Project Prioritization: Using BlueBikes Ridership and Spatial Network Analysis to analyze Boston-area Bicycle facilities

A thesis submitted by

Andrew Brieff

In partial fulfillment of the requirements for the degree of

Master of Arts

In

Urban and Environmental Policy and Planning

Tufts University

May 2024

Thesis Advisor: Sumeeta Srinivasan

Thesis Reader: Shan Jiang

Abstract

Many cities have chosen to promote increased cycling mode-share as a key component of transportation planning. Increased cycling has positive impacts on traffic congestion, air pollution, and public health. Research shows, however, that most potential cyclists will not do so in mixed traffic with automobiles. This thesis analyzes the intersection between investments in bicycle-sharing systems and bicycle infrastructure, analyzing where the network of cycling infrastructure does not correspond with the areas of highest demand.

This thesis uses traffic stress, traffic flow assignment, and equity to analyze the bicycle infrastructure for three cities served by BlueBikes. It identifies locations where highly central streets are high-stress and particularly deserving of prioritization. The findings of the thesis show significant gaps in safe routes along the most heavily trafficked bicycle-share routes in the system. In addition, it provides a new broadly applicable, open-source tool for analyzing the relationship between bicycle share and city infrastructure.

Acknowledgments

I would like to thank my thesis advisor Sumeeta Srinivasan, for her patience, support, and guidance in completing this process. Completing this would not have been possible without her help, and her direction and knowledge base on geospatial methods were invaluable. I would also like to thank my reader, Shan Jiang, for her feedback and support.

I would also like to thank the community of contributors to OpenStreetMap, as well as the authors of OSMnx and the broader open-source community. This research would not have been possible without your generous spirit.

Finally, I would like to thank my family, friends, and partner, Lindsay, for supporting me throughout this process. At points when I wasn't sure whether I would ever complete this work, you encouraged me to continue.

Table of Contents

Project Prioritization: Using BlueBikes Ridership and Spatial Network Analysis to analyze Boston-area Bicycle facilities ... i

Abstract ... ii

Acknowledgments ... iii

Table of Contents ... iv

List of Tables ... vii

List of Figures ... viii

Chapter 1: Introduction ... 1

Chapter 2: Literature Review ... 5

The Benefits of Increased Cycling ... 5

What makes cyclists comfortable? ... 8

Level of Traffic Stress Measures ... 13

Bikeability ... 16

Modeling Cyclist Flows ... 18

Project Prioritization ... 21

Chapter 3: Methodology + Data ... 22

Literature Search + Review ... 22

Determining the Study Area ... 23

Data Collection ... 24

Traffic Stress Analysis ... 28

Network Centrality Analysis ... 38

Equity Analysis ... 44

Overlay With Planned Projects ... 48

Chapter 4: Analysis and Results ... 51

Network Centrality and LTS ... 51

Overlay with Socioeconomic Indicators ... 57

Analyzing Potential Projects ... 62

Chapter 5: Recommendations and Limitations ... 66

Planning new Cycling Infrastructure ... 66

Limitations ... 67

Recommendations for future research ... 72

Appendix A: Bicycle Infrastructure Maps ... 73

Somerville ... 73

Cambridge ... 73

Boston ... 74

Appendix B: Equity Factor Maps ... 75

Somerville ... 75

Cambridge ... 76

Boston 76

References 78

List of Tables

Table 1: Data Sources 27

Table 2: Missing Information Assumptions 30

Table 3: Column Merging Strategies 31

Table 4: Cycleway Tags to Bicycle Class 32

Table 5: LTS Score Calculation Rules for Non-Residential Streets 36

Table 6: Top 5 O-D Pairs by Ridership 41

List of Figures

Figure 1: distribution of survey respondents by cyclist type. (Dill and McNeil 2016) 8

Figure 2: Conflicts Increase with Speed and Volume (NACTO 2017)..... 10

Figure 3: LTS Stress Criteria for Bike Lanes (Asadi-Shekari, Moeinaddini, and Zaly Shah 2013)..... 14

Figure 4: Bicycle Network Analysis (People for Bikes 2021)..... 16

Figure 5 (left): Bicycle Infrastructure (OSMnx left side)..... 32

Figure 6 (right): Bicycle Infrastructure (OSMnx Right Side) 32

Figure 7: LTS 1 Configuration Example (Streetmix 2023)..... 33

Figure 8: Residential LTS Scores (Study Area) 35

Figure 9 (left): Non-residential LTS Scores (OpenStreetMap Left Direction) 37

Figure 10 (right): Non-residential LTS Scores (OpenStreetMap right direction) . 37

Figure 11: BlueBikes Station Locations (By Andrew Brieff) 40

Figure 12: Illustration of Betweenness Centrality 41

Figure 13: Average Projected Daily BlueBikes Ridership (By Andrew Brieff) 44

Figure 14: Bicycle Equity Index - Census Block Groups (by Andrew Brieff) 47

Figure 15: High-Stress Routes by Ridership and Bicycle Equity Index (By Andrew Brieff)..... 48

Figure 16: High Stress Routes by Average Projected Daily BlueBikes Ridership (Somerville) (By Andrew Brieff)..... 52

Figure 17: High-Stress, 90% Percentile Ridership Routes (Somerville) (By Andrew Brieff) 52

Figure 18: : High Stress Routes by Average Projected Daily BlueBikes Ridership (Cambridge) (By Andrew Brieff) 54

Figure 19: High-Stress, 90% Percentile Ridership Routes (Cambridge) (By Andrew Brieff) 54

Figure 20: High Stress Routes by Average Projected Daily BlueBikes Ridership (Boston) (Andrew Brieff) 56

Figure 21: Routes by LTS Score and Bicycle Equity Index (Somerville) 58

Figure 22: : High-Stress Routes by Ridership and Bicycle Equity Index 58

Figure 23: Routes by LTS Score and Bicycle Equity Index (Cambridge) (By Andrew Brieff) 59

Figure 24: High Stress Routes by Average Projected Daily Bluebikes Ridership and Bicycle Equity Index (Cambridge) (By Andrew Brieff) 59

Figure 25: Routes by LTS Score and Bicycle Equity Index (Boston) (By Andrew Brieff) 60

Figure 26: High Stress Routes by Average Projected Daily BlueBikes Ridership and Bicycle Equity Index (Boston) (By Andrew Brieff) 61

Figure 27: Boston Planned Projects (By Andrew Brieff) 62

Figure 28: Boston Planned Projects by Average Daily Projected BlueBikes Ridership and Bicycle Equity Index (By Andrew Brieff) 62

Figure 29: Cambridge Planned Projects (By Andrew Brieff) 63

Figure 30: Cambridge Planned Projects by Average Daily Projected BlueBikes Ridership and Bicycle Equity Index) ... 63

Figure 31: Somerville Planned Projects ... 64

Figure 32: Somerville Planned Projects by Average Daily Projected BlueBikes Ridership and Bicycle Equity Index ... 64

Figure 33: Somerville Bicycle Infrastructure - Left Direction (By Andrew Brieff) . 73

Figure 34: Somerville Bicycle Infrastructure - Right Direction (By Andrew Brieff) ... 73

Figure 35: Cambridge Bicycle Infrastructure - Left Direction (By Andrew Brieff) 73

Figure 36: Cambridge Bicycle Infrastructure - Right Direction (By Andrew Brieff) ... 73

Figure 37: Boston Bicycle Infrastructure - Left Direction (By Andrew Brieff) ... 74

Figure 38: Boston Bicycle Infrastructure - Right Direction (By Andrew Brieff) ... 74

Figure 39: Youth Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff) ... 75

Figure 40: Elderly Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff ... 75

Figure 41: Zero-Car Household Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff) ... 75

Figure 42: Non-white or Hispanic Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff) ... 75

Figure 43: Population in Poverty Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff) ... 75

Figure 44: Youth Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 45: Elderly Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 46: Zero-Car Household Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 47: Non-white or Hispanic Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 48: Population in Poverty Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 49: Youth Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 50: Elderly Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff) ... 76

Figure 51: Zero-car Household Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff) ... 77

Figure 52: Non-white or Hispanic Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brief ... 77

Figure 53: Population in Poverty Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff) ... 77

Chapter 1: Introduction

In recent years, there has been a growing realization among cities that traditional methods of transportation planning putting all of the emphasis on personal vehicles has been destructive to the environment and detrimental to city life. Transportation primarily by personal automobile has become unsustainable given ambitious climate targets and increasing levels of traffic congestion. Around the United States, city and state transportation departments see increasing the mode-share of cycling as one of the most powerful tools for reducing congestion and meeting climate targets, among a variety of other co-benefits for cities and riders.

To increase cycling mode-share, many cities have introduced Bicycle Share Programs (BSPs), where bicycles are made available for short-term rental throughout the city. While BSPs come in a variety of forms, the most popular programs in the United States involve a number of stations throughout the city, where residents can rent and drop off cycles. BSPs allow users to avoid having to store and maintain a personal bicycle. They also can be combined with other forms of sustainable transportation, either as a form of last-mile connectivity from public transportation stations or for one-way commutes.

The benefits of increasing cycling mode share more broadly and introducing Bicycle Share Programs specifically are clear. Bicycle Share Programs have been shown to lead to lower air pollution, including lower carbon dioxide and nitrogen oxide emissions. Bicycle use is correlated with increased public health, including benefits for fitness, lower rates of obesity, heart disease, and all-cause mortality. By serving as a vital last-mile link, bicycle share programs can serve as a complementary system to supplement the usage of public transportation.

Along with investments in Bicycle Share Programs, cities have been making investments in remaking the streetscape to accommodate cyclists in separate infrastructure. While there exists a large population of potential cyclists, many will not do so in mixed traffic with motor vehicles. For these relatively risk-averse cyclists, who may be less confident in their cycling ability or less able to keep up with normal traffic speed, cycling in mixed traffic is perceived as too dangerous. To encourage this group of people to cycle, cities are developing ways that accommodate cyclists through on-street lanes, separated cycle tracks, and off-street dedicated cycleways. To be effective in protecting cyclists, these street configurations must be connected in a network that reaches the prominent residential and commercial areas individuals may want to cycle to. For users of the bicycle share system, this means safe, separated cycling conditions between origin and destination pairs of BSP stations. Without confidence that the entirety of a rider’s route will be on safer, more comfortable roads with dedicated cycling infrastructure, risk averse travelers will be unlikely to adopt cycling.

This thesis is intended to address the relationship between investments in bicycle-sharing programs and investments in safe cycling infrastructure. It will model mobility flows for riders on the bicycle share system and evaluate the safety and stress levels riders face. It will investigate how well cyclists using the bicycle-sharing system are served by the safe infrastructure investments that have been made. In doing so, it will operationalize a toolset to view future investments in cycling infrastructure based on the operational impact they may have on the bike-share network. This thesis will use data from bicycle share program traffic patterns to identify corridors of particular importance to the overall network, where additional investment in bicycle infrastructure can have the greatest impact on the most cyclists, and potentially drive the most additional growth in cycling mode share and usage of the bicycle sharing program.

The research will use primarily open-source tools and datasets, to build a tool that is easily transferable to cities outside the study area of this research. It will employ concepts from network science to locate the streets most central to the overall network of bike-share users, and concepts from the literature about traffic stress to identify the streets most suitable for cycling.

The thesis will address the following research question:

1. What streets in the coverage area are the most suitable for infrastructure intervention, given their overall ridership and existing cycling stress?

This thesis makes an important contribution to the current literature because of its broader applicability as a model for cities looking to align their transportation investments with demonstrated cyclist needs. It may serve as a useful tool for bridging the gap between cities and the private contractors that run bike-share systems in making decisions about bike-sharing and street-level bicycle infrastructure. It will take a unique network and link-focused approach to bike-share systems, which are often considered only at the station level due to data constraints. The tools produced will allow planners to analyze in real-time the potential network impacts of discrete street-segment-level improvements in bicycle infrastructure, and to visualize how cyclists may be using their existing street networks.

The portions of this research focused at the community level on the relationship between bicycle share ridership, stress, and socioeconomic factors will provide an additional useful layer of analysis for ensuring cycling investments are made not just with respect to existing ridership patterns, but also as part of a broader strategy of remedying inequities in access to safe and reliable transportation. This research will provide guidance towards specific places where intervention will have the largest impact in the study area but also provide a framework for making similar assessments in other cities with bicycle share programs.

Chapter 2: Literature Review

This section will discuss the existing literature surrounding planning and evaluating transportation networks for cyclists. It will first introduce the research concerning the benefits that cities experience through various efforts to increase cycling mode share, identifying why cities are focused on building out cycling infrastructure and offering bicycle share programs. It will then include a discussion on what exactly makes a street safe and welcoming for cyclists, including the specific conditions and considerations for designing streets that are safe for all populations to use. It will look at the methodologies researchers have designed for planning and prioritizing what streets are most suitable for new cycling infrastructure. The review will then explore the metrics by which researchers and cities can evaluate the performance of entire cycling networks, both quantitatively and qualitatively. Finally, I will examine the history and development of bicycle-sharing programs, looking at methods of evaluation through performance and equity lenses.

The Benefits of Increased Cycling

For cities engaged in building out bicycle-share systems and bicycle infrastructure, one of the primary drivers for doing so is the potential of these investments to increase the number of residents who cycle and to increase the percentage of overall trips that are done by bicycle. Various studies have shown that making streetscape changes focused on increasing bicycle safety, like traffic calming and building dedicated infrastructure, are correlated with increased amounts of cyclists (Pucher, Dill, and Handy 2010). Similarly, expansions of bicycle share services are associated with increased cycling, as they provide access to cycling for a broad array of users and use cases (Félix, Cambra, and Moura 2020). There is a myriad of benefits that flow from these efforts to increase cycling, which the following section will explore in depth. These include increased road safety for cyclists and pedestrians, improvements in public health and the environment, and economic benefits.

Safety

Contrary to popular expectations, increasing mode share of cyclists is correlated with a decrease in the rate of crashes and the average severity of crashes (Elvik and Bjørnskau 2017). While some of the safety benefits from building cycling infrastructure accrue from its safer design, these are compounded by the additional benefits of increased cyclists on the road. While the exact mechanism by which this lower rate of crashes occurs may be context-dependent, the increased visibility of groups of cyclists and the normalization of interactions with cyclists for motor vehicle users are contributing factors (Elvik and Bjørnskau 2017). This dynamic of lower rates of crashes and injury is true even for users of bicycle share systems, who are less likely to wear helmets than private bicycle riders (Fishman and Schepers 2016).

Public Health & Environmental Impacts

Increasing cycling mode-share within a city has several public health and environmental-related benefits. Studies have linked increased cycling to lower rates of cardiovascular disease, type 2 diabetes, and significant reductions in all-cause mortality, despite the increased risk of traffic fatality and increased exposure to air pollution for cyclists. (Götschi, Garrard, and Giles-Corti 2016; Oja et al. 2011). These benefits are, however, contingent on the percentage of cycling trips that replace car usage, which provide the greatest benefits to physical health, greenhouse gas reduction, and air pollution reduction (Teixeira, Silva, and Moura e Sá 2021).

