TECHNICAL REPORT STANDARD PAGE

1. Title and Subtitle
   Analyzing Human Mobility for Active Transportation Planning in Louisiana
2. Author(s)
   Ruijie "Rebecca" Bian and Tara Tolford
3. Performing Organization Name and Address
   Louisiana Transportation Research Center
   4101 Gourrier Ave.
   Baton Rouge, LA, 70808
4. Sponsoring Agency Name and Address
   Louisiana Department of Transportation and Development
   P.O. Box 94245
   Baton Rouge, LA 70804-9245
5. Report No.
   FHWA/LA.24/693
6. Report Date
   February 2024
7. Performing Organization Code
   LTRC Project Number: 22-5SS
   SIO Number: DOTLT1000430
8. Type of Report and Period Covered
   Final report
   March 2022 – November 2023
9. No. of Pages
   231
10. Supplementary Notes
    Conducted in Cooperation with the U.S. Department of Transportation, Federal Highway Administration
11. Distribution Statement
    Unrestricted. This document is available through the National Technical Information Service, Springfield, VA 21161.
12. Key Words
    Active Transportation; Walking; Biking; Transportation Planning; Complete Streets
13. Abstract

Existing walking and biking data are often insufficient to support active transportation planning activities. This study utilized an emerging large-scale human mobility dataset to identify places with a higher number of short-distance trips to non-residential locations. These locations are more likely to be served by active modes of transportation, given adequate infrastructure and network connectivity. Demographic variables (i.e., population density and poverty level) were weaved into the mobility index design to prioritize access for more people and address equity concerns. In addition, a safety index, which takes into account the number of injurious crashes involving pedestrians and bicyclists, and a connectivity index, which reflects the density of existing active transportation infrastructure, were also calculated. These indices were considered alongside the mobility index while generating an active transportation investment potential score. The scores are statewide standardized values, where a higher score indicates a greater need for safety improvement (i.e., more injuries/fatalities), greater mobility needs (i.e., more short-distance trips), and lower network density (i.e., inhibiting current demand). All the indices and scores were generated at both the grid level (in 0.1 km^2) and the segment level (in 0.1-

mile). They were then mapped and published on an online dashboard for public access. Over 100 equity and contextual indicators were included in the same dashboard to assist various needs. The developed dashboard is expected to support active transportation planning needs and assist in decision-making for project selection and prioritization. The proposed methodology is based on data sources that are typically available to public agencies and can be replicable in any U.S. states that lack adequate active transportation facilities and where pedestrian/bicyclist count data are not sufficient to directly measure or model demand.

Project Review Committee

Each research project will have an advisory committee appointed by the LTRC Director. The Project Review Committee is responsible for assisting the LTRC Administrator or Manager in the development of acceptable research problem statements, requests for proposals, review of research proposals, oversight of approved research projects, and implementation of findings.

LTRC appreciates the dedication of the following Project Review Committee Members in guiding this research study to fruition.

LTRC Administrator/Manager
Elisabeta Mitran
Safety Research Manager

Members
Chris Fakouri, Jessica DeVille, Jessica Kemp
Nicholas Hernandez, Jason Sappington, Mike Sewell
Laura Phillips, Jason Duet

Directorate Implementation Sponsor
Chad Winchester, P.E.
DOTD Chief Engineer

Analyzing Human Mobility for Active Transportation Planning in Louisiana

By
Ruijie "Rebecca" Bian
Tara Tolford
Manika Rana Bhat

Louisiana Transportation Research Center
4101 Gourrier Ave.
Baton Rouge, LA, 70808

UNO Transportation Institute
2000 Lakeshore Dr.
New Orleans, LA 70148

LTRC Project No. 22-5SS
SIO No. DOTLT1000430

conducted for
Louisiana Department of Transportation and Development
Louisiana Transportation Research Center

February 2024

Abstract

Existing walking and biking data are often insufficient to support active transportation planning activities. This study utilized an emerging large-scale human mobility dataset to identify places with a higher number of short-distance trips to non-residential locations. These locations are more likely to be served by active modes of transportation, given adequate infrastructure and network connectivity. Demographic variables (i.e., population density and poverty level) were weaved into the mobility index design to prioritize access for more people and address equity concerns. In addition, a safety index, which takes into account the number of injurious crashes involving pedestrians and bicyclists, and a connectivity index, which reflects the density of existing active transportation infrastructure, were also calculated. These indices were considered alongside the mobility index while generating an active transportation investment potential score. The scores are statewide standardized values, where a higher score indicates a greater need for safety improvement (i.e., more injuries/fatalities), greater mobility needs (i.e., more short-distance trips), and lower network density (i.e., inhibiting current demand). All the indices and scores were generated at both the grid level (in 0.1 km^2) and the segment level (in 0.1-mile). They were then mapped and published on an online dashboard for public access. Over 100 equity and contextual indicators were included in the same dashboard to assist various needs. The developed dashboard is expected to support active transportation planning needs and assist in decision-making for project selection and prioritization. The proposed methodology is based on data sources that are typically available to public agencies and can be replicable in any U.S. states that lack adequate active transportation facilities and where pedestrian/bicyclist count data are not sufficient to directly measure or model demand.

Acknowledgments

The authors would like to thank LTRC/DOTD for funding our research. The authors would also like to thank all the Project Review Committee members and all the participants who responded to our survey requests. Your participation has helped the research team improve research output quality and dashboard presentation.

Table of Contents

List of Tables

List of Figures

Introduction

Active transportation refers to any mode of transportation powered by humans, such as walking and biking. The concept of complete streets aims to improve transportation infrastructure to promote active transportation and balance multiple modes of transportation. In 2010, the Louisiana Department of Transportation and Development (DOTD) adopted a Complete Streets Policy to “balance access, mobility, and safety needs” of all road users [1]. However, justifying walking and biking demand has been recognized as a challenge in practice. Bicyclists and pedestrians are not always “seen.” For instance, data from platforms like Strava may have biases in the types of road users who choose to participate. Short duration “peak hour” counts may miss the days or times when activity is the most likely to occur. Relying solely on such data may lead to the false conclusion that there are “no observed walking or biking activities.” This issue is not limited to Louisiana but is common among states that lack sufficient data on bicyclist/pedestrian counts for demand modeling and forecasting. Additionally, it is difficult to measure latent demand in areas with few existing facilities. This challenge leaves the DOTD, MPOs, and local authorities without strong data support when making decisions regarding investments in bike and pedestrian infrastructure. When the amount of funding is limited, projects serving biking/walking activities may lose their competitiveness easily due to a lack of evidence supporting existing or potential demand. The absence of biking and walking facilities in Louisiana prevents the state from: (1) improving safety of pedestrians and bicyclists, (2) enhancing mobility of people living in low-income and minority communities by providing access to affordable transportation options, (3) protecting the environment by reducing vehicle emissions, (4) mitigating congestion by reducing the number of short-distance trips made by automobile, and (5) helping metropolitan growth by diversifying available travel modes.

In addition to the challenge in long-term planning and investment, short-term decisions also face challenges that would benefit from a better understanding of potential roadway demand. Some states and cities promoted “Slow/Open Streets” interventions during the early stages of the pandemic in 2020 to promote physical activity and social distancing. However, these interventions were generally proposed based on limited public feedback, as participation was dependent on the number and types of individuals who chose to participate [2]. Additionally, we have observed an increase in natural disasters, such as tropical and winter storms as well as inland flooding. How do human mobility patterns change before, during, and after these disasters? Do any of the pattern changes suggest a sudden surge in travel needs that must be addressed in a short term? Timely responses from DOTD will increase the resilience of transportation infrastructure in serving a variety of travel demands in emergencies [3]. This study aims to utilize emerging human mobility data sources to assist long-term decision-making for active transportation planning in Louisiana as well as exploring the potential of using this data to increase transportation infrastructure resilience during major disruptions. While this study was conducted specifically for Louisiana, the data sources, methodologies, and outreach activities are expected to be applicable to other states and government agencies that face similar challenges in their decision-making processes.

Literature Review

The 2017 National Household Travel Survey discovered that over 40% of the trips taken in the U.S. are less than three miles, but most are completed by autos [4]. Encouraging active transportation could help reduce short-distance trips by autos, mitigate congestion, reduce emissions, and support active and livable communities. The use of mobility data in transportation planning (e.g., demand modeling and forecasting) is a relatively new field that presents both challenges and opportunities [5]. This literature review aims to summarize current research and practice, with a focus on active transportation planning and the potential of big data sources to address key challenges. These challenges include limited availability of direct count data [6], insufficient granularity of trip and auxiliary data used in modeling [7], and difficulties in assessing relative exposure and risk for active users at the node or neighborhood level [8]. This review is comprised of three sections. First, it provides a summary of traditional and emerging data sources and methods for measuring and predicting existing and latent active transportation demand, which supports mobility measures. Second, it reviews literature related to measures of network connectivity, which inform and refine connectivity measures. Lastly, it scans best practices for stakeholder and public engagement.

The objective of this review was to assess potential gaps in detail and identify refinements in the proposed methodology for data application. This is done in service of the underlying goal of improving methods to understand opportunities for modal shift based on the origins and destinations of relatively short trips as well as other factors linked to walking and bicycling. Additionally, the goal is to invest in nodes, corridors, and communities where new or improved active transportation infrastructure, as well as non-infrastructure efforts aimed at encouraging use, can have the biggest impact in Louisiana. Summary findings are outlined below. For an expanded perspective on the literature of active transportation data and analysis, which includes summary tables to guide selection of analytic methods based on planning needs and data available, see Appendix A. Furthermore, Appendix B presents an additional scan of existing research that uses mobility data to evaluate impacts of disruptive events such as disasters and COVID-19.

Data Sources and Methods of Measuring Demand

Lack of consistent and comprehensive bicycle and pedestrian data is a frequently identified limitation of the implementation and/or evaluation of projects and plans [9], [10]. However, the quantity and range of data sources used in active transportation planning have expanded dramatically in recent decades. Previously, active transportation planning was primarily limited to survey-based data (e.g., American Community Survey and National Household Travel Survey). Gradually, a variety of direct counts and proxy data sources (e.g., data collected from mobile devices) have become available to understand, model, predict, and evaluate active transportation demand.

The National Household Travel Survey (NHTS) [11], along with the American Community Survey (ACS), is one of the most widely used references for data related to walking and bicycling trends. NHTS data provides information about daily trips of all modes, distances, and purposes. This survey is conducted every 5-7 years (most recently in 2017) and provides a valuable benchmark for national trends. However, NHTS data is not sufficient at the levels of geography relevant to local or even state-level planning, unless states or Metropolitan Planning Organizations (MPOs) participate in optional "add-on" survey sampling. Household travel surveys led by states/MPOs are common in many regions. However, long intervals between data points are common, and many jurisdictions lack the resources to conduct extensive sampling at all.

The collection of direct pedestrian and bicycle counts has expanded significantly in recent decades. This includes simple manual observation-based counts [12] as well as the installation of robust networks of permanent counters [13]–[15]. National guidance has been issued regarding the methods and technologies available for these activities [16], [17], as well as applications for data management and use [17], [18]. In Louisiana, recent research has led to the implementation of a pilot set of permanent non-motorized count stations [19], including the development of preliminary adjustment factors for estimating demand on other network segments based on short-duration counts.

However, it is not feasible for any jurisdiction is able to collect counts on all network segments at all times. Therefore, models and other planning and forecasting tools are necessary to contextualize and apply both count and survey data in order to gain a holistic understanding of demand for walking and bicycling. The key components of typical current travel planning practice can be divided into two primary categories [20]:

- *Regional travel forecasting tools* (i.e., regional travel demand models, typically used by MPOs and aggregating trips at the Traffic Analysis Zone (TAZ) level, and
- *Facility demand models*, based on direct counts and/or contextual variables associated with active transportation.

Some of the challenges associated with established tools and models include the tendency to combine walking and bicycling, a lack of consideration for land use and the extent of the facility network extent, as well as insufficient consideration for trip purpose, setting, safety, and demographic or environmental factors. To address these limitations, a variety of next-generation models have been developed. These models utilize finer geographic units, focus on tour-generation or mode split, incorporate environmental or accessibility characteristics as variables, or heavily rely on measures of direct demand [20].

It is important to note that modeling approaches that do not rely on travel survey data have their limitations. Instead of using survey data, direct demand models, in particular, rely on the availability of network counts for model development, calibration, and validation. Variables used in such models typically include population and employment densities and volumes, land use mix, facility characteristics, vehicle speeds, average daily traffic (ADT) [21], or other measures of exposure, transit availability, and the presence of major activity generators. These models require extensive reliability testing and are best applied as a screening tool, rather than for forecasting new demand [20].

Collectively, household travel surveys, counts, and demand models, which incorporate one or both along with data to account for built environment, facility, and sociodemographic variables, form the foundation of traditional non-motorized transportation demand analysis. However, as noted, many regions lack recent or sufficiently robust survey data. Even jurisdictions with well-developed count programs may struggle to derive comprehensive network-wide demand models based solely on direct counts. Moreover, the technical and analytic capabilities required for developing such models may exceed those of many local agencies. To address these challenges, there is a need for additional, scalable, and low-cost data sources to better support decision-making related to walking and bicycling. This would facilitate the routine integration of active transportation activity and potential into project and area-wide planning.

As smartphones have become nearly ubiquitous over the last decade, their potential as a data source for a variety of planning and evaluation purposes has risen. In transportation planning, this “big” data from smartphones is used for traffic monitoring and analyzing mobility in various ways. There is an increasing body of literature that explores the current and potential uses of new data sources, particularly Global Positioning System (GPS) and mobile phone-based datasets. The use of this data can help to overcome key challenges in the use of traditional data, namely, small sample sizes and limited counts.

These datasets can be categorized in various ways: by target population, whether the mode of travel is specified, and the characteristics of data produced [22]. A key benefit of mode-unspecified data sources is that they collect large volumes of data passively, improving sample reliability. However, most transportation research utilizing these datasets has focused on motor vehicles [22], with a few notable exceptions [23], [24]. On the other hand, mode-specified data sources have been widely used for pedestrian and bicycle planning purposes. They are used for travel pattern identification, route choice modeling, travel demand prediction, crash exposure estimation, and other analytical uses. Whereas, such data sources are limited by small or skewed samples, which may hinder their usefulness for some planning and demand analysis purposes, and raise concerns about data validity.

Several recent studies have attempted to evaluate the detection, classification, spatial precision, and overall accuracy of smartphone/probe-based passive data sources. These studies often use direct counts as the basis for measuring deviation between observed volumes and estimated or modeled vendor outputs [25]– [27]. The findings from these studies are mixed but generally find better reliability at higher traffic volumes. For active transportation applications, low volumes combined with limited spatial precision, modal classification errors, and privacy concerns present compounding challenges in using these emerging data [28], [29]. The fusion of multiple datasets can help address and overcome these challenges to correct for over- and/or under-representation. Furthermore, continued advancements in machine learning are helping improve modal classification [22], [28], [29].

More focused analyses have highlighted specific uses of mobile data for certain contexts. For example, it has been used to monitor travel demand in parks by estimating motor vehicle volumes at entrances [30]. Mobile data has also been used to measure the results of efforts to reduce greenhouse gas emissions, such as modal shifts on a college campus [31]. Additionally, mobile data has been used to identify indicators and barriers within multimodal mobility, with the goal of better supporting the integration of active modes in public transit [32]. Researchers in these cases generally found that the use of mobile data yields comparable results relative to traditional survey/count-based demand modeling methods. In some cases, mobile data has even addressed sample bias or gaps identified in the latter.

More sophisticated methods for distilling and utilizing passive data are still being developed, such as extracting data through real-time traffic monitoring locations [33] or from multiple sources [34]. The potential to substitute passive data for travel surveys, particularly, is of significant interest to MPOs and state DOTs as it may provide a lower cost means of forecasting travel behavior [35]. Passive data can also unlock the ability to rapidly monitor the number of people at specific locations, as well as to develop dynamic origin-destination matrices. Both of which have important planning and operations application potential not only for transportation but also to address health, economic, and other public policy goals [33]. As technology advances, the literature indicates that all such data can be enhanced through machine learning to optimize transportation outcomes at both the individual project and system-wide level [36]. In Appendix A, we discuss in greater detail the potential applications for and limitations of mobile-phone based location data in demand estimation or forecasting, exposure/safety analysis, and/or benefit-cost analysis.

No matter whether we are using direct counts or estimates derived from mobile devices, the number of people currently traveling by active modes on a particular road segment or intersection does not necessarily represent the total number of people who need or desire to access that location. Latent demand can be described as "the activities and travel that are desired but unrealized because of constraints," [37] (p.2). In economic theory, latent demand means "the unobserved portion of the demand curve that becomes realized after there is decrease in costs (or travel times) resulting in increased consumption" [37] (p.4). In other words, even if there is currently no walking or bicycling (or other activity) observed in a given location, it does not necessarily indicate that there is no potential for such activities in the future. Latent demand can serve as a conceptual framework for understanding unmet needs and highlighting equity issues [37].

Several studies have attempted to quantify latent demand through the effects of increases in capacity, elasticity of demand with travel costs, or decreases in travel times. However, these analyses are typically focused on specific facilities or projects rather than systems or networks, with most attention given to automobile demand [37], [38]. Tools for forecasting active transportation demand specifically are considerably less regulated and standardized compared to motor vehicle demand forecasting. However, they can be organized by whether they focus on individual or collective travel choices, whether their purpose is demand estimation or project prioritization, and the geographic scope [38]. For example, sketch planning methods can be upgraded to account for variables that impact travel behavior (e.g., measures of connectivity, streetscape features, land use mix, etc.).

However, the transferability of such models from one location to another without extensive data collection tends to be limited [38].

Researchers have identified and tested a wide range of pedestrian and bicycle attractors and detractors which have been found to influence demand [7], [36], [39], [40]. These include trip categories, measures of impedance, number or density of people or jobs, pedestrian support measures and barriers, traveler characteristics, perceptual factors, and environmental factors. Summaries of these studies, as well as an overview of latent demand estimation methods with their pros and cons, and several examples of latent demand estimation in practice, can be found in Appendix A.

Network Connectivity Measures

Active transportation network connectivity is key to encouraging travel by active modes [41]. This section focuses on recent research and tools that measure network connectivity and their supporting data. Connectivity, as a transportation performance metric, measures whether people can travel safely and easily to their intended destinations using their preferred mode of transportation. Many communities worldwide are prioritizing the development of connected active transportation networks by identifying connectivity gaps, instead of creating ad-hoc infrastructure wherever convenient. This approach is supported by the Federal Highway Administration (FHWA) [41].

FHWA's Guidebook for Measuring Multimodal Network Connectivity [42] provides a comprehensive review of current literature, summarizing various methods and measures for identifying projects that address priority network gaps, resulting in co-benefits, and evaluating the impacts of investments on transportation network performance. The Guidebook outlines five key components of multimodal network connectivity:

- Network completeness
- Network density
- Route directness
- Access to destinations
- Network quality

Analytic methods and measures employed may address one or more of these five fundamental facets of connectivity, depending on the goal(s) of the exercise. The selection of an analysis method is determined by the key question for which insight is needed, as well as the availability of data for the target network. Some analysis methods (e.g., network completeness and network density) require straightforward and widely available data like shapefiles of existing and planned facilities, including street network centerlines. However, other methods (e.g., route directness and network quality) may require detailed network data with a wide variety of attributes, which many jurisdictions lack [40], [43].

The definition of the network itself is a critical task. It involves considering both the geographic scope and the type of facilities to be included (e.g., roadways, trails, designated bicyclist/pedestrian facilities, or other specific attributes which are linked to active transportation feasibility or safety). Depending on analysis objective, it may not be appropriate to analyze only existing, dedicated pedestrian and bicycle facilities. This is because a significant portion of cycling activities take place on streets without dedicated amenities, where bicyclists share roadways with auto travelers [44]. Similarly, walking activities may occur in areas without dedicated infrastructure, with people walking directly on the roadway or in adjacent right-of-way.

Recommended basic data sources for network definition [42] include:

- Line street network data from the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) system
- OpenStreetMap (OSM) data (likely to include shared-use paths, which do not appear in TIGER data)
- State and federally owned roads recorded in the Highway Performance Monitoring System/All Roads Network of Linear Referenced Data (HPMS/ARNOLD)
- Other network data collected by state Departments of Transportation (DOTs)
- Private and proprietary data developed by GPS/navigation companies.

Network types can be broadly defined as either facility-based (designated bicyclist/pedestrian facilities OR all streets where walking and bicycling are allowed) or quality-weighted (defined based on criteria through an objective rating system like Level of Traffic Stress) [42], [45]. There are various tools for assessing these measures. However, it is worth noting that tools, supporting quality-weighted measures require a variety of data inputs and are more data-intensive to set up compared to using facility-based network measures [16], [42], [46], [47]. Both network type can be assessed for one or more of the dimensions of connectivity as described above. Appendix A presents a breakdown of facility types and quality-weighted attributes frequently used in connectivity analysis. It also identifies additional metrics in connectivity analysis and summarizes a selection of connectivity analysis findings from example locations.

Safety Measures

In addition to network connectivity, safety is a critical dimension of active transportation planning and evaluation. The presence, quantity, or severity of crashes is the most used metric to assess safety, and a key part of any safety analysis [8]. There has also been significant progress in the quality of data and methods used to analyze non-motorized road user crashes over the last decade. This progress has helped identify crash “hot spots” (typically intersections), determine statistically significant clusters of crashes, and incorporate systemic factors likely to contribute to crash risk, even where actual crash frequency is low [48].

The use of “risk” as a measure of safety, rather than simple crash totals, represents a significant advancement in the state of the practice. Its use helps address the condition that places perceived as very unsafe to walk or bicycle may have few recorded crashes due to low activity volumes (even if there is significant latent demand). Risk can be defined by calculating the observed crash rate (using an exposure measure to normalize crashes by number of users, trips, or miles) or by predicting the number of expected crashes within a defined time horizon based on past crash history and/or other risk factors found to correlate with crash incidence [8].

Population-based measures of exposure may be readily applied at the areawide scale, while site counts can support robust exposure estimates for individual segments or nodes. However, for analysis across an entire network, demand models based on counts, surveys, or other data (such as roadway, traffic, or land use characteristics) must typically be developed as a substitute for direct measures of exposure [15].

Many cities have started using the concept of High Injury Networks (HIN) to address systemic needs across the transportation network, rather than focusing only on crash “hot spots.” HINs provide a measure of crash density along overlapping segments of a street network, effectively generalizing the location of crashes to more consistently evaluate crash distribution [48]. Such analyses support a systemic safety approach, allowing network-wide screening of corridors sharing similar characteristics to determine where crashes are more likely to occur.

Recent projects have made HIN development and screening more accessible, even in cases where robust exposure data is lacking. Mansfield et al. developed a pedestrian risk model based on built environment and demographic data, which was used to model crash risk across the entire U.S. by census tract [49]. Schoner et al. [48] expanded on this model to link the results to specific locations along the transportation network. This allows for analysis of predicted crash risk for both pedestrians and bicyclists using relatively low-barrier data inputs to develop a preliminary HIN, and facilitating project prioritization. The resulting tool, called the Safer Streets Priority Finder, also provides severity-based crash cost outputs to project the societal cost of anticipated crashes over a five-year period. Such tools greatly enhance local agencies' ability to evaluate network-wide safety relatively quickly and efficiently in a more actionable manner than simply mapping crash hot spots. However, data and processing limitations inhibit simultaneous statewide analysis, and model outputs may be less accurate and/or useful in rural areas where crashes involving pedestrians or bicyclists are very rare [48].

Moreover, reported crashes (and variables associated with such crashes) may not provide the entire picture. Police crash reports tend to underreport total crashes, particularly those that do not involve a motor vehicle (such as pedestrian falls, or cyclist collisions with fixed objects), as well as many minor crashes [40]. Where data is available, additional safety data variables "near misses," and road user behaviors, may be utilized in addition to the locations of reported crashes.

Equity Measures

Finally, all dimensions of analysis for active transportation can (and should) be evaluated through a lens of improving equity. A wide range of variables can be used to assess equity, depending on the goals of a jurisdiction or agency. Efforts to improve equitable access to walking and bicycling have proliferated in recent years, and have been integrated into network-level evaluations for pedestrian and bicycle planning [40], [50]–[55].

Equity can be measured using socioeconomic variables from the American Community Survey, public health agencies, local or regional planning agencies, school districts, or other household surveys [40]. These variables can be cross-referenced with compliance variables (for example, Americans with Disabilities Act requirements, maintenance issues) to identify high-priority locations within the network for intervention, based on equity goals such as, inclusivity, affordability, and social justice [51]. The National Cooperative Highway Research Program (NCHRP) *ActiveTrans Priority Tool* [40] outlines a range of commonly used indicators for assessing equity, based on their relevance to people who walk and/or bicycle, as well as their geographic scale of applicability.

Numerous recent planning efforts have specifically focused on equity as a key consideration for network-level evaluation, illustrating the relative differences among areas on a network compared to an areawide mean. Commonly used indicators that serve as proxies for transit dependence and environmental justice issues include [50], [53], [54]:

- Lack of access to a vehicle
- Children under 18
- Adults over 65
- Race/ethnicity
- Income below the federal poverty level
- Physical disability

Researchers emphasize that data regarding the extent and quality of infrastructure can pose limitations in equity analysis. The indicators noted above can illustrate likely need/demand for active transportation (including transit), but may not adequately reveal disparities in access compared to more privileged populations [55], [56]. For example, there have been established correlations between neighborhoods with higher populations of color and/or lower incomes and poor sidewalk maintenance [55].

Several federal agencies, including the U.S. Environmental Protection Agency (EPA), the U.S. Department of Housing and Urban Development (HUD), and the U.S. Department of Transportation (USDOT) have developed resources for evaluating and indexing equity. Appendix A provides a list of these resources, as well as a summary of potential metrics for incorporating equity into network analysis either as a standalone measurement or to weight other variables.

Public Engagement and Data Dissemination

There are challenges in engaging the public in planning processes, and even more obstacles for meaningful engagement that goes beyond mere information dissemination. Methods that prioritize projects based on complaints, as well as abstract planning processes that seek input from the "general public," tend to allocate resources toward communities that already have the most resources, rather than those that are most in need. Similarly, the groups and individuals most likely to participate in traditional planning outreach efforts tend to overrepresent certain communities and underrepresent others

[54]. Involving traditionally underserved populations requires a commitment to equity and inclusion at all stages, and it involves three basic steps [57]:

1. Identifying and locating underserved populations
2. Fostering participation of those populations, and
3. Creating opportunities for meaningful involvement.

FHWA defines traditionally underserved populations as those who are [54]:

- Low-income
- Minority
- Older adults (defined as 65 years or older)
- Limited English proficiency (LEP)
- Persons with disabilities (physical or mental, as defined by the Americans with Disabilities Act (ADA)

Underserved populations are less likely to own a vehicle, more likely to have jobs with non-traditional hours, more likely to walk, bike, and take transit, and/or more likely to experience social isolation [54]. At the same time, these populations are more likely to live in communities without access to high-quality walking, bicycling, and transit facilities and are disproportionately impacted by traffic violence [5].

Meaningful and inclusive engagement requires clarity about the impact that public participation can or will have, as well as how the outcomes of the engagement will be used [58]. It is also important to acknowledge disparities and power imbalances between transportation decision-makers and marginalized communities whom they are charged to serve. Effectively and sensitively communicating with diverse communities (i.e., cultural competency) and ensuring reasonable accommodation for participation in planning processes are critical to advancing equitable outcomes [54], [57]. Overcoming limited access to online resources is a key concern of developing an equitable planning process, along with ensuring that both digital and analog communications materials are available in multiple languages [54]. Many communities, including rural areas as well as low income and older individuals, may lack reliable broadband internet access. Limited internet access restricts engagement with information and communications technologies (ICTs) and contributes to a "digital divide" that can negatively impact inclusivity [57]. Additionally, acknowledging past injustices and considering the history of communities that have suffered from those injustices is a key prerequisite to building trust [54].

Digital engagement has become the norm in the wake of the COVID-19 pandemic. Many practices were developed to advance urban planning work during this transformative period, which also included significant concurrent discussion in planning and governance spheres about social justice and how to more effectively engage and shift power to marginalized communities. These practices include virtual meeting options, creative approaches to linking digital and analog outreach (e.g., QR codes), and working directly with compensated community members as leaders and collaborators [59]. Best practice research indicates that compelling virtual experiences with more visuals and less text reduce barriers to engagement [60]. Practitioners also recommend closely monitoring and evaluating community engagement impacts in real-time as we collectively move toward hybrid engagement models that combine digital and analog strategies. The purpose is to ensure adequate representation from target geographies or groups. Past studies have also recommended integrating engagement as a direct component of the fundamental planning task rather than treating it as an "add on" after the fact. It is important to develop virtual platforms for ongoing, asynchronous engagement and explicitly seek out historically underrepresented voices [59]. Furthermore, as our ability to foster participation from broader or more representative audiences expands, there is a professional obligation to support the understanding of planning, governance, and implementation processes. It is critical for the public to be aware of involvement opportunities, particularly in the early stages of planning processes, and have enough background information to provide relevant feedback [61].

Digital tools to support public participation in urban planning have significantly grown in recent years due to technological innovation especially with the onset of the COVID-19 pandemic [62]. These tools aim to address identified barriers to participation in planning and facilitate more inclusive, and in some cases, more nuanced feedback [61]. However, it is important to note that many specific applications of interactive digital engagement tools are either purpose-built and temporally limited (e.g., web pages or apps developed for a completed project and subsequently taken offline at the conclusion of a project or contract) while others may come from a range of vendors and be subject to change or discontinuation. Some digital tools created for specific projects or organizations are closed once the initiative concludes, while others remain open, either to collect comments and feedback or in view-only mode. Regardless of the platform used, the following visualization best practices for map-based engagement should be kept in mind [63], [64]:

- Show existing and (where available) proposed facility networks for relevant modes;
- Do not allow detailed content (icons, symbols etc.) to overwhelm the user;
- Include local landmarks and points of interest to help users orient themselves;
- Tools/visualizations must be mobile-friendly.

Additionally, it is important to remember that in most communities, a "digital divide" persists, and access to engagement tools and full participation may be limited among groups with limited access to technology and/or limited digital literacy [62]. Engaging underserved groups in virtual public involvement initiatives may also require complementary offline methods (e.g., print materials), multilingual social media outreach, and/or addressing the needs of the visually impaired [64].

Collecting community feedback on spatial data, whether network- or project-based, is most frequently facilitated by interactive Geographic Information System (GIS) maps. Feedback is collected either through embedded comment functionality or linked surveys. Practitioners must balance the level of engagement and the level of digital knowledge required to allow full participation [62].

Appendix A summarizes:

1) Additional contextual information defining the spectrum of engagement;
2) Specific strategies for fostering participation in underserved or underrepresented communities (particularly low-income) and optimizing online engagement efforts;
3) Tools for analyzing equity and increasing inclusivity in processes and outcomes; and
4) Several examples of digital engagement platforms, vendors, and outreach tools.

Key Findings from Literature Review

Overall, the review of the state of practice for active transportation data collection and analysis, methods for holistically evaluating multimodal transportation networks, and more effectively communicating data, plans, and projects to the public reveal significant advances in recent years. The proliferation of smart phones and related emerging data sources provides an enormous opportunity to fill gaps in understanding where more established data collection methods (counts, surveys, etc.) either lack specificity or are impractical to collect at scale.

However, emerging data and new models still have limitations in practice. Mobile phone-based data sets still underrepresent disadvantaged groups, and the expected margins of error (as with all data sources) can be high in places where sample sizes are small. Questions around privacy and anonymity of data, as well as transparency and the ability to validate of proprietary third-party data sets, continue to be debated. Researchers have found that wholesale substitution of traditional data for emerging data is inappropriate. Traditional data has a crucial role in validating, adjusting, and contextualizing the emerging data.

Along with these new data sources and opportunities, a wealth of new analytic methods, many of which hinge on increased availability of fine-grained spatial data, have emerged. Researchers have tested a wide range of variables to better understand their association with the demand for, and safety/comfort of, active transportation. This has led to notable improvements in the range of tools and guidance available for estimating latent demand, in locations where existing conditions undermine the feasibility of active transportation where it might otherwise be an important component of transportation networks.

For the purpose of this study, three of the five established dimensions of multimodal network connectivity can be considered feasible based on the available data. These dimensions are network completeness, which refers to the presence of walking and/or bicycling facilities in the current infrastructure; network density, which measures the extent of facilities in relation to lane area or other metrics; and access to destinations, which examines the relationship between the network and the points of interest it connects to. This study also draws from the literature for best practices in evaluating safety (i.e., assessing crash density within a network). It also focuses on incorporating equity by directly integrating equity indicators into scoring models, and providing supplemental layer information to facilitate equity analysis based on users' needs.

Finally, this review of practice identifies several goals for public engagement and data dissemination that inform the development and testing of this tool. These goals include the development of an interactive online platform and testing to improve its legibility for a broad range of audiences. Additionally, implementation recommendations are provided on how to publicly share the findings and potentially integrate the project output into future collaborative public engagement efforts for long-range planning, project identification, and project prioritization.

Objective

The main objective of the research is to identify areas in Louisiana that require active transportation infrastructure (such as sidewalks and crosswalks) the most. The needs were determined based on continuously collected anonymous human mobility data from mobile devices. An active transportation mobility index was developed based on the human mobility data, which is expected to illuminate areas where significant demand exists to access a given location, and a high proportion of trips could potentially be captured by active modes. Connectivity, safety, and equity-related factors were then integrated into the index and helped derive an active transportation infrastructure investment potential score, offering comprehensive decision-making support.

The results are expected to provide valuable insights for active transportation planning at both statewide and local levels. With the developed mobility index and investment potential score, decision-makers will have stronger data-driven support for making investment decisions regarding active transportation infrastructure. The research team is committed to ensuring equity from multiple perspectives including data source, data analysis, methodology development, research result presentation, and access to research output.

A by-product of this study, two case studies were conducted to investigate how human mobility patterns deviated from normal during the outbreak of COVID-19 (2020) and Hurricane Ida's (2021) landfall. The results from these case studies are expected to be useful in understanding how mobility data can guide responses to public health crises, tropical storms, and other future disaster events. This will contribute to informed decision-making and enhance transportation infrastructure resilience. All the related content from this perspective was included in Appendix B without disrupting the main research objective.

Scope

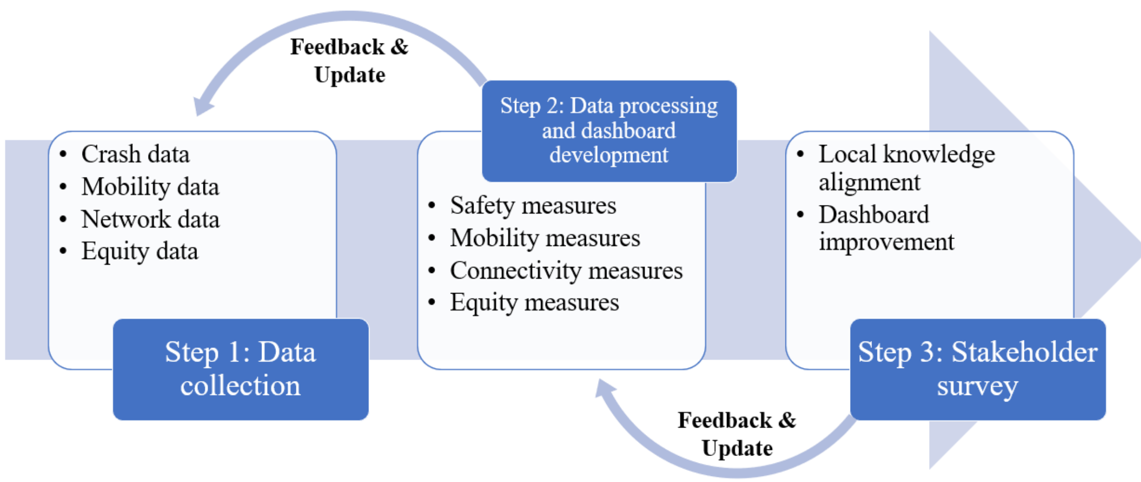
The main purpose of this project is to provide statewide planning support to Louisiana, taking into consideration safety, mobility, and accessibility needs. This research focuses on serving home-based trips to improve residents' access to jobs, recreational activities, health services, etc. All mobility records were extracted from SafeGraph and cover the time range from 1/1/2018 to 12/31/2021. Correspondingly, records of crashes involving bicyclists/pedestrians were extracted from the same temporal and spatial range. The sidewalk network data was obtained from the Automatic Road ANalyzer (ARAN), collected most recently in 2010. The dedicated bikeway and shared-use trail network data were obtained from a previous project conducted by the research team [65] and updated by the co-PI project in 2023. The developed investment potential score was calculated based on all the data mentioned above and included in the developed online dashboard to assist decision-making.

Currently, transit network data is not included in the mentioned index/score, except as a reference layer in the dashboard. The data was also obtained from the research team's previous work and updated in 2023. Future research may consider including a walkshed or travel-time-based analysis of transit connections and incorporating as a factor in relative scores.

Methodology

This section introduces how safety, mobility, and accessibility/connectivity (which are the three most common goals of Complete Streets policies [66], were measured. The data sources being used for these measurements were summarized for active transportation planning purposes. Additionally, multiple equity indicators were collected from official sources. All the indices, scores, and indicators were incorporated into an online dashboard (Version 1.0) to engage stakeholders for testing during the project time. The measures and the dashboard have been updated to address major concerns expressed in the survey. The updated dashboard (Version 2.0) with improved measures has been released after the project conclusion to allow public access. Figure 1 shows the project workflow, which includes feedback loops among steps to incorporate changes and improve research output.

Figure 1. Project workflow



Measure Mobility Potential

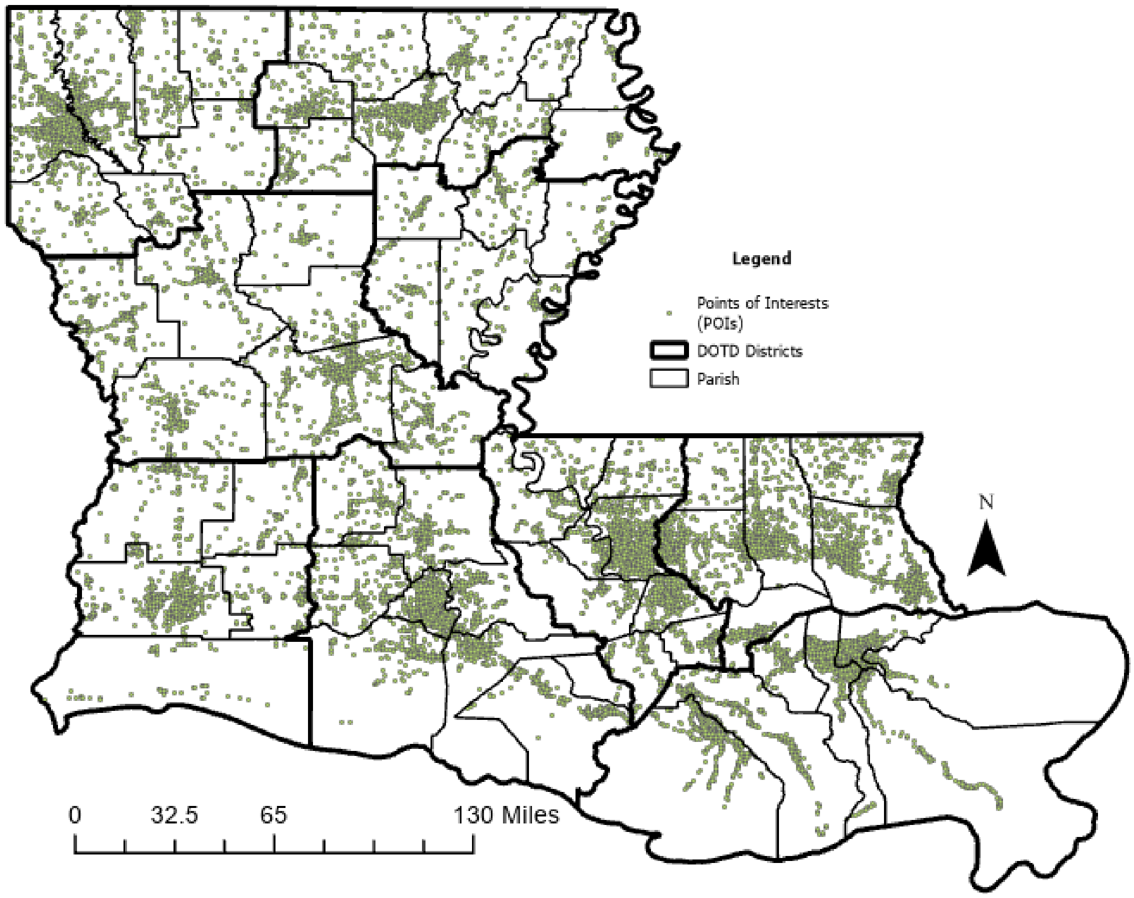
Mobility Data Source

This study used a large-scale mobility dataset called "Patterns" from SafeGraph. The dataset collects data passively and anonymously from mobile devices year-round. The Patterns data is available from January 2018 to December 2022. Specifically, the dataset presents how often 18 million points of interests (POIs) were visited by people in the U.S. each month. SafeGraph's POIs are public places that fall in categories recorded in the North American Industry Classification System (NAICS). The POI data is validated using information from Google Maps (i.e., Google Places API) and updated on a monthly basis to track business openness/closure status. Overall, the dataset has covered core public places in the U.S. During the study period, there were 116,935 POIs located within Louisiana (refer to Figure 2). The following information was extracted from the dataset for the purpose of this study: the number of visitors to a POI i in month m (i.e., $visitor_i^m$), the median travel distance from visitors' residence to a POI i in month m (i.e., $Median(distance_i^m)$), and the median activity duration time at a POI i in month m (i.e., $Median(dwelling_i^m)$).

Like other mobility data sources, there may be concerns regarding sampling representativeness. However, approximately 10% of the total population in the U.S., which is considered statistically significant enough to draw meaningful results. Additionally, there could be sampling bias for some individual POIs, as noted by SafeGraph. To address this, equity indicators such as population density and poverty level were included in the mobility measurement to reduce the sampling bias. This study also aggregated mobility index values by cluster (which is a hexagon or roadway segment in this study) to remedy potential sampling issues from individual POIs.

While the dataset might not be entirely perfect as a data source due to sampling concerns, its granularity and span of the data provide rich information for conducting longitudinal analysis on human mobility patterns. This dataset becomes even more valuable to areas where walking/biking demand data or counting data is not available.

Figure 2. Point of interests (POIs) provided by SafeGraph



Mobility Measurement and Data Cleaning

Stage 1 Cleaning. Data records with extremely large median travel distance from home ($Median(distance_i^m)$) or extremely large median activity duration time ($Median(dwelling_i^m)$) were removed. For example, a POI with an extremely large median travel distance from home may be attributed to a high number of tourists visiting it. Specifically, the following criteria were applied based on observing histograms to remove extremely skewed values. There are 75% (=87,447/116,935) POIs left in the dataset after this stage of data cleaning.

- Remove records with median travel distance from home greater than 50 km/30 miles (i.e., over 50% of the visitors traveled at least 50 km/30 miles to reach a POI). The top three place categories removed based on this criterion were restaurants and other eating places, traveler accommodation, and gasoline stations.

- Remove records with median activity duration time greater than 600 minutes/10 hours (i.e., over 50% of the visitors stayed at a POI for at least 600 minutes/10 hours). The top three place categories removed based on this criterion were restaurants and other eating places (especially those with low volume of customers that resulted in low sampling rate), traveler accommodation, and general medical and surgical hospitals.

Mobility Measurement. The mobility index considers the number of visitors, their travel distances from home, and the duration of their activities at POI. The mobility value increases when a POI is visited more frequently and when most of its visitors live nearby and spend more time there. The greater the value, the more likely that active transportation infrastructure can better serve walking/biking needs to access the POI. The mobility index is calculated using the following equation. It is designed to reflect latent demand rather than solely representing current, potentially limited existing demand (due to the lack of existing facilities) for planning purposes.

$$Mobility_i^m = \frac{visitor_i^m \times Median(dwelling_i^m)}{Median(distance_i^m)} \quad [1]$$

where,

$visitor_i^m$ is the total number of visitors to POI i in month m.

$Median(distance_i^m)$ is the median travel distance from where visitors live to POI i in month m.

$Median(dwelling_i^m)$ is the median activity duration time at POI i in month m.

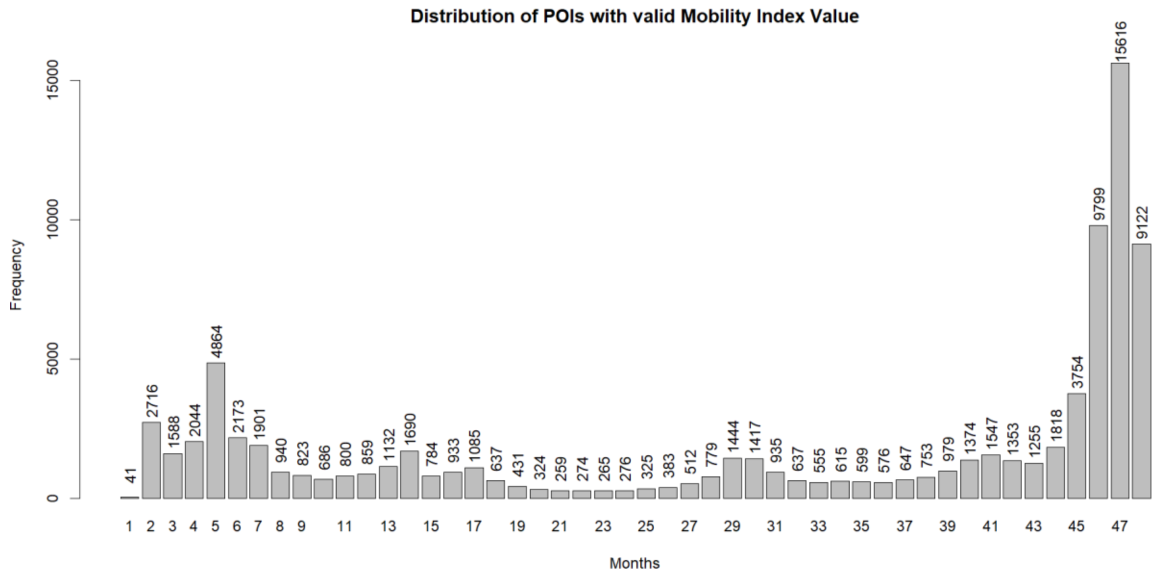
$Mobility_i^m$ is the calculated mobility value for POI i in month m.

Stage 2 Cleaning. The study period spans from the beginning of 2018 to the end of 2021, covering 48 months. Temporal variations are expected to occur, and a POI may have its $Mobility_i^m$ for a given month significantly deviate from the other months due to outstanding events (e.g., the outbreak of COVID-19 in 2020 and the landfall of Hurricane Ida in 2021). These $Mobility_i^m$ values were identified and removed from the subsequent calculations for long-term planning and investment purposes. Specifically, the calculated mobility index values were checked in two dimensions by following the criteria described below:

- Horizontal comparison (i.e., comparing by POI). Each POI's mobility index values were compared over months to identify unexpected mobility fluctuations (i.e., ±2.5 standard deviations). This step identified 67,873 mobility outlier values, which account for about 1.62% of the data (i.e., 67,873/(87,447*48)*100% =1.62%).
- Vertical comparison (i.e., comparing by month). Any POI with out-of-range mobility index values (i.e., ±2.5 standard deviations) in a month should not be used for planning purposes and their mobility index values of that month were thus removed. This step identified an additional 15,426 mobility outlier values, which account for about 0.37% of the data (i.e., 15,426/(87,447*48)*100% =0.37%).

After the two-stage data cleaning, 72% (=84,319/116,935) of the POIs are left in the dataset with valid mobility index values. It should be noted that not all POIs have mobility index values for the entire 48-month study period due to business opening/closure and the above-mentioned data cleaning. Figure 3 describes the distribution of POIs with valid mobility index values. For example, the first bar to the right-hand-side means 9,122 POIs have valid mobility index values for 48 months. The first bar to the left-hand-side means 41 POIs have valid mobility index values for only one month.

Figure 3. Histogram of POIs with valid mobility index



Then valid mobility index values were averaged for each POI to represent its typical mobility status in the study period.

$$Mobility_i = average(Mobility_i^m) \qquad [2]$$

where,

$Mobility_i$ is the calculated mobility index for POI i in the 48-month study period.

Result Aggregation

A single POI with a greater mobility value may not be sufficient to justify an investment. Additionally, aggregating the mobility index by cluster (i.e., grid/hexagon or roadway segment as explained below) could also help address the potential sampling issue from individual POIs. This study summarized mobility index values of all POIs within certain distance to a cluster j. Mobility index for cluster j is calculated as:

$$MIndex_j = \sum_i Mobility_i \, , POI \; i \in Cluster \; j \qquad [3]$$

A cluster j with a greater mobility index value indicates a greater number of short-distance trips to the POIs within that region. This, in turn, suggest that walking/biking facilities are likely needed to optimize efficient, multimodal travel. This study created two types of clusters for practical use: grids/hexagons and roadway segments.

Cluster Level 1: Grids/Hexagons. The study began by testing grid cells in 100 m, 500 m, 800 m, and 1000 m. Initially, it was found that 500 m grid cells provided more satisfying visualizations (i.e., resolution and coverage) among the four tested grid sizes. However, based on collected survey responses, stakeholders expressed a preference for data to be presented at a finer resolution using hexagons instead of grids. As a result, the study utilized the hexagonal hierarchical geospatial indexing system (H3) to enhance data presentation [67]. Table 1 displays hexagon resolutions ranging from Level 8 to Level 10. For comparison, a hexagon at Level 9 is about 1/3 the size of a 500m grid. A full set of hexagons covering all the locations in Louisiana was then generated. Level 9 resulted in 1,201,535 hexagons covering Louisiana. In addition, mobility index values were aggregated for each hexagon within its 0.2 km radius. The 0.2 km distance threshold accomplished two objectives: 1) it matches the average edge length of Level 9 hexagons, and 2) adds up to a 0.4 km (0.25 mile) walking radius from a hexagon's centroid, which aligns with the acceptable walking distance commonly reported in U.S. research studies [68].

Table 1. Hexagon resolution table

Resolution	Average Hexagon Area (km^2)	Ratio (P/H)	Min Hexagon Area (km^2)	Max Hexagon Area (km^2)	Ratio (max/min)	Average edge length (km)
8	0.737	0.504	0.446	0.889	1.992	0.531
9	0.105	0.504	0.063	0.127	1.992	0.200
10	0.015	0.504	0.009	0.018	1.992	0.075

Cluster Level 2: Roadway Segment. The sliding window technique is used frequently to evaluate safety conditions and was applied to this study to summarize the mobility index values. According to the Highway Safety Manual (HSM), predictive methods require the roadway network to be divided into homogeneous segments with a recommended minimum segment length of 0.1 mi. The Guidebook on Identification of High Pedestrian Crash Locations uses a window length of 0.19 mile (300 m) with a moving increment of 0.06 mile (100 m) in pedestrian crash analysis [69]. The Safer Streets Priority Finder (SSPF) utilizes a window length of 0.5 mile (800 m) with a moving increment of 0.1 mile (160 m) [48]. The approach taken by the Texas A&M Transportation Institute (TTI) sets the window size at 0.3 mile (500 m) with a moving increment of 0.1 mile (160 m) [70].

In this study, the window size was set at 0.3 mile with a moving increment of 0.1 mile to summarize mobility index values. In actual operation, it should be noted that not all the segments can be cut at the same length (in 0.1 mile) and some of the segments could be very short (closer to 0) since there are intersections and road ends. When "per mile" or "per square mile" values were calculated, those short segments (i.e., length less than 0.1 mile) were considered equivalent as 0.1-mile segments to avoid inflated values.

Consider Equity in Mobility Measurement

As noted in the previous texts, equity indicators were integrated into mobility measurement to address concerns regarding sampling bias. Population density (Table B01003) and poverty status (Table B17017) at census block group level were collected from the "2016-2020 American Community Survey 5-Year Estimates." Hexagons/roadway segments were spatially joined with census block groups using the "Have their center in" as the match option to speed up the process of obtaining the corresponding demographic information. Specifically, two adjustments were made to the mobility measurement as shown below.

Adjustment 1:

For non-residential hexagon/segment j, the adjusted mobility index value is zero.

$$MIndex\_1_j = 0 \quad [4]$$

For residential hexagon/segment j, the adjusted mobility index value is calculated as:

$$MIndex\_1_j = (1 + poverty_j) \times MIndex_j \quad [5]$$

where,

$poverty_j$ is the proportion of households whose income below poverty level of hexagon/segment j, which assumes to be the same as the block group where hexagon/segment j belongs.

Adjustment 2:

$$MIndex\_2_j = \frac{PopDen_j}{\max(PopDen_j)} \times (1 + poverty_j) \times MIndex_j \quad [6]$$

where,

$PopDen_j$ is the population density of hexagon/segment j, which assumes to be the same as the block group where hexagon/segment j belongs.

$poverty_j$ is the same as described above for equation [5].

Table 2 is a summary of measures related to mobility. A cluster (i.e., a hexagon or roadway segment) with a positive standardized/normalized mobility index value (i.e., $StdMob_j$) means that there are more active short-distance trips in that cluster than the state average. In contrast, a cluster with a negative mobility index value (i.e., $StdMob_j$) means that the cluster has fewer trips in short-distance or long-time durations than the state average.

Table 2. Mobility measures by hexagon/segment

Variable name	**Variable description**
POICount	The number of points of interest (POIs) within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)
MIndex	The sum of mobility index values of all POIs within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)
MIndex_1	The first type of adjustment to mobility index in considering equity factors
MIndex_2	The second type of adjustment to mobility index in considering equity factors
MIndex_3	The second type of adjustment to mobility index in considering equity factors and the variation of roadway segment lengths. This index is to account for inflated values in the "roadway segment" case.
StdMob	The standardized/normalized value of MIndex_2 (for hexagon) or MIndex_3 (for roadway segment) with statewide average and deviation.

Consider Network Connectivity for Systematic Development

This section introduces how network connectivity ($StdCon_j$) was measured. Specifically, the state's active transportation infrastructure (including sidewalk, dedicated bicycle facility, and shared-use trail) network was considered and used in calculating the connectivity index in this study. Other networks (e.g., non-interstate roadways and transit) were also included in the dashboard to serve diverse needs and meet different expectations.

