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 II

June 2025

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

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16. Abstract
This study explores the organizational and contextual factors, including funding, that influence the adoption and integration of emerging data sources by state Departments of Transportation (DOTs), with a focus on active transportation and vulnerable road user (VRU) safety. Building on Phase 1 planning efforts, this phase involved a national survey of DOT professionals and a practitioner workshop. Using a hybrid framework that combines the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework, the study applies Partial Least Squares Structural Equation Modeling to examine how internal factors such as organizational support and funding, and external factors such as stakeholder pressure and perceived benefits, shape agency attitudes, behavioral intentions, and integration outcomes. Results show that organizational support and peer pressure are the strongest drivers of adoption, while funding and perceived benefits alone have limited impact. Despite generally positive attitudes among DOTs, the actual integration of emerging data sources remains limited. This underscores the need for greater institutional readiness and technical capacity. The study offers actionable insights for agencies aiming to modernize data practices and improve VRU safety.

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Non-motorist, Funding, Unconventional data, Survey, Workshop, Technology Adoption, PLS-SEM, Technology Acceptance Model (TAM)

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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 II

A Center for Pedestrian and Bicyclist Safety Research Report

June 2025

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Acronyms, Abbreviations, and Symbols

ATT	Attitude Toward New Data Sources
AVE	Average Variance Extracted
BI	Behavioral Intention to Use
CA	Cronbach's Alpha
CR	Composite Reliability
DOT	Department of Transportation
EE	Effort Expectancy
FND	Funding
GIS	Geographic Information System
LUI	Level of Usage and Integration
OS	Organizational Support
PB	Perceived Benefits
PC	Pressure from Competitors/Customers
PLS-SEM	Partial Least Squares Structural Equation Modeling
SD	Standard Deviation
TAM	Technology Acceptance Model
TOE	Technology–Organization–Environment Framework
TTAT	Texas Trails and Active Transportation Conference
VRU	Vulnerable Road User

Abstract

This study explores the organizational and contextual factors, including funding, that influence the adoption and integration of emerging data sources by state Departments of Transportation (DOTs), with a focus on active transportation and vulnerable road user (VRU) safety. Based on the planning efforts outlined in Phase 1, this phase included a national survey of DOT professionals and a workshop held at the 2024 Texas Trails and Active Transportation Conference. Using a hybrid framework that combines the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework, the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine how internal factors (e.g., organizational support, funding) and external factors (e.g., stakeholder pressure, perceived benefits) shape agency attitudes, behavioral intentions, and the integration of unconventional data sources. Results show that organizational support and peer pressure are key drivers of adoption, while funding and perceived benefits alone do not significantly influence attitudes. Despite positive perceptions and strong behavioral intentions, actual integration of emerging data sources remains limited, highlighting the need for stronger institutional readiness, technical capacity, and interdepartmental coordination. Workshop findings further revealed limited practitioner familiarity with emerging tools and emphasized the importance of targeted training, knowledge-sharing, and supportive policy alignment. This study provides actionable insights for DOTs and transportation agencies seeking to modernize data practices, enhance planning effectiveness, and improve VRU safety through the integration of innovative data sources.

Executive Summary

This study investigates how organizational and contextual factors, including funding, influence the adoption and integration of emerging data sources, such as crowdsourced data, computer vision, and IoT technologies, by state DOTs, with a focus on improving safety for vulnerable road users. The project builds on planning efforts from Phase I and, in Phase II, focuses on collecting and analyzing data through a national survey of DOT professionals and a practitioner workshop. Key steps and findings are summarized below:

1. Survey Development and Conceptual Framework

   The study employs a hybrid conceptual framework that integrates the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework. TAM provides insight into how agency staff form attitudes toward new technologies based on perceived usefulness and ease of use. TOE, in turn, captures broader organizational and environmental factors, such as organizational support, external pressures, and perceived benefits that influence adoption behavior. Using this framework, a structured questionnaire was developed and distributed to DOT professionals involved in active transportation planning and data use.

2. Workshop Engagement

   A one-hour workshop was held at the 2024 Texas Trails and Active Transportation (TTAT) Conference, where practitioners discussed challenges and opportunities related to emerging data sources. Interactive polling revealed that most participants were only somewhat familiar with these technologies. Key concerns included data reliability, integration with existing systems, and privacy. Improved decision-making emerged as the most commonly perceived benefit of new data sources.

3. Analysis of Survey Results

   The survey results revealed a noticeable gap between positive organizational attitudes and the actual integration of emerging data sources into agency workflows. While respondents generally expressed strong behavioral intentions and recognized the value of these tools, reflected in high average scores for perceived benefits and intention to use, the level of usage and integration had the lowest mean score among all measured constructs. Findings from the structural equation model show that organizational support and peer agency or stakeholder/customer pressure were statistically significant predictors of a positive attitude toward adoption, while funding availability and perceived benefits were not. This suggests that even when emerging data sources are viewed as valuable, funding alone is not sufficient to drive adoption. Many agencies continue to face challenges related to internal readiness, cross-department coordination, and limited technical capacity, all of which hinder implementation at scale. As a result, these tools remain underutilized despite growing interest, highlighting the need for stronger institutional support, workforce training, and better integration into existing workflows.

Overall, this study provides actionable insights into the organizational dynamics that shape the adoption of unconventional data sources in the public sector. The results emphasize the importance of building internal capacity, fostering leadership engagement, encouraging cross-agency collaboration, and investing in targeted training programs. These findings can help guide transportation agencies in effectively scaling the use of emerging data to support improved planning, decision-making, and safety outcomes for vulnerable road users.

1. Introduction

Active, or non-motorized, transportation refers to modes of transport that are powered by human energy. While walking and cycling are the most common forms, active transportation also includes other activities such as skateboarding, rollerblading, scootering, and the use of manual wheel chairs (Cook et al., 2022). In recent years, active transportation has gained significant popularity among both the public and transportation agencies, largely due to its wide-ranging benefits. These modes offer not only personal advantages, such as improved cardiovascular health, reduced stress, and lower travel costs, but also broader societal gains. These include reductions in greenhouse gas emissions, traffic congestion, and noise pollution, as well as improved use of public spaces and the development of more livable, walkable, and connected communities (Fishman et al., 2015). As a result, many cities have begun implementing policies and infrastructure designed to support and promote active travel as a key component of sustainable urban mobility.

However, this growing popularity has been accompanied by increasing concerns over the safety of non-motorist users, also known as vulnerable road users (VRUs). These individuals face a disproportionately high risk of serious injury or death due to their exposure to motor vehicle traffic and lack of physical protection. For example, according to the Governors Highway Safety Association (GHSA), approximately 7,400 pedestrians were killed in motor vehicle crashes in the United States in 2023, representing a 14% increase compared to pre-pandemic levels in 2019 (Ahsan et al., 2025; GHSA, 2024). Similarly, in 2020, approximately 850 bicyclists lost their lives in traffic crashes across the United States, representing a 5% increase from the previous year (Salmon et al., 2022). These alarming figures highlight the urgent need for transportation systems that better protect VRUs through safer infrastructure and policy interventions.

To effectively support this shift toward increased active transportation, particularly in the face of growing safety concerns, transportation agencies and state DOTs require timely, accurate, and comprehensive data on non-motorist activities and infrastructure conditions. Information such as non-motorist traffic volumes, behavior patterns, crash hot spots, infrastructure quality, and user preferences is not only critical for effective planning, prioritization, and evaluation but also essential for identifying safety risks and implementing targeted interventions to protect vulnerable road users. However, traditional data collection methods used by transportation agencies, such as manual counts, household travel surveys, and police crash reports, are often limited in both spatial and temporal coverage. These approaches tend to be labor-intensive, costly to scale, and prone to various forms of bias, resulting in significant data gaps in the understanding of active transportation (Feng et al., 2021). As a result, these limitations have caused an ongoing lack of reliable, high-quality data on non-motorist travel patterns and infrastructure usage, making it difficult for agencies to make informed decisions, prioritize investments, and implement effective strategies that support active transportation.

However, as technology continues to evolve, new methods of data collection and emerging data sources are making it easier and more effective to gather information on populations, such as non-motorists, that were previously difficult to capture through traditional means (Alattar et al., 2021). For example, crowdsourced data from fitness applications like Strava and passive mobility platforms such as StreetLight provide continuous, high-resolution insights into walking and biking patterns (Dadashova & Griffin, 2020). Bike-share systems record real-time trip origins and destinations, while GPS-enabled devices offer detailed information on travel trajectories and behavior(Kim & Cho, 2021). Computer vision (CV) models can automatically detect features such as crosswalks and curb ramps from street-level imagery (Chen et al., 2021), and Internet of Things (IoT) sensors enable real-time monitoring of environmental and traffic conditions (Kodali & Sahu, 2016). Additionally, Geographic Information Systems (GIS) and open mapping platforms like OpenStreetMap (OSM) offer flexible, up-to-date spatial data infrastructure to support the development and maintenance of pedestrian and cycling networks (Ferster et al., 2020). Collectively, these emerging data sources represent a transformative opportunity for transportation agencies. They have the potential to address long-standing data gaps, enhance safety analysis, inform performance-based planning, and support more equitable investment in active transportation infrastructure.

Nonetheless, despite the growing availability and demonstrated utility of these emerging data sources related to non-motorist behaviors, their adoption within public-sector planning and decision-making processes, particularly among DOTs, remains limited and inconsistent. One of the primary reasons for this gap lies in the historical evolution of most state DOTs in the United States, which have traditionally focused on highway design, construction, and the management of motorized traffic. Although policy reforms such as the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 signaled a shift toward more inclusive transportation planning by encouraging consideration of active transportation in funding and policy frameworks, institutional priorities and data systems have largely continued to center around motorized transportation (Dill et al., 2017) . This legacy orientation creates organizational inertia, making it challenging to incorporate new data practices, particularly those focused on understanding the behaviors, preferences, and infrastructure needs of pedestrians and bicyclists. Another contributing factor is the rapid pace at which new technologies and data collection methods are being developed and introduced. While these innovations offer powerful tools for understanding and supporting non-motorist travel, many transportation agencies and state DOTs, like many large organizations, struggle to keep up with the speed of technological advancement. This often results in institutional resistance to change, as agencies may lack the technical expertise, resources, or internal flexibility needed to evaluate, adopt, and integrate new tools into existing workflows (Miller & Lambert, 2014).

More fundamentally, the challenge lies in the fact that the adoption of emerging data sources and technologies is shaped by a complex set of organizational dynamics (Matikiti et al., 2018). Even when such data are affordable or freely available, many transportation agencies and DOTs find it difficult to move from limited experimentation to sustained, routine use. Like other large institutions, DOTs operate within broader organizational systems, where the implementation of new practices depends on multiple interrelated factors. These include internal organizational culture, leadership and managerial support, staff capacity and technical expertise, funding availability, competing priorities, external stakeholder pressure, and overall institutional readiness. As a result, adopting and integrating emerging data sources is not simply a technical decision, it is a strategic and organizational challenge that requires coordinated alignment across people, processes, and policies (Framework for Managing Data from Emerging Transportation Technologies to Support Decision-Maki, 2020).

1.1 Technology Acceptance Model

Given the complexity of organizational behavior, particularly regarding changes in data practices and technology adoption, researchers have developed a range of theoretical frameworks and models to better understand how organizations respond to new tools, systems, and processes (Matikiti et al., 2018; Verma et al., 2018). These models aim to capture not only the characteristics of the technologies themselves but also the broader organizational and contextual factors that shape adoption, resistance, and long-term integration. In the context of active transportation, where emerging data tools are sometimes unfamiliar, underfunded, or perceived as peripheral to core agency functions, understanding the organizational dynamics surrounding their adoption becomes especially important. Gaining such insight can help identify the conditions under which new tools are likely to be embraced or dismissed, and can inform strategies aimed at fostering lasting, meaningful change in agency practices.

Among the most widely used models for analyzing technology adoption is the Technology Acceptance Model (TAM). While other frameworks, such as the Diffusion of Innovation (DOI) (García-Avilés, 2020), the Technology-Organization-Environment (TOE) framework (Awa et al., 2017), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2012), offer valuable perspectives, TAM remains one of the most frequently applied and validated, particularly in organizational settings (Intan Salwani et al., 2009). Introduced by Davis (1989), TAM provides a structured approach for examining how perceptions of new technologies shape user attitudes and intentions (Davis, 1989). The model highlights two main beliefs that influence adoption. One is the idea that a technology can improve how effectively a person performs their job. The other is the perception that the technology is simple to learn and operate. Together, these beliefs shape a user's attitude, which ultimately affects their intention to use the technology.

Several studies have applied the TAM, extended it, or combined it with other theoretical frameworks to examine organizational behavior, particularly in relation to the adoption of new technologies and data tools. These adaptations aim to more accurately capture the complexities of decision-making in institutional environments, where factors beyond individual perceptions often influence outcomes (Dobrinić, 2021). For example, Sciarelli et al. (2022) examined the adoption of blockchain technology among more than 100 small and medium-sized Italian companies by extending the traditional TAM. To better reflect organizational priorities, they expanded the model by incorporating additional constructs such as efficiency and security, along with reduced cost. The study found that perceived usefulness and perceived efficiency and security were significant predictors of adoption, while cost-related factors did not have a statistically significant effect. These results suggest that companies may place greater importance on the strategic value and practical benefits of a technology than on its affordability. In another study, Chou et al. (2022) developed an extended TAM framework integrated with the Stimulus-Organism-Response (SOR) theory to examine factors influencing sustainable marketing practices in the catering industry. Using survey data from 300 catering employees, the model incorporated green marketing orientation and entrepreneurship as external stimuli and analyzed their impact on two key TAM constructs, namely perceived usefulness (PU) and perceived ease of use (PEOU) of big data technologies. The findings showed that both PU and PEOU significantly influenced the adoption of big data applications, which in turn supported more sustainable marketing processes.

1.2 Technology–Organization–Environment

While TAM has been widely used to understand how individuals and organizations form attitudes and intentions toward new technologies, it does not fully capture the broader organizational and environmental influences that often impact adoption, particularly within government agencies and complex institutions. To address this gap, researchers have increasingly adopted alternative models that take a more holistic approach to understanding technology adoption. One such model is the Technology–Organization–Environment (TOE) framework**,** which is frequently used to study adoption at the organizational level. Over the years, TOE has been applied on its own and in combination with TAM, offering a more comprehensive perspective by integrating internal user perceptions with external organizational and environmental factors (Dobrinić, 2021).

Originally introduced by Tornatzky and Fleischer in 1990, the Technology–Organization–Environment (TOE) framework outlines three key dimensions that influence an organization's decision to adopt new technologies (Tornatzky et al., 1990). The first is the technological context, which refers to the characteristics, capabilities, and availability of the technology itself. The second is the organizational context, which involves internal factors such as management support, available resources, staff expertise, and the size and structure of the organization. The third dimension is the environmental context, which includes external forces such as competitive pressure, regulatory requirements, and prevailing industry norms. Together, these dimensions provide a comprehensive view of the various factors that can either support or hinder the adoption of technology within an organization. In addition, the TOE framework has been noted for its ability to account for not only technological and organizational factors, but also social and environmental influences on adoption decisions (Wang et al., 2010).

1.3 TAM-TOE Hybrid Model

Building on these strengths, the combined use of TAM and TOE has proven especially valuable in research on emerging technologies such as artificial intelligence (AI) (Chatterjee et al., 2021). In such contexts, understanding both the individual-level factors that shape user acceptance and the organizational-level conditions that determine readiness is essential. By integrating TAM's focus on user perceptions with TOE's broader view of institutional and environmental influences, researchers are able to capture a more complete picture of what drives or inhibits technology adoption in complex organizational settings. For instance, Na et al. (2022) investigated the adoption of AI-based technologies in construction firms by integrating the TAM and TOE frameworks into a unified model. To capture the multifaceted nature of adoption in this context, the study included factors such as organizational support, technological readiness, environmental conditions, and individual personality traits. The results indicated that technological and organizational factors had a significant impact on perceived ease of use, while personality traits strongly influenced both perceived usefulness and ease of use. In contrast, environmental factors, such as external suggestions or pressure, had a negative impact, suggesting that internal capabilities and individual readiness may play a more influential role in adoption decisions than external forces. In another study, a TAM–TOE integrated framework was used to investigate how small tourism businesses in South Africa adopt social media marketing tools. Based on responses from 150 travel agencies and tour operators, the study identified both internal and external factors influencing adoption decisions. Internally, strong managerial support and higher levels of managerial education were linked to more favorable attitudes toward adoption. Externally, perceived ease of use, competitive pressure, and expected benefits were key motivators. The study also found that technical knowledge strengthened the relationship between attitude and actual usage, highlighting the importance of organizational readiness in translating intention into effective implementation (Matikiti et al., 2018).