The research on the impact of bicycle-share systems on public health and environmental outcomes is mixed, largely dependent on the degree to which cycling trips replace car usage. In areas where cycling trips largely replace walking and public transit usage, for example, the impacts on overall VMT and air pollution reduction may be minimal, or even negative, given the potentially heavy usage of automobiles to rebalance the system (Fishman, Washington, and Haworth 2014). Studies showing high levels of greenhouse gas emissions reductions from the introduction of bicycle-sharing systems largely rely on high rates of car replacement rates, which do not reflect the current reality of bicycle-sharing usage in most cities (Fishman, Washington, and Haworth 2014). Nevertheless, a 2014 study of five operating bicycle-sharing systems across the US, Australia and Great Britain saw reductions in corresponding annual VMT, with the lone exception of London (Fishman, Washington, and Haworth 2014). The impact of bicycle-sharing systems on public health measures is clearer, with most studies showing lower rates of a range of diseases, and increased rates of physical activity, with even greater benefits for older populations (Teixeira, Silva, and Moura e Sá 2021). One such example demonstrating this benefit is a 2018 study conducted in NYC on the cost-effectiveness of expanding bicycle sharing programs to low-income neighborhoods, which showed system expansion to be amongst the most cost-effective public health measures, even given the additional expense of subsidizing service to low-income users (Yu et al. 2018).

What makes cyclists comfortable?

To encourage greater levels of cycling, much research has been conducted into the factors that influence the decisions of people to ride or not to ride. Foremost among those factors are the concepts of safety and stress - most people will not cycle if it feels unsafe or stressful. In 2006, Roger Geller, then acting as the bicycle coordinator for the city of Portland, introduced a popular typology for grouping potential cyclists based on their propensity to ride (Dill and McNeil 2013). These groupings, ranging from the most likely to cycle to the least, were labeled as "strong and the fearless", "enthused and confident", "interested but concerned" and "no way no how." A 2013 study examining this typology through survey data in Portland identified that most residents fit into the "interested but concerned" category, who might cycle but will only do so on infrastructure that feels exceptionally safe. A later national study confirmed these findings, showing more than 2/3rds of metro area residents have some interest in cycling, but the majority are limited by various concerns, including safety, and the accessibility of key destinations (Dill and McNeil 2016).

TABLE 1 Distribution of Survey Respondents by Cyclist Type

Type	Description	City of Portland[a] (%)	Rest of Region[b] (%)	All[c] (%)	Geller's Estimate for City[d] (%)
Strong and the fearless	Very comfortable without bike lanes	6	2	4	<1
Enthused and confident	Very comfortable with bike lanes	9	9	9	7
Interested but concerned	Not very comfortable, interested in biking more Not very comfortable, currently cycling for transportation but not interested in biking more	60	53	56	60
No way, no how	Physically unable Very uncomfortable on paths Not very comfortable, not interested, not currently cycling for transportation	25	37	31	33

Figure 1: distribution of survey respondents by cyclist type. (Dill and McNeil 2016)

For cities looking to increase cycling mode share, surveys like this help identify the population of residents who may be induced to cycle by constructing new safer cycling infrastructure.

Exactly what kind of roadway design makes cyclists feel comfortable and safe is a subject of considerable debate. While much attention has focused on the impact of specific cycling infrastructure, most miles cycled are spent on roads shared with motor vehicles, despite a preference for separated facilities (Buehler and Dill 2016). This is likely due to the limited number of separate facilities available and a desire to not deviate far from the shortest route possible. On these shared roadways, cyclists generally prefer roads with fewer travel lanes, lower traffic volume, slower speeds, and fewer interactions with parked vehicles (Buehler and Dill 2016). Two of those factors broadly considered to be of particular importance are motor vehicle speed and volume, which are both inversely related to comfort and safety and can compound one another in causing stress to cyclists (Fitch, Sharpnack, and Handy 2020). Research shows the risk of fatal injury to pedestrians and cyclists greatly increases when cars are driving faster than 30 mph, and that most cyclists are not comfortable riding in mixed traffic with vehicles driving over 25 mph (Kim et al. 2007). As speed and volume increase, cyclists experience a greater number of passing events, where a motor vehicle overtakes a cyclist, each causing an increase in cycling stress (“Motor Vehicle Speed & Volume Increase Stress” 2017). This effect is even greater for slower, less confident cyclists, increasing the barrier to ridership. Some research suggests women are also subject to more passing incidents than men (Aldred and Crosweller 2015).

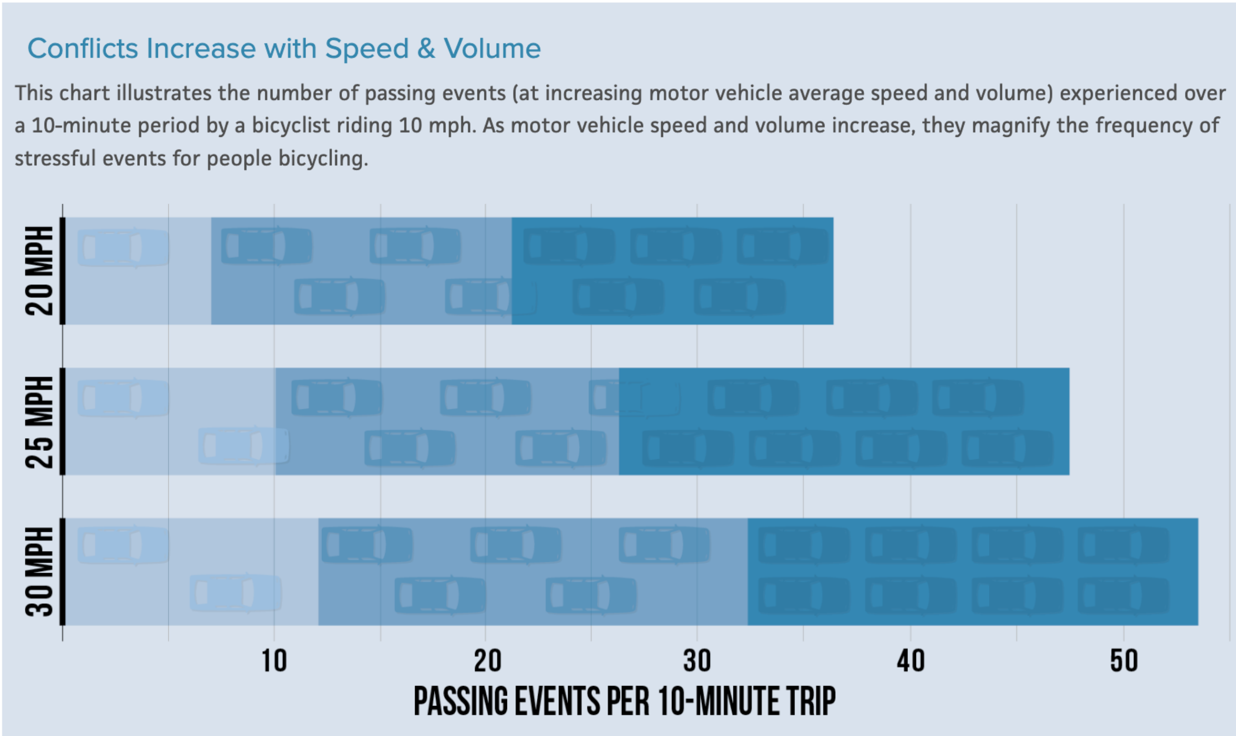


Figure 2: Conflicts Increase with Speed and Volume (NACTO 2017)

To protect cyclists from these dangerous interactions with motor vehicles, research suggests greater separation between cars and cyclists leads to higher levels of cyclist comfort. One method of categorizing cycling infrastructure is by the degree to which cyclists are kept separate from other road users. At the highest degree of separation, stated preference surveys have found cyclists are willing to take significant detours to travel on off-street multi-use paths (Tilahun, Levinson, and Krizek 2007).

The next cycle facility type in order of separation are cycle tracks, which are generally on-street paths, for use by cyclists only, with barriers between cyclists and motor vehicles (Thomas and DeRobertis 2013). One survey of 690 cyclists injured in Toronto or Vancouver, Canada found that cycle tracks were associated with only 1/9th the risk of injury when compared with major streets with parked cars and no infrastructure (Teschke et al. 2012). A survey of cyclists conducted in Portland in 2009 showed improved perceptions of comfort by cyclists using separated cycle tracks when compared to on-street bicycle lanes (“Multiuser Perspectives on Separated, On-Street Bicycle Infrastructure,” n.d.).

The evidence concerning the safety benefits of on-street bicycle lanes, which provide designated space for cyclists without a barrier from motor vehicle traffic, are somewhat more mixed in the literature. One study evaluating the installation of bicycle lanes in Copenhagen between 1988 and 2002 revealed increases in crashes on roadway segments with bicycle lanes, although these increases were not statistically significant. A later 2-stage study of bicycle lanes installed in New York found no increases in crashes on streets with bicycle lanes, despite increases in the number of cyclists (Chen et al. 2012).

While cyclists generally prefer separated facilities to on-street cycling, one specific category of street design, referred to alternatively as “neighborways”, “bicycle boulevards” or “shared streets,” proves an exception. These are mostly residential streets with low traffic volume but no specific separated bicycle facilities. In 2012, researchers conducted a revealed preferences route-choice study in Portland, Oregon using GPS trackers to analyze cyclist infrastructure preferences. The research showed that cyclists have a strong preference for low traffic volume in particular, estimating that streets with traffic volumes greater than 20,000 per day are only used when alternatives would require very long detours (Broach, Dill, and Gliebe 2012). In the Portland Study, as well as additional studies of cyclist preferences in Vancouver and Dublin, riders consistently preferred these low-traffic volume corridors over striped on-street bicycle lanes (Winters and Teschke 2010; Broach, Dill, and Gliebe 2012; Caulfield, Brick, and McCarthy 2012).

Cycling stress and safety are not felt equally by all people on all trips. Without significant bicycle infrastructure, it is often confident, young male cyclists who feel the most comfortable riding in otherwise stressful conditions (“Who Is the ‘All Ages & Abilities’ User?” 2017). Studies in New York, Washington DC, and Boston persistently show higher rates of usage of the bike-sharing systems for men than women (Peters and Gordon 2014). A survey of cyclists conducted by the Minnesota Department of Transportation in 2003 found women were significantly less likely to perceive the state as safe for cycling, noting the lack of dedicated facilities and poor road conditions as primary reasons. Women were also more willing to deviate further from the shortest path route to ride on preferred separated facilities (Board 2005).

There are significant and unique barriers to cycling among black and Hispanic communities as well. A recent survey showed less than 20% of adult members of these communities in New Jersey felt comfortable cycling in traditional on-street cycling lanes, with exposure to crime, being targeted by police enforcement, and the risk of traffic injury being cited barriers (Brown and Sinclair 2017). In addition, because of historic disinvestment in safe street infrastructure in communities of color, those who choose to ride are disproportionately likely to be killed in vehicle accidents (“Who Is the ‘All Ages & Abilities’ User?” 2017).

Age is likewise relevant to consider in addressing relative perceptions of cycling stress levels. Cycling is of immense potential benefit to both children and older adults, both as a source of physical activity and as a means of expanding mobility, but they each face unique challenges in cycling. With potential functional and sensory impairments, older adults may be more likely to have difficulty with complicated traffic patterns, hills, and poor road quality (Van Cauwenberg et al. 2018). They are disproportionately likely to be involved in bicycle accidents and face more severe injuries when they do (Cripton et al. 2015). Children likewise struggle with complicated traffic patterns, and can be less visible to other road users in mixed traffic (Ghekiere et al. 2014). In bike-along interviews with both groups in Flanders, Belgium, researchers found traffic safety to be a key concern for older adults, parents, and children alike when deciding whether to ride, with traffic speed, volume, and traffic separation being frequently raised concerns (Ghekiere et al. 2014; Van Cauwenberg et al. 2018).

Level of Traffic Stress Measures

While the exact levels of stress a given cyclist will feel on a given road is variable based on dedicated infrastructure, road surfacing, weather, socioeconomics, and the perceptions of the cyclist, there nevertheless exists a need to quantify and rate streets for network-level analyses. Many such metrics for rating the stress levels of roads have been developed, alternatively called “Bicycle Stress Levels,” “Bicycle Suitability,” “Bicycle Level of Service,” or “Level of Traffic Stress.” Generally, these rating systems use discrete road characteristics to produce a score corresponding to the level of comfort a cyclist might feel using the road(Asadi-Shekari, Moeinaddini, and Zaly Shah 2013).

Early methods for modeling cycling stress were based on the Highway Capacity Manual’s designations for vehicle throughput (Asadi-Shekari, Moeinaddini, and Zaly Shah 2013). These models often failed to consider the needs of cyclists as a discrete group of street users, focusing on measures important to motorists like throughput and speed. Motor vehicle lanes were included as a basic form of cyclist infrastructure, producing ratings incongruent with what might be safe and comfortable for cyclists.

Later models have built upon the cyclist typology outlined by Geller, categorizing roads by the types of cyclists that would likely feel comfortable riding on them. The result is a four-level scale, with Levels of Traffic Stress (LTS) 1 and 2 representing roads and intersections accessible to “interested but concerned” cyclists, LTS 3 “enthused and confident” cyclists, and LTS 4 representing roads inaccessible to all but “strong and fearless cyclists” (Geller 2009; Pritchard, Frøyen, and Snizek 2019) The LTS 2 category, designed to represent the level of comfort required for the mainstream adult stress-adverse population to cycle, was designed based on design guidelines from the Netherlands and Denmark, where large proportions of the adult population have been induced to cycle (Furth, Mekuria, and Nixon 2016).

TABLE 2 Traffic Stress Criteria for Bike Lanes

	Value by LTS Limit			
Lane Factor	LTS 1	LTS 2	LTS 3	LTS 4
Alongside a Parking Lane				
Street width (through lanes per direction)	1	na	2 or more	na
Reach from curb (sum of bike lane and parking lane width, including marked buffer and paved gutter)	15 ft or more	14 or 14.5 ft[a]	13.5 ft or less[a]	na
Speed limit or prevailing speed	25 mph or less	30 mph	35 mph	40 mph or more
Bike lane blockage (common in commercial areas)	Rare	na	Frequent	na
Not Alongside a Parking Lane				
Street width (through lanes per direction)	1	2, if directions are separated by a median	More than 2, or 2 without a median	na
Reach from curb (sum of bike lane and parking lane width, including marked buffer and paved gutter)	6 ft or more	5.5 ft or less	na	na
Speed limit or prevailing speed	30 mph or less	na	35 mph	40 mph or more
Bike lane blockage (typically applies in commercial areas)	Rare	na	Frequent	na

NOTE: na = not applicable.
[a]On noncommercial streets with speed limit ≤ 25 mph, any reach is acceptable for LTS 2 or 3.

Figure 3: LTS Stress Criteria for Bike Lanes (Asadi-Shekari, Moeinaddini, and Zaly Shah 2013)

Variations on this newer LTS model use a wide variety of factors to categorize and rank roads, including the number of vehicle lanes, speed limits, bicycle infrastructure, on-street parking, marked centerlines, slope, road surface conditions, and traffic volume (Asadi-Shekari, Moeinaddini, and Zaly Shah 2013). These models use a series of thresholds at the street segment and intersection levels to categorize road safety, as shown in Figure 3.

Modelers of traffic stress are faced with a series of trade-offs between accurately modeling the stress of streets at a micro-level with the availability of data needed at the macro-level to consider entire networks of streets. While traditional LTS models construct a reasonably accurate picture of cycling stress levels, they rely on data with limited public availability, limiting the extensibility of research (Furth, Mekuria, and Nixon 2016). To address this problem, People for Bikes, a non-profit advocacy organization for cyclists, introduced a simplified traffic stress metric with streets classified only as high or low stress ("PeopleForBikes BNA," n.d.). These scores were based only on street-infrastructure tags in OpenStreetMap, an open-source mapping service. Because OpenStreetMap tags may be inconsistently applied, People for Bikes combines an LTS logical analysis table with a series of expected defaults for missing data. Despite these inconsistencies, researchers in Canada have found reasonably high rates of accuracy for OpenStreetMap inventories of bicycle infrastructure when compared to municipal datasets (Ferster et al. 2020). Nevertheless, there remains difficulty in validating the results of the People for Bikes tool and similar measures of quantifying stress levels, with limited data availability and the high costs of collecting it (Abad and Van der Meer 2018).