Network Data Source

Official roadway datasets released by DOTD were selected and used in this project. These roadways were marked with information from the DOTD's Linear Reference

System (LRS), which could assist in quick identification of roadways and facilitate subsequent project selection/construction/maintenance activities. Specifically, the geospatial datasets are named “Sidewalk Outside,” “Sidewalk Inside,” and “LRSID Routes,” which were generated based on the most recent data collected by the Automatic Road ANalyzer (ARAN) in 2010 [71]. The length of non-interstate roadways was calculated by considering both directions of the highways, instead of simply counting the length of route centerline. It is important to note that the number of lanes was not considered in this calculation. Similarly, both directions of inside/outside sidewalks were counted to calculate the length of sidewalks. The bicycle facility and shared-use trail network were obtained from a previous project conducted by the research team [65], which was updated by the co-PI of this project in 2023. Again, both directions (instead of route centerline) of the bicycle and shared use trail network were counted.

Connectivity Measurement

Cluster Level 1: Hexagons. The hexagon Level 9 selected from the previous step was used in the connectivity summary. This study calculated network completeness (e.g., ConIndex) and network density (e.g., ConIndex_1 and ConIndex_2), while considering types of active transportation infrastructure as shown in Table 3.

Cluster Level 2: Roadway Segment. The sliding window technique was applied in summarize the connectivity index for each 0.1 mile roadway segment. The issue with short-length segments was also addressed here (i.e., ConIndex_3).

Table 3 provides a summary of measures related to connectivity. A cluster (i.e., a hexagon or roadway segment) with a positive standardized/normalized connectivity index value (i.e., $StdCon_j$) indicate that its active transportation infrastructure density is calculated to be above the state average. In contrast, a cluster with a negative standardized/normalized connectivity index value (i.e., $StdCon_j$) indicates that its active transportation infrastructure density ratio is below the state average.

Table 3. Connectivity measures by hexagon/segment

Variable name	Variable description	Unit
LenHwy	Length of non-interstate roadways (both directions were counted but the number of lanes were not considered) within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)	miles
LenWalk	Length of sidewalk (both directions were counted) within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)	miles
LenTrail	Length of shared use trail (both directions were counted) within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)	miles
LenBike	Length of bicycle facilities (both directions were counted) within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)	miles
ConIndex	Sidewalk completeness, which equals LenWalk divided by LenHwy	(na)
ConIndex_1	Density of walking facilities (including sidewalk and shared use trail), which equals (LenWalk + LenTrail) divided by the hexagon area (or the roadway segment catchment area)	mile per square miles
ConIndex_2	Density of active transportation facilities (including sidewalk, bicycle facility, shared-use trail), that equals (LenWalk + LenTrail + LenBike) divided by the hexagon area (or the roadway segment catchment area)	mile per square miles
ConIndex_3	This index is to account for inflated values in the "roadway segment" case. Density of active transportation facilities (including sidewalk, bicycle facility, shared-use trail) in considering the variation of roadway segment lengths	mile per square miles
StdCon	The standardized/normalized value of ConIndex_2 (for hexagon) or ConIndex_3 (for roadway segment) with statewide average and deviation.	(na)
DenWalk	The density of sidewalk within 0.2-km radius of the edges of a hexagon, which equals LenWalk divided by the hexagon area	mile per square miles

(Note: "na" means not applicable.)

Integrate Safety Factors

This section addresses the third goal of the Complete Streets Policy in Louisiana—safety. This study focuses on extracting data on pedestrians and bicyclists-involved crashes that occurred between 1/1/2018 and 12/31/2021 from DOTD Crash Database to match the period of mobility data used in this study. All codes of crash severity (i.e., A = Fatal, B = Severe, C = Moderate, and D = Complaint) were considered in counting injuries and fatalities for the pedestrian/bicyclist involved crashes. Crash data is cleaned and published on a yearly basis.

Cluster Level 1: Hexagons. The hexagon Level 9 selected from the previous step was used in the crash summary. Frequency of bicyclist/pedestrian-involved crashes (i.e., total number of crashes; NumCrash) and the severity of those crashes (i.e., injuries and fatalities for each involved in the crash; NumCrashIF) were both summarized and included in the output dataset. The safety index represented as, $StdSafe_j$, was calculated as the standardized value of NumCrashIF.

Cluster Level 2: Roadway Segment. To match the threshold selected in the previous step, crashes were summarized into two factors: 1) the number of bicyclist and pedestrian crashes within a 0.1 mile distance from each road segment (i.e, NumCrash) and 2) the number of injuries and fatalities in bicyclist/pedestrian crashes within 0.1 mile distance from each road segment (NumCrashIF). The issue with short-length segments was also addressed here (i.e., CrashFQ_BP). Similarly, $StdSafe_j$ was generated in considering severity (i.e., CrashFQ_BP) in this research.

Table 4 is a summary of safety measures. A cluster (i.e., a hexagon or roadway segment) with a positive standardized/normalized safety index value (i.e., $StdSafe_j$) means the cluster has higher number of injuries and facilities in bicyclist/pedestrian involved crashes than the state average. In contrast, a cluster with a negative standardized/normalized safety index value (i.e., $StdSafe_j$) means the crash severity is below the state average.

Table 4. Safety measures by hexagon/segment

Variable name	Variable description
NumCrash	The number of bicyclist/pedestrian involved crashes within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)
NumCrashIF	The number of injuries and fatalities in the bicyclist/pedestrian involved crashes within 0.2-km radius of the edges of a hexagon (or 0.1-mile radius to a segment)
CrashFQ_BP	The frequency (per mile) of injuries and fatalities in the bicyclist/pedestrian involved crashes within 0.1-mile radius to a segment (Unit: per mile)
StdSafe	The standardized/normalized value of NumCrashIF (for hexagon) or CrashFQ_BP (for roadway segment) with statewide average and deviation.

(Note: crash data were collected for the period from 1/1/2018 to 12/31/2021 to match the mobility analysis period.)

Develop an Investment Potential Score for Summary

As shown before, each index (safety, mobility, and connectivity) was standardized using z-scores with their statewide averages. Each z-score represents the difference between the value for a given cluster and the state average, measured in terms of the standard deviation. Then, the three z-scores were summarized to reflect the total investment potential (i.e., $InvScore_j$) in order to identify active transportation “hot areas.” In other words these are locations where there is a higher likelihood that infrastructure investments will lead to increased opportunities for walking or bicycling. Clusters with greater mobility needs (more short-distance trips), lower network density which inhibits current demand, and a greater number of injuries and fatalities in pedestrian/bicyclist-involved crashes should be prioritized for near-term investment in safety, mobility, and/or connectivity. The following equation shows the calculation, where a higher value indicates that a cluster has a greater investment potential.

$$InvScore_j = StdSafe_j + StdMob_j - StdCon_j \qquad [7]$$

It should be noted that a cluster (i.e., a hexagon or roadway segment) with a negative investment potential score simply means that the investment potential of the cluster is lower than the state average. A city/parish/MPO/district may want to extract the portion of data for their own jurisdiction and examine the rank of scores to identify places with relatively higher investment potential within their own jurisdiction.

Incorporate Equity into Active Transportation Planning

In this study more equity indicators were considered and incorporated into the dashboard, in addition to the two equity indicators (i.e., population density and poverty level) used in calculating the mobility index.

EPA’s Smart Location Database

The Smart Location Database (SLD) Version 3.0 was released by the U.S. Environmental Protection Agency (EPA) in 2021 [72]. The SLD “summarizes more than 90 different indicators associated with the built environment and location efficiency. These indicators include density of development, diversity of land use, street network design, and accessibility to destinations, as well as various demographic and employment statistics. Most attributes are available for all U.S. block groups” [73].

USDOT’s Transportation Disadvantaged Census Tracts

The first data source that provides equity information is from the U.S. Department of Transportation (USDOT) [74]. This tool is currently being used by the federal funding program “Reconnecting Communities Pilot Program” to determine community economic disadvantage status [75]. Each of the six disadvantage indicators shown in Table 5 is presented at the census tract level in the dataset. The overall disadvantage score is generated based on these six disadvantage indicators to determine whether a census tract is disadvantage or not. Specifically, census tracts exceeding the 50th percentile (75th for resilience) across at least four of the six disadvantaged indicators are identified as disadvantaged in this tool [74].

Table 5. USDOT's Transportation Disadvantaged Census Tracts

Variable name	Variable description	Data sources
DisTrans	Whether a census tract is identified as transportation disadvantaged by USDOT. Transportation disadvantage is considered as places that spend more, and longer, to get where they need to go	CDC Social Vulnerability Index; Census America Community Survey; EPA Smart Location Map; HUD Location Affordability Index
DisHealth	Whether a census tract is identified as health disadvantaged by USDOT depends on whether it is considered a place exposed to negative environmental impacts that induced adverse health outcomes	CDC Social Vulnerability Index
DisEcon	Whether a census tract is identified as economic disadvantaged by USDOT. Economic disadvantage is considered as places with more populations in high poverty, low wealth, lack of local jobs, low homeownership, low educational attainment, and high inequality	CDC Social Vulnerability Index; Census America Community Survey; FEMA Resilience Analysis & Planning Tool
DisEquity	Whether a census tract is identified as social disadvantaged by USDOT. Social disadvantage is considered as places that with a high percentile of persons (age 5+) who speak English "less than well"	CDC Social Vulnerability Index
DisResilt	Whether a census tract is identified as resilience disadvantaged by USDOT. Resilience disadvantage is considered as places that are vulnerable to hazards caused by climate change	FEMA National Risk Index
DisEnvir	Whether a census tract is identified as environmental disadvantaged by USDOT. Environment disadvantage is considered as places that with disproportionate pollution burden and inferior environmental quality	EPA EJ Screen
DisUSDOT	Whether a census tract is identified disadvantaged by USDOT in general (when four or more of the above-mentioned disadvantaged indicators are marked as "yes")	(USDOT)

(Note: "na" means not applicable.)

U.S. Census data

More social, economic, and demographic variables were collected from the U.S. Census to reflect equity from different perspectives [76] . Table 6 presents all the 15 equity-related indicators included in the developed dashboard. Data at census tract level were collected from “2016-2020 American Community Survey 5-Year Estimates” to maintain consistency with the geographic unit used by the USDOT in describing community disadvantages.

Table 6. Equity indicators from the U.S. census

Variable name	Variable description	ACS table ID (column ID: column name)
edu	Percentage of populations with no high school diploma (age 25+)	ACSDP5Y2020.DP02 (DP02_0067PE: Percent!!EDUCATIONAL ATTAINMENT!!Population 25 years and over!!High school graduate or higher)
disab	Percentage of noninstitutionalized populations with a disability	ACSDP5Y2020.DP02 (DP02_0072PE: Percent!!DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION!!Total Civilian Noninstitutionalized Population!!With a disability)
lang	Percentage of populations speaking English less than very well	ACSDP5Y2020.DP02 (DP02_0115PE: Percent!!LANGUAGE SPOKEN AT HOME!!Population 5 years and over!!Language other than English!!Speak English less than very well"")
unemp	Percentage of unemployment	ACSDP5Y2020.DP03 (DP03_0009PE: Percent!!EMPLOYMENT STATUS!!Civilian labor force!!Unemployment Rate)
food	Percentage of households receiving nutrition/SNAP benefits	ACSDP5Y2020.DP03 (DP03_0074PE: Percent!!INCOME AND BENEFITS (IN 2020 INFLATION-ADJUSTED DOLLARS)!!Total households!!With Food Stamp/SNAP benefits in the past 12 months)
health	Percentage of noninstitutionalized populations without health insurance coverage	ACSDP5Y2020.DP03 (DP03_0099PE: Percent!!HEALTH INSURANCE COVERAGE!!Civilian noninstitutionalized population!!No health insurance coverage)
veh0	Percentage of occupied housing unit without vehicles	ACSDP5Y2020.DP04 (DP04_0058PE: Percent!!VEHICLES AVAILABLE!!Occupied housing units!!No vehicles available)
age65	Percentage of populations over 65 years old	ACSDP5Y2020.DP05 (DP05_0024PE: Percent!!SEX AND AGE!!Total population!!65 years and over)
raceW	Percentage of White populations	ACSDP5Y2020.DP05 (DP05_0064PE: Percent!!Race alone or in combination with one or more other races!!Total population!!White)
raceBAA	Percentage of Black or African American populations	ACSDP5Y2020.DP05 (DP05_0065PE: Percent!!Race alone or in combination with one or more other races!!Total population!!Black or African American)

Variable name	Variable description	ACS table ID (column ID: column name)
raceAIAN	Percentage of American Indian and Alaska Native populations	ACSDP5Y2020.DP05 (DP05_0066PE: Percent!!Race alone or in combination with one or more other races!!Total population!!American Indian and Alaska Native)
raceA	Percentage of Asian populations	ACSDP5Y2020.DP05 (DP05_0067PE: Percent!!Race alone or in combination with one or more other races!!Total population!!Asian)
raceNH	Percentage of Native Hawaiian and Other Pacific Islander populations	ACSDP5Y2020.DP05 (DP05_0068PE: Percent!!Race alone or in combination with one or more other races!!Total population!!Native Hawaiian and Other Pacific Islander)
raceOther	Percentage of other race populations	ACSDP5Y2020.DP05 (DP05_0069PE: Percent!!Race alone or in combination with one or more other races!!Total population!!Some other race)
poverty	Percentage of populations below poverty level	ACSST5Y2020.S1701 (S1701_C03_001E: Estimate!!Percent below poverty level!!Population for whom poverty status is determined)

Output Testing and Sharing

Table 7 presents a summary of the outputs from this study. These output datasets are in different geographic resolutions and are expected to be used by stakeholders with different job responsibilities. This study used the ArcGIS dashboard (which is an online platform enabling interactive data visualizations) to visually present these outputs and enable public access to ensure equity in data access. Appendix C presents the data dictionary for each layer included in the dashboard to support the use of the dashboard.

Table 7. Outputs and data sharing

Layer name	Feature type	Data source
DOTD Sidewalk	Line	DOTD Geospatial Gateway
Bicycle network	Line	LTRC Project 21-2SS and LCRT Project H.014664
Shared-use trail network	Line	LTRC Project 21-2SS and LCRT Project H.014664
Transit network	Line	LTRC Project 21-2SS
Hexagon (All_Hex9)	Polygon	(This study)
Block group	Polygon	Environmental Protection Agency (EPA)
Census Tract (tl_2020_22_tract20)	Polygon	U.S. Census and USDOT
Parish (Parish_Score)	Polygon	U.S. Census and this study
District (District_Score)	Polygon	DOTD and this study
Segment	Line	DOTD and this study

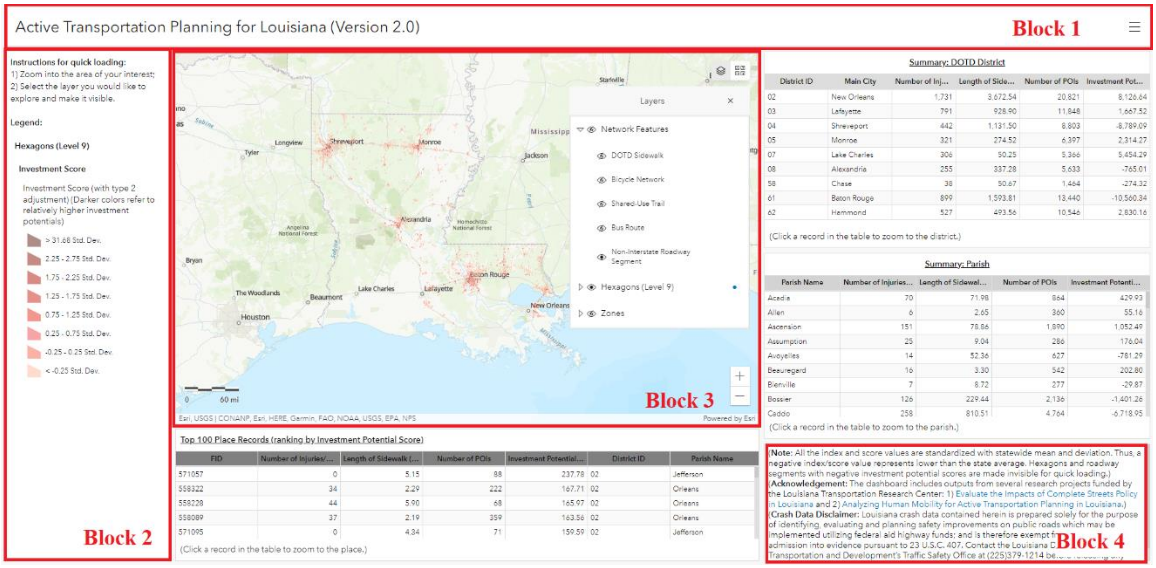
Result Visualization via ArcGIS Dashboard

The dashboard has five blocks in its desktop view, presenting different types of information as shown in Figure 4 (a). The first block presents introductory information (e.g., titles, acknowledgements, and links to gain more information, facilitating dashboard use). The second block presents the map legend, depending on which layers are made visible. The third block presents the map with layers listed in Table 7. The upper right "stack" button within the block enables users navigate through available layers and turn on different layers for use. Note that the hexagon layer is duplicated four times to present safety, mobility, connectivity, and investment potential scores separately. The fourth block presents additional notes, acknowledgements, and disclaimers. The remaining space presents several tables, including the top 100 places with a higher investment potential score (i.e., $InvScore_j$), district-level summary, and parish-level summary. The dashboard was internally tested and reviewed before being released to a small group of stakeholders (~10 persons) with the most relevant knowledge and experience. After that, the dashboard was released to a larger group of stakeholders (over 100 individuals from different regions in the state) for review. The survey procedure is described in detail in the next section.

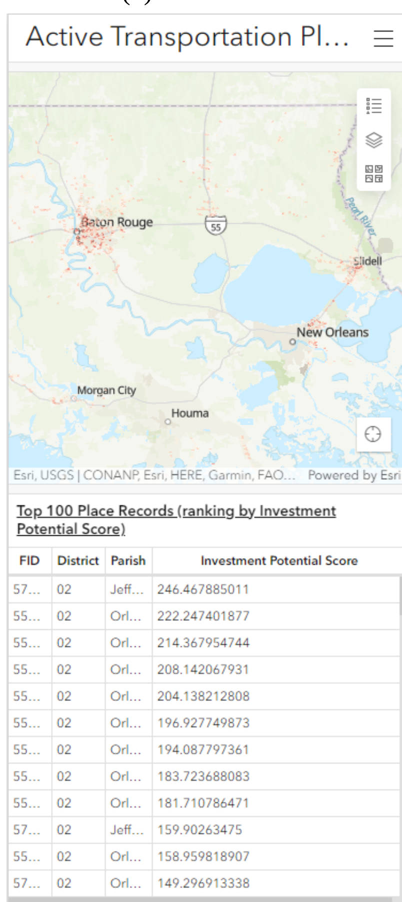
To simplify the mobile viewing experience, the dashboard only has three blocks in its mobile view, as shown in Figure 4 (b). The top block shows introductory information, the center block showcases maps layers, and the bottom block lists the top 100 places with higher investment potential scores.

Figure 4. Dashboard appearance

(a) desktop view



(b) mobile view



Survey Procedure

The objective of the survey was to share initial results and data visualizations for testing and validation. Its purpose was to guide beta test participants in fully exploring the interactive map interface, gain a preliminary understanding of whether the results align with local knowledge, and ultimately identify potential improvements to the platform or underlying indices. The survey instrument (Appendix D) was developed in Qualtrics software and included the following categories of information and inquiry:

1. Instructions for using the beta tool
2. Stakeholder respondent characteristics (role, geographic region)
3. Alignment of the presented data with local knowledge of active transportation conditions along each indexed dimension
4. Alignment of the presented data with locally collected models, analyses, counts, and/or plan documents
5. Potential improvements to data visualization, user interface, or questions about methodology
6. Recommendations for incorporating equity into the tool and/or other data layers
7. Potential data applications and future research needs to support active transportation planning, policy, and infrastructure implementation in Louisiana

A list of stakeholders, including representatives from a variety of offices in DOTD, staff of MPOs, local planning departments, transit agencies, active transportation advocacy organizations, downtown development districts, regional safety coalitions, and professional planning associations, was compiled to invite them to participate in providing feedback. The invitation (including survey link, project information capsule, and link to interactive map platform) was distributed via email on March 20, 2023. Participants were initially given two weeks to respond, and weekly reminder emails were sent to encourage participation. Responses were accepted until April 13, 2023.

Discussion of Results

This section first summarizes statistics of safety, mobility, and connectivity measurements developed in this study to support active transportation planning in Louisiana. Then this section presents stakeholder survey results and several case studies to facilitate understanding of the developed dashboard.

Data Summary

This subsection presents statistics of attributes included in the output layers: hexagon, segment, census tract, parish, and district.

Hexagon

There are 1,201,535 hexagons created to cover the entire state. Table 8 shows the summary statistics of these hexagons. The area of each hexagon is almost the same, approximately 0.04 square miles. Within a 0.2 km radius of these hexagons, there were as many as 157 reported crashes resulting in 121 injuries/fatalities and 430 POIs (in a destination-dense area of the French Quarter, New Orleans). There are 18 hexagons that were calculated to have a sidewalk coverage value greater than or equal to one. It may be of a surprise that the length of sidewalks can be up to 1.53 times the length of non-interstate roadways, for a hexagon, the maximum identified within the dataset, as was found in New Orleans near Audubon Park. This is because most of the area in such a hexagon (with its vicinity being considered) covers non-residential places (e.g., open water areas like rivers) and the rest of its area covers recreational facilities (e.g., river front parks). The aggregate investment potential score could be as low as -26.68 (in St. Bernard Parish) and as high as 246.47 (in Jefferson Parish), which presents a large range of variation. Analysis of the individual components of the composite score can yield insight into the type of investment needed. For example, an excessively large number of injuries/fatalities occurring in a hexagon and its vicinity could explain most of the cases with the highest investment scores. Addressing safety concerns instead of building new facilities might need to be done first in those cases.

Table 8. Data summary for hexagon layer

Variable name	Variable description	Theme	Range	Mean	Std. Dev
Area	The area of a hexagon (Unit: square miles)	(na)	[0.04, 0.04]	0.04	0.00
NumCrash	The number of bicyclist/pedestrian involved crashes within 0.2-km radius of the edges of a hexagon	Safety	[0, 157]	0.04	0.63
NumCrashIF	The number of injuries and fatalities in the bicyclist/pedestrian involved crashes within 0.2-km radius of the edges of a hexagon	Safety	[0, 121]	0.03	0.60
StdSafe	The standardized/normalized value of NumCrashIF	Safety	[-0.06, 199.96]	0.00	1.00
POICount	The number of POIs within 0.2-km radius of the edges of a hexagon	Mobility	[0, 430]	0.30	2.93
MIndex	The sum of mobility index values of all POIs 0.2-km radius of the edges of a hexagon	Mobility	[0, 137.37]	0.14	1.68
MIndex_1	The first type of adjustment to mobility index in considering equity factors	Mobility	[0, 167.17]	0.16	1.99
MIndex_2	The second type of adjustment to mobility index in considering equity factors	Mobility	[0, 57.54]	0.01	0.23
StdMob	The standardized/normalized value of MIndex_2 with statewide average and deviation	Mobility	[-0.05, 251.75]	0.00	1.00
LenHwy	Length of non-interstate roadways within 0.2-km radius of the edges of a hexagon (Unit: miles)	Connectivity	[0, 13.99]	0.53	1.02
LenWalk	Length of sidewalk in a bin/hexagon within 0.2-km radius of the edges of a hexagon (Unit: miles)	Connectivity	[0, 9.80]	0.03	0.33
LenTrail	Length of shared use trail (both directions were counted) within 0.2-km radius of the edges of a hexagon (Unit: miles)	Connectivity	[0, 3.00]	0.00	0.02
LenBike	Length of bicycle facilities (both directions were counted) within 0.2-km radius of the edges of a hexagon (Unit: miles)	Connectivity	[0, 3.43]	0.00	0.02
ConIndex	Sidewalk completeness, which equals LenWalk divided by LenHwy	Connectivity	[0, 1.53]	0.01	0.05
ConIndex_1	Density of walking facilities (including sidewalk and shared use trail) that equals (LenWalk + LenTrail) divided by the hexagon area	Connectivity	[0, 52.41]	0.17	1.77
ConIndex_2	Density of active transportation facilities (including sidewalk, bicycle facility, shared-use trail) that equals (LenWalk + LenTrail + LenBike) divided by the hexagon area	Connectivity	[0, 53.75]	0.17	1.81

Variable name	Variable description	Theme	Range	Mean	Std. Dev
StdCon	The standardized/normalized value of ConIndex_2	Connectivity	[-0.09, 29.68]	0.00	1.00
DenWalk	The density of sidewalk within 0.2-km radius of the edges of a hexagon	Connectivity	[0, 52.41]	0.16	1.75
InvScore	Investment potential score, which equals StdSafe plus StdMob minus StdCon	Investment	[-26.68, 246.47]	0.00	1.51

Segment

There are 1,868,280 non-interstate roadway segments created to cover the entire state in this study. Table 9 shows the summary statistics of all the segments. Unlike hexagons of equal areas, the length of segments varies from 0.00 miles to 0.15 miles. Although the 0.1-mile threshold was applied in generating segments, not all the segments on roadways can be cut exactly by 0.1 miles. At last, an average length of around 0.1 miles was achieved. Figure 5 shows the length distribution of the created non-interstate roadway segments with an increment unit of 0.01-mile.

Table 9 shows the summary statistics of these segments. The frequency of bicyclist/pedestrian-involved crashes could be as high as 500 in the vicinity of a one-mile equivalent segment. The number of POIs could exceed 1,800 in the vicinity of a one-mile equivalent segment, indicating a highly dense area. Taking the variation of roadway segment lengths into consideration, the density of active transportation facilities (including sidewalk, bicycle facility, shared-use trail) could be as much as 62.78 miles/square mile. A notable observation from the data is that two DOTD districts (i.e., District 7, Lake Charles and District 58, Chase) do not have any identified shared-use trails or bicycle facilities. The aggregate investment potential score could be as low as -7.47 (on Benton Street, New Orleans) and as high as 95.92 (on Napoleon Avenue, New Orleans).

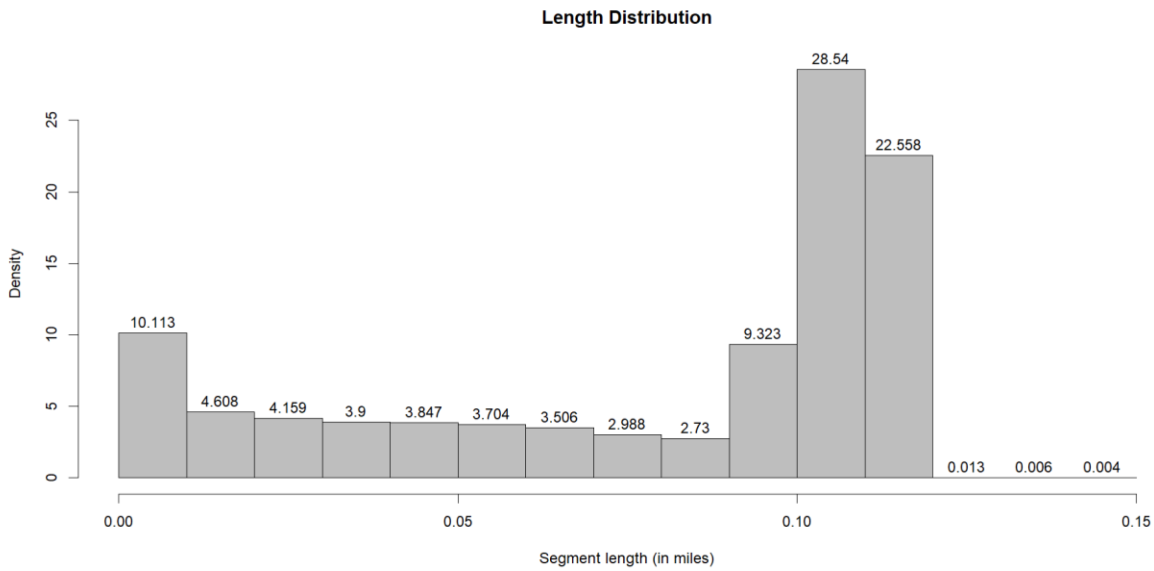
Table 9 Data summary for segment layer

Variable name	Variable description	Theme	Range	Mean	Std. Dev
length	The length of each roadway segment (Unit: miles)	(na)	[0, 0.15]	0.08	0.04
Area2	The area covered within 0.1-mile radius to a segment (Unit: square miles)	(na)	[0.03, 0.06]	0.05	0.01
NumCrash	The number of bicyclist/pedestrian involved crashes within 0.1-mile radius to a segment	Safety	[0, 66]	0.16	0.94

Variable name	Variable description	Theme	Range	Mean	Std. Dev
NumCrashIF	The number of injuries and fatalities in the bicyclist/pedestrian involved crashes within 0.1-mile radius to a segment	Safety	[0, 53]	0.15	0.91
CrashFQ_BP	The frequency (per mile) of injuries and fatalities in the bicyclist/pedestrian involved crashes within 0.1-mile radius to a segment (Unit: per mile)	Safety	[0, 499.52]	1.48	9.03
StdSafe	The standardized/normalized value of CrashFQ_BP	Safety	[-0.16, 55.14]	0.00	1.00
POICount	The number of POIs within 0.1-mile radius to a segment	Mobility	[0, 164]	1.09	3.47
MIndex	The sum of mobility index values of all POIs within 0.1-mile radius to a segment	Mobility	[0, 76.61]	0.45	1.90
MIndex_1	The first type of adjustment to mobility index in considering equity factors	Mobility	[0, 101.18]	0.55	2.28
MIndex_2	The second type of adjustment to mobility index in considering equity factors	Mobility	[0, 27.24]	0.04	0.28
MIndex_3	The second type of adjustment to mobility index in considering equity factors and the variation of roadway segment lengths	Mobility	[0, 272.42]	0.42	2.75
StdMob	The standardized/normalized value of MIndex_2	Mobility	[-0.15, 99.02]	0.00	1.00
LenHwy	Length of non-interstate roadways within 0.1-mile radius to a segment (Unit: miles)	Connectivity	[0.01, 5.04]	1.06	0.56
LenWalk	Length of sidewalk within 0.1-mile radius to a segment (Unit: miles)	Connectivity	[0, 3.20]	0.15	0.38
LenTrail	Length of shared use trail (both directions were counted) within 0.1-mile radius to a segment (Unit: miles)	Connectivity	[0, 1.13]	0.00	0.02
LenBike	Length of bicycle facilities (both directions were counted) within 0.1-mile radius to a segment (Unit: miles)	Connectivity	[0, 1.59]	0.00	0.03
ConIndex	Sidewalk completeness, which equals LenWalk divided by LenHwy	Connectivity	[0, 9.01]	0.08	0.21
ConIndex_1	Density of walking facilities (including sidewalk and shared use trail), which equals (LenWalk + LenTrail) divided by Area2	Connectivity	[0, 84.95]	3.57	9.11
ConIndex_2	Density of active transportation facilities (including sidewalk, bicycle facility, shared-use trail), which equals (LenWalk + LenTrail + LenBike) divided by Area2	Connectivity	[0, 84.95]	3.64	9.29
ConIndex_3	Density of active transportation facilities (including sidewalk, bicycle facility, shared-use trail) in considering the variation of roadway segment lengths	Connectivity	[0, 62.78]	2.99	7.68
StdCon	The standardized/normalized value of ConIndex_3	Connectivity	[-0.39, 7.78]	0.00	1.00

Variable name	Variable description	Theme	Range	Mean	Std. Dev
InvScore	Investment potential score, which equals StdSafe plus StdMob minus StdCon	Investment	[-7.47, 95.92]	0.00	1.60

Figure 5. Length distribution of the created non-interstate roadway segments



Census Tract

The census tract layer includes 1,388 tracts in Louisiana and provides a diverse group of equity indicators to meet different needs. Table 10 shows the summary statistics of these census tracts.

Table 10. Data summary for census tract layer

Variable name	Variable description	Theme	Range	Mean	Std. Dev
DisTrans	Transportation access: places that spend more, and longer, to get where they need to go	Equity	[0, 1]	0.64	0.48
DisHealth	Health: places that are exposed to negative environmental impacts that induced adverse health outcomes	Equity	[0, 1]	0.69	0.46

Variable name	Variable description	Theme	Range	Mean	Std. Dev
DisEcon	Economic: places with more populations in high poverty, low wealth, lack of local jobs, low homeownership, low educational attainment, and high inequality	Equity	[0, 1]	0.64	0.48
DisEquity	Equity: places that with a high percentile of persons (age 5+) who speak English “less than well”	Equity	[0, 1]	0.28	0.45
DisResilt	Resilience: places that are vulnerable to hazards caused by climate change	Equity	[0, 1]	0.68	0.47
DisEnvir	Environment: places that with disproportionate pollution burden and inferior environmental quality	Equity	[0, 1]	0.73	0.44
DisUSDOT	The overall disadvantage score generated to answer whether a census tract is disadvantage or not.	Equity	[0, 1]	0.59	0.49
Edu	Percentage of populations with no high school diploma (age 25+)	Equity	[0, 56.4]	14.67	9.36
Disab	Percentage of noninstitutionalized populations with a disability	Equity	[0, 57.3]	15.61	6.96
Lang	Percentage of populations speaking English less than very well	Equity	[0, 37.8]	2.70	4.31
Unemp	Percentage of unemployment	Equity	[0, 43.3]	6.99	5.87
Food	Percentage of households with food stamp	Equity	[0, 77.4]	16.29	12.79
Health	Percentage of noninstitutionalized populations without health insurance coverage	Equity	[0, 37.8]	8.82	5.44
veh0	Percentage of occupied housing unit without vehicles	Equity	[0, 70.7]	9.31	10.49
age65	Percentage of populations over 65 years old	Equity	[0, 70.0]	15.74	7.54
raceW	Percentage of White populations	Equity	[0, 100]	60.56	30.63
raceBAA	Percentage of Black or African American populations	Equity	[0, 100]	35.10	30.12
raceAIAN	Percentage of American Indian and Alaska Native populations	Equity	[0, 42.4]	1.34	2.73
raceA	Percentage of Asian populations	Equity	[0, 45.6]	2.01	3.78
raceNH	Percentage of Native Hawaiian and Other Pacific Islander populations	Equity	[0, 9.6]	0.11	0.52
raceOther	Percentage of other race populations	Equity	[0, 31.6]	2.15	3.55
Poverty	Percentage of populations below poverty level	Equity	[0, 85.8]	19.83	13.65

Parish

The parish layer includes 64 parishes in Louisiana and provides a summary of the index values and scores calculated at the parish level. The calculation approach is similar to the case of Hexagon (Level 9) since both are polygons. Table 11 shows the summary statistics of these parishes. Orleans Parish has the largest number (i.e., 2,407) of injuries and fatalities resulting from bicyclist/pedestrian involved crashes. East Baton Rouge Parish has the most POIs (i.e., 9,047), but its mobility index value ranks third, following Orleans Parish and Jefferson Parish. Additionally, the three parishes (i.e., Orleans, Jefferson, and East Baton Rouge) have higher density of active transportation facilities compared to that of other parishes in Louisiana. The aggregate investment potential score ranges as low as -0.57 (St. Bernard Parish) and as high as 5.56 (Orleans Parish).

Table 11. Data summary for parish layer

Variable name	Variable description	Theme	Range	Mean	Std. Dev
ALAND	Land area of a parish (Unit: 10^9 square meters)	Built environment	[0.44, 3.44]	1.75	0.76
TotalPop	The number of populations in a parish (in thousands)	Demographics	[4.44, 443.16]	72.88	98.79
PopDen	The population density in a parish (Unit: per square miles)	Demographics	[5.42, 2308.4]	163.47	362.53
TotalHH	The number of households in a parish (in thousands)	Demographics	[1.69, 170.40]	27.37	37.95
TotalPoor	The number of households whose income in the past 12 months below poverty level in a parish (in thousands)	Demographics	[0.20, 35.72]	4.95	6.58
poverty	The proportion of households whose income in the past 12 months below poverty level in a parish	Demographics	[0.07, 0.41]	0.20	0.06
NumCrash	The number of bicyclist/pedestrian involved crashes within a parish (between 1/1/2018 and 12/31/2021)	Safety	[0, 2489]	152.94	363.38
NumCrashIF	The number of injuries and fatalities occurred in the above-mentioned crashes within a parish (between 1/1/2018 and 12/31/2021)	Safety	[0, 2407]	146.86	345.17
StdSafe	The standardized/normalized value of NumCrashIF	Safety	[-0.43, 6.60]	0.00	1.00
POICount	The number of POIs within a parish	Mobility	[93, 9047]	1317.48	1937.88
MIndex_2	The second type of adjustment to mobility index in considering equity factors	Mobility	[0.03, 4270.81]	209.69	763.02
StdMob	The standardized/normalized value of MIndex_2	Mobility	[-0.28, 5.36]	0.00	1.00

Variable name	Variable description	Theme	Range	Mean	Std. Dev
LenHwy	The length of non-interstate roadways within a parish (Unit: miles)	Connectivity	[669.65, 5583.92]	2293.73	1192.52
LenWalk	The length of sidewalks within a parish (Unit: miles)	Connectivity	[0.10, 1624.09]	133.33	329.21
LenTrail	Length of shared use trail (both directions were counted) within a parish (Unit: miles)	Connectivity	[0.00, 52.67]	3.57	9.80
LenBike	Length of bicycle facilities (both directions were counted) within a parish (Unit: miles)	Connectivity	[0.00, 92.01]	2.53	12.46
ConIndex_2	(LenWalk + LenTrail + LenBike)/ALAND (Unit: mile per square miles)	Connectivity	[0.00, 9.31]	0.41	1.40
StdCon	The standardized/normalized value of ConIndex_2	Connectivity	[-0.29, 6.40]	0.00	1.00
InvScore	Investment potential score, which equals StdSafe plus StdMob minus StdCon	Investment	[-0.57, 5.56]	0.00	0.99

(Note: "na" means not applicable.)

District

Similarly, the district layer includes nine DOTD districts and provides a summary of the index values and scores calculated at the district level. The calculation approach is similar to the case of Hexagon (Level 9) since both are polygons. Table 12 shows the summary statistics of these districts. District 2 (New Orleans) has the following distinctions: 1) the largest number (i.e., 3,779) of injuries and fatalities occurred in bicyclist/pedestrian-involved crashes, 2) the most POIs (i.e., 20,821) and mobility index values (i.e., 13640.22), and 3) the best coverage of active transportation facilities in the state. The aggregate investment potential score ranges as low as -0.94 (District 58, Chase) to as high as 2.77 (District 2, New Orleans).

Table 12 Data summary for district layer

Variable name	Variable description	Theme	Range	Mean	Std. Dev
ALAND	Land area of a district (Unit: 10^9 square meters)	Built environment	[9.20, 18.63]	12.43	3.05
TotalPop	The number of populations in a district (in thousands)	Demographics	[78.57, 1158.28]	518.29	317.76
PopDen	The population density in a district (Unit: per square miles)	Demographics	[20.75, 275.55]	117.10	85.08
TotalHH	The number of households in a district (in thousands)	Demographics	[28.17, 445.32]	194.66	121.48

Variable name	**Variable description**	**Theme**	**Range**	**Mean**	**Std. Dev**
TotalPoor	The number of households whose income in the past 12 months below poverty level in a district (in thousands)	Demographics	[6.68, 79.49]	35.18	20.73
poverty	The proportion of households whose income in the past 12 months below poverty level in a district	Demographics	[0.14, 0.24]	0.19	0.04
NumCrash	The number of bicyclist/pedestrian involved crashes within a district (between 1/1/2018 and 12/31/2021)	Safety	[29, 3941]	1087.56	1157.62
NumCrashIF	The number of injuries and fatalities occurred in the above-mentioned crashes within a district (between 1/1/2018 and 12/31/2021)	Safety	[49, 3779]	1044.33	1104.72
StdSafe	The standardized/normalized value of NumCrashIF	Safety	[-0.96, 2.63]	0.00	1.00
POICount	The number of POIs within a district	Mobility	[1464, 20821]	9368.78	5666.51
MIndex_2	The second type of adjustment to mobility index in considering equity factors	Mobility	[26.17, 13640.22]	3072.56	4292.72
StdMob	The standardized/normalized value of MIndex_2	Mobility	[-0.75, 2.61]	0.00	1.00
LenHwy	The length of non-interstate roadways within a district (Unit: miles)	Connectivity	[9014.34, 22492.21]	16310.97	4301.54
LenWalk	The length of sidewalks within a district (Unit: miles)	Connectivity	[50.25, 3672.54]	948.11	1146.73
LenTrail	Length of shared use trail (both directions were counted) within a district (Unit: miles)	Connectivity	[0.00, 95.55]	25.38	32.18
LenBike	Length of bicycle facilities (both directions were counted) within a district (Unit: miles)	Connectivity	[0.00, 100.49]	17.98	33.33
ConIndex_2	(LenWalk + LenTrail + LenBike)/ALAND (Unit: mile per square miles)	Connectivity	[0.01, 0.92]	0.23	0.30
StdCon	The standardized/normalized value of ConIndex_2	Connectivity	[-0.78, 2.47]	0.00	1.00
InvScore	Investment potential score, which equals StdSafe plus StdMob minus StdCon	Investment	[-0.94, 2.77]	0.00	1.11

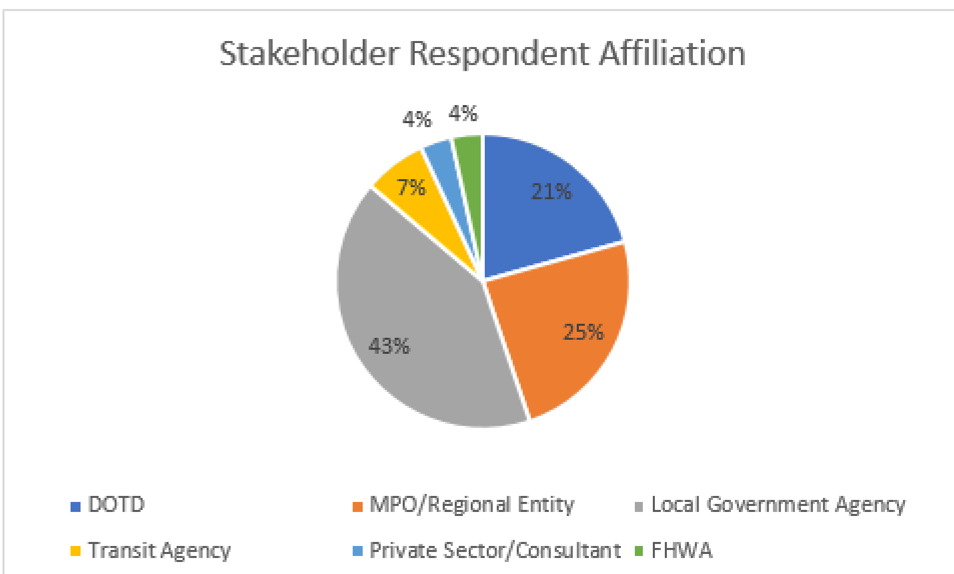
(Note: “na” means not applicable.)

Stakeholder Survey Results

The objective of the survey was to share the initial results and data visualizations of the analysis for testing and validation with likely end-users from different geographic areas and professional roles around the state. This was especially important for those with local knowledge of safety, mobility, and connectivity issues in their jurisdiction or community. The feedback from the respondents was intended to "groundtruth" the findings, finding out whether the results align with local knowledge, and identify possible improvements to the platform or underlying indices to make the data more easily understood and more actionable. A total of 28 invited stakeholders completed the tool walkthrough/tutorial and accompanying feedback survey, representing approximately 25% of those invited.

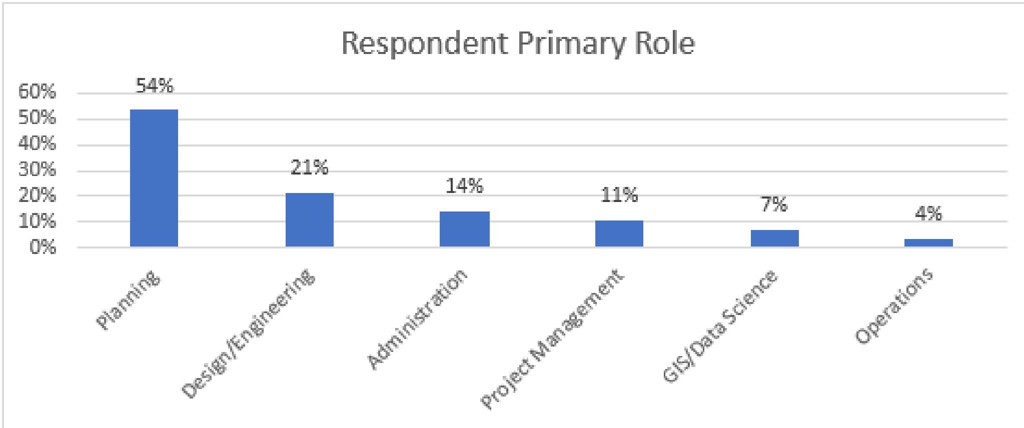
Respondents reflected a mix of primarily consisting of local government agency (43%), followed by MPO (25%), and DOTD (21%) employees. There was also limited representation from transit agencies, the private sector, and FHWA (Figure 6).

Figure 6. Stakeholder survey respondent affiliation



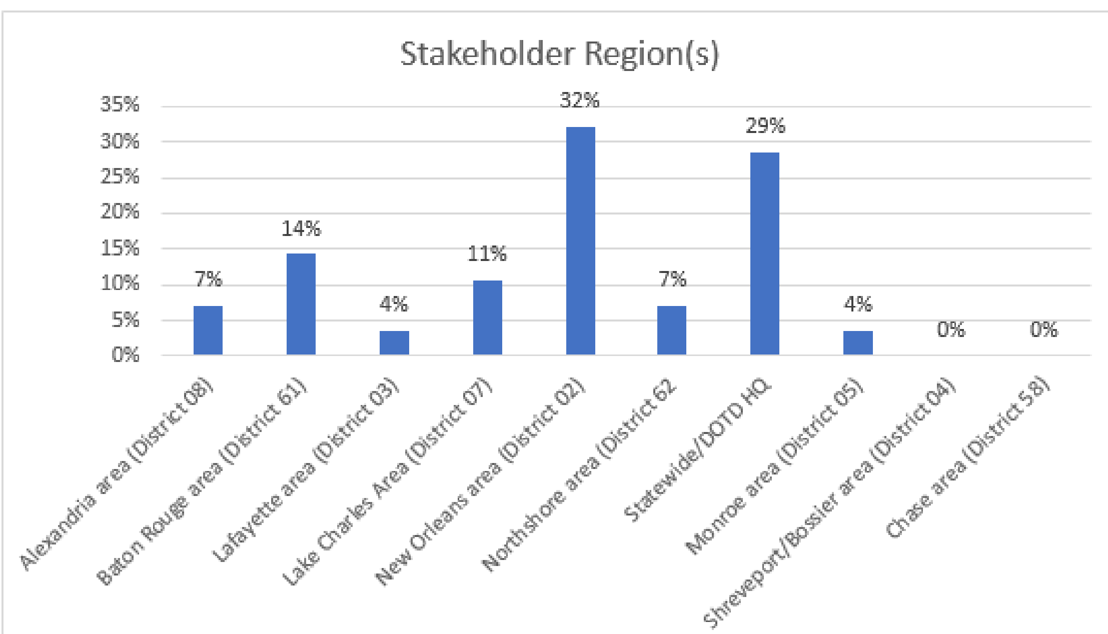
The majority (54%) of respondents indicated that their professional role is primarily planning, with representation from engineering (21%), administration (14%), project management (11%), GIS/data science (7%), and operations (4%) also included (Figure 7).

Figure 7. Stakeholder survey respondent primary professional role



The largest share of respondents (32%) principally work or are based in the District 02 (New Orleans) region (Figure 8). The next largest group consist of stakeholders who work at DOTD headquarters or have statewide responsibilities (29%). They are followed by those in the District 61 (Baton Rouge) area (14%) and the District 07 (Lake Charles) area. Smaller shares of stakeholders responded from District 08 (Alexandria), District 62 (Northshore area), District 03 (Lafayette), and District 05 (Monroe). No stakeholders from the District 04 (Shreveport/Bossier) or District 58 (Chase) areas provided responses.

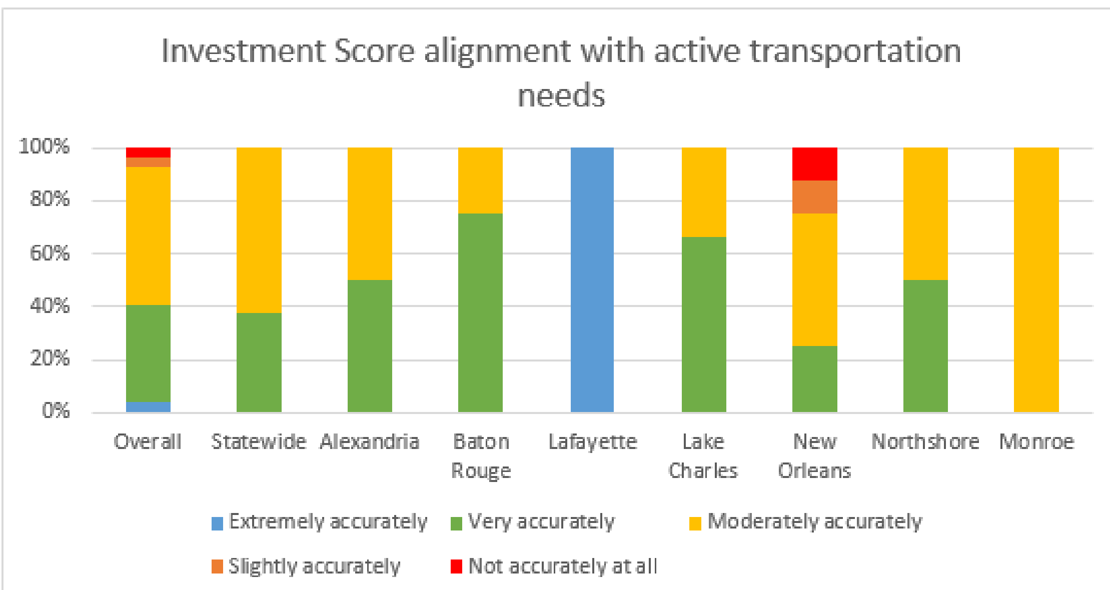
Figure 8. Stakeholder survey respondent region



Respondents were asked (with guided step-by-step tutorial) to review the three indices and the overall investment score, focusing on an area of the state they are familiar with and exploring neighborhoods, corridors, and individual cells. After exploring the data, they were asked to assess how well the scores align with their professional understanding of safety concerns, mobility patterns, and pedestrian and bicycle connectivity in their region, as well as active transportation needs.

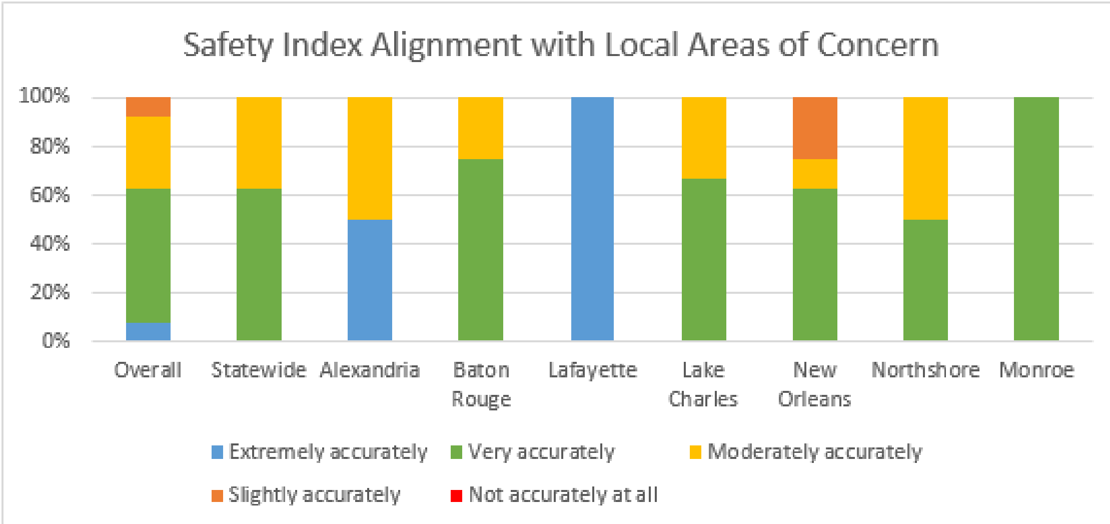
Approximately 40% of respondents indicated that the composite investment score aligns with active transportation needs either “extremely” or “very” accurately (Figure 9). Concerns about overall score accuracy were most prominent in the New Orleans region, with over 20% of respondents indicating that the scores are not accurate at all or only slightly accurate.

Figure 9. Investment score alignment with active transportation needs



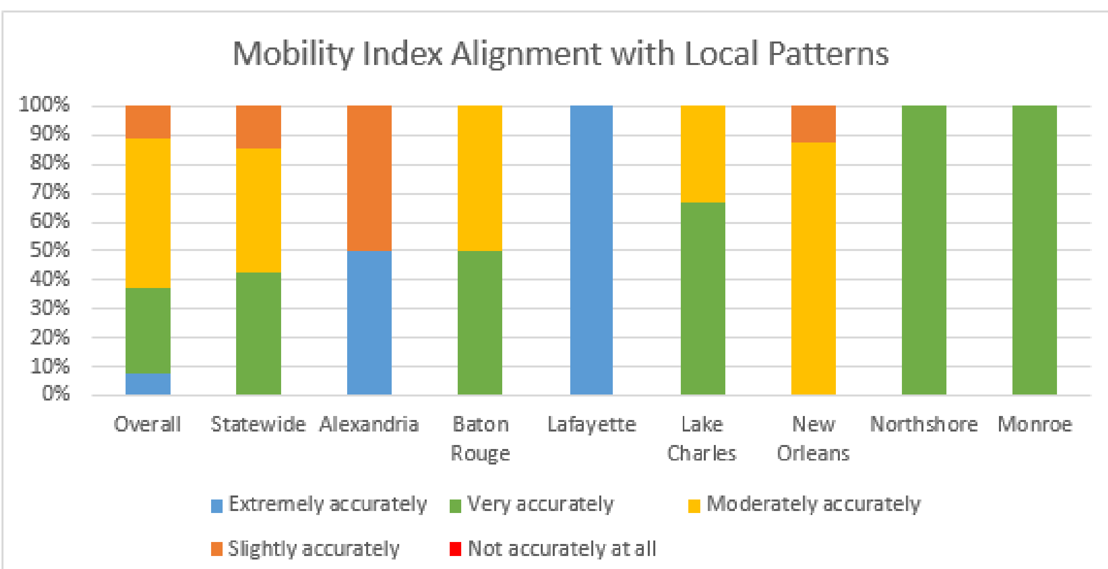
Looking at each of the three indices individually, the safety index appears to align well with stakeholders’ understanding of local areas of concern, with over 60% of respondents indicating that it is extremely or very accurate. However, misalignment is primarily observed in the New Orleans region (Figure 10). One respondent identified a potential data error in an area where a serious crash occurred within the analysis period, but it did not appear in the dataset. This prompted the researchers to identify and import a subset of missing crash records.