In the context of transportation agencies and state DOTs, developing a well-structured hypothetical model that integrates both individual and organizational perspectives, such as a TAM–TOE hybrid, can offer valuable insights into the factors that influence the adoption of emerging data sources and technologies. Such a model allows researchers and practitioners to systematically examine how both internal and external factors shape organizational attitudes toward new data sources, as well as their actual usage behaviors. This approach is particularly useful for identifying key barriers to adoption, evaluating organizational readiness, and designing targeted strategies that align with agency goals. By addressing both perceptual and structural dimensions of technology use, a tailored hypothetical model can support more informed decision-making, facilitate the integration of innovative data practices, and ultimately contribute to improved planning, safety, and equity in active transportation initiatives.

1.4 Objectives of the Study

The primary objective of this study is to examine the key internal and external factors that influence the adoption and integration of unconventional and emerging data sources within transportation agencies, with a specific focus on active transportation. To guide this investigation, a conceptual framework was first developed by integrating the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework. This hybrid model introduces mediating pathways through which internal and external factors, such as organizational support, funding, competitive pressure, effort expectancy, and perceived benefits, shape agency attitudes. These attitudes, in turn, influence behavioral intentions and ultimately affect the level of usage and integration of new data sources. By focusing on state DOTs and their practices related to non-motorist data, the study aims to generate actionable insights that support data-driven innovation and improve planning and safety outcomes in the active transportation domain.

In addition to the survey component, this study incorporates a qualitative engagement phase through workshop sessions designed to facilitate direct dialogue with public sector professionals. These sessions were intended to enrich the survey data by fostering interaction, idea sharing, and a deeper exploration of agency experiences with emerging data sources. A key element of this effort was a workshop conducted at the 2024 Texas Trails and Active Transportation Conference, which provided valuable qualitative input to complement and contextualize the survey findings.

The remainder of this report is organized as follows: Section 2 introduces the conceptual framework and research hypotheses; Section 3 outlines the survey instrument, sampling strategy, and the design of the workshop engagement; Section 4 presents results from the measurement and structural models and discusses key findings and their implications for practice; Section 5 summarizes outcomes from the workshop engagement; and Section 6 concludes with recommendations and directions for future research.

2. Methodology

This study investigates how organizational and contextual factors influence the adoption and integration of emerging data sources within transportation agencies, specifically state DOTs. It explores how internal drivers such as organizational support and funding, along with external factors like effort expectancy, competitive pressure, and perceived benefits, shape agency attitudes toward adopting new data tools. These attitudes are expected to influence both the intention to use and the extent of actual integration of these data sources into agency operations.

To guide this investigation, the study adopts a hybrid framework that combines the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework. This integrated model (see Figure 1) captures both individual-level perceptions and broader organizational and environmental conditions, offering a comprehensive view of the factors shaping data adoption behavior in public-sector settings. By applying this hybrid approach, the study aims to generate actionable insights that support strategic planning, organizational readiness, and the effective use of innovative data practices to enhance decision-making, safety, and equity in active transportation planning.

2.1 Conceptual Framework and Research Model

To examine the factors that influence the adoption of emerging data sources within transportation agencies, this study adopts a hybrid framework that integrates two widely used models: the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework.

TAM provides insight into how individuals or organizations form attitudes toward new technologies. It explains how perceived usefulness (the belief that a technology enhances job performance), and perceived ease of use (the belief that a technology is simple to use), shape users' attitudes, which then influence their behavioral intentions and ultimately lead to adoption. In this study, TAM is used to explore how transportation professionals and their agencies form attitudes toward emerging data sources, and how those attitudes affect decision-making and implementation. The TOE framework complements this by focusing on organizational-level adoption. It highlights three contexts that influence technology uptake: the technological context (features such as compatibility and usability), the organizational context (internal elements like leadership support, staff capacity, and funding), and the environmental context (external factors such as peer agency practices, regulations, and stakeholder expectations). Unlike TAM, TOE does not follow a sequential process but instead emphasizes how these factors collectively shape organizational readiness and decision-making. By combining TAM and TOE, the hybrid framework offers a comprehensive view of both behavioral and structural factors that influence adoption. The conceptual framework adopted in this study builds on the model proposed by Matikiti et al. (2018), which combines the Technology Acceptance Model (TAM) with the Technology–Organization–Environment (TOE) framework.

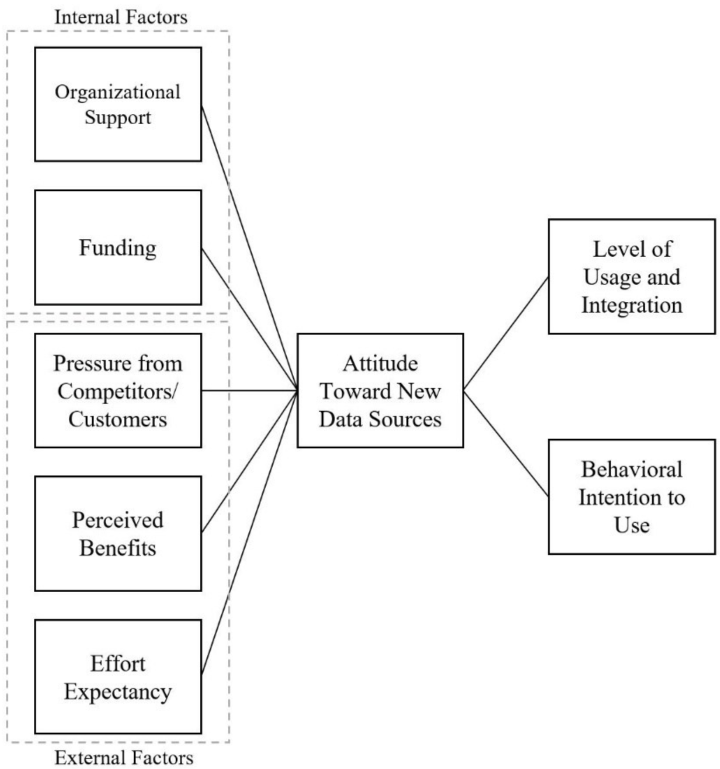

Figure 1: Framework for the Adoption of Emerging Data Sources in Transportation Agencies

Their original model demonstrated how internal and external factors shape organizational attitudes, which in turn influence behavioral intentions and actual technology use. This study applies that framework to transportation agencies, focusing specifically on the adoption of emerging data sources for active transportation planning. The simplified yet robust structure is particularly suitable for research with smaller sample sizes, where more complex models may be impractical due to data limitations. By focusing on the most critical pathways while maintaining theoretical integrity, this approach offers a practical and effective way to examine the organizational and behavioral factors driving innovation in the public sector. Based on the literature and the adopted hybrid framework, five key constructs were identified and classified as either internal or external factors that are expected to shape an agency’s attitude toward adopting emerging data sources. These constructs are presented in Figure 1.

Internal factors refer to elements within the agency's structure and control. The first internal factor is organizational support, which reflects the extent to which top management shows interest in adopting emerging data sources and ensures that staff either possess the necessary skills or have access to appropriate support. The second internal factor is funding, which refers to the financial resources allocated to support the adoption and integration of new data technologies. This includes both the pursuit of external funding and the internal monitoring of return on investment. Based on the expected impact of these internal elements, the following hypotheses are proposed:

- H1. Organizational support positively influences the organization's attitude toward adopting emerging data sources.
- H2. Funding positively influences the organization's attitude toward adopting emerging data sources.

On the other hand, external factors refer to influences that originate outside the organization but shape its perception and decision-making regarding technology adoption. These include pressure from stakeholders or competitors, which captures expectations from external partners and the influence of peer organizations, such as other state DOTs that have implemented similar systems. Perceived benefits is also treated as an external factor, as it reflects the organization’s assessment of the potential value provided by the technology, such as cost-effectiveness or improved safety outcomes. Although this assessment is made internally, it is based on anticipated outcomes from an external system. Similarly, effort expectancy is classified as an external factor because it relates to the perceived design and usability of the technology itself, including the time, training, and resources required for successful implementation. This interpretation aligns with previous research applying the TOE framework, in which perceived usefulness and ease of use are viewed as attributes of the external technological environment rather than internal organizational beliefs (Matikiti et al., 2018). The proposed hypotheses for the external factors are as follows:

- H3. Pressure from stakeholders or competitors positively influences the organization's attitude toward adopting emerging data sources.
- H4. Perceived benefits positively influence the organization's attitude toward adopting emerging data sources.
- H5. Effort expectancy positively influences the organization's attitude toward adopting emerging data sources.

These five factors are hypothesized to influence the organization's overall attitude toward adoption, which in turn is expected to affect two key outcomes: the behavioral intention to use and the level of usage and integration of emerging data sources. The final set of hypotheses reflects these outcome relationships:

- H6. A positive attitude toward emerging data sources positively influences behavioral intention to use them.
- H7. A positive attitude toward emerging data sources positively influences the level of usage and integration within the organization

3. Study Design

3.1 Survey

3.1.1 Measurement Development

To collect the data required for this study, a structured questionnaire was developed and organized into three main sections (see Appendix A). The first section gathered demographic and organizational background information. This included the respondent's affiliated agency or DOTs, their job role, and their experience with non-motorist data sources. The second section focused on contextual information regarding the agency's use of emerging data sources. Respondents were asked about the duration of use, the types of technologies employed (e.g., sensors, video analytics, mapping platforms), and the key applications of these data, such as safety assessment, urban planning, and traffic operations. This section also included questions on perceived benefits and the funding sources used to support emerging data sources, such as whether agencies relied on internal budgets or pursued external grants.

Table 1: Measurement Constructs and Item Descriptions

Constructs	Item	Measure	Source
Organizational Support	OS1	Top management shows a high level of interest in adopting emerging data sources	(Li, 2011; Venkatesh et al., 2016)
	OS2	Our personnel are proficient in using emerging data sources , and/or support is readily available when needed	
Effort Expectancy	EE1	The time required to preprocess and utilize emerging data s ources is manageable within our organization's capabilities	(Hussain et al., 2025; Matikiti et al., 2018)
	EE2	Using emerging data sources requires minimal additional ti me, resources, and training	
Pressure from Competitors/Customers	PC1	Key partners expect our agency to actively adopt and integr ate emerging data sources	(Kwarteng et al., 2024)
	PC2	Other state DOTs have utilized and continue to use emergin g data sources effectively	
Perceived Benefits	PB1	Adopting emerging data sources is perceived as a cost-effec tive alternative to traditional data	(Verma et al., 2018)
	PB2	The use of emerging data sources enhances VRU safety (e. g., identifying high-risk areas, offering real-time informatio n, and enabling continuous safety monitoring for proactive planning)	
Funding	FND1	We actively seek external funding opportunities to support t he adoption and integration of emerging data sources	(Venkatesh et al., 2003)
	FND2	Our agency monitors the return on investment (ROI) from f unding allocated to emerging data sources.	
Attitude Toward New Data Sources	ATT1	The use of emerging data sources is widely perceived as po sitive within our agency.	(Matikiti et al., 2018)

Constructs	Item	Measure	Source
	ATT2	Our agency allocates sufficient financial resources to suppo rt the usage of emerging data sources	
Level of Usage and Integration	LUI1	Plans are in place to increase the budget for further integrati on of emerging data sources.	(Hewavitharana et al., 2021)
	LUI2	Our agency has a comprehensive policy (i.e. guidelines) for integrating emerging data sources.	
Behavioral Intention to Use	BI1	Our organization is committed to the continued use of emer ging data sources	(Verma et al., 2018)
	BI2	Our agency is prepared to support staff through the transitio n to using emerging data sources	

The third section assessed the theoretical constructs outlined in the conceptual framework. Each construct was measured using two items rated on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). These items were designed to capture perceptions related to organizational support, funding, effort expectancy, perceived benefits, stakeholder pressure, attitude toward adoption, behavioral intention to use, and the level of integration of emerging data sources. The measurement items were adapted from established, validated instruments in the literature and reworded as needed to align with the context of transportation agencies. Initially, this section included 30 items, but based on feedback from a pilot test and expert review, the survey was refined to 16 core items. This reduction aimed to improve clarity, enhance response rates, and reduce respondent burden without compromising the reliability and validity of the constructs. Table 1 presents the final set of measurement constructs, their corresponding items, and source references used in the study.

3.1.2 Survey Sample and Data Collection

To gather insights from state DOTs regarding the adoption and use of emerging data sources, the survey was distributed to individuals involved in active transportation planning and data-related decision-making. An initial contact list was created by identifying publicly available email addresses of state bicycle and pedestrian coordinators and program managers from official DOT websites. Survey invitations were then sent directly to these individuals with a request that they either complete the survey themselves or forward it to the most relevant staff member within their agency. This approach aimed to ensure responses from those with direct knowledge and experience related to non-motorist data use.

The survey was administered using Qualtrics, a web-based platform that allowed participants to complete it at their convenience. While the survey was anonymous by default, respondents had the option to voluntarily provide their email address if they wished to receive the study results or be contacted for follow-up communication. The first round of invitations was distributed in

September 2024, followed by several reminder emails throughout the fall and winter. The data collection period remained open through January 2025 to maximize participation and ensure an adequate sample size for analysis. To expand participation, the survey was also verbally promoted at the 2024 Association of Pedestrian and Bicycle Professionals (APBP) Annual Meeting in Detroit. This event provided an opportunity to raise awareness among additional practitioners and encourage broader engagement.

As a result of this outreach strategy, the final sample comprised professionals most directly engaged in non-motorist data applications. These included bicycle and pedestrian program managers, engineers, planners, and coordinators, as well as transportation alternatives coordinators and Safe Routes to School coordinators, individuals who regularly interact with non-motorist data in their planning, safety, and policy work.

3.2 Workshop Engagement

To present project findings and engage stakeholders in active transportation, a one-hour workshop was planned as part of selected professional conferences. An initial list of relevant events in transportation, urban planning, and active transportation was compiled. After contacting organizers and evaluating feasibility, three venues were considered: the Texas Trails and Active Transportation (TTAT) Conference, an Association of Pedestrian and Bicycle Professionals (APBP) webinar, and the Transportation Research Board (TRB) Annual Meeting. Ultimately, the 2024 TTAT Conference, held in Austin from September 4–6, was selected and accepted for presentation. This biennial event brings together professionals from Texas and beyond who are involved in bicycling, walking, and other active transportation modes. It provided a valuable platform for sharing research findings and engaging a diverse audience of practitioners, researchers, and policymakers.

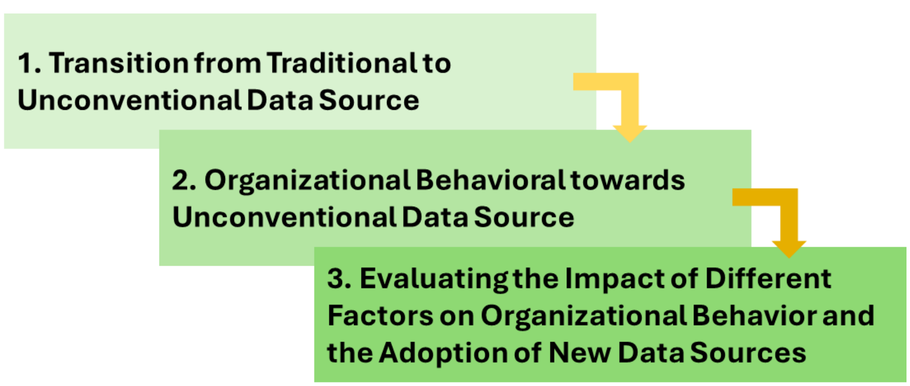

Figure 2: Key Themes Covered During the Workshop Session

As shown in Figure 2, the session focused on three main themes. Presentation was developed using project results from this study as well as a related Wisconsin-based study conducted by the team one year prior, which explored the use of crowdsourced data in pedestrian and bicyclist modeling. To promote interaction, several live poll questions were posed to participants:

1. How do you currently collect data for your projects? (select all that apply)
    a. Manual counts (e.g., pedestrians, bicycles)
    b. Automated traffic counters
    c. Accident reports
    d. Road design and infrastructure data
2. Where do you allocate most of your data collection effort?
    a. Planning and initial stages
    b. Ongoing monitoring
    c. Post-implementation reviews
3. How familiar are you with emerging data source?
    a. Very familiar
    b. Somewhat familiar
    c. Not very familiar
    d. Not familiar at all
4. What major limitations do you face (or anticipate facing) with emerging data sources? (Select all that apply)
    a. Technical challenges
    b. Privacy concerns
    c. Data reliability
    d. Integration with existing systems
5. What benefits have you observed (or anticipate observing) by using emerging data sources? (Select all that apply)
    a. Improved accuracy of information
    b. Enhanced decision-making capabilities
    c. Cost reductions
    d. Increased safety measures

Appendix B includes selected slides from the conference presentation.

