreation modes from around Texas and beyond. This event provides an excellent platform to discuss our research findings and engage with a diverse audience of practitioners, researchers, and policymakers.
- The APBP Webinar, to be held in December, offers another valuable opportunity to connect with professionals dedicated to improving walking and biking conditions and safety. The focus of this conference aligns well with our study's objectives, making it an ideal venue for presenting our findings and facilitating discussions on the adoption and use of new technologies and data sources in active transportation.
- The TRB Annual Meeting, a premier event for transportation research, will enable us to reach a broader audience of transportation experts and policymakers, and present the final results and analysis of our survey and study.

First Session: Transition from Traditional to Unconventional Data Sources

In the first workshop, we will start with a discussion on traditional data sources used in active transportation, such as manual counts, automated traffic counters, video surveillance, crash reports, and road design data. We'll explore their benefits, including reliability and historical comparison, as well as their limitations, such as high costs and spatial and temporal restrictions. Interactive polls will be conducted to gather insights on the audience's current data usage and the perceived benefits and challenges. This phase aims to provide a comprehensive understanding of traditional data sources and their role in active transportation planning.

Next, we'll shift our focus to new data sources and technological advancements, including mobile GPS data, social media insights, sensor networks, crowdsourced data, and satellite imagery. We'll discuss their features, benefits, and challenges, such as privacy concerns and data ownership issues. Through interactive polls and discussions, we'll assess the audience's familiarity with these new data sources and their experiences in implementing them. The final segment will delve into organizational attitudes, exploring factors like funding strategies and technical skills that affect the adoption of new data sources. By engaging with the audience, we aim to understand the barriers and drivers of adopting these new technologies. The agenda for this workshop session can be seen in the appendix.

Second Session: Organizational Attitudes towards Unconventional Data Sources

In this session, we will discuss organizational attitudes and the factors affecting how organizations adopt new technologies and data sources. Key factors such as managerial support, time commitment, perceived benefits, technical knowledge and expertise, perceived ease of use, external pressures from competitors or customers, funding strategies, and data quality will be explored. We will explain two important concepts in organizational attitudes: organizational readiness for change and resistance to change, and their significance in the adoption of new technologies. Following this, we will engage in a discussion with the audience about the attitude of their organizations towards new data sources and their thoughts on the importance of these factors. This interactive segment aims to gather insights and experiences from the participants, providing a practical perspective on the challenges and drivers of adopting new data sources in their respective organizations. We will then explain models that can be used to study organizational attitude, with a particular focus on the Technology Acceptance Model (TAM) and its implications. Finally, we will explain our questionnaire's structure and design, detailing the factors it addresses and the methodology used. We will also provide a brief overview of the preliminary results, highlighting key findings and trends observed in the survey responses.

Third Session: Evaluating the Impact of Different Factors on Organizational Attitudes and the Adoption of New Data Sources

In the final session, we will combine the insights from the first two sessions to provide a comprehensive overview. We will begin by discussing traditional data sources used in active transportation. Next, we will delve into new data sources and technological advancements. Following this, we will explore organizational attitudes and the key factors affecting the adoption of new technologies. We will then discuss models used to study organizational attitude. Finally, we will explain the design of our survey, detailing the factors it addresses and the methodology used. We will present the results of the survey, integrating findings from the previous sessions. This comprehensive approach will ensure participants gain a thorough understanding of the theoretical models, practical applications, and real-world insights related to organizational attitude and the adoption of new data sources in active transportation.

Summary

This project serves as the planning stage for our next phase which will focus on conducting a survey and several regional/national workshops/webinars. In this planning stage, we have accomplished the following:

1. **Literature Review**: We explored the impact of funding for unconventional data collection on VRU safety improvements. The literature indicates a significant gap in comprehensive data on pedestrian and bicyclist activities and behaviors. It highlights the potential of unconventional data sources such as crowdsourced data, computer vision, and IoT to address this gap. While the adoption of these new data sources likely faces organizational and financial challenges, the current body of literature does not provide comprehensive insights or hard evidence to support this conclusion. This lack of detailed information underscores the need for our planned survey and workshops to gather more concrete data and insights.
2. **Survey Design and Distribution Plan**: We designed a comprehensive survey to gather insights and information directly from transportation agencies and institutions regarding their adoption and use of new technologies and data sources in active transportation. The survey is structured to explore organizational attitudes towards these new data sources and will be guided by the Technology Acceptance Model (TAM). The distribution plan for this survey is set for the next phase in the near future.
3. **Workshop/Webinar Sessions Design and Plan**: We designed workshop and webinar sessions aimed at presenting our findings and engaging with stakeholders in the field of active transportation. These sessions will discuss traditional and new data sources, organizational attitudes towards adopting new technologies, and factors affecting this adoption. The plan is to conduct these sessions in the next phase.

In conclusion, this research aims to bridge the gap between funding decisions, data access, and safety improvements for VRUs. By providing insights and guidance from our literature review and planned activities, we hope to assist transportation organizations in effectively incorporating unconventional data into their strategies and prioritizing safety improvements for VRUs.

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Appendix: First Workshop Session Sample Agenda

Phase 1 (30-45min): Traditional and Current Data Sources

• Overview of traditional data sources used in active transportation:
  ○ Manual counts (pedestrians, bicycles)
  ○ Automated traffic counters
  ○ Video surveillance analyses
  ○ Crash reports
  ○ Road design and infrastructure data

• Discussion on how these sources are typically gathered and the logistics involved. • Conduct polls to learn about the data sources the audience currently uses and their purposes.

• Benefits of traditional data sources
  ○ Reliability
  ○ Historical comparison
  ○ Regulatory compliance
• Limitations of traditional data sources
  ○ Cost and resource intensity: High expenses and labor requirements for data collection and processing.
  ○ Spatial and temporal limitations: Data often limited to specific times and locations, lacking broader applicability.
  ○ Operational challenges

• Discussion with audience:
  ○ Benefits and limitations of traditional data sources
  ○ Feedback
  ○ Alternatives

[Scheduled Break (15min); optional if phase 1 lasts more than 45min]

Phase 2 (30-45min): New Data Sources in Active Transportation

• Introduction to new types of data and collection methods that have become available due to advances in technology (comprehensive list):
  ○ Mobile GPS data from smartphones and fitness trackers.
  ○ Social media data providing real-time location-based insights.
  ○ Sensor networks embedded in urban infrastructure.
  ○ Satellite imagery
  ○ etc.
• Features of new types of data
  ○ Different characteristics compared to traditional methods
  ○ How it is collected
  ○ Benefits
  ○ Challenges: Privacy concerns, data ownership issues

• Interactive Polls:
  ○ Necessity of integrating new data sources
  ○ Assess familiarity with new data sources
  ○ Evaluate experience and usage.
• Discussion
  ○ What new data sources are you familiar with, or consider innovative in active transportation?
  ○ Have you implemented any of these new data sources in your projects? If so, what has your experience been like?
  ○ Could you describe the scope and scale of data you managed with these new technologies?
  ○ How do you compare the effectiveness of these new data sources with traditional methods you have used in the past?
  ○ What barriers have you encountered in adopting these new data sources, or what has limited their usage in your projects?
  ○ etc.

Scheduled Break (15min)

Phase 3 (45min): Organizational Decision-Making in New Data Sources Utilization

• Introduction to organizational attitudes and behavior:
  ○ Organizational attitudes and behavior as a complex process.
  ○ Importance of studying organizational attitudes and behavior in the context of adopting new data sources.
• Factors affecting organizational attitudes towards new data sources:
  ○ Focus on funding strategies: various strategies and return on investment (ROI).
• Organizational challenges in adopting new data sources:
  ○ Discuss common organizational barriers such as budget constraints, resistance to change, and lack of technical skills.

• Discuss factors that affect the tendency of organizations towards adopting new data sources.
• Interactive Poll:
  ○ Interactive poll asking the audience which factor they believe is most important in influencing the adoption of new data sources.
  ○ Assess the impact of these challenges on the willingness and ability of organizations to integrate new data sources.

Closing Section (15min)
• Debrief, feedback on the workshop, a recap of next steps (Webinar in Dec. 2024).