Figure 10. Safety index alignment with local areas of concern



The alignment of the mobility index with local perception and understanding of travel patterns was lower, as less than 40% of respondents overall indicated a high degree of accuracy (Figure 11). In some cases, specific locations of misalignment were identified such as the New Orleans' French Quarter. The locations correlate to areas where a higher percentage of POI data was excluded, based on the parameters for identifying outliers (noted above).

Figure 11. Mobility index alignment with local patterns



Finally, the beta version of the connectivity index was identified by participants as the least aligned with local knowledge, with approximately 30% of respondents confirming that the index aligns extremely or very well with the current pedestrian and bicycle networks in their area of interest (Figure 12). Respondents in several regions indicating poor accuracy for bicycle networks, in particular (Figure 13). This was an anticipated result, as there are known deficiencies in the comprehensiveness and recency of DOTD's ARAN-derived sidewalk layer. Additionally, due to a lack of published, statewide bicycle network data, dedicated bikeways are not reflected in the index score at all.

Overall, over 90% of respondents indicated that the index aligns reasonably well with their professional knowledge and experience, with the most significant opportunities for improvement in the connectivity index to better reflect on-the-ground conditions (Figure 14).

In addition to assessing the indices, respondents were asked to reflect on the alignment of the results with local demand models, traffic counts, or other analyses. Overall, over 80% of respondents indicate that the tool is extremely or somewhat aligned with existing local data, with the most notably divergence reported in the New Orleans region, where a majority of respondents indicated some degree of misalignment (Figure 15).

Figure 12. Connectivity index alignment with pedestrian network

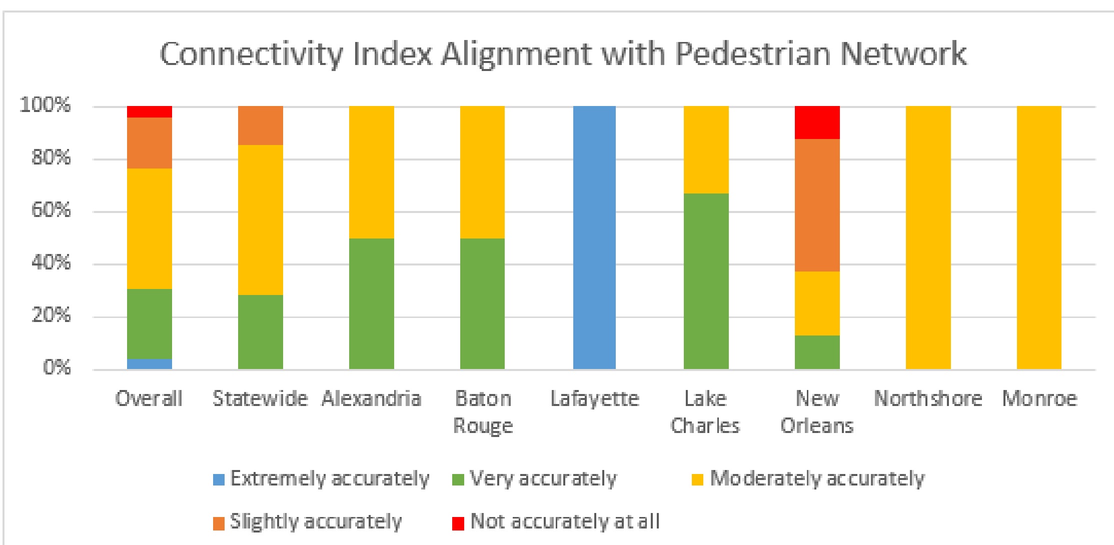


Figure 13. Connectivity index alignment with bicycle network

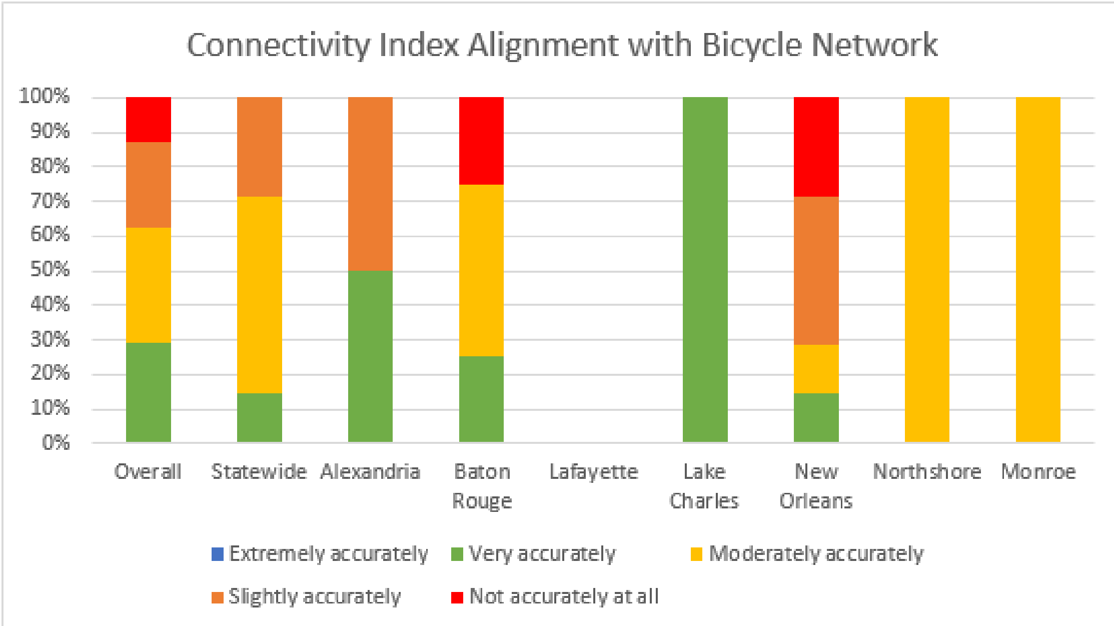


Figure 14. Overall index alignment—all respondents

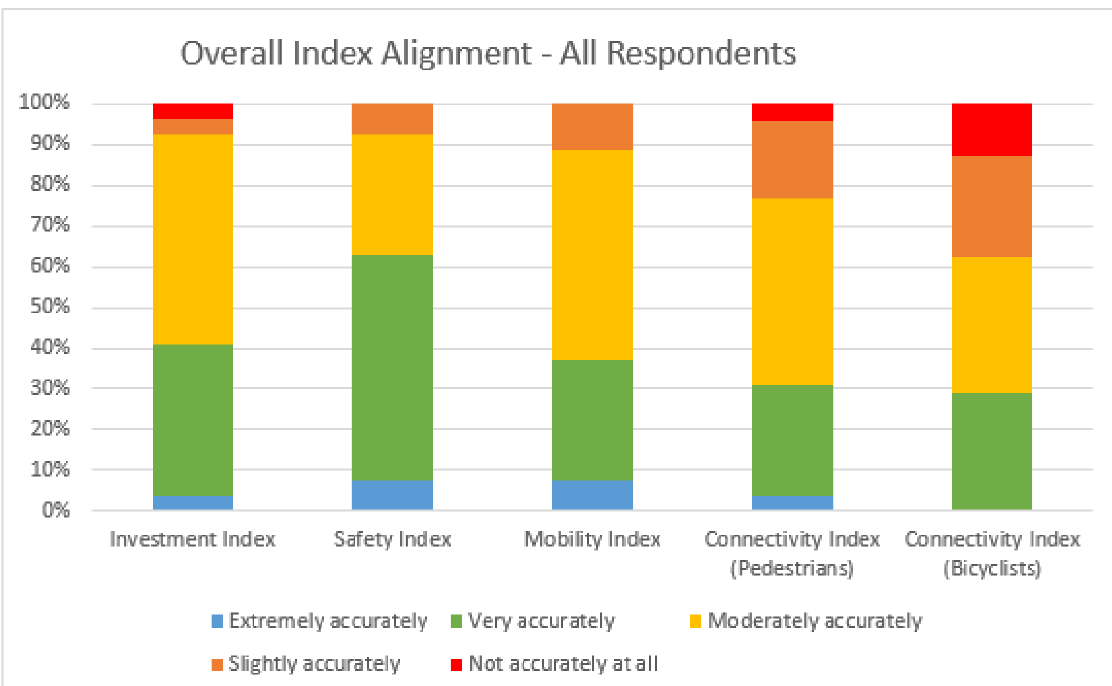
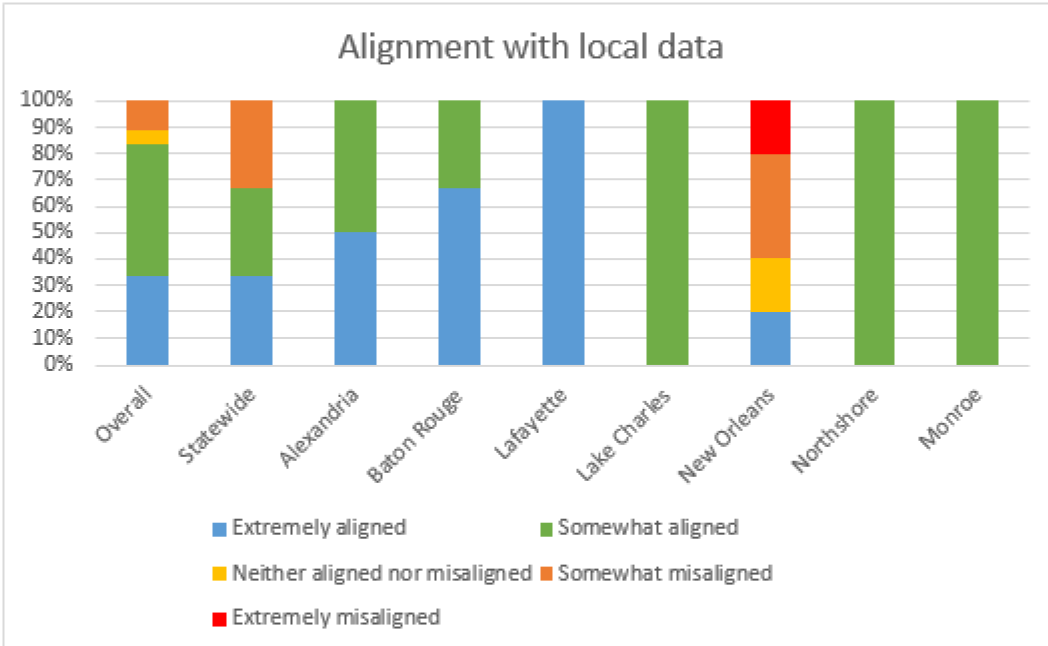
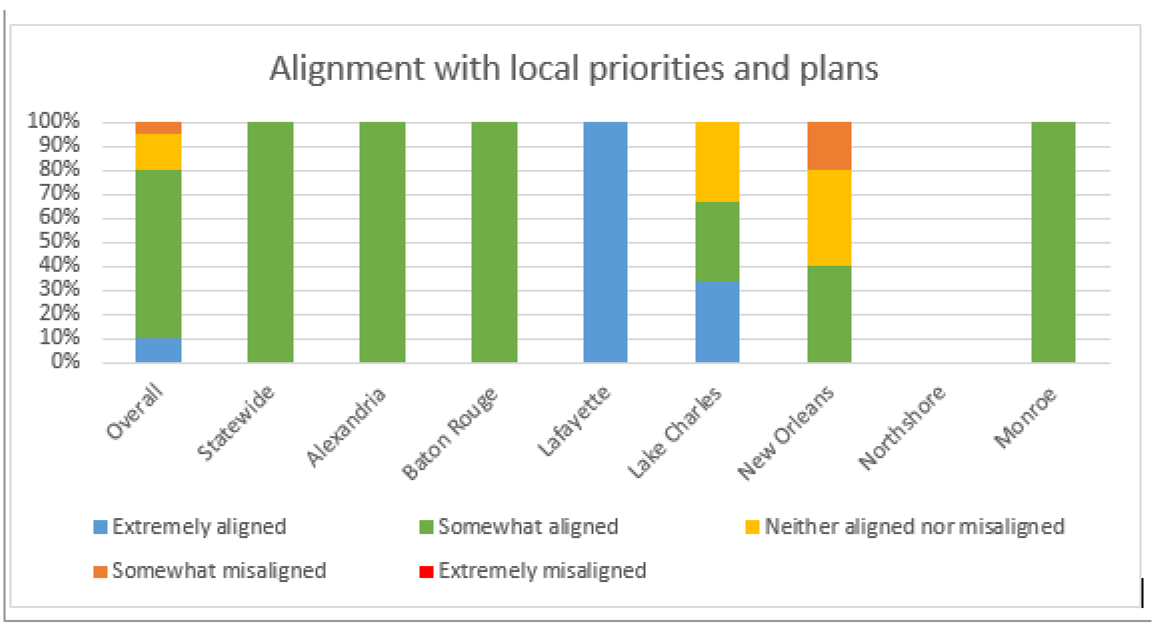


Figure 15. Alignment with local data sources



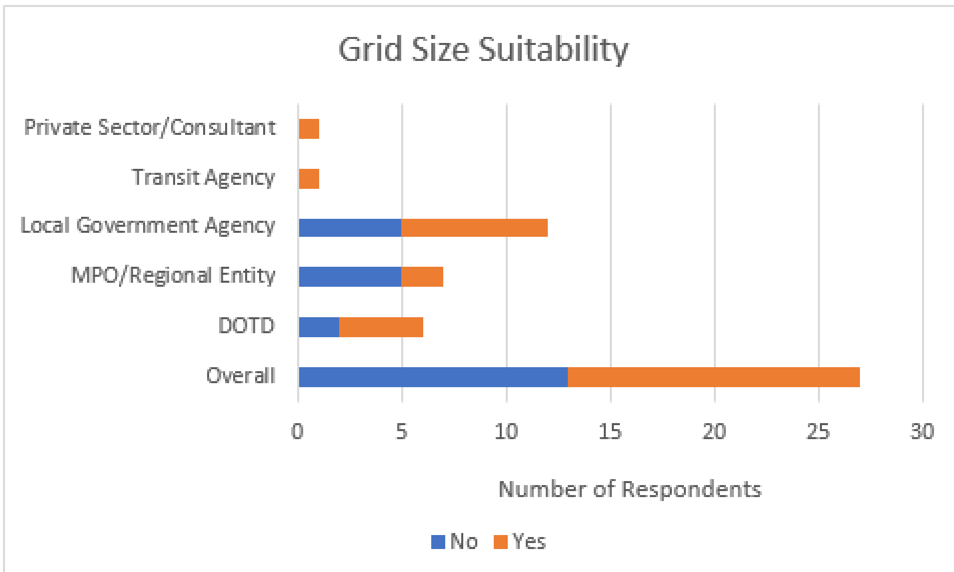
Similarly, approximately 80% of respondents indicate alignment with previously identified local plans and priorities, with misalignment limited to the New Orleans area (Figure 16).

Figure 16. Alignment with local priorities and plans



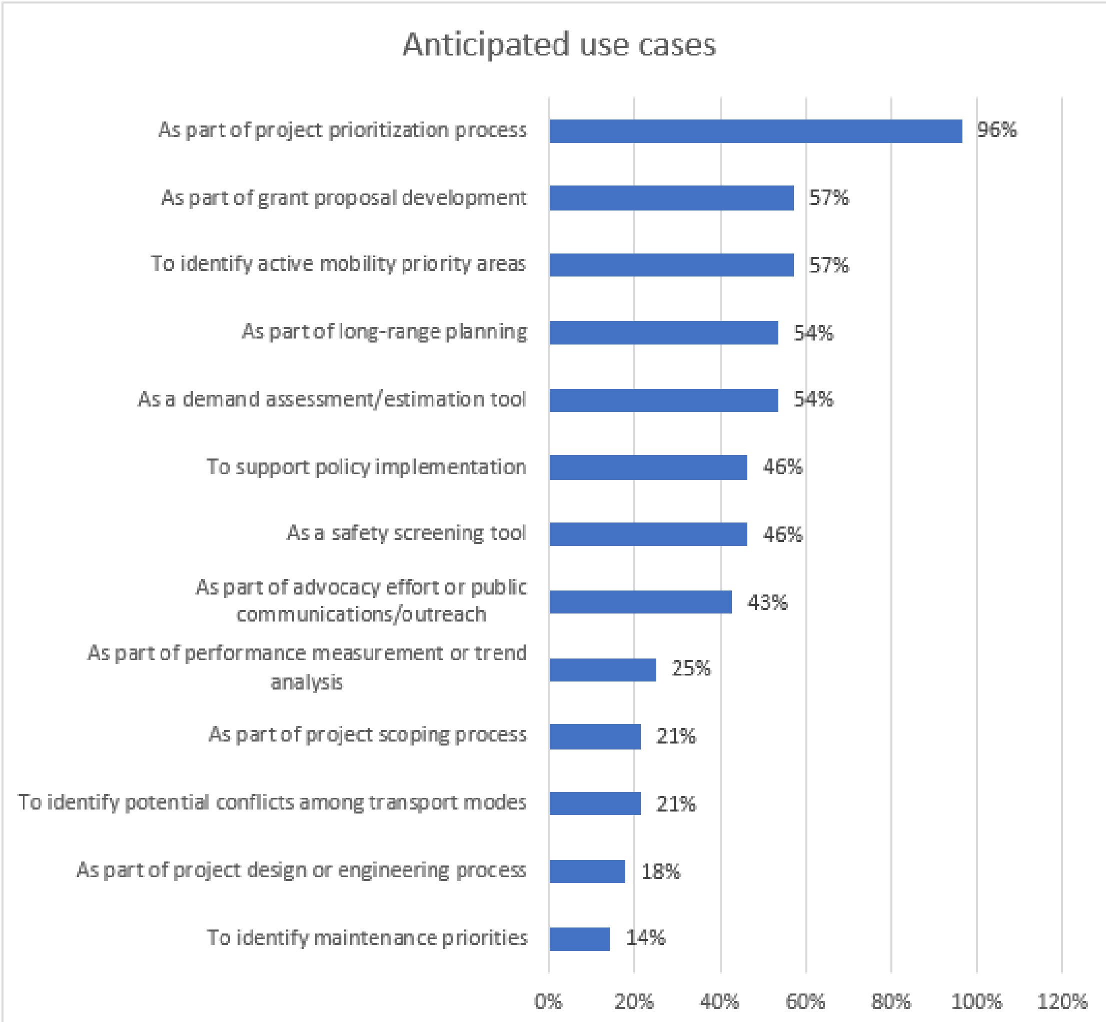
When asked specifically to reflect on the way data was presented in a 500m grid for the beta test, respondents were nearly evenly split about the suitability of the current grid size. Among respondents who indicated "no," most suggested presenting the data at the segment level, while a few suggested that smaller grids—particularly in denser urban areas—are needed (Figure 17).

Figure 17. Grid size suitability



Finally, respondents were asked to reflect on a range of potential use cases for the interactive tool and/or underlying data (Figure 18). Nearly all identified the data as potentially useful for project prioritization. A majority also indicated that grant proposal development, screening to highlight priority areas, long-range planning, and demand estimation are all potentially valuable applications. A plurality perceived the data to be useful for policy implementation support, safety screening, or advocacy. Relatively few respondents indicated that the results were likely to be useful for performance measurement, project scoping, design, engineering, conflict analysis, or to assist maintenance management.

Figure 18. Anticipated use cases



In addition to the above responses, stakeholders were provided several opportunities to reflect and elaborate further about their findings, questions, or recommendations. Over 100 detailed, specific comments were received. These responses were tabulated and addressed, either through updates to the methodology (reflected in the discussion above), updates to the dashboard user interface, and/or the accompanying materials (e.g., data dictionary). The general range and content of comments received (excluding hyper-specific or personally identifying remarks), organized by theme, and tagged based on whether the comment was directly addressed, discussed in the methodology and/or Application Case Studies sections of this report, or identified as an opportunity for future research, are summarized in Table 13.

Table 13. Summary of stakeholder survey free-response comments

Theme	Paraphrased Comment Topic	Response Category
Overall Investment Score	Need a way to incorporate residential land uses into investment score	Addressed in version 2.0
	Address plan for future updates to underlying data and score calculation	See Discussion
	Additional information needed regarding how to use the data to estimate latent demand	See Discussion
	Parks, waterways, and other large features may require additional interpretation and/or data	Future research
	Schools may not be adequately reflected in investment score	Future research
Safety	Inspection of specific crash numbers indicates missing data	Addressed in version 2.0
	Show precise crash location points	See Discussion
Mobility	Mobility index does not reflect disparities in propensity to walk/bike based on demographics	Addressed in version 2.0
	New Orleans' French Quarter indicates lower than expected mobility scores	See Discussion
	Consider weighting certain types of POIs to reflect community priorities	See Discussion
	Clarify the definition of "mobility" to reflect that this is an indicator of potential demand	See Discussion
Connectivity	Bicycle connectivity should be calculated separately using bicycle network	Partially addressed in version 2.0
	Shared-use trails are a data gap in some areas	Addressed in version 2.0
	Transit network connectivity is a data gap	See Discussion
	Recent projects/new facilities are not reflected in DOTD sidewalk layer	Future research
	Bridges are a data/connectivity index gap	Future research
	Quality/facilities at intersections are a data gap	Future research
	Data gaps in connectivity index in New Orleans (especially downtown and French Quarter) is an issue	Future research
	Bicycle network data should include facility class/quality	Future research
Equity	Expensive housing areas are scoring too high relative to need	Addressed in version 2.0
	Additional equity indicators are needed in addition to the USDOT Transportation Disadvantaged Communities layer	Addressed in version 2.0

	Downtown areas with robust sidewalk networks score too high, relative to need	See Discussion
	High priority areas based on plans and equity goals may have low investment scores	See Discussion
User Interface	Provide landing page with user information	[check]
	Spell out any acronyms for public-facing output	Refer to data dictionary
	Segment-level data would be more useful	Addressed in version 2.0
	A data dictionary to aid interpretation is needed	Addressed in version 2.0
	Smaller grid size needed	Addressed in version 2.0
	Negative investment scores/“blank” grid cells should be more clearly explained	Addressed in version 2.0
	Beta version square grid is too imprecise, has boundary issues	Addressed in version 2.0
	Adjust symbology to highlight equity priority areas	Addressed in version 2.0
	Ability to query by corridor or neighborhood needed	See Discussion
	Grid level does not mitigate the need for traffic studies/more detailed validation	See Discussion
	Allow ability to query by roadway functional class/ownership	See Discussion
	Increase user customization options (transparency, additional layers, etc.)	See Discussion
	Make the data available for download in multiple formats	See Discussion
	Grid size should be scalable based on urban form/land use	Future Research
	Adjust symbology to allow visualization of all four indices at once at segment-level	Future Research

Application Case Studies

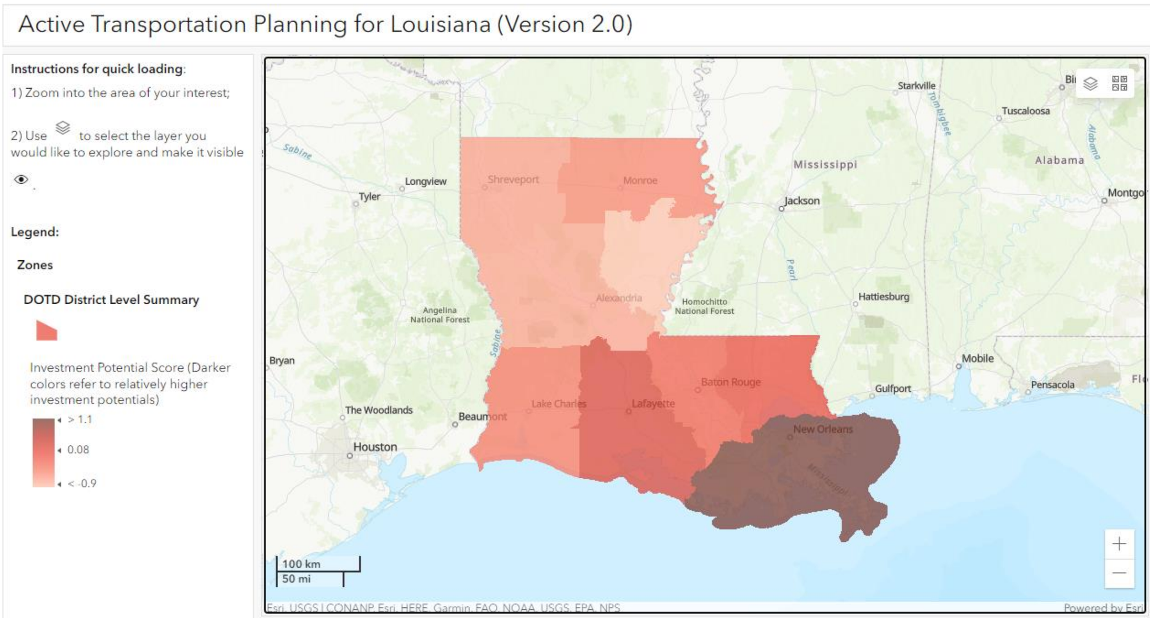
As indicated in the stakeholder feedback results, there are a variety of possible use cases for the tool and underlying indices. Some applications may be more suitable for certain types of stakeholder/agency and specific levels of geography. This section outlines three example use cases for state, urban, and rural applications focusing on the top five identified uses: project prioritization, grant proposal development, identification of active mobility priority areas, long range planning, and demand estimation. The section also discusses additional potential applications, limitations, and future research directions that have emerged from preliminary testing, development, and feedback.

Statewide Screening

First, this study was principally intended to provide a resource for statewide evaluation of active transportation opportunities. The state has already developed a Bicycle Planning Tool that identifies existing level of service (as of 2014 conditions) and estimated demand (using several indicators of revealed and derived demand) for state routes. However, this tool does not cover the local roads, which represent the bulk of the network, nor does it consider pedestrian facilities or existing mobility patterns (i.e., the number of short-distance potential walking/biking trips in a given area). This study aims to fill the gap in data availability to identify areas more holistically, where not only are new facilities, safety improvements, or other interventions are needed for people already walking or bicycling, but also where they are likely to have a proportionately large impact on encouraging active mobility among neighboring populations overall.

One of the built-in features of this tool is the ability to analyze data at multiple scales, from individual segments up to the state as a whole. The investment scores are calculated relative to the statewide mean, so any statewide analysis (of top segments, hexagonal/grid cells, or larger areas of geography) can be easily applied to statewide screening or long-range planning analyses. Allocating funds equitably for transportation statewide must consider a wide range of factors, including political considerations. However, this tool offers a means to simultaneously consider multiple dimensions of potential impact (safety, mobility, and connectivity), highlighting areas where there may be greater opportunity to optimize the benefits of investment. Currently in Louisiana, DOTD District 02 (which includes the New Orleans metro area) stands out as the area with the greatest investment potential (Figure 19). Reviewing of the summary statistics presented in the tool indicates a very high total number of crashes involving vulnerable road users, an outsized share of POIs and trips to those POIs, and a relatively well-developed sidewalk, trail, and bicycle network. In other words, there is a demonstrable need and a solid foundation to build on in terms of both demand and previous investment.

Figure 19. Screenshot of investment potential score by DOTD District



Of course, the state must consider the needs of all its districts. While from a resource efficiency standpoint, it may make sense to allocate funds proportionately to investment potential, it would be both unwise and politically infeasible to invest in population- and activity-dense urbanized areas at the expense of other regions and community types.

The second-lowest scoring DOTD district (other than predominantly rural District 58) is District 08, which includes the Alexandria-Pineville metro area (Figure 20). Within this region, Parish-level aggregate scores provide a quick tool to focus on investment opportunity areas relative to other portions of the district. In District 08, Rapides Parish stands out as having the highest relative score and an overall investment score above the state median. Further inspection indicates that this is primarily attributable to a higher-than-average number of bicycle and pedestrian involved crashes resulting in injury or fatality (Table 14).

Figure 20. Screenshot of overall investment potential score, parishes in District 08

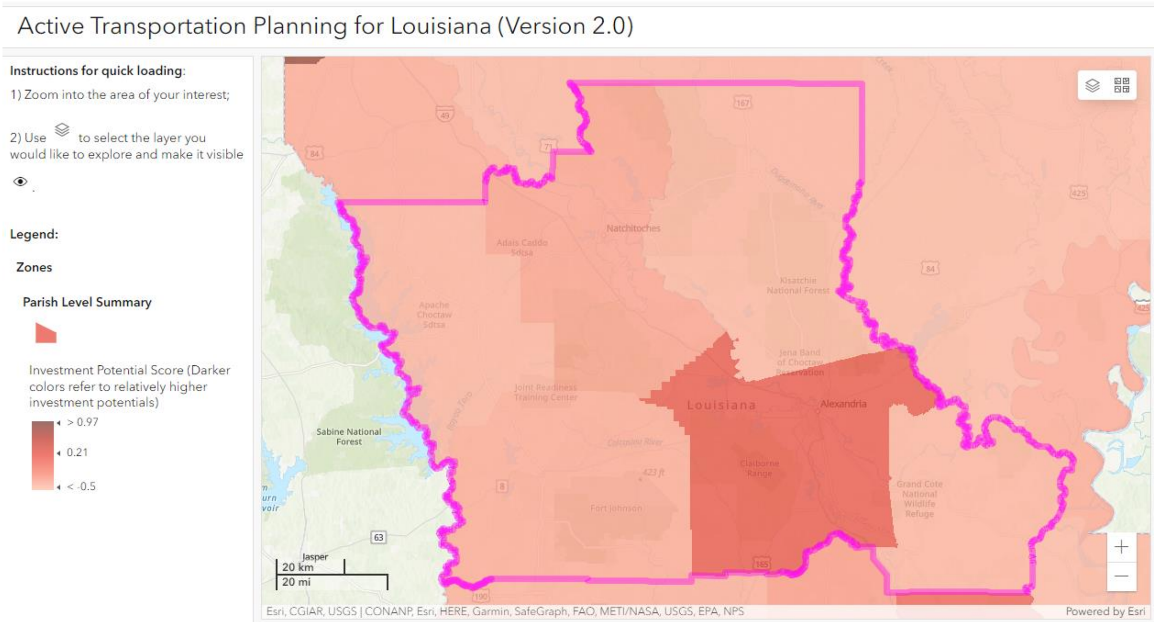
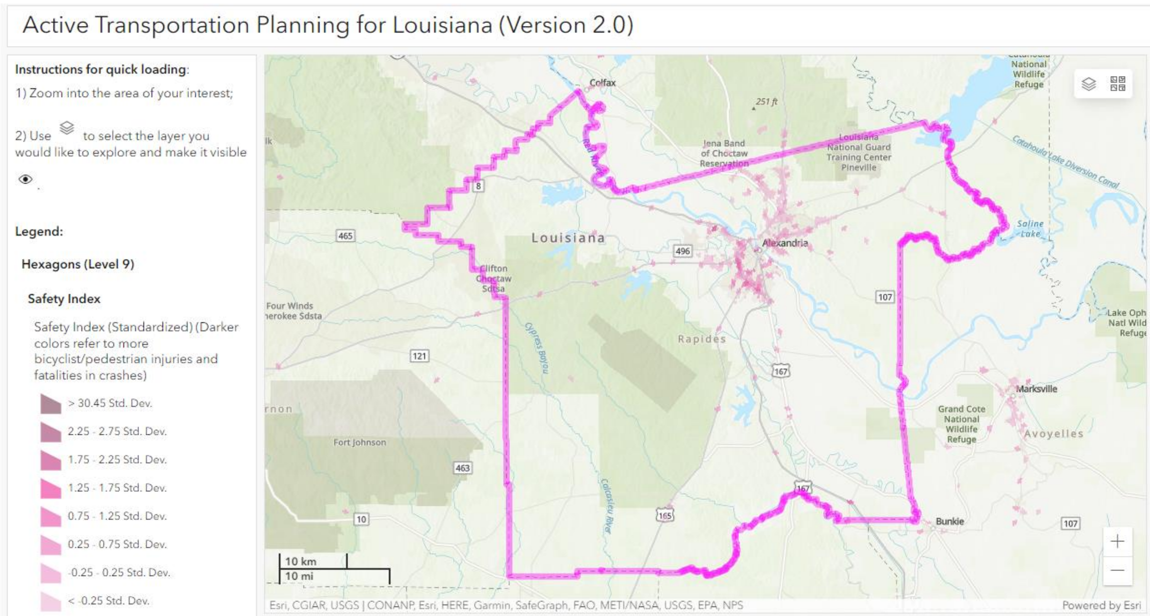


Table 14. Summary of index scores, parishes in District 04

Parish	Safety Index (Standardized)	Mobility Index (Standardized)	Connectivity Index (Standardized)	Total Investment Potential Score
Rapides	0.28	-0.21	-0.17	0.24
Evangeline	-0.27	-0.27	-0.29	-0.26
Natchitoches	-0.29	-0.27	-0.27	-0.29
Vernon	-0.35	-0.27	-0.28	-0.34
Sabine	-0.39	-0.28	-0.28	-0.39
Winn	-0.39	-0.28	-0.28	-0.39
Grant	-0.41	-0.28	-0.28	-0.40

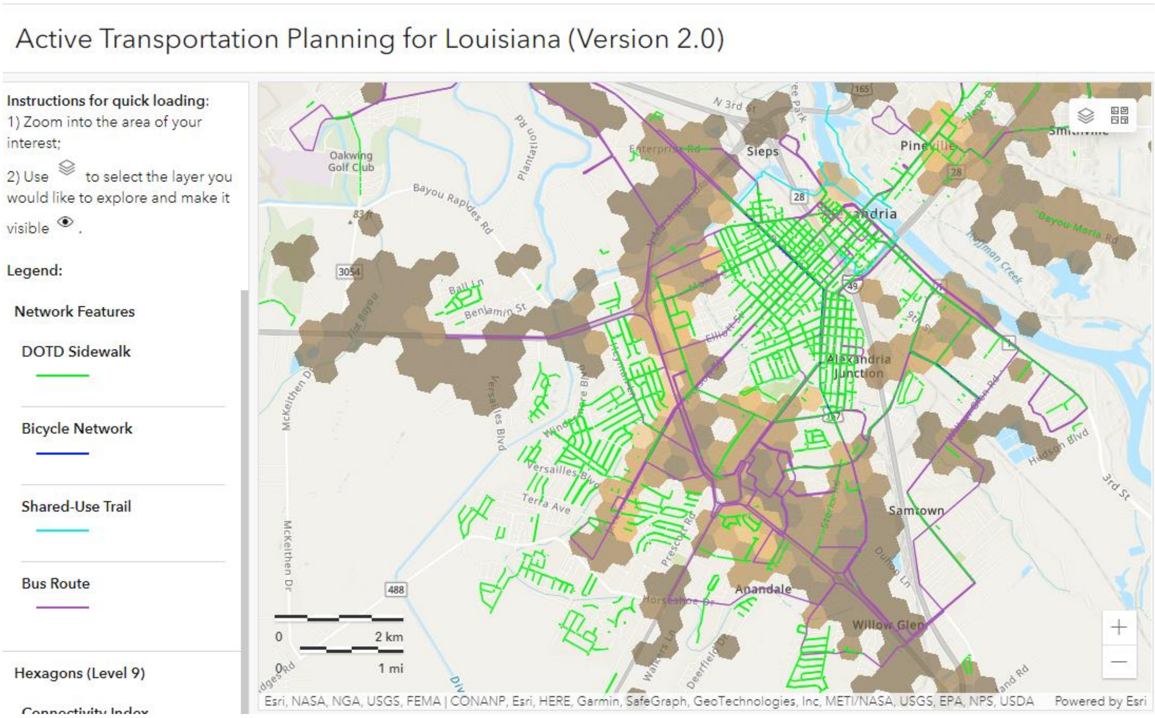
Given the identified disparity in safety outcomes relative to other areas of the region, a closer inspection of the specific areas of concern within Rapides parish may be warranted. Zooming in specifically on the Safety Index, the Macarthur Drive corridor, as well as a few apparent hotspots in downtown Alexandria, N. Bolton Avenue, and in the vicinity of Louisiana College in Pineville, emerge as areas of interest (Figure 21).

Figure 21. Screenshot of safety index layer, Rapides Parish



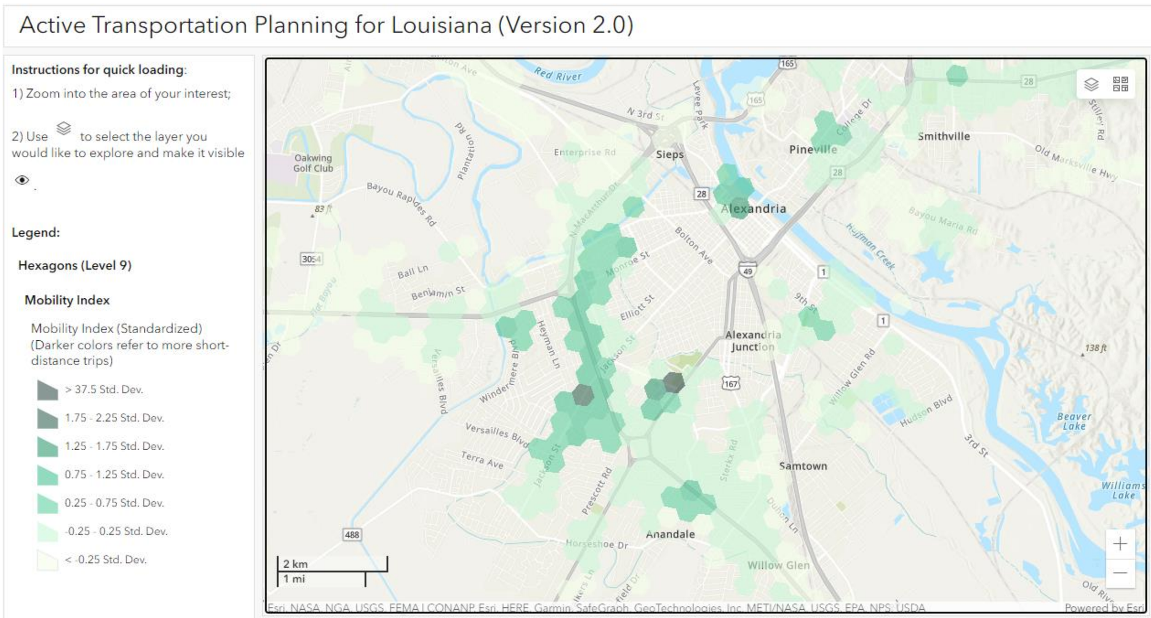
Further inspection of the Macarthur Drive corridor, as an example of a state route that is likely to be of interest to DOTD, indicates that while there are areas of robust pedestrian connectivity and the corridor itself is served by transit, there are few pedestrian or bicycle facilities along or across the roadway to connect adjacent, walkable neighborhoods with the destinations along Macarthur or to and from downtown (Figure 22).

Figure 22. Screenshot of connectivity index and network features for Alexandria area



Finally, cross-referencing this same area with the Mobility Index highlights specific areas of interest where there are more short-distance trips that could be served by walking and bicycling. Two grid cells within a short distance of Macarthur Drive are highlighted as drawing relatively high numbers of visitors in this example: one contains, among other land uses, a supermarket (at Dorcester Drive and Jackson Street), while the other includes the Alexandria Youth Baseball Complex and is adjacent to Bringhurst Park and the Alexandria Zoo (Figure 23). Taken together, the data indicate that this corridor—the primary commercial thoroughfare of the Alexandria area—serves as a safety hazard and a connectivity barrier for people walking, bicycling, or accessing transit, including to key regional destinations and daily needs.

Figure 23. Screenshot of mobility index, Alexandria area



This example highlights how state planners could use this tool to quickly investigate multiple dimensions of active transportation demand and potential within a region of interest. They can achieve this by identifying patterns within a jurisdiction of interest and evaluating a) how sub-areas within that jurisdiction compare to one another (e.g., parishes within a district), b) how the three indices that comprise the investment potential score interrelate within a specific sub-area, and c) existing transportation network connections and priority land uses (as indicated by high mobility scores) that must be considered to identify appropriate interventions.

More broadly, long-range planners can integrate summary index rankings (e.g., top ten parishes or top 100 grid-cell locations) into the analysis of existing conditions to identify intersectional objectives and inform implementation strategies. Program managers can consider the data for the development of competitive funding criteria recommendations and/or performance measurement. Changes in these rankings over time can help highlight areas of increasing or decreasing need for investment—as well as illuminate the specific dimensions (safety, mobility, connectivity) contributing to those changes. In any state-level use case, the data may be used to help communicate how and why investment decisions are made by providing standardized metrics measured against a statewide average, and facilitating quick visualization of findings.

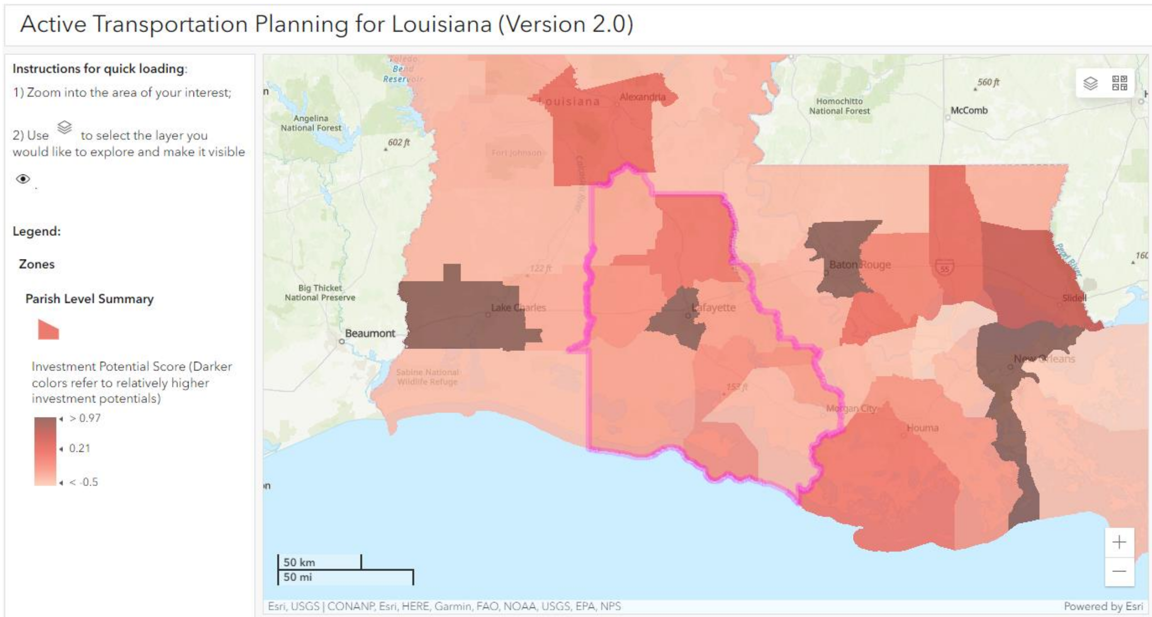
Small Town Transportation Planning and Grant Development Support

A second, high implementation potential use case identified in the course of this study centers on supporting smaller towns, rural parishes, and even small cities with limited planning capacity in the development of transportation plans and grant proposals. Increasingly, the existence of a local transportation plan (either as an independent document or as a substantial portion of a comprehensive or master plan) is an expectation or requirement of state and federal agencies responsible for distributing competitive funds. The state's Complete Streets policy calls for "coordination to identify whether a reconstruction or new construction project will impact a route identified on a local Complete Street plan" (as defined in the corresponding Engineering Directives and Standards Manual), while Louisiana's Transportation Alternatives Program application calls for a clear identification of and justification for how "high-need areas and equity" have been considered and prioritized. However, many local government entities have limited staff, time, and resources for the development of plans or sophisticated analytic methods for such justifications.

DOTD is currently addressing the need to support smaller communities with planning through the implementation of a statewide pilot program aimed at developing a feasible, scalable template for long-range municipal transportation planning. Stakeholders responding to the beta version of this study identified this pilot program and its resulting suite of resources for communities interested in developing local transportation plans. Other feedback indicated potential utility for organizations that provide planning support for smaller communities (e.g., Center for Planning Excellence, CPEX), where limited funding may be available for data collection and/or the development of sophisticated demand analyses tailored to the unique conditions and constraints of the subject area as might be expected in larger cities. This tool can be used by any community with or without the benefit of professional support to extract and analyze Geographic Information System (GIS) data outside of the web interface.

Opelousas, in St. Landry parish, with a population of approximately 15,000, is one of the communities participating in DOTD's long-range planning pilot. As an example of how a small city might incorporate the findings of this study into planning activities and/or grant proposal development, we review the data available via the online tool to identify potential active mobility priority areas in support of a hypothetical grant proposal submission. St. Landry Parish, overall, has an Investment Potential Score of 0.14 which is above the state average and 12th among all 64 parishes. It has the second highest score among parishes in District 03, after Lafayette Parish (Figure 24).

Figure 24. Screenshot of District 03 parishes, overall investment potential score



Looking at the parish overall, Opelousas stands out as the largest cluster of areas with high investment potential scores, along with Eunice to the west (Figure 25). Zooming in further on the municipality, it becomes clear that the majority of the town has above-average investment potential (Figure 26). Extracting the underlying data to rank individual grid cells within St. Landry Parish or District 03 could be used to support the case that Opelousas deserves additional attention. However, a simple visual inspection allows the user to confirm that the highest-scoring areas (grid cells) within the parish are located in downtown Opelousas, in the neighborhood bounded by LA-182 (S Main St/S Union St), I-49, Cresswell Lane, and US Hwy 190 (E Vine St/E Landry St).

Figure 25. Screenshot of St. Landry Parish overall investment score priority areas

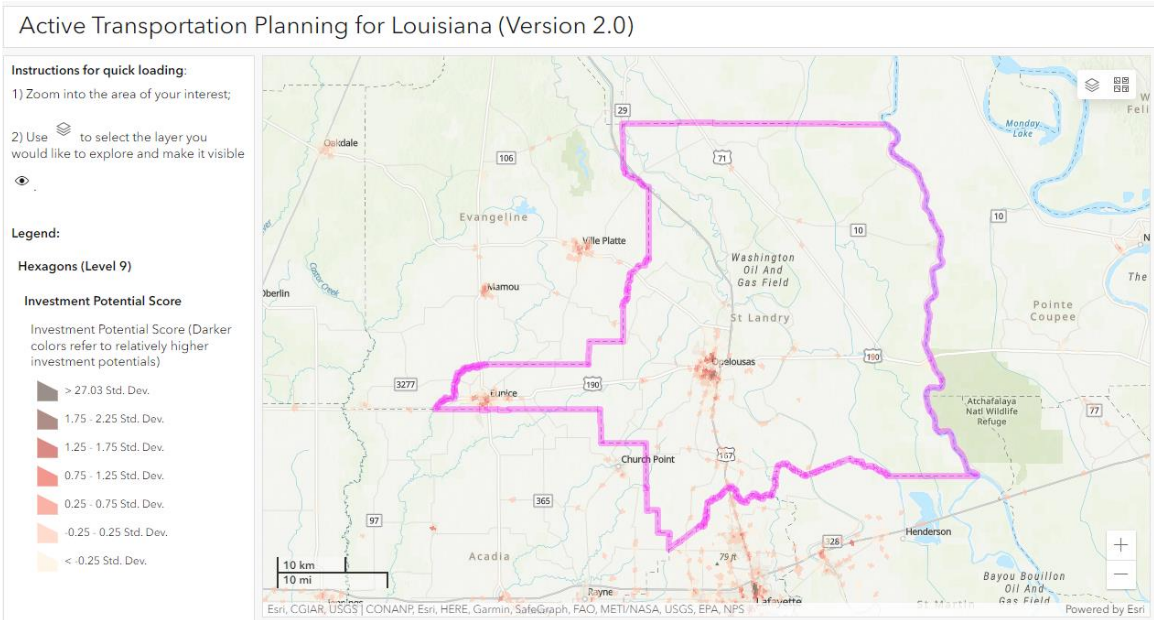
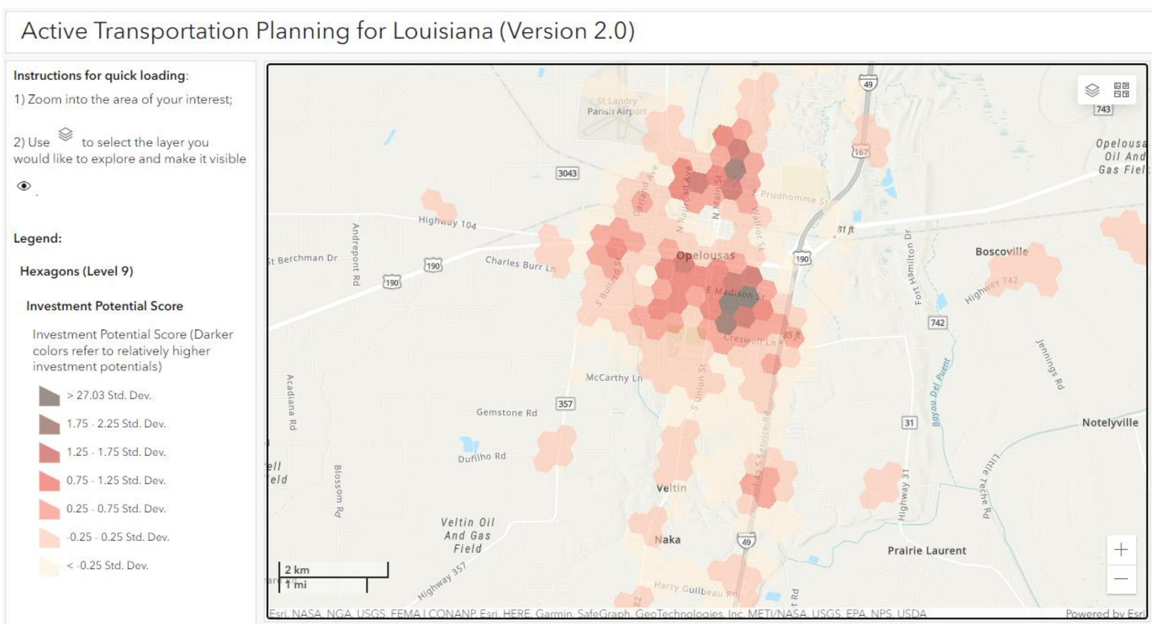


Figure 26. Screenshot of investment potential scores: Opelousas, LA



Review of the Safety Index for this area highlights a similar area of focus. Although the tool is not designed to reveal the location of each individual crash within a given area, it is revealed that over a dozen injuries to pedestrians and bicyclists occurred within the vicinity of the darkest areas featured, which represents the highest crash density in the parish (Figure 27). This also corresponds to areas of high demand, as indicated by the Mobility Index (Figure 28). This area is proximate to a school, several blocks of commercial uses, and a city park, all of which generate activity. Combined with compact urban form (i.e., dense residential neighborhoods) and socioeconomic variables that equate to a higher mobility score, this layer reinforces that, although most trips may currently be taken by automobile, there is significant potential to create a walkable, bikeable environment that connects area residents to surrounding jobs, shopping, services, and more. Another neighborhood in the vicinity of Opelousas' hospital similarly emerges as an opportunity zone for safety and mobility.

Figure 27. Screenshot of safety index values, Opelousas, LA

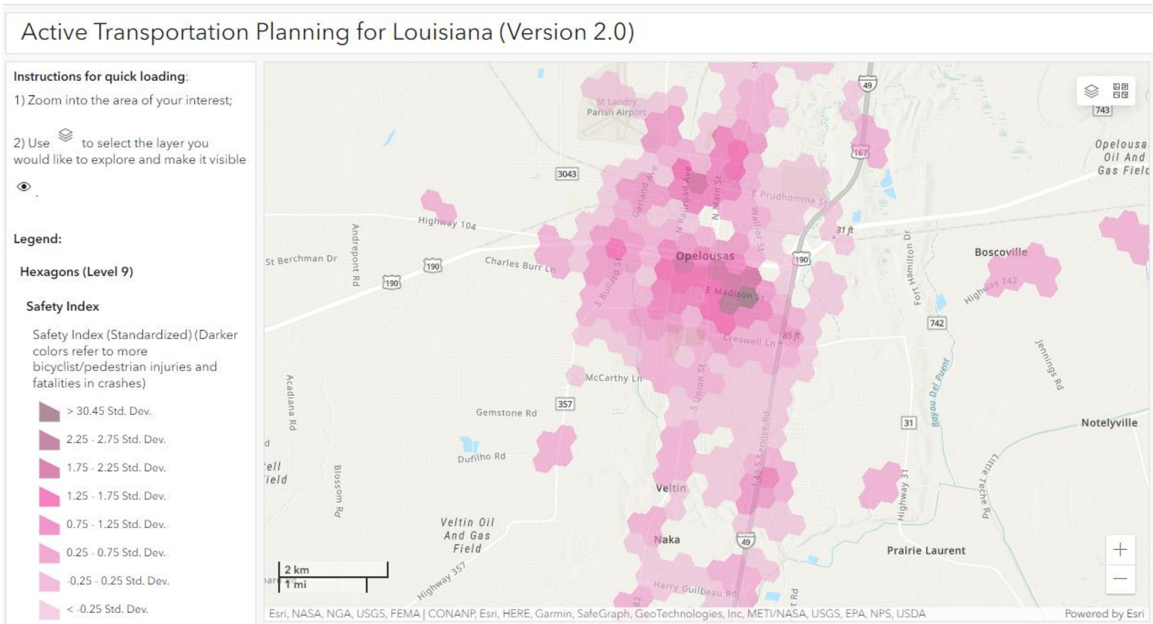
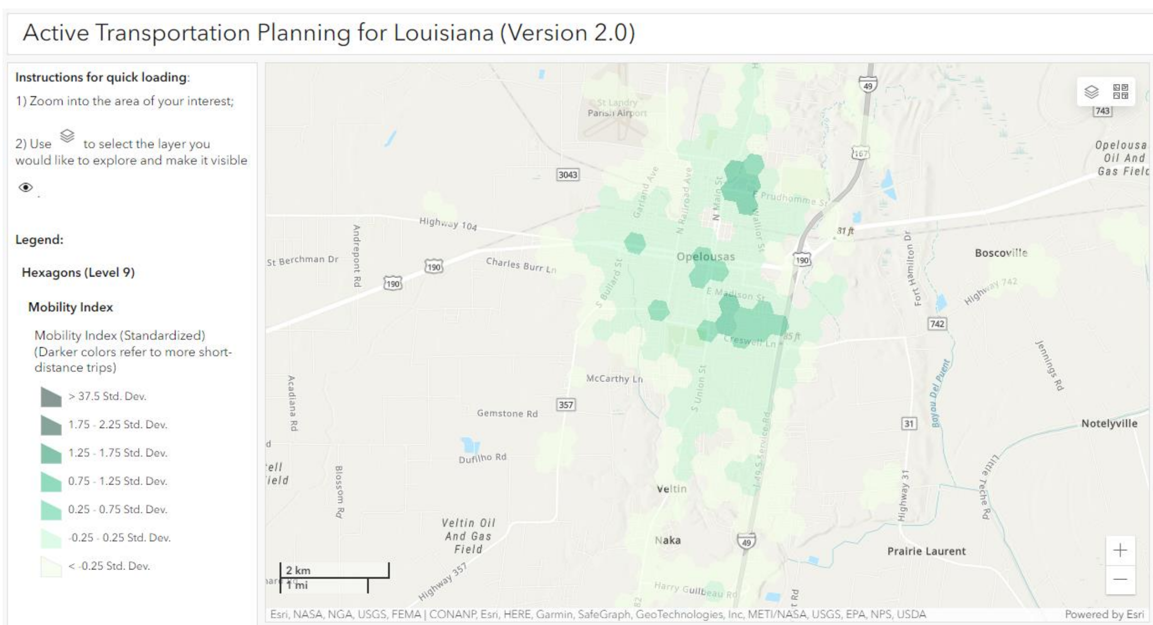


Figure 28. Screenshot of mobility index values, Opelousas, LA



The connectivity index, however, tells a slightly different story. Here, we can see that while multimodal connectivity is relatively high along and across the main highways that run through the core of the city (although, importantly, the quality, safety, and comfort of the crossings themselves is not accounted for with the data available), facilities are limited in the areas highlighted in the two other indices (Figure 29). Very few sidewalks (and no dedicated bicycle or transit facilities) are available within downtown Opelousas or surrounding residential neighborhoods. A limited follow-up check of several locations within the area of interest via Google Street View to verify the accuracy of the ARAN-derived sidewalk layer reveals that, while this finding generally holds true, there are a few instances where pedestrian facilities not indicated in DOTD's data exist. These include narrow, curb-adjacent sidewalks near Magnet Academy for Cultural Arts and several other locations (Figure 30). Local efforts to more accurately map existing pedestrian and bicycle facilities—especially those installed subsequent to DOTD's data collection effort, can help refine this data layer. Meanwhile, the relatively low coverage of sidewalks compared to the potential demand and identified safety concerns suggests several areas where investment in new facilities could significantly improve walkability for Opelousas residents.