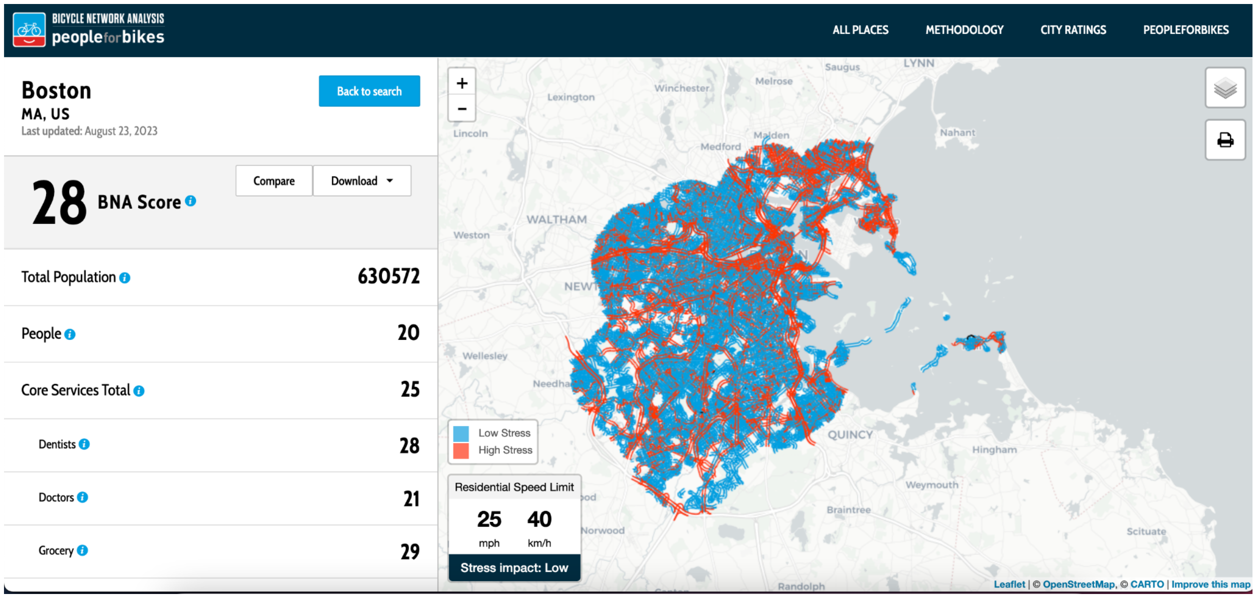


Figure 4: Bicycle Network Analysis (People for Bikes 2021)

In 2021, the Boston Transportation Department, working with Teele Design group, created a level of traffic stress map for the city of Boston. [("Bicycle Level of Traffic Stress Map | Boston.Gov" 2020)]() In building their LTS metric, transportation officials used traffic speed, average daily traffic volume, the number of lanes, on-street parking, functional class, and potential conflict zones such as bus lanes and school zones. In contrast with studies that focus only on on-street infrastructure conditions, the inclusion of conflict zones addresses a significant source of stress for cyclists, although requires a significant increase in available data about land-use to be conducted.

Bikeability

While measuring and quantifying the cycling stress levels of specific street and intersection alignments is important for designing particular street interventions, it does not on its own reflect the overall level of safety and comfort a rider might experience on a given journey. For low stress cycling infrastructure to be effective, it must be connected to a network of routes that bring cyclists from where they are to where they need to go. By analyzing the strength of the overall network of cycling routes, researchers attempt to construct a metric of the “bikeability” of a community (Lowry et al. 2012).

While there is no universally agreed-upon definition of bikeability, definitions in the literature generally focus on how conducive and safe the environment of a community is for cycling (Kellstedt et al. 2021). Methods of measuring bikeability include both qualitative methods like interviews and surveys, and more quantitative measures using GIS and audits of bike infrastructure (Kellstedt et al. 2021).

Cities use a range of quantitative metrics to describe the overall quality of their cycling networks, with various measures for size, directness, connectivity, and accessibility. Some of the simplest and most commonly used measures focus on size, including counting the total mileage of bicycle lanes, the number of streets with LTS 1 or 2, or the number of intersections with protected infrastructure (Boisjoly, Lachapelle, and El-Geneidy 2020). These metrics are limited in their ability to provide information about the effectiveness or quality of a network. The mileage of bicycle lanes in a city says little on its own about how stressful the routes are for cyclists on the network, as they may not provide direct, low-stress routes.

Measures focusing on network efficiency include route diversion necessary to use low-stress routes between popular OD pairs when compared with the shortest path route. Researchers in Montreal used a 2009 survey of cyclists' route preferences to construct a cost reduction coefficient for low-stress routes, measuring the additional distance cyclists are willing to travel to use a bicycle facility. This data was used to predict the lowest-cost routes between OD pairs in a 2013 travel survey, with the difference in length between a predicted lowest-cost route and the most direct route from origin to destination used to derive a measure of the overall directness of the bicycle network (Boisjoly, Lachapelle, and El-Geneidy 2020).

One-way researchers have sought to measure connectivity and accessibility is to combine a traffic stress analysis based on LTS with a basket of destinations, measuring how many important destinations are reachable using low-stress routes. In a case study in Moscow, Idaho, researchers created a set of GIS tools to measure bikeability based on the ability to reach all commercial destinations within a city, weighted by the importance and distance of the destination (Lowry et al. 2012). Other researchers have focused on measuring the number of jobs accessible at varying LTS traffic stress thresholds (Furth, Putta, and Moser 2018).

Many bikeability models use a scoring system to compile composite metrics of the accessibility of key destinations by bicycle. In the methodology used by People for Bikes, census blocks are scored by the availability of low-stress routes to surrounding census blocks. In the analysis both the total number of destinations accessible and the ratio of accessible to non-accessible destinations are considered in constructing an overall score, building a composite measure of network completeness and access to destinations. WalkScore produces a simpler form of this analysis in its Bike Score® metric, using a sum of all of the lengths of bike facilities in a community as its metric for network completeness (“Bike Score Methodology,” n.d.).

Modeling Cyclist Flows

Traditional transportation planning methods for modeling transportation behavior have involved the use of a four-step mode which models transportation in terms of trip generation for particular origins or destinations, distributing those trips throughout a network, modeling what mode choice individuals make, and assigning those trips to particular routes (Cooper 2018). Because real-time data on cyclist traffic is limited, researchers use these models to predict the mobility flows of cyclists across an entire network and how cyclist behavior and traffic flows may change with new street interventions.

More recently, spatial network analysis has emerged as an alternative to traditional four-step models, which are more accurate in larger transportation areas and can miss link-level details important for cyclist mode and route choice. Spatial Network Analysis uses characteristics of the network itself to assign traffic volumes, namely betweenness, or the proportion of shortest paths between all origins and destinations that use a particular link in a network(Cooper 2018). Betweenness is weighted by factors that influence cycling mode and route choice and offers a simpler approach that can incorporate both existing cycling behavior and projections for the future.

To build accurate models of cycling transportation flow, with either a four-step model or a spatial network analysis approach, researchers have focused on understanding the factors that influence cyclist route choice. A primary focus is on what factors influence cyclist's willingness to divert from the shortest routes to avoid traffic stress(Tilahun, Levinson, and Krizek 2007). These diversion factors are used as inputs to transportation models, to assign traffic volumes to streets given origins, destinations and demand (Cooper 2018). In one study analyzing cyclist route preferences using an adapted stated preference survey, researchers asked survey participants to choose between bicycle facility types and travel times to try to determine the degree to which cyclists will accept detours to take more desirable bicycle infrastructure. The study determined that cyclists were willing to travel up to 20 minutes further from a base trip of 20 minutes on-street, with the largest impact accruing from the addition of on-street bike lanes (Tilahun, Levinson, and Krizek 2007).

In Copenhagen, researchers used a revealed preference study and GPS trackers to examine how cyclists choose from among a set of options to get from their origins to their destinations. The authors found with statistical significance that cyclists prefer shorter routes, residential streets, streets with segregated bikeways, or on-street bike lanes without parking. In other research, riders were found to be willing to travel up to 40% further to travel on segregated bikeways (Skov-Petersen et al. 2018).

The willingness to divert from the shortest path to access safer cycling facilities is not uniform across all populations. Some research suggests that more frequent cyclists are less likely to divert from their shortest path to use facilities than those who cycle only occasionally(Larsen and El-Geneidy 2011). One study run by the Georgia Department of Transportation found that women are less likely to take a larger diversion to use cycling facilities, and are more heavily deterred by stressful traffic conditions than men, pointing to the importance of providing cycling facilities along the most direct routes to destinations (Misra and Watkins 2018).

Other modeling efforts have focused on understanding trip demand throughout a transportation network. Analyzing open-source data from bicycle share systems allows transportation planners to gain real-life data about cyclist behavior. In a 2021 analysis of the BlueBikes system in Boston, researchers devised a BikeScience toolset for grouping BlueBikes stations into distinct equally sized regions, to analyze cyclist mobility flows at the neighborhood-to-neighborhood level. While this research did not consider potential bicycle traffic at the resolution of individual streets, it identified key corridors of bicycle traffic for further study (Kon et al. 2021).

Project Prioritization

Given limited public resources and the need to quickly improve the connectivity and reach of existing cycling networks, there exists a great need to understand and model which streets are the best candidates for improvement given their impact on the larger network. Various performance criteria have been proposed, including bicycle connectivity between origins and destinations, connectivity between bike-share stations and destinations, low-stress connectivity, and directness of low-stress routes(Zuo and Wei 2019; Lowry, Furth, and Hadden-Loh 2016). Other models prioritize socioeconomic needs, focusing on whether new cycling infrastructure will reduce inequality in access to transportation resources(Grisé and El-Geneidy 2018). Other prioritization metrics include focusing on routes that will reduce the greatest numbers of greenhouse gas emissions, and focusing on routes that have the greatest potential to shift mode choice from cars (Zhao and Manaugh 2023).

Previous research conducted by Kelsey Tustin as part of her 2022 Thesis focused primarily on equity as a determining factor in project prioritization, using a spatial analysis to examine whether Complete Streets projects in the Greater Boston area were constructed in the areas of the greatest need. In her analysis, she included low-income residents, minority population, educational attainment, rate of zero-car households, elderly residents, access to transit service, the presence of separated bicycle infrastructure, walkability, crash rates, and populations of service workers (Tustin 2022).

Chapter 3: Methodology + Data

Literature Search + Review

As part of the research in this study, I conducted a thorough literature search concerning the development of cycling infrastructure networks. The review encompassed the motivations and benefits of developing a low-stress bicycle network, the forms that bicycle infrastructure can take, and strategies for measuring the relative strength of bicycle networks in terms of directness, accessibility, and comfort. The review provided examples of previous methodologies of modeling cycling traffic given limited available data sources and measuring the stress levels of individual streets given inconsistent data availability on existing cycling infrastructure. After conducting this review, it became apparent that there needed to be more literature using spatial analysis on extensible open-source data to analyze cycling networks. There was also a gap concerning the relationship between bicycle-sharing ridership and bicycle infrastructure, and for assessing the equity of the strength of existing bicycle networks for bicycle-share users.

The literature review also explores established criteria for measuring equity in access to transportation resources. When considering equity in bicycle infrastructure, special care is needed to identify the most vulnerable road users in most need of “All Ages and Abilities” facility consideration. While there exists some commonality in the variables used to quantify bicycle equity, there is some variation in the techniques used to measure those variables. Factors for equity in the analysis were ultimately chosen based on established practice for measuring equity in bicycle-share and bicycle infrastructure development, and existing metrics for equity chosen in bicycle planning practices in the chosen focus cities.

Determining the Study Area

To be able to conduct a study with reasonable accuracy using only open-source data, it was important to choose cities with a reasonable degree of information in OpenStreetMap, which limited some smaller cities with fewer active OpenStreetMap updates. The chosen cities also needed to have significant amounts of existing bicycle infrastructure and bicycle ridership to be able to draw meaningful conclusions about key gaps in the cycling network. The bicycle-share system chosen needed to have easily parseable data about ridership at the station level, with a large enough system to investigate patterns of mobility flows. I chose to focus on the cities in the coverage area of the BlueBikes system, with a particular lens on the cities with the highest concentrations of ridership and infrastructure in Somerville, Cambridge, and Boston. Each of these cities has well-developed but inconsistently applied bicycle networks, relatively high levels of bicycle ridership, and existing processes for planning expansions of the bicycle network. Because the bicycle-sharing system ridership data and OpenStreetMap data on bicycle infrastructure exist in similar formats for many cities across the country with docked bicycle-sharing systems, it is intended that the process developed in this research can be replicated to provide easily accessible, meaningful results for other cities in the country. Time in the study was taken to develop an ingestion process for cycling data that could be easily extensible to different bicycle share systems.

Data Collection

Before beginning the data collection process, it was necessary to consider the goal and comparative advantage of this study: to produce an easily replicable set of results through openly available sources outlining the most suitable streets in the street network for new cycling infrastructure. In light of this primary goal to produce a model that is easily replicable across cities, I constrained my data collection process primarily to datasets that are publicly available, open-source, and accessible programmatically. This approach informed each step of the analysis process, as I focused on building a simplified, generalizable model over a more detailed analysis of the focus cities.

The first method applied in this suitability analysis was to produce a level of traffic stress score at the street level, using a range of street configuration and infrastructure factors to determine the streets with the highest level of stress in the focus cities. This process would include a decision matrix tool based on findings from the literature for determining the stress level of a street. Next, an origin-destination matrix was overlaid on the street network for stations on the blue bikes system, modeling the approximate routes of the existing population of riders. By totaling ridership on all routes at the street-segment level, a model of street-segment centrality to the overall cycling network would be constructed, identifying the streets most crucial to increasing connectivity in the network. These streets represent the streets most likely to have the highest ridership given existing riding conditions and demand patterns.

The results of these two analyses would be combined with an equity-based overlay, which used several prominent factors in the literature indicating populations that are particularly vulnerable cyclists to build an indicator of all ages and abilities populations present in a particular area. Finally, the results of these three analyses would be overlaid with planned cycling infrastructure projects in the focus cities, to analyze whether planned projects align with demonstrated cyclist needs. By doing so, this research can provide insight into whether the focus cities are making cycling infrastructure investments that have the greatest possible impact on overall cycling stress.

The first part of the analysis was to produce a routable street network of the focus cities to be able to measure the properties of the low stress cycling network. This required street-level data for each of the focus cities, with information about network topology included, and roads inaccessibly by bicycle excluded. The Python geographic networking library OSMnx was used for this process, which contains a series of functions for converting OpenStreetMap locations into a weighted, directed graph with street segments as edges, and intersections as nodes (Boeing, G. 2017). This data structure, implemented by NetworkX, implements functionality such as finding the shortest distance between two intersections.