4. Survey Result Analysis

4.1. Basic Information about Survey Respondents and Organizational Context

A total of 54 survey responses were initially received. After excluding incomplete responses and filtering out participants who indicated no experience working in the field of active transportation or with related data, 31 valid responses were kept for analysis. These responses represent a diverse group of professionals actively engaged in the use of emerging data sources for active transportation planning and safety initiatives. The 31 valid responses came from 26 different state DOTs, along with the District of Columbia, reflecting broad geographic representation and varied agency perspectives. Figure 3 presents the distribution of responses across DOTs, with the number of responses from each state shown in parentheses.

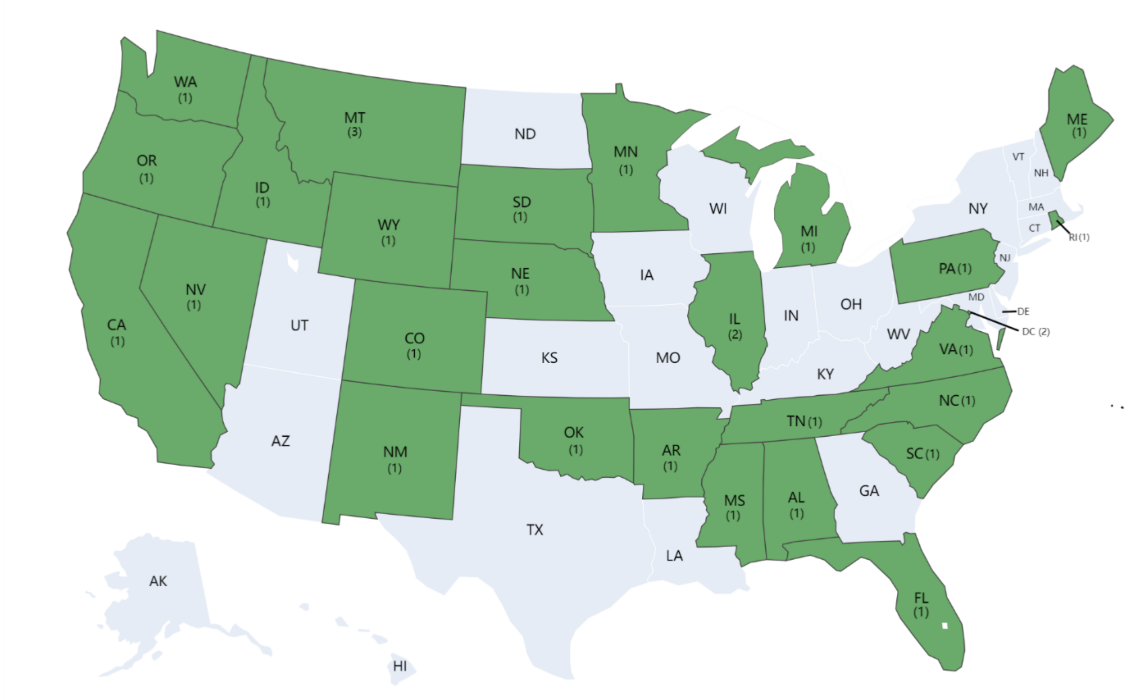

Figure 3: Respondents by state (states shown in green; number of responses indicated in parentheses)

Table 2 summarizes the respondents' job roles and their levels of experience with non-motorist data. Based on the results, the most common job category among respondents was planner, engineer, or designer, representing 41.9% (13 individuals). Program managers made up 29.0% (9), followed by program coordinators at 22.6% (7). A smaller share, 6.5% (2 individuals), identified as data scientists or analysts.

In terms of experience with non-motorist data, nearly half of the respondents (48.4%) reported having moderate experience, while 32.3% indicated limited experience. An additional 19.3% reported extensive experience. No participants selected "no experience," as those responses (n = 4) were excluded during data cleaning. This distribution indicates that most respondents had meaningful familiarity with non-motorist data, supporting the reliability and relevance of their input for the goals of this study.

Table 2: Characteristics of the respondents (n = 31)

Variables	Values	Frequency	Percentage
Job Role	Planner / Engineer / Designer	13	41.9%
	Program Manager	9	29.0%
	Program Coordinator	7	22.6%
	Data Scientist / Analyst	2	6.5%
Experience with Non-Motorist Data	No Experience	0	0.0%
	Limited Experience	10	32.3%
	Moderate Experience	15	48.4%
	Extensive Experience	6	19.3%

In addition to participant background, Table 3 presents descriptive statistics on organizational use of emerging data sources, covering aspects such as duration of use, types of technologies employed, primary applications, perceived benefits, and funding sustainability. With the exception of questions on duration of use and funding sources, respondents were allowed to select multiple answers.

The results indicate that a majority of participants (64.2%) reported their agency had been using emerging data sources for more than two years. Another 21.5% had adopted them within the past one to two years, while 14.3% had used them for less than a year. The most commonly reported technologies included sensor technologies (61.3%) and image or video processing tools (51.6%), followed by mapping technologies (45.2%) and Internet of Things (IoT)-based tools (22.6%). Regarding primary applications, the most frequently cited use was for safety assessments and improvement (77.4%), followed by urban planning and development (64.5%) and research and development (45.2%). Less commonly reported applications included traffic management (16.1%) and public engagement and feedback (12.9%). The relatively low usage of emerging data for public engagement suggests that agencies may not yet be fully leveraging these tools to gather public input or assess community needs.

Respondents also identified a range of perceived benefits associated with emerging data sources. Enhanced decision-making capabilities were the most frequently reported advantage (74.2%), underscoring the role of these tools in supporting more timely and informed planning. Other commonly cited benefits included improved data accuracy and reliability (41.9%), increased operational efficiency (38.7%), and cost savings (32.3%). These findings indicate that many agencies view emerging data not merely as a supplement to traditional methods, but as a strategic asset that can improve overall performance and resource allocation in active transportation planning.

In terms of funding sustainability, over half of respondents (53.5%) indicated that securing stable funding remains a challenge for supporting emerging data initiatives. While 25.0% reported having access to sustainable internal funding, 21.5% relied primarily on external funding sources. These results suggest that, although some agencies have established stable funding mechanisms, many continue to face financial uncertainty in planning and maintaining emerging data programs.

Table 3: Descriptive Statistics on DOTs' Adoption and Perceptions of Emerging Data Sources in Active Transportation

Category	Item	Frequency	Percentage
Duration of Emerging Data Use in the Organization	6 Months to 1 Year	4	14.3%
	1 to 2 Years	6	21.5%
	More than 2 Years	18	64.2%
Technologies Used	Sensor Technologies (e.g., Counting Sensors)	19	61.3%
	Image and Video Processing	16	51.6%
	Mapping Technologies (Crowdsourced & High-Resolution Map Data)	14	45.2%
	Internet of Things (IoT)	7	22.6%
	Other	4	12.9%
Primary Applications of Emerging Data Sources	Safety Assessments and Improvement	24	77.4%
	Urban Planning and Development	20	64.5%
	Research and Development	14	45.2%
	Traffic Management and Control	5	16.1%
	Public Engagement and Feedback	4	12.9%
	Others (please specify)	4	12.9%
Perceived Benefits of Emerging Data Sources	Enhanced Decision-making Capabilities	23	74.2%
	Improved Data Accuracy and Reliability	13	41.9%
	Increased Efficiency	12	38.7%

Category	Item	Frequency	Percentage
	Cost Savings	10	32.3%
	Other	8	25.8%
Funding Sustainability for Emerging Data Usage	Lack of Sustainable Funding	15	53.5%
	Sustainable Internal Funding	7	25.0%
	Supplemented by External Funding	6	21.5%

4.2 Measurement Model Assessment

This section presents the results from the third part of the survey, which focused on key internal and external factors influencing the adoption of emerging data sources in active transportation. The goal is to examine how these factors affect respondents' attitudes toward adoption, their agency's behavioral intention, and the actual integration of emerging data sources into organizational practices. To test the proposed model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied. This method was implemented in R using the plspm package, which supports path modeling with latent variables through a variance-based approach. This method was selected due to its suitability for small to medium sample sizes and its ability to handle non-normal data distributions, making it a practical alternative to traditional covariance-based SEM techniques (Hair et al., 2011).

Before evaluating the structural model and testing the significance of the hypothesized relationships, it is essential to first assess the measurement model to ensure that the latent constructs are measured reliably and validly. This involves evaluating internal consistency, convergent validity, and discriminant validity to confirm that the indicators accurately represent the underlying theoretical concepts (Verma et al., 2018). Table 4 presents the results of the measurement model assessment, including descriptive statistics and key validity indicators for each construct. Specifically, the table shows the mean, standard deviation (SD), Cronbach's alpha (CA), composite reliability (CR), average variance extracted (AVE), and the correlation matrix between constructs.

Table 4: Construct Reliability, Validity, and Correlation Matrix

Construct	Mean	SD	CA	CR	AVE	OS	EE	PC	PB	FND	ATT	LUI	BI
OS	4.06	1.35	0.71	0.87	0.77	**0.877**							
EE	3.59	0.95	0.60	0.84	0.72	0.541	**0.849**						
PC	4.69	1.11	0.68	0.88	0.78	0.472	0.365	**0.883**					
PB	4.98	0.96	0.68	0.86	0.76	0.491	0.446	0.493	**0.872**				
FND	3.48	1.42	0.75	0.89	0.8	0.499	0.186	0.604	0.254	**0.894**			
ATT	4.0	1.14	0.76	0.89	0.81	0.876	0.424	0.522	0.334	0.514	**0.900**		
LUI	3.2	1.24	0.62	0.84	0.73	0.547	0.236	0.696	0.465	0.681	0.541	**0.854**	
BI	4.2	1.2	0.85	0.93	0.87	0.741	0.440	0.441	0.290	0.488	0.816	0.554	**0.933**

Note: SD=standard deviation, CA=Cronbach's alpha, CR=Composite reliability and AVE=Average variance extracted.

To assess internal consistency, two widely used indicators, Cronbach's alpha and Composite Reliability (CR), were employed. Cronbach's alpha measures how closely related a set of items are as a group, reflecting the coherence of each construct's measurement. While a threshold of 0.70 or higher is typically recommended, values above 0.60 are generally considered acceptable in exploratory research (Gottems et al., 2018). In our case, Cronbach's alpha values for all constructs ranged from 0.60 to 0.85, indicating acceptable levels of reliability. To complement this, composite reliability (CR) was also used as it accounts for the individual loadings of indicators, offering a more accurate assessment of internal consistency. All CR values exceeded the recommended threshold of 0.70, confirming that the observed items reliably measure their respective constructs (Schuberth, 2021). Convergent validity was also assessed using average variance extracted (AVE). All constructs demonstrated AVE values above the 0.50 threshold, indicating that a substantial portion of variance in the indicators is explained by the underlying construct (Purwanto & Sudargini, 2021). This supports the conclusion that the indicators are appropriately capturing their respective latent variables.

To examine discriminant validity, the Fornell–Larcker criterion was applied. This approach determines whether a construct is more strongly associated with its own indicators than with those of other constructs. According to this method, the square root of the AVE for each construct should be greater than its correlations with all other constructs (Fornell & Larcker, 1981). As shown in Table 4, this condition was met for all constructs. The square root of the AVE (displayed on the diagonal of the correlation matrix) was greater than the correlations between constructs, indicating that each construct is empirically distinct and demonstrates adequate discriminant validity. These findings confirm that the constructs are valid, conceptually distinct, and provide a strong foundation for analyzing the structural relationships in the next section.

In addition to reliability and validity assessments, the mean scores of each construct provide useful insights into respondents' overall perceptions. Among the eight constructs, Perceived Benefits (PB) had the highest mean score (4.98), suggesting strong agreement among participants regarding the value of emerging data sources, particularly in terms of cost-effectiveness and safety enhancement. This was followed by Pressure from Competitors/Customers (PC), with a mean score of 4.69, indicating that respondents felt a high level of competitive pressure and peer influence from other agencies to adopt emerging data sources. Behavioral Intention to Use (BI) and Organizational Support (OS) also showed relatively high means of 4.20 and 4.06 respectively, indicating general readiness within agencies and support from leadership. In contrast, lower mean scores were observed for Effort Expectancy (EE) at 3.59 and Funding (FND) at 3.48, suggesting that respondents may perceive practical or resource-related barriers to implementation. The lowest mean was reported for Level of Usage and Integration (LUI) at 3.20, which implies that although attitudes and intentions are positive, full operational integration of emerging data sources remains limited in many agencies. These patterns highlight a gap between perceived value and actual usage, reinforcing the importance of addressing organizational capacity and resource constraints.

Finally, to assess indicator reliability, the outer loadings of the measurement items were examined. Outer loadings reflect the extent to which each observed item correlates with its underlying latent construct. According to Hair et al. (2017), an outer loading of 0.708 or higher is considered ideal, as it indicates that the construct explains more than 50% of the variance in that indicator. However, loadings between 0.50 and 0.708 are still acceptable if the overall construct meets the criteria for composite reliability and convergent validity (Hair et al., 2017; Rasoolimanesh & Ali, 2018).

Table 5: Factor loading

Construct	Item	Loading	T-value
Organizational Support	OS1	0.766	4.579
	OS2	0.715	4.186
Effort Expectancy	EE1	0.99	1.149
	EE2	0.214	0.801
Pressure from Competitors/Customers	PC1	0.969	5.668
	PC2	0.588	3.182
Perceived Benefits	PB1	0.541	2.886
	PB2	0.95	5.376
Funding	FND1	0.806	4.637
	FND2	0.755	4.288
Attitude Toward New Data Sources	ATT1	0.739	4.407
	ATT2	0.831	5.187
Level of Usage and Integration	LUI1	0.563	3.046
	LUI2	0.808	4.58
Behavioral Intention to Use	BI1	0.747	4.464
	BI2	0.980	6.936

As shown in Table 5, the majority of items demonstrated satisfactory outer loadings. Several indicators, including PC1 (0.969), PB2 (0.950), and BI2 (0.980), exhibited strong item-to-construct relationships. Items such as FND1, ATT2, and OS1 also exceeded the recommended threshold of 0.708, further supporting indicator reliability. While a few indicators had loadings below 0.70 (but above the minimum acceptable threshold of 0.50), specifically PC2 (0.588), PB1 (0.541), and LUI1 (0.563), they were retained in the model because they were statistically significant and theoretically meaningful. Moreover, the constructs to which these items belong satisfied all other validity criteria, including composite reliability and average variance extracted (AVE), thereby supporting convergent validity. In contrast, the Effort Expectancy (EE) construct was removed from the final structural model. Although EE1 had a high loading (0.990), its corresponding t-value (1.149) was not statistically significant. EE2 also demonstrated a very low loading (0.214). Since neither item met the required thresholds for indicator reliability or significance, the EE construct was excluded to maintain the overall measurement quality of the model.

4.3 The Structural Model

As noted earlier, PLS-SEM was used to evaluate the significance of the hypothesized relationships, employing a bootstrapping procedure with 1,000 resamples. Bootstrapping is a non-parametric resampling method that estimates the precision and stability of path coefficients by repeatedly drawing samples with replacement. This approach allows for the calculation of t-values and confidence intervals without assuming a normal distribution of the data.