Each of the index layers can individually contribute to an analysis of existing conditions for long-range planning. Furthermore, these layers can be used as tools to focus community engagement. Presentation of these results can verify any data gaps with local knowledge, encourage consideration of multiple dimensions of walkable, bikeable neighborhoods, and instigate discussion of community priorities: do the highlighted cells and corridors adequately reflect community need? Or are there other factors which are not represented here? In particular, the outputs are identified by stakeholders as presenting an opportunity to highlight areas that may have been overlooked in previous discussions or project planning efforts: are there areas that have surprisingly high investment scores? If so, why might that be? In some cases, this may help a community identify specific communities who have not been engaged in dialogue about investment priorities. In turn, the findings can be used to help articulate need (including equity priorities), by extracting data about local population (e.g., the Smart Location Database layer), and about a project area's relative score within the larger jurisdiction (e.g., by determining that the project is within the top quintile).

Figure 29. Connectivity index values for Opelousas, LA, with DOTD sidewalks highlighted

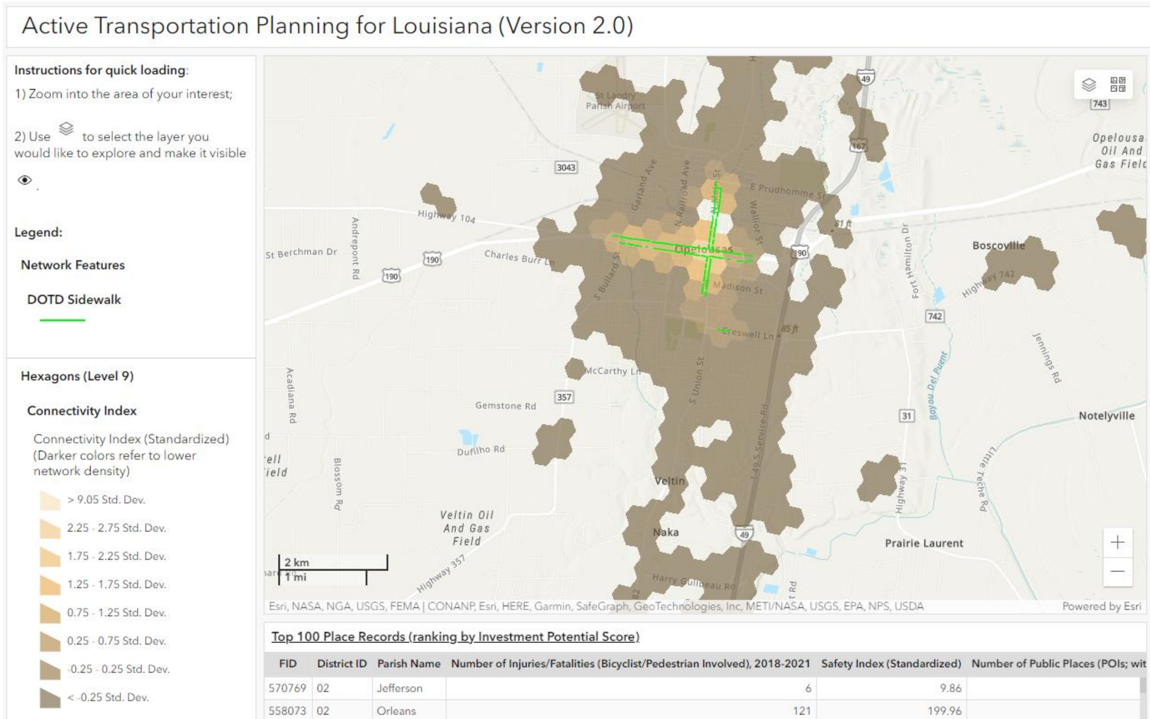


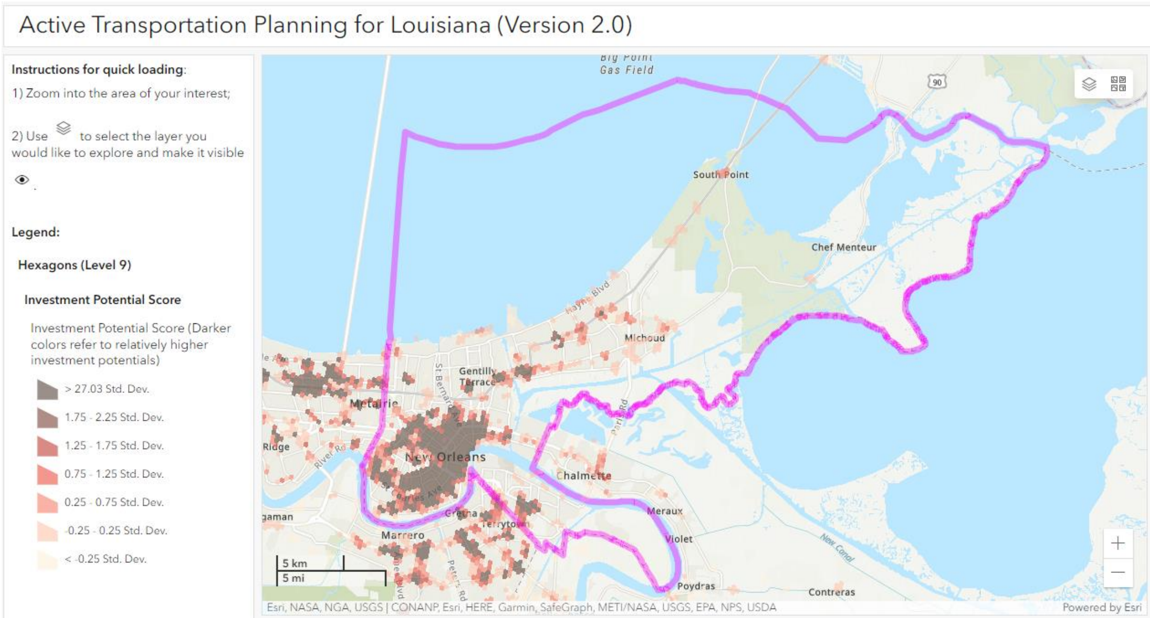
Figure 30. Google Street View image, March 2022, E. Leo St at Pamella St.

Urban Equity-Focused Project Prioritization

In larger cities, it is likely that major safety issues have already been identified. Additionally, there may be a demand and necessity to improve access for people walking or bicycling which may already be presumed or codified by local complete streets policy. Furthermore, the infrastructure networks in these cities tend to be much more complex. Given these factors, the gridded hexagons used for pinpointing and justifying potential projects may have limited value in such cases. Instead, a more detailed view, (e.g., segment-level) is needed to add value to local planning and project development processes. This could include using the tool for highlighting sub-areas (e.g., top investment locations for each City Council district). The tool could also serve as a reference point to validate previous or concurrent related analyses. By cross-referencing the results, it could identify any gaps or anomalies that require further investigation or highlight areas that are clearly important in both analyses. Additionally, the tool could serve as a starting point for community engagement, as noted above.

In the case of New Orleans, virtually the entire downtown core of the city and surrounding neighborhoods receive in the highest tier of scores in the state, which is more than 2.25 standard deviations above the statewide average (Figure 31). While reviewing individual index layers provides some additional insight, such as highlighting areas with less facility network coverage or areas with strong indicators of existing and potential demand, it does not provide an comprehensive picture for developing clear and actionable strategies to improve mobility for all.

Figure 31. Orleans Parish overall investment potential score

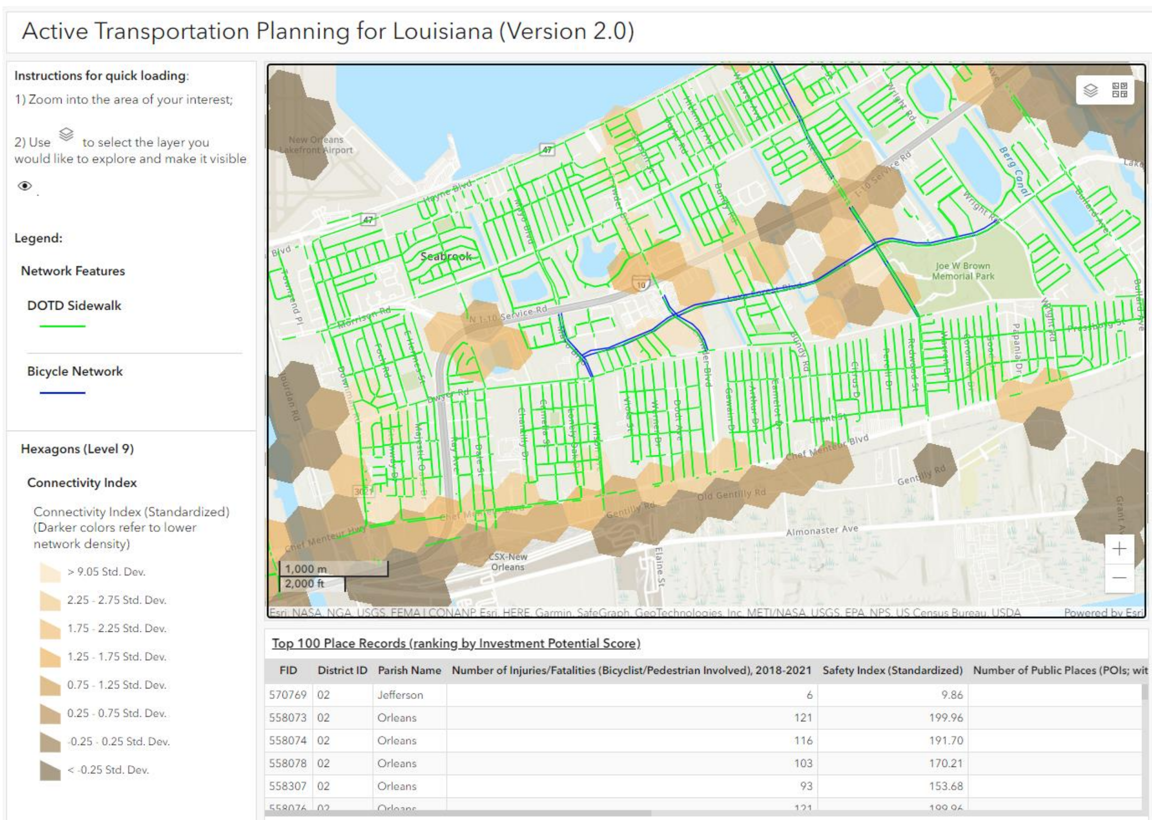


Instead, more value is likely to be extracted from the segment-level results, which attach index scores to individual segments of streets, as discussed in the Methodology section above. This allows the user to focus more precisely on individual corridors within a highlighted hexagon or neighborhood to reveal areas with particularly high demand potential, an undue number of crash records, the opportunity to leverage and connect existing infrastructure, or all three. In addition, external manipulation of the data would allow the user to adjust the weights assigned to each of the three index scores. For instance, one can prioritize safety over demand or incorporate additional factors into the score itself.

These features may be incorporated into efforts to prioritize projects at the segment level, where focus neighborhoods have already been identified. For instance, a suite of projects is planned in New Orleans to address gaps in access for people walking, bicycling, and using transit in New Orleans East. A comprehensive Bicycle Equity Index was previously developed in 2019 to serve as the foundation for developing a plan for future bikeway implementation. However, most of these projects are only now entering the planning and design stages. Meanwhile, the city has devoted increased attention to improving walking and transit access in this underinvested portion of the city. The Active Transportation Planning tool can serve as an additional layer to compare to the findings of previously completed studies and analyses, helping to unpack the land use, demographic, and built environment conditions that foster active transportation use.

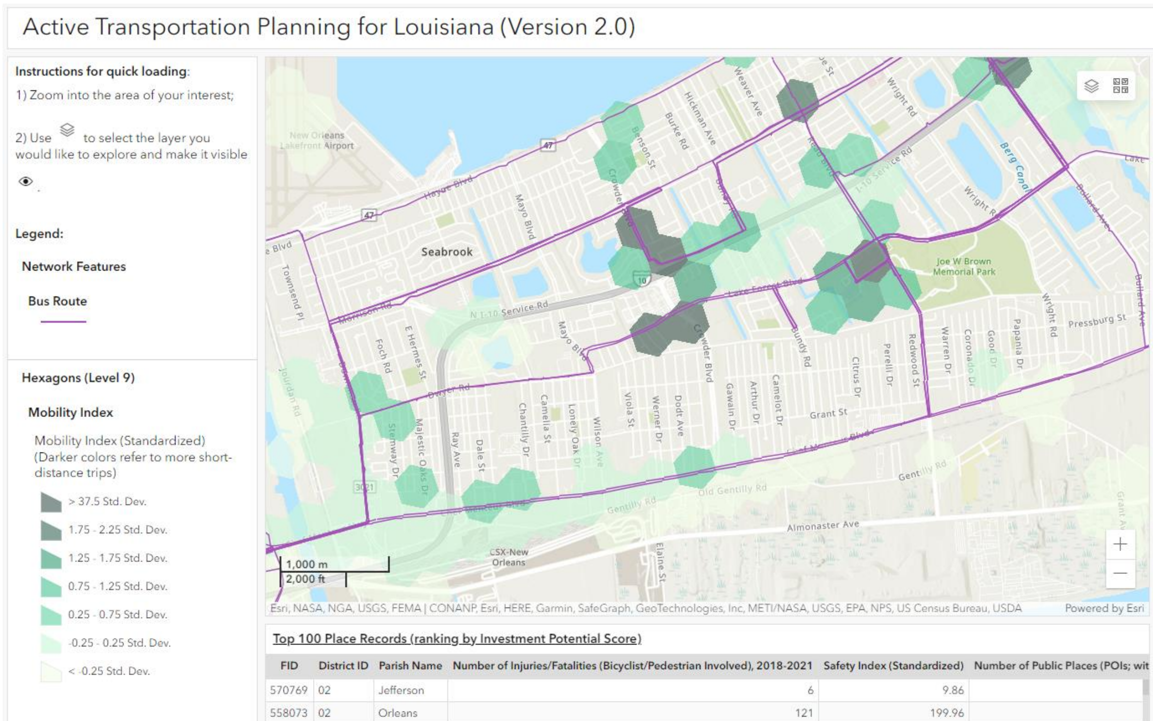
For example, the Connectivity Index and underlying component layers reveals that while much of the area is well-served by sidewalks within neighborhoods and subdivisions, many of these are separated from one another by physical barriers such as canals, and the interstate. There are also infrastructure deficiencies, such as sidewalk networks that end or become discontinuous right where they are needed most: on the arterial corridors which stitch communities together (Figure 32).

Figure 32. Screenshot of connectivity index and pedestrian/bicycle network, New Orleans East



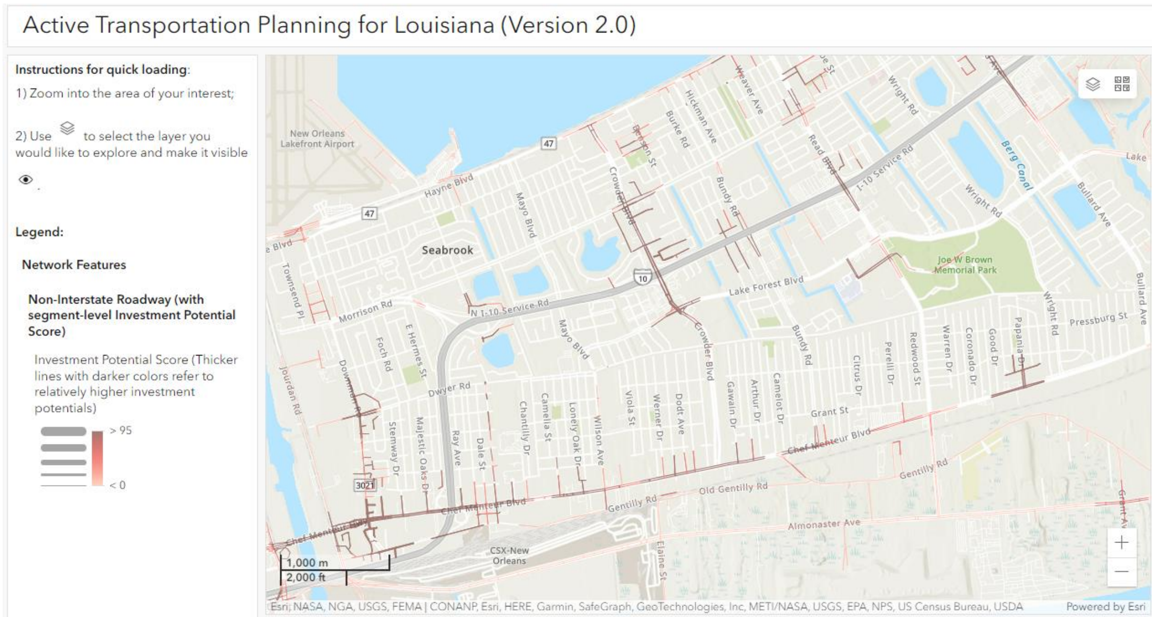
Meanwhile, areas with the highest potential demand (measured here in terms of short-distance trips and factoring in socioeconomic factors) highlight that the areas where the existing network fails overlap distinctly with where people are trying to go. These high-demand areas are served by transit but are difficult to access from surrounding neighborhoods (Figure 33).

Figure 33. Screenshot of mobility index and bus routes, New Orleans East



Finally, as noted above, some potential users (particularly those in urban areas) may prefer to work with segment-level data. This allows a more precise analysis of specific corridors or nodes that have an impact on a grid cell's index score. In the case of New Orleans East, this additional level of detail clarifies that within the investment potential "hot spots," one corridor (Chef Menteur Highway) stands out as likely to offer impactful opportunities. Additionally, several shorter segments that run perpendicular to Interstate 10 are also highlighted. These segments may represent key priorities for mitigating negative impacts on safety and mobility presented by this facility (Figure 34). Efforts to develop a cohesive network for non-motorized road users can be guided by reviewing of high-scoring segments. These segments can be strategically linked together to optimize residents' safety, access, and overall network connectivity. Once priority corridors have been selected (e.g., Chef Menteur Highway), individual segment-level scores can be beneficial in identifying specific areas or intersections where certain interventions, like high visibility crosswalks, enhanced lighting may be most needed.

Figure 34. Example visualization of grid-level and segment-level investment index scores, New Orleans East



Discussion of Applications and Limitations

Importantly, active transportation planning must necessarily focus on creating an interconnected network. Isolated segments that only serve specific destinations without connecting to one another are unlikely to facilitate significant changes in travel behaviors. In order to create such networks, it is necessary not only to connect to points of interest but also to connect through areas with little apparent demand potential. This is essential to create a functional network overall. Furthermore, as the quality and extent of network data improve, and new facilities are built, it may be advisable to recalculate a separate connectivity score for bicyclists and pedestrians. This would be instead of the current composite score which reflects sidewalks and dedicated bicycle or shared-use facilities.

One of the current limitations of the tool is the lack of data specifically addressing the need to overcome physical or contextual barriers, like bodies of water, overpasses or underpasses, etc. The index does not yet specifically address urban form and street network design as factors. For example, a neighborhood that has full sidewalk coverage and is near several POIs may score well, even though it may not be realistically feasible to walk to anything nearby due to a “loops and lollipops” street pattern. To address this, additional analysis can be conducted to incorporate a walkshed or bikeshed, rather than relying on Euclidean distance measurements. This could help more realistically highlight the challenges of active transportation network building in non-gridded street environments.

In addition, several special cases can be identified in the use of this tool which may warrant caution and/or further exploration and research. These include:

- **Parks**: particularly large parks and natural areas. POIs may be unevenly represented; a large park may have several POIs or may have only one POI in the dataset at its primary entrance. Parks and other large, regional destinations can be major drivers of demand, which warrants more prioritization to connect both to and through than is revealed by the tool. A few possible solutions for future studies are: 1) creating duplicated POIs for a park at each of its major entrances. However, this solution is subject to the criticism of why parks are counted repeatedly and emphasized over the other types of places; or 2) using polygons instead of points to reflect park shapes, subject to data availability. In addition, it should be noted that this study focuses on home-based trips (i.e., between homes and parks) and thus does not support walking and biking trail planning within a park.
- **Tourist destinations**: areas with a significant number of "outlier" data points, e.g., high volumes of visitors from outside of the region. This research focuses on home-based trips. Therefore, a high share of tourist-attraction POIs and their associated trips were excluded from analysis in the data cleaning process, which impacts the Mobility Index and the Overall Investment Potential Scores. The most significant instance of this is in New Orleans' French Quarter, and portions of the Central Business District (CBD), which were skewed by tourist visits indicating very long travel distances. Mobility values appear artificially reduced in these areas, given the apparent demand for the major destinations within them. Future analyses should consider evaluating mobility specifically for areas with intense non-local visitor activity, as well as mobility patterns during special events. Future research with detailed GPS traces for each individual could consider first identifying who are tourists and then using their nighttime location instead of home location in calculating the Mobility Index.
- **Schools, social services, and other facilities**: or land uses where mobile phone data are likely to underrepresent key populations. In particular, elementary schools are likely to be under-reflected in investment scores (because many children do not have location-enabled smartphones), as are facilities that

specifically serve disadvantaged populations, such as homeless shelters, libraries, etc. This indicates that users should be encouraged to consider this tool as one asset for screening and focusing planning discussion. However, like any sample-based dataset, it should not be relied on solely without additional local insight and input. This common short-coming among Location Based Services (LBS) data potentially be corrected by collecting visit counts from a sample of sites by group and then calculating expansion factors by group with ambient characteristics (including socio-demographic factors for equity concerns). In addition, future research could also consider using multiple data sources (e.g., school records and bike sharing data) to observe access to these locations.

- **Areas of interest with negative scores**: The underlying data provides score values for each dimension for all segments and grid hexagons statewide after downloading the map layers. In the online version, only those with values greater than the statewide average are made visible for quick webpage loading. However, a negative index or score value does not necessarily mean the area does not need investment or attention to its infrastructure. In many cases, specific areas may have already been identified for focus, such as census tracts identified by USDOT as Transportation Disadvantaged. Many such neighborhoods have suffered historical underinvestment, which significantly impacts current conditions (e.g., limited facility extent, decreased housing density and depressed commercial activity, etc.). In such cases, the user may still derive value from the dataset by extracting out data for the areas of interest and analyzing it relatively to other areas: a higher score is still a higher score for that area, regardless of whether it is above or below the state average.

Conclusions

This study focuses on identifying locations where there is a high number of short-distance trips to non-residential locations relative to other areas of the state. In theory, this reflects a higher number of trips that could be taken by active modes if facilities are in place. In practice, demographic variables are generally the better predictor of current, observable demand for walking and bicycling. Modifications to the model have been made based on stakeholder feedback to adjust the number and income of residents to better reflect existing and potential demand. Iterative updates to the index calculations have been made to address stakeholder feedback and make the interface more intuitive, resulting in aggregate investment potential scores ranging from -26.68 to 246.47. Some of the highest scores are explained by excessive numbers of injury crashes. It is imperative to review the three sub-indices to determine whether appropriate interventions are likely to consist of new facilities or changes to address safety issues where facilities already exist. A variety of equity indicators are presented in the online dashboard to meet varying user needs. The revised version of the Mobility Index includes modifications that adjust for both the share of households in poverty and the population density. These modifications help increase the score for areas where investments are likely to benefit more people especially those with lower incomes. However, it is worth noting that this method of identifying high investment potential is originally focuses on identifying locations where improvements to conditions for walking or bicycling are likely to enable many trips to be taken by active modes. In some cases, there may also be significant potential in wealthier areas that are close to destinations to encourage mode shift. In this sense, there is a high investment impact potential, although not necessarily a high need.

Results are calculated at both the area (i.e., hexagonal) level and at the segment level. For quick webpage loading, the dashboard only makes areas/segments with positive investment potential scores. Advanced users have the option to download the shared map package and import all the map layers into their own GIS platform. This allows them to unlock many other analytic possibilities, such as querying by corridor or neighborhood, roadway ownership or functional class, etc. (as well as customizing the data visualizations according to their use case).

Bridges and certain geographic “chokepoints” in the network are an important limitation of this study. This is because there are likely to be few network segments, few POIs, and households located in the immediate vicinity of these areas. A holistic approach to evaluating connectivity and access should include an analysis of key barriers. For instance, it is important to scrutinize a bridge that separates an area with high investment impact potential scores from an area with less activity but with one or more equity indicators. This scrutiny ensures that investment benefits extend to nearby disadvantaged communities. Future improvements to network connectivity measurement methods could also identify and assign weights to network gaps and barriers to emphasize their importance. Additional improvements to the connectivity index are needed to incorporate variables that reflect the quality of the built environment for non-motorists, rather than just the extent, such as the presence of marked crosswalks, and pedestrian signals, and traffic speed.

The current version of this analytic model is limited by the quality and recency of its input datasets. It is known that the ARAN sidewalk data has certain deficiencies and does not reflect recent investments in new or improved pedestrian facilities. Upon, visual evaluation and point-based cross-checking of the DOTD sidewalk layer, significant accuracy issues have been identified in certain areas of New Orleans, in particular. In the revised version of the tool, we have included preliminary bicycle and fixed-route transit network layers as supplemental references. Future work should focus on standardizing methods for reporting and aggregating facility network data to ensure the maintenance of up-to-date statewide data layers, which may be used for recalculating scores.

In urban areas, particularly, grid-level data may not be sufficient to pinpoint target investment locations and prioritize among a dense network of roadways. To address this gap, the analysis has been rerun at the segment level using a sliding windows analysis. This highlights relative investment scores for individual segments.

The investment score represents the potential for new or improved facilities to support a greater number of trips and encourage possible mode shift, rather than a direct measurement of investment need based on existing demand. It is crucial to balance this with measures of equity and need to avoid reinforcing historic patterns of disinvestment.

At the local level, the findings should be considered a starting point, supplemental reference, or tool to inform discussion about local priorities and needs. While in some areas, users may find very strong alignment with score outputs and local knowledge, there may be circumstances where the findings deviate from the local understanding of conditions and mobility patterns. For instance, downtown areas with robust existing sidewalk networks may have high scores due to a density of activity generators and elevated crash counts. However, these areas may not be considered high priority in local plans because they do not align with adopted equity goals.

Use cases for this data include statewide screening, long range planning, grant proposal development, project prioritization, and demand estimation. The ability to relatively quickly compare either the composite index score or an individual index against either the statewide average or a set of peer geographies (DOTD district, parish, grid cell, etc.) enables for efficient identification of areas that may particularly benefit from investments in network planning, safety enhancement, or new facility development.

Recommendations

The developed dashboard is not 100% perfect due to existing data limitations. However, the research team expects the situation to continue improving as attention towards non-motorized road users increases and data availability evolves in practice. The following recommendations are to promote the use of existing tools and fill in existing data gaps through collaborative activities:

- The research team expects the developed online dashboard to be useful for DOTD Planning Section in supporting their long-range planning and project selection activities. Thus, engaging relevant planning staff and consultants would be the first step.
- The research team has developed a post-project survey to continue collecting stakeholder knowledge after project conclusion. Continuous outreach activities (e.g., LTAP trainings and DOTD Complete Streets site announcements) are needed to engage a broader group of audiences, build awareness of the developed online dashboard (along with other tools like the Bicycle Planning Tool), and encourage stakeholders to share their user experience. This activity will facilitate our understanding of different use cases and data/dashboard limitations in different scenarios.
- Stakeholders are also encouraged to share their data for consolidation, which will facilitate future dashboard updates and benefit other activities as well. First, non-motorized user counts and site visit counts might be available from other agencies (e.g., MPOs and district offices) and/or activities for other purposes (e.g., improving pedestrian/bicyclist safety or updating ITE trip generation rates). This type of data will help calibrate data collected passively, allowing us to gain a better understanding of human mobility. Second, acquiring bikeway, trail, pedestrian, and transit network updates can be done by: 1) streamlining the DOTD project delivery process to map projects funded by DOTD, which should be technically feasible in considering that DOTD had a public engagement platform for Highway Priority Program and has a public-facing website showing projects under construction; 2) collaborating with local agencies to map projects funded by local government (e.g., streamlined data submission or collaborative map updates); or 3) leveraging motivations from the public for crowd-sourcing updates. This ad-hoc map update plan should help fill in the gap brought by the lower-than-expected ARAN data collection frequency. This can also include

refinements to the classification schema for active transportation facilities to reflect quality, level of traffic stress, etc.

- What elements are counted as active transportation infrastructure and are of concern to transportation agencies? These are questions to answer before launching collaborative data collection and mapping. For example, the quality and presence of facilities at intersections (e.g., pedestrian signals, crosswalks, bike boxes, and ADA accessibility) are key determinants of active transportation safety and convenience. However, we lack adequate data to include intersections as part of the connectivity index in the current study.

Acronyms, Abbreviations, and Symbols

Term	**Description**
AADT	Annual Average Daily Traffic
AASTHO	American Association of State Highway and Transportation Officials
ACS	American Community Survey
ADA	Americans with Disabilities
ADT	Average Daily Traffic
API	Application Programming Interface
ARAN	Automatic Road ANalyzer
ARNOLD	All Roads Network of Linear Referenced Data
BCA	Benefit-Cost Analyses
BEI	Bike Equity Index
BNA	Bike Network Analysis
BTS	Bureau of Transportation Statistics
CBD	Central Business District
CNR	Connected Node Ratio
CPEX	Center for Planning Excellence
DOT	Department of Transportation
DOTD	Department of Transportation and Development
EPA	Environmental Protection Agency
FEMA	Federal Emergency Management Agency
FHWA	Federal Highway Administration
FQ	Frequency
FRA	Federal Railroad Administration
FTA	Federal Transit Administration
GES	General Estimates System
GIS	Geographic Information System
GPS	Global Positioning System
GTFS	General Transit Feed Specification
HAWK	High intensity Activated cross Walk
HIN	High Injury Networks
HPMS	Highway Performance Monitoring System
HSM	Highway Safety Manual
HUD	Housing and Urban Development
IAP	International Association for Public Participation

Term	**Description**
ICTs	Information Communications Technologies
IF	Injuries and Fatalities
Km	kilometer(s)
KS	Kansas City
KY	Kentucky
LA	Louisiana
LADOTD	Louisiana Department of Transportation and Development
LBS	Location Based Services
LEHD	Longitudinal Employer-Household Dynamics
LEP	Limited English proficiency
LOS	Level of Service
LRS	Linear Reference System
LSU	Louisiana State University
LTAP	Local Technical Assistance Program
LTRC	Louisiana Transportation Research Center
LTS	Level of Traffic Stress
MA	Massachusetts
MI	Mobility Index
MN	Minneapolis
MPOs	Metropolitan Planning Organizations
NAICS	North American Industry Classification System
NCHRP	National Cooperative Highway Research Program
NEISS	National Electronic Injury Surveillance System
NHTS	National Household Travel Survey
NHTSA	National Highway Traffic Safety Administration
NPTS	Nationwide Personal Transportation Survey
OSM	OpenStreetMap
PAZ	Pedestrian Analysis Zone
PIE	Pedestrian Index of the Environment
PIMA	Public Involvement Management Application
PLTS	Pedestrian Level of Traffic Stress
POIs	Point of interests
QR	Quick Response
RQI	Route Quality Index
RRFB	Rectangular Rapid Flashing Beacon

Term	**Description**
SLD	Smart Location Database
SNAP	Supplemental Nutrition Assistance Program
SSPF	Safer Streets Priority Finder
TAZ	Traffic Analysis Zone
TIGER	Topologically Integrated Geographic Encoding and Referencing
TTI	Texas A&M Transportation Institute
UNO	University of New Orleans
US	United States
USDOT	U.S. Department of Transportation
VA	Virginia
VMT	Vehicle Miles Traveled
WSDOT	Washington State Department of Transportation

References

[1] LADOTD, “Louisiana Department of Transportation and Development: Complete Streets Policy (Revised),” 2016, [Online]. Available: http://wwwsp.dotd.la.gov/Inside_LaDOTD/Divisions/Multimodal/Highway_Safety/Complete_Streets/Misc Documents/cs-la-dotpolicy.pdf

[2] “Three Healthy Streets move forward in Hyde Park, Windsor Park and South Austin,” *FOX 7 Austin*, Jul. 14, 2020. https://www.fox7austin.com/news/three-healthy-streets-move-forward-in-hyde-park-windsor-park-and-south-austin (accessed Jul. 24, 2023).

[3] “Transportation System Resilience to Extreme Weather and Climate Change - Technical Staff - FHWA Office of Operations.” https://ops.fhwa.dot.gov/publications/fhwahop15025/index.htm (accessed Jul. 17, 2023).

[4] “Active Transportation Plan, 2020 and Beyond,” 2021.

[5] K. C. Desouza and K. L. Smith, “Big data and planning,” *APA Planning Advisory Service Reports*, vol. 2016, no. 585, pp. 2–102, 2016.

[6] P. Ryus, E. Ferguson, K. M. Lausten, R. J. Schneider, F. R. Proulx, T. Hull, and L. Miranda, *Guidebook on Pedestrian and Bicycle Volume Data Collection*. Washington, D.C.: Transportation Research Board, 2014. doi: 10.17226/22223.

[7] “Evaluation of Walk and Bicycle Demand Modeling Practice,” Art. no. NCHRP Project 08-36, Task 141, May 2019, Accessed: Jul. 18, 2023. [Online]. Available: https://trid.trb.org/view/1669020

[8] S. M. Turner, I. N. Sener, M. E. Martin, L. D. White, S. Das, R. C. Hampshire, M. Colety, K. Fitzpatrick, R. K. Wijesundera, and U. S. FHWA, “Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists,” FHWA-SA-18-032, Jul. 2018. Accessed: Jul. 18, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/43673

[9] C. L. Porter and W. Schwartz, “Bicycle and Pedestrian Data: Sources, Needs, & Gaps,” BTS00-02, Jan. 2000. doi: 10.21949/1501653.

[10] U. S. D. FHWA, “Moving to a Complete Streets Design Model: A Report to Congress on Opportunities and Challenges,” Mar. 2022, Accessed: Jul. 20, 2023. [Online]. Available: https://policycommons.net/artifacts/3506787/moving-to-a-complete-streets-design-model/4307643/

[11] “National Household Travel Survey.” https://nhts.ornl.gov/ (accessed Jul. 18, 2023).

[12] "National Bicycle and Pedestrian Documentation Project." http://www.bikepeddocumentation.org/ (accessed Jul. 21, 2023).

[13] J. Schoner, F. Proulx, E. Moorman, R. Panik, and S. Brodie, "MnDOT Pedestrian and Bicyclist Data Program: Strategic Plan for Counting People Walking and Bicycling".

[14] D. Johnstone, K. Nordback, M. Lowry, and Portland State University. Transportation Research and Education Center, "Collecting Network-wide Bicycle and Pedestrian Data: A Guidebook for When and Where to Count," WA-RD 875.1, Sep. 2017. Accessed: Jul. 21, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/34663

[15] S. M. Turner, R. J. Benz, J. G. Hudson, G. P. Griffin, P. Lasley, B. Dadashova, and S. Das, "Improving the amount and availability of pedestrian and bicyclist count data in Texas," Texas A&M Transportation Institute, 2019.

[16] P. Ryus, E. Ferguson, K. M. Lausten, R. J. Schneider, F. R. Proulx, T. Hull, and L. Miranda, *Guidebook on Pedestrian and Bicycle Volume Data Collection*. Washington, D.C.: Transportation Research Board, 2014. doi: 10.17226/22223.

[17] P. Ryus, E. Ferguson, K. M. Lausten, R. J. Schneider, F. R. Proulx, T. Hull, and L. Miranda, *Methods and Technologies for Pedestrian and Bicycle Volume Data Collection*. Washington, D.C.: Transportation Research Board, 2014. doi: 10.17226/23429.

[18] "Traffic Monitoring Guide (TMG) | FHWA." https://highways.dot.gov/safety/data-analysis-tools/rsdp/rsdp-tools/traffic-monitoring-guide-tmg (accessed Jul. 18, 2023).

[19] T. M. Tolford, "Pedestrians and Bicyclists Count, Phase 2: Implementing and Applying Multimodal Demand Data," 2023.

[20] J. R. Kuzmyak, J. Walters, M. Bradley, and K. M. Kockelman, *Estimating Bicycling and Walking for Planning and Project Development: A Guidebook*. Washington, D.C.: Transportation Research Board, 2014. doi: 10.17226/22330.

[21] "STEP 4. SELECT EXPOSURE MEASURE | FHWA." https://highways.dot.gov/safety/pedestrian-bicyclist/safety-tools/guide-scalable-risk-assessment-methods-pedestrians-and-9 (accessed Jul. 18, 2023).

[22] K. Lee and I. N. Sener, "Emerging data for pedestrian and bicycle monitoring: Sources and applications," *Transportation Research Interdisciplinary Perspectives*, vol. 4, p. 100095, Mar. 2020, doi: 10.1016/j.trip.2020.100095.

[23] C. Nicholas and L. Schewel, "Real-World Big Data for Active Transportation Planning," 2018.

[24] A. Kurkcu and K. Ozbay, “Estimating Pedestrian Densities, Wait Times, and Flows with Wi-Fi and Bluetooth Sensors,” *Transportation Research Record*, vol. 2644, no. 1, pp. 72–82, Jan. 2017, doi: 10.3141/2644-09.

[25] I. Tsapakis, S. Turner, P. Koeneman, P. R. Anderson, and Texas A&M University. Texas Transportation Institute, “Independent Evaluation of a Probe-Based Method to Estimate Annual Average Daily Traffic Volume,” FHWA-PL-21-032, Sep. 2021. Accessed: Jul. 18, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/64899

[26] J. K. Fish, S. E. Young, A. Wilson, B. Borlaug, and National Renewable Energy Laboratory (NREL) (U.S.), “Validation of Non-Traditional Approaches to Annual Average Daily Traffic (AADT) Volume Estimation,” FHWA-PL-21-033, Sep. 2021. Accessed: Jul. 18, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/64900

[27] L. Schewel, S. Co, C. Willoughby, L. Yan, N. Clarke, J. Wergin, and StreetLight Data, “Non-Traditional Methods to Obtain Annual Average Daily Traffic (AADT),” FHWA-PL-21-031, Sep. 2021. Accessed: Jul. 18, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/64898

[28] K. Lee and I. N. Sener, “Emerging Data Mining for Pedestrian and Bicyclist Monitoring: A Literature Review Report,” 2017.

[29] S. M. Turner *et al.*, “Exploring Crowdsourced Monitoring Data for Safety,” SAFE-D: Safety Through Disruption National University Transportation Center, Report, Mar. 2020. Accessed: Jul. 18, 2023. [Online]. Available: https://vtechworks.lib.vt.edu/handle/10919/98795

[30] C. Monz, M. Mitrovich, A. D’Antonio, and A. Sisneros-Kidd, “Using Mobile Device Data to Estimate Visitation in Parks and Protected Areas: An Example from the Nature Reserve of Orange County, California,” *JPRA*, 2019, doi: 10.18666/JPRA-2019-9899.

[31] T. Kawahara, B. Liu, A. Pande, C. Thigpen, and C. Voulgaris, “Moving from Walkability? Evaluation Traditional and Merging Data Sources for Evaluating Changes in Campus-Generated Greenhouse Gas Emissions,” *Mineta Transportation Institute Publications*, Nov. 2019, doi: 10.31979/mti.2019.1857.

[32] C. Lemonde, E. Arsenio, and R. Henriques, “Integrative analysis of multimodal traffic data: addressing open challenges using big data analytics in the city of Lisbon,” *Eur. Transp. Res. Rev.*, vol. 13, no. 1, p. 64, Dec. 2021, doi: 10.1186/s12544-021-00520-3.

[33] J. D. Kressner, “Synthetic Household Travel Data Using Consumer and Mobile Phone Data,” no. 184, Art. no. NCHRP IDEA Project 184, Mar. 2017, Accessed: Jul. 18, 2023. [Online]. Available: https://trid.trb.org/view/1480014

[34] M. Ghahramani, M. Zhou, and G. Wang, “Urban sensing based on mobile phone data: approaches, applications, and challenges,” *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 3, pp. 627–637, May 2020, doi: 10.1109/JAS.2020.1003120.

[35] F. Wang, J. Wang, J. Cao, C. Chen, and X. (Jeff) Ban, “Extracting trips from multi-sourced data for mobility pattern analysis: An app-based data example,” *Transportation Research Part C: Emerging Technologies*, vol. 105, pp. 183–202, Aug. 2019, doi: 10.1016/j.trc.2019.05.028.

[36] O. Iliashenko, V. Iliashenko, and E. Lukyanchenko, “Big Data in Transport Modelling and Planning,” *Transportation Research Procedia*, vol. 54, pp. 900–908, 2021, doi: 10.1016/j.trpro.2021.02.145.

[37] K. J. Clifton and F. Moura, “Conceptual Framework for Understanding Latent Demand: Accounting for Unrealized Activities and Travel,” *Transportation Research Record*, vol. 2668, no. 1, pp. 78–83, Jan. 2017, doi: 10.3141/2668-08.

[38] A. Aoun, J. Bjornstad, B. DuBose, M. Mitman, and M. Pelon, “Bicycle and Pedestrian Forecasting Tools: State of the Practice,” Apr. 2015, Accessed: Jul. 18, 2023. [Online]. Available: https://trid.trb.org/view/1485198

[39] J. Beetham, V. Ivory, J. Thomas, P. Kortegast, D. Cooper, J. Burton, C. Bowie, L. Malde, and C. Moore, *Latent demand for walking and cycling*, no. 676. 2021. Accessed: Jul. 18, 2023. [Online]. Available: https://trid.trb.org/view/1845259

[40] P. A. Lagerwey, M. J. Hintze, J. B. Elliott, J. L. Toole, and R. J. Schneider, *Pedestrian and Bicycle Transportation Along Existing Roadsâ€"ActiveTrans Priority Tool Guidebook*. Washington, D.C.: Transportation Research Board, 2015. doi: 10.17226/22163.

[41] J. Boldry, M. Anderson, and M. Roskowski, “Defining Connected Bike Networks,” May 2017, Accessed: Jul. 18, 2023. [Online]. Available: https://www.pedbikeinfo.org/cms/downloads/InfoBrief_PBIC_Networks.pdf

[42] H. Twaddell, E. Rose, J. Broach, J. Dill, K. J. Clifton, C. Lust, K. Voros, H. Louch, E. David, ICF, Portland State University, and Alta Planning+Design, “Guidebook for Measuring Multimodal Network Connectivity,” FHWA-HEP-18-032, Feb. 2018. Accessed: Jul. 18, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/50786

[43] J. Dill, “Measuring Network Connectivity for Bicycling and Walking,” 2004. Accessed: Jul. 18, 2023. [Online]. Available: https://www.semanticscholar.org/paper/Measuring-Network-Connectivity-for-Bicycling-and-Dill/329ec82486b5dece3b9a939beb67484da9f10c1a

[44] R. Buehler and J. Dill, "Bikeway Networks: A Review of Effects on Cycling," *Transport Reviews*, vol. 36, no. 1, pp. 9–27, Jan. 2016, doi: 10.1080/01441647.2015.1069908.

[45] J. Boldry and R. Davies, "Using Connectivity Measures to Evaluate and Build Connected Bicycle Networks," 2019, Accessed: Jul. 18, 2023. [Online]. Available: https://trid.trb.org/view/1657668

[46] M. C. Mekuria, P. G. Furth, and H. Nixon, "LOW-STRESS BICYCLING and NETWORK CONNECTIVITY," 2012.

[47] R. Geller, "Four Types of Cyclists," *Portland Office of Transportation*, 2006.

[48] T. Putta, J. Schoner, T. Tolford, M. Izadi, R. Finfer, D. Patterson, J. Nigro, B. Murphy, D. Jatres, J. Ruley, and R. Stickney, *Safer Streets Priority Finder: Building A Dashboard for Vulnerable Road User Safety Analysis and Prioritization*. US Department of Tansportation, 2021.

[49] T. J. Mansfield, D. Peck, D. Morgan, B. McCann, and P. Teicher, "The effects of roadway and built environment characteristics on pedestrian fatality risk: A national assessment at the neighborhood scale," *Accident Analysis & Prevention*, vol. 121, pp. 166–176, 2018.

[50] R. Prelog, "Equity of Access to Bicycle Infrastructure: GIS methods for investigating the equity of access to bike infrastructure," Dec. 30, 2015. https://issuu.com/bikeleague/docs/bicycle_equity_index_final_web (accessed Jul. 20, 2023).

[51] T. A. Litman, "Evaluating Transportation Equity: Guidance for Incorporating Distributional Impacts in Transport Planning".

[52] "New Orleans' Bicycle Equity Index," *PeopleForBikes*. https://www.peopleforbikes.org/news/new-orleans-bicycle-equity-index (accessed Jul. 20, 2023).

[53] G. Lindsey, T. Tao, J. Wang, and J. Cao, "Pedestrian and bicycle crash risk and equity: Implications for street improvement projects," 2019.

[54] L. Sandt, T. Combs, and J. Cohn, "Pursuing equity in pedestrian and bicycle planning," 2016.

[55] Y. Freemark, P. Gwam, and E. Noble, "Redefining Walkability: Examining Equity and Creating Safer Streets for All in DC," 2022.

[56] B. Patterson and D. Mitic, "Pedestrian Priority Index: Objectively Assessing Investments in Pedestrian Infrastructure in North Vancouver", [Online]. Available: https://www.railstotrails.org/resourcehandler.ashx?name=pedestrian-priority-index-

objectively-assessing-investments-in-pedestrian-infrastructure-in-north-vancouver&id=4464&fileName=Brian_Patterson_and_Dragana_Mitic.pdf.

[57] *Practical Approaches for Involving Traditionally Underserved Populations in Transportation Decisionmaking*. Washington, D.C.: Transportation Research Board, 2012. doi: 10.17226/22813.

[58] "Smart Growth America. Improving public engagement," *Smart Growth America*, 2018, [Online]. Available: https://smartgrowthamerica.org/wp-content/uploads/2019/03/Improving-public-engagement_FINAL.pdf.

[59] M. Denker, M. Flynn, S. Dovovan, and A. Zazula, "It's Time for Public Participation to Evolve With Transportation Planning," 2021. https://www.planetizen.com/features/115279-its-time-public-participation-evolve-transportation-planning (accessed Jul. 20, 2023).

[60] D. Biggs, "Three Big Steps Towards Equity in Virtual Public Engagement for Transportation Planning," *MetroQuest*, Nov. 09, 2021. https://metroquest.com/steps-to-equity-vpe-transportation-planning/ (accessed Jul. 20, 2023).

[61] A. Wilson, M. Tewdwr-Jones, and R. Comber, "Urban planning, public participation and digital technology: App development as a method of generating citizen involvement in local planning processes," *Environment and Planning B: Urban Analytics and City Science*, vol. 46, no. 2, pp. 286–302, 2017, doi: 10.1177/2399808317712515.

[62] A. Estefam, "Strategic overview of digital public participation tools for urban planning," Jun. 2021, doi: 10.33797/SIDE.21.008.

[63] "Bike Network Mapping Idea Book | FHWA," 2016. https://highways.dot.gov/safety/pedestrian-bicyclist/safety-tools/pg-1-57-bike-network-mapping-idea-book (accessed Jul. 20, 2023).

[64] M. Salerno, A. Lubin, A. M. Voorhees, and P. Lebeaux, *Virtual Public Involvement: Lessons from the COVID-19 Pandemic*. Washington, D.C.: Transportation Research Board, 2022. doi: 10.17226/26827.

[65] R. Bian and T. Tolford, "LTRC 21-2SS: Evaluate the Impacts of Complete Streets Policy in Louisiana," 2023.

[66] R. Bian and T. Tolford, "Evaluating the implementation of the complete streets policy in Louisiana: a review of practices and projects in the last 10 years," *Transportation research record*, vol. 2677, no. 3, pp. 505–520, 2023.

[67] Uber, "Tables of Cell Statistics Across Resolutions | H3," *Uber Technologies, Inc.*, 2023. https://h3geo.org/docs/core-library/restable/ (accessed Jul. 20, 2023).

[68] Y. Yang and A. V. Diez-Roux, “Walking distance by trip purpose and population subgroups,” *American journal of preventive medicine*, vol. 43, no. 1, pp. 11–19, 2012, doi: doi: 10.1016/j.amepre.2012.03.015.Walking.

[69] FHWA, “Guidebook on Identification of High Pedestrian Crash Locations,” 2018. https://www.fhwa.dot.gov/publications/research/safety/17106/008.cfm (accessed Jul. 20, 2023).

[70] I. Tsapakis, W. Holik, S. Geedipally, and S. Samant, “Statewide Implementation of Innovative Safety Analysis Tools in Identifying Highway Safety Improvement Projects: Technical Report,” [Online]. Available: https://static.tti.tamu.edu/tti.tamu.edu/documents/5-6912-01-R1.pdf.

[71] “DOTD Geospatial Gateway.” https://maps.dotd.la.gov/portal/apps/sites/#/app-public (accessed Jul. 20, 2023).

[72] O. US EPA, “Smart Location Mapping,” Feb. 27, 2014. https://www.epa.gov/smartgrowth/smart-location-mapping (accessed Jul. 20, 2023).

[73] J. Chapman, E. H. Fox, W. Bachman, L. D. Frank, J. Thomas, and A. Rourk Reyes, “Smart Location Database Technical Documentation and User Guide Version 3.0,” 2021.

[74] “Transportation Disadvantaged Census Tracts,” 2023. https://usdot.maps.arcgis.com/apps/dashboards/d6f90dfcc8b44525b04c7ce748a3674a (accessed Jul. 20, 2023).

[75] “Reconnecting Communities and Neighborhoods Grant Program | US Department of Transportation,” 2023. https://www.transportation.gov/grants/rcnprogram/about-rcp (accessed Jul. 20, 2023).

[76] “Explore Census Data,” 2022. https://data.census.gov/cedsci (accessed Jul. 20, 2023).

[77] “Iowa Bicycle and Pedestrian Long Range Plan,” IOWADOT, 2018.

[78] “Connecticut Active Transportation Plan,” 2019.

[79] “Pennsylvania Active Transportation Plan,” *Pennsylvania Department of Transportation*. https://www.penndot.pa.gov:443/TravelInPA/active-transportation/Pages/default.aspx (accessed Jul. 20, 2023).

[80] “Statewide Active Transportation Plan,” 2021. https://www.tn.gov/tdot/multimodal-transportation-resources/bicycle-and-pedestrian-program/statewide-active-transportation-plan.html (accessed Jul. 20, 2023).

[81] “National Household Travel Survey.” https://nhts.ornl.gov/ (accessed Jul. 21, 2023).

[82] K. Clifton, P. Singleton, C. Muhs, and R. Schneider, "Development of a Pedestrian Demand Estimation Tool," *Civil and Environmental Engineering Faculty Publications and Presentations*, Sep. 2015, doi: 10.15760/trec.124.

[83] "Demand Analysis Summary | Ohio Department of Transportation," 2020. https://www.transportation.ohio.gov/programs/walkbikeohio/existing-future-conditions-analysis/wbo-demand-analysis (accessed Jul. 21, 2023).

[84] "Pedestrian Master Plan," *LouisvilleKY.gov*. https://louisvilleky.gov/government/bike-louisville/pedestrian-master-plan (accessed Jul. 22, 2023).

[85] "Bicycle Network Demand Analsysis," 2016. https://bikewalkkc.org/about/consulting/kcmo-bike-demand-analysis/kcmo-bicycle-network-demand-analysis-bikewalkkc-nov2016/ (accessed Jul. 23, 2023).

[86] "New Orleans Bikeway Blueprint: Executive Summary," 2020.

[87] "Jefferson Parish Bicycle Master Plan," Regional Planning Commission for Jefferson, Orleans, Plaquemines, St. Bernard, and St. Tammany Parishes, 2013. [Online]. Available: https://jefferson-parish-government.azureedge.net/documents/departments/planning/envision-2020/bicycle-master-plan/JPBicycleMasterPlan-2013-12-27.pdf

[88] G. Lindsey, J. Wang, S. Hankey, and M. Pterka, "Modeling Bicyclist Exposure to Risk and Crash Risk: Some Exploratory Studies," 2018.

[89] N. Fournier, E. Christofa, and M. A. Knodler Jr, "A mixed methods investigation of bicycle exposure in crash rates," *Accident Analysis & Prevention*, vol. 130, pp. 54–61, 2019.

[90] M. Holian and R. McLaughlin, "Benefit-cost analysis for transportation planning and public policy: towards multimodal demand modeling," 2016.

[91] "The Benefits of Complete Streets," 2021. https://benefits.completestreets.org/ (accessed Jul. 23, 2023).

[92] United States. Federal Highway Administration, "Measuring Multimodal Network Connectivity Pilot Grant Program Final Report," FHWA-HEP-21-024, Oct. 2021. Accessed: Jul. 24, 2023. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/58167

[93] "Bike Network Analysis: Methodology," *PeopleForBikes*. https://cityratings.peopleforbikes.org/about/methodology. (accessed Jul. 24, 2023).