The next portion of the analysis concerned building a map of traffic stress for the streets in the focus cities. Street-level characteristics known to be associated with traffic stress for cyclists were derived from OpenStreetMap tags, which contain metadata about street infrastructure at the street segment level. A wide array of OpenStreetMap tags relating to street conditions were considered as part of the analysis, but ultimately tags related to bicycle infrastructure, speed limits, road classification, and vehicle lanes were ingested, as they had the broadest availability within the focus cities. Because OpenStreetMap tagging can be incomplete, a series of defaults based on the

OpenStreetMap street classification, and the laws of the focus cities were used to fill in the gaps of missing information. These factors would be combined to produce LTS scores per direction per street segment, using a hierarchical classification approach.

The third portion of the analysis involved producing a model of mobility flows for bicycle share users across the focus areas, which required trip-level details and locations for bicycle share users. Many of the major bicycle share systems operated by cities make their data available online, in monthly CSV files containing records of every trip undertaken in the system, with origin and destination stations, but no detailed GPS tracking information. Data for the year 2022 was collected, as it represented the most recent complete year of service. Like other docked bicycle share systems, BlueBikes does not include accurate GPS traces of the exact routes chosen by riders, which is a primary limitation on this research. Without exact GPS traces, shortest paths between origin and destination were used as the most reasonable approximation, given cyclist preferences for shorter routes demonstrated in the literature.

The equity portion of the analysis required information about key vulnerable road users at the census block group level, to add additional scoring criteria for road projects that provide the most benefit to the most vulnerable. Metrics representing disadvantaged groups include the percentage of elderly residents, the percentage of young residents, the percentage of households without a car, the percentage of low-income households, and the percentage of a community that is a minority in a given block group. These values were taken from the ACS 5-year community survey estimates and mapped at the block-group level.

Finally, a selection of planned bicycle infrastructure projects across all three key focus cities will be used as a comparison set, to evaluate how each project rates on stress, centrality, and equity metrics. The stress-level data, bicycle-share data, and equity index were combined to produce a scoring method for weighing potential bicycle infrastructure projects by their high street-level stress, their centrality to the bicycle street network, and the degree to which these projects would reduce inequity in access to alternative modes of transportation. Table 1 below shows the datasets collected for this research and used in the analysis.

Table 1: Data Sources

Data	Source	Year	Description
Bicycle Facilities	OpenStreetMap	2023	This data uses OpenStreetMap tags to rate the quality of bicycle infrastructure in the study area.
Road Classification	OpenStreetMap	2023	This data represents the road classification and serves as a stand-in for vehicle volume.
Vehicle Lanes	OpenStreetMap	2023	This data includes the # of lanes for all travelable roads in the study area.
Speed Limits	OpenStreetMap	2023	This data includes the speed limits for each street segment.
BlueBikes Stations	BlueBikes Ridership Database	2023	This dataset includes the geocoded locations of each of the docking stations in the BlueBikes system.
BlueBikes Ridership	BlueBikes Ridership Database	2022	Organized at the individual trip level, the ridership dataset was used to obtain the origin and destination station locations and the time of each trip.
Census Block Groups	MassGIS Data: 2020	2021	This layer shows the block groups

Data	Source	Year	Description
	U.S. Census		in Massachusetts.
Elderly Population	ACS 2021 Five Year Estimates	2021	This data was used to show the block groups with the highest percentages of elderly (65+) populations.
Youth Population	ACS 2021 5-year estimates	2021	This data was used to show the block groups with the highest percentages of youth populations (< 18).
Zero Car Household Population	ACS 2021 5-year estimates	2021	This data was used to show the block groups with the highest percentage of residents without a car.
Minority Population	ACS 2021 5-year estimates	2021	This data was used to show the block groups with the highest percentages of minority populations.
Low-income population	ACS 2021 5-year estimates	2021	This data was used to show the block groups with the highest percentages of low-income populations.

Traffic Stress Analysis

To understand which streets in the study area have the highest levels of existing stress for cyclists, a Level of Traffic Stress (LTS) analysis was conducted using OpenStreetMap, OSMnx, and data analysis tooling in Pandas (Boeing, G. 2017). To assign LTS values to the street network, a series of hierarchical classification rules were applied based on OSM tag data. These rules closely follow the work of researchers at People for Bikes, Conveyal, and others in translating tag data to on-street conditions. This approach has been found in the literature to have reasonable accuracy, tested in a

2017 comparison between OpenStreetMap-derived LTS values and ground truth in Montgomery County, Maryland (Prabhakar and Rixey 2017).

The main factors considered in this analysis were the OpenStreetMap road classification hierarchy, the number of lanes on the road, the speed limit, the presence of a centerline, and the quality of the bicycle facilities. These were chosen based on their prominence in the literature as important factors in traffic stress for cyclists, and their relative completeness in OpenStreetMap when compared to other potentially significant factors, like the presence of street parking.

Data Cleaning

Several steps were undertaken to clean and organize the data for the traffic stress analysis. First, a relevant geographic boundary was selected, using the `graph_from_place` tooling supplied by OSMnx for downloading topologically accurate routable networks from OpenStreetMap. Information from the target cities of Boston, Somerville, and Cambridge were selected, along with Brookline and Chelsea to provide geographic continuity for routes traversing these cities (Boeing, G. 2017). A 1000m buffer zone was also included, to eliminate edge-related effects that would otherwise artificially reduce the connectivity of stations at the edges of the study area. Streets downloaded were limited only to those accessible by bicycle, excluding highways and other inaccessible roadways. The resulting dataset from OSMnx is a directed graph of nodes (intersections) and edges (street segments) (Boeing, G. 2017).

Along with information about the geographic locations and relationships of streets in the study area, OpenStreetMap includes user-specified meta tags that represent specific conditions about the nature of street segments and intersections. The literature review provided strategies for determining street infrastructure designs correlated with higher degrees of cyclist safety, and for deriving bicycle infrastructure and street-level properties from OpenStreetMap. Given its uneven accuracy and completeness and community-driven nature, it was important to verify ample coverage of tags in OpenStreetMap of the study areas in question. To determine which factors would be included in the bicycle stress analysis, I surveyed various possibly relevant OpenStreetMap tags, selecting only those with significant availability. Table X below shows the tags selected and their coverage for streets in the study area.

To compensate for the incompleteness of OpenStreetMap data, a series of defaults were assigned for speed limits and lanes based on the focus city and hierarchy of the given road. For all three cities, the speed limit is 25 mph unless otherwise posted. Missing lane information was assigned based on the categorization chart in Table X below, with higher numbers of lanes assigned for streets with higher road classifications in OpenStreetMap. These defaults were derived from a previous analysis conducted by the People for Bikes as part of their Bicycle Network Analysis Tool.

Table 2: Missing Information Assumptions

Missing Information Assumptions (based on road classification)		
Functional class	Speed	Number of lanes
Primary	40	6
Secondary	40	4
Tertiary	30	3
Residential/Unclassified	25	2

When building the routable graph of streets, OSMnx simplifies the network, removing nodes where there are no intersections, for example, where a street segment curves. Because multiple edges are combined into one street segment edge, many street segments have multiple values for the key variables in the analysis (Boeing, G.

2017). To arrive at a singular variable for each edge, a merging strategy was applied according to the rules detailed in Table X below based on the type of data in the column.

Table 3: Column Merging Strategies

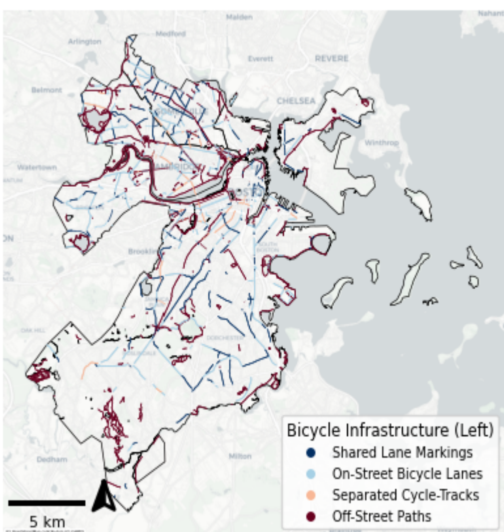
Handling Street Segments with multiple tag values	
OpenStreetMap Tag	**Merging Strategy**
highway	Maximum value chosen according to the following hierarchy: "cycleway", "track", "trunk", "trunk_link", "primary", "primary_link", "secondary", "secondary_link", "tertiary", "tertiary_link", "living_street", "pedestrian", "service", "residential", "path", "shoulder", "unclassified"
Cycleway (:left, :right, :both)	Maximum value chosen according to the following hierarchy: "track", "lane", "opposite_lane", "separate", "sepatate", "shoulder", "yes", "share_busway", "shared_lane", "no"
maxspeed	Maximum value
lanes	Maximum value

There was considerable difficulty in building the dataset of dedicated bicycle facilities from OpenStreetMap tags. While there exist established patterns of tagging bicycle facilities to characterize their quality and degree of separation, special care was needed to map the directions of bicycle facilities, which are often only present on one side of the road, to directions in the directed digraph produced by OSMnx (Boeing, G. 2017). Based on the literature outlining cyclist preferences for greater separation from motor vehicles, off-street cycleways were considered the highest quality bicycle facility, followed in order by separated cycle tracks, on-street bicycle lanes, bus-bike lanes, and finally shared lane markings. These rankings correspond to rider preferences denoted in the literature, and studies showing higher degrees of separation from drivers lead to less stressful riding conditions. Each street segment with any present tags for bicycle facilities was graded according to the decision matrix in Table X below.

Table 4: Cycleway Tags to Bicycle Class

Ranking Bicycle Infrasructure	
Bicycle Class Ranking	**Cycleway Tag Value**
4 (lowest stress)	cycleway, path
3	track, buffered_lane
2	lane, share_busway, yes
1 (highest stress)	shared, shared_lane

In cases where street segments were tagged with “cycleway:left” or “cycleway:right” tags, only the relevant direction of traffic was marked with a cycleway class rating. By marking cycleway class rankings for street segments separately in both the forward and backward directions, the network routing analysis can accurately reflect the conditions in the direction of travel for cyclists. The results for the study area are shown in Figures X and Y, with closer city-level results shown in Appendix A.



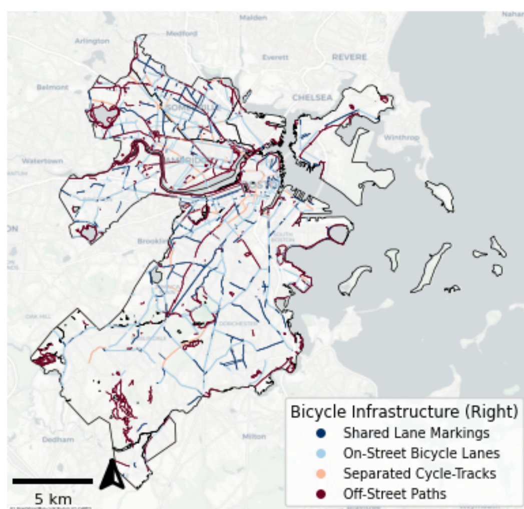


Figure 5 (left): Bicycle Infrastructure (OSMnx left side)

Figure 6 (right): Bicycle Infrastructure (OSMnx Right Side)

<u>LTS Classification</u>

After the data was cleaned and missing tag values in OpenStreetMap were imputed, the roads in the network were ingested into a hierarchical classification system, which classified street segments into four categories of traffic stress. An LTS score of 1 represents roads with the lowest levels of traffic stress, and are thus suitable for the largest potential base of cyclists, including groups that are particularly susceptible to stress. These roads mostly consist of off-street cycle paths and cycle tracks with a high degree of separation from vehicle traffic, like the separated bicycle lanes shown in Figure 7.

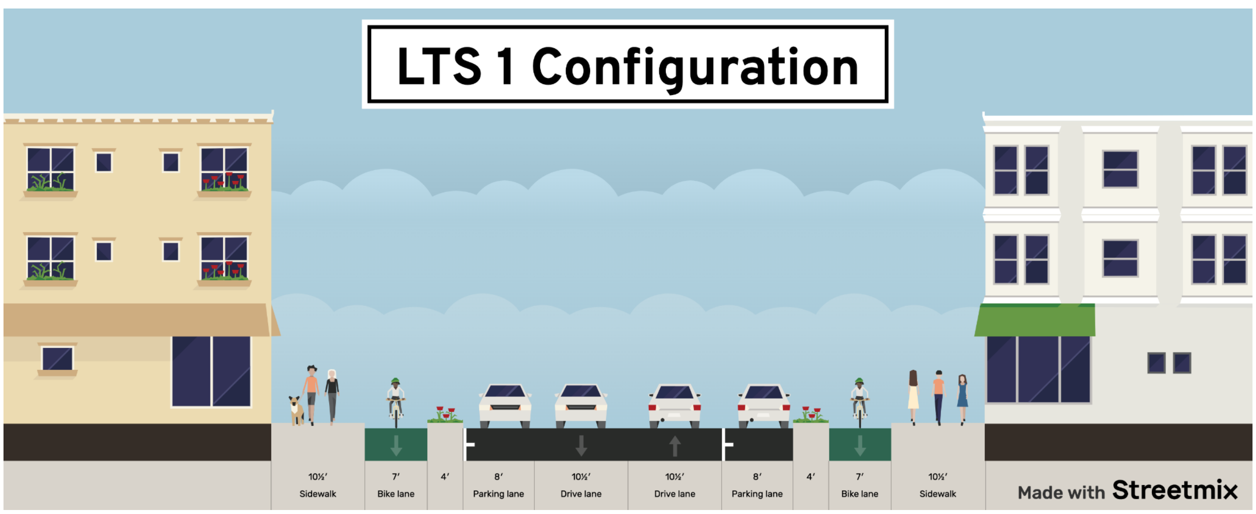


Figure 7: LTS 1 Configuration Example (Streetmix 2023)

An LTS Score of 2 represents roads suitable for most cyclists, including residential streets and separated bicycle lanes on calm streets. An LTS Score of 3 includes streets that only confident cyclists would be comfortable riding on, with speeds higher than 30 mph and a lack of dedicated infrastructure. Finally, an LTS Score of 4 represents roads inaccessible to all but the most fearless cyclists. These are main, arterial roads with no or little dedicated cycling infrastructure, high speeds, and high traffic volume. The classification system was built using a series of data queries in Pandas, which created a new LTS column based on rules concerning the OpenStreetMap tag factors. These scores were compiled separately for the forward and backward directions of travel.

The first step in the analysis was to separate the road network into two distinct categories, residential streets, and non-residential streets, based on the OpenStreetMap `highway` tag. Separate sets of classification rules were applied to each grouping of streets. These street types were separated primarily because of the relatively low volumes of vehicle traffic on residential streets. These streets are often unlikely to have dedicated cycling infrastructure, but instead provide stress-reducing properties with low speeds, low traffic volume, and low numbers of lanes. For this analysis, residential streets were considered LTS 1 if they had speeds less than 20 mph, LTS 2 for speeds less than 25 mph, and LTS 3 for all higher speed limits. The result of this classification is shown in Figure 8, which includes all residential streets and their LTS classification. All residential streets in Somerville and Cambridge have either a LTS 1 or LTS 2 score. The few exceptions in Boston with an LTS Score of 3 and a residential highway classification, include the service road for the West Roxbury Parkway, and Saratoga Street in in East Boston, both of which are likely to represent errors in OpenStreetMap data around both street classification and speed limits. Despite these few exceptions, largely due to low default speed limits throughout the study area, all residential streets are rated as low stress for cyclists.