Table 6 summarizes the structural model results, including path coefficients, t-values, and significance levels. The results indicate that Organizational Support (OS) had a strong and statistically significant effect on Attitude Toward New Data Sources (ATT) ($\beta = 0.8501$, $t = 6.93$, $p < 0.001$), supporting H1. Additionally, the path from Pressure from Competitors/Customers (PC) to ATT was significant ($\beta = 0.2233$, $t = 1.78$, $p = 0.0895$), supporting H3 at the 90% confidence level. The effect of ATT on Behavioral Intention (BI) was also statistically significant and strong ($\beta = 0.8204$, $t = 7.17$, $p < 0.001$), as was its effect on Level of Usage and Integration (LUI) ($\beta = 0.5697$, $t = 3.47$, $p = 0.0019$), supporting H6 and H7, respectively. In contrast, the paths from Perceived Barriers (PB) ($\beta = -0.1573$, $t = -1.37$, $p = 0.186$) and Funding (FND) ($\beta = 0.0021$, $t = 0.02$, $p = 0.987$) to ATT were not statistically significant, and thus H2 and H4 were not supported. Beyond significance levels, the signs of the path coefficients offer additional insight into the nature of relationships. Positive coefficients (e.g., OS → ATT, PC → ATT, ATT → BI, and ATT → LUI) suggest that increases in the predictor variables are associated with increases in the outcome variables. For instance, greater organizational support and external pressure are associated with more favorable attitudes, which in turn drive stronger intentions and greater usage of emerging data sources.

Table 6: Structural Model Results

Hypothesis	Path	Coefficient	T-value	Significance (p-value)	Support
H1	OS → ATT	0.8501	6.93	< 0.001*	Yes
H2	FND → ATT	0.0021	0.02	0.987	No
H3	PC → ATT	0.2233	1.78	0.0895**	Yes
H4	PB → ATT	-0.1573	-1.37	0.186	No
H5	EE→ AT	-	-	-	-
H6	ATT → BI	0.8204	7.17	< 0.001*	Yes
H7	ATT → LUI	0.5697	3.47	0.0019*	Yes

* >95% level of significance.
** >90% level of significance.

The model also demonstrated strong explanatory power, accounting for 80.6% of the variance in Attitude (ATT), 67.3% in Behavioral Intention (BI), and 32.5% in Level of Usage and Integration (LUI). These R^2 values suggest that the model is particularly effective in explaining organizational attitudes and intentions toward adopting emerging data sources.

4.4 Discussion

To further interpret the findings, a closer examination of key constructs was conducted, focusing on both the respondents' average perceptions and the strength of their effects within the structural model.

Based on the results OS emerged as one of the most important predictors in the model. With a mean score of 4.06, it reflects a generally positive perception of internal readiness to adopt emerging data sources. OS was measured using two indicators: OS1, which captures top management's interest in adoption, and OS2, which reflects staff proficiency and the availability of support. The high and significant path coefficient from OS to Attitude ($\beta = 0.8501$, $p < 0.001$) suggests that levels of leadership engagement and internal capacity have a strong influence on shaping positive organizational attitudes. These findings highlight that institutional endorsement and technical readiness are not just present but are critical drivers of how new data technologies are perceived within agencies.

Pressure from Competitors/Customers (PC) also had a relatively high mean score of 4.69, indicating that agencies are experiencing external pressure to modernize their practices. PC was measured by PC1, which gauges expectations from key partners, and PC2, which captures observed adoption among peer DOTs. The positive and significant path to Attitude (ATT) ($\beta = 0.2233$, $p = 0.0895$) suggests that peer influence and industry trends may contribute meaningfully to the formation of favorable attitudes toward new data tools, particularly in competitive or collaborative environments. Although DOTs operate in the public sector, they are nonetheless influenced by market-driven dynamics, including the practices of commercial partners and technology vendors. This external pressure may lead agencies to align with industry standards, follow the best practices adopted by others, and avoid falling behind in data-driven decision-making.

On the other hand, Funding (FND) received a relatively low average score of 3.48, indicating that many respondents perceive funding as a barrier to adopting and integrating emerging data sources. The construct was measured using FND1, which reflects the agency's efforts to seek external funding, and FND2, which assesses whether the agency actively monitors return on investment (ROI) from allocated funding. These items suggest that respondents may not feel their organizations are consistently pursuing or managing funding streams for innovation. Despite this perception, the path from FND to Attitude Toward New Data Sources (ATT) was not statistically significant ($\beta = 0.0021$, $p = 0.987$), pointing to a disconnect between perceived funding challenges and actual influence on organizational attitudes. This may imply that while funding is a concern, it does not directly shape how agencies attitude about emerging data sources unless it interacts with other factors such as leadership support or staff readiness. Another explanation is that many emerging data sources are now accessible at low or no cost, thereby lowering the financial barrier to entry. For instance, platforms like Strava Metro and OpenStreetMap (OSM) offer valuable data with no cost. Furthermore, access through partnerships, pilot programs, or research collaborations often reduces the need for dedicated internal funding. However, the effective use of such resources still requires internal capacity, such as proficient staff, technical infrastructure, and institutional support. Therefore, while funding concerns are evident in the descriptive statistics, their direct statistical impact on attitudes may be limited by the growing accessibility of low-cost data and the greater importance of organizational readiness.

Perceived Benefits (PB) had the highest average score among all constructs, with a mean of 4.98, indicating strong agreement among respondents regarding the value of emerging data sources. PB was measured using two items: PB1, which captures the perception that emerging data sources are a cost-effective alternative to traditional methods, and PB2, which reflects their perceived role in enhancing vulnerable road user (VRU) safety. This high mean suggests that respondents widely recognize the practical and strategic advantages of adopting such data sources, particularly in improving safety outcomes and reducing costs. However, the corresponding path from PB to ATT was not statistically significant ($\beta = -0.1573$, $p = 0.186$), indicating that despite strong belief in the benefits, these perceptions alone do not strongly shape organizational attitudes toward adoption. This may reflect a situation where recognition of value is not enough to change behavior unless other enabling conditions, such as organizational support, external pressure, or internal capacity, are also present. This is especially relevant for organizations in the public sector, where decision-making often involves institutional inertia, multiple layers of accountability, and limited flexibility to act on perceived benefits alone. In essence, while agencies acknowledge the strategic promise of emerging data sources, this recognition may not fully translate into attitude shifts without the structural or institutional means to implement meaningful change.

Attitude Toward Emerging Data Sources (ATT), Behavioral Intention to Use (BI), and Level of Usage and Integration (LUI) represent the core outcome constructs in the model, each offering insight into how organizational perceptions translate into action. ATT, with a mean score of 4.00, reflects a generally neutral stance among respondents and their organizations toward new data sources. It was measured using ATT1, which captures overall positivity within the agency, and ATT2, which assesses whether financial resources are allocated to support adoption. While the average perception is neutral, ATT plays a central role in the model, as shown by its strong and statistically significant paths to both BI ($\beta = 0.8204$, $p < 0.001$) and LUI ($\beta = 0.5697$, $p = 0.0019$), suggesting that when attitudes are favorable, they are strongly associated with both the intention to adopt and early steps toward integration.

BI, with a slightly higher mean of 4.20, indicates that organizations are generally inclined to continue using emerging data sources, reflecting a sense of commitment and institutional momentum. This construct was measured using BI1, which captures long-term intent, and BI2, which assesses readiness to support staff during the transition. In contrast, LUI received the lowest mean score of 3.20, indicating that most agencies have not yet fully implemented or formalized their use of emerging data sources. This construct was measured using LUI1 (plans to increase budgets for integration) and LUI2 (presence of comprehensive policies or guidelines). The low score suggests that while many agencies intend to continue using emerging data sources, this usage is likely not yet occurring at a large scale or in a fully integrated, institutionalized way. In many cases, emerging data may be used in isolated projects or pilot programs, rather than as a standard part of agency operations or decision-making workflows.

These results confirm that attitude functions as a key mediating construct between organizational drivers (such as OS and PC) and downstream outcomes like behavioral intention and integration. They also highlight a common challenge in public sector innovation: agencies may recognize the value of emerging data sources and express a willingness to adopt them, but actual large-scale integration is often hindered by structural limitations, bureaucratic processes, or resource gaps.

Therefore, translating intention into widespread and sustained practice requires not only favorable attitudes but also long-term investment, cross-agency coordination, and internal capacity building efforts. Another important point is that strong leadership support and a skilled staff are essential for building a positive attitude within agencies. When staff members have the tools and knowledge to work with new data sources, they are more likely to support their use and help integrate them into practice. The findings also challenge a common assumption about the role of funding. While many believe that funding is the main barrier, the model shows that it does not directly shape attitudes toward adoption. This suggests that internal readiness and pressure from peer agencies matter more than simply having financial resources. In other words, even with limited funding, agencies that are well-organized, supportive of innovation, and equipped with capable staff are more likely to move forward in adopting new data practices. However, a gap remains between positive intentions and full integration. Bridging this gap requires more than just favorable attitudes, it demands long-term coordination across departments, ongoing staff training, and a sustained effort to build internal capacity for using and managing emerging data sources effectively.

5. Results of Workshop

As part of the 2024 Texas Trails and Active Transportation (TTAT) Conference, a one-hour workshop session was conducted to present preliminary findings and engage participants in a series of interactive poll questions related to their experiences with data collection and the use of emerging data sources in active transportation planning. Approximately 20–30 individuals attended the session, the majority of whom were from the public sector in Texas, with a few participants joining from other states. Figure 4 illustrates the workshop presentation and interactive engagement activities conducted during the session.

Figure 4: Workshop Engagement and Interactive Polling at the 2024 Texas Trails and Active Transportation Conference

The poll results provided valuable qualitative insights that complemented the survey findings and highlighted current practices, challenges, and perceptions among professionals in the field.

Current Data Collection Methods: Participants were asked how they currently collect data for their projects. Manual counts (e.g., pedestrians, bicycles) emerged as the most frequently used method, selected by 15 respondents. Accident reports followed with 10 selections, while automated traffic counters and road design/infrastructure data were each selected by 8 participants.

These responses indicate that while traditional methods are still prevalent, some agencies are beginning to diversify their data sources through automation and infrastructure-based information.

Focus of Data Collection Effort: When asked where most data collection efforts are focused, the vast majority (13 respondents) indicated the planning and initial stages of projects. Only 3 participants cited ongoing monitoring, and just 2 reported a focus on post-implementation reviews. This suggests a gap in continuous data tracking and evaluation that could otherwise support more adaptive and evidence-based planning.

Familiarity with Emerging Data Sources: Participants were also asked about their familiarity with emerging data sources such as crowdsourced data, computer vision, and IoT. Most respondents (13) described themselves as somewhat familiar, while only one individual reported being very familiar. Meanwhile, 6 participants indicated low familiarity (4 not very familiar and 2 not familiar at all). These findings highlight the need for increased awareness, training, and outreach to improve comfort and proficiency with emerging technologies.

Perceived Limitations: Regarding perceived challenges, the top concern was data reliability (11 responses), followed by privacy concerns (9), integration with existing systems (6), and technical challenges (5). These results reflect common institutional and operational barriers to the adoption of unconventional data and suggest that agencies may benefit from clearer data standards and stronger cross-system compatibility.

Perceived Benefits: Finally, when asked about benefits observed or anticipated from using emerging data sources, enhanced decision-making capabilities was by far the most selected response (17 participants), followed by improved accuracy of information (10). Fewer respondents cited cost reductions (4) or increased safety measures (3). This implies that, at present, the value of emerging data is perceived more in terms of analytical and planning improvements than immediate operational or financial outcomes.

These workshop results reinforce the survey's findings and demonstrate both interest and hesitation in the adoption of emerging data sources. The poll insights will inform the final recommendations by identifying gaps in familiarity, priorities in application, and barriers to broader organizational change.

6. Conclusion

This study explored the organizational and contextual factors, including funding, that influence the adoption and integration of emerging data sources within state DOTs, with a particular focus on applications in active transportation. Using a hybrid framework that combines the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework, the study examined how internal drivers (e.g., organizational support, funding) and external influences (e.g., Competitors/Customers pressure, perceived benefits) shape agency attitudes, behavioral intentions, and implementation outcomes.

The survey and structural equation modeling results revealed that organizational support was the most influential factor in shaping attitudes toward adoption, highlighting the importance of leadership engagement and internal capacity. Pressure from peer agencies and stakeholders also played a meaningful role, suggesting that competitive or collaborative influences can drive innovation. While perceived benefits were rated highly by respondents, their influence on attitude was not statistically significant, indicating that recognition of value alone is insufficient without organizational readiness. Moreover, funding, often considered a key barrier, did not significantly impact attitudes in this model, reinforcing the idea that internal culture and leadership may outweigh financial concerns when it comes to adoption. Based on the survey and workshop results, despite a generally positive outlook on emerging data sources and strong behavioral intentions to use them, actual integration within transportation agencies remains limited, as reflected by the low mean score for usage. This gap suggests that favorable perceptions alone are insufficient; sustained integration will require deliberate investments in staff training, workflow adaptation, and long-term resource planning.

Based on the findings from both the survey and workshop engagement, it is evident that while transportation agencies demonstrate strong interest and behavioral intention to adopt emerging data sources, the actual integration of these tools into daily practice remains limited. This gap underscores the need for a comprehensive, multi-faceted strategy that extends beyond positive attitudes and addresses structural, technical, and organizational barriers. The following recommendations are offered to support transportation agencies and policymakers in advancing the adoption and sustained use of emerging data sources in active transportation planning:

1. Strengthen Organizational Support and Internal Capacity

The analysis revealed that organizational support was the most significant predictor of positive attitudes toward emerging data sources. Agencies should actively engage leadership and invest in building technical capacity among staff. Empowering internal champions and providing access to training and support resources can help sustain long-term adoption.

2. Facilitate Peer Learning and Professional Collaboration
Workshop results showed that many practitioners are only somewhat familiar with emerging technologies. Participation in professional networks, conferences, and peer-to-peer forums can foster knowledge sharing, demystify new tools, and reduce implementation uncertainty through real-world case examples.

3. Prioritize Institutional Readiness Over Funding Alone
Although sustainable funding was identified as a challenge, it did not significantly predict organizational attitudes. This suggests that institutional readiness, including cross-departmental coordination, process alignment, and clearly defined protocols, may be more critical than funding alone in enabling adoption.

4. Embed Emerging Data Sources into Routine Practices
Survey responses revealed that the primary applications of emerging data sources are during urban planning and safety assessment phases. While these uses are valuable, maximizing their impact requires integrating such tools into ongoing monitoring, post-implementation reviews, and establishing effective feedback mechanisms, particularly those that capture the preferences and behaviors of non-motorists. This ensures that data-driven insights inform decision-making throughout the entire project lifecycle.

5. Expand Training and Outreach on Emerging Tools
Given the limited familiarity with many technologies, agencies should invest in targeted outreach efforts. Educational programs, technical assistance, and practical case studies can help build confidence, enhance usability, and support broader institutional uptake of emerging data practices.