[94] D. Berrigan, L. W. Pickle, and J. Dill, “Associations between street connectivity and active transportation,” *Int J Health Geogr*, vol. 9, no. 1, p. 20, Apr. 2010, doi: 10.1186/1476-072X-9-20.

[95] W. Shi, “The Impacts of the Bicycle Network on Bicycling Activity: A Longitudinal Multi-city Approach,” Ph.D., Portland State University, United States -- Oregon, 2020. Accessed: Jul. 24, 2023. [Online]. Available: https://www.proquest.com/docview/2424057734/abstract/B16C3A6531624072PQ/1

[96] M. Lowry and T. H. Loh, “Quantifying bicycle network connectivity,” *Preventive medicine*, vol. 95, pp. S134–S140, 2017.

[97] T. Reardon, E. Wallace, and C. Brown, “Local Access Scores: Active Transportation Network Utility Scores,” 2016.

[98] “Improving public engagement. Smart Growth America,” 2018, [Online]. Available: https://smartgrowthamerica.org/wp-content/uploads/2019/03/Improving-public-engagement_FINAL.pdf.

[99] C. Zeilinger, “Developing and advancing effective public involvement and environmental justice strategies for rural and small communities,” Federal Highway Administration (US), 2016.

[100] A. Read, “Using Online Tools for Public Engagement (PAS QuickNotes 51),” *American Planning Association*, 2014. https://www.planning.org/media/document/9007646/ (accessed Jul. 24, 2023).

[101] R. Washington, “Lessons Learned from FHWA’s Virtual Public Involvement Initiative: Key VPI Resources and Activities and Overview of the USDOT Equity Action Plan,” presented at the Presentation at TRB Annual Meeting 2023, Washington D.C., 2023.

[102] E. Falco and R. Kleinhans, “Digital Participatory Platforms for Co- Production in Urban Development: A Systematic Review,” *International Journal of E-Planning Research*, vol. 7, pp. 1–27, Mar. 2018, doi: 10.4018/IJEPR.2018070105.

[103] R. Bian, K. Smiley, S. Parr, J. Shen, and P. Murray-Tuite, “Analyzing Gas Station Visits during Hurricane Ida: Implications for Future Fuel Supply.,” *Transportation Research Record: Journal of the Transportation Research Board*, pp. 1-13., 2023.

[104] K. Wang, Y. Liu, S. M. Mashrur, P. Loa, and K. N. Habib, “COVid-19 influenced households’ Interrupted Travel Schedules (COVHITS) survey: Lessons from the fall 2020 cycle,” *Transport Policy*, vol. 112, pp. 43–62, Oct. 2021, doi: 10.1016/j.tranpol.2021.08.009.

[105] P. Borkowski, M. Jażdżewska-Gutta, and A. Szmelter-Jarosz, “Lockdowned: Everyday mobility changes in response to COVID-19,” *Journal of Transport Geography*, vol. 90, p. 102906, Jan. 2021, doi: 10.1016/j.jtrangeo.2020.102906.

[106] M. De Haas, R. Faber, and M. Hamersma, “How COVID-19 and the Dutch ‘intelligent lockdown’ change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands,” *Transportation Research Interdisciplinary Perspectives*, vol. 6, p. 100150, Jul. 2020, doi: 10.1016/j.trip.2020.100150.

[107] S. Shaheen and S. Wong, “Future of Public Transit and Shared Mobility: Scenario Planning for COVID-19 Recovery,” 2021.

[108] R. Bian, P. Murray-Tuite, and B. Wolshon, “Predicting Grocery Store Visits During the Early Outbreak of COVID-19 with Machine Learning,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2677, no. 4, pp. 79–91, Apr. 2023, doi: 10.1177/03611981211043538.

[109] T. Campisi, S. Basbas, A. Skoufas, N. Akgün, D. Ticali, and G. Tesoriere, “The Impact of COVID-19 Pandemic on the Resilience of Sustainable Mobility in Sicily,” *Sustainability*, vol. 12, no. 21, p. 8829, Oct. 2020, doi: 10.3390/su12218829.

[110] A. Shaer, M. Rezaei, and B. Moghani Rahimi, “Assessing the COVID-19 outbreak effects on active mobility of men in comparison with women,” *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, pp. 1–18, Nov. 2021, doi: 10.1080/17549175.2021.1995028.

[111] Y. Fan, X. Qian, N. Linscheid, and G. Ryan, “Understanding Post-COVID Safety Concerns toward the Use of Transit and Shared Mobility in Greater Minnesota,” Minnesota. Department of Transportation, 2023.

[112] T. Yabe and S. V. Ukkusuri, “Effects of income inequality on evacuation, reentry and segregation after disasters,” *Transportation Research Part D: Transport and Environment*, vol. 82, p. 102260, May 2020, doi: 10.1016/j.trd.2020.102260.

[113] H. Younes, A. Darzi, and L. Zhang, “How effective are evacuation orders? An analysis of decision making among vulnerable populations in Florida during hurricane Irma,” *Travel Behaviour and Society*, vol. 25, pp. 144–152, Oct. 2021, doi: 10.1016/j.tbs.2021.07.006.

[114] R. Bian, C. G. Wilmot, and L. Wang, “Estimating spatio-temporal variations of taxi ridership caused by Hurricanes Irene and Sandy: A case study of New York City,” *Transportation Research Part D: Transport and Environment*, vol. 77, pp. 627–638, Dec. 2019, doi: 10.1016/j.trd.2019.10.009.

[115] R. Bian and C. G. Wilmot, “Observing transient behavior during Hurricane Sandy through passively collected data,” *Transportation Research Part D: Transport and Environment*, vol. 77, pp. 606–614, Dec. 2019, doi: 10.1016/j.trd.2019.09.025.

[116] R. Bian, P. Murray-Tuite, and J. Li, "Investigating COVID-19 Induced Taxi and For-Hire Vehicle Ridership Disparities," *J. Urban Plann. Dev.*, vol. 148, no. 4, p. 04022038, Dec. 2022, doi: 10.1061/(ASCE)UP.1943-5444.0000887.

[117] Z. Berezvai, "Short- and long-term effects of COVID-19 on bicycle sharing usage," *Transportation Research Interdisciplinary Perspectives*, vol. 15, p. 100674, Sep. 2022, doi: 10.1016/j.trip.2022.100674.

[118] Y. Chen, X. Sun, M. Deveci, and D. Coffman, "The impact of the COVID-19 pandemic on the behaviour of bike sharing users," *Sustainable Cities and Society*, vol. 84, p. 104003, Sep. 2022, doi: 10.1016/j.scs.2022.104003.

[119] Q. Li and W. Xu, "The impact of COVID-19 on bike-sharing travel pattern and flow structure: evidence from Wuhan," *Cambridge Journal of Regions, Economy and Society*, vol. 15, no. 3, pp. 477–494, Dec. 2022, doi: 10.1093/cjres/rsac005.

[120] A.-M. Schweizer, A. Leiderer, V. Mitterwallner, A. Walentowitz, G. H. Mathes, and M. J. Steinbauer, "Outdoor cycling activity affected by COVID-19 related epidemic-control-decisions," *PLoS ONE*, vol. 16, no. 5, p. e0249268, May 2021, doi: 10.1371/journal.pone.0249268.

[121] A. M. Sadri, S. Hasan, S. V. Ukkusuri, and M. Cebrian, "Crisis Communication Patterns in Social Media during Hurricane Sandy," *Transportation Research Record*, vol. 2672, no. 1, pp. 125–137, Dec. 2018, doi: 10.1177/0361198118773896.

[122] Y. Martín, S. L. Cutter, Z. Li, C. T. Emrich, and J. T. Mitchell, "Using geotagged tweets to track population movements to and from Puerto Rico after Hurricane Maria," *Popul Environ*, vol. 42, no. 1, pp. 4–27, Sep. 2020, doi: 10.1007/s11111-020-00338-6.

[123] Q. Wang and J. E. Taylor, "Patterns and Limitations of Urban Human Mobility Resilience under the Influence of Multiple Types of Natural Disaster," *PLoS ONE*, vol. 11, no. 1, p. e0147299, Jan. 2016, doi: 10.1371/journal.pone.0147299.

[124] R. F. Hunter, L. Garcia, T. H. De Sa, B. Zapata-Diomedi, C. Millett, J. Woodcock, A. Pentland, and E. Moro, "Effect of COVID-19 response policies on walking behavior in US cities," *Nat Commun*, vol. 12, no. 1, p. 3652, Jun. 2021, doi: 10.1038/s41467-021-23937-9.

[125] Y. Song, S. Lee, A. Park, and C. Lee, "COVID-19 impacts on non-work travel patterns: A place-based investigation using smartphone mobility data," *Environment and Planning B: Urban Analytics and City Science*, vol. 50, p. 239980832211249, Sep. 2022, doi: 10.1177/23998083221124930.

[126] A. Darzi, V. Frias-Martinez, S. Ghader, H. Younes, and L. Zhang, "Constructing Evacuation Evolution Patterns and Decisions Using Mobile Device Location Data:

A Case Study of Hurricane Irma." arXiv, Feb. 24, 2021. doi: 10.48550/arXiv.2102.12600.

[127] Z. Chen, Z. Gong, S. Yang, Q. Ma, and C. Kan, "Impact of extreme weather events on urban human flow: A perspective from location-based service data," *Computers, Environment and Urban Systems*, vol. 83, p. 101520, Sep. 2020, doi: 10.1016/j.compenvurbsys.2020.101520.

[128] A. Wu, X. Yan, E. Kuligowski, R. Lovreglio, D. Nilsson, T. J. Cova, Y. Xu, and X. Zhao, "Wildfire evacuation decision modeling using GPS data," *International Journal of Disaster Risk Reduction*, vol. 83, p. 103373, Dec. 2022, doi: 10.1016/j.ijdrr.2022.103373.

[129] A. Li, P. Zhao, H. He, and K. W. Axhausen, "Understanding the variations of micro-mobility behavior before and during COVID-19 pandemic period," p. 20 p., Aug. 2020, doi: 10.3929/ETHZ-B-000430395.

[130] A. M. El-Geneidy and D. M. Levinson, "Access to destinations: Development of accessibility measures," 2006.

[131] V. Kolarova, C. Eisenmann, C. Nobis, C. Winkler, and B. Lenz, "Analysing the impact of the COVID-19 outbreak on everyday travel behaviour in Germany and potential implications for future travel patterns," *European Transport Research Review*, vol. 13, no. 1, pp. 1–11, 2021.

[132] J. Jay, F. Heykoop, L. Hwang, A. Courtepatte, J. De Jong, and M. Kondo, "Use of smartphone mobility data to analyze city park visits during the COVID-19 pandemic," *Landscape and Urban Planning*, vol. 228, p. 104554, Dec. 2022, doi: 10.1016/j.landurbplan.2022.104554.

[133] L. Juhasz and H. Hochmair, "Studying Spatial and Temporal Visitation Patterns of Points of Interest Using SafeGraph Data in Florida," *GIS Center*, Jun. 2020, doi: 10.1553/giscience2020_01_s119.

[134] R. Bian, K. Smiley, S. Parr, J. Shen, and P. Murray-Tuite, "Analyzing Gas Station Visits during Hurricane Ida: Implications for Future Fuel Supply," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 1–13, 2023, doi: (https://doi.org/10.1177/03611981231186600).

[135] "Active Transportation Planning for Louisiana (Version 2.0)." https://www.arcgis.com/apps/dashboards/c1848d849ab8480e93f419bbaf4dacd9 (accessed Jul. 10, 2023).

[136] A. S. Yeboah, J. Codjoe, and R. Thapa, "Estimating Average Daily Traffic on Low-Volume Roadways in Louisiana," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2677, no. 1, pp. 1732–1740, Jan. 2023, doi: 10.1177/03611981221106166.

[137] J. Jiao, Y. Chen, and A. Azimian, “Exploring temporal varying demographic and economic disparities in COVID-19 infections in four U.S. areas: based on OLS, GWR, and random forest models,” *Comput.Urban Sci.*, vol. 1, no. 1, p. 27, Dec. 2021, doi: 10.1007/s43762-021-00028-5.

[138] L. Breiman, “Random forests,” *Machine learning*, vol. 45, pp. 5–32, 2001.

[139] X. Yan, X. Liu, and X. Zhao, “Using machine learning for direct demand modeling of ridesourcing services in Chicago,” *Journal of Transport Geography*, vol. 83, p. 102661, 2020.

[140] J. Jiao, N. Degen, and A. Azimian, “Understanding the relationships among e-scooter ridership, transit desert index, and health-related factors,” *Transportation research record*, vol. 2676, no. 12, pp. 728–739, 2022.

[141] S. Meena, “Impact of novel Coronavirus (COVID-19) pandemic on travel pattern: A case study of India,” *IJST*, vol. 13, no. 24, pp. 2491–2501, Jun. 2020, doi: 10.17485/IJST/v13i24.958.

[142] M. E. G. Parker, M. Li, M. A. Bouzaghrane, H. Obeid, D. Hayes, K. T. Frick, D. A. Rodriguez, R. Sengupta, J. walker, and D. G. Chatman, “Public transit use in the United States in the era of COVID-19: Transit riders’ travel behavior in the COVID-19 impact and recovery period,” *Transport Policy*, vol. 111, pp. 53–62, Sep. 2021, doi: 10.1016/j.tranpol.2021.07.005.

Appendix A: Expanded Review of Active Transportation Demand Literature

Data Sources and Methods of Measuring Demand

Many states have updated their statewide active transportation plans (sometimes referred to as “bicycle and pedestrian master plan”) in recent years [4], [77]–[80]. Most of these plans recognize the lack of consistent and comprehensive bicycle and pedestrian data collection as a common limitation for implementation and/or evaluation, with many key limitations for each of the most commonly used data sources, which prevent planners from getting a complete picture of statewide walking/biking activities. However, the quantity and range of data sources used in active transportation planning have expanded dramatically in recent decades. Once limited to primarily survey-based data (e.g., U.S. Census, National Household Travel Survey), there are now a variety of direct and indirect data sources available to understand, model, predict, and evaluate active transportation demand. This literature review summarizes different types of data and their uses, with a particular focus on methods of assessing latent demand and the necessary data required to implement those methods. It also explores the use of mobile device data for analyzing active transportation demand and discusses the limitations of using mobile data, particularly as it pertains to equity.

Traditional Data Sources: Surveys, Counts, and Demand Models

Over two decades ago, the Bureau of Transportation Statistics conducted an assessment of pedestrian and bicycle data needs, developing an inventory of relevant data sources available at the time (Table 23) and identifying recommended priorities for expanding or improving the quality of pedestrian and bicycle data [9]. The assessment identified key uses for bicycle and pedestrian data for research studies, namely:

- informing recommended practices
- guiding planning and design of facilities, project selection, and policy and program implementation, and
- analyzing conditions and trends to inform policymaking

BTS found that top priorities pertaining to demand included better data on the number of bicyclists or pedestrians by facility or geographic area through counts, surveys, and research on trip length distributions. They also highlighted the importance of understanding the socioeconomic and demographic characteristics associated with walking and bicycling. The assessment recognized the limitations of using journey-to-work based mode share data and identified the lack of a non-motorized equivalent of the Highway Performance Monitoring System (HPMS) as key barriers to effective pedestrian and bicycle planning.

In subsequent decades, data availability has improved substantially, particularly with the expansion of Census Bureau survey data to include annual estimates from the American Community Survey (ACS). Additionally, there has been more widespread count collection (discussed below). However, fundamental issues still persist, limited data on non-work bicycling and walking trips and the lack of a standardized systematic approach to volume data collection.

The National Household Travel Survey [81], along with ACS, is one of the most widely used references for data on walking and bicycling trends. It provides information about daily trips of all modes and lengths for all purposes. This survey is collected every 5-7 years (most recently in 2017) and serves as a valuable benchmark for national trends. However, unless states or MPOs participate in optional “add-on” survey sampling, NHTS findings are not available at levels of geography relevant to local or even state-level planning. State or regionally led household travel surveys are common in many regions; however, long intervals between data points are common, and many jurisdictions lack the resources to conduct extensive sampling.

The collection of direct pedestrian and bicycle counts has expanded significantly in recent decades, ranging from simple manual observation-based counts [12] to the installation of robust networks of permanent counters [13]–[15]. National guidance has been issued around methods and technologies available for such activities [16], [17], as well as applications for data management and use [17], [18]. Recent research in Louisiana has led to the implementation of a pilot set of permanent non-motorized count stations [65] and the development of preliminary adjustment factors for estimating demand on other network segments based on short-duration counts.

However, no jurisdiction can collect counts on all network segments at all times, making models and the other planning and forecasting tools necessary to contextualize and apply both count and survey data in order to holistically understand demand for walking and bicycling. The NCHRP's primary guide for demand analysis, Report 770 [20], outlines factors impacting active transportation demand and best practice methods for estimating bicycling and walking activity, and tools for practice. The key components of typical current travel planning practice are broken into two primary categories:

- *Regional travel forecasting tools* (i.e., regional travel demand models typically used by MPOs and aggregating trips at the Traffic Analysis Zone (TAZ) level, and
- *Facility demand models*, based on direct counts and/or contextual variables associated with active transportation.

NCHRP 770 summarized previous research on demand estimation for walking and bicycling, including a summary of the range of factors that affect active transportation activity (Table 15), and compiling regional, corridor/subarea, and facility planning tools and methods, as well as examples of their use.

Table 15. Key factors affecting walking and bicycling [20]

Land Use and the Built Environment	Facilities	Natural Environment	Socio-demographic	Attitudes and Perceptions
Density (residential and employment)	Type of facility	Climate	Gender	Health
Diversity (mix and entropy)	Safety	Temperature extremes	Age	Disability
Design	Grade	Precipitation	Income	Safety
Distance to Transit	Crossing Difficulties	Darkness	Vehicle Ownership	Security
Destination accessibility		Topography	Education	
			Ethnicity	

The report then sought to address gaps in the foundation and application of available tools, including the distinct differences between walking and bicycling (often lumped together in regional models), the role of land use and facility network extent, and nuanced characteristics of active transportation trips based on purpose, setting, safety, socio-demographics, and environmental features. The resulting tools or recommendations developed or highlighted include the following:

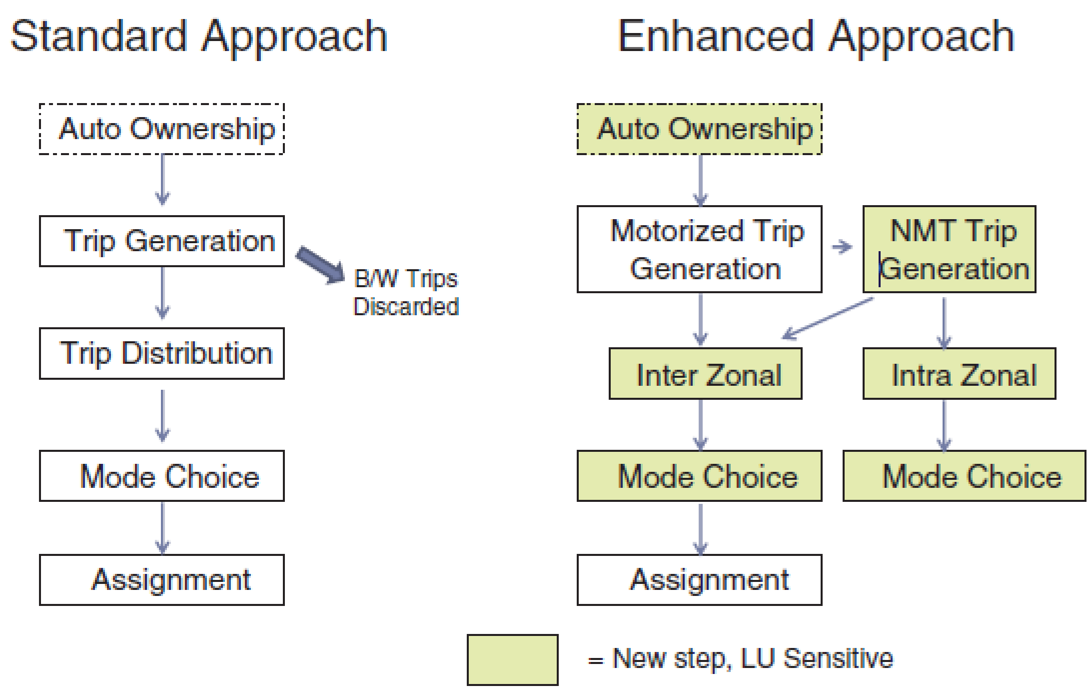
- Pedestrian and bicycle tour-generation and mode split models to predict walk, bike, transit, and automobile use for five tour purposes (i.e., series of interrelated, sequential trips) based on sociodemographic, land use, accessibility, and transportation network characteristics. This tool is available as a spreadsheet model for sketch planning and incorporates a variety of readily available traveler, accessibility, and land use metrics (Table 16)

Table 16. Tour-based and walk accessibility model variables [20]

Traveler Characteristics	**Accessibility**	**Land Use**	**Transportation**
Age	Employment	Household density	Distance/travel time by mode
Gender	Schools	Employment density	slope/gradient
Work/student status	Retail	Mix of uses (entropy)	Sidewalk coverage
Income	Food Service	intersection Density	Bikeway coverage
Vehicle ownership	Entertainment/Recreation	transit stop density	Directional efficiency
Children		distance to transit stop	Parking cost
			Transit fare

- **GIS-based Walk-Accessibility model** using readily available GIS procedures to calculate accessibility to any point by mode or destination type, estimate mode split, and generate walk trip tables. This tool does not apply to bicycle demand at this time.
- A template for **enhancing conventional, TAZ/Trip-based models** by increasing sensitivity to land use and non-motorized travel accessibility to better account for intra-zonal trips (Figure 35)

Figure 35. NCHRP 770 four-step model suggested enhancements for non-motorized travel estimation [20]



- **PedContext** and **MoPeD models**, which estimate walk trips and facility volumes for neighborhoods or sub-areas based on block-sized pedestrian analysis zones (PAZs)
- **The Portland Pedestrian Model** also uses PAZs and estimates walk trips by purpose, based partly on a measure of "pedestrian index of the environment" (PIE) to account for land use and accessibility characteristics
- **Facility Demand models** based on route choice (facility, slope, directness, exposure) or direct demand (based on observed counts and regression models).

Overall, the study summarizes tool properties and capabilities, including geographic scale applicability, modeling steps, planning applications, key indicators (outputs), variable sensitivities, and data requirements.

Notably, modeling approaches that do not rely on travel survey data are limited to direct demand models (further discussed below) and the Portland Pedestrian Model. In lieu of survey data, direct demand models particularly rely on the availability of network counts for model development, calibration, and validation. Variables used in such models typically include population and employment densities and volumes, land use mix, facility characteristics, vehicle speeds, ADT, or other measures of exposure, transit availability, and presence of major activity generators. Although direct demand models have been in use for decades, NCHRP identified key limitations and guidelines for use, highlighting for need for extensive reliability testing and advising to use direct demand models primarily for screening, not for forecasting new demand or network change.

Collectively, household travel surveys, counts, and demand models that incorporate one or both, along with other data to account for built environment, facility, sociodemographic, and other variables, make up the foundation of traditional non-motorized transportation demand analysis. However, as noted, many regions lack recent or sufficiently robust survey data, and even jurisdictions with well-developed count programs may not be able to derive comprehensive network-wide demand models based on direct counts alone. Models themselves may be beyond the technical analytic capabilities of many local agencies. Additional scalable and low-cost data sources are needed to better support decision-making around walking and bicycling to facilitate routine integration of active transportation activity and/or potential into project and area-wide planning.

Emerging Data Sources: Active and Passive Crowdsourced Data

As smartphones have become nearly ubiquitous over the last decade, their potential as a data source for a variety of planning and evaluation purposes has risen. In transportation planning, this “big” data is used for traffic monitoring and analyzing mobility in a variety of ways. A growing body of literature has emerged documenting current and potential uses for new data sources, especially GPS and mobile phone-based datasets. The use of this data can help to overcome key challenges in the use of traditional data, namely small sample sizes and limited counts.

Lee and Sener [22] categorized data sources and summarized the application of mobile data to pedestrian and bicycle travel analysis. They contrast these data sources with traditional primary data sources and further break down emerging data based on target population and collection methodology into mode specified (e.g. apps that target specific users or otherwise classify mode choice for individual trips) and mode unspecified (e.g. general GPS or location-based services, Bluetooth, etc.) categories (Figure 36). Each of these classifications is reviewed to determine common attributes and applications, and specific vendors or datasets in use for transport planning.

Figure 36. Pedestrian and bicycle data source classification [22]

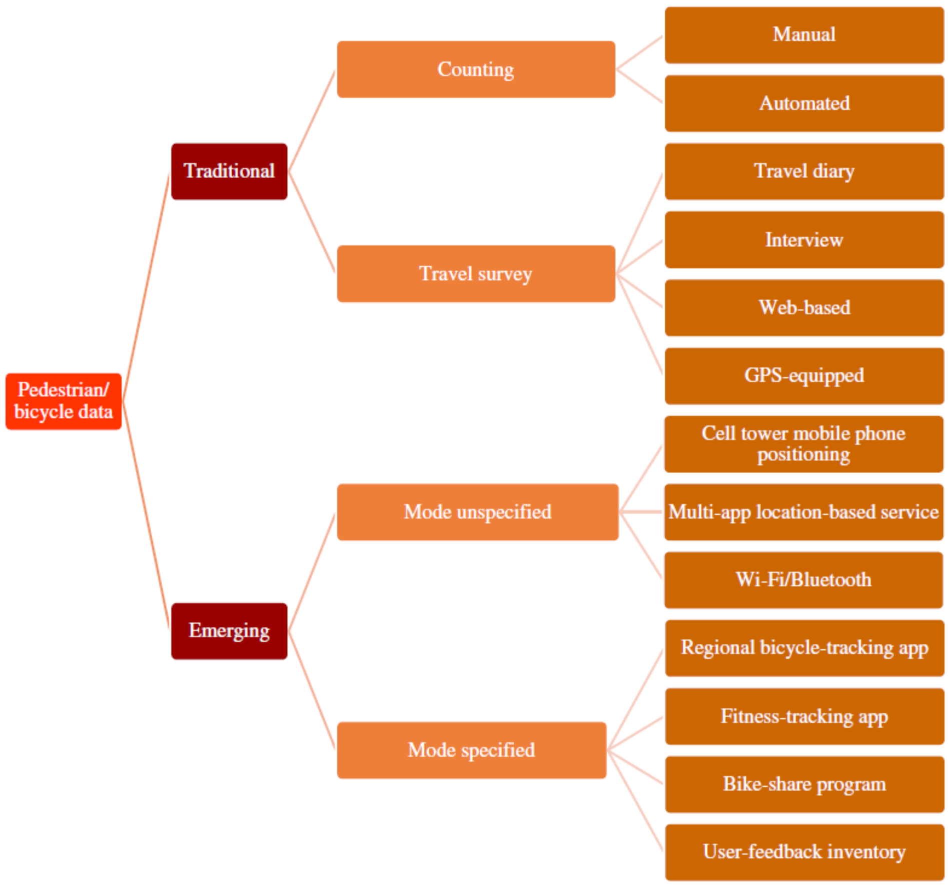


Table 17. Summary of emerging data sources [22]

	Data produced	**Planning uses**	**Key Characteristics**	**Examples/Vendors**
Mode Unspecified				
Cell tower MPP	Time, duration, location of cell phone use; travel between tower zones	O/D pairs, traffic speed and volume, imputed trip purpose, home/work location, demographics	More accurate in urban areas with more cell tower density (200-1000m) generally not disaggregated to mode	Airsage, Orange
Multi-app location-based service	Real-time location of users, inferred mode (based on modeling)	O/D pairs, traffic attributes by time frame and geometry, inferred trip purpose, network-wide traffic flow	High location precision (5-50m) but accuracy errors common	Social network platforms, Streetlight, Cuebiq

	Data produced	Planning uses	Key Characteristics	Examples/Vendors
Wi-Fi/Bluetooth	Anonymous, passively collected time stamped volumes within a specific zone	Volumes, travel times (with ingress/egress control), activity density and dwell time	Detection range of up to 100 m	(Various)
Mode Specified				
Regional bicycle tracking app	Demographics, GPS traces	O/D pairs, route choice, trip frequency and distance	Typically developed by/for government agencies for planning purposes, detailed data but limited sample sizes	CycleTracks, Orcycle, Cycle Atlanta
Fitness tracking app	Demographics, GPS traces, health data	O/D pairs, route choice, trip frequency and distance	Inherent sample bias toward recreational trips; some datasets available by public API	Strava Metro, Fitbit, Garmin
Bike share program	GPS trace, start/end times, member information	O/D pairs, route choice, trip frequency and distance	Detailed trip data; user characteristics may not be representative of all bicycle activity/geographically constrained	Mobike, Dropbike, local apps
User-feedback inventory	Geo-crowdsourced information about infrastructure, safety, etc.	Network/project priorities, route choice, deficiencies, etc.	Crowdsourced information, tailored to planning need, about user preferences, infrastructure deficiencies, etc.	OpenStreetMap, BikeMaps, WalkOn

A key benefit of mode-unspecified data sources is that large volumes of data, passively collected, improve sample reliability. However, most transportation research utilizing these datasets has focused on motor vehicles [22]. Exceptions include efforts by StreetLight Data and government clients to isolate and analyze bicycling and walking trips for specific analysis (such as evaluating activity around light rail stations in Sacramento) or for statewide planning purposes [23], and the use of Bluetooth traces at transit terminals to estimate pedestrian flows and wait times [24]. Mode specified data sources, on the other hand, have been widely used for pedestrian and bicycle planning purposes, travel pattern identification, route choice modeling, travel demand prediction, crash exposure estimation, and other analytic uses. However, such data are limited by small or skewed samples, which may inhibit their utility for some planning and demand analysis purposes and call into question data validity.

Several recent studies have attempted to evaluate detection, classification, spatial precision, and/or overall accuracy of smartphone/probe-based passive data sources, often by using direct counts as the basis for measuring deviation between observed volumes and estimated or modeled vendor outputs. Tsapikis et al. [25] evaluated motor vehicle AADT estimates provided by StreetLight Data, using a set of permanent continuous DOT-owned traffic counters, using a series of statistical tests. Results from this analysis were mixed, but overall the researchers found that the estimates were generally valid for traffic monitoring on higher (5000+) volume roadways. Fish et al. [26] similarly compared volume data from 500 permanent traffic counters to validate StreetLight AADT estimates, finding strong correlations except for specific applications such as those with complex roadway geometry. Their findings were limited by relatively small sample sizes. A larger FHWA pooled fund study led by Streetlight itself [27] compared AADT estimates to 4,255 permanent counters to assess error rates, factoring methods, special contexts (e.g., ramps, work zones, special events), specific vehicle types, and other applications. They found that the passive data estimates outperformed short-term counters for higher (2000+) volume roadways. However, none of these evaluations specifically focused on the application of StreetLight or other big data sources for active transportation demand estimation, for which permanent continuous count data is much more limited, and for which user volumes are often orders of magnitude smaller.

Lee and Sener [28] acknowledged this gap in their summary of findings pertaining to use of emerging data sources for active transportation planning and analysis, finding particular gaps in the use of crowdsourced data for pedestrian applications and citing low spatial precision and data fusion challenges as key barriers (e.g., attaching user or trip characteristics to individual journeys). GPS-based geolocation data is noted for its relatively high level of spatial precision, and the authors note a small set of studies focused specifically on assessing passive data uses for pedestrian and bicycle trips, highlighting key limitations of emerging crowdsourced data use. Specifically, Lee and Sener identify challenges associated with accurate detection and classification of mode (for non-specified data sources), analysis of very short trips or those where geolocation is imprecise, as well as concerns around privacy in the use of this data (which, in turn, limits availability of user-specific demographic or contextual data which could aid in identifying sample bias, etc.). Fusion of multiple datasets can help address and overcome these challenges to correct for over-and underrepresentation, along with continued advancement in machine learning to improve modal classification [22], [28].

Turner et al. [29] likewise turned their attention to the uses of passively collected data (again sourced from StreetLight) to assess bicycle activity for use in safety analysis, finding “promising” correlations (R2 of 62-69%) relative to 32 bicycle count locations and high correlation with countywide volumes modeled from Strava data, finding the StreetLight Index data likely to provide sufficient reliability for use at aggregate levels. However, researchers recommended continued development of more nuanced data expansion methods to account for variance based on context and roadway functional class.

More focused analyses have highlighted specific uses of mobile data for certain contexts, such as monitoring travel demand in parks (using motor vehicle volume estimates at entrances) [30] or measuring results of efforts to reduce greenhouse gas emissions (through modal shift on a college campus) [31]. Researchers in Lisbon used a variety of active and passive data sources to focus on identifying indicators of and barriers to multimodal mobility, in order to better support integration of active modes with public transit [32]. In these cases, researchers generally found that the use of mobile data yields comparable results relative to traditional survey/count-based demand modeling methods, in some cases addressing sample bias or gaps identified in the latter.

More sophisticated methods for distillation and use of mobile data continue to be developed. Ghahramani et al. [33] compared various approaches for the use and analysis of mobile data, with a focus on real-time traffic monitoring applications, identifying pros and cons (including accuracy, ease of use, network demands, etc., Figure 37). Wang et al. [34] detailed existing methods for extracting trips from non-transportation mobile data sources and proposed a framework to do so for increasingly prevalent multi-sourced data (e.g., those derived from a combination of GPS, cellular network, and/or WiFi data). The framework was tested against household travel survey data to confirm the validity of the approach.

Figure 37. Approaches to mobile phone data analysis [34]

Methodology	Pros	Cons
GPS-equipped handset as probes to gather mobility related information within a cellular network.	High Accuracy	Low penetration of GPS-equipped devices in population.
A real-time representation of city dynamics through handover or cellphone trajectories from registered users.	Using pervasive computing.	High complexity.
Utilizing handover and CDRs to estimate traffic volume and human mobility.	CDRs are relatively easy for mobile phone operators to collect.	Limiting the number of observable devices to a small fraction of the whole population.
Clustering data into representative groups according to their daily activities.	Help urban management by answering when, where, and how individuals interact with different places.	Need to compose social networks and human interactions.
Analyzing spatial-temporal characteristics of human mobility via billing data.	Able to recognize the location of employment based on the regularity of individual trajectory.	Lacking real-time analysis.
Investigating urban activity destinations and human travel patterns to monitor the concentration of people.	Able to quantify the long-term effect of events in the context of destination marketing.	Tracing by applying passive mobile positioning data can be biased by frequent users.
Developing Origin-Destination matrices, using CDRs.	Able to detect the congestion.	Lacking real-time estimation.
Proposing popularity index that utilizes diversity and density index of channels to identify the hot lines by using CDRs.	Exploring the human flows in an urban area with a quantitative measurement of an urban spatial structure.	Suffering from different spatial accuracy of cells.
Exploiting the set of signaling events generated by both idle and active devices.	Able to overcome the limitation of a small number of observable devices.	Increasing the communication load of the network.
Analyzing population concentration by using GPS devices in transportation systems.	Able to provide high accuracy.	Requiring each phone to send information to monitoring system; and line-of-sight dependency.

The ability to supplement and/or substitute passive data for travel surveys, in particular, is of significant interest to MPOs and state DOTs as it may provide a lower cost means of forecasting travel behavior while reducing overall sample bias. It can substitute larger and potentially more representative "synthetic populations" for survey respondents, with the added benefit of being able to update forecasts much more frequently than would be possible with traditional survey-based demand models [35]. Mobile data can also directly unlock the ability to rapidly monitor the number of people at specific locations, as well as to develop dynamic origin-destination matrices. Both of these have important planning and operations applications not only for transportation but also to address health, economic, and other public policy goals [33].

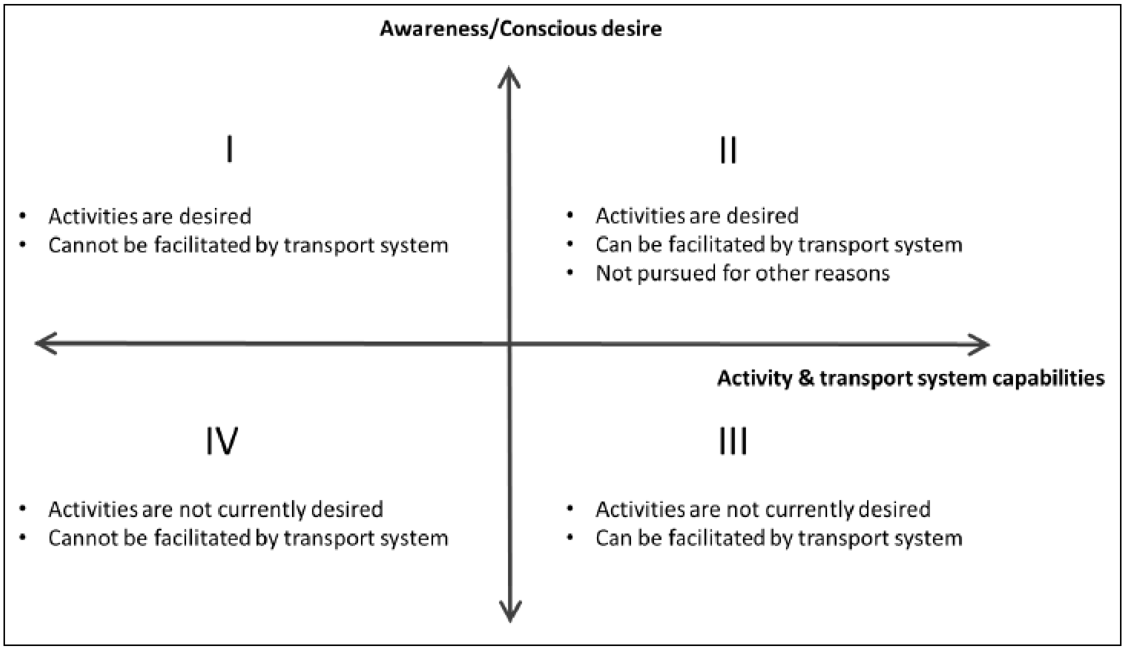
Latent Demand and Forecasting Methods and Tools

Whether direct counts or estimates derived from mobile devices, the number of people currently traveling by active modes on a particular segment or intersection does not necessarily represent the total number of people who need or desire to access that location. NCHRP 770 (discussed above) outlined several key variables that impact demand and models aimed at estimating current usage given existing conditions. This section provides additional insight into methods for estimating latent demand (which accounts for potential additional users or trips that would be made if certain changes to current conditions were made) and methods for forecasting future use under potential alternative scenarios.

Clifton and Moura [37] define latent demand, as it pertains to transportation, as "the activities and travel that are desired but unrealized because of constraints," (p.2) or, in economic theory terms, "the unobserved portion of the demand curve that becomes realized after there is decrease in costs (or travel times) resulting in increased consumption" (p.4). In other words, even if there is currently no walking or bicycling (or other behavior) observed in a given location, it does not necessarily indicate that there is no potential for such activities in the future. The authors remind us that latent demand is primarily a function of demand to participate in specific activities or access certain destinations, rather than to travel or use specific modes of transportation for their own sake.

Latent demand, defined here as either redistributed demand or generative demand, is presented as a framework for understanding unmet needs and highlighting key equity issues (Figure 38). This model charts consumer desires against community/transport system capability, with an emphasis on the role of "awareness" of potential activities or travel options. It reflects that demand is contingent on factors beyond the provision of transportation services or facilities alone (i.e., other barriers to participation). Activities and trips below the X-axis in this model represent travel that could be activated/induced, given changes in awareness and/or capacity. The authors emphasize the need, in long-range transportation planning during this era of rapid technological and social change, to consider these difficult-to-quantify forms of latent demand and explore the gap between current travel demand studies and as-yet unrealized opportunities to meet human needs in ways not yet conceived of by participants [37].

Figure 38. Proposed framework for latent and induced demand [37]



Several studies have attempted to quantify latent demand through the effects of increases in capacity, elasticity of demand with travel costs, or decreases in travel times. However, these analyses are typically focused on specific facilities or projects rather than systems or networks, and most focus on automobile demand [37], [38]. Research centered on changes in VMT or modal shift sometimes fails to account for the underlying purposes of travel. Travel models based on predicted future growth and changes in travel destinations, modes, etc. (i.e., redistributed demand) are typical of household travel-survey-based forecasting [37]. Conversely, latent generative demand derived from exogenous factors (social, economic, cultural, or technological) is less understood and requires new approaches for modeling, particularly in order to understand the needs of disadvantaged communities [37].

Tools to forecast active transportation demand specifically are considerably less regulated and standardized compared to motor vehicle demand forecasting. Aoun et al. [38] organize active transportation forecasting tools into two structures: aggregate (i.e., using existing collective travel choice data to predict future travel choices at the areawide level) and disaggregate (i.e., analyzing individual travel choices to make assumptions about population-wide outcomes). They also break down forecasting tools by purpose: demand estimation (e.g., how many people will use a new facility) versus project prioritization (e.g., which proposed alternative will have the highest relative volume of users) and geographic scope (Table 18).

Table 18. Forecasting tool categorization summary [38]

Structure	Purpose	Geographic Scope
Aggregate	Demand Estimation	Regional
Disaggregate	Project Prioritization	Corridor/Subarea
		Project/Facility

Basic forecasting methods, which estimate future demand, include the use of Census and ACS mode share data to extrapolate the number of users likely to use a proposed project (which, may be scaled for future population growth), estimates based on Level of Traffic Stress (LTS) multipliers, and extraction of short-distance trips from existing travel demand models to estimate potential demand for active transportation (whether or not those trips are currently made by walking or bicycling). Of these, only the latter begins to account for latent demand and does not depend, to some extent, on direct count data [38]. These sketch planning methods can be upgraded to account for variables that impact travel behavior (e.g., measures of connectivity, streetscape features, land use mix, etc.). However, the transferability of models from one location to the next - without extensive data collection required - tends to be limited [38].

Aggregate demand models center on key contextual predictors of bicycling and walking and can be applied to a range of geographic scopes to forecast activity. These models may or may not incorporate current, observed, or reported activity levels in some way [38], [82]. Clifton et al. [82] analyzed pedestrian choice behaviors using household travel survey data to model six trip purpose types against built environment factors, trip distances, and sociodemographic characteristics. They found that employment (particularly retail) is a strong pedestrian trip attractor, as are pedestrian-friendly features defined by the researchers using an aggregate indexed value. Table 19 outlines the variables included in this pedestrian demand model, as well as the trip categories used to understand varying sensitivities for different types of trips and travelers. Notably, the use of employment data as the principal input for quantifying pedestrian attractors (as well as a proxy for identifying pedestrian barriers, e.g., proportion of industrial jobs) is a limitation to this research. Recently available data about actual activity levels at various destinations can address and enhance this limitation.

Table 19. Pedestrian destination choice model variables [82]

Trip Categories	Impedance measures	Size/attractiveness measures	Pedestrian support measures	Pedestrian barrier measures	Traveler Characteristics
Home-based work	Distance to destination (miles)	# of retail jobs	Parks (presence of)	Slope (degrees)	Auto ownership
Home-based shopping		# of service jobs	PIE (Pedestrian Index of the Environment)	Freeway (presence of)	Children
Home-based recreation		# of finance jobs		Proportion of industrial jobs	
Home-based other		# of government jobs			
Non-home-based work		# of all other jobs			
Non-home-based-non-work		# of households			

Similarly, GIS-based network simulation tools link those same context variables, as well as any other variables for which spatial data is available (such as block size, attraction locations, crashes, etc.) to every node or link within a network, typically calibrated using direct counts [38]. Such models can be adapted to estimate latent demand by changing input variables to reflect post-intervention conditions, such as to improvements in network connectivity.

Beetham et al. [39] undertook an extensive review of latent demand estimation methodologies in a New Zealand context (though their review spans research and practice in numerous countries). They reviewed factors linked to pedestrian and bicycle activity, compiled methods for latent demand estimation (including a breakdown of methods into a variety of categories based on input, approach, and output), and conducted an international practitioner survey to develop recommendations for latent demand estimation.

Beetham et al. caution that transferability of model variables - and even basic determinants of active modes of transport - may diverge significantly from place to place and vary considerably between walking and bicycling. Practitioners must carefully assess factors and parameters and are advised to consider the modes separately in order to develop accurate estimates. Table 20 outlines the range of factors determined in their review to be broadly relevant to demand estimation, although the direction and magnitude of relationships may vary by location/study.

Table 20. Factors associated with walking and bicycling [39]

Individual and Household Factors			
Perceptions	**Sociodemographic characteristics**	**Capability and Competency**	**Trip Purpose**
Safety	Gender	Competence and confidence	Exercise/recreation vs. utilitarian
Aesthetics	Income	Experience	Trip-chaining
Awareness of infrastructure	Age	Access to bicycle/bike share and gear	Cargo requirements
Driver attitudes and behaviors	Employment status	Facilities at destinations	Children
Environmental Factors			
Infrastructure	**Built Environment**	**Natural Environment**	**Policy and Society**
Bike/walk facilities	Destinations	Weather	Congestion pricing
Lighting	Mix of land uses	Topography	Traffic speed
Bicycle storage	Urban form	Aesthetics/natural features	Social norms
Speed management	Density	Greenery/trees	Incentives/encouragement
Modal separation			Disincentives/costs

Table 21 summarizes Beetham et al.'s overall findings. The authors note that revealed preference data (into which category mobile device GPS data would fall) are generally seen as more reliable and accurate than stated preference data but limited in its ability to represent latent demand. In cases where existing networks are inadequate to support walking or cycling, current behaviors may not reveal most people's actual preference, only their current, constrained reality [39].

Table 21. Summary of latent demand estimation methods [39]

Approach	**Overview**	**Assessment**
Pragmatic approaches	Where what goes in, the process it goes through, and what comes out are chosen considering what is at hand, what is needed, and what works for the given situation	• Tend to be quick and cost effective, employing data at hand, and adaptable to fit the purpose; generally seen as having inconsistent accuracy • Tend to be used for smaller scale and budget applications
Informed expert estimation: As the basis of the forecast	Subjective estimate based on available data and local context, combined with professional experience and judgement	• Potentially prone to subjectivity and bias
Informed expert estimation: To rationally adjust a	Using judgement to modify or complement output from another method	• Potentially accurate or inaccurate depending on the skill and experience of the practitioner

Approach	Overview	Assessment
forecast from another method		
Informed expert estimation: To make assumptions about components of a method or model	Judgement is applied to the use, processing, and interpretation of data or information within a latent demand estimation method	• Used to overcome data and knowledge limitations
Comparison approaches	Looking at walking and cycling levels, or changes in levels due to some interventions, in certain places, and using this information to estimate latent demand in other similar types of places	• Requires that walking and cycling case study data is readily available • Requires skill in assessing the transferability of findings from place to place
Sketch planning	Relatively coarse and generic formulas or factoring	• Quick and cost effective • Tend to be generic and coarse to an extent that they have lower accuracy
Demand typologies	Categorization of a population to identify groups with latent demand for walking and cycling	• Useful for understanding demand and latent demand characteristics across a population
Stated preference based	Methods that are primarily based on stated preference data and techniques	• Useful for testing perceptions, and the potential behavioral response of those people with latent demand for walking and • Can be seen as unreliable and prone to bias • Best used in combination with other data (i.e., revealed preference data)
Revealed preference based	Methods that are primarily based on revealed preference data and techniques	• Tend to be seen as being more reliable than stated preference-based methods • Have limitations when real choices are constrained, applied to latent demand, or something new
Traditional transport models	Conventional transport modelling processes are adapted to improve suitability for walking and cycling	• The accuracy of any model is dependent on the quality of data and the robustness of the parameters of the model • May not readily account for behavioral 'tipping points' or changes in system dynamics • Applications for cycling much more advanced than for walking • Capable of representing complex land-use and transport interactions and trends over time, and multimodal transport systems at a network level • Various enhancements possible to better represent walking and cycling behavior • Data and technology intensive
Geospatial assessments	Data is processed and/or presented in a GIS	• Capable of integrating a wide range of complex geospatial information (including output from transport and other models) to form a comprehensive

Approach	Overview	Assessment
		and multi-criteria assessment of walking and cycling demand
		• Data and technology intensive

In addition, Beetham et al. warn that demand forecasting can reinforce existing patterns of transportation inequity. For instance, they caution that many studies have over-represented certain populations in determining factors that influence active transportation behavior (e.g., university students). They recommend a decision-tree approach to developing a demand estimation approach based on the scale of the project and the cost/resources available. Small (e.g., intersection, node) projects with small budgets are best suited to basic sketch planning or informed expert estimation methods, whereas larger efforts (e.g. network-wide) and bigger projects warrant more sophisticated methods such as geospatial assessment and full-scale modeling with locally-specific data [39].

Factors for incorporating latent demand into various planning tools are common, though the degree of sophistication varies. The ActiveTrans Priority Tool Guidebook [40] includes both existing and potential demand as a key factors for project prioritization. It highlights proximity of bicycle/pedestrian attractors such as schools, parks, transit, and mixed-use and high-density land use. The guidebook asserts that resources and investments should be focused on areas with the greatest multimodal potential, rather than simply areas with high present observed demand.

As noted above, direct demand models have been extensively used to operationalize these factors in order to derive activity estimates. Munira and Sener [36] summarized explanatory variables from a variety of studies and modeling approaches, highlighting challenges and opportunities associated with their use (Table 22). Their review also describes the direction of relationships (positive or negative) for explanatory variables identified in the literature on user volumes.

Table 22. Nonmotorized direct demand model explanatory/independent variables [36]

Category	Variable
Demographic	Population density
	Percentage of population younger than 5 and older than 65 years
	Percentage of African-American population
	Percentage of Hispanic population
	Percentage of other ethnicity population (excluding White and African American)
	Percentage of population 25+ with a college degree
	Number of children
	Household density

Category	Variable
	Total housing units
	Vacant housing units
	Rented housing units
	Percentage of male, single, and multifamily housing
	Commuting population
	Walking and biking commuters
Socioeconomic	Household income
	Employment density
	Unemployment rate
	Households with no automobile
	Households below the poverty line
	Number of workers
Network/interaction with vehicle traffic	Number of street segments
	Average length of network street segments
	Steeper slopes
	Presence of traffic signals
	Number of intersections
	Percentage/length of major roads
	Length of local roads
	Presence of three-way or four-way intersections
	Mean block length
	Presence of arterial streets/freeways
	Maximum average daily traffic volume
	Average curb-to-curb length
	Average number of lanes
	Speed limit
	Bridges
	Intersection density
	Connected node ratio
	Road classification
	Lane visibility
	Network accessibility
	Maximum radial line of sight
Pedestrian or bicycle-specific infrastructure	Presence of bike lanes
	Length of off-street trail
	Length/presence of bike paths
	Area of sidewalk coverage
	Sidewalks with buffer
	Number of marked crosswalks
	Median refuge areas
	Bike-lane width
	Curb-lane width
	Sharrows, crosswalks, and pedestrian heads
	Bicycle facility characteristics on the road
Transit facilities	Presence of subway stations
	Number of bus/light-rail stops
	Mileage of bus route
	Percentage of commuters who walk or take transit
	Distance to stations
	Number of jobs accessible by transit
	Transit ridership
	Total bus-km of bus routes

Category	Variable
Major generators	Distance to downtown
	Distance to ocean or a water body
	Distance to a university
	Number of schools
	Number of college campuses
Weather and environmental	Temperature
	Precipitation
	Snow accumulation
	Sunshine
	Solar radiation
	Wind
	Humidity
Temporal or time related	Month, hour, or day
	Weekend
	Holiday
	School day
	Season or year
Land use	Housing units, all households, residential addresses, non-residential addresses
	House density, low density residential space, medium density residential space, high density residential space, dwell, single family housing, multi-family housing
	Number of vacant housing units, proportion of vacant housing
	Urban residential area, urban residential commercial area, residential - mobile, resort residential
	Neighborhood business
	Job accessibility
	Historic district, community service
	Park recreation education
	Manufactured house, public buildings
	Open space area, vacant space
	Tree canopy, non-tree vegetation, patch richness density, Shannon's (species) diversity index, impervious surface
	Paved parking
	Slope
	Institutional, research district, neighborhood service district, cultural, and entertainment space
	Business, office space, retail area, industrial area, commercial space, storage, and maintenance space
	Government
	Hotel, restaurant, commercial center
	Airport
	Direct control space
	Hazardous waste district
	High-activity zone, high crime
	Land use mix, land use characteristics, land use type, mixed land use
	Visibility, maximum radial line of site
	Accessibility
	Planned unit development

Most (though not all) of the commonly used independent variables are readily available through local or national data sources. Munira and Sener reiterate the need for count programs to improve model performance but cite emerging technologies like GPS data as cost-effective inputs in lieu of direct counts. They also caution that although certain sociodemographic characteristics are typically associated with walking and bicycling, other segments of the population may be inclined to choose active modes given "the right circumstances," hinting at the limitations of models based on observed use to fully capture latent demand. Researchers have attempted to address this by incorporating variables reflecting perceptions of safety or stress, though it is noted that this data is difficult to obtain (often requiring extensive attitudinal and/or discrete choice survey data collection) and challenging to apply to modeling and forecasting [7]. Rather, proxy indicators understood to relate to such variables (defined to include safety, comfort, convenience, awareness, bicycle facilities, bicycle ability, and social norms) are sometimes used [7].

Examples of Latent Demand Estimation in Practice

Many cities and regions have developed model-based approaches to quantifying existing and latent demand across a network for planning and project prioritization purposes.

- In Ohio, a statewide demand analysis was completed in 2020 for the state DOT to derive a composite demand score for facilities across the state, based on attractor and generator measures, using readily available datasets and assigned scores by quantile [83]. The resulting output included statewide and areawide maps highlighting relative demand for each indicator as well as a composite score but lacks a means to integrate data pertaining to actual trips taken (Figure 39).