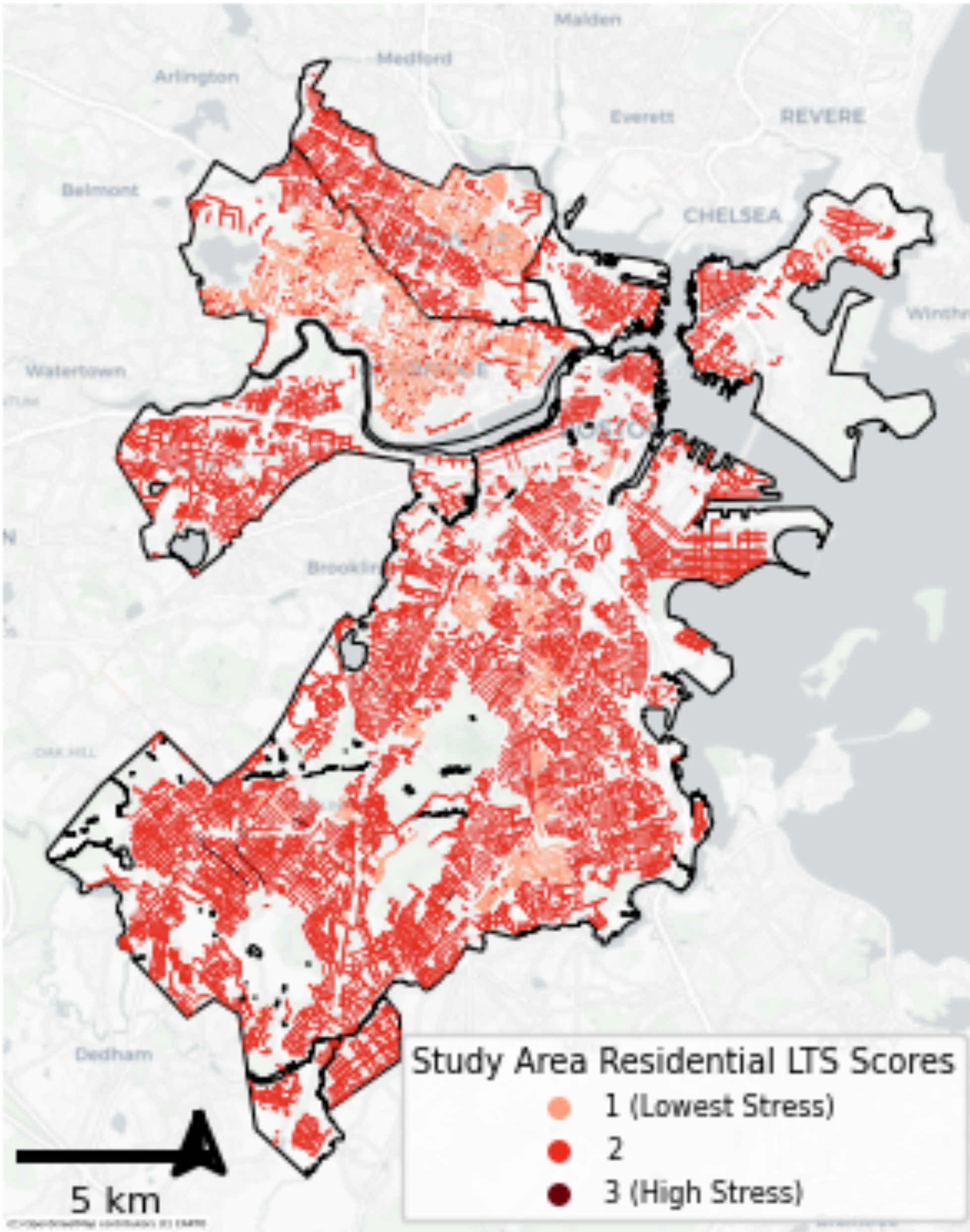


Figure 8: Residential LTS Scores (Study Area)

Non-residential streets were filtered using a more complex set of rules, as higher traffic volumes on roads with a higher classification require slow speeds and separation between vehicles and cyclists to have lower stress. The roads were first split by the level of bicycle facility present on the street. Streets with bicycle facilities of class 3 or 4, which represent either off-street cycleways and paths, or buffered or protected cycle tracks, were considered to be LTS 1 in all circumstances. These facilities were considered separate enough from road conditions to provide a low-stress experience for all riders.

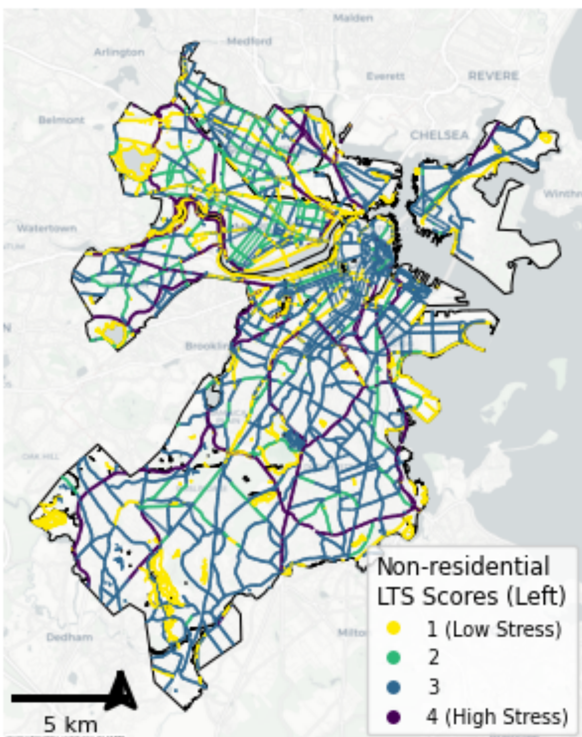
On-street bicycle lanes, represented as a class 2 bicycle facility, were considered to have an LTS score of 2 only at vehicle speeds less than 25 mph, or on roads with vehicle speeds less than 30 mph and having 2 or fewer lanes. While on-street bicycle lanes provide some degree of separation between cars and cyclists, at higher speeds or traffic volume passing incidents will lead to higher stress levels than tolerable for most potential cyclists (“Motor Vehicle Speed & Volume Increase Stress” 2017). Bicycle lanes on roads with speeds greater than 40 mph or more than 6 lanes were given a score of LTS 4, as the level of separation provided is not enough to overcome the stress from the level of throughput and speed of the traffic. The full list of rules for determining the LTS score for streets with bicycle lanes is included in Table 5 below.

Table 5: LTS Score Calculation Rules for Non-Residential Streets

Non-residential LTS Scores			
Facility type	**Speed**	**Number of lanes**	**LTS Score**
Off-Street path or Cycle track (Bicycle Class 3 or 4)	----------	----------	1
On-street Bicycle Lane or Bus-Bike Lane (Bicycle Class 2)	> 40	----------	4
	30-40	<= 3	3
		> 3	4
	25 - 30	> 2	3
		<= 2	2
	<= 20	> 4	3
		<= 4	2
Shared Lane, or no infrastructure (Bicycle Class I and n/a)	<= 20	<= 2	2
		> 2	3
	20-30	< 3	3
	> 30	----------	4

Streets without any dedicated cycling infrastructure or streets with “sharrows”, which are not shown to lead to significant reductions in traffic stress, were evaluated based on speeds and the number of lanes. Roads with 2 or fewer lanes and speeds less than 20 mph were considered to be LTS 2. Those with speeds less than 30 mph, or roads with speeds less than 20 mph but greater than 2 lanes, were considered to be LTS 3. Finally, those with speeds greater than 30 mph were considered to be LTS 4.

Because streets may have different levels of stress based on the direction of travel, the above set of LTS classifications was run twice, once for each direction, creating both a ‘left’ and ‘right’ LTS score. Many roads in the network area only have bicycle infrastructure in one direction of travel, making the distinction of direction important. In Figures 9 and 10, a high-level view of the final LTS calculations for both the ‘left’ and ‘right’ directions of travel are shown, with the results analyzed in the next chapter.



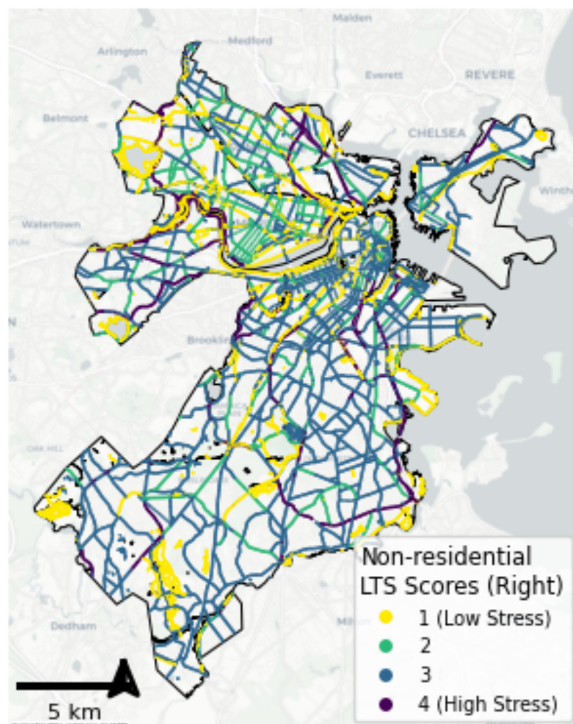


Figure 9 (left): Non-residential LTS Scores (OpenStreetMap Left Direction)

Figure 10 (right): Non-residential LTS Scores (OpenStreetMap right direction)

Mobility Flow Analysis

To understand which street segments in the street network are most important to existing cyclists, a model of existing mobility flows was developed using origin-destination data from the BostonBlueBikes network. This process was conducted using data analysis and graph analysis tooling in Python, including the OSMnx library, the GeoPandas library, and the NetworkX library (Boeing, G. 2017). To model bicycle-ridership counts at the street level, an Origin-Destination route-finding analysis was conducted using shortest paths as an approximation for the likely route taken between each pair of BlueBikes stations, given demonstrated cyclist preferences for the shortest route in the literature and the lack of more detailed GPS tracking data for cyclists in the region. This analysis resulted in a traffic flow assignment tool for cyclists based on patterns in BlueBikes ridership, giving a measure of the centrality of an individual edge to all shortest paths in the BlueBikes network.

Data Cleaning

Organizing the data for the mobility flow analysis required several steps to ingest, clean, and organize the data. To match the automated process of ingesting data provided by OSMnx's `graph_from_place` tooling, an ingestion engine for the BlueBikes system data was developed to pull information from the BlueBikes OpenData portal into Pandas Databases (Boeing, G. 2017). The BlueBikes System publishes records of rides taken on its system as origin-destination pairs every month. These records are available online in CSV format from a publicly accessible Amazon S3 bucket. These CSV tables are at the individual ride level, with the attached origin and destination information, along with basic data about the riders and timestamps for arrival and departure. The OpenData portal stores ridership data in monthly files, which are combined to provide statistics for an entire operating season. The process for ingesting BlueBikes data from the open portal was written in Python, takes in a start and end date, and returns a Pandas database with all trips on the system during that period. For this analysis, May through October of 2022 were chosen, as they represent the peak operating season of the most recently completed year.

In addition to the monthly trip CSVs, BlueBikes publishes a list of all stations within the system, with attached geographic coordinates. These station locations were loaded into a GeoPandas database, a Python data analysis tool for working with spatial databases. Layers representing the geographic boundaries of the three study cities were merged, and the resulting layer of the study area was used as a clipping tool to return only the BlueBikes stations in Boston, Cambridge, or Somerville. These stations are shown in Figure 11. There were 360 total stations considered for this analysis.

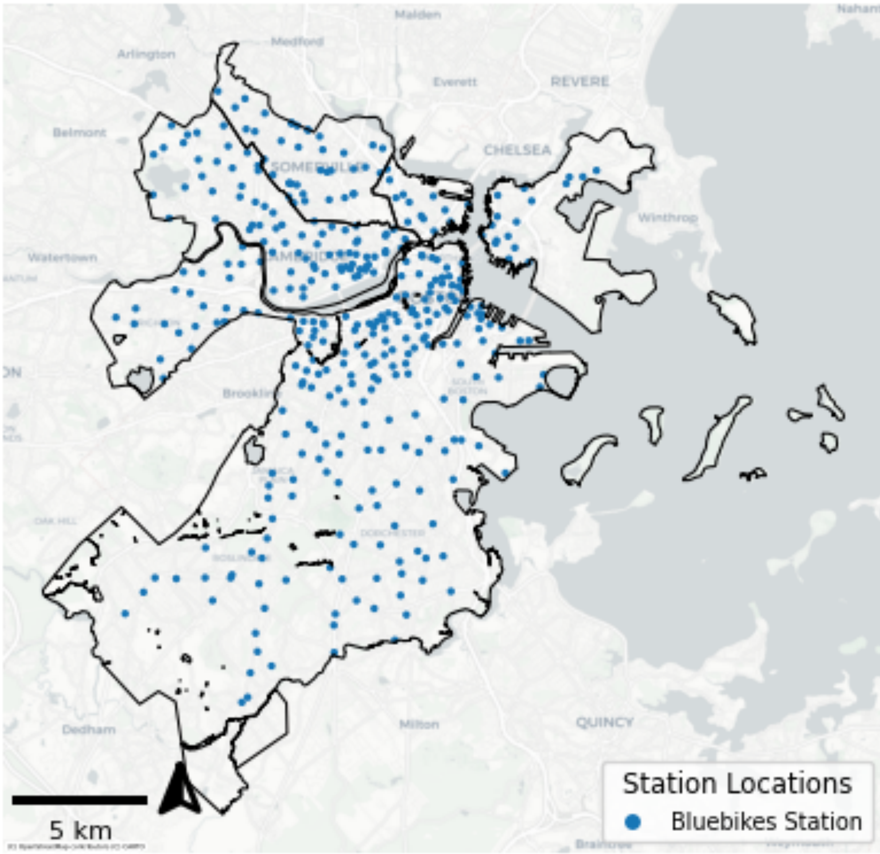


Figure 11: BlueBikes Station Locations (By Andrew Brieff)

Once ingested, several functions were run to remove data outside the scope of this analysis. Round-trip routes, which are usually recreational, were removed because it was not possible to approximate the route chosen by the given rider. Rides taken with origins or destinations at stations outside the three chosen study cities were excluded as well. Rides taken outside of the peak operating season, May through October, were removed to eliminate the skewing effects of the reduced size of the network in the winter. Once filtered, the individual trips were aggregated to the origin-destination pair level, using the Pandas `group_by` and `agg` functions to return the number of trips taken per route over the period. There were 71,322 unique station pairs in the group. The average seasonal daily bicycle traffic was calculated by dividing the total bicycle volume for each O-D pair by the number of days between May and October. There were 12,817 average daily trips accounted for in this analysis. The 5 highest traffic O-D pairs are included in Table X below, with the shape of the resulting data frame.

Table 6: Top 5 O-D Pairs by Ridership

Start Station	End Station	Average Seasonal Daily Bicycle Traffic
MIT at Mass Ave / Amherst St	Beacon St at Massachusetts Ave	24.02173913
Beacon St at Massachusetts Ave	MIT at Mass Ave / Amherst St	22.99456522
Harvard Square at Mass Ave/ Dunster	Harvard University Radcliffe Quadrangle at Shepard St / Garden St	18.14130435
MIT at Mass Ave / Amherst St	Central Square at Mass Ave / Essex St	16.86956522
Harvard University Radcliffe Quadrangle at Shepard St / Garden St	Harvard Square at Mass Ave/ Dunster	14.70108696

Assigning Traffic Flows

To obtain a measure of the importance of an individual street segment to the network of BlueBikes riders, a mobility flow analysis was conducted on the BlueBikes System. This analysis borrowed concepts from the idea of network centrality, which seeks to identify the nodes in a network that have the highest importance and influence within that network. An example of centrality can be seen below, where the edge outlined in red in Figure 12 has the highest centrality because it is present in the largest number of shortest paths between all nodes in the network (Lu and Zhang 2013).