This study was limited to data collected from 31 survey respondents and approximately 30 workshop participants. While these responses provided valuable insights, the relatively small sample size may limit the generalizability of the findings. Future research could benefit from a larger and more diverse sample to enhance statistical robustness and explore variation across agency types, regions, or levels of experience. Additionally, incorporating more complex structural models with additional constructs, such as perceived risk, stakeholder engagement, or data governance, may offer deeper insights into the nuanced organizational dynamics that influence adoption and integration of emerging data sources in transportation planning

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Appendix A: Survey Questionnaire

1. Do you currently work for a public transportation agency (e.g., city/county/regional government, MPO, or state DOT)?

- Yes
- No

2. Which agency are you affiliated with?
[Open text response]

3. Which of the following best matches your job role and responsibilities?

- Program Manager
- Program Coordinator
- Planner / Engineer / Designer
- Data Scientist / Analyst
- Other (please specify)

4. Which of the following best describes your experience with non-motorist (e.g., bicyclist, pedestrian) data?

- No Experience
- Limited Experience
- Moderate Experience
- Extensive Experience

5. Which of the following emerging data sources has your agency used for active (non-motorized) transportation?
(Select all that apply)

- Imaging and Video Processing
- Sensor Technologies (e.g., Counting Sensors)
- Mapping Technologies (Crowdsourced & High-Resolution Map Data)
- Internet of Things (IoT)
- Other
- No, we don't use any

6. How long has your agency been using emerging data sources for active transportation?

- Less than 6 Months

- 6 Months to 1 Year
- 1 to 2 Years
- More than 2 Years

7. What are the primary applications of emerging non-motorist data in your agency?
(Select all that apply)

- Traffic Management and Control
- Urban Planning and Development
- Safety Assessments and Improvement
- Public Engagement and Feedback
- Research and Development
- Other (please specify)

8. What are the primary benefits of emerging technologies in your role or organization?
(Select all that apply)

- Increased Efficiency
- Cost Savings
- Improved Data Accuracy and Reliability
- Enhanced Decision-Making Capabilities
- Other (please specify)

9. Please rate your level of agreement with the following statements:
(1 = Strongly Disagree, 7 = Strongly Agree)

- Top management shows a high level of interest in adopting emerging data sources.
- Our personnel are proficient in using emerging data sources, and/or support is readily available when needed.
- The time required to preprocess and utilize emerging data sources is manageable within our organization's capabilities.
- Using emerging data sources requires minimal additional time, resources, and training.
- Key partners expect our agency to actively adopt and integrate emerging data sources.
- Other state DOTs have utilized and continue to use emerging data sources effectively.
- Adopting emerging data sources is perceived as a cost-effective alternative to traditional data.
- The use of emerging data sources enhances VRU safety (e.g., identifying high-risk areas, offering real-time information, and enabling continuous safety monitoring for proactive planning).
- We actively seek external funding opportunities to support the adoption and integration of emerging data sources

- Our agency monitors the return on investment (ROI) from funding allocated to emerging data sources.
- The use of emerging data sources is widely perceived as positive within our agency.
- Our agency allocates sufficient financial resources to support the usage of emerging data sources/
- Plans are in place to increase the budget for further integration of emerging data sources.
- Our agency has a comprehensive policy (i.e. guidelines) for integrating emerging data sources.
- Our organization is committed to the continued use of emerging data sources
- Our agency is prepared to support staff through the transition to using emerging data sources

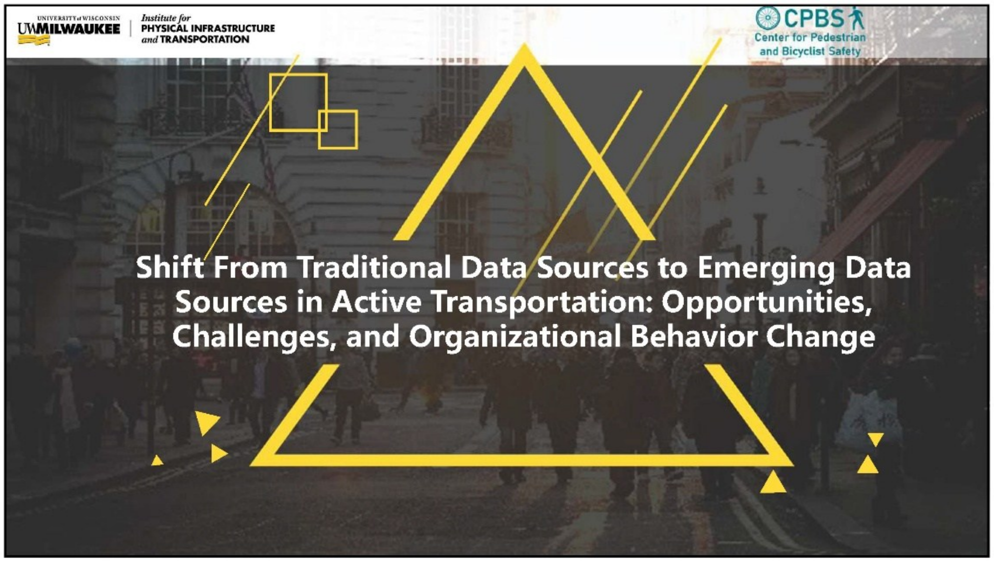
10. Is your agency able to sustain sufficient funding for continued use of emerging data?

- Yes, internal funding is sufficient
- No
- Yes, but we rely on external funding

11. Could you provide additional details about external funding opportunities that have helped your agency start or sustain the use of emerging data sources?
[Open text response]

12. Please share any final thoughts about your experience with emerging data sources or what you hope they will contribute to in the future.
[Open text response]

Appendix B: Sample Slides from Conference Presentation



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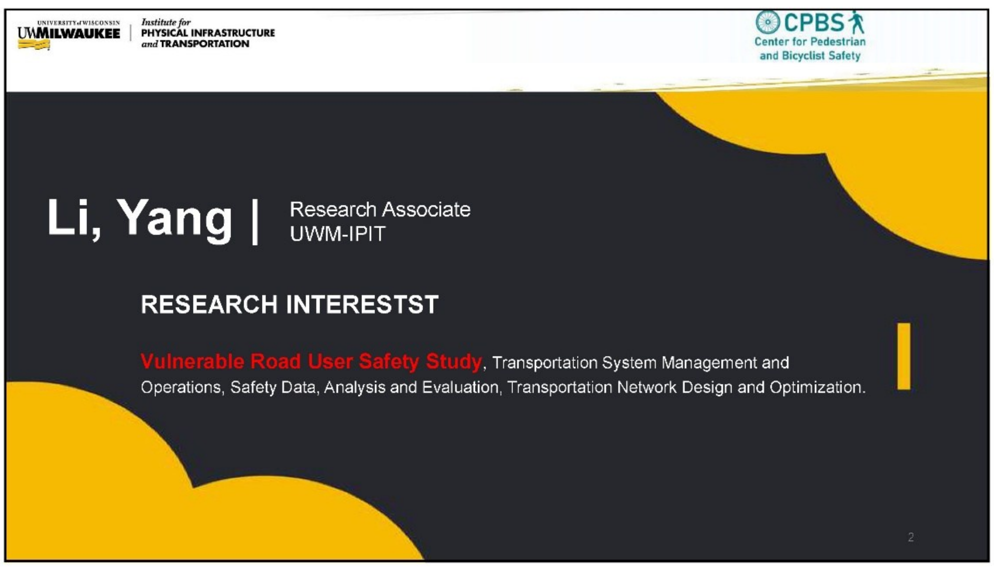

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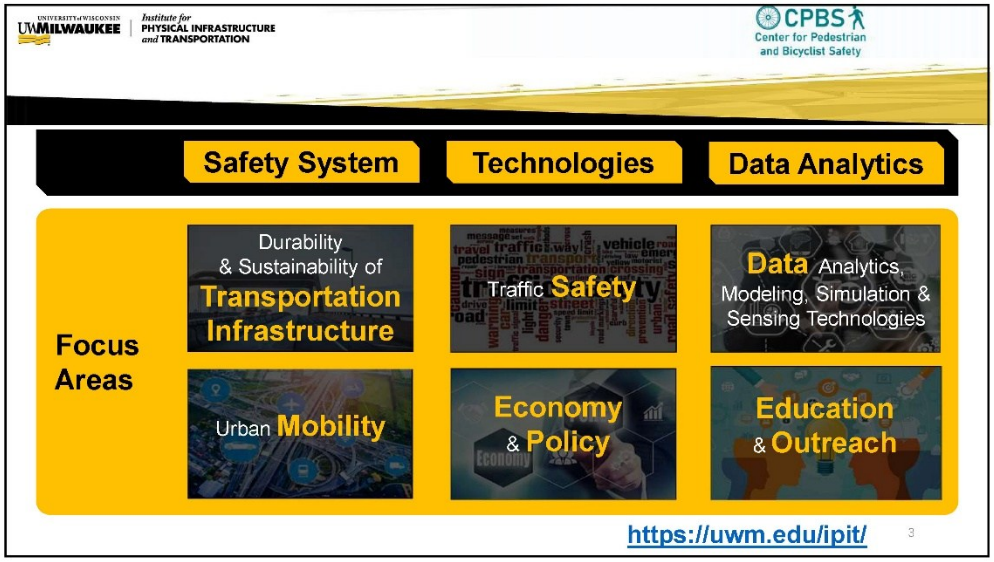

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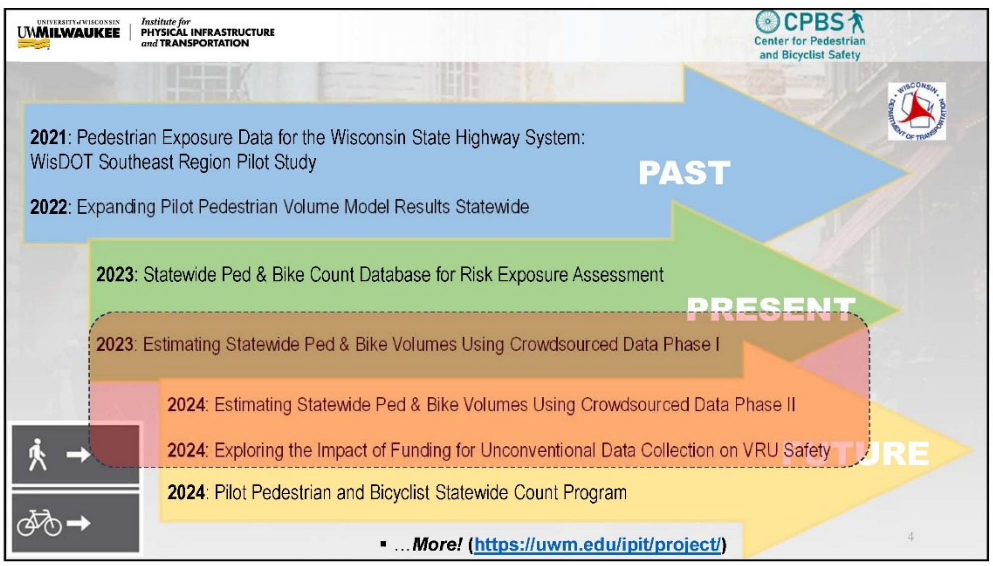
Data Analytics
Focus Areas
Durability & Sustainability of Transportation Infrastructure
Traffic Safety
Data Analytics, Modeling, Simulation & Sensing Technologies
Urban Mobility
Economy & Policy
Education & Outreach
https://uwm.edu/ipit/
3

3



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2021: Pedestrian Exposure Data for the Wisconsin State Highway System: WisDOT Southeast Region Pilot Study
2022: Expanding Pilot Pedestrian Volume Model Results Statewide
PAST
2023: Statewide Ped & Bike Count Database for Risk Exposure Assessment
PRESENT
2023: Estimating Statewide Ped & Bike Volumes Using Crowdsourced Data Phase I
2024: Estimating Statewide Ped & Bike Volumes Using Crowdsourced Data Phase II
2024: Exploring the Impact of Funding for Unconventional Data Collection on VRU Safety
FUTURE
2024: Pilot Pedestrian and Bicyclist Statewide Count Program
▪ …More! (https://uwm.edu/ipit/project/)
4

4


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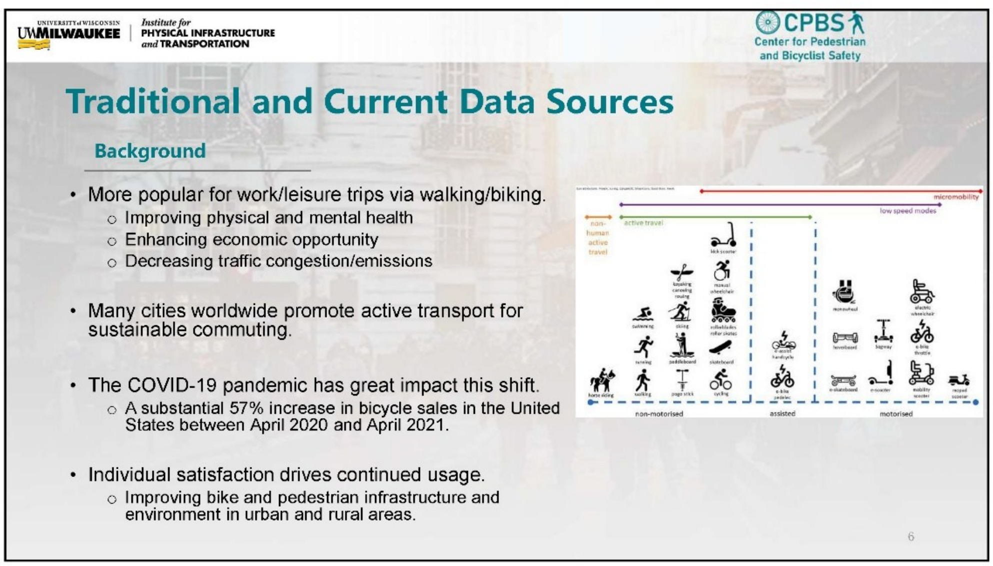
CONTENTS
Traditional And Current Data Sources
New Data in Active Transportation – Example of Crowdsourced Data
Organizational Decision-Making in New Data Sources Utilization
5

5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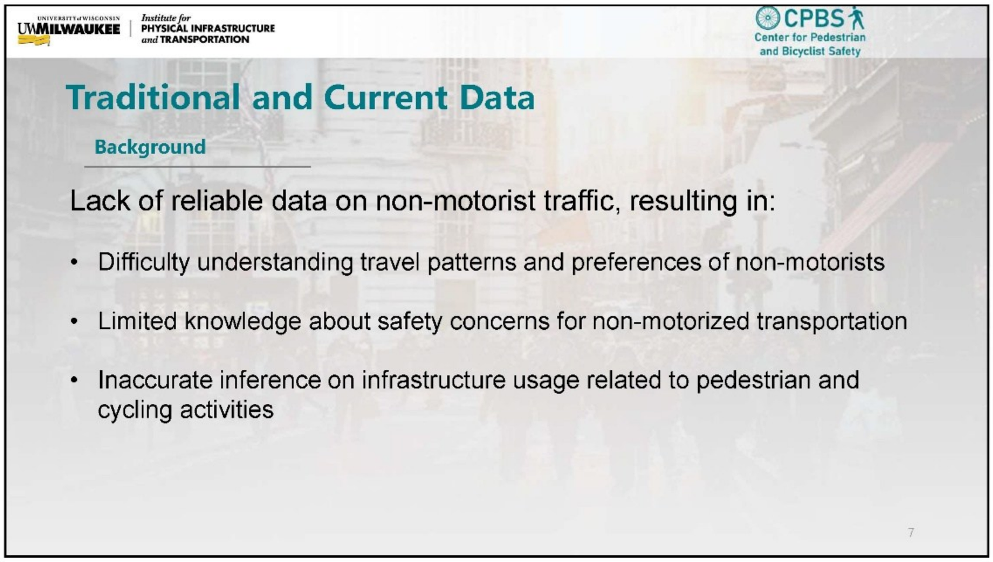
Traditional and Current Data Sources
Background
• More popular for work/leisure trips via walking/biking.
○ Improving physical and mental health
○ Enhancing economic opportunity
○ Decreasing traffic congestion/emissions
• Many cities worldwide promote active transport for sustainable commuting.
• The COVID-19 pandemic has great impact this shift.
○ A substantial 57% increase in bicycle sales in the United States between April 2020 and April 2021.
• Individual satisfaction drives continued usage.
○ Improving bike and pedestrian infrastructure and environment in urban and rural areas.
micromobility
low speed modes
active travel
non-human active travel
non-motorised
assisted
motorised
6

6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Traditional and Current Data
Background
Lack of reliable data on non-motorist traffic, resulting in:
• Difficulty understanding travel patterns and preferences of non-motorists
• Limited knowledge about safety concerns for non-motorized transportation
• Inaccurate inference on infrastructure usage related to pedestrian and cycling activities
7

7


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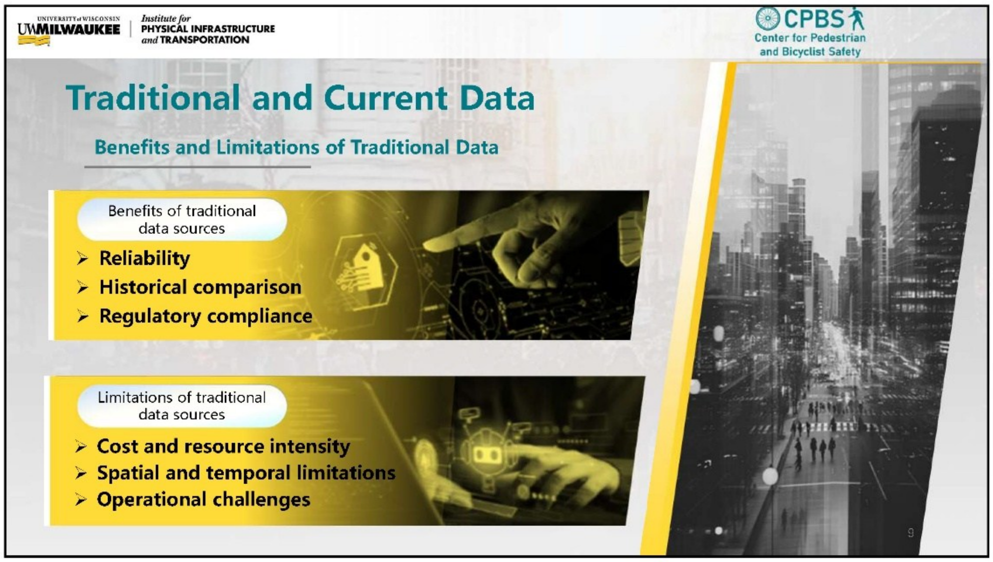
Traditional and Current Data
Overview of Traditional Data in Active Transportation
01
Manual counts (pedestrians, bicycles)
02
Automated traffic counters
03
Accident reports
04
Road design and infrastructure data
8