Figure 39. Walk bike Ohio demand analysis inputs and scoring [83]

DEMAND INDICATOR	RATIONALE	METRIC	SCORING
Employment Density	A measure of where people work	2015 Longitudinal Employer-Household Dynamic (LEHD), Work-Area Characteristics	0: Employment = 0 1-5: Assigned score by quantile
Population Density	A measure of where people live	2012-2017 American Community Survey (US Census)	0: Population = 0 1-5: Assigned score by quantile
Walk/Bike Commute Mode Share	A measure of existing active transportation usage	2012-2017 American Community Survey (US Census)	0: Bike/Ped Mode Share = 0 1-5: Assigned score by quantile
Park Density	A measure of parkland expressed as acreage per Census Tract	Park data obtained from ESRI dataset; calculated according to parkland acreage per Census Tract	0: Park Acres = 0 1-5: Assigned score by quantile
Presence of College/ Universities	A measure of where people attend college	College/university data obtained from ESRI dataset; calculated based on whether or not a Census Tract contains a college/ university location	Score of 0 if there are no College/University locations within a census tract and score of 5 if there is at least one College/ University location within a census tract
Retail Employment Density	A measure of where people shop and are employed by retail industries	2015 Longitudinal Employer-Household Dynamic (LEHD), Work-Area Characteristics	0: Retail = 0 1-5: Assigned score by quantile
Number of People 200% Below Poverty Line	A measure of concentrated poverty. Equity factors, including poverty, should be included in planning decisions to enable an equitable distribution of transportation resources	2012-2017 American Community Survey (US Census)	0: Poverty = 0 1-5: Assigned score by quantile

- In Salt Lake City, Utah, the Utah DOT led a multi-jurisdictional study using a GIS-based latent demand model in order to identify walk/bike routes with the greatest potential demand. The model incorporated population and employment densities, distance to major destinations, land use mix, and network connectivity to model a bicycle and pedestrian network based on demand. This information was then used to identify propriety projects for investment [38]. The model is intended to be easily updated with new population and land use data over time.
- Louisville, Kentucky incorporated latent demand into their 2010 Pedestrian Master Plan [84], along with revealed demand (i.e., counts) and an analysis of bicycle and pedestrian trip generators and attractors. The plan emphasized the importance of including all types of generators, rather than just typical schools,

parks, and neighborhood retail centers. This plan only reflected one end of each potential trip. In order to estimate latent demand, Louisville employed a gravity model (Figure 40) within a GIS environment. In this model, demand is a function of trip productions (residences) and attractions (workplaces, shopping, school, etc.), modified by impedance (i.e., travel distance or time, route conditions, etc.) [84]. The latter facet, impedance, is particularly important for active transportation trips compared to similar models for motor vehicles, with certain trip purposes being more sensitive than others. Accordingly, the model was calculated differently for work trips, shopping/errand trips, school trips, and social/recreational trips [84]. The resulting output was a visual representation of total demand distributed across the network and ranked in five "tiers" to inform plan implementation.

Figure 40. Louisville, KY basic latent demand algorithm

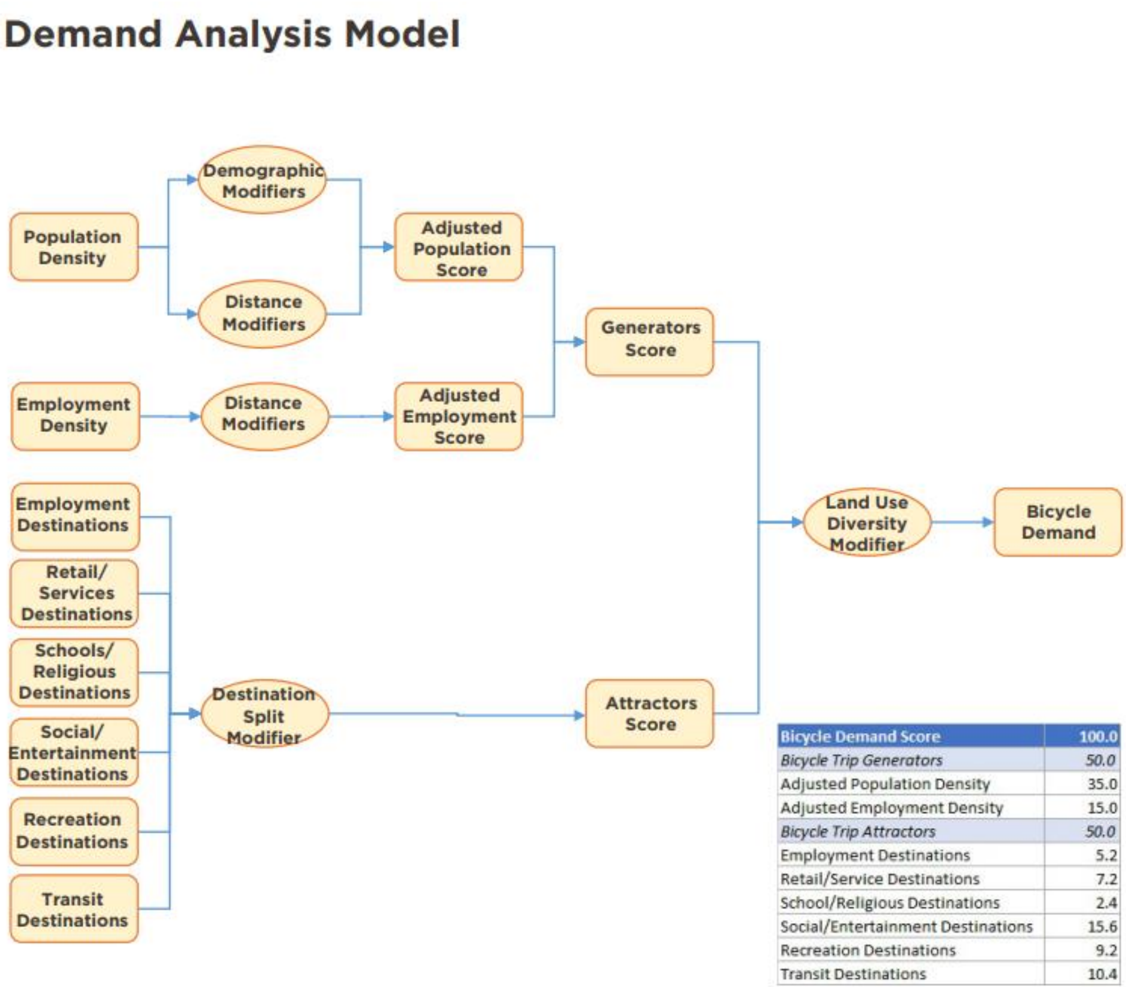
$$LDS = \sum_{n=1}^{4} TTS_n \times \frac{\sum_{n=1}^{4}\left(GA_n \times \overline{TG}_n\right)}{\left(GA_n \times \overline{TG}_n\right)} \times \left[\overline{TG}_n \sum_{d=1}^{I} P_{nd} \times ga_n\right]$$

n	= bicycle trip purpose (e.g., work, personal/business, recreation, school)
TTS	= trip purpose share of all bicycle trips
GA	= number of generators or attractors per trip purpose
$\overline{TG}$	= average trip generation of attractor or generator
P	= effect of travel distance on trip interchange, expressed as a probability
ga	= number of generators or attractors within specified travel distance range
d	= travel distance range from generator or attractor

- The City of Berkeley, CA used the Space Syntax model, a simulation tool incorporating connectivity, distance, and accessibility variables on top of the current pedestrian and bicycle network, to assign a score for relative route attractiveness. Using count data to interpolate observed demand to other locations on the network, this model was used in conjunction with crash data in the city's Pedestrian Master Plan to calculate exposure and identify high-priority corridors [38].

Kansas City, Missouri employed similar methods, including with public feedback regarding barriers to active transportation, crash data, measures of network connectivity, and analysis of major physical barriers (topography, railroads, etc.). Additionally, equity was incorporated into their demand scoring methodology (Figure 41) for a proposed bicycle network planning tool. This methodology assigns weights attractors and generators based on propensity for cycling identified in National Household Travel Survey data, with the goal of achieving an indexed composite score [85]. It is recommended to revise the model after collecting local data to verify assumptions.

Figure 41. Kansas City, MO bicycle network demand analysis model [85]



- In Louisiana, both New Orleans and Jefferson Parish incorporated measures of latent demand into their bicycle plans: New Orleans emphasizing level of traffic stress (LTS), connectivity to destinations within a 10-minute bicycle radius, and concentrations of historically marginalized populations through a Bike Equity Index (BEI) [86]. In Jefferson Parish, the Bicycle Master Plan relied on a relatively simple GIS-based Bicycling Demand Index to identify locations where there is existing and/or latent demand, based on the following indicators [87]:
    - Community input
    - Zero vehicle households
    - Population density
    - Locations of public facilities, shopping centers, connections to adjacent parishes
    - Locations of key connections/chokepoints across parish lines and water boundaries
    - Jefferson transit hub locations and bike rack usage data

These local efforts to develop indices holistically assessing active transportation demand have been critical in planning future investments. However, the resources required to develop them place comparable analyses out of reach for many Louisiana communities.

Key Applications and Limitations of Mobile Data for Active Transportation Planning

Emerging data sources such as mobile-phone based passive data - as well as data derived from sensors or internet-connected objects (or other "smart" technology), can be used for a variety of applications, from monitoring existing traffic to forecasting future demand to optimizing efforts to reduce environmental impacts resulting from transportation. Using active data sources, whether direct counts or crowdsourced data from applications targeting people walking or bicycling, is relatively straightforward. A key limitation of passive data sources, by contrast, is the level of effort required to extract and clean raw data to derive relevant information [28]. If the goal is to estimate current levels of pedestrian and/or bicycle activity, accurate modal detection is, obviously critical. The use of emerging data sources to assess potential demand, therefore, represents an opportunity to eschew this challenge and assess trip patterns independent of mode. Similarly, the use of GPS-based data largely mitigates the heightened need for spatial precision inherent in active transportation planning relative to motor vehicles. However, barriers exist, such as the inability to connect contextual information at the individual or household level to trip data due to privacy concerns [28], as well as, sampling bias inherent in data which excludes those not carrying smartphones for all trips. As the state of technology advances, the literature indicates that all such data can be enhanced through machine learning to optimize transportation outcomes at the individual and system-wide level [36].

In addition to sketch-planning models and indices of relative demand, as described above, additional key applications of robust, network-wide mobility analysis are to 1) provide a critical, often missing component of exposure analysis, and 2) serve as an input for cost-benefit analysis. A growing body of research describes the historical challenge and current state of the practice of assessing risk and describing exposure for nonmotorized road users, for which an absence of comprehensive user volume data often inhibits accurate analysis of safety performance. Turner et al. [8] provide a comprehensive review of methods and define a scalable approach to developing risk estimates. Volume data – whether directly collected or modeled estimates - is a key component of such analyses at all but the broadest level of geography. Lindsey et al. [88] describe exploratory methods for modeling exposure where robust networks of continuous counters exist, using origin-destination centrality indices as explanatory variables and finding that these correlate with bicycle volumes. However, in locations with limited count data available, alternative approaches to modeling are required. As Fournier et al. observe, this is compounded by the relatively higher data requirements of active transportation demand models relative to those for automobiles, in order to account for higher inherent variability (of bicycles in particular) [89].

Measuring exposure, particularly at the node and neighborhood level, is often a key gap for transportation planning and evaluation. Though without refined methods for identifying existing modal splits it cannot stand in directly for direct counts, mobile device data can provide a valuable input for outcome evaluation by facilitating modeling of existing activity and expected results of proposed scenarios.

Finally, the use of active transportation and modeled demand are valuable as inputs for benefit-cost analyses (BCA). Holian and Mclaughlin [90] identify failure to account for induced demand – including both perceived positive effects of increased multimodal demand, as well as perceived negative impacts of increased automobile trips - as a key common failure of current BCA practices, and recommend development of measures to account for these effects in BCA methodology. Smart Growth America's *Benefits of Complete Streets* tool [91] explicitly account for induced multimodal demand. Their tool estimates numbers of new users or trips based on community-wide active transportation growth rates and surrounding population density. However, the tool does not necessarily account for the specific impacts of the project on reducing impedance for would-be users, or the share of trips which originate and end within the study area. The use of mobile device data to better understand trip origins and destinations, and to examine the share of those that could be feasibly induced to convert to active modes, is one potential solution to this problem.

Return on investment can also be measured in terms of the degree to which a specific project addresses identified agency or community goals, many of which cannot be easily described in monetary terms. NCHRP's ActiveTrans Priority Tool Guidebook [40] provides a step-by-step methodology for identifying top priority bicycle and pedestrian network improvements, based on flexible agency and community goals. The factors incorporated into this methodology include safety, connectivity, demand, and equity, as well as stakeholder input, and the specific constraints, opportunities, and existing conditions of the community, including compliance with current pedestrian and bicycle standards. It allows the user to assign weights to each of these factors and develop a spreadsheet-based ranked priority list based on numeric scores for each factor to assess relative impact, with an emphasis on procedural transparency and communication to the public.

Data for use in demand estimation or forecasting, exposure/safety analysis, and/or benefit-cost analysis needs to be sufficiently granular for application at a variety of scales. The use of mobile device data addresses this need and can be used to understand existing and latent demand across a network, to stand in for direct counts (with calibration), for origin and destination analysis, to understand route choice (in some cases), and to assess trip durations and dwell times at specific locations.

However, planners and practitioners must keep in mind key usage limitations, particularly pertaining to equity and privacy. Namely, although the majority of American adults own internet-connected devices and use location-enabled app [5], the "digital divide" persists and ownership and use varies across populations and demographic groups [22]. As a result, the origins, destinations, and trips of individuals and communities with lower technology use may be underrepresented, resulting in the exacerbation of longstanding inequities in the provision of transportation infrastructure. This important limitation can be addressed by fusing device data with counts, survey data, or other traditional sources, and by adjusting data to address under- or over-representation where possible.

Second, privacy protection is critical for use of passive data sources. Typically, data is anonymized prior to release to end users. However, there is still a possibility of revealing individual movement patterns, particularly when studying active modes and/or areas with relatively low population (and thus lower total sample sizes) [22]. Protocols for identifying and scrubbing any sensitive data associated with datasets in use are needed, and care should be taken at each step of data use to balance the need for geographic precision with privacy concerns.

Summary Table: Existing Sources of Bicycle and Pedestrian Data

Table 23. Existing sources of bicycle and pedestrian data (includes national and multistate-level sources only)

Data Source	Agency	Scale	Freq uency	Coverage	Contents	Uses	Updates since 2000	Updated Link/Resour ce
USAGE, TRIP, AND USER CHARACTERISTICS; PREFERENCES, NEEDS, AND ATTITUDES								
U.S. Census Summary Files, Census Transportation Planning Package	U.S. Census Bureau	National	10 years	U.S. population (entire)	Aggregate socio-economic data, journey to work mode share	Journey to work mode shares/trends; correlations with socio-economic data	Now available annually as American Community Survey sample data	https://data.census.gov/cedsci/
U.S. Census Public Use Microsample	U.S. Census Bureau	National	10 years	U.S. Population (5% at county level, 1% at metropolitan level)	Disaggregate household and individual socioeconomic and journey to work data	Possible applications in bike/pedestrian analysis	Now available annually as American Community Survey sample data	https://www.census.gov/programs-surveys/acs/microdata.html
Metropolitan Area Household Travel Surveys	MPOs	Metropolitan Area	10-20 years	Metropolitan area population (random sample of 1000 to 10,000 households)	Disaggregate household and individual socioeconomic data, trip patterns	Mode shares/trends, socioeconomic data characteristics, trip characteristics, behavior modeling	Availability varies by region	Varies by region
National Personal Transportation Survey	U.S. DOT, FHWA	National	5 years	U.S. Population (random sample of 22,000 households)	Disaggregate household and individual socioeconomic data, trip patterns	Mode shares/trends, socioeconomic data characteristics, trip characteristics, behavior modeling	NPTS historic data available for 1983, 1990, 1995; Now NHTS available for 2001, 2009, 2017	https://nhts.ornl.gov/downloads

Data Source	Agency	Scale	Frequency	Coverage	Contents	Uses	Updates since 2000	Updated Link/Resource
National Sporting Goods Association Sports Participation Survey	National Sporting Goods Association	National	Annual	U.S. Population (Random sample)	Cycling participation by age and gender	Conditions and trends analysis	Ongoing; available through 2022	https://www.nsga.org/research/nsga-research-offerings/sports-participation-us-2022/
National Bike Helmet User Survey	Consumer Product Safety Commission	National	1991, 1998	U.S. Population (1000+ Sample	User and usage characteristics	Helmet usage, bicyclist characteristics, crash/exposure analysis	No longer active	
Adult Bicyclist Survey	University of Washington	National	1995	Adults (2,300+ sample)	Characteristics, exposure	Bicyclist characteristics	One-time survey	https://doi.org/10.3141/1636-01
Rodale Press Surveys	Rodale Press	National	Varies	Adults (1000+ Sample)	Cycling, walking, running participation, user characteristics, purpose, facility availability	Conditions and trends analysis, user preferences	Defunct; no surveys identified after 1990s	
National Health Interview Survey	CDC	National	Annual	Sample of U.S. Population	Frequency of physical activity, demographic information	Conditions and trends analysis	Ongoing; restructured 2019	https://www.cdc.gov/nchs/nhis/index.htm
Behavioral Risk Factor Surveillance System	CDC	National/State	continuous	Monthly random sample	Optional module on exercise distance and frequency; can include questions on helmet use	Conditions and trends analysis, pedestrian recreation characteristics	Ongoing; annual data through 2020 available	https://www.cdc.gov/brfss/index.html
Survey on Public Beliefs and Awareness About	USDOT/NHTSA	National	1999	U.S. Population (Random sample of 4000)	Socioeconomic characteristics, exposure, attitudes and	Outreach and education, safety countermeasures	Not found; NHTSA National Survey of	https://one.nhtsa.gov/Driving-

Data Source	Agency	Scale	Frequency	Coverage	Contents	Uses	Updates since 2000	Updated Link/Resource
Pedestrian and Bike Safety Problems					knowledge of road users and usage		Bicyclist and Pedestrian Attitudes and Behavior conducted in 2002, 2012	Safety/Research-&-Evaluation/2012-National-Survey-of-Bicyclist-and-Pedestrian-Attitudes-and-Behavior
FACILITIES								
Census TIGER/Line files	U.S. Census Bureau	National	continuous	Entire road network in U.S.	Location, name, address, ranges	Conditions analysis, connectivity, route density, etc.	Updated annually	https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html
National Transportation Atlas Databases	U.S. DOT, BTS	National	continuous	Nationally significant roads	Location, name, capacity, classification, traffic volume	Attributes of major roads	Updated continuously	https://www.bts.gov/ntad
Rail Trail database	Rails to Trails Conservancy	National	continuous	All rail trails in US	Location, length, surface, cost, contacts	Conditions and trends analysis	Now includes other types of trails	https://www.traillink.com/?utm_source=railstotrails.org&utm_medium=link_page-content&utm_campaign=RTCreferrals

Data Source	Agency	Scale	Freq uency	Coverage	Contents	Uses	Updates since 2000	Updated Link/Resour ce
State Road Database	State DOTs	State	contin uous	Federal, state highways	Road characteristics, traffic volume, crashes	Facilities inventory, needs identification, crash studies	Public data availability varies	Varies by state
CRASHES AND SAFETY								
Fatality Analysis Reporting System	USDOT /NHTS A	Natio nal	contin uous	All fatal crashes involving motor vehicles on public roads	Attributes of crash, vehicle, person, driver (100+ attributes)	Fatal crash analysis	Published annually	https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars
National Automotive Sampling System - General Estimates System	USDOT /NHTS A	Natio nal	contin uous	Sample of police crash reports for motor vehicle reports	Attributes of crash, vehicle, person, driver (90+ attributes)	Crash analysis	Annual traffic Safety Facts report published annually	https://crashstats.nhtsa.dot.gov/#!/PublicationList/12
National Transportation Statistics	U.S. DOT, BTS	Natio nal	Annu al	Summary statistics based on GES	Motor vehicle crashes by type, costs, trends	Conditions and trends analysis	260+ data tables, updated quarterly	https://www.bts.gov/product/national-transportation-statistics
National Vital Statistics System	CDC, National Center for Health Statistic s	Natio nal	Annu al	All deaths in US	Cause, circumstances	Conditions and trends analysis	Downloadable and interactive files; available through 2020	https://www.cdc.gov/nchs/nvss/index.htm
National Hospital Ambulatory Medical Care Survey	CDC, National Center for Health	Natio nal	Annu al	Sample of injuries in United States	Cause (including motor vehicles)	Conditions and trends analysis	Available through 2019	https://www.cdc.gov/nchs/ahcd/index.htm

Data Source	Agency	Scale	Frequency	Coverage	Contents	Uses	Updates since 2000	Updated Link/Resource
	Statistics							
Accident Facts	National Safety Council	National	Annual	Based on GES, National Center for Health Statistics data	Summary statistics on pedestrian, bicyclist, motor vehicle injuries	Conditions and trends analysis	Now "Injury Facts"	https://injuryfacts.nsc.org/all-injuries/overview/
National electronic Injury Surveillance System	CPSC	National	Annual	Sample of injuries associated with consumer products	Injury characteristics and circumstances	Bicycle injury analysis	Data highlights reports published annually	https://www.cpsc.gov/Research--Statistics/NEISS-Injury-Data
State Data System	U.S. DOT, NHTSA	State	Varies	Data from police crash reports for motor vehicle crashes	Varies by state	Crash analysis, conditions and trends analysis	34 states now participating including Louisiana	https://www.nhtsa.gov/research-data/state-data-programs
Crash Outcome Data Evaluation System	USDOT/NHTSA	State	Continuous/Annual		Links highway crash data to medical and financial outcome data	Cost and cost burden analysis	Contact individual states for detailed data	https://www.nhtsa.gov/crash-data-systems/crash-outcome-data-evaluation-system-codes
State-level crash databases	State DOTs	State	Continuous	Federal, state highways	Crashes (location, characteristics)	Deficiency and needs identification, crash analysis		Varies
Police Crash Reports	State, local	Local	Continuous	All crashes with minimum damage value	Crashes (location, characteristics)	Crash analysis		Varies

Data Source	Agency	Scale	Frequency	Coverage	Contents	Uses	Updates since 2000	Updated Link/Resource
	Police agencies							
Safety Management Information Statistics	USDOT, FTA	National	Continuous/Annual	Incidents on transit property	Incident characteristics	Pedestrian incidents involving transit vehicles, property	Discontinued; National Transit Database replaces	https://www.transit.dot.gov/ntd
Federal Railroad Administration	USDOT, FRA	National	Continuous/Annual	Incidents on railroad property/Right of way	Incident characteristics	Pedestrian incidents involving railroad vehicles, property		https://safetydata.fra.dot.gov/OfficeofSafety/default.aspx
EXPENDITURES AND CAPITAL STOCKS								
Bicycle Manufacturers Association	Bicycle Manufacturers Association	National	5 years	Bicycles sold in the US	Sales of bicycles with 20+ inch wheels	Conditions and trends analysis	Unclear; National Bicycle Dealers Association produces periodic market reports (available for 2020)	https://nbda.com/store/
Consumer Expenditure Survey	Bureau of Labor Statistics	National	Continuous/Annual	U.S. Population (Random sample)	Expenditures on bicycles by personal and household characteristics	Conditions and trends analysis	Current release through 2020	https://www.bls.gov/cex/
Rodale Press Surveys	Rodale Press	National	1990	Sample of new bike purchasers	Bicycle expenditures purchase, user characteristics	Conditions and trends analysis	Defunct; no surveys identified after 1990s	
GENERAL SOURCES								
National Transportation Statistics	USDOT, BTS	National	Annual	N/A	Various Summary Statistics	Conditions and trends analysis		https://www.bts.gov/product/national-transportation-statistics

Network Evaluation, Modeling, and Project Prioritization

This section focuses on recent research and tools that aim to quantify safety, connectivity, and/or equity through measures of network connectivity. The measurement might be at the segment/node level as well as the network/area level. Some aspects of these topics were already discussed in Part 1, and this section aims to more fully articulate the metrics and measures suitable for geospatial analysis relevant to the proposed investment suitability index. Active transportation network connectivity is key to increasing use of active modes, as well as safety [41]. While network connectivity can generally be assumed for transit (within a specified service area), automobile travel, walking, and bicycling networks are often subject to major accessibility barriers that make it impossible or impractical to travel from one destination or another in a reasonable amount of time or comfort level. Efforts to develop connected active transportation networks by prioritizing connectivity gaps, rather than developing ad-hoc infrastructure wherever it is convenient, are widespread in communities across the globe and supported by FHWA [41].

Measuring Network Connectivity: Key Principles

Connectivity, as a transportation performance metric, is a measure of whether people can travel to their intended destinations safely and easily by whichever mode of transport they need or prefer.

FHWA's Guidebook for Measuring Multimodal Network Connectivity [42] provides an extensive review of current literature and summarizes various methods and measures that for transportation planning to identify priority network gaps, projects that result in co-benefits, and to measure impacts of investments on transportation network performance goals. The Guidebook outlines five key components of multimodal network connectivity:

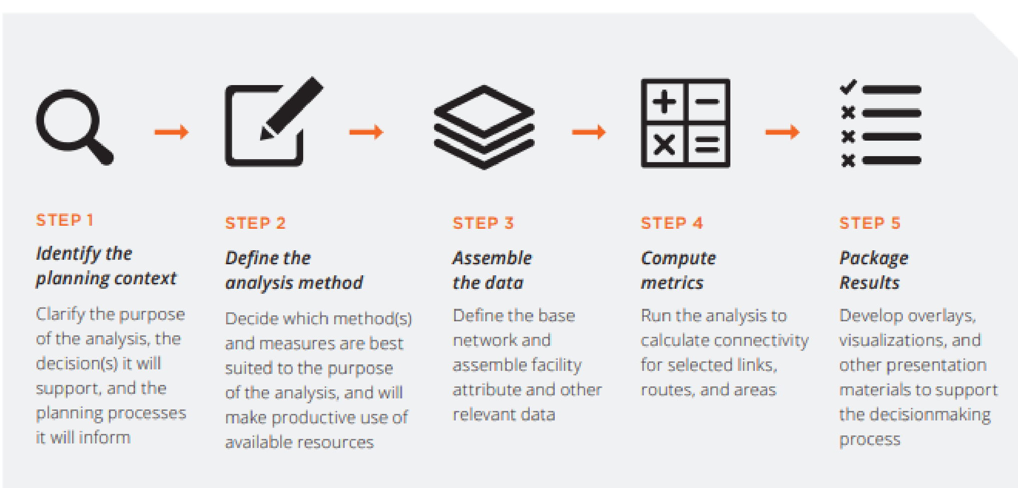
- Network completeness
- Network density
- Route directness
- Access to destinations
- Network quality

The Guidebook organizes measures and methods of analysis around questions pertaining to each of these components, as well as by planning process or stage (Figure 42). It then defines a five step "connectivity analysis process" to guide practitioners in selecting and applying appropriate measures that are linked to a specific context and goal (Figure 43), while cautioning that these steps are typically iterative.

Figure 42. Assessing multimodal connectivity throughout the planning process [42]

PLANNING PROCESS STEP	RELEVANT PLANNING TASKS	QUESTIONS INFORMED BY CONNECTIVITY ANALYSIS
Vision and Goals	Monitoring and Benchmarking	• What are the needs, priorities, and desires of community members and stakeholders? How and where do they want to see connections that will support their everyday needs and their bigger-picture goals, such as economic revitalization and job growth? • How has multimodal network connectivity changed over time? • How does connectivity in one area compare to other similar communities, regions, or states?
Alternate Improvement Strategies	Gap Identification Needs Assessment	• Where are missing or low-quality connections in existing facilities? Where are fixes needed?
Evaluation and Prioritization of Strategies	Scenario Analysis Project Prioritization	• How do different projects or strategies compare when it comes to improving the connectivity of the network? • What small but important improvements, such as connecting a bike route bisected by a highway intersection or fixing broken sidewalks, could make a big difference in achieving local goals for access to jobs, training, and essential services for all users?
Development of Transportation Plan	Scenario Analysis Gap Identification Needs Assessment Project Prioritization	• What destinations can people reach by biking and walking? • Which neighborhoods have higher or lower accessibility to the network or to specific destinations? • How does multimodal connectivity relate to other planning issues such as safety, system use, job growth, and equity?
Development of Transportation Improvement Programs	Project Prioritization	• How can the most cost-effective connectivity improvement be achieved while still advancing other high-priority needs? • How can funding be leveraged to best improve connectivity and achieve multiple agency goals for economic revitalization and job growth?
Project Development and System Operations	Feedback Loop to Inform Iterative Plan Updates	• How can multimodal connectivity be maintained or improved during project construction? • How can multimodal connectivity be preserved and enhanced during routine system maintenance and operation?

Figure 43. Connectivity analysis process (FHWA guidebook) [42]



Key considerations of planning context identification include defining the overarching goal of the analysis and the agency's role, defining the modal focus and scale, evaluating existing plans and policies, as well as existing and planned networks, and identifying any precedent analyses with which consistency is desired. The authors emphasize that even where the agency performing the analysis does not fully control all roadways within a network (e.g., a state DOT), assessments of connectivity only on, for example, state routes are unlikely to yield meaningful results relative to those that consider the full network.

Analytic methods and measures employed may address one or more of the five fundamental facets of connectivity, depending on the goal(s) of the exercise. Selection of analysis method is determined by the key question for which insight is needed (Figure 44), as well as the availability of data for the target network.

Figure 44. Multimodal connectivity analysis methods and measures (FHWA guidebook) [42]

ANALYSIS METHOD	KEY QUESTION	EXAMPLE MEASURES	SCALE	PLANNING TASK
Network Completeness	How complete is the planned bicycle and pedestrian network?	• Percent of planned nonmotorized facility-miles that are complete • Miles of planned nonmotorized facilities that have been built	• Small area • Large area	Monitoring and Benchmarking
	What portion of streets contain nonmotorized facilities?	• Percent of street-miles with nonmotorized facilities • Percent of street-miles that meet level of service or low-stress thresholds	• Small area • Large area	Needs Assessment, Scenario Analysis
Network Density	Does the street network allow for travel between destinations via a number of routes?	• Intersection density • Connected node ratio • Block length • Network density (street-miles per square mile)	• Route • Small area • Large area	Needs Assessment; Scenario Analysis
	Do designated bicycle and pedestrian facilities allow people to travel between destinations via a number of routes?	• Network density of nonmotorized facilities (lane miles per square mile) • Intersection density of nonmotorized facilities	• Small area • Large area	Scenario Analysis, Project Prioritization
Route Directness	Do nonmotorized facilities allow users to travel throughout a community via direct routes?	• Out of direction travel as a percentage of shortest path route • Network permeability	• Corridor • Small area • Large area	Scenario Analysis, Gap Identification, Project Prioritization, Benchmarking
Access to Destinations	How well do bicycle facilities connect to key destinations?	• Nonmotorized travelshed size • Number of homes/jobs accessible by bike/foot • Accessibility indices (e.g. Walk Opportunity Index) • Number of homes/jobs accessible by bike/foot using a certain level of network quality	• Corridor • Small area • Large area	Needs Assessment, Gap Identification, Project Prioritization
Network Quality	What is the objective quality of connectivity provided by an existing or planned network?	• Percent or area of network with high ratings for nonmotorized Level of Service, Bicycle Route Quality, or Pedestrian Index of Environment • Percent or area of network with low ratings for Level of Traffic Stress	• Link • Route • Small area • Large area	Needs Assessment, Gap Identification, Scenario Analysis

Some of these analysis methods (e.g., Network Completeness, Network Density) require only relatively straightforward, widely available data, like shapefiles of existing and planned facilities, street network centerlines. However, others (e.g., Route Directness, Network Quality) may require detailed network data with a wide variety of attributes, which many jurisdictions lack.

The selection of specific metrics for analysis will depend on both data availability and analysis objective. For instance, network density indicators are more likely to be of interest to planners engaged in comprehensive planning, zoning, and establishing policy and codes that support greater connectivity (such as through smaller blocks, a high connected node ratio (CNR), etc. Dill [43] defines and describes a variety of such connectivity measures in the planning literature. Lagerway et al. [40] also suggest considering nuanced impediments to active transportation and accessibility, such as sidewalk maintenance issues and obstructions, as key details for measuring connectivity. However, detailed network-wide data is unlikely to be readily available in most places.

The definition of the network itself is a critical task, both the geographic scope as well as the facility types (e.g., roadways, trails, designated bike/ped facilities, or other specific attributes which are linked to active transportation feasibility or safety) to be included. In other words, the definition of "complete" may vary and will have a significant impact on the analysis outcome. A network where it is technically possible (or at least legal) to walk or bike is very different from a network of dedicated pedestrian or bicycle facilities, and different still from a safe, comfortable, "high quality" facility network. Importantly, in most cases (depending on analysis aim), it is not necessarily appropriate to analyze only existing, dedicated pedestrian and bicycle facilities, because most cycling (and in some areas of walking) takes place on streets without such amenities [44].

Recommended basic data sets for network definition [42] include:

- Census TIGER/Line street network data
- OpenStreetMap (OSM) data (likely to include shared-use paths, which do not appear in TIGER data)
- Highway Performance Monitoring System/All Roads Network of Linear Referenced Data (HPMS/ARNOLD) for state and federally owned roads
- State DOT data
- Private, proprietary data such as developed by GPS/navigation companies.

The Guidebook notes that inconsistent local data attributes, reference geographies, and/or data conventions may inhibit analysis, highlighting an area for state leadership in the development of standards or recommendations to improve compatibility across jurisdictions.

Network types are broadly defined as either facility-based (designated bike/ped facilities OR all streets where walking and bicycling are allowed) or quality-weighted (defined based on criteria through an objective rating system like Level of Traffic Stress). For facility-based networks, the following typical facility types and definitions (Figure 45) are typical [42] (noting that naming conventions sometimes vary regionally and care should be taken to standardize and consolidate like categories where possible).

Figure 45. AASHTO bicycle and pedestrian network facility types [42]

FACILITY TYPE	DEFINITION
Sidewalk	That portion of a street or highway right-of-way, beyond the curb or edge of roadway pavement, which is intended for use by pedestrians*
Sidepath	A shared use path located immediately adjacent and parallel to a roadway*
Shared Use Path	A bikeway physically separated from motor vehicle traffic by an open space or barrier and either within the highway right-of-way or within an independent right-of-way*
Bike Lane	A portion of roadway that has been designated for preferential or exclusive use by bicyclists by pavement markings and, if used, signs*
Buffered Bike Lane	Conventional bicycle lanes paired with a buffer space designated by markings that separates the bicycle lane from the adjacent motor vehicle travel lane and/or parking lane
One-Way Separated Bike Lane / One-Way Protected Bike Lane / One-Way Cycle Track	An exclusive one-way facility for bicyclists that is located within or directly adjacent to the roadway and that is physically separated from motor vehicle traffic with a vertical element
Contraflow Bike Lane	A portion of the roadway that has been designated to allow for bicyclists to travel in the opposite direction from traffic on a roadway that allows traffic to travel in only one direction
Contraflow Buffered Bike Lane	A buffered bike lane that has been designated to allow for bicyclists to travel in the opposite direction from traffic on a roadway that allows traffic to travel in only one direction
Contraflow Separated Bike Lane / Protected Bike Lane / Cycle Track	A separated bike lane that has been designated to allow for bicyclists to travel in the opposite direction from traffic on a roadway that allows traffic to travel in only one direction
Two-Way Separated Bike Lane / Two-Way Protected Bike Lane / Two-Way Cycle Track	An exclusive two-way facility for bicyclists that is located within or directly adjacent to the roadway and that is physically separated from motor vehicle traffic with a vertical element
Bike Boulevard / Neighborhood Greenway	A street segment, or series of contiguous street segments, that has been modified to accommodate through bicycle traffic and minimize through motor vehicle traffic*
Paved Shoulder	The portion of the roadway contiguous with the traveled way that accommodates stopped vehicles, emergency use, and lateral support of subbase, base, and surface courses. Shoulders, where paved, are often used by bicyclists*

** American Association of State Highway and Transportation Officials, 2012, Guide for the Development of Bicycle Facilities, 4th ed.*

For quality-weighted networks, Level of Service (LOS), Level of Traffic Stress (LTS), or preference models may be (and have been) applied (Figure 46) [45]. Various specific tools for assessing these measures exist, requiring a variety of data inputs (Figure 47), and all are more data-intensive to set up and apply than a similar facility-based network, which may impact scalability.

Figure 46. Measures of bicycle network connectivity [45]

	Common Measures	Features	Key Citations
Road Stress Rating	**Bicycle Level of Service (BLOS)**	Originally referenced LOS for car travel Well documented and researched over time with many variations and extensions Rates network segments on a six-point scale Early forms of this measure do not evaluate separated bicycle facilities or intersections Typically calculated as a regression analysis, mathematically more complex than LTS	Transportation Research Board, 2016 Foster, Monsere, Dill, & Clifton, 2015 Jensen, 2013 Harkey, Reinfurt, & Sorton, 1998 Landis, Vattikuti, & Brannick, 1997 Dixon, 1996
Road Stress Rating	**Bicycle Level of Traffic Stress (LTS)**	Rates network roads, paths, and intersections on a 1-4 scale Rating scale is based on four distinct bicycle rider types (Geller, 2006) Calculated as a numerical rating method, mathematically simpler than BLOS and route choice models Fewer empirical studies to verify method efficacy and accuracy	Mekuria, Furth, & Nixon, 2012 Sorton & Walsh, 1994
Road Stress Rating	**Rural road stress rating**	Adapts road stress rating framework for rural contexts	Williams, 2006 Jones & Carlson, 2003 Noël, Leclerc, & Lee-Gosselin, 2003
Road Stress Rating	**Multimodal stress rating**	Road stress rating systems for pedestrian and/or car facilities that can be used in conjunction with bicycle road stress rating systems	Zuniga-Garcia, Ross & Machemehl, 2018 Phillips & Guttenplan, 2003 Mozer, 1998
Connectivity	**Bicycle Low-Stress Connectivity**	Combines road stress rating results with destination information to measure connectivity When applied to planned rather than existing networks, can quantify prospective improvement Additional output measure of network centrality can be used to identify the most important links in the network Computationally more complex than road stress rating, but provides more detailed insights	Lowry, Furth, & Hadden-Loh, 2016 Schoner & Levinson, 2014 Lowry, Callister, Gresham, & Moore, 2012
Route Choice	**Route Choice Models**	Highly tailored to local conditions Very data intensive Emphasis on preferences and characteristics of current rather than prospective riders Strong empirical basis for results Outputs can be used to inform or validate road stress ratings	Pritchard, 2018 Broach, Dill, & Gliebe, 2012 Hood, Sall, & Charlton, 2011

Figure 47. Network quality analysis methods and data [7]

	LEVEL OF SERVICE MODELS	TRAFFIC STRESS RATINGS	PREFERENCE MODELS
Bicycle and pedestrian facility data			
Bike lanes	✓	✓	✓
Shared-use paths	✓	✓	✓
Bicycle boulevards			(✓)
Sidewalks	✓		✓
Signed routes		(✓)	(✓)
Intersection features	✓	✓	✓
Slope		(✓)	✓
Supporting data			
Number of lanes	✓	✓	
Traffic volume	✓	✓	(✓)
Traffic speed	✓	✓	
Functional class			(✓)
Street / lane widths	✓	✓	✓
Presence of on-street parking	✓	✓	
Heavy vehicle traffic	✓		
Potential obstacles (driveways, blockages, right turn lanes, bridge crossings)		✓	

(✓) For each type of quality rating scheme, a number of specific measures have been developed. Parentheses around a data item indicate that a particular attribute is not required by all measures in a class. In other words, agencies lacking such data might still find a measure of this type that can be applied.

Level of Traffic Stress (LTS) measures, in particular, help to address the variance in tolerance for perceived danger, noise, exhaust, and other factors associated with walking or bicycling in traffic, without detailed traffic volume and lane width data required for LOS analysis. Mekuria, Furth, and Nixon [46] defined a scheme for classifying LTS based on Geller's [47] four categories (plus additional consideration for the specific needs and abilities of children cycling) of cyclist tolerance (Figure 48). These classifications are contingent on road width, traffic speed (both posted and observed, where these are known to diverge), parking lane presence, and operating space/degree of bicyclist protection (accounting for blockages in dedicated facilities), as well as similar criteria for classifying intersection approaches and unsignalized crossings. Aligning network segments with traffic stress tolerance levels emphasizes what Mekuria et al. refer to as the "weakest link" principle. The stress level of a route is determined by its most stressful link, rather than a corridor- or area-wide average. This important because people less tolerant to traffic stress will choose not to make trips by active modes at all if the stressful link is part of the route [46].

Figure 48. Level of traffic stress typologies (54)

Traffic Stress Tolerance	Type of Transportation Cyclist*	LTS Level of Comfort	Description
Less	**No Way, No How**	Not Applicable	Not interested in riding a bicycle for transportation.
	Interested but Concerned	LTS 1(incl. children) LTS 2 (not incl. children)	Little tolerance for traffic stress with major concerns for safety. Strongly prefer separation from traffic on arterials by way of protected bike lanes and paths.
	Enthused and Confident	LTS 1, LTS 2, LTS 3	Some tolerance for traffic stress. Confident riders who will share lanes with cars, especially on rural roads, but prefer separated bike lanes, paths, or paved shoulders on roads with higher traffic levels.
More	**Strong and Fearless**	LTS 1, LTS 2, LTS 3, LTS 4	High tolerance for traffic stress. Experienced riders who are comfortable sharing lanes on higher speed and volume arterials. These riders may use protected bike lanes and paths if available but will ride without them as well.

For bicycling specifically, some jurisdictions (e.g., Portland Metro MPO) have utilized a Route Quality Index (RQI) to identify the best available routes between origins and destinations for various purposes to improve travel demand models. Furthermore, a compound metric of directness, accessibility, and quality, combining level of traffic stress with the Route Quality Index (RQI), is identified as an emerging measure of low-stress connectivity. This metric can be used for scenario testing at both the area and corridor level [6]. Additional metrics identified for use in connectivity analysis are summarized in Table 24.

Historically, established data for measuring access to destinations has focused on Census and LEHD data, travel analysis zones (TAZs), or regionally specific lists of places determined through the planning process. The FHWA Guidebook also notes the application of OpenStreetMap data to evaluate connectivity to a broad range of destination categories (Figure 49).

Figure 49. Connectivity measures and data sources for analyzing access to destinations (FHWA guidebook)

ANALYSIS PURPOSE	PRIMARY MEASURE	ORIGIN DATA (PEOPLE)	DESTINATION DATA (PLACES)
Assessing community-wide bikeability*	Community-wide access to destinations	Census Blocks	Census/LEHD: Population, employment OpenStreetMap: Education, health/medical, recreation/ community, retail, transit
Assessing community wide bikeability (M. Lowry et al. 2012)	Community-wide access to destinations	Regularly spaced points representing residential origins	Commercial parcels (weighted by square footage and distance from origin)
Predicting bicycle commuting patterns (Broach and Dill 2017)	Connectivity to employment	Census Block Group centroids (weighted by population)	Census Block centroids (weighted by number of jobs)
Identifying low-stress streets (Mekuria, Furth, and Nixon 2012)	Overall connectivity	Census Block vertices	Census Block vertices
Prioritizing bicycle network improvements (M. B. Lowry, Furth, and Hadden-Loh 2016)	Home-based access to destinations	Residential parcels	Selected groups or "baskets" of important and/or desirable types of destinations (21 types)
Quantifying local access to destinations (Kuzmyak, Baber, and Savory 2007)	Home-based access to destinations	Traffic Analysis Zones (TAZs, weighted by number of households)	TAZs (weighted by jobs and distance)
Assessing bicycle access to regional centers**	Home-based access to destinations	Census Blocks	Centers designated by the community, such as Livable Centers Initiative communities in the Atlanta region
Assessing bicycle access to local K-12 schools ***	Home-based school access	Census Block centroids	K-12 Schools

** https://bna.peopleforbikes.org/#/methodology*
*** Atlanta case study*
**** Ft. Collins case study*

Network connectivity analysis outputs may be reported at three scales: link, route, or area/network. Metrics for link-level analysis consist of a single score or rating for each link, such as LTS or LOS. Route-level metrics are sensitive to how expected user behavior is calibrated. Different user groups may make different route choices that differ from the model inputs for "best" choice routes. However, these measures cannot capture gaps in the network that render walk or bicycling trips effectively impossible or require impractical, circuitous routes [46]. Route-level connectivity allows for the calculation of modal travelsheds or can be used to define routes from specific origins to identified destinations. Mekuria et al. define connectivity at the route level as "the ability to get between the two points without exceeding a specified stress threshold and without exceeding the specified level of detour" [46]. Of course, this definition requires the definition of what degree of detour is considered acceptable to the presumed user (Mekuria et al. use the criterion that the lower-stress route should not exceed 125% of the distance of the shortest route overall). Area or network-level analysis provides a single score or rating for a specified area, to measure density, directness, or fragmentation of the network [42].

At any of these levels, additional datasets can be overlaid with connectivity results to add a layer of analysis (e.g., crash data for understanding safety, demographic data for assessing equity disparities, or volume data to assess impacts of connectivity improvements).

Select Connectivity Analyses and Findings

Following publication of the *Guidebook* [42], FHWA awarded grant funding to eight agencies, including two DOTs, to support multimodal transportation network analysis using the framework. In Washington State, WSDOT evaluated the extent to which state highways inhibit active transportation by evaluating their "permeability." They used a Route Directness Index to measure how far out of their way people walking or bicycling must go to reach destinations across such barriers [92]. This analysis identified how improvements to existing crossings could maximize network utility, particularly for those with disabilities and those without access to cars or public transit.

Utah DOT, also part of the FHWA pilot, measured network connectivity throughout the urbanized Wasatch region to identify gaps and opportunities that align with community planning goals. UDOT integrated the resulting metrics on an online interactive map [92] and published Python scripts to facilitate replication of their methodology. The metrics emphasized included:

- Percent of road network with designated bicycle facilities
- Intersection density
- Out-of-direction travel
- Multimodal travelsheds
- Bicycle LTS

Mekuria et al. [46] used census blocks as the primary geographic unit for connectivity analysis and used their corner vertices as the connectors for defining shortest-path routes to define low-stress connections from every vertex pair to every other vertex pair using connections at a defined, acceptable level of traffic stress. They then modeled "attraction strength" based on employment, population data, and zoning for each block to calculate the percentage of trips within a regional trip table connected without exceeding stress or detour thresholds. They also modeled "percent nodes connected" as an alternative not requiring a regional travel model-derived trip table, measuring the share of network nodes that are connected to each other.

Similarly, People for Bikes developed a Bike Network Analysis (BNA) tool [93] that measures traffic stress (using a variation on Mekuria et al's classification scheme with some updates for additional facility types, see Appendix) and destination access. The BNA's connectivity model is based on a maximum biking distance of ten minutes or 1.67 miles and a 25% detour tolerance relative to car trips. It assigns "points" for each analysis area based on the number of destinations reachable by low-stress routes. The outputs are visualized with a heat map to indicate relatively connected or disconnected blocks. People for Bikes' scoring protocols and assumptions are available for download to facilitate replication, and the analysis (relying in large part on Open Street Map data) has been calculated and mapped for 10 cities in Louisiana (Baton Rouge, Bossier City, Kenner, Lafayette, Lake Charles, Mandeville, Metairie, Monroe, New Orleans, and Shreveport). Of these, New Orleans scored the highest overall with 34 out of 100 points, while Lake Charles and Bossier City scored the lowest with 16 points. This tool can also be run to evaluate performance of proposed network improvements against existing conditions: in New Orleans' Algiers Neighborhood, proposed low-stress bikeway additions were estimated to result in an overall 20-point change in BNA score by expanding access to opportunities, housing, and recreation [45].

Berrigan et al. [94] analyzed spatial correlation of connectivity variables as a means to examine propensity for and duration of active transportation in Los Angeles and San Diego counties. They analyzed variance in nine measures of street connectivity against findings from the California Health Interview Survey, finding that short, densely connected blocks or longer blocks in a gridded pattern are positively associated with active transportation after accounting for demographic and health variables. This study highlights the potential value of network connectivity analysis as a component for strategic promotion of healthy behaviors by identifying areas where the built environment may hinder the use of active modes.

Shi [95] applied regional and route level measures based on a Level of Traffic Stress approach to evaluate bike networks in Portland and Minneapolis. They then analyzed the relationship between the networks and bicycle ridership over six years, finding that low-stress networks are associated with high ridership and mode share and that improvements to bicycle networks would disproportionately benefit disadvantaged populations. However, this analysis did not incorporate measures of access to destination or intersection features. Shi also notes that use of mobile data providing insight into actual route selection (rather than computer-derived shortest-path route) could improve the validity of the results.

Lowry and Loh [96] compared bicycle network connectivity for 28 neighborhoods in Seattle against existing facilities and in the context of a proposed bicycle master plan to identify projects which would have significant impacts for different types of bicyclists (defined as confident and non-confident riders). The connectivity analysis utilized (potential) bicycle trip origin points, destination points by type, street network data, intersection data (signals, bicycle accommodations, etc.), and topography. They found significant disparities in connectivity between the two categories of cyclists: the proposed bicycle master plan would provide minimal increase in access for bicyclists who are already confident, except in a couple of specific neighborhoods. Specific projects in the master plan were ranked based on their impact for each user group, finding that neighborhood greenways make the biggest impact among "concerned" cyclists, whereas more confident bicyclists (generally already willing to ride on local streets) achieve the highest connectivity gains with the development of multi-use trails. In addition, they found that travel distance remains a critical variable for most potential cyclists, highlighting the role of land use policy in development of effective active transportation networks.

The Metropolitan Area Planning Council in Massachusetts piloted a prioritization method called the "Active Transportation Network Utility Score" to support decision-making based on the connectivity between origins and destinations and using a four-step travel demand model for school, shopping/restaurant, park, and transit-connecting trips to estimate latent demand [97]. The model operates at the census block level and results in eight weighted scores that combine into one composite local access score for each roadway segment. The results were published online as a tool for public engagement in project prioritization.

Additional Examples of Network Connectivity Analyses:

- *Atlanta* – Bicycle project prioritization assessment via access to destinations analysis (Facility based and level of stress) to compute 3-mile travelsheds along low-stress networks
- *Baltimore* – Pedestrian connectivity measure of network completeness for planning and benchmarking using sidewalks and level of stress to compute link-level scores. Completeness measured based on presence or absence for full network, and drills down into quality of facilities for areas with built-out networks

- *California* (Caltrans District 4) – Assessment of route directness for bicycle mobility across high speed state highways to compute level of traffic stress, network shortest paths to measure amount of out-of-direction travel required to cross the highway at a low stress crossing
- *Fort Collins, CO* – Network completeness analysis of bike network for planning and benchmarking, computing LTS, route directness to schools on low-stress network, link centrality
- *Portland* - Combined-methods analysis of connectivity gaps at TAZ level to measure change, equity impacts
- *King County Metro* – Non-Motorized Connectivity study, 2014 to prioritize planned projects, update local plans. Included route directness connectivity analysis (with all streets included) to calculate shortest paths, distance to transit, etc. http://metro.kingcounty.gov/programs-projects/nmcs/pdf/nmcs-report-091214.pdf
- *Cambridge, MA* – Calculated Bicycle Comfort Level rating, then refined through public comment to identify projects that close gaps in low stress network
- *Alameda County* – Expanded facility classification schema to identify low-cost spot improvement connections
- *Kansas City* (KS) Walkability Plan – PLOWS to score and group areas, identify needed improvements https://www.acpwa.org/s/Bike-Ped-Plan-for-Unincorporated-Final.pdf
- *Minneapolis, MN* – Pedestrian plan mapped walk connectivity based on block size to identify priority locations for midblock crossings
- *San Jose, CA* – Low Stress Bicycling Network Connectivity Analysis by Mekuria et al, 2012: This study demonstrated two proposed measures of connectivity as a tool to define proposed improvements that would significantly improve low-stress connectivity

Measuring Network Safety

The presence, quantity, or severity of crashes is the most used metric to assess safety and a key part of any safety analysis [8]. There has also been significant progress in the quality of data and methods used to analyze non-motorized road user crashes over the last decade. This progress has helped to identify crash "hot spots" (typically intersections), determine statistically significant clusters of crashes, and incorporate systemic factors likely to contribute to crash risk, even where actual crash frequency is low [48].

The use of "risk" as a measure of safety, rather than simple crash totals, is a significant advancement in the state of the practice. This approach addresses the fact that in situations where conditions are perceived as very unsafe for walking or cycling, there may be few recorded crashes due to low activity volumes, even if there is significant latent demand. Risk may be defined by calculating the observed crash rate (using an exposure measure to normalize crashes by number of users, trips, or miles, e.g., Figure 50) or by predicting the number of expected crashes within a defined time horizon based on past crash history and/or other risk factors found to correlate with crash incidence [8].

Figure 50. Exposure measure matrix [8]

Category of Exposure Measure	Typical measures	Typical scale				Typical data sources
		Point	Segment	Network	Region	
Distance Traveled	Miles of travel	○	●	●	●	• Site counts or demand estimation models, multiplied by segment length • Sometimes travel surveys
	Miles crossed per entering vehicle	◐				
Time Traveled	Hours of travel	○	○	●	●	• Travel surveys • Sometimes site counts combined with crossing time or average travel speed data.
	Product of crossing time and vehicle volume	○	○			
Volume/ Count	Volume/count	●	●			• Site counts • Demand estimation models
	Product of pedestrian /bicyclist volumes and motor vehicle volumes	◐	◐			
Trips Made	Number of trips			●	●	• Travel surveys
Population	Number of people that walk or cycle on regular basis			●	●	• U.S. Census data products
	Percent of the population that walk or cycle on regular basis			●	●	

Legend: ○ = to a small extent; ◐ = to a moderate extent; ● = to a great extent.

Population-based measures of exposure may be readily applied at the areawide scale, while site counts can support robust exposure estimates for individual segments or nodes. However, while analyzing an entire network, demand models based on counts, surveys, or other data (such as roadway, traffic, or land use characteristics) are typically used as substitutes for direct methods of measuring exposure [15].

Many cities have turned to the concept of High Injury Networks (HIN) to address systemic needs across the transportation network, rather than focusing only on crash “hot spots.” HINs provide a measure of crash density along overlapping segments along a street network, effectively generalizing the location of crashes for a more consistent evaluation of crash distribution [48]. Such analyses support a systemic safety approach, allowing network-wide screening of corridors sharing similar characteristics to determine where crashes are more likely to occur.

Recent projects have begun to make HIN development and screening more accessible, even in situations where robust exposure data is lacking. Mansfield et al. developed a pedestrian risk model based on built environment and demographic data to model crash risk across the entire US by census tract [49]. Schoner et al. [48] built on this model to link results to specific locations along the transportation network, allowing the analysis of predicted crash risk for both pedestrians and bicyclists using relatively low-barrier data inputs and facilitating project prioritization. The resulting tool known as the Safer Streets Priority Finder, also provides severity-based crash cost outputs to estimate the societal cost of anticipated crashes over a five-year period. These tools greatly enhance local agencies’ ability to evaluate network-wide safety quickly and efficiently, in a more actionable manner than simply mapping crash hot spots. However, data and processing limitations inhibit simultaneous statewide analysis, and model outputs may be less accurate and/or useful in rural areas where crashes involving pedestrians or bicyclists are very rare [48].

Moreover, reported crashes (and variables associated with such crashes) may not provide the complete picture. Police crash reports tend to underreport total crashes, particularly those that do not involve a motor vehicle (such as pedestrian falls, or cyclist collisions with fixed objects), as well as many minor crashes [40]. Where data is available, additional safety data variables (e.g., Figure 51) may be utilized beyond where reported crashes occur.