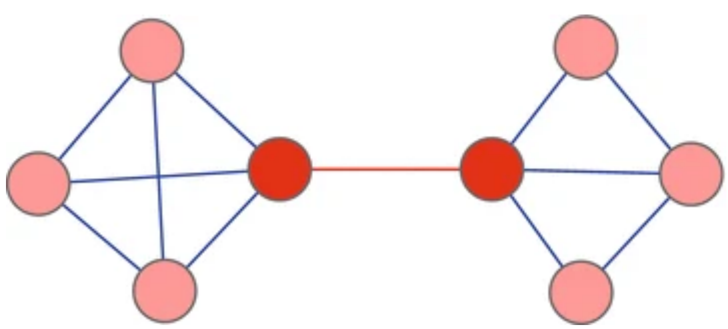


Figure 12: Illustration of Betweenness Centrality ("Community Structure in Social and Biological Networks | PNAS," n.d.)

To assign traffic flows, this analysis measured the number of shortest-paths between BlueBikes stations that pass through a given street segment. This value was then weighted by the daily ridership for each of those origin-destination pairs, such that a final value represented the overall daily projected ridership on a given street-segment, assuming each rider on a particular route took the shortest path between their origin and destination.

The first step in the mobility flow analysis was to map the BlueBikes stations onto the directed bi-graph produced in the traffic-stress analysis. This was done using the OSMnx `nearest_node` function, which given a Pandas series of geometric point data, returns the node, or intersection, that is the smallest Euclidean distance away. Next, the shortest path between each of the node combinations was produced, using the NetworkX `distance.shortest_path` function, which takes in a directed graph, a start and end node, and an edge weight, and returns a list of nodes that comprise the shortest path between the start and end nodes. This function uses Dijkstra's algorithm for calculating shortest paths, which is frequently used in the literature for routing purposes. Dijkstra's algorithm has a time complexity of $O(E\ log\ V)$, where E is all edges, or street segments, in the study area, and V is all nodes, or intersections, in the study area. Because this function needs to be run for every origin-destination pair in the BlueBikes system, the resulting time complexity of calculating all shortest paths is $O(N^2 E\ log\ V)$, where N is the number of bluebikes stations in the analysis. Given the relatively large size of the study area, and the high number of BlueBikes stations, the runtime of the algorithm was a limitation of this study and prevented extending the routing analysis to include all BlueBikes stations in the region. Nevertheless, the list of nodes provided by each run of the shortest-path algorithm was converted to a list of edges, each represented as (v_1, v_2), where v_1 is the starting node, and v_2 is the end node. This list of edges represents the street segments present in the shortest route for each possible trip within the study area on the BlueBikes system.

To approximate average daily ridership given the assumptions about riders taking the shortest path to their destination, the total ridership for each route was applied to each street segment in the shortest path, so that the ridership value for a given street segment can be represented as the sum of all ridership for each origin-destination that has a given street segment in its shortest path. This can be represented as

$$c_B(e) = \sum_{s,t \in V} \sigma(s, t \mid e) * w_{st}$$

where s and t represent each possible combination of BlueBikes Stations, $\sigma(s, t \mid e)$ is the number of shortest paths that pass through the given street segment, and w_{st} is the bicycle traffic of the given O-D pair.

In Python, this was done by using the `explode` function, which converted the shortest path for each row in the origin-destination matrix database into multiple rows, one for each street segment. These rows were then grouped by street segment across all shortest paths, and the `agg` function was used to sum the total daily ridership for each segment. Streets with no projected ridership were excluded, for additional clarity. The results of this analysis can be seen in Figure 13 below, showing the entire cycling network. Analyses of particularly central routes will be included in the next chapter.

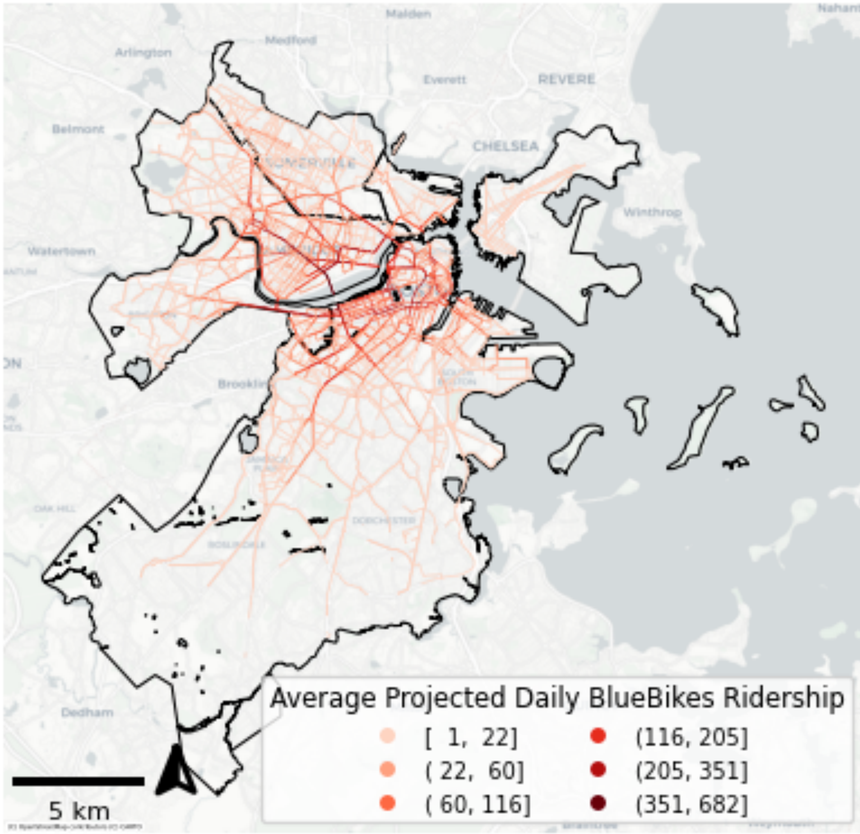


Figure 13: Average Projected Daily BlueBikes Ridership (By Andrew Brieff)

Equity Analysis

While the traffic stress and bike-share mobility analyses provide insight into which of the most stressful streets in the system are the most central to providing direct routes between heavily trafficked origins and destinations, they exclude key additional measures of stress. The literature suggests that traffic stress is not felt equivalently by all potential cyclists. Certain populations, including the elderly and youth, may have a lower tolerance for traffic stress, and require additional consideration in network planning. Other areas, like communities with high levels of minority groups, or large low-income populations, have been historically disadvantaged in access to transportation and deserve additional consideration. To account for the potential biases in the centrality analysis, which attributes higher link importance to centrally located streets which may be predominantly in high-income areas, an equity overlay was introduced, to focus on areas where redesigning high-stress, highly central streets intersects with city goals in reducing transportation inequality. Using the Bicycle Equity Index developed by the League of American Bicyclists as a model, information concerning transportation-disadvantaged populations was overlaid to produce a composite bicycle equity index score at the census block group level. Unlike a similar equity analysis conducted by Kelsey Tustin as part of a previous research project analyzing the equity of complete streets projects in the Boston area, this equity index focuses entirely on the characteristics of the residents residing in each area, rather than including considerations about existing transportation resources or job distributions (Tustin 2022).

Data Cleaning

To automate the ingestion process of ACS Community Survey data, the `censusdis` data `download` function was used, which given a dataset, year, set of variables, and geographic location, returns a GeoPandas data frame with the columns and geometry attached (Vengroff [2022] 2023). For this study, demographics from the ACS 5-Year Estimates in 2022 were chosen as the base dataset. All census block groups in Massachusetts were downloaded and then clipped to the study area using the geographic boundary layers for the three cities. Factors included in the analysis were variables corresponding to the elderly population, the young population, households without a car, nonwhite and/or Hispanic households, and individuals in poverty. Each variable was divided by the total population in the census block group, to return a percentage of residents in an area in a specific group.

Measuring Equity

In order to produce one comprehensive metric combining the five chosen indicators of bicycle equity needs, each indicator was first standardized, so that the value of a given indicator is relative to the mean of the surrounding population. This was done at the city level, so bicycle equity is considered only within the boundaries of each study city. While this limits the ability to compare equity index scores directly across cities, it provides the relevant frame of reference for city planners making decisions on project prioritization. The Z-score statistic was used for standardization, which can be defined as $z = \frac{x - \mu}{\sigma}$, where x is the percentage of the given indicator in the census block group, μ is the mean, and σ is the standard deviation. Only positive z-scores are used in the construction of the index, to prevent the lack of one disadvantaged group from decreasing the overall bicycle equity need. To build the Bicycle Equity Index score, the 5 z-scores from the block group are combined, so that the Bicycle Equity Index score is equal to the sum of the z-scores for the youth, elderly, zero-car households, minority, and low-income populations. The resulting index is shown in Figure 14, which includes index scores for the entire study area.

A full discussion of the results of the bicycle equity index will be included in Chapter 4, but a preliminary analysis shows the highest values in Somerville in its easternmost and westernmost edges, like the Inner Belt neighborhood. In Cambridge, high values are clustered in the Port and Cambridge port neighborhoods, and low values in the areas surrounding Harvard Square. In Boston, the highest values are concentrated in Dorchester, with additionally high clusters in Brighton, East Boston and Roxbury. Neighborhoods like South Boston, Back Bay, and Downtown have consistently low values.

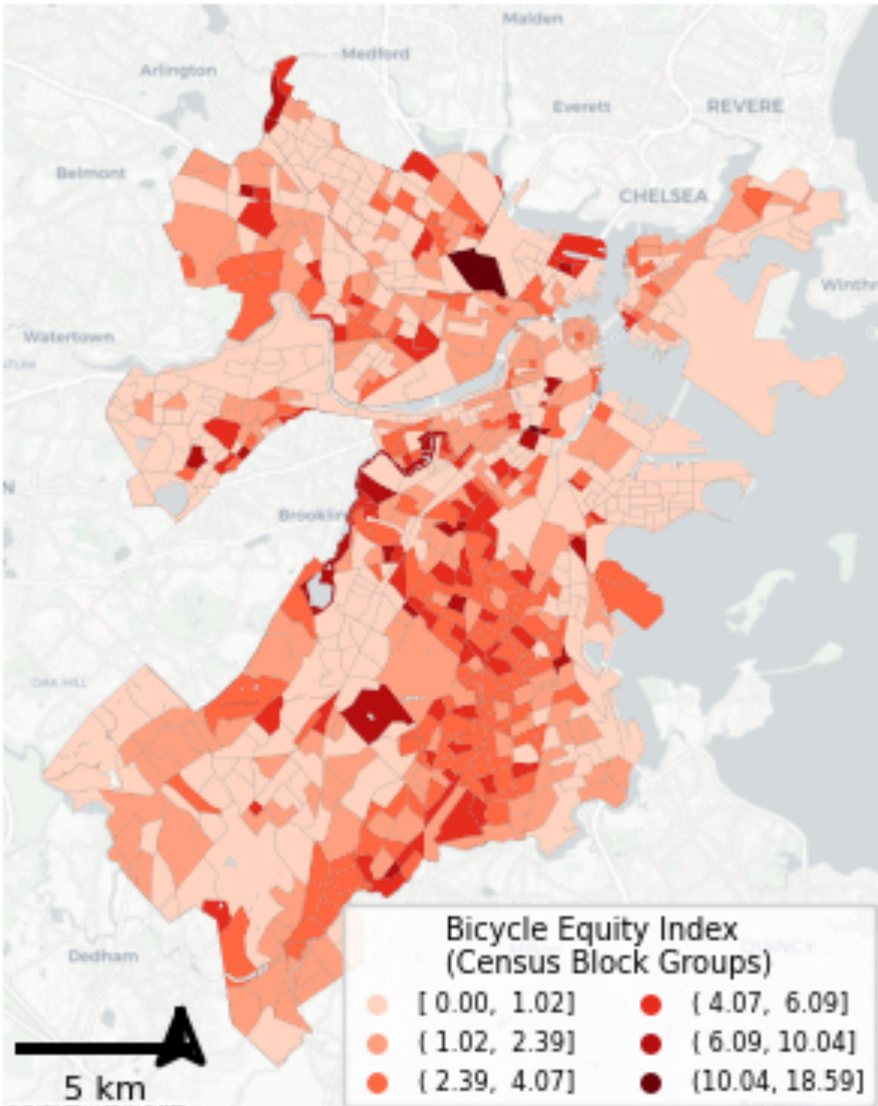


Figure 14: Bicycle Equity Index - Census Block Groups (by Andrew Brieff)

The Bicycle Equity index scores at the block group level were then overlaid with the layer representing high-stress routes across the study area. Natural breaks color schemes were used for the equity index score and daily ridership layers. Only streets with LTS scores of 3 or above and projected BlueBikes traffic are included. The resulting map allows for analyzing the interaction between stress driven by socioeconomic factors, and stress driven by street infrastructure factors, to further narrow down routes in need of prioritization. The results were analyzed visually, to explore the areas of greatest need in each of the study cities. The results for the entire study area are shown in Figure 15.

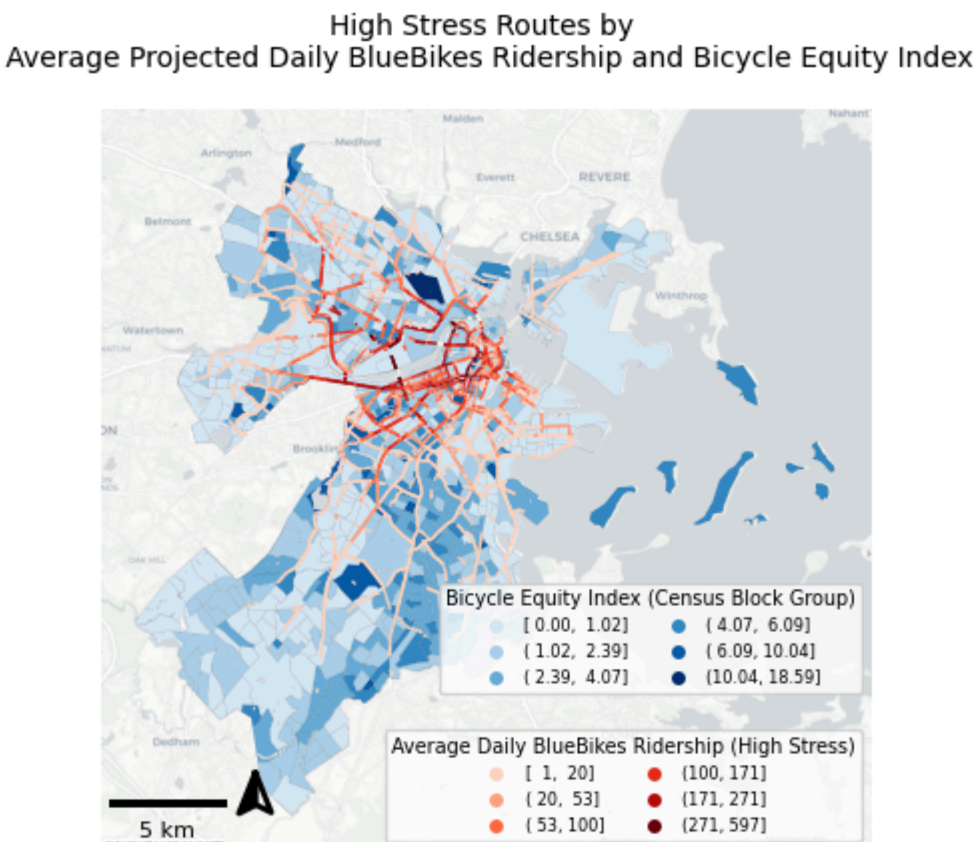


Figure 15: High-Stress Routes by Ridership and Bicycle Equity Index (By Andrew Brieff)

Overlay With Planned Projects

To provide a comparison set and opportunity to evaluate how well currently planned projects in the study areas align with demonstrated need in terms of street-level stress, street centrality, and equity, a selection of planned projects were chosen from each of the three study areas, and scored based on their existing stress and centrality to the network. They were also overlaid with the bicycle equity index scores, to identify the projects that most directly serve the communities most in need. The projects chosen were pulled from the Boston Bikes Plan, the Cambridge Bike Plan, and the Somerville Bike Plan, and represent cycling infrastructure slated for construction soon or as part of a comprehensive cycling planning process.