8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Traditional and Current Data
Benefits and Limitations of Traditional Data
Benefits of traditional data sources
➢ Reliability
➢ Historical comparison
➢ Regulatory compliance
Limitations of traditional data sources
➢ Cost and resource intensity
➢ Spatial and temporal limitations
➢ Operational challenges
9

9


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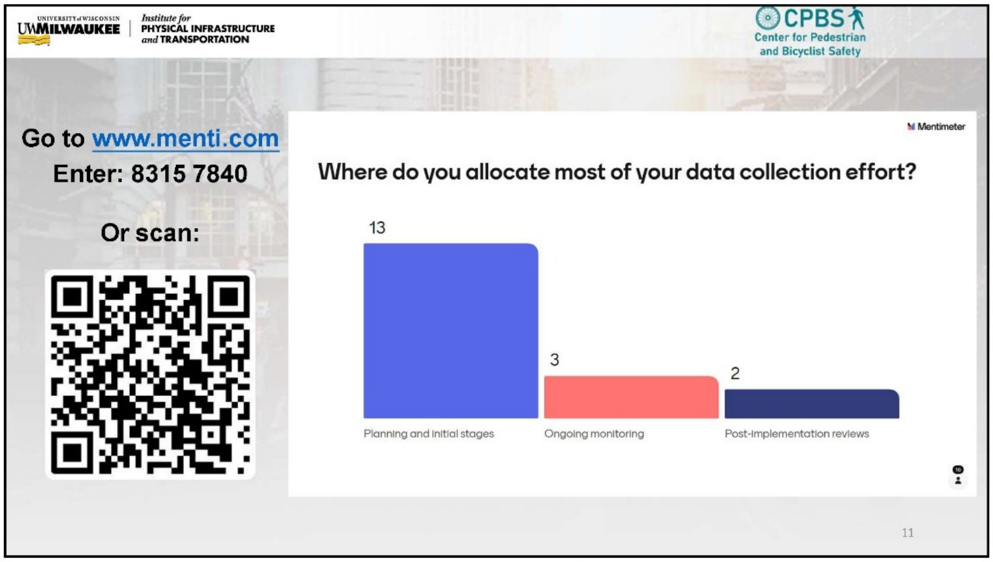
Go to www.menti.com
Enter: 8315 7840
Or scan:
Mentimeter
How do you currently collect data for your projects? (select all that apply)
15
8
10
8
Manual counts (e.g. pedestrians, bicycles)
Automated traffic counters
Accident reports
Road design and infrastructure data
10

10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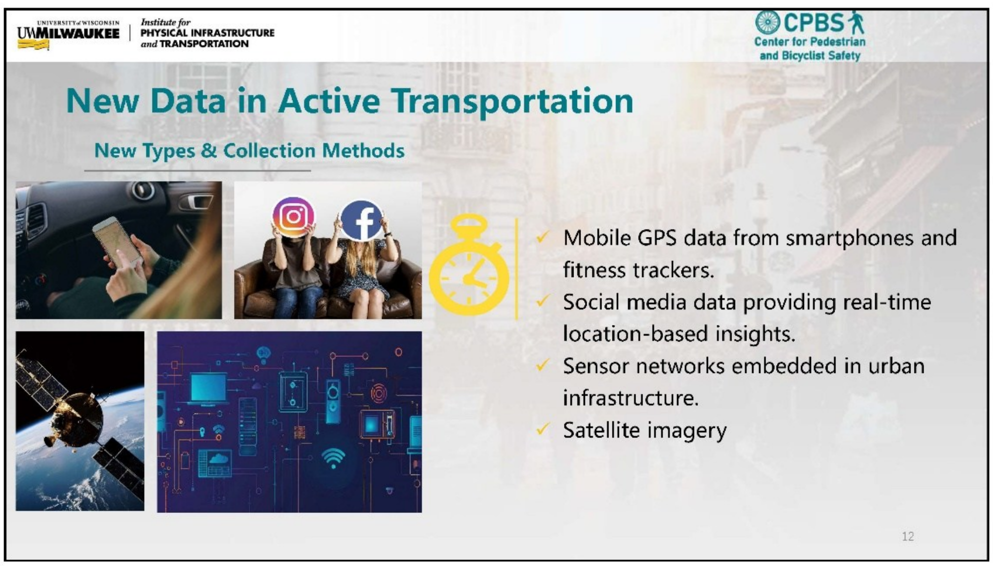
Mentimeter
Where do you allocate most of your data collection effort?
13
3
2
Planning and initial stages
Ongoing monitoring
Post-implementation reviews
11

11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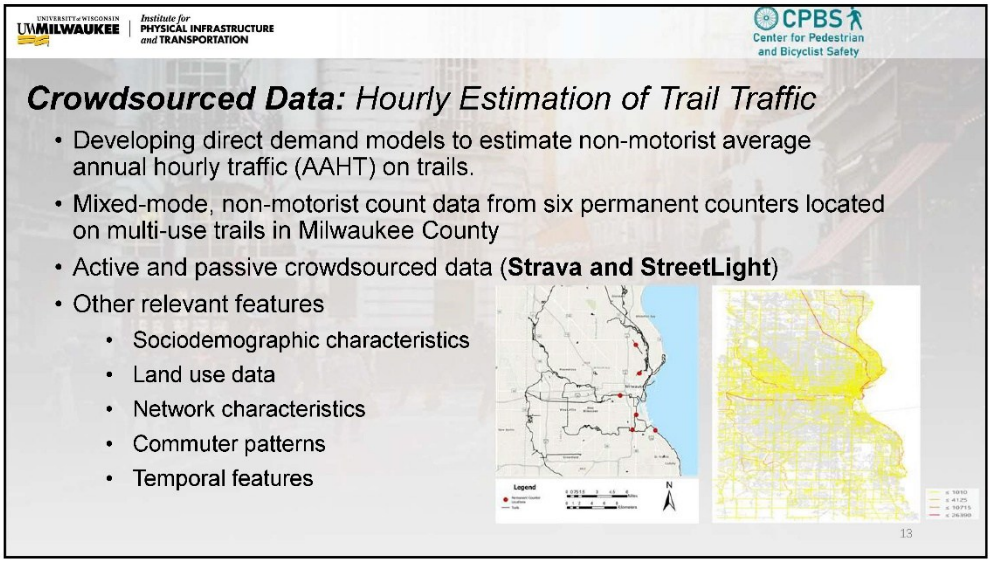
New Data in Active Transportation
New Types & Collection Methods
Mobile GPS data from smartphones and fitness trackers.
Social media data providing real-time location-based insights.
Sensor networks embedded in urban infrastructure.
Satellite imagery
12

12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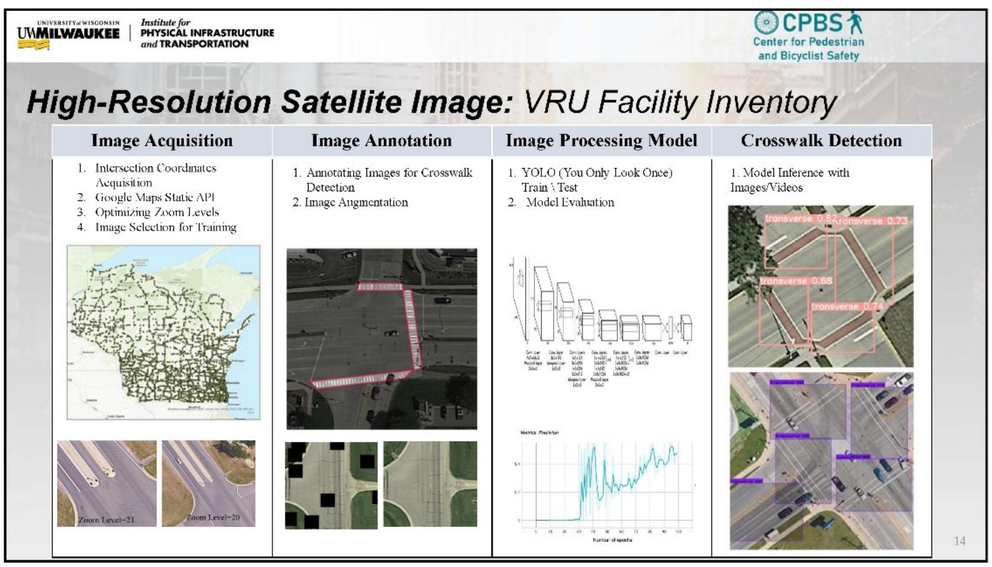
Crowdsourced Data: Hourly Estimation of Trail Traffic
• Developing direct demand models to estimate non-motorist average annual hourly traffic (AAHT) on trails.
• Mixed-mode, non-motorist count data from six permanent counters located on multi-use trails in Milwaukee County
• Active and passive crowdsourced data (Strava and StreetLight)
• Other relevant features
• Sociodemographic characteristics
• Land use data
• Network characteristics
• Commuter patterns
• Temporal features
Legend
13

13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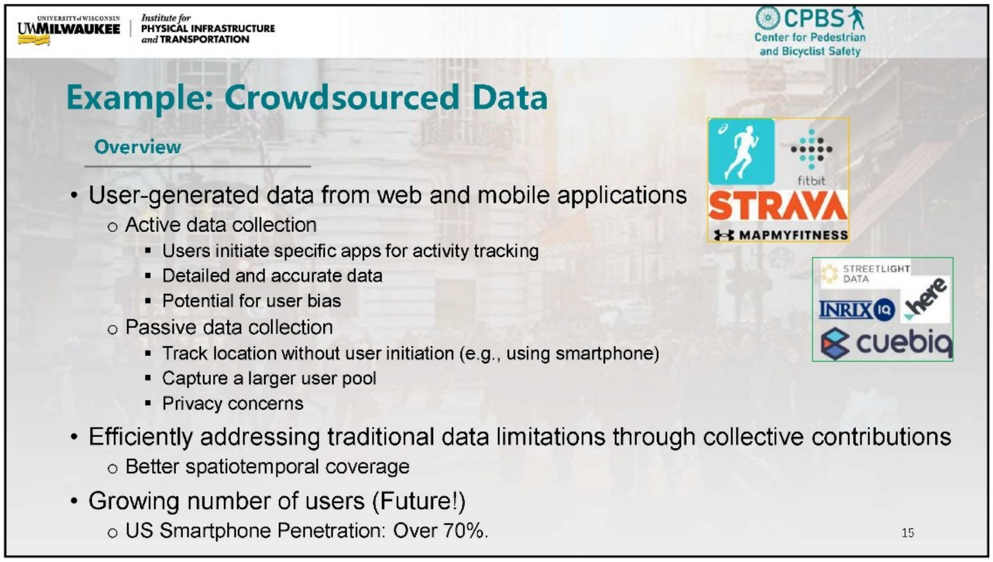
High-Resolution Satellite Image: VRU Facility Inventory
Image Acquisition
1. Intersection Coordinates Acquisition
2. Google Maps Static API
3. Optimizing Zoom Levels
4. Image Selection for Training
Zoom Level=21
Zoom Level=20
Image Annotation
1. Annotating Images for Crosswalk Detection
2. Image Augmentation
Image Processing Model
1. YOLO (You Only Look Once) Train \ Test
2. Model Evaluation
Crosswalk Detection
1. Model Inference with Images/Videos
transverse 0.73
transverse 0.68
transverse 0.74
14

14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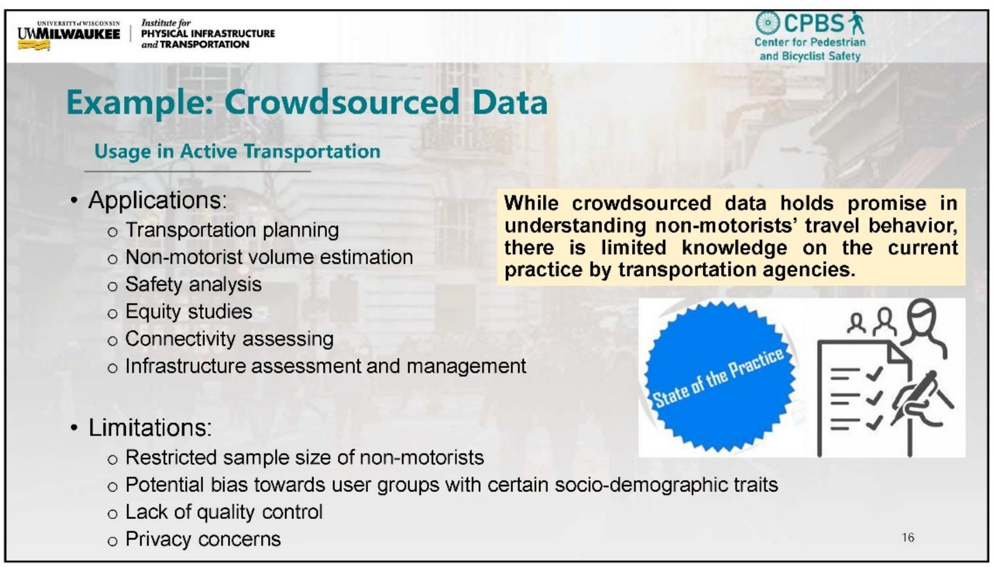
Example: Crowdsourced Data
Overview
• User-generated data from web and mobile applications
o Active data collection
▪ Users initiate specific apps for activity tracking
▪ Detailed and accurate data
▪ Potential for user bias
o Passive data collection
▪ Track location without user initiation (e.g., using smartphone)
▪ Capture a larger user pool
▪ Privacy concerns
• Efficiently addressing traditional data limitations through collective contributions
o Better spatiotemporal coverage
• Growing number of users (Future!)
o US Smartphone Penetration: Over 70%.
fitbit
STRAVA
MAPMYFITNESS
STREETLIGHT
DATA
INRIX IQ
here
cuebiq
15

15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Example: Crowdsourced Data
Usage in Active Transportation
• Applications:
o Transportation planning
o Non-motorist volume estimation
o Safety analysis
o Equity studies
o Connectivity assessing
o Infrastructure assessment and management
While crowdsourced data holds promise in understanding non-motorists' travel behavior, there is limited knowledge on the current practice by transportation agencies.
State of the Practice
• Limitations:
o Restricted sample size of non-motorists
o Potential bias towards user groups with certain socio-demographic traits
o Lack of quality control
o Privacy concerns
16

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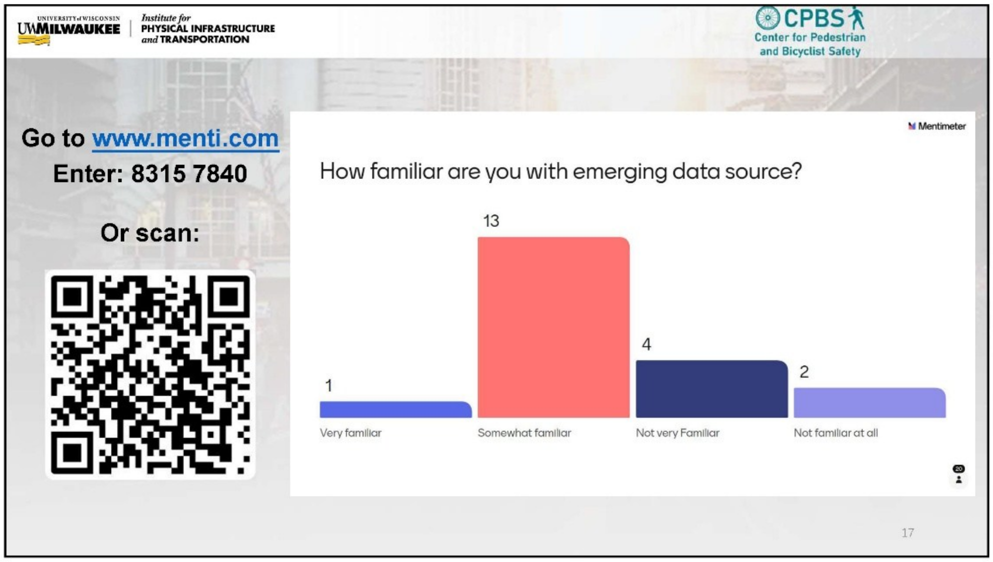
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Go to www.menti.com
Enter: 8315 7840
Or scan:
Mentimeter
How familiar are you with emerging data source?
1
13
4
2
Very familiar
Somewhat familiar
Not very Familiar
Not familiar at all
17

17


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Go to www.menti.com
Enter: 8315 7840
Or scan:
Mentimeter
What major limitations do you face (or anticipate facing) with emerging data sources? (Select all that apply)
5
9
11
6
Technical challenges
Privacy concerns
Data reliability
Integration with existing systems
18

18


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Go to www.menti.com
Enter: 8315 7840
Or scan:
Mentimeter
What benefits have you observed (or anticipate observing) by using emerging data sources? (Select all that apply)
10
17
4
3
Improved accuracy of information
Enhanced decision-making capabilities
Cost reductions
Increased safety measures
19

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National Survey
Scope & Overall Design
• Objective:
o Investigate current practices, limitations, and benefits of crowdsourced data in active transportation
• Main target:
o Transportation agencies (i.e., state DOTs, MPOs, transportation institutes)
• Survey design:
o Six topics
o Total of 15 questions
▪ Likert scale
▪ Multiple-choice questions
▪ Open-ended
1 Current Practices Usage
2 Benefits & Challenges
3 Method to Address Issues & Limitations
4 Quality Assessment
5 Integration Practices w/ Other Sources
6 Collaboration w/ Other Institutions
20

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Topic 1 – Basic Information about Survey Participants: This section includes two questions to gather information about the job titles and experience of the survey participants in using non-motorist crowdsourcing data.