Figure 51. Example safety variables (42)

Example Safety Variable	Data Considerations/Sources
Total number of pedestrian/bicycle crashes	Police crash database, often available at the state or local level
Fatal and severe injury pedestrian/bicycle crashes	Police crash database, often available at the state or local level
Pedestrian/bicycle crash rate	Police crash database combined with measure of exposure (e.g., pedestrian/bicycle counts, pedestrian/bicycle demand proxy variables)
Proportion of pedestrians walking in the roadway	Pedestrian counts (generally manual counts in the field, with instruction to note pedestrians in roadway)
Proportion of pedestrians complying with "Don't Walk" signals	Pedestrian counts (generally manual counts in the field, with instruction to note "Don't Walk" compliance)
Proportion of bicyclists complying with red lights	Bicycle counts (generally manual counts in the field, with instruction to note red light compliance)
Proportion of motorists complying with right-turn-on-red restrictions	Vehicle counts (generally manual counts in the field, with instruction to note right-turn-on-red movements)
Proportion of motorists yielding to pedestrians in crosswalks	Vehicle counts (generally manual counts in the field, with instruction to note yielding rates)
Number of "near misses" involving pedestrians/bicyclists	Multimodal counts (generally manual counts in the field, or based on video footage of a location)

Measuring Network Equity

Equity can be measured using socioeconomic variables from the American Community Survey, public health agencies, local or regional planning agencies, and school districts, or other household surveys [40]. These can be cross-referenced with compliance variables to identify high priority locations within the network for intervention, based on equity goals. The *ActiveTrans Priority Tool* [40] outlines a range of commonly used indicators used to assess equity, based on their relevance to people who walk and/or bicycle, as well as their geographic scale of applicability (Figure 52 and Figure 53).

Efforts to improve equitable access to walking and bicycling have proliferated in recent years. Litman [51] define five types of transportation equity and identify key metrics for evaluating these (Figure 54), and outline equity implications of typical metrics used to assess transportation systems (Figure 55).

Figure 52. Example equity variables [40]

Example Variables	Relevance		Potential Location
	Ped	Bike	
Note: The relevance designations in this table are meant to provide general guidance. Ultimately, variable relevance depends on the prioritization purpose. Agencies are encouraged to review each variable and consider how relevant it may be considering their purpose.	● = Very relevant ◐ = Less relevant ○ = Not likely relevant		S = Segment Cr = Crossing Co = Corridor A = Area
Household automobile ownership	●	●	S, Cr, Co, A
Household income	●	●	S, Cr, Co, A
Percent unemployed	●	●	S, Cr, Co, A
Proportion of population under age 18	●	●	S, Cr, Co, A
Proportion of population over age 64	●	○	S, Cr, Co, A
Proportion of population with physical disabilities	●	○	S, Cr, Co, A
Minority populations	●	●	S, Cr, Co, A
Proportion of school children receiving subsidized lunches	◐	◐	S, Cr, Co, A
Proportion of population with asthma or diabetes	◐	◐	S, Cr, Co, A
Proportion of population that is overweight or obese	◐	◐	S, Cr, Co, A

Figure 53. Example compliance variables [40]

Example Variables	Relevance		Potential Location
	Ped	Bike	
Note: The relevance designations in this table are meant to provide general guidance. Ultimately, variable relevance depends on the prioritization purpose. Agencies are encouraged to review each variable and consider how relevant it may be considering their purpose.	● = Very relevant ◐ = Less relevant ○ = Not likely relevant		S = Segment Cr = Crossing Co = Corridor A = Area
Facilities not compliant with local, state, and federal design requirements or guidelines	●	●	S, Cr, Co
Sidewalk condition—segments that are not compliant with accessibility guidelines (e.g., clear width obstructions, vertical heave obstructions)	●	○	S, Co
Curb ramps that are not compliant with ADA guidelines (e.g., excessive slopes, lack of level landings)	●	○	Cr, Co, A
Bicycle facilities that are not compliant with national or state bicycle design guidelines or standards (e.g., AASHTO, NACTO)	○	●	S, Co, A

Figure 54. Transportation equity evaluation factors [51]

Types of Equity	Impacts	Metrics	Groups
A fair share of resources. "Get what you pay for and pay for what you get." **External costs** Minimize costs imposed on other people. **Inclusivity** Ensure that transport systems serve everybody. Multimodal planning and Universal design. **Affordability** Ensure that everybody can afford basic mobility. Quality of low-price modes. Targeted subsidies. **Social Justice** Considers structural injustices	**Facilities and Services** Funding and subsidies. Planning and design. Involvement in planning. **User benefits and costs** Costs and affordability. Service quality (convenience, comfort, speed, safety). Fares, fees and taxes. **External Impacts** Congestion delays. Crash risk. Noise and air pollution. **Economic Impacts** Economic opportunities. Job and business impacts. **Regulation and Enforcement** Regulations and enforcement.	**Level of Impacts** *Inputs* (funding, road space, etc.). *Outputs* (amount of mobility and accessibility). *Outcomes* (destinations accessed, cost burdens, crash casualties, etc.). **Units of People** Per person, household, commuter, or peak-period travel. **Units of travel** Per vehicle-mile/km. Per passenger-mile/km. Per trip (by type). **Financial** Per dollar. Subsidies. Cost recovery.	**Demographics** Age and household type. Physical and cognitive ability. Income and poverty. Race and ethnicity. **Location** Jurisdiction and neighborhood. Urban/suburban/rural. **Mode** Active (walking & bicycling). Vehicle ownership & licensure. Transit user/dependent. **Industries** Equipment/service providers. Shippers and Employees. **Trip type** Commutes and errands. Commercial/freight. Recreational/tourist.

Figure 55. Transportation metric equity implications [51]

Unit	Description	Equity Implications
Congestion impacts	Transportation funds are allocated based on their expected congestion reductions.	Favors people who frequently drive on congested roads.
Vehicle Miles Traveled (VMT)	Transportation funds are allocated based on vehicle-miles driven in an area.	Favors people who drive their automobile more mileage than average.
Passenger Miles Traveled (PMT)	Transportation funds are allocated based on passenger-miles travelled in an area.	Favors people who travel by any mode, with more funding for longer trips.
Passenger Trips	Transport investments are evaluated according to where trips occur.	Provides more support for shorter trips, including active modes and local travel.
Access	Transport investments can support many types of transport improvements.	Can benefit the largest range of users, particularly non-drivers.
Mobility Need	Transport investments maximize benefits to people with mobility impairments.	Favors people with disabilities and other special needs.
Affordability	Transport user fees are evaluated with respect to users' ability to pay.	Favors more affordable modes and lower-income people.
Cost Recovery	Transport expenditures are evaluated according to whether users pay their costs.	Favors wealthier travelers because they tend to spend the most.

Various practitioners have incorporated equity as a key consideration of network-level evaluations. Practitioners specifically centered equity as the primary driver of pedestrian and bicycle planning. Developed in 2015, one framework for measuring transit dependence and environmental justice issues is The League of American Bicyclists' Bicycle Equity Index (BEI), which relies on five demographic indicators from the American Community Survey as proxies for transit dependence and environmental justice issues: lack of access to a vehicle, children under 18, adults over 65, race/ethnicity, and income below the federal poverty level [50]. The BEI maps residents meeting these criteria and calculates a composite index score (z-score) to determine the standard deviations from the mean value, which helps identify network gaps in existing or planned bicycle infrastructure. The methodology for replication of the basic BEI at any scale is provided, but the authors note that it can (and should) be adjusted to reflect specific community needs [50]. For instance, New Orleans adapted the BEI to heavily weight communities with multiple indicators of disadvantage (rather than weighting each equally). They applied results in 2019 to develop their Bikeway Blueprint and identify high-priority areas for implementation [52].

Similar methods and metrics may apply to pedestrian equity. Minorities and low-income populations have been broadly found to be disadvantaged in terms of pedestrian safety [53], [54]. However, measures of transit dependence and/or physical disability are likely to be heavily weighted [55], [56]. Researchers note an additional challenge is not to assess just sidewalk presence but to consider quality as a critical input for evaluating pedestrian access. Access quality measures may include obstructions, unevenness, and other maintenance issues represent particular hinderances for certain communities such as people with disabilities and older adults [55]. Collecting data for sidewalk conditions at a detailed level can present challenges: 311-data for sidewalk repair requests, illegal dumping reports, or similar are typically only available at a local level and may reflect disparities in access to these reporting mechanisms. Meanwhile, correlations between neighborhoods with high populations of color and/or lower incomes and poor sidewalk maintenance have been established [55].

Additional resources which may have applications for evaluating and indexing equity include:

- EPA's Environmental Justice Screening Toolkit
- HUD and USDOT's Location Affordability Index
- EPA's Smart Location Mapping tool
- USDOT Plan Equity Tool
- TransportSE Transportation for Social Equity Dashboard
- US DOT Transportation Disadvantage Census Tract Layer

Summary Tables: Connectivity Analysis and Stress Classification Measures

Table 24. Summary of connectivity analysis measures (adapted from FHWA Guidebook for Measuring Multimodal Network Connectivity (55))

Connectivity Measure	Mode	Method	Outputs	Connectivity Analysis Methods	Explicit consideration of accessibility for people with disabilities	Use in Practice	Level of Effort
Bicycle Level of Service	Bicycle	Inputs entered into weighted formula; GIS tool available to make calculations easier	Numeric scores converted by formula to a six-point scale (A through F)	Quality	No	Common among agencies with strong interests in multimodal planning	Low
Bicycle Level of Traffic Stress (BICYCLE LTS)	Bicycle	Classify roadway Common links by type by highest stress attribute	Traffic stress rating of 1 through 4 for street segments and intersection	Completeness, Density, Directness, Accessibility to Destination, Quality	No	Common	Moderate
Bicycle Low-StressConnectivity	Bicycle	Assess routes among types ("basket") of destinations based on link and attribute weighting; aggregate connectivity at range of scale	Centrality by link or project; percent of destinations reached; impedance	Directness, Accessibility, Quality	No	Emerging	High
Bicycle Route Quality Index (RQI)	Bicycle	Link and intersection attributes are scored by	RQI measure for a route (relative to	Accessibility to Destinations,	Not in current	Emerging	High

Connectivity Measure	Mode	Method	Outputs	Connectivity Analysis Methods	Explicit consideration of accessibility for people with disabilities	Use in Practice	Level of Effort
		weighted formula; routes are solved between a defined set of destinations. Route scores are indexed and aggregated to origin points/areas.	distance) or facility (for origin/ destination areas); ranges from 0 to the best facility possible, with 1.0 reflecting an "adequate" or reference facility	Directness, Quality	forms, but could possibly be added given the complexity of the infrastructure data supporting the measure.		
Pedestrian Index of the Environment (PIE)	Pedestrians	Calculate a series of form-based factors around a given destination. Enter the factors into a weighting equation to calculate PIE	PIE, a standardized score of walkability (20 to 100) at the Pedestrian Analysis Zone (PAZ) scale. Predicted walk share of trips to given destination, based on PIE, is also possible with additional demand data	Directness, Accessibility to Destinations, Quality	No, but could potentially be added	Experimental	High
Pedestrian Level of Traffic Stress (PLTS)	Pedestrians	Classify sidewalk segments by type by highest stress attribute	Pedestrian stress rating of 1 through 4 for sidewalk centerline and intersections	Directness, Accessibility to Destinations, Quality	Yes	Emerging	High

Table 25. People for Bikes BNA Tool segment stress classification table - primary, secondary, and tertiary functional class (63)

Facility type	Speed	Number of lanes	Parking	Facility width	Stress
Cycle track	--------------------------------------	--------------------------------------	--------------------------------------	--->	Low
Buffered bike lane	> 35	> 1	--------------------------------------	--->	High
		1	--------------------------------------	--->	High
	35	> 1	--------------------------------------	--->	High
		1	Yes	--->	High
			No	--->	Low
	30	> 1	Yes	--->	High
			No	--->	Low
		1	--------------------------------------	--->	Low
	<= 25	--------------------------------------	--------------------------------------	--->	Low
Bike lane without parking	>30	--------------------------------------	--------------------------------------	--->	High
	25-30	> 1	--------------------------------------	--->	High
		1	--------------------------------------	--->	Low
	<= 20	> 2	--------------------------------------	--->	High
		<= 2	--------------------------------------	--->	Low
Bike lane with parking	--------------------------------------	--------------------------------------	--->	>= 15 ft	*Treat as buffered lane*

Facility type	Speed	Number of lanes	Parking	Facility width	Stress
				13-14 ft	*Treat as bike lane without parking*
				< 13 ft	*Treat as shared lane*
Shared lane	<= 20	1	--------------------------------------	--->	Low
		> 1	--------------------------------------	--->	High
	> 20	--------------------------------------	--------------------------------------	-------------------------->	High

Table 26. People for Bikes BNA Tool segment stress classification table - residential or unclassified functional class (63)

Facility type	Speed	Number of lanes	Parking	Road width	Stress
Cycle track	--	--	--	-->	*Treat as tertiary*
Buffered bike lane	--	--	--	-->	*Treat as tertiary*
Combined bike / parking lane	--	--	--	-->	*Treat as tertiary*
Bike lane	--	--	--	-->	*Treat as tertiary*
Shared lane	>=30	--	--	-->	*Treat as tertiary*
	25	>1	--	-->	*Treat as tertiary*

Facility type	Speed	Number of lanes	Parking	Road width	Stress
		1	One side or none	>= 19 ft	Low
				18 ft	High
				< 18 ft	High
			Both sides	>= 27 ft	Low
				26 ft	High
				< 26 ft	High
	<= 20	>1	-- -- --------	-- -- ------>	*Treat as tertiary*
		1	One side or none	>= 19 ft	Low
				18 ft	Low
				< 18 ft	Low
			Both sides	>= 27 ft	Low
				26 ft	Low
				< 26 ft	Low

Table 27. People for Bikes BNA traffic stress classification for intersections (63)

Intersection control	Number of crossing lanes	Crossing speed limit	Median island	Stress
None/yield to cross traffic	> 4	--	--------------------------->	High
	4	>30	--------------------------->	High
		30	Yes	Low
			No	High
		<= 25	--------------------------->	Low
	< 4	> 30	Yes	Low
			No	High
		<= 30	--------------------------->	Low
RRFB	> 4	--	--------------------------->	High
	4	>= 40	--------------------------->	High

Intersection control	Number of crossing lanes	Crossing speed limit	Median island	Stress
		35	Yes	Low
			No	High
		<= 30	------------------------->	Low
	< 4	> 35	Yes	Low
			No	High
		<= 35	------------------------->	Low
Signalized, HAWK, four way stop, or priority based on class	-------------------------------------	-------------------------------------	------------------------->	Low

Public Engagement and Data Dissemination for Active Transportation Planning

This section explores key questions pertaining to implementation and dissemination of research results, specifically by asking how we can improve public engagement in active transportation planning and facilitate inclusive participation and feedback through outreach, inclusion, digital dashboards, portals, and tools.

Equity and Inclusion

There are many barriers to public involvement in planning processes, and even more barriers to meaningful involvement that goes beyond informing the public about governmental actions. Complaint-based project prioritization methods, as well as abstract planning processes soliciting input from the "general public," tend to direct resources toward communities that already have the most resources, rather than to those most in need. Similarly, the groups and individuals most likely to participate in traditional planning outreach efforts are likely to overrepresent certain communities and underrepresent others [54]. Involving traditionally underserved populations requires a commitment to equity and inclusion at all stages, and three basic steps [57] :

1. Identifying and locating underserved populations
2. Fostering participation of those populations, and
3. Creating opportunities for meaningful involvement.

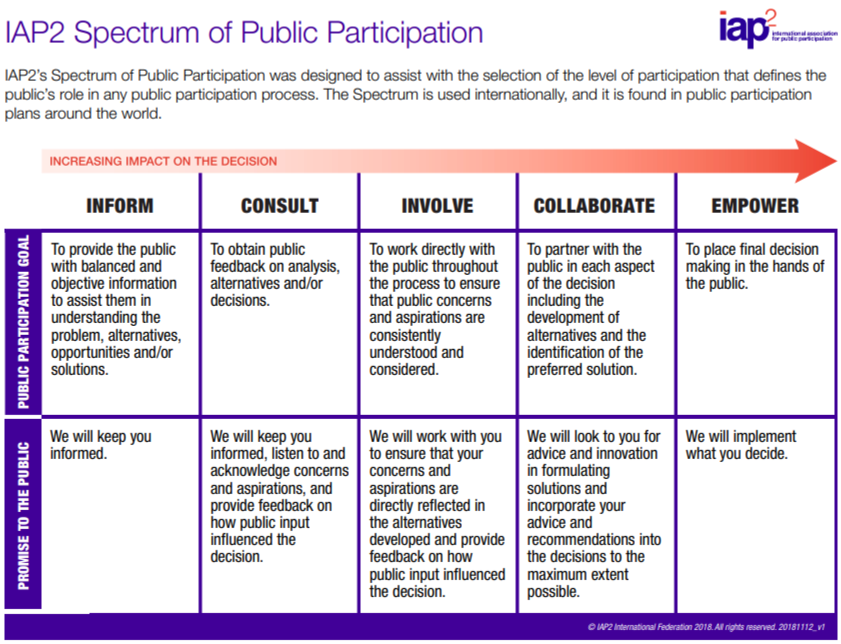
Traditionally underserved groups, by FHWA's definition, include [54]:

- Low-income
- Minority
- Older adults (defined as 65 years or older
- Limited English proficiency (LEP)
- Persons with disabilities (physical or mental, as defined by ADA)

Individuals in these groups are less likely to own a vehicle, more likely to have jobs with non-traditional hours, are more likely to walk, bike, and take transit, and/or are more likely to experience social isolation [54]. At the same time, these communities are more likely to live in areas without access to high quality walking, bicycling, and transit facilities and are disproportionately impacted by traffic violence [5].

Meaningful and inclusive engagement requires clarity about what impact public participation can or will have, as well as how the outcomes of the engagement will be used [98]. The International Association of Public Participation defines a spectrum of public participation that articulates the role and expectations of various levels of engagement impact, ranging from “informing” the community to “empowering” it to make final decisions (Figure 56).

Figure 56. IAP2 spectrum of public participation (80)



IAP2 Spectrum of Public Participation

IAP2's Spectrum of Public Participation was designed to assist with the selection of the level of participation that defines the public's role in any public participation process. The Spectrum is used internationally, and it is found in public participation plans around the world.

INCREASING IMPACT ON THE DECISION

	INFORM	CONSULT	INVOLVE	COLLABORATE	EMPOWER
PUBLIC PARTICIPATION GOAL	To provide the public with balanced and objective information to assist them in understanding the problem, alternatives, opportunities and/or solutions.	To obtain public feedback on analysis, alternatives and/or decisions.	To work directly with the public throughout the process to ensure that public concerns and aspirations are consistently understood and considered.	To partner with the public in each aspect of the decision including the development of alternatives and the identification of the preferred solution.	To place final decision making in the hands of the public.
PROMISE TO THE PUBLIC	We will keep you informed.	We will keep you informed, listen to and acknowledge concerns and aspirations, and provide feedback on how public input influenced the decision.	We will work with you to ensure that your concerns and aspirations are directly reflected in the alternatives developed and provide feedback on how public input influenced the decision.	We will look to you for advice and innovation in formulating solutions and incorporate your advice and recommendations into the decisions to the maximum extent possible.	We will implement what you decide.

It is also important to acknowledge disparities and power imbalances between transportation decision-makers and marginalized communities whom they are charged to serve. Effectively and sensitively communicating with diverse communities (i.e., cultural competency) and ensuring reasonable accommodation for participation in planning processes are critical to advancing equitable outcomes [54], [57]. Overcoming limited access to online resources is a key concern of developing an equitable planning process, along with ensuring that both digital and analog communications materials are available in multiple languages [54]. Many communities, including rural areas as well as low income and older individuals, may lack reliable broadband internet access, limiting engagement with information communications technologies (ICTs) and contributing to a “digital divide” that can negatively impact inclusivity [57]. In addition, acknowledging past injustices and considering the history of communities that have suffered from them is a key prerequisite to building trust [54].

Specific strategies aimed at fostering participation of underserved communities include [54], [57]:

- Utilizing a mix of digital and non-digital outreach tools, such as including social media, fliers, connecting through existing community networks and partners, and local media (especially media serving underrepresented communities).
- Hosting in-person meetings in informal, non-governmental locations, schools, and/or joining meetings that are already happening within underrepresented community networks. Providing childcare and scheduling meetings at various times to accommodate different schedules.
- Providing accommodations for people with vision or hearing impairments and ensuring digital materials are accessible to screen readers wherever possible.
- Developing dynamic, interactive, and mobile technology-friendly web resources that promote transparency and citizen involvement through content creation, editing, or distribution.

In addition, FHWA identified a framework of steps to guide outreach efforts for targeted engagement of underrepresented communities (particularly low-income), including [99] : What's the general context behind your need for low-income community engagement?

1. What preliminary expectations does the planner hold about the input being sought from low-income community stakeholders?
2. What low-income community has a stake in the subject of this engagement?
3. What information does the planning agency already possess about the identified low-income community?
4. What institutions, organizations, formal and informal social networks, etc., are active within the low-income community being considered?
5. What strategies seem most viable for the transportation planner to use these identified intermediary groups or networks to get community stakeholder input?
6. What are identified as the transportation-related benefits and risks – both real and imagined – among the low-income community?
7. How will the low-income community and its stakeholders know that their views were heard?

The American Planning Association's Planners Advisory Service, meanwhile, recommends four key strategies for optimizing online public engagement efforts [100]:

1) Supplementing existing engagement strategies (rather than replace), as not all households have reliable internet access (approximately 1 in 10 per FHWA's Every Day Counts Virtual Public Involvement Initiative [101].
2) Select tools that meet needs for both who you are trying to reach (total reach as well as geography and demographics), and the depth of engagement required, and evaluate engagement efficacy at every step.
3) Develop a strategy to manage, analyze, and utilize all data that is collected.
4) Connect outreach to outcomes by sharing results across the same platforms through which feedback was solicited.

In the wake of the COVID-19 pandemic, digital engagement has become the norm, and many of the practices and tools developed to advance planning work during this transformative period are expected to continue. These practices including virtual meeting options, creative approaches to linking digital and analog outreach (e.g., QR codes) and working directly with compensated community members as leaders and collaborators [59]. Best practice research indicates that compelling virtual experiences with more visuals and less text reduce barriers to participation [60]. Practitioners also recommend as we collectively move toward hybrid engagement models that mix digital and analog strategies, that community engagement impacts should be closely monitored and evaluated in real time to ensure adequate representation from target geographies or groups, integrating engagement as a direct component of the fundamental planning task rather than an "add on" after the fact, developing virtual platforms for ongoing, asynchronous engagement, and explicitly seeking out historically underrepresented voices [59]. Finally, as our ability to foster participation from broader or more representative audiences expands, so too does the professional obligation to support the understanding of planning, governance, and implementation processes within our communities: citizens need to be aware of opportunities to be involved, particularly in early stages of planning processes, and have enough background information to provide relevant feedback [61].

Additional tools for analyzing equity and increasing inclusivity in both processes and outcomes include:

- Race Forward's Racial Equity Impact Assessment Toolkit
- The Greenlining Institute's Mobility Equity Framework
- FHWA's Performance-Based Planning and Programming Guidebook
- U.S. Department of Transportation (USDOT) and Centers for Disease Control's Transportation and Health Tool
- HUD and USDOT's Location Affordability Index
- EPA's Smart Location Mapping Tool and Environmental Justice Screening Toolkit
- NCHRP REPORT 710: Practical Approaches for Involving Traditionally Underserved Populations in Transportation Decisionmaking
- How to Engage Low-Literacy and Limited-English-Proficiency Populations in Transportation Decision-making

Digital Tools

Digital tools to support public participation in urban planning, defined as a "specific type of civic technology explicitly built for participatory engagement and collaboration purposes” [102], have existed since the 1990s with the development of public participation GIS. However, they have grown significantly in recent years with technological innovation and, particularly, the advent of the COVID-19 pandemic [62].

A wide range of applications and tools relevant to planning and/or transportation have been developed to support digital outreach efforts, ranging from the broad (e.g., using existing features of social media platforms) to the specific (e.g., developing purpose-built mobile apps to support specific planning initiatives). The intent of such tools is to address identified barriers to participation in planning and facilitate more inclusive, and in some cases more nuanced feedback [61]. Strategies for maximizing engagement in digital platforms center on pre-launch planning: mapping the networks of target stakeholders/communities, reaching out to leaders within those communities to understand their needs and networks, and use specific, individualized messaging to recruit participation based on identified core interests [100].

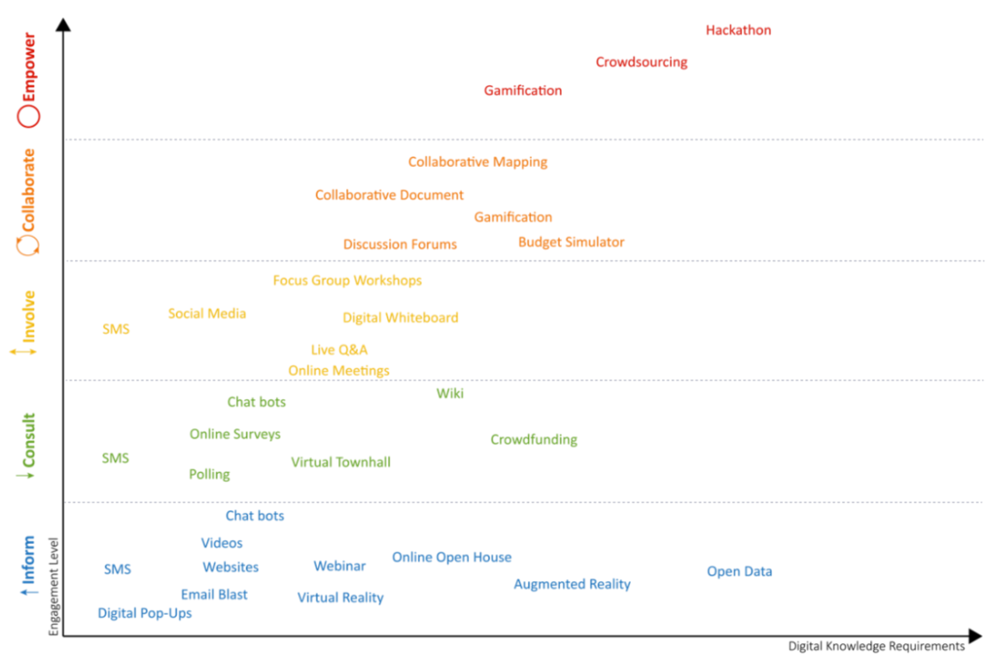
Many specific applications of interactive digital engagement tools are either purpose-built and temporally limited (e.g., web pages or apps developed for a completed project and brought offline) or from an ever-shifting range of vendors and subject to change or discontinuation. Some digital tools created for specific projects or organizations are closed with the conclusion of the specific initiative, while others are left open, either continuing to collect comments and feedback or in view-only mode. Regardless of platform, the following visualization best practices for map-based engagement should be kept in mind [63], [64]:

- Show existing and (where available) proposed facility networks for relevant modes
- Do not allow detailed content (icons, symbols etc.) to overwhelm the user
- Include local landmarks and points of interest to help users orient themselves
- Tools/visualizations must be mobile-friendly

In addition, it is important to remember that in most communities, a “digital divide” persists, and both access to engagement tools and full participation in them may be constrained among groups with limited access to technology and/or limited digital literacy [62]. Therefore, engaging underserved groups in virtual public involvement initiatives may also require complementary offline methods (e.g., print materials), multilingual social media outreach, or providing accommodations for the visually impaired [64].

Collecting community feedback on spatial data, whether network-based or project based, is most frequently facilitated by interactive GIS-linked maps. These maps can have embedded comment functionality or with linked surveys. Estefam [62] charts a range of digital tools for engagement, considering against two key dimensions: level of engagement, and level of digital knowledge required to participate fully (Figure 57). This analysis places collaborative mapping high on the level of engagement and in the center of the digital knowledge required. A slightly simpler interactive map (with survey or comment-box based feedback, but not specific contributions to the map itself) may be more accessible to a wider range of stakeholders, though the community contributions may be less significant to the outcome.

Figure 57. Level of engagement and digital knowledge required for public participation strategies [62]



Several examples, as well as a list of identified platforms or vendors with relevant product capabilities, are listed below. Suggested metrics for measuring the success of any public involvement initiative include:

- Number of website hits

- Number of participants
- Demographic distribution of participants
- Documentation of how public input was used and whether it affected outputs/outcomes
- % of project budget spent on engagement; cost per participant

Interactive Map Examples

- Louisiana DOTD Highway Priority Program
  - Collected feedback from geo-located comment boxes for features in project layer
  - Built with Aurigo Engage platform
- Walk & Roll Memphis Region Pedestrian and Bicycle Master Plan
  - Collects feedback on desired walk/bike destinations, routes that need improvement, routes currently used, barriers to walking/biking/micromobility, barriers to mobility devices/accessibility
  - Shows existing and planned facilities, locations of previous comments
- TriMet Pedestrian Access to Transit Plan
  - Landing page shows explanation of project purpose and process
  - Map walks user through proposed projects; allows users to set priority level for equity, safety, and demand; collects data about user home and work neighborhoods
  - "Barriers" page allows users to mark location of safety or comfort issues, with specific categories and an open comment box
- Alamo Area MPO Interactive Map
  - GIS-based map, paired with linked survey for feedback
- Iowa DOT Public Involvement Management Application (PIMA)
  - Includes an interactive map component with configurable comment forms
  - Comment forms include tags for topic, an option to request a response, and required submitter contact information
- Ozarks Transportation Organization interactive comment map
  - Allows point-based or linear input for transportation suggestions for all modes; users encouraged to upload photos and write comments. Also includes box for general (non-spatial) comments
- Palm Beach Transportation Planning Agency Comment Map
  - Built with Survey123; requests location services in order to pinpoint respondent location, or user can enter address
  - Topics organized by mode or issue (lighting, drainage, land use, etc.)
  - Photos may be included

    - Anchorage Bowl and Chugiak-Eagle River Metropolitan Transportation Plan
        - Dashboard-based map with comment type data; no longer collecting comments

Vendors/platforms:

- Mapbox https://www.mapbox.com/
    - Wide-ranging functionality, high cost and technical expertise requirement
- ArcGIS Storymaps https://storymaps.arcgis.com/
    - Presentation of data – may be paired with crowdsourced or survey application to add user-generated content/feedback
    - GeoPoint questions in ArcGIS Survey123 can be used to link these
- Google Maps https://www.google.com/maps/about/mymaps/
    - Limited GIS/coding expertise required; Can be paired with other google products (e.g. forms) to solicit feedback
- StoryMapJS https://storymap.knightlab.com/
    - Free, slide-based StoryMap tool integrated with Google Drive and Dropbox
- Visme https://www.visme.co/
    - Geared toward presenting statistical data/infographics along with maps; comment functionality unknown
- Zeemaps https://www.zeemaps.com/
    - Builds interactive maps from spreadsheets; mobile friendly
- Shorthand https://shorthand.com/the-craft/how-to-tell-stories-with-maps/index.html
    - Animated storymap from static image with optional annotations
- Felt https://felt.com/
    - Free, collaborative mapping tool with annotation tools (marker, highlighter, notes, etc); supports vector data
    - Intended for team or stakeholder collaboration rather than general public feedback
- Mapme https://mapme.com/
    - Customizable, crowdsourced map tool with built-in engagement tracking dashboard
    - Links with Google Forms to send submissions to map in real time with API
- Scribble Maps https://www.scribblemaps.com/
    - Interactive map intended for API integration
- Community Remarks https://communityremarks.com/
    - Interactive maps with graphics, project pins, comment boxes

Other types of virtual public involvement/digital outreach tools:

- Virtual Public Meetings (live) or Open Houses (may be on-demand)
  - Zoom, Webex, GoToMeeting, etc
- Telephone Town Halls
  - Eg., Access Live, which sends outbound calls to landlines and mobile phones to solicit real-time participation
- Social media
  - Twitter Town Halls
  - Facebook/Youtube Live
  - Google Hangouts
- Digital newsletters
- Story maps and embedded mapping tools
  - OpenLayers – an open source dynamic map tool, based on JavaScript
- Polling/Survey tools
  - Surveymonkey
  - QuestionPro
  - Alchemer
  - Qualtrics
- Wiki tools for collaboratively posting and editing documents (note: two resources referenced in this space, wikispace and wikiplanning, have since ceased operations)
  - OpenStreetMap
  - Wikimapia
- Geolocated apps for reporting issues in the built environment, on-site
  - SeeClickFix - service linked to local government 311 systems to facilitate improvements in citizen-reported issues
  - FixMyStreet – a web-based platform on which citizens can report place-based issues (e.g., potholes) in the UK
  - Change Explorer – an IoS app (built for Apple Watch) prompting users to identify changes to the built environment they would like to see, when they enter specific physical locations in the community
- Apps for collecting real-time route choice data for walking or bicycling
  - Cycle Atlanta – a smartphone app used in conjunction with a charrette to report concerns and organize discussion around potential solutions
- All-in-one Tools
  - Project information, survey, draft materials, etc
    - MetroQuest
    - IowaDOT Public Involvement Management Application – includes project as well as live feedback and documentation of outreach process
- Digital tools for in-person outreach
  - Meetings-in-a-box
  - Live polling

- Online-in-the-field surveys and crowdsourcing with tablets
- Tablet kiosks
- Virtual Reality

Appendix B: Use Human Mobility Data in Disaster Response

Recent studies have recognized the value of human mobility datasets and started using them for disaster preparedness and response purposes. For example, several studies have used raw GPS records to gain a better understanding of disaster evacuation/re-entry behavior (e.g., evacuate/stay, destination, and route choices), which was usually observed via conducting post-disaster household behavioral surveys in the past. This appendix describes these studies in detail in the literature review section.

The project team demonstrated the use of another type of human mobility data (i.e., Location Based Service records) for disaster preparedness/response in two scenarios. First, SafeGraph data (which was used for active transportation planning purposes as described in the current report) was analyzed by day with a focus on a particular type of place category. Specifically, the extracted data was used in analyzing gas station visits during Hurricane Ida (2021) to support future fuel supply planning and/or responses during hurricanes [103]. The results from the study have been used to assist a parish office in updating their emergency management plans. The same procedure could be applied to any other place categories that are of interest to DOTD operation/planning activities.

Second, this appendix expands our explorations with SafeGraph data to cover all the place categories, but with a focus on monthly-scale outcomes. The following content describes how to use Location Based Service records in understanding human mobility (or destination access) changes during major disruptions (i.e., COVID-19 and Hurricane Ida). The procedure could be streamlined and applied to develop a dashboard describing monthly destination access status by place category (e.g., parks, restaurants, and grocery stores) and/or by jurisdiction (e.g., parish and DOTD districts). Such information has the potential for use in the following scenarios: 1) capturing abnormal/surging/depressed human activities at an aggregate level (e.g., evaluating congestion impacts brought by large volumes of visitors that are present in certain places during holidays); 2) tracking economic development and its association with transportation investment (e.g., the number of visits to restaurants; it should be noted that SafeGraph and some other data vendors recently started providing transaction data, which could better support this use case), and 3) monitoring public health by measuring the ease of destination access (e.g., active travels to city/community parks).

Introduction

Major disruptions (like public health crises and natural disasters) can have great impacts on transportation systems, which could prevent people from meeting their daily needs (e.g., working, shopping, and recreational). The COVID-19 pandemic affected travel patterns for a significant time duration [104]–[106] and had major effects on various transportation sectors, including public transit and shared mobility [107]. During its early outbreak, non-essential travel greatly declined due to travel restrictions and business closures [108]. Some prior studies have investigated the pandemic's social impacts by analyzing the relationship between socio-demographic variables and change in travel behavior [109], [110]. The lasting social impacts of COVID-19 on human mobility have not yet explicitly studied [111]. Natural disasters may influence human mobility over a shorter duration and smaller geographic regions (e.g., from neighborhoods to regions) in comparison with COVID-19's global impacts. Analyzing human mobility changes during disasters can help regions experiencing recurring events to proactively propose countermeasures to increase their infrastructure resiliency and serve travel needs during disaster response and recovery. This includes evaluating population differences in evacuation and reentry behavior to identify vulnerabilities and mitigation strategies [112], [113].

This study aims to understand the social impacts of major disruptions on human mobility from the perspective of destination access. A better understanding of when and how travel behaviors change during disruptions can help illuminate solutions to improve job access, increase economic vitality, connect communities with food/medical services/parks, etc. The following section provides a review of past studies related to the topic. The mobility dataset used in the study and the analysis scope are introduced. The next sections discuss mobility variations and present models that investigated which factors might have linear or non-linear associations with those variations. The paper concludes by summarizing our major findings, contributions, and limitations.

Literature Review

The first subsection provides a scan of recent literature pertaining to large-scale datasets employed to analyze the impacts of disruptive events (especially COVID-19 and disaster events like hurricanes) on human mobility. The second subsection discusses in more detail the impacts of disruptions on destination access.

Large-scale datasets used in understanding human mobility

Ridership records from ride-sourcing and taxi companies have been used to analyze the major disruptions on these services. For instance, researchers have analyzed and estimated taxi ridership before hurricanes to support fleet management [114] and address the needs of vulnerable populations [115]. The effects of COVID-19 on ride-sourcing and taxi companies have also been studied to identify and reduce service disparity [116].

Cities with bike and/or scooter-sharing programs typically have rich datasets that document trip origins, destinations, and routes for shared fleet trips [117]. For example, Chen et al. found that bike sharing in Washington D.C. significantly decreased dramatically during COVID-19 and rebounded slowly [118]. Berezvai found that bike sharing rose during the first wave of the pandemic in Budapest but subsequently declined after restrictions were lifted [117]. In Wuhan, China, Li and Xu found that bike sharing became a critical means of transportation in Wuhan, China during the pandemic, including travels to hospitals). However, bike sharing decreased in denser commercial areas while increasing in suburban areas [119].

Some studies have used data from fitness applications (like Strava) to analyze travel behavior. For example, one study in Germany analyzed trips to public green spaces in a mix or urban and rural communities [120]. It was found that cycling increased by 55-81% per month in urban areas, highlighting the role of public green spaces and convenient access to them during the pandemic. The study also revealed that rural areas showed no significant change in trip frequency during COVID-19.

Social media data (e.g., geotagged tweets) was also utilized to understand human mobility during disruptions [121]. Martin et al. used Twitter data to estimate the timing, magnitude, and destination of evacuation and reentry in Puerto Rico during Hurricane Maria (2017) [122]. Wang and Taylor analyzed human mobility using Twitter data in 15 natural disasters of various types [123].

Data collected from mobile devices (e.g., GPS traces and Location Based Service data) is another popular source to understand human mobility during disruptions. For example, Hunter et al. used Cuebiq data in analyzing walking patterns of 1.62 million unidentified users during COVID-19 in ten metropolitan areas in the U.S. [124]. Bian et al. used data from Google Mobility Reports to examine and predict grocery store visit variation in six U.S. states during the early outbreak of COVID-19 [108]. One study used SafeGraph data to analyze non-working activity patterns before and during COVID-19 in El Paso, Texas

[125]. Data from mobile devices were also used to analyze evacuation patterns. For example, one study examined data from two months before and after Hurricane Irma to track evacuee departure and reentry dates of evacuees in Florida [126]. Another study in China analyzed human mobility during a typhoon with data from over 840,000 points of interests (POIs) [127]. Impacts of other disaster types also showcased the use of emerging mobility data and tools. For example, GPS data was used to simulate wildfire evacuation behavior during the 2019 Kincade fire in California [128].

Some studies employed multiple data sources to leverage the strengths of data from different sources. For example, researchers in Zurich combined shared micro-mobility data from bike and scooter sharing systems, POI data from OpenStreetMap, and GPS data from a Switzerland Mobility Behavior Survey in analyzing travel behavior across a variety of place categories and activity types [129].

Impacts of major disruptions on destination access

Transportation systems serve people's daily activities and needs. Destination accessibility reflects the overall effectiveness of the integration of land use and transportation systems, which indicates how well the complex system meets travel demands [130]. Major disruptions have great impacts on human mobility. Therefore, measuring the impacts of major disruptions on destination access is crucial for understanding the economic and social consequences of disruptions and developing mitigation strategies. The following past studies involved destination access in their investigations of major disruptions' impacts on human mobility.

Among COVID-19 related studies, researchers in Zurich found that the distance and duration of micro-mobility trips increased during the early outbreak of COVID-19, particularly trips to parks and grocery stores, while trips for leisure and shopping declined [129]. Hunter et al. found that utilitarian walking (e.g., for shopping) decreased significantly during early lockdown restrictions in all 10 metro areas in the U.S., while recreational walking increased and exceeded pre-pandemic levels [124]. Bian et al. found that grocery store visits surged by more than 20% following the declaration of a national emergency then dropped below the pre-pandemic baseline level within a week [108]. Song et al. found that COVID-19 had relatively limited impacts on the number of visits to restaurants, supermarkets, and grocery stores, which indicates communities' persistent need of food despite major disruptions [125]. However, notable decreases in travel distance were found in half of the destination categories (e.g., restaurants, bars, and parks). Kolarova et al. indicated that most individuals reduced their in-person shopping trips following the first COVID-19 lockdown in Germany in 2020 with a simultaneous rise in online shopping [131]. Jay et al. found a significant reduction of trips (by 36%) to parks compared to pre-pandemic levels (i.e., from March to November 2020) [132].

Pertaining to disasters, Juhász and Hochmair found visits to gas stations and grocery stores rose before the landfall of Hurricane Irma in the Miami metropolitan area but dropped rapidly after the evacuation order was issued [133]. After the storm passed, visits to grocery stores and gas stations increased faster than visits to universities and colleges [133]. Bian et al. found that gas station visits surged within two days before the landfall of Hurricane Ida (2021) in coastal Louisiana, while evacuation destinations and intermediate trip connectors had longer visit surges [134]. Zones with higher vehicle ownership, more daily commuters driving alone, lower residential stability, more mobile homes, and fewer storm impacts tended to have more gas station visits (i.e., greater fuel demand) [134].

Data Description

SafeGraph data and mobility measures

This study is based on a large-scale dataset from SafeGraph, which collects data passively and anonymously from mobile devices year-round. The dataset presents how often 18 million points of interests (POIs) were visited by people in the U.S. each month. Among all the POIs, about 116,935 POIs (in 165 destination categories) are within Louisiana. The destination categories align with the North American Industry Classification System (NAICS).

Data of three years (from January 2019 to December 2021) was used in this study. Three mobility measures are available in the dataset and were extracted for this study: the number of visitors to a POI in a month, the median travel distance from visitors' residence to a POI in a month, and the median activity duration time at a POI in a month.

Monthly variations

The three mobility measures were first plotted by month to observe their changes over time, which helps define an appropriate temporal analysis scope for each major disruption analyzed in this study (i.e., COVID-19 and Hurricane Ida). Figure 58 presents the average number of visitors to destinations per month (on the left axis) with percentage changes relative to the baseline year 2019 (on the right axis). It was found that the number of visitors dropped dramatically (>20%) between March and May 2020 possibly related to COVID-19 outbreak and lockdown implementation. There are eight months in 2020 observing at least 10% fewer visitors compared with corresponding months in 2019. In 2021, the number of visitors decreased more in September (10.53%) and in August (7.38%) possibly related to the landfall of Hurricane Ida. However, its impact magnitude was much smaller than that of COVD-19.

Figure 58. Average number of visitors (with percentage change) by month

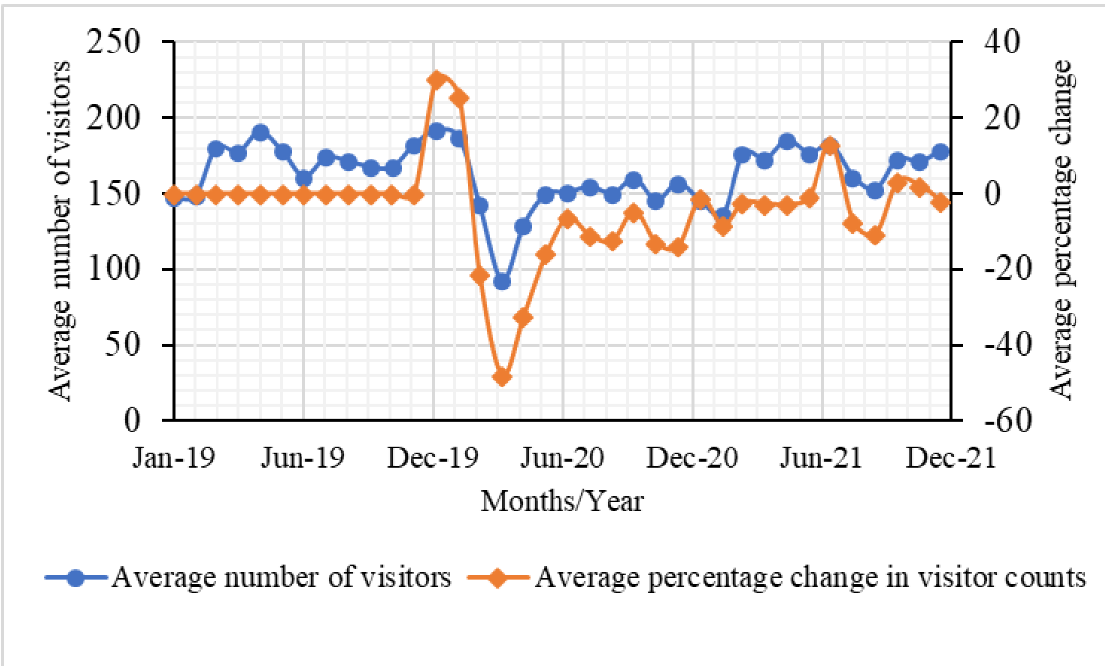


Figure 59 presents activity duration time per month. Firstly, activity duration time increased almost 10% in March 2020, which might be related to COVID-19 outbreak and emergency declarations (e.g., food stocking). Secondly, activity duration time dropped notably around July 2020 (9.74%), which might be related to travel restrictions and subsequent summertime trip cancellations. In 2021, the only month that observed a 10% change of activity duration was September, which might be related to Hurricane Ida's impacts to coastal Louisiana.

Figure 59. Average activity duration (with percentage change) by month

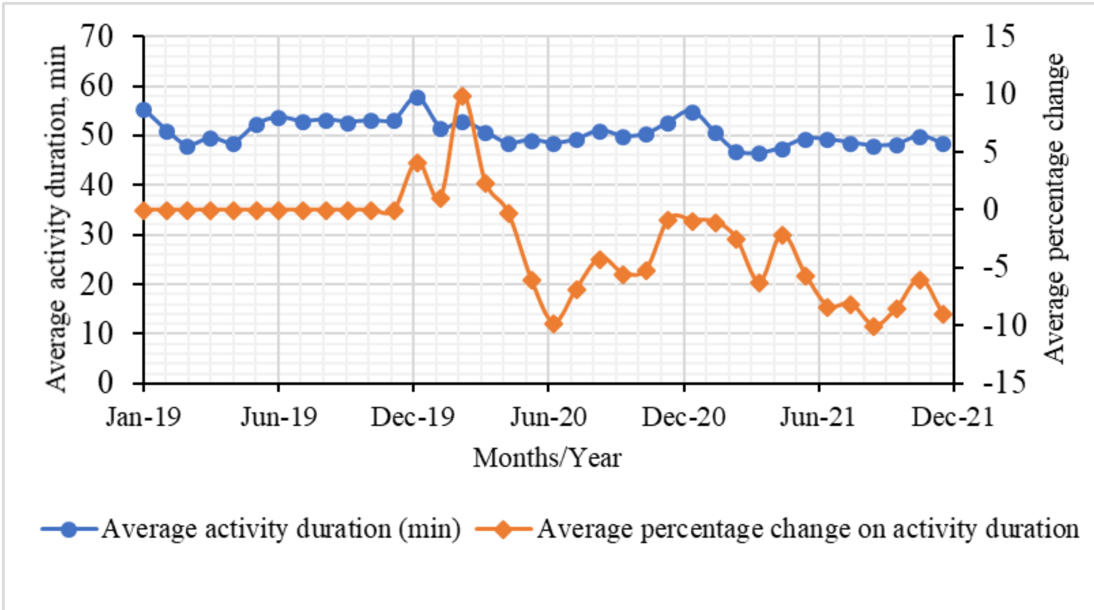
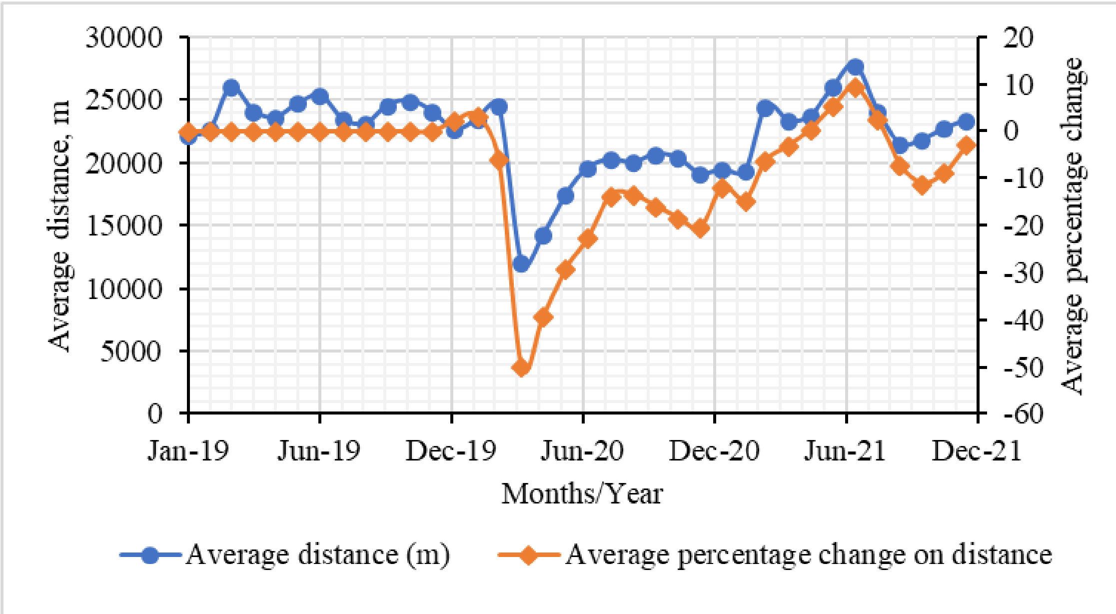


Figure 60 presents the average trip distance to destinations per month. It was found that trip distance to destinations dropped dramatically (50%) in April 2020 possibly related to COVID-19 and the implementation of lockdown measures. There were nine months in 2020 that observed a significant drop in trip distance (>10%). In the case of Hurricane Ida, no significant change was observed in trip distances. Trip distances increased by 2.6% in August 2021, possibly related to evacuation, then dropped 7.1% in September 2021, possibly related to the aftermath of widespread power outage.

Figure 60. Average travel distance (with percentage change) by month



Study scope

This study focused on the impacts of two major disruptions (COVID-19 and Hurricane Ida) on people's mobility challenges and changes in their travel patterns in Louisiana. Based on findings from the previous section, COVID-19 resulted in significant changes of human mobility measures. There was a notable decrease in the number of visitors, reduced activity duration, and shorter distances traveled from home to destinations in 2020. These deviations provided a unique opportunity to analyze the impact of the pandemic on destination access. The period from January to December 2020 (with nationwide lockdown and business re-opening) is considered the COVID-19 analysis period in this study. All the cities within Louisiana were included in the following analysis.

The second case study focuses on Hurricane Ida (2021) as hurricanes are recurring inclement weather events in Louisiana. In addition, the previous observations showed that the number of visitors dropped by 10% and activity durations became shorter by 5% in August and September 2021. Thus, the study period for Hurricane Ida is considered the two months of August and September 2021. Hurricane Ida made landfall in southeast Louisiana on 8/29/2021 and induced widespread power outages till 9/13/2021. The baseline period for comparison is August and September 2019, as the year 2020 was impacted by the pandemic and could have confounded the analysis. New Orleans was selected as our study focus as the city was more severely affected by the storm.

Mobility Index and Its Variations

Calculation of mobility index

A mobility index was created to combine the three measures and to reflect active short-distance trips (i.e., ease of destination access) as shown in the following equation.

$$Mobility_i^m = \frac{visitor_i^m * Median(dwelling_i^m)}{Median(distance_i^m)}$$

where,

$visitor_i^m$ is the total number of visitors to POI i in month m,

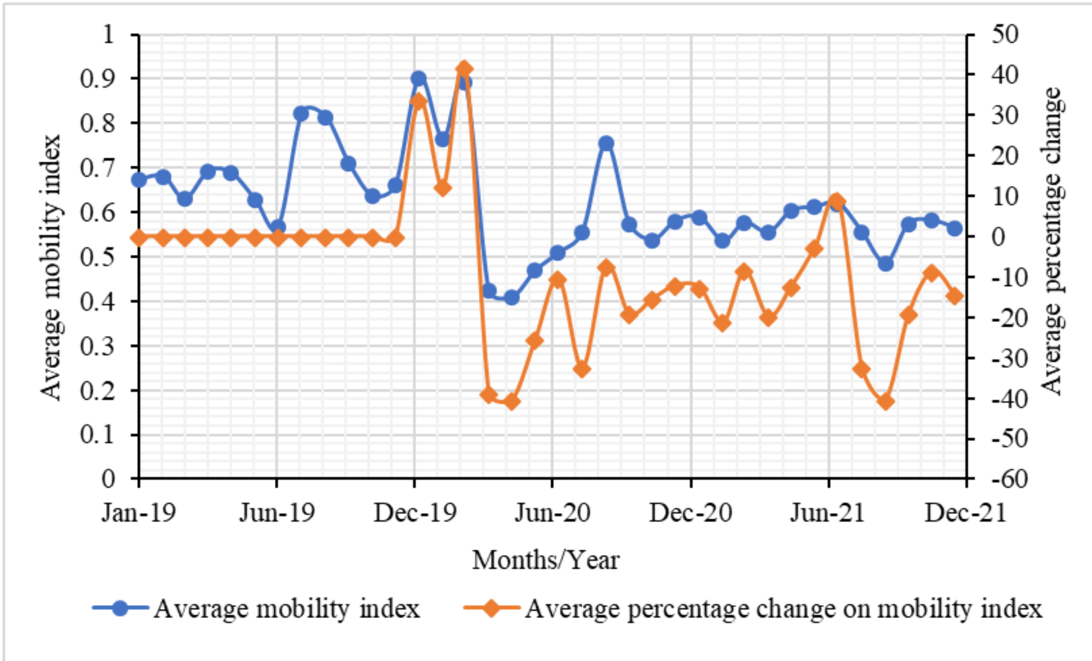
$Median(distance_i^m)$ is the median travel distance from where visitors live to POI i in month m,

$Median(dwelling_i^m)$ is the median activity duration time at POI i in month m,

$Mobility_i^m$ is the calculated mobility value for POI i in month m.