Data Cleaning

Unlike the previous sets of analyses, these sets of projects were not available in a format that could be easily ingested programmatically. Each city has a proposed set of bicycle infrastructure to be constructed as part of a long-term vision. Still, there are no publicly available shapefiles for the relevant projects. For Somerville, this vision is included as part of the Somerville Bicycle Network plan, which includes a map and listing of proposed future projects. For Cambridge, planned bicycle projects were taken from the 2020 Bicycle Plan’s proposed quick-build corridors, representing the most comprehensive available projects. In Boston, projects were selected from the routes planned for the next 5 years outlined on the Boston Better Bikes website. To ingest these projects into the network dataset for analysis, each project's start and end node values based on the cross-streets specified in the reports were manually isolated using the GeoPandas `explore` interactive mapping functionality. The OSMNX `shortest_path` and `route_to_gdf` functions were then used to create data frames of all the street segments comprising each potential project, and the project name was assigned to those routes.

Prioritizing Projects

To compare the selected projects based on the results of the previous analyses, the projects were first joined with the database of all street segments, attaching LTS scores and daily bicycle counts for each of the street segments comprising the project. The projects were then aggregated using the GeoPandas `dissolve` function, taking the maximum daily bicycle count and LTS score for each project. The results were then overlaid with the bicycle equity index map, for visually analyzing the impacts on equity for each project. Projects were considered higher priority if they had a high centrality score, high stress, and served populations with high BEI index scores.

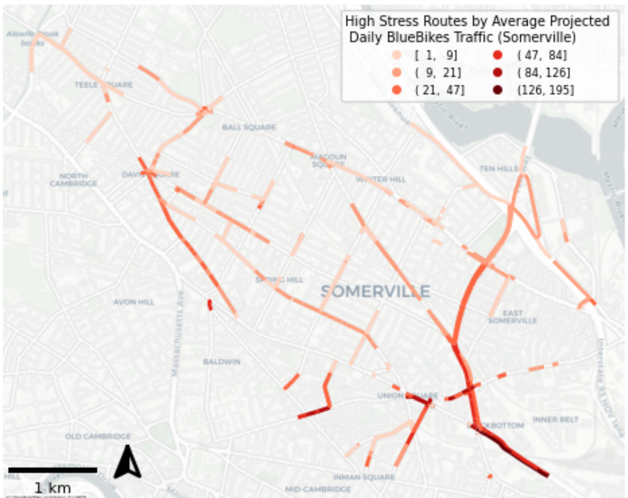
Chapter 4: Analysis and Results

Traffic Flow and LTS

The LTS and Mobility Flow analyses conducted in the previous step produced data at the street segment level concerning both how important a given street is to cyclists using BlueBikes, and how stressful that particular street is for riders to traverse. In looking at the intersection of those results at high-stress, high-traffic corridors, city planners can gain an understanding as to what streetscape improvements have been the most impactful for riders, and can offer hints as to where additional infrastructure is most needed. Key corridors that have been identified from these results in each of the study cities will be discussed in this section.

To focus on the most important streets, given limited public resources for constructing bicycle lanes, the 90% percentile of BlueBikes ridership per street segment was chosen as the cut-off for high-traffic streets. These percentiles were calculated based on the street segments within each of the cities, to reflect separate decision-making authority and the differing absolute levels of bicycle traffic. High-stress streets were considered to have an LTS score of 3 or 4, usually reflecting little or no existing bicycle infrastructure, high vehicle traffic, high speeds, and a high number of lanes. The intersection of high stress and high ridership is explored for each city in the following sections.

<u>Somerville</u>



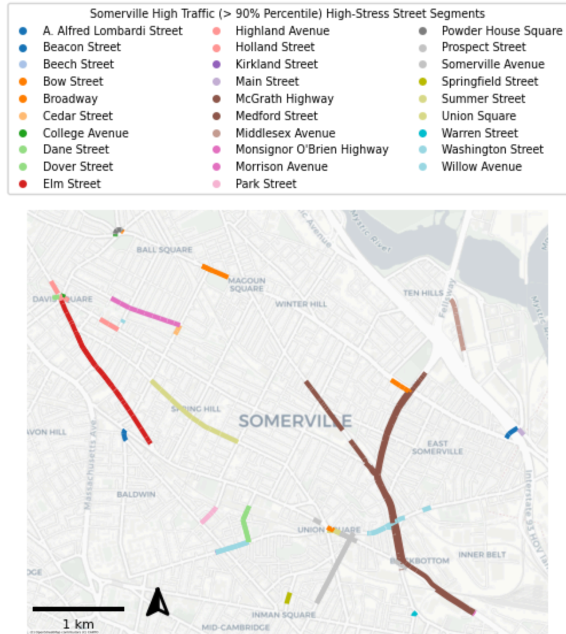


Figure 16: High Stress Routes by Average Projected Daily BlueBikes Ridership (Somerville) (By Andrew Brieff)

Figure 17: High-Stress, 90% Percentile Ridership Routes (Somerville) (By Andrew Brieff)

The analysis of high-stress and high-ridership routes in Somerville is somewhat sparse, reflecting the broad progress Somerville has already made in reducing bicycle traffic stress overall, and there were few significant arterial streets in the city, especially in the city center. Nevertheless, a few key routes emerge from an analysis of the data. McGrath Highway, an arterial north-south road that funnels traffic from the suburbs north of Somerville into Boston, is a key route, especially for riders from Assembly Square, East Somerville, and Gilman Square. It comprises the most direct route for many cyclists into East Cambridge and Downtown Boston. This section of McGrath is undergoing reconstruction and resurfacing as part of a larger project to replace an aging viaduct. The results of the centrality analysis lend additional credence to the need for the inclusion of separated bicycle facilities as the highway is redone, in addition to other traffic calming measures, such as lower speed limits and reduced lanes.

Elm Street is a key, high-stress, high-ridership connecting route between Davis Square, Porter Square, and Somerville Avenue. Elm Street also links to the Somerville Community Path, and the neighborway located on Hancock Street. With multiple MBTA stations, including a commuter rail station and significant bus traffic, traffic stress on Elm Street is significant given its effect on multimodal transportation options.

One key finding from the results, which repeated in each of the study cities, was the issue of intersection approaches. Even on streets with high-quality bicycle infrastructure and low-stress scores, like Beacon Street, which has grade-separated bicycle infrastructure, cyclists are merged into mixed traffic as they approach the intersection. This leads to short stretches of higher-stress street segments, which can still be a barrier to particularly stress-averse cyclists. Protected intersections, which protect cyclists throughout an intersection, are one way to approach reducing stress at these key points.

Cambridge

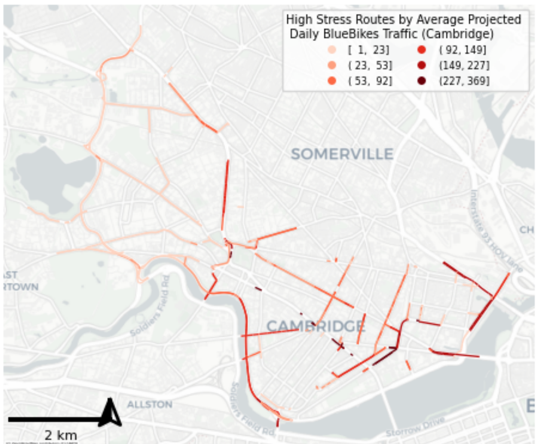


Figure 18: High Stress Routes by Average Projected Daily BlueBikes Ridership (Cambridge) (By Andrew Brieff)

Figure 19: High-Stress, 90% Percentile Ridership Routes (Cambridge) (By Andrew Brieff)

Cambridge has significantly higher levels of cycling traffic than Somerville. Many streets in Cambridge, including Massachusetts Avenue, Main Street, and Broadway are among the highest-traffic streets in the entire study area. While the implementation of the cycling safety ordinance has greatly increased the mileage of separated bicycle facilities, there still exist many key routes that remain stressful. In particular, Broadway emerges as a key street in connecting within Cambridge, as it provides a direct pathway between Harvard Square, significant job clusters near Kendall Square, and the Longfellow Bridge into Boston.

One of the key drivers of street importance to the overall network in Cambridge is the importance of the Charles River and the limited number of bridges that cross it.

Because all cyclists who want to cross to or from Boston are forced to route through one of six main bridges, the bridges and the streets that approach the bridges are particularly high traffic. Some of these approaches already have significant bicycle infrastructure, like the separated bicycle lanes on the Longfellow Bridge and the quick-build pilot project for separated lanes built on the Massachusetts Avenue bridge. Other bridges remain relatively stressful, including the BU bridge, which has an on-street bicycle lane but no other protection despite high street traffic. The Western Avenue and River Street bridges similarly do not have dedicated bicycle infrastructure, and are highly central according to the network analysis. These bridges have planned separated bicycle facilities, which will be important connectors between Cambridge and Boston when they are completed in the future.

Boston

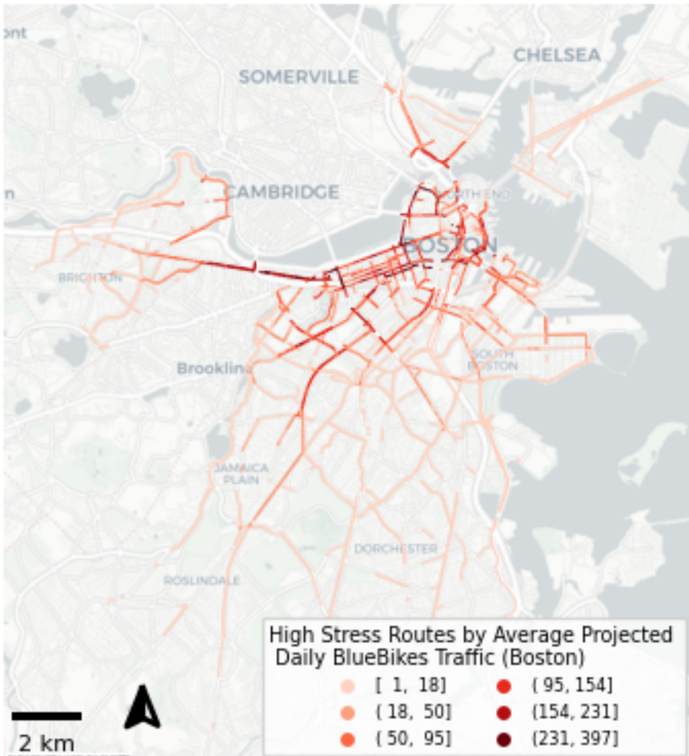


Figure 20: High Stress Routes by Average Projected Daily BlueBikes Ridership (Boston) (Andrew Brieff)

Boston has significantly higher amounts of high-stress streets than both Cambridge and Somerville, both because it contains more high-traffic arterial routes, and because it has built comparatively less cycling infrastructure in recent years. Similar to Cambridge, bridge approaches emerge as prime targets for bicycle infrastructure improvements. These include the BU Bridge, Massachusetts Avenue, Western Avenue, Cambridge Street, Charles Street, and North Washington Street to Cambridge. They also include Traveler Street and West 4th Street to South Boston, and Summer Street, Congress Street, and the Seaport Boulevard to the Seaport.

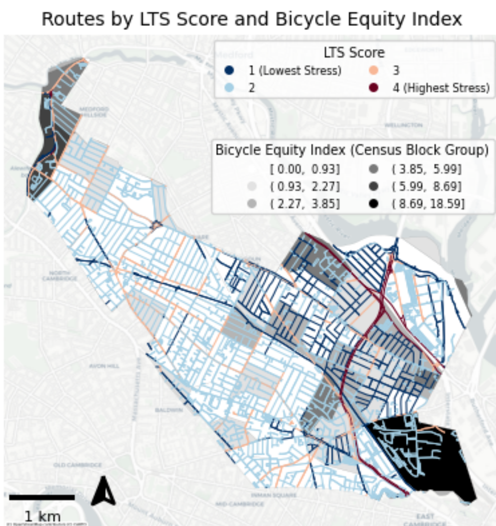
With a few exceptions, the highest ridership, high-stress routes are concentrated in the downtown Boston area, especially in Back Bay, the Financial District, and the West End neighborhoods. These areas include some of the most prominent tourist sites in the city, a high density of jobs, and a high density of transit options. In recent years, there has been some build-out of protected cycling infrastructure in this area, including separated cycling tracks surrounding the public garden, and a separate cycle track on Beacon Street between Charlesgate and Berkeley Street. Given the level of ridership in Back Bay, there exists a real need for a wider array of east-west and north-south protected cycling options.

Because of the high concentration of BlueBikes ridership in the downtown Boston areas, considering BlueBikes riders alone does not adequately provide information about the cycling needs of many of the communities in the neighborhoods in the South of Boston, including Mattapan, Dorchester, West Roxbury, Hyde Park, and Roslindale, as well as East Boston. These communities, many of which have faced historic transportation disadvantages, have a lower concentration of BlueBikes stations and lower ridership, in addition to the network effects that make downtown Boston more central to the overall network. Despite the sparseness of BlueBikes data, some prominent high-stress streets with significant ridership include Massachusetts Avenue and Columbia Road in Dorchester, Centre and Lamartine Streets in Jamaica Plain, Washington Street from Roslindale northwards and Meridian Avenue in East Boston.

Overlay with Socioeconomic Indicators

The following section will discuss the results of the previous analysis within a socioeconomic context, analyzing where the highest traffic stress and highest ridership routes intersect with the areas of specific concern for planners designing for all ages and abilities. By including an equity index component, these results shine light on where cycling infrastructure would either provide additional protection to particularly vulnerable road users, like young children or the elderly, or help to alleviate historic disadvantages in access to transportation.