Topic 2 – Agency's Use of Non-Motorist Crowdsourcing Data: In this section, participants answer questions related to their agency's use of non-motorist crowdsourcing data. The questions explore the current practices, duration of use, sources of data, and applications of non-motorist crowdsourcing data.

Topic 3 – Perceived Benefits, Challenges, and Limitations: Participants provide ratings on the benefits, challenges, and limitations associated with non-motorist crowdsourcing data.

Topic 4 – Approaches to Addressing Issues and Quality Assessment: This section focuses on how agencies tackle issues and limitations related to non-motorist crowdsourcing data. Participants also provide information on the metrics used to assess the quality of the data.

Topic 5 – Integration and Collaboration: Questions in this section explore whether agencies integrate non-motorist crowdsourcing data with other sources and the nature of their collaborations with other organizations.

Topic 6 – Additional Insights: The final section provides an opportunity for participants to share any additional information or insights regarding their agency's use of non-motorist crowdsourcing data.

1. What is your job title?
2. Which of the following best describes your experience with using non-motorist (e.g., bicyclist, pedestrian) crowdsourcing data?
   a. Very experienced b. Somewhat experienced
   c. Not very experienced d. Not at all experienced
3. Has your agency ever used non-motorist crowdsourcing data? If yes, please briefly describe the current practice by your agency.
   a. Yes b. No
4. How long has your agency been utilizing non-motorist crowdsourcing data as a source of information?
   a. Less than 6 months b. 6 months to 1 year
   c. 1 year to 2 years d. More than 2 years
5. Which sources does your agency use to obtain non-motorist crowdsourcing data?
   a. In-house application (e.g., agency-developed mobile app or website, such as ORcycle developed by the Oregon Department of Transportation, etc.)
   b. Commercial application (e.g., Streetlight, Strava, CycleTracks, MapMyRide, etc.)
   c. Other (please specify):
6. In your opinion, what is the main application of using non-motorist crowdsourcing data in your agency? (Select all that apply)
   a. Facility design (e.g., bike lane design)
   b. Safety studies (e.g., identifying high-risk intersections, crash analysis)
   c. Planning studies (e.g., traffic impact analysis, bike route planning)
   d. Travel demand studies (e.g., bicycle volume estimation, mode share analysis, demand forecasting)
   e. Other (please specify):
7. Please rate the following benefits of using non-motorist crowdsourcing data based on your opinion, using a scale of 1 to 5, where 1 means "Not at all important" and 5 means "Extremely important".
   a. Cost savings
   b. Time savings
   c. Larger spatial coverage
   d. Better data quality as compared to short-duration counts (e.g., 24-48 hours)
8. Please rate the following challenges that your agency faces when using non-motorist crowdsourcing data based on your experience, using a scale of 1 to 5, where 1 means "Not challenging at all" and 5 means "Extremely challenging".
   a. Cost for acquiring crowdsourcing data
   b. Lack of experience with data processing and analysis
   c. Difficulty in integrating with existing bike counts
9. Please rate the following limitations of non-motorist crowdsourcing data based on your opinion, using a scale of 1 to 5, where 1 means "not a limitation at all" and 5 means "a significant limitation".
   a. Cost of acquiring, processing, and analyzing the data
   b. Bias in the sample data (e.g., demographic, geographic, or activity)
   c. Small data sample due to low market penetration rate
   d. Low data quality (e.g., incomplete, inconsistent, inaccurate)
10. If applicable, how does your agency tackle the issues and limitations related to non-motorist crowdsourcing data?
11. What metrics does your agency use to determine the quality of non-motorist crowdsourcing data?
12. Does your agency integrate non-motorist crowdsourcing data with other data sources? If yes, please specify which sources are integrated and briefly describe how the integration works.
    a. Yes b. No
13. What challenges has your agency encountered when integrating non-motorist crowdsourcing data with other data sources?
14. Does your agency collaborate with other organizations, such as local governments, cycling organizations, universities or research institutions, to collect and use non-motorist crowdsourcing data? How do you collaborate? (interagency agreements, contracts?)
    a. Yes b. No
15. Is there anything else you would like to share about your agency's use of non-motorist crowdsourcing data?

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National Survey

Implementation

- Implemented in Qualtrics
  - Pilot study with expert review
- Distributed to key organizations involved in ped/bike transportation:
  - Transportation Research Board (TRB) Pedestrian Committee (ACH10)
  - Bicycle Committee (ACH20)
  - Association of Pedestrian and Bicycle Professionals (APBP)
  - Center for Pedestrian and Bicyclist Safety (CPBS)
- Duration: May 8th, 2023, to June 28th, 2023

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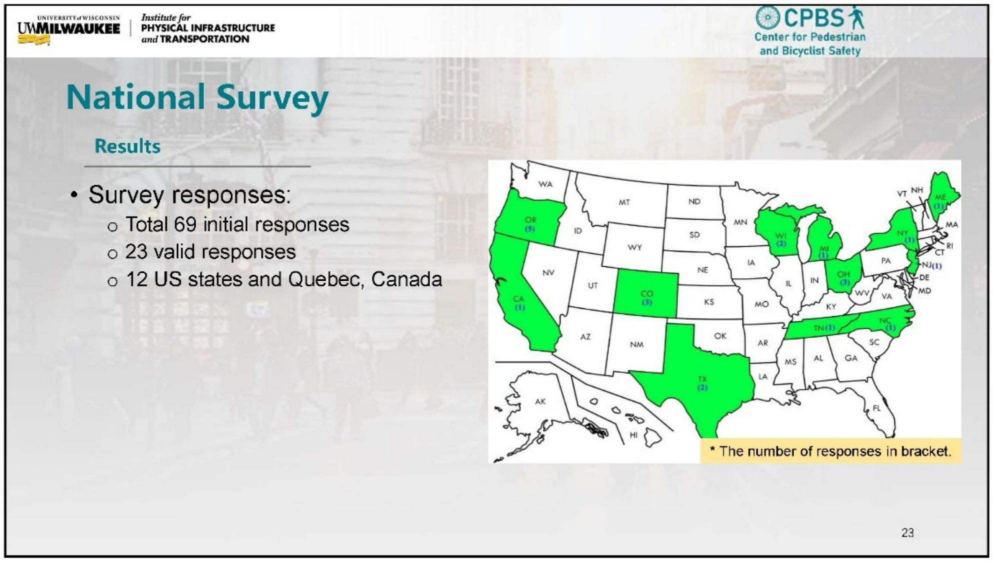
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National Survey
Results
• Survey responses:
o Total 69 initial responses
o 23 valid responses
o 12 US states and Quebec, Canada
* The number of responses in bracket.
23

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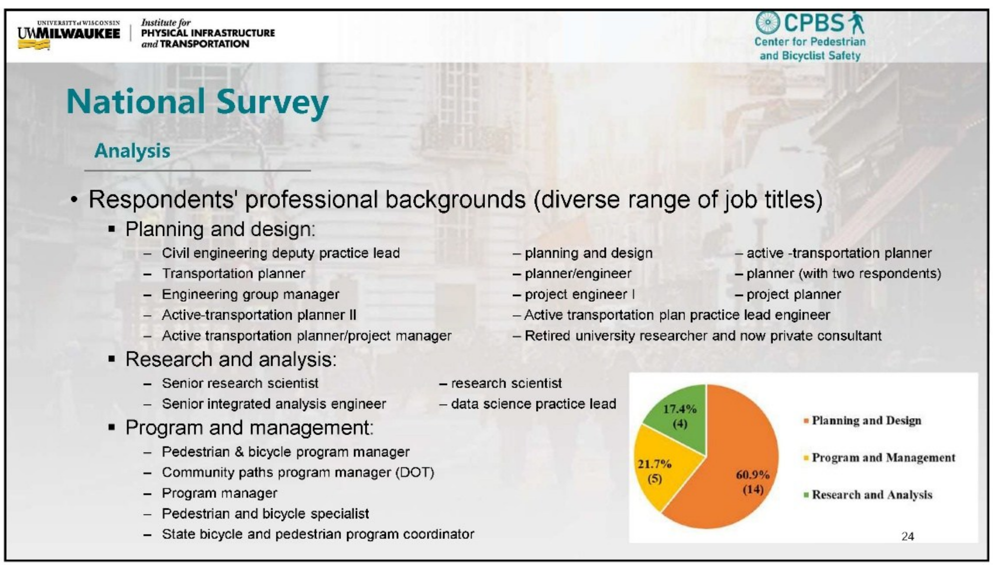
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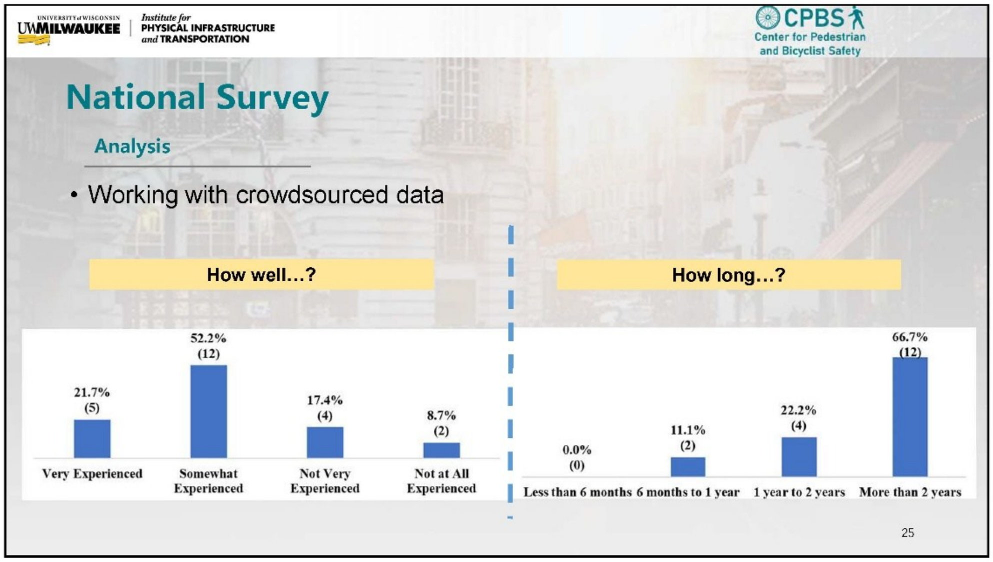
Analysis
• Respondents' professional backgrounds (diverse range of job titles)
▪ Planning and design:
– Civil engineering deputy practice lead
– Transportation planner
– Engineering group manager
– Active-transportation planner II
– Active transportation planner/project manager
– planning and design
– planner/engineer
– project engineer I
– Active transportation plan practice lead engineer
– Retired university researcher and now private consultant
– active -transportation planner
– planner (with two respondents)
– project planner
▪ Research and analysis:
– Senior research scientist
– Senior integrated analysis engineer
– research scientist
– data science practice lead
▪ Program and management:
– Pedestrian & bicycle program manager
– Community paths program manager (DOT)
– Program manager
– Pedestrian and bicycle specialist
– State bicycle and pedestrian program coordinator
17.4% (4)
21.7% (5)
60.9% (14)
Planning and Design
Program and Management
Research and Analysis
24

24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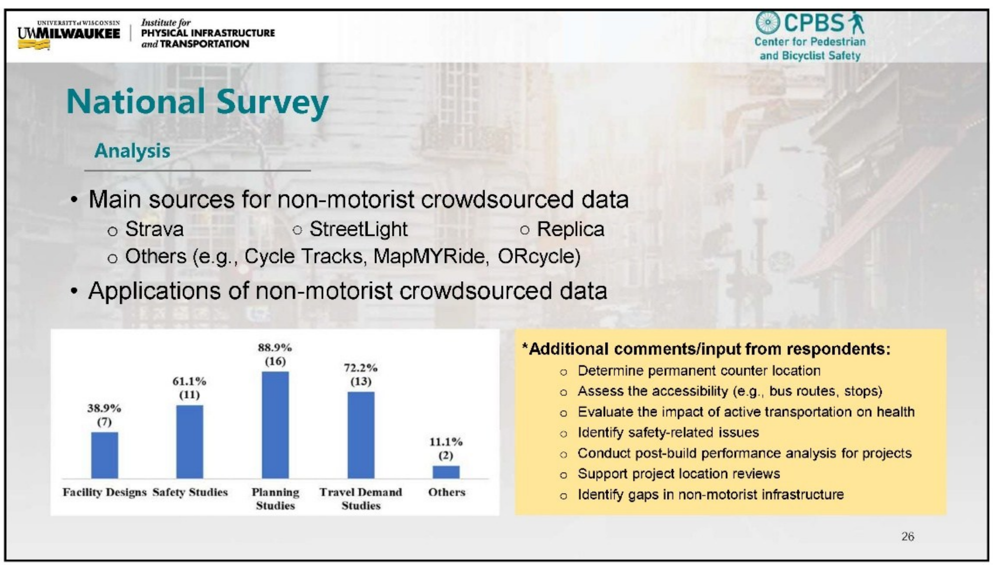
National Survey
Analysis
• Working with crowdsourced data
How well…?
How long…?
21.7%
(5)
52.2%
(12)
17.4%
(4)
8.7%
(2)
Very Experienced
Somewhat Experienced
Not Very Experienced
Not at All Experienced
0.0%
(0)
11.1%
(2)
22.2%
(4)
66.7%
(12)
Less than 6 months
6 months to 1 year
1 year to 2 years
More than 2 years
25

25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Analysis
• Main sources for non-motorist crowdsourced data
○ Strava
○ StreetLight
○ Replica
○ Others (e.g., Cycle Tracks, MapMYRide, ORcycle)
• Applications of non-motorist crowdsourced data
38.9%
(7)
61.1%
(11)
88.9%
(16)
72.2%
(13)
11.1%
(2)
Facility Designs
Safety Studies
Planning Studies
Travel Demand Studies
Others
*Additional comments/input from respondents:
○ Determine permanent counter location
○ Assess the accessibility (e.g., bus routes, stops)
○ Evaluate the impact of active transportation on health
○ Identify safety-related issues
○ Conduct post-build performance analysis for projects
○ Support project location reviews
○ Identify gaps in non-motorist infrastructure
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National Survey

Analysis

- Perceived benefits:
  - Cost saving
  - Larger spatial coverage
  - Time savings
  - Better data quality
- Challenges:
  - Cost for acquiring crowdsourced data
  - Lack of experience with data processing and analysis
  - Difficulty in integrating with existing bike counts
- Limitations:
  - Cost of acquiring, processing, and analyzing the data
  - Bias in the sample data
  - Small data sample due to low market penetration rate
  - Low data quality

The responses from these series questions allow us to provide a **direct comparison**, offering a clear understanding of their relative significance.