Figure 61 presents the average mobility index values by month. It was found that mobility dropped dramatically (>40%) around April and May of 2020 during the early outbreak of COVID-19. The six subsequent months also observed significant mobility declines (>10%) compared to the corresponding months in 2019. In 2021, there were even higher reductions in mobility in September (about 40%) and August (about 32%) compared with the corresponding months in 2019, possibly related to the landfall of Hurricane Ida.

Figure 61. Average mobility index (with percentage change) by month



Define and identify mobility index outliers

The previous analysis and plots focused on the aggregated impacts of disruptions on the entire region. This section presents our analysis at POI-level to observe the disaggregated impacts of disruptions. As discussed above, disruptive events can induce human mobility pattern changes and affect how people access their destinations. Therefore, it is expected to observe a POI's mobility index values that fall out of its normal range (i.e., outliers). In this study, mobility index outliers for each POI were identified by using its interquartile range (IQR). IQR is a statistical measure calculated as the difference between the third quartile (Q3) and the first quartile (Q1) of the data. Any data point that falls below $Q1 - 1.5 * IQR$ is considered a lower bound outlier, while any data point that falls above $Q3 + 1.5 * IQR$ is considered an upper bound outlier. The IQR method is preferred over the other outlier detection methods (e.g., average value with standard deviation) because it is less sensitive to extreme values and non-normal distributions.

Lower bound outliers indicate a lower frequency of activities with shorter visit durations and longer distance travels. These outliers represent cases where the number of activities at a particular destination is significantly lower than what is typically observed (i.e., lower accessibility to the destination). On the other hand, upper bound outliers indicate a higher frequency of activities with longer visit durations and shorter-distance travels.

These outliers represent cases where the number of activities at a specific destination is notably higher than the typical range of values (i.e., higher accessibility to the destination).

Figure 62 and Figure 63 present the monthly lower- and upper-bound outlier counts in Louisiana from 2019 to 2021. First, there are generally more upper-bound outliers (typically over 2,000) than the lower-bound outliers (typically less than 200). Second, April 2020 observed a significant increase in the number of lower-bound outliers, which can be attributed to COVID-19 and lockdown measures, as shown in Figure 62. In addition, May and June 2020 also had a relatively higher number of lower-bound outliers compared to 2019. Conversely, Figure 63 demonstrates that the number of upper-bound outliers was lower in the same months of 2020 than in 2019. Third, September 2021 displayed an increased number of lower-bound outliers compared to its adjacent months, while August 2021 witnessed an increased number of upper-bound outliers compared to adjacent months. Both observations could be potentially related to the impacts of Hurricane Ida.

Figure 62. Lower bound mobility outlier counts by month throughout Louisiana

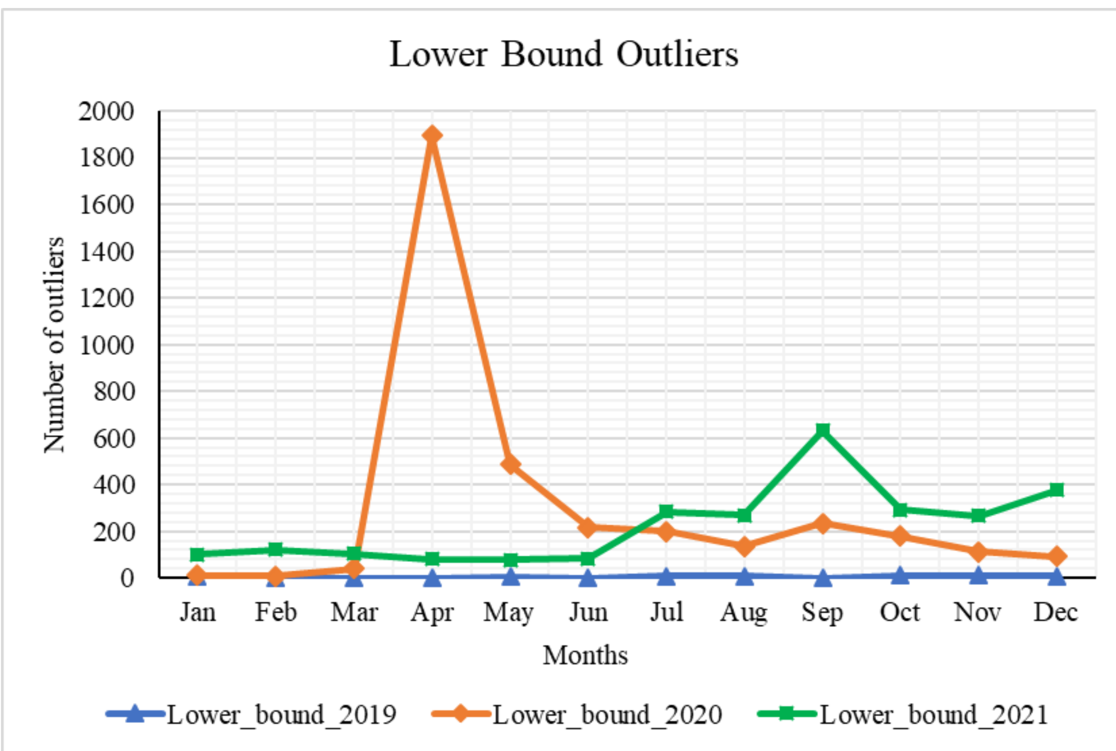
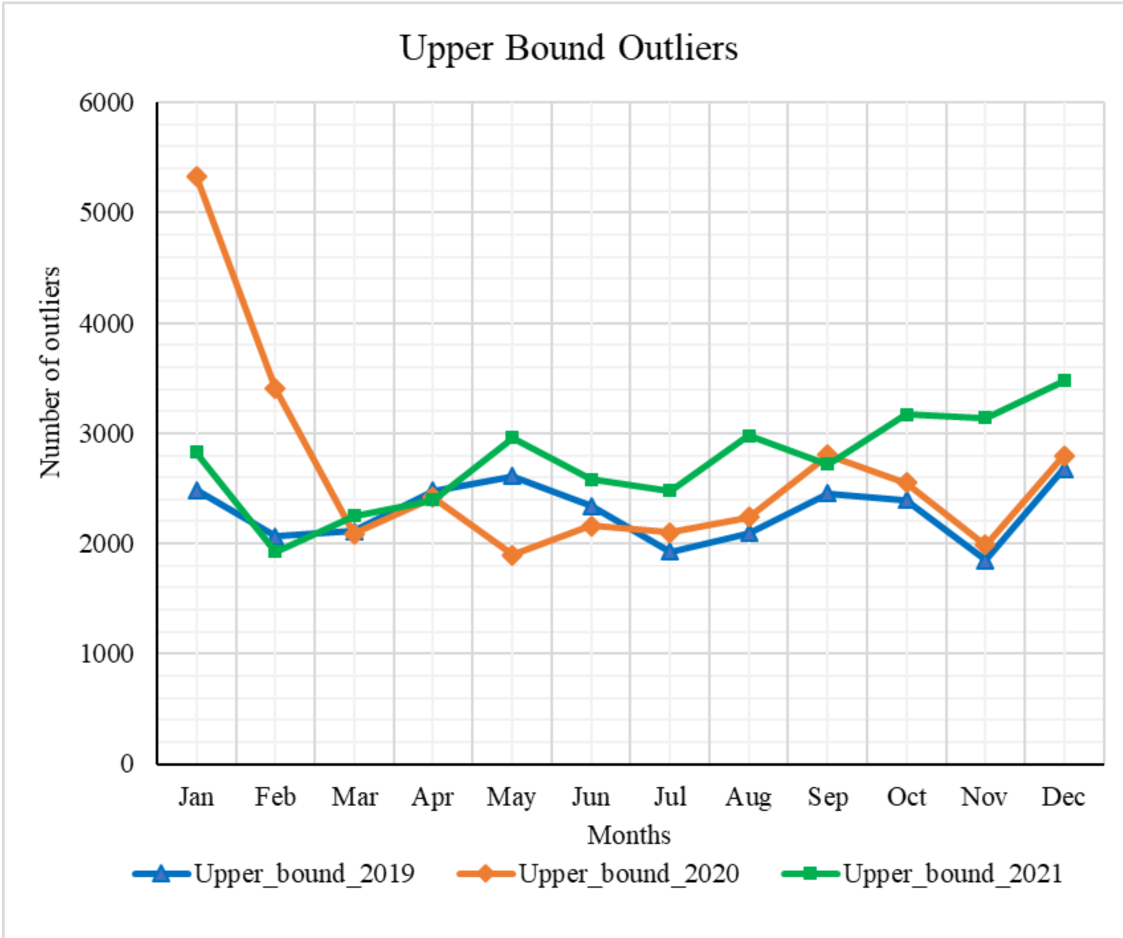


Figure 63. Upper bound mobility outlier counts by month throughout Louisiana



Mobility impacts by city and destination category

This section summarizes identified outliers by city and destination category for each case (i.e., COVID-19 and Hurricane Ida) to examine the associated magnitude and pattern changes. The magnitude change was measured by absolute and proportional changes while the pattern change was measured by conducting paired t-tests (when applicable).

COVID-19

Table 28 presents the top ten cities in Louisiana with over 1,600 POIs that experienced a greater average proportional change in outlier counts during COVID-19. Cities with proportional changes greater than 0.50 were marked in Table 28. A positive proportional change in lower-bound outliers indicates that a city experienced lower mobility and restricted access to destinations during the COVID-19 period. Meanwhile, a positive proportional change in counting upper-bound outliers indicates that a city experienced higher mobility and greater access to destinations during COVID-19. Table 1 also marks cities with their p-values from paired t-tests less than 0.05, which means the monthly distribution of outliers was significantly different in 2020 from that in 2019. Such a significant pattern change means human mobility and destination access were heavily disrupted.

When we examined lower-bound outliers, only one city – Lake Charles – experienced significant reductions in destination access during COVID-19. This finding reflects the two measures of magnitude (i.e., proportion change) and pattern (i.e., paired t-test results) simultaneously. A possible explanation is related to the role of active transportation infrastructure in serving walking/biking demands for social distancing and outdoor recreational activities during COVID-19. Calcasieu Parish, the main seat of Lake Charles, only has 33.22 miles of sidewalk and no shared-use trails or bicycle facilities [135]. The lack of active transportation infrastructure might contribute to reduced destination access during the pandemic.

Shifting to the upper-bound outlier, destination access in Slidell and New Orleans was significantly improved during COVID-19. This result might sound counter intuitive but could be explained by the relatively adequate active transportation infrastructure in that region. For example, Orleans Parish, as the main seat of New Orleans, has 1,464.15 miles of sidewalk, 22.27 miles of shared use trails, and 92.01 miles of bicycle facilities [135].

Table 28. Top 10 cities that were significantly affected by COVID-19

City	Total number of POIs	Average absolute difference (2020-2019)	Average proportion change (2020-2019)	p-value from paired t-test
Lower-bound outlier				
Lake Charles	2477	23.00	0.93	0.04
Lafayette	4052	24.50	0.60	0.13
Bossier City	1717	10.08	0.59	0.12
Metairie	3038	16.08	0.53	0.12
Shreveport	4513	19.58	0.43	0.14
Monroe	1919	8.25	0.43	0.13
Baton Rouge	7233	30.92	0.43	0.11
Slidell	1701	6.83	0.40	0.18
Alexandria	1609	5.58	0.35	0.04
New Orleans	8166	15.42	0.19	0.01
Upper-bound outlier				
Slidell	1701	21.33	1.25	0.02
New Orleans	8166	99.25	1.22	0.00
Lafayette	4052	20.75	0.51	0.14

City	Total number of POIs	Average absolute difference (2020-2019)	Average proportion change (2020-2019)	p-value from paired t-test
Metairie	3038	12.92	0.43	0.21
Bossier City	1717	6.25	0.36	0.10
Monroe	1919	6.67	0.35	0.38
Shreveport	4513	11.00	0.24	0.27
Baton Rouge	7233	9.58	0.13	0.68
Lake Charles	2477	-7.67	-0.31	0.54
Alexandria	1609	-7.83	-0.49	0.32

Table 29 presents the top ten destination categories that experienced greater human mobility variations during the COVID-19 period compared to the baseline period. Table 29 also marks destinations that: 1) have proportional changes greater than 0.50 or 2) with p-values from the paired t-test that are less than 0.05.

When both measures (i.e., proportion change and paired t-test results) are considered in analyzing lower-bound outliers, none of the destination categories experienced significant access reductions during COVID-19 according to the mentioned thresholds. However, it should be noted that some of the destination categories are critical infrastructure serving lifeline needs (e.g., health care and food), which were observed to have significant access pattern changes during COVID-19 (p-value < 0.01).

Regarding the upper-bound, nine out of the 10 place categories were accessed more frequently during COVID-19, considering three measures. First, none of the place categories had a significant (>10%) increase in the number of visitors during COVID-19. Second, some of the place categories (i.e., Other Miscellaneous Store Retailers, Support Activities for Air Transportation, and Traveler Accommodation) observed a significant drop of travel distances (i.e., -13.23% to -34.53%, reduced inter-city/state travels). Third, some of the place categories (i.e., Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly, Nursing Care Facilities (Skilled Nursing Facilities), and Support Activities for Air Transportation) had visitors spending more time at these destinations (i.e., 15.54% to 36.01% increase).

Table 29. Top 10 destination categories that were significantly affected by COVID-19

Destination Categories	Total number of POIs	Average absolute difference (2020-2019)	Average proportion change (2020-2019)	p-value from paired t-test
Lower-bound outlier				
Health and Personal Care Stores	2451	8.50	0.35	0.01

Destination Categories	Total number of POIs	Average absolute difference (2020-2019)	Average proportion change (2020-2019)	p-value from paired t-test
General Merchandise Stores, including Warehouse Clubs and Supercenters	1511	5.17	0.34	0.01
Nursing Care Facilities (Skilled Nursing Facilities)	471	1.42	0.30	0.00
Medical and Diagnostic Laboratories	352	1.00	0.28	0.00
Traveler Accommodation	1121	3.17	0.28	0.01
Personal and Household Goods Repair and Maintenance	339	0.92	0.27	0.00
Grocery Stores	2634	6.33	0.24	0.01
Specialty Food Stores	752	1.08	0.14	0.01
Offices of Other Health Practitioners	1592	2.00	0.13	0.00
Depository Credit Intermediation	1712	1.50	0.09	0.01
Upper-bound outlier				
Traveler Accommodation	1121	44.50	3.97	0.00
Support Activities for Air Transportation	64	2.17	3.39	0.00
Outpatient Care Centers	690	10.17	1.47	0.00
Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly	219	2.92	1.33	0.01
Specialty (except Psychiatric and Substance Abuse) Hospitals	237	2.58	1.09	0.01
Other Miscellaneous Store Retailers	1165	12.42	1.07	0.01
Gasoline Stations	3722	38.67	1.04	0.00
General Medical and Surgical Hospitals	747	7.58	1.02	0.00
Nursing Care Facilities (Skilled Nursing Facilities)	471	4.75	1.01	0.00
Foundation, Structure, and Building Exterior Contractors	73	-1.83	-2.51	0.01

Hurricane Ida

Our hurricane-related analysis only involves one city, New Orleans, so discussions by city are not applicable in this case. Table 30 presents the top ten destination categories that experienced greater variations in human mobility during the Hurricane Ida period compared to the baseline period in New Orleans. Table 30 marks destinations that have proportional changes greater than 0.50. Assessing pattern changes via a paired t-test is not possible in this case because we only have two data/month groups.

Regarding the lower-bound, nine out of the 10 place categories experienced significant reductions in destination access during Hurricane Ida. Firstly, all the nine place categories had fewer visitors (i.e., -17.94% to -51.94%). Secondly, some of the place categories (i.e., Office Supplies, Stationery, and Gift Stores, Offices of Physicians, and Other Amusement and Recreation Industries) observed significant increases in travel distance from home (i.e., 15.16% to 32.96%). Thirdly, certain place categories (e.g., General Merchandise Stores, including Warehouse Clubs and Supercenters, Grocery Stores, and Offices of Other Health Practitioners) had visitors spending less time at these destinations (i.e., -11.08% to -37.15%).

Regarding the upper-bound, nine out of the 10 place categories became more accessible during the study period. First, none of the place categories had more visitors during the study period. Second, some of the place categories (i.e., Book Stores and News Dealers, Health and Personal Care Stores, Museums, Historical Sites, and Similar Institutions, Other Miscellaneous Store Retailers, and Traveler Accommodation) observed significant drops in travel distance from home (i.e., 11.25 to 35.14%). Third, one place category (i.e., Drinking Places (Alcoholic Beverages)) had visitors spending more time at this destination (i.e., 14.49%).

These findings indicate that access to these place categories saw higher variations during the period affected by Hurricane Ida compared to other destination place categories, suggesting that they were more vulnerable to disruptions and access restrictions.

Table 30. Top 10 destination categories that were significantly affected by Hurricane Ida in New Orleans

Destination Categories	Total number of POIs	Average absolute difference (2021-2019)	Average proportion change (2021-2019)
Lower-bound outlier			
General Merchandise Stores, including Warehouse Clubs and Supercenters	63	1.50	2.38
Health and Personal Care Stores	207	4.00	1.93
Office Supplies, Stationery, and Gift Stores	61	1.00	1.64
Grocery Stores	198	2.00	1.01
Museums, Historical Sites, and Similar Institutions	277	2.50	0.90
Offices of Physicians	231	2.00	0.87

Destination Categories	Total number of POIs	Average absolute difference (2021-2019)	Average proportion change (2021-2019)
Other Amusement and Recreation Industries	301	2.50	0.83
Offices of Other Health Practitioners	154	1.00	0.65
Restaurants and Other Eating Places	1564	10.00	0.64
Religious Organizations	691	1.50	0.22
Upper-bound outlier			
Other Miscellaneous Store Retailers	184	17.00	9.24
Used Merchandise Stores	79	7.00	8.86
Book Stores and News Dealers	32	2.50	7.81
Sporting Goods, Hobby, and Musical Instrument Stores	122	6.00	4.92
Traveler Accommodation	280	13.00	4.64
Drinking Places (Alcoholic Beverages)	372	10.00	2.69
Automotive Repair and Maintenance	137	3.50	2.55
Museums, Historical Sites, and Similar Institutions	277	7.00	2.53
Health and Personal Care Stores	207	4.00	1.93
Restaurants and Other Eating Places	1564	6.50	0.42

Modeling Mobility Impacts

The previous section presents and discusses mobility variations by city or place category. However, it is important to consider many other factors, such as social, economic, and demographic characteristics, and examine their associations with mobility variations through statistical modeling. This section presents our statistical modeling results after testing various methods.

Methodology

The dependent variable used in the modeling is the proportional change of the human mobility index. Mobility variations during COVID-19 were selected for modeling due to its widespread impacts and greater mobility variation values. The POI dataset, consisting of 60,405 eligible observations, was aggregated to the census tract level by averaging the mobility index change values of all the POIs within each tract. The purpose of this aggregation is to achieve more social, demographic, and economic information, which was collected from the 2019 American Community Survey (ACS) 5-Year Estimates Data.

Additionally, destination place categories from SafeGraph were aggregated by census tract to capture zonal destination composition characteristics.

Various modeling techniques were examined to assess the associations between potential influencing factors and mobility variations. Initially, a linear regression was employed, but the results of the multiple linear regression modeling did not yield a satisfying enough goodness-of-fit statistic. However, this process marked 16 socio-economic/demographic characteristics and four place categories with greater statistical significance (p-value < 0.02), as shown in Table 31, for further analysis.

Table 31. Variables with significant linear associations with mobility variations

Variable	Range	Mean	Std. Dev.	Parameter estimates	P-value
Dependent Variable: Proportion change in mobility during COVID period (Jan-Dec, 2020) relative to baseline period (Jan-Dec, 2019)	[-0.65, 1.31]	0.14	0.23	na	na
Independent Variables: socio-economic and demographic					
Percentage of male	[26.1, 91.7]	48.62	5.07	0.006	0.00
Percentage of populations who are at least 60 years old	[0, 52.4]	22.16	6.65	0.003	0.01
Percentage of populations who are Hispanic or Latino	[0, 52.2]	5.20	6.19	-0.003	0.01
Percentage of populations who are White	[0, 99.8]	57.57	29.61	0.002	0.00
Percentage of populations who are Asian	[0, 47]	1.65	3.32	-0.006	0.00
Percentage of workers (16 years and over) commuting to work by driving alone	[0, 97.5]	80.46	10.87	0.004	0.00
Percentage of workers (16 years and over) commuting to work by walking	[0, 76.1]	2.38	4.81	-0.004	0.01
Percentage of workers (16 years and over) commuting to work by public transportation excluding taxicab	[0, 31.1]	2.09	4.19	-0.014	0.00
Percentage of workers (16 years and over) commuting to work by other means	[0, 27.7]	2.36	3.37	-0.010	0.00
Percentage of low-income households (less than $25K)	[0, 91.1]	30.46	15.08	-0.002	0.00
Percentage of civilian noninstitutionalized populations with health insurance coverage	[64, 100]	89.98	4.95	0.0052	0.00
Percentage of renter-occupied housing units	[0, 100]	37.63	21.02	-0.0031	0.00

Variable	Range	Mean	Std. Dev.	Parameter estimates	P-value
Percentage of households with at least one vehicle	[34.3, 100]	89.56	10.19	0.0057	0.00
Percentage of married couple families	[0, 100]	39.90	15.88	0.0044	0.00
Estimates of total housing units	[3, 6974]	1834.48	924.54	0.00005	0.00
Estimates of households with computer and internet use	[3, 6371]	1548.98	838.40	0.00005	0.00
Independent Variables: destination place category counts					
Count of General Merchandise Stores, including Warehouse Clubs and Supercenters	[0, 8]	1.13	1.33	0.023	0.00
Count of Grocery Stores	[0, 12]	1.96	1.86	0.016	0.00
Count of Depository Credit Intermediation	[0, 15]	1.12	1.77	0.009	0.02
Count of Gasoline Stations	[0, 13]	2.10	2.14	0.018	0.00

Subsequently, other approaches such as polynomial regression and generalized additive modeling techniques were explored, but their goodness-of-fit statistics did not yield satisfying enough results as well. Thus, a random forest (RF) regression model was selected to further explore non-linear associations. Random forest is an ensemble technique that uses the potential of bagging or bootstrapping to construct multiple subsets from training samples by selecting them randomly and with replacement [136]. It is a supervised learning algorithm that builds upon the foundation of decision trees, possesses the advantages of simplicity and ease of implementation, and has remarkable performance specifically in regression tasks [137]. RF stands out for its ability to model complex nonlinear associations between independent variables and the dependent variable, as well as capture higher-order interactions among variables due to its flexible and adaptable modeling structure [138]. In regression scenarios where the dependent variable is continuous, random forest predictions are obtained by averaging the predictions generated by multiple decision trees [139].

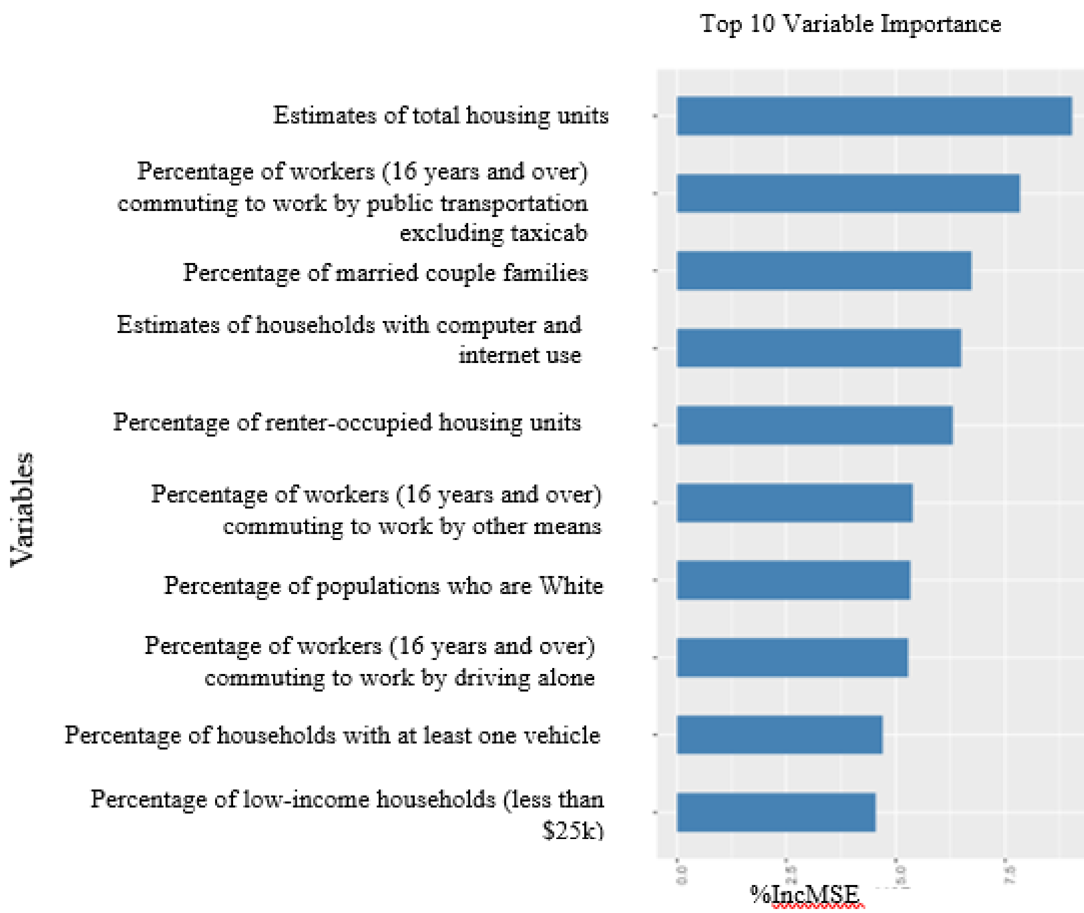
Our dataset includes 1,122 eligible observations (i.e., census tracts), which were split into a training set (90% of the data) for model estimation and a testing set (10% of the data) for model evaluation. To achieve optimal model generalization ability, the selection of model hyperparameters was done using a five-fold cross-validation technique. This approach ensures the identification of the best hyperparameters that result in a well-performing and robust model. In RF, a variable importance measure is generated to help us understand how the prediction process works and identify and remove less important variables, which simplifies the model and allows clear understanding of key influencing factors [136].

Results from random forest models

The random forest package in R was used for model estimation. The %IncMSE (percentage increase in mean squared error) was used to determine variable importance, where a larger value indicates a greater importance of the variable [140]. Figure 64 presents a plot illustrating the percentage mean squared error (%IncMSE) for the top 10 important variables.

First, as shown in Figure 64, housing-related factors play a significant role. The estimates of total housing units (9.04%) and the percentage of renter-occupied housing units (6.31%) suggest that mobility changes are associated with residential capacity and composition. Secondly, variables related to family structure and connectivity are notable. The percentage of married couple families (6.73%) and the estimates of households with computer and internet use (6.49%) highlight the influence of family structure and digital connectivity in mobility variations. Additionally, commuting-related mode choices are important contributors. The percentage of workers (16 years and over) commuting to work by public transportation excluding taxicab (7.83%), as well as the percentage of workers (16 years and over) commuting to work by other means (5.39%) and driving alone (5.29%), indicate that travel modes influence mobility patterns. Areas with a higher dependence on public transportation may experience unique mobility changes [141], [142]. Finally, demographic and economic factors play a role. The percentage of populations who are White (5.34%) and the percentage of low-income households (less than $25K) (4.54%) suggest that the ethnicity and income levels of an area influence mobility changes. The percentage of households with at least one vehicle (4.70%) reflects that the availability of private vehicles shapes mobility behavior.

Figure 64. Independent variables against their corresponding %IncMSE



The model performed well on the test data, which represented 10% of the entire dataset. The Mean Square Error (MSE) value of 0.036 shows that the model's predicted values deviate minimally from the actual values on average. Model performance can be further improved by incorporating more influential variables from other perspectives.

Conclusions

This paper used a large-scale dataset from SafeGraph collected over a three-year period to explore the social impacts of major disruptions (including COVID-19 and Hurricane Ida) on human mobility from the perspective of accessing destinations in Louisiana.

The findings from measuring mobility during the COVID-19 showed that the number of visitors dropped notably between March and May 2020. Trip distances to destinations declined dramatically in April 2020, while activity duration increased in March 2020 (which might be related to emergency declarations) and dropped notably in July 2020 (which might be related to travel cancelations). This shows that COVID-19 had a greater impact on human mobility during its early outbreak. Destination access patterns changed significantly among destinations providing health care and food, which might need more attention in the future to serve lifeline needs.

In the case of Hurricane Ida, notable decreases were observed in the number of visitors and activity duration in August and September in 2021. However, the impact magnitude of Hurricane Ida was relatively smaller compared to COVID-19, but still resulted in reductions in destination access. However, some destination categories did experience increased access during the hurricane in terms of shorter travel distance from home (e.g., museums and traveler accommodations due to lower volume of out-of-state travelers) or greater activity duration time (e.g., open bars served as community hubs where people charge their phone, access mutual aid, or go to communicate with neighbors about the ongoing issue).

Two modeling approaches were eventually used to analyze both linear and non-linear relationships between community characteristics and mobility variations during the COVID-19 study period. The four common variables from the two models showed negative associations with mobility variations. Specifically, a census tract is more likely to experience decreased mobility (i.e., restricted destination access) if it has a higher percentage of workers commuting by public transportation (excluding taxicabs) or other means, a higher percentage of low-income households, and/or more renter-occupied housing units. This finding suggests that communities relying on public transit and other miscellaneous modes of commuting are more likely to face destination access limitations compared with those relying on private vehicles. The disparities may be mainly due to discontinued/reduced transit services as well as concerns about virus transmission in shared mobility options and the financial difficulties faced by low-income populations. Meanwhile, the study also found that some cities with more destination access during COVID-19 (e.g., New Orleans) have much better active transportation infrastructure (e.g., sidewalk and bike lanes) than those with reduced destination access (e.g., Lake Charles).

These findings remind transportation authorities of the importance of developing multimodal transportation systems and coming up with temporary countermeasures to address travel demands during disruptions (e.g., implementing “slow streets” during COVID-19). The modeling results also showed the importance of income levels in influencing mobility changes during COVID-19. Thus, communities with the above-mentioned characteristics should be our focus in providing equitable access to destinations during public health crises in the future.

Appendix C: Dashboard Data Dictionary

Active transportation refers to any human-powered mode of transportation, such as walking and biking. This dashboard is designed to support Louisiana's statewide active transportation planning with safety, mobility, and accessibility needs in mind. The following data dictionary only includes final versions of the indices and scores to guide dashboard uses. Testing versions are not included here to improve clarity. Any dashboard users who are interested in learning about the research process are welcome to refer to our final project report.

Feature layer name	**Feature type**	**Data source**	**Data sharing**	**Layer and attribute description**
Disaggregate data				
DOTD Sidewalk	Line	DOTD	Online Dashboard	Sidewalk data are collected by Fugro in 2011 and published on DOTD Geospatial Gateway. • FID • RouteID: route ID. • Type: whether this sidewalk is marked as "Outside" or "Inside." • DataYear: the year when the data was collected. • Deficiency (as defined by DOTD)
Bicycle Network	Line	LTRC Project 21-2SS and LCRT Project H.014664	Online Dashboard	Bicycle facilities collected by the research team with local inputs for a research project completed in 2022. Data were collected from publicly available sources (e.g., open data portals, static maps, and plan documents) and may contain errors and omissions. These preliminary layers are included as a reference for planning purposes only. • FID • Fac_Name: Facility name.

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• Install_Ye: when the facility was installed. • FacilityTy: facility types which include bike boulevard, bike lane, buffered bike lane, bus/bike lane, mountain bike trail, and protected bike lane. • PARISH: the parish where the facility is located.
Shared-use trail network	Line	LTRC Project 21-2SS and LCRT Project H.014664	Online Dashboard	Shared-use trails collected by the research team with local inputs for a research project completed in 2022. Data were collected from publicly available sources (e.g., open data portals, static maps, and plan documents) and may contain errors and omissions. These preliminary layers are included as a reference for planning purposes only. • FID • Fac_Name: Facility name. • Install_Ye: when the facility was installed. • FacilityTy: facility types which include shared-use trail. • PARISH: the parish where the facility is located.
Transit network	Line	LTRC Project 21-2SS	Online Dashboard	Transit network collected by the research team with local inputs for a research project completed in 2022. Data were collected from publicly available sources (e.g., open data portals, static maps, and plan documents) and may contain errors and omissions. These preliminary layers are included as a reference for planning purposes only. • FID • route_id: route ID (where specified for GTFS). • Agency: the name of the transit agency operating the transit service. • rt_shrt_nm: route name or number in short.

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• rt_long_nm: Full name of a route. This name is generally more descriptive than the route_short_name and often includes the route's destination or stop. • rt_typ_txt: route type in text.
Summary 1: by hexagon				
Hexagon (All_Hex9)	Polygon	LTRC Project 22-5SS	Online Dashboard	This layer summarizes the safety, mobility, and connectivity index values and the generated investment score by hexagon. The edge length of a hexagon is 0.2 km, and its area size is 0.1 km^2. • FID • BLKGP: the census block group in which a hexagon is located. • Tract: the census tract in which a hexagon is located. • Parish: the parish in which a hexagon is located. • District: the DOTD district in which a hexagon is located. • Area: the area of a hexagon (Unit: square miles). • Area2: the area within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid) (Unit: square miles). Safety (Note: crash data are collected by DOTD. The data covers bicyclist/pedestrian involved crashes that occurred between 1/1/2018 and 12/31/2021): • NumCrash: the number of bicyclist/pedestrian involved crashes within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid). • NumCrashIF: the number of injuries and fatalities in the bicyclist/pedestrian involved crashes within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid).

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• StdSafe: the standardized/normalized value of NumCrashIF with statewide average and deviation. The "Hexagons (Level 9): Safety Index" layer on the online dashboard presents this value. Mobility (Note: mobility data are collected from SafeGraph. The data covers activities between 1/1/2018 and 12/31/2021. Mobility outliers were removed for planning purposes): • POICount: the number of point of interests (POIs, which are public places with a NAICS code) within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid). • MIndex_2: the sum of mobility index values of all POIs within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid). This figure represents the number and duration of short-distance trips (by any travel mode) to the POI from the surrounding area. In addition, the mobility index was adjusted to incorporate equity factors (i.e., population density and the proportion of households whose income is below poverty level), to reflect the potential for high-impact investments in areas where population density and need are both greater. Refer to the Methodology section in our final report for more details. • StdMob: the standardized/normalized value of MIndex_2 with statewide average and deviation. The "Hexagons (Level 9): Mobility Index" layer on the online dashboard presents this value. Connectivity: • LenHwy: the length of non-interstate roadways within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid) (Unit: miles) (Note: roadway data are collected by Fugro in 2011

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				and published on DOTD Geospatial Gateway. One direction of one-way roads is counted, while both directions of two-way roads are counted. The number of lanes is not considered.) • LenWalk: the length of sidewalks within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid) (Unit: miles) (Note: sidewalk data are collected by Fugro in 2011 and published on DOTD Geospatial Gateway.) • LenTrail: the length of shared-use trail within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid). (Unit: miles) • LenBike: the length of bicycle facilities within 0.2-km radius of the edges of a hexagon (or 0.4 km from its centroid). (Unit: miles) • ConIndex_2: the connectivity index value calculated for each hexagon and reflects pedestrian and bike facility density. (ConIndex_2 = (LenWalk + LenTrail + LenBike)/Area2) (Unit: mile per square miles) • StdCon: the standardized/normalized value of ConIndex_2 with statewide average and deviation. The "Hexagons (Level 9): Connectivity Index" layer on the online dashboard presents this value. <u>Investment potential score</u>: • InvScore: a score reflecting the likely potential of a hexagon (i.e., higher bicyclist/pedestrian injuries and fatalities, more short-distance trips with longer activity duration times, and lower bicyclist/pedestrian facility density) for investments in active transportation facilities to have a higher impact on the number and safety of trips taken by walking or bicycling. The investment score with the second type adjustment to the mobility index and

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				the second type of connectivity index. The "Hexagons (Level 9): Investment Score" layer on the online dashboard presents this value. $$InvScore = StdSafe + StdMob - StdCon$$
Summary 2: by zone				
Block group (EPA_SLD)	Polygon	EPA	Online Dashboard	This layer provides data from the Smart Location Database (SLD) Version 3.0, which is released by the U.S. Environmental Protection Agency (EPA) in 2021. SLD "summarizes more than 90 different indicators associated with the built environment and location efficiency. Indicators include density of development, diversity of land use, street network design, and accessibility to destinations as well as various demographic and employment statistics. Most attributes are available for all U.S. block groups." A full list of variables and data dictionary could be found from here.
Census Tract (tl_2020_22_tract20)	Polygon	US Census and USDOT	Online Dashboard	This layer provides the following information related to equity at the census tract level: • FID • GEOID20: census tract ID as defined in the US Census database. Data from 2016-2020 American Community Survey 5-Year Estimates: • edu: Percentage of populations with no high school diploma (age 25+). • disab: Percentage of noninstitutionalized populations with a disability. • lang: Percentage of populations speaking English less than very well.

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• unemp: Percentage of unemployment. • food: Percentage of households receiving nutrition/SNAP benefits. • health: Percentage of noninstitutionalized populations without health insurance coverage. • veh0: Percentage of occupied housing units without vehicles. • age65: Percentage of populations over 65 years old. • raceW: Percentage of White populations. • raceBAA: Percentage of Black or African American populations. • raceAIAN: Percentage of American Indian and Alaska Native populations. • raceA: Percentage of Asian populations. • raceNH: Percentage of Native Hawaiian and Other Pacific Islander populations. • raceOther: Percentage of other race populations. • poverty: Percentage of populations below poverty level. Data from USDOT's Transportation Disadvantaged Census Tracts (released in 2022): • DisTrans: whether a census tract is identified as transportation disadvantaged by USDOT. • DisHealth: whether a census tract is identified as health disadvantaged by USDOT. • DisEcon: whether a census tract is identified as economy disadvantaged by USDOT. • DisEquity: whether a census tract is identified as social disadvantaged by USDOT.

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• DisResilt: whether a census tract is identified as resilience disadvantaged by USDOT. • DisEnvir: whether a census tract is identified as environment disadvantaged by USDOT. • DisUSDOT: whether a census tract is identified as disadvantaged by USDOT in general (when four or more of the above-mentioned disadvantaged indicators are marked as "yes")
Parish (Parish_Score)	Polygon	US Census and LTRC Project 22-5SS	Online Dashboard	This layer provides the following information at parish level: • FID • NAME20: parish name • District: DOTD district ID • ALAND: land area (Unit: square meters) • TotalPop: population size of a parish • PopDen: population density (Unit: per square miles) • TotalHH: number of households • TotalPoor: number of households whose income in the past 12 Months below poverty level • poverty: poverty level Safety: • NumCrash: the number of bicyclist/pedestrian involved crashes within a parish (between 1/1/2018 and 12/31/2021). • NumCrashIF: the number of injuries and fatalities that occurred in the above-mentioned crashes within a parish (between 1/1/2018 and 12/31/2021). • StdSafe: the standardized/normalized value of NumCrashIF with statewide average and deviation. Mobility:

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• POICount: the number of POIs within a parish. • MIndex_2: the sum of mobility index values of all POIs within a parish. This figure represents the number and duration of short-distance trips (by any travel mode) to the POI from the surrounding area. In addition, the mobility index was adjusted to incorporate equity factors (i.e., population density and the proportion of households whose income below poverty level), to reflect the potential for high-impact investments in areas where population density and need are both greater. • StdMob: the standardized/normalized value of MIndex_2 with statewide average and deviation. Connectivity: • LenHwy: the length of non-interstate roadways within a parish. (Unit: miles) • LenWalk: the length of sidewalks within a parish. (Unit: miles) • LenTrail: the length of shared-use trail within a parish. (Unit: miles) • LenBike: the length of bicycle facilities within a parish. (Unit: miles) • ConIndex_2: the connectivity index value calculated for each parish and reflects pedestrian and bike facility density. (ConIndex_2 = (LenWalk + LenTrail + LenBike)/ALAND) (Unit: mile per square miles) • StdCon: the standardized/normalized value of ConIndex_2 with statewide average and deviation. Investment:

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• InvScore: the investment score values calculated at parish level by using StdSafe, StdMob, and StdCon.
District (District_Score)	Polygon	DOTD and LTRC Project 22-5SS	Online Dashboard	This layer provides the following information at district level: • FID • DOTD_DIS_1: DOTD district name. • Main_city: main city where a district sits. • ALAND: land area (Unit: square meters) • TotalPop: population size of a district • PopDen: population density (Unit: per square miles) • TotalHH: number of households • TotalPoor: number of households whose income in the past 12 Months below poverty level • Poverty: poverty level Safety: • NumCrash: the number of bicyclist/pedestrian involved crashes within a district (between 1/1/2018 and 12/31/2021). • NumCrashIF: the number of injuries and fatalities that occurred in the above-mentioned crashes within a district (between 1/1/2018 and 12/31/2021). • StdSafe: the standardized/normalized value of NumCrashIF with statewide average and deviation. Mobility: • POICount: the number of POIs within a district. • MIndex_2: the sum of mobility index values of all POIs within a district. This figure represents the number and duration of short-distance trips (by any travel mode) to the POI from the surrounding area. In addition, the mobility index was adjusted to

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				incorporate equity factors (i.e., population density and the proportion of households whose income is below the poverty level). To reflect the potential for high-impact investments in areas where population density and need are both greater. • StdMob: the standardized/normalized value of MIndex_2 with statewide average and deviation. Connectivity: • LenHwy: the length of non-interstate roadways within a district (Unit: miles). • LenWalk: the length of sidewalks within a district (Unit: miles). • LenTrail: the length of shared-use trail within a district. (Unit: miles) • LenBike: the length of bicycle facilities within a district. (Unit: miles) • ConIndex_2: the connectivity index value calculated for each district and reflects pedestrian and bike facility density. (ConIndex_2 = (LenWalk + LenTrail + LenBike)/Area2) (Unit: mile per square miles) • StdCon: the standardized/normalized value of ConIndex_2 with statewide average and deviation. Investment: • InvScore: the investment score values calculated at district level by using StdSafe, StdMob, and StdCon.
Summary 3: by roadway segment				

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
Segment	Line	DOTD and LTRC Project 22-5SS	Online Dashboard	This layer summarizes index and score values by non-interstate highway segment of equivalent sizes (0.1 mile). • FID • RouteID: LRSID of a route. • FullName: full name of a route. • ControlSec: control section ID. • ParishNumb: DOTD parish ID. • DOTDDistri: DOTD district ID. • length: segment length. (Unit: miles) Safety (Note: crash data are collected by DOTD. The data covers bicyclist/pedestrian involved crashes that occurred between 1/1/2018 and 12/31/2021): • NumCrash: the number of bicyclist/pedestrian involved crashes within 0.1-mile radius to a segment (between 1/1/2018 and 12/31/2021). • NumCrashIF: the number of injuries and fatalities occurred in the above-mentioned crashes within 0.1-mile radius to a segment (between 1/1/2018 and 12/31/2021). • CrashFQ_BP: the frequency (per mile) of injuries and fatalities occurred within 0.1-mile radius to a segment (i.e., "NumCrashIF" adjusted by "length"). • StdSafe: the standardized/normalized value of CrashFQ_BP. Mobility (Note: mobility data are collected from SafeGraph. The data covers activities between 1/1/2018 and 12/31/2021. Mobility outliers were removed for planning purposes):

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• POICount: the number of POIs within 0.1-mile radius to a segment • MIndex_3: the sum of mobility index values of all POIs within 0.1-mile radius to a segment. This figure represents the number and duration of short-distance trips (by any travel mode) to the POI from the surrounding area. First, the mobility index was adjusted to incorporate equity factors (i.e., population density and the proportion of households whose income below poverty level), that reflects the potential of high-impact investments in areas where population density and need are both greater. Second, the mobility index was adjusted to account for the variation of segment lengths. • StdMob: the standardized/normalized value of MIndex_3 with statewide average and deviation. Connectivity: • LenHwy: length of non-interstate roadways within 0.1-mile radius to a segment. (Unit: miles) • LenWalk: length of sidewalk in a bin/hexagon within 0.1-mile radius to a segment. (Unit: miles) • LenTrail: the length of shared-use trail within 0.1-mile radius to a segment. (Unit: miles) • LenBike: the length of bicycle facilities within 0.1-mile radius to a segment. (Unit: miles) • ConIndex_3: Density of active transportation facilities (including sidewalk, shared-use trail, and bicycle facilities). The connectivity

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				index was adjusted to account for the variation of segment lengths. • StdCon: the standardized/normalized value of ConIndex_3 with statewide average and deviation. Investment potential score: • InvScore: a score reflecting the likely potential of a segment (i.e., higher bike/ped injuries and fatalities, more short-distance trips with longer activity duration times, and lower sidewalk coverage) for investments in active transportation facilities to have a higher impact on the number and safety of trips taken by walking or bicycling. The “Network Features: Non-Interstate Roadway Segment” layer on the online dashboard presents this value. $InvScore = StdSafe + StdMob - StdCon$

Appendix D: Stakeholder Engagement Survey Instrument

Analyzing Active Mobility - Stakeholder Beta Test Feedback

Start of Block: Default Question Block

Q12 The purpose of this beta release is to share the overall findings of the analysis with stakeholders, especially those with local knowledge of safety, mobility, and connectivity issues in their jurisdiction or community. We want to ground-truth the findings and identify possible improvements to make the data more easily understood and more actionable. Thank you for your interest and your assistance!

How to use this beta tool:

We recommend beginning by zooming in on an area of the state with which you are familiar.

On the dashboard, there are two summary tables of aggregate findings at the parish and district level, as well as a table representing the top 100 locations where safety, mobility, and connectivity indexes results in a very high investment score.

If you click on a grid cell (any colored square) on the map, a record card will pop up providing the three index scores, the overall investment score, the length of roadway miles, the length of sidewalks (as reported in DOTD's ARAN asset management system), and the number of total crashes and total injuries or fatalities. Note that the number of injuries/fatalities may be higher than the number of total crashes if multiple victims were involved.

The darker the color of the cell, the higher the investment score. Note that the data is symbolized based on the degree to which it deviates from the statewide average: darker colors represent higher-than-average scores, while light colors represent lower-than-average scores. This does not necessarily mean that these areas are unsuitable for investment, but rather that the current data indicates that there may be less potential for active transportation relative to other locations in the state.

Please explore additional locations that you are familiar with and then respond to this survey. Be sure to click on individual cells of interest to see the individual connectivity, mobility, and safety index scores.

For additional reference information about the tool and methods, please refer to the project capsule and the email invitation to participate in testing.

Q1 Stakeholder Respondent Role:

- ○ DOTD (2)
- ○ MPO or other regional entity (3)
- ○ Local Government Agency (4)
- ○ Non-governmental stakeholder: Consultant/Private Sector (7)
- ○ Non-governmental stakeholder: Advocate/Non-Profit Organization (8)
- ○ Transit Agency (5)
- ○ Other (Specify) (6) ____

Q24 Which of the following best describes your role?

- ▢ Design/Engineering (1)
- ▢ Administration (2)
- ▢ Planning (3)
- ▢ Project Management (4)
- ▢ Operations (5)
- ▢ Consultant (6)
- ▢ Other (Describe) (7)

____

Q25 Which of the following best describes the region(s) in which you work? (select all that apply)

- ☐ Statewide/DOTD HQ (1)
- ☐ New Orleans area (District 02) (2)
- ☐ Lafayette area (District 03) (3)
- ☐ Shreveport/Bossier area (District 04) (4)
- ☐ Monroe area (District 05) (5)
- ☐ Lake Charles Area (District 07) (6)
- ☐ Alexandria area (District 08) (7)
- ☐ Chase area (District 58) (8)
- ☐ Baton Rouge area (District 61) (9)
- ☐ Northshore area (District 62) (10)

3 **1. Alignment with local knowledge**

This section addresses the extent to which the data makes sense and aligns with local knowledge of active transportation safety, mobility, and connectivity around the state. First, zoom in on an area of the state with which you are familiar. (Tip: Clicking a record in the summary tables will take you to that district/parish.)

Q26 Does the appearance of the map (presenting the Investment Score) align with your professional understanding of active transportation (i.e., walking/biking) needs in your area? (e.g., darker colors represent areas with greater needs)

- ○ Extremely accurately (14)
- ○ Very accurately (15)
- ○ Moderately accurately (16)
- ○ Slightly accurately (17)
- ○ Not accurately at all (18)

Q27

Next, click the “Layers” button on the top right corner of your map and then click the “Eye” symbol to make the Safety Index layer visible (and turn any other layers off), as indicated in the following figure:

Does the appearance of the map (presenting the Safety Index) align with your professional understanding of **safety concerns** in your area? (e.g., darker colors typically represent areas with more crashes)

- ◯ Extremely accurately (14)
- ◯ Very accurately (15)
- ◯ Moderately accurately (16)
- ◯ Slightly accurately (17)
- ◯ Not accurately at all (18)

Q4 Now, click the "Layers" button again in the top right corner of your map and then click the "Eye" symbol to make the Mobility Index layer visible (and turn any other layers off), as indicated in the following figure:

Does the appearance of the map (presenting the mobility index) align with your professional understanding of **mobility patterns** in your area? (e.g., darker colors represent more trips, more public places, and specifically more short-distance trips to those destinations)

- ◯ Extremely accurately (1)
- ◯ Very accurately (2)
- ◯ Moderately accurately (3)
- ◯ Slightly accurately (4)
- ◯ Not accurately at all (5)

Q5 Finally, click the “Layers” button again in the top right corner of your map and then click the “Eye” symbol to make the Connectivity Index layer visible, (and turn any other layers off), as indicated in the following figure:

Does the appearance of the map (representing the Connectivity Index) align with your professional understanding of **pedestrian connectivity** in your area? (e.g., darker colors indicate areas where there is less sidewalk coverage relative to roadway mileage)

- ○ Extremely accurately (1)
- ○ Very accurately (2)
- ○ Moderately accurately (3)
- ○ Slightly accurately (4)
- ○ Not accurately at all (5)

Q6 As noted, the Connectivity Index is based on statewide data about pedestrian facilities, which are being used as an interim proxy for active mobility while standardized statewide bicycle facility data is being developed. To what extent do you think the Connectivity Index also reflects **bicycle connectivity** in your area?

- ◯ Extremely accurately (1)
- ◯ Very accurately (2)
- ◯ Moderately accurately (3)
- ◯ Slightly accurately (4)
- ◯ Not accurately at all (5)

Q7 Are there any areas where the results are surprising, counterintuitive, or simply seem incorrect? If so, please identify the general area or corridor or click on the grid cell in question and report the FID number. Please briefly explain the nature of any discrepancies or unusual results you have identified:

____

____

____

____

____

Q8 Now, please reload the webpage (to reset the dashboard) and click any grid cell to investigate an area you are interested.

In your perception, do the results generally align with local **demand model or analysis outputs, and/or local multimodal traffic counts**?

- ○ Extremely aligned (1)
- ○ Somewhat aligned (2)
- ○ Neither aligned nor misaligned (3)
- ○ Somewhat misaligned (4)
- ○ Extremely misaligned (5)
- ○ Not applicable/Unknown (6)

Q10 Please elaborate on any observations about the extent to which the data presented aligns or diverges from previous analyses or data with which you are familiar.

____

____

____

____

____

Q9 In your perception, do the results generally align with priorities identified in **local bicycle or pedestrian plan documents**?

- ○ Extremely aligned (1)
- ○ Somewhat aligned (2)
- ○ Neither aligned nor misaligned (3)
- ○ Somewhat misaligned (4)
- ○ Extremely misaligned (5)
- ○ Not applicable/Unknown (6)

Q11 Please elaborate on any observations about the extent to which the data presented aligns or diverges from **other maps or plans** with which you are familiar.

____

____

____

____

____

End of Block: Default Question Block

Start of Block: Block 1

Q13 **2. Improvements to the platform or underlying indices**

The goal of this project is to make the underlying indices, as well as an updated online map platform, available to the public. The primary audience for this platform includes planners, project managers, and transportation agency staff. With that in mind, please consider about any improvements you suggest to make the pilot platform usable and understandable.

Q14 Data Visualization and User Interface: Does the current analysis grid size (500 meters) provide a sufficient level of detail for interpreting the data for your jurisdiction and/or potential use case?

- ○ Yes (1)
- ○ No (2)

Q15 Why or why not?

____

____

____

____

____

Q16 Do you have any suggested improvements to the current online map **symbology/presentation** to make it easier to understand or interpret?

____

____

____

____

____

Q17 Do you have any questions or suggestions about the **connectivity, mobility, and safety indices**, or about the overall **investment score**?

____

____

____

____

____

Q28 Returning to the map, we have included a layer to indicate equity opportunity areas, as defined by the USDOT's Transportation Disadvantaged Census Tracts Layer. This layer is the most commonly the most commonly used tool in USDOT discretionary grant programs to determine disadvantaged community status (you can toggle this on by clicking "Zones" in the menu, as in the figure below).

This layer can be used to identify whether a high index or investment score falls within a federally designated Justice40 Initiative focus area.

Do you have any comments regarding the inclusion of **equity** in this tool, or questions or suggestions about **other data** that should be displayed or summarized, in addition to the index scores?

____

____

____

____

____

Q19 **3. Potential Data Applications and Future Research Needs**

This section asks you to consider on how you or your colleagues could utilize the final data outputs derived from this analysis. This helps us identify the next steps for developing this project and/or for conducting future research that will support active transportation planning, policy, and infrastructure implementation in Louisiana

Q20 In your professional role, do you think that you would use this data (either via online map platform, or by downloadable data extract) in any aspect of your practice? (Select all that apply)

- ☐ As a demand assessment/estimation tool (1)
- ☐ As a safety screening tool (2)
- ☐ To identify active mobility priority areas (3)
- ☐ To identify potential conflicts among transport modes (4)
- ☐ To support policy implementation (5)
- ☐ As part of performance measurement or trend analysis (6)
- ☐ To identify maintenance priorities (7)
- ☐ As part of long-range planning (8)
- ☐ As part of project prioritization process (9)
- ☐ As part of project scoping process (10)
- ☐ As part of project design or engineering process (11)
- ☐ As part of grant proposal development (12)
- ☐ As part of advocacy effort or public communications/outreach (13)
- ☐ Other (Specify) (14) ____
- ☐ N/A - I do not perceive any direct applications for use of this data in my work (15)

Q23 Do you have any other questions, comments, or suggestions about this study?

Feel free to let us know: how you would anticipate using the platform or underlying data (including any needed enhancements to make it more useful) about other safety, mobility, or connectivity data needs not addressed by this study?
Please provide contact information if you'd like us to follow up with you! (optional)

- ○ Comments (1) ____
- ○ Name (2) ____
- ○ Email (3) ____
- ○ Phone (4) ____

End of Block: Block 1