Somerville



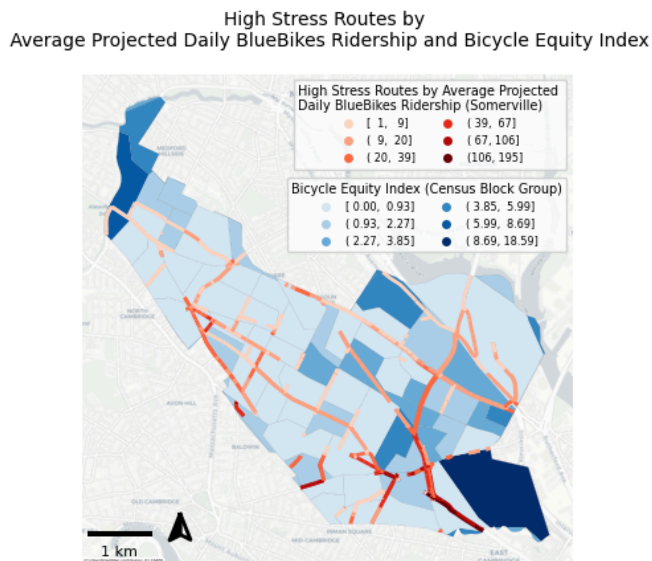


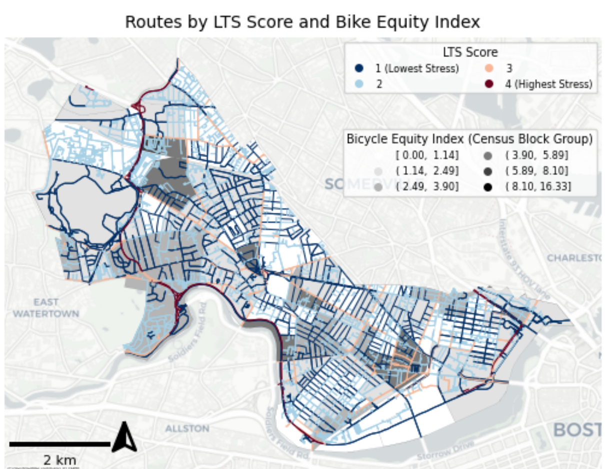
Figure 21: Routes by LTS Score and Bicycle Equity Index (Somerville)

Figure 22: High-Stress Routes by Ridership and Bicycle Equity Index

The areas with the highest Bicycle Equity Index score values are concentrated primarily in the East Somerville, Inner Belt, Winter Hill, and West Somerville neighborhoods. The Inner Belt neighborhood has the highest equity index score, driven by very high numbers of residents over 65, nonwhite and Hispanic residents, residents in poverty, and zero-car households. This neighborhood, the proposed site of a 1960s-era highway project for which it shares its name, is cut off from much of Somerville by the high-stress McGrath Highway. The neighborhoods of East Somerville and Winter

Hill, also bordering on the high-stress McGrath Avenue in addition to Mystic Avenue, show high levels of non-white and Hispanic populations, poverty, in addition to high levels of children under the age of 16. The high-stress, high-potential ridership segments of McGrath Highway, Medford Street, and Broadway connect these communities with the rest of Somerville and the BlueBikes region, making them high-priority links for additional protective infrastructure. The West Somerville neighborhood, which has high levels of zero-car households, children, the elderly, and residents in poverty, does not have particularly high levels of BlueBikes ridership. Nevertheless, the high-stress segment of Broadway between Teele Square and Mystic Valley Parkway serves as an important potential link between this neighborhood and the rest of the system and a potential barrier to higher ridership levels.

Cambridge



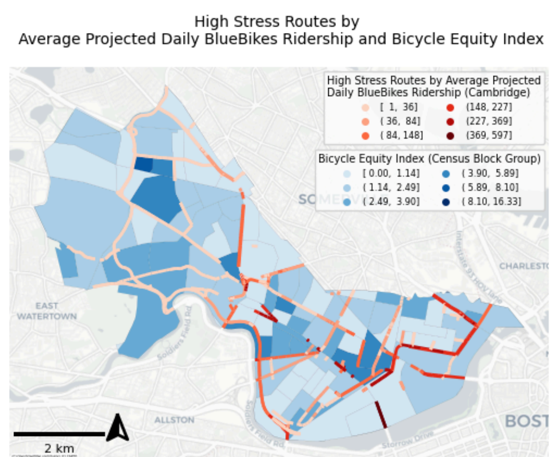


Figure 23: Routes by LTS Score and Bicycle Equity Index (Cambridge) (By Andrew Brieff)

Figure 24: High Stress Routes by Average Projected Daily Bluebikes Ridership and Bicycle Equity Index (Cambridge) (By Andrew Brieff)

The areas with the highest Bicycle Equity Index scores are concentrated in the Port neighborhood in Eastern Cambridge, some communities along the Charles River in

Cambridgeport, and North Cambridge near Porter Square. While it does not have a high percentage of residents in poverty, Non-white residents, Hispanic residents, or zero-car households, the communities along the Charles River in Western Cambridge also rate highly for bicycle equity because of the high percentage of residents that are children or elderly. The greatest overlap between high BEI index communities and high ridership occurs in and around the Port neighborhood, which is one of the highest ridership areas in the entire BlueBikes network. North-south roads like Portland Street and Windsor Street re important, high-stress links for these residents reaching job centers in Boston or Somerville. Broadway additionally emerges as a central east-west route serving this community.

In Western and Northern Cambridge, BlueBikes' ridership is much lower than in Eastern Cambridge. Despite lower ridership, Concord Avenue and Fresh Pond Parkway are routes that would link the high BEI index communities here with the rest of the city.

Boston

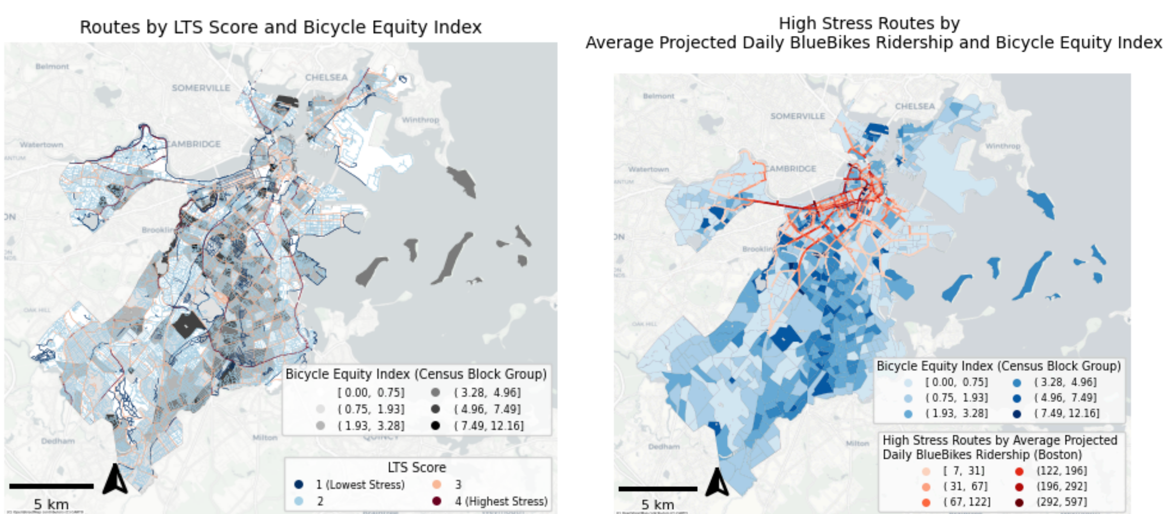


Figure 25: Routes by LTS Score and Bicycle Equity Index (Boston) (By Andrew Brieff)

Figure 26: High Stress Routes by Average Projected Daily BlueBikes Ridership and Bicycle Equity Index (Boston) (By Andrew Brieff)

There exists a significant gap between the areas with the highest values for the bicycle equity index and the areas with high BlueBikes ridership. Many of the communities with high BEI index scores in the south of Boston, like Mattapan, Dorchester, Roxbury and Mission Hill have few streets with significant BlueBikes ridership according to the mobility flow analysis. There is a much lower density of BlueBikes stations in these neighborhoods when compared to the other regions in the study area, which may partially explain the low ridership levels. Additionally, there are few high ridership routes in East Boston, likely due in part to the lack of accessible bicycle connections between East Boston and downtown. These exclusions represent a limit of the usefulness of the mobility flow analysis, in that it only reflects the system as currently constructed today. Given the high numbers of populations included in the BEI, these areas are strong candidates for further investment in bicycle infrastructure, including additional BlueBikes stations.

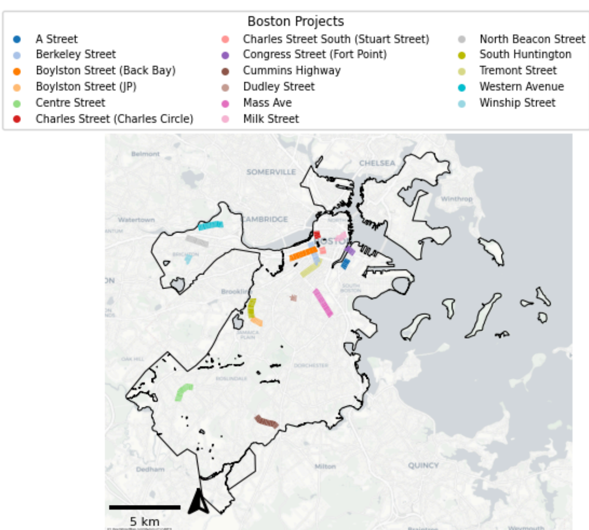
Despite the above limitations, there are areas in Boston with significant overlap between BlueBikes ridership, traffic stress, and high levels of the bicycle equity index. One such location is Commonwealth Avenue, which links high BEI index populations in Eastern Brighton and Allston with the rest of the city. It also includes Massachusetts Avenue, especially the stretch east of Huntington Avenue. which is a key corridor linking the South End, Roxbury, and Dorchester with Back Bay and Cambridge. Chelsea Street links high BEI index communities in Northeast Charlestown with the North Washington Bridge into downtown Boston. The largest concentrations of high BEI index communities in downtown Boston are in the census block groups comprising

Chinatown, for whom Albany Street, Harrison Avenue, Washington Street, Essex Street, and Stuart Street are high-stress, high-traffic corridors.

Analyzing Potential Projects

The results from the previous set of traffic flow assignment, traffic stress, and equity analysis were used as the basis for analyzing a selection of planned bicycle infrastructure projects in each of the study cities. The projected daily BlueBikes ridership on each project is shown and ranked, providing data about which streets will have the greatest impact on the BlueBikes network. These results are overlaid on the BEI index, to provide additional context about the populations likely to be directly affected by these projects.

Boston



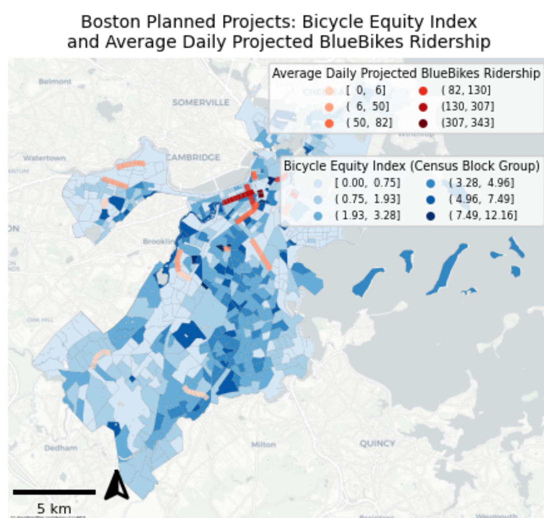
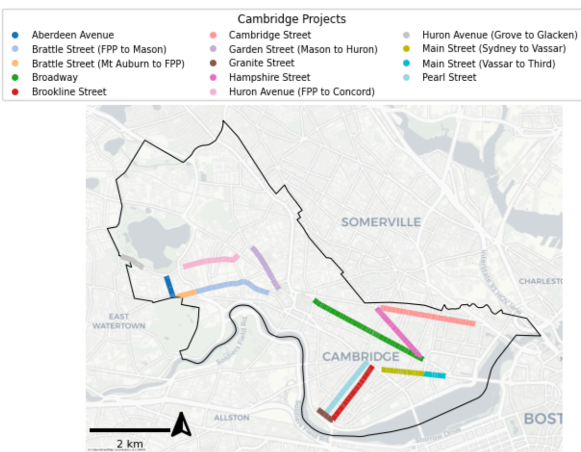


Figure 27: Boston Planned Projects (By Andrew Brieff)

Figure 28: Boston Planned Projects by Average Daily Projected BlueBikes Ridership and Bicycle Equity Index (By Andrew Brieff)

The projects in Boston with the highest projected ridership are Charles Street South, Boylston Street in Back Bay, and Berkeley Street. All three streets serve Back Bay and Downtown Boston and are highly central in part because of their proximity to the most heavily used routes into Cambridge. Outside of the downtown core, South Huntington Avenue, Congress Street in Fort Point, and Dudley Street in Roxbury have reasonably high projected ridership numbers. For projects like Cummins Highway or Winship Street, a lack of density of BlueBikes stations and ridership limits the overall importance of these corridors in driving BlueBikes ridership, despite their value in serving high BEI index communities.

Cambridge



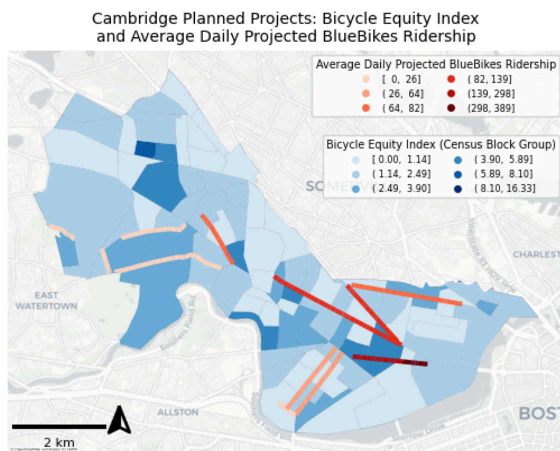
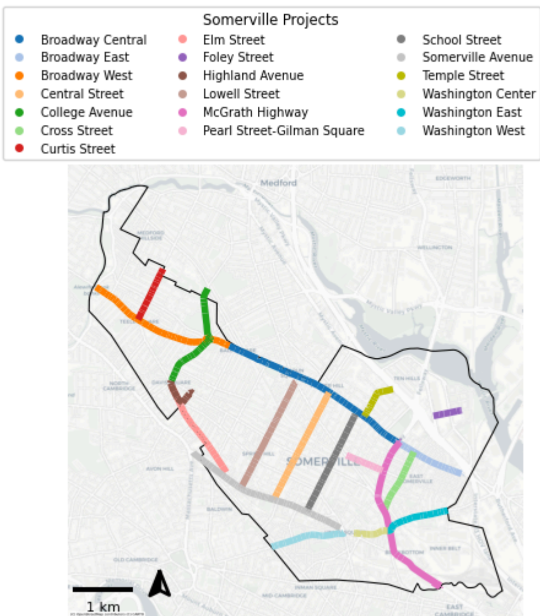


Figure 29: Cambridge Planned Projects (By Andrew Brieff)

Figure 30: Cambridge Planned Projects by Average Daily Projected BlueBikes Ridership and Bicycle Equity Index)

The highest priority route in the selection of Cambridge quick-build projects by both projected ridership and the BEI index populations it serves is Main Street, which serves communities in the Port neighborhood and provides a potential low-stress link to Boston. Broadway and Hampshire Street, which converge in the same neighborhood and provide links to Somerville, Harvard Square, and Inman Square, are the next highest corridors in terms of ridership, stress, and equity. While Brookline Street, Huron Avenue, and Brattle Street score lower according to the traffic flow assignment metric, they provide important links for BEI index populations.

Somerville