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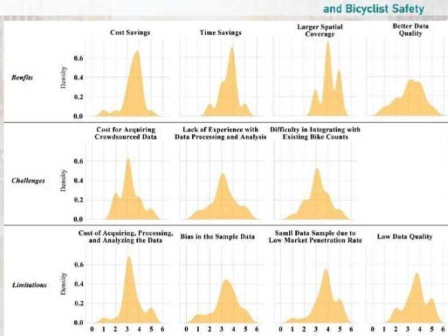
National Survey

Analysis

Density Distribution & Statistics



Categories	Min.	Max.	Mean	Std. Dev.	Count
Benefits					
Cost savings	1	5	3.5	0.94	16
Time savings	2	5	3.61	0.83	18
Larger spatial coverage	3	5	4.17	0.76	18
Better data quality as compared to short-duration counts	1	5	3.17	1.21	18
Challenges					
Cost for acquiring crowdsourcing data	2	5	3.17	0.96	18
Lack of experience with data processing and analysis	1	5	3.17	1.21	18
Difficulty in integrating with existing bike counts	1	5	3.17	1.07	18
Limitations					
Cost of acquiring, processing, and analyzing the data	1	5	3.35	1.03	17
Bias in the sample data (e.g., demographic, geographic, or activity)	1	5	3.35	1.23	17
Small data sample due to low market penetration rate	1	5	3.75	1.15	16
Low data quality (e.g., incomplete, inconsistent, inaccurate)	2	5	3.69	1.10	16

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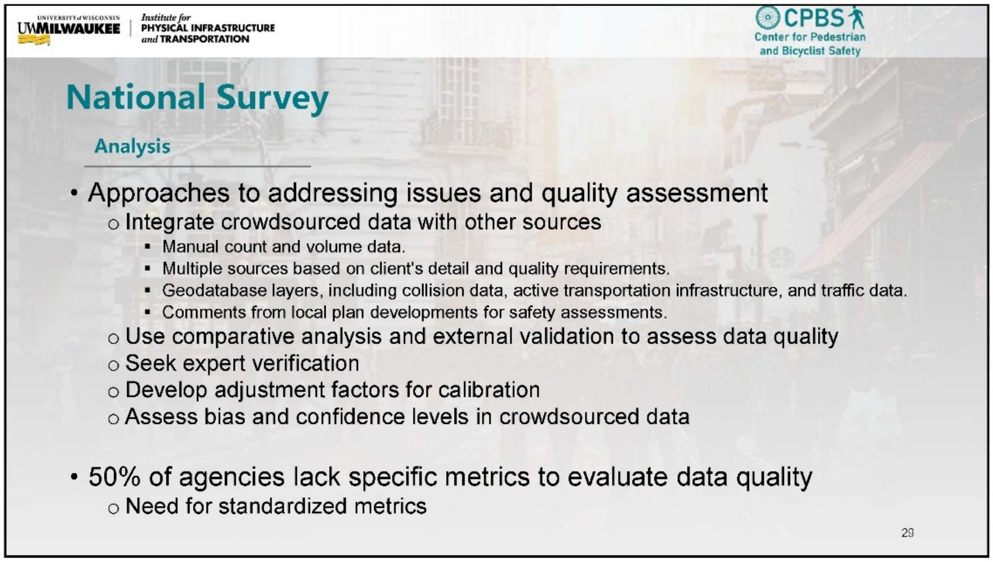
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National Survey
Analysis
• Approaches to addressing issues and quality assessment
○ Integrate crowdsourced data with other sources
▪ Manual count and volume data.
▪ Multiple sources based on client's detail and quality requirements.
▪ Geodatabase layers, including collision data, active transportation infrastructure, and traffic data.
▪ Comments from local plan developments for safety assessments.
○ Use comparative analysis and external validation to assess data quality
○ Seek expert verification
○ Develop adjustment factors for calibration
○ Assess bias and confidence levels in crowdsourced data
• 50% of agencies lack specific metrics to evaluate data quality
○ Need for standardized metrics
29

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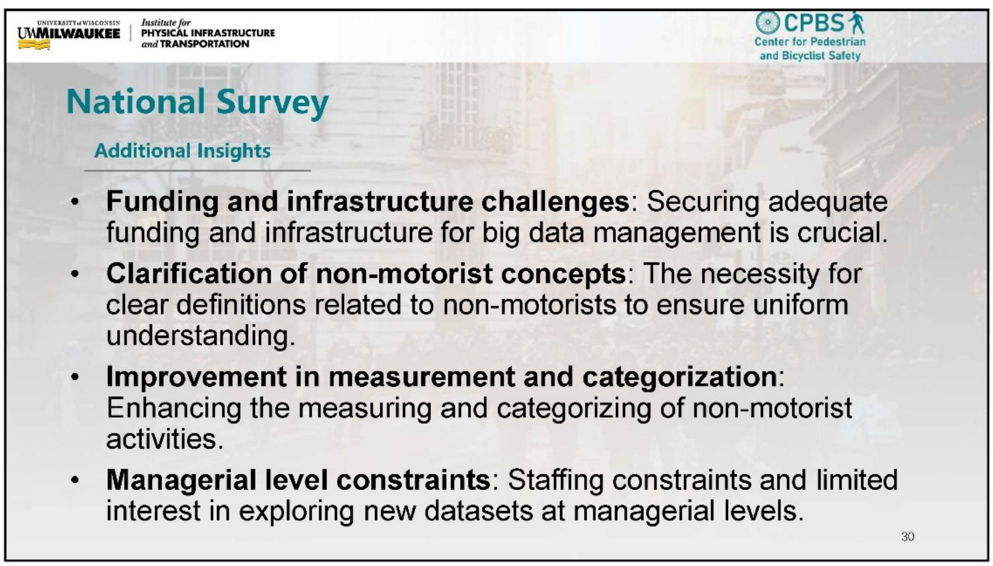
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Additional Insights
• **Funding and infrastructure challenges**: Securing adequate funding and infrastructure for big data management is crucial.
• **Clarification of non-motorist concepts**: The necessity for clear definitions related to non-motorists to ensure uniform understanding.
• **Improvement in measurement and categorization**: Enhancing the measuring and categorizing of non-motorist activities.
• **Managerial level constraints**: Staffing constraints and limited interest in exploring new datasets at managerial levels.
30

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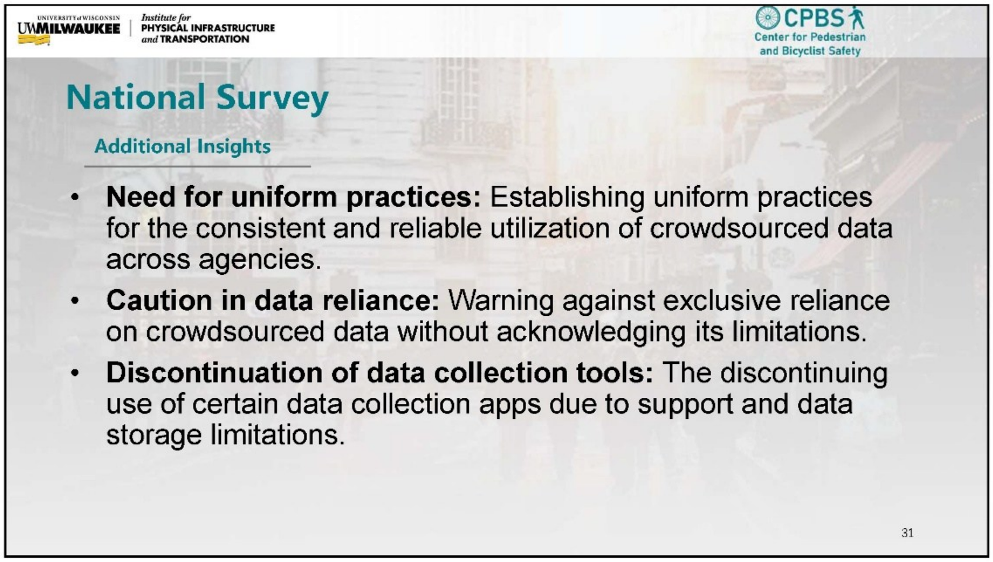
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Additional Insights
• Need for uniform practices: Establishing uniform practices for the consistent and reliable utilization of crowdsourced data across agencies.
• Caution in data reliance: Warning against exclusive reliance on crowdsourced data without acknowledging its limitations.
• Discontinuation of data collection tools: The discontinuing use of certain data collection apps due to support and data storage limitations.
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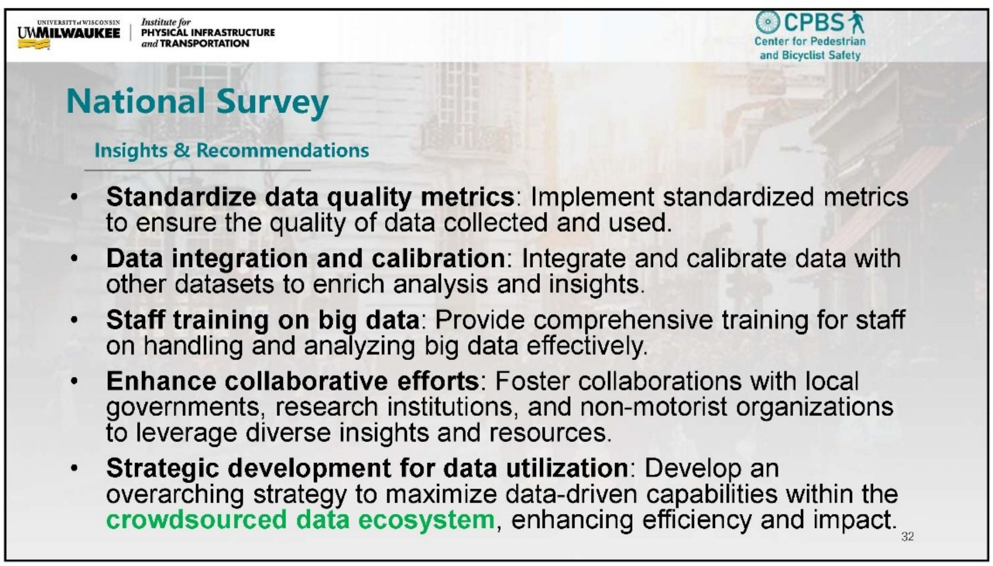
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Insights & Recommendations
• Standardize data quality metrics: Implement standardized metrics to ensure the quality of data collected and used.
• Data integration and calibration: Integrate and calibrate data with other datasets to enrich analysis and insights.
• Staff training on big data: Provide comprehensive training for staff on handling and analyzing big data effectively.
• Enhance collaborative efforts: Foster collaborations with local governments, research institutions, and non-motorist organizations to leverage diverse insights and resources.
• Strategic development for data utilization: Develop an overarching strategy to maximize data-driven capabilities within the crowdsourced data ecosystem, enhancing efficiency and impact.
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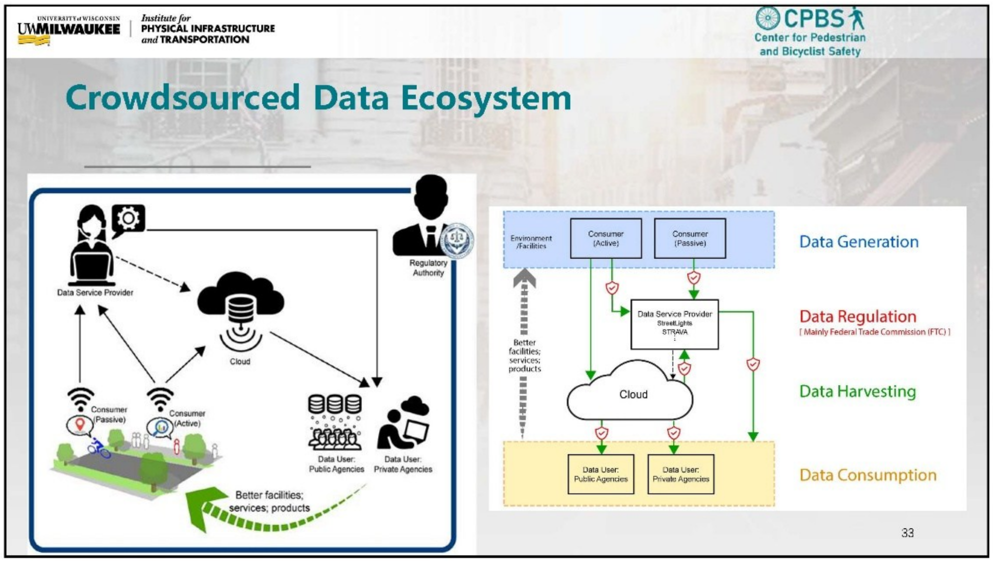
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Crowdsourced Data Ecosystem
Data Service Provider
Regulatory Authority
Cloud
Consumer (Passive)
Consumer (Active)
Data User: Public Agencies
Data User: Private Agencies
Better facilities; services; products
Environment /Facilities
Consumer (Active)
Consumer (Passive)
Data Service Provider
StreetLights
STRAVA
Better facilities; services; products
Cloud
Data User: Public Agencies
Data User: Private Agencies
Data Generation
Data Regulation
[Mainly Federal Trade Commission (FTC)]
Data Harvesting
Data Consumption
33

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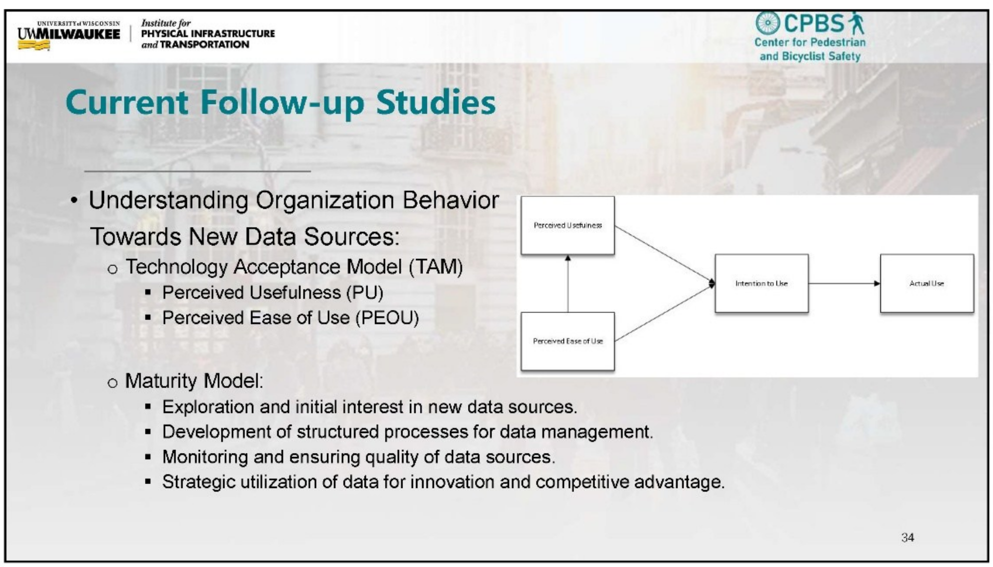
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Current Follow-up Studies
• Understanding Organization Behavior Towards New Data Sources:
o Technology Acceptance Model (TAM)
▪ Perceived Usefulness (PU)
▪ Perceived Ease of Use (PEOU)
o Maturity Model:
▪ Exploration and initial interest in new data sources.
▪ Development of structured processes for data management.
▪ Monitoring and ensuring quality of data sources.
▪ Strategic utilization of data for innovation and competitive advantage.
Perceived Usefulness
Perceived Ease of Use
Intention to Use
Actual Use
34

34


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Current Follow-up Studies
Survey on Emerging Data Sources for Enhancing Vulnerable Road User (VRU) Safety:
https://milwaukee.qualtrics.com/jfe/form/SV_b2DealqyMeVyfL8
Contact:
Yang Li
yangli22@uwm.edu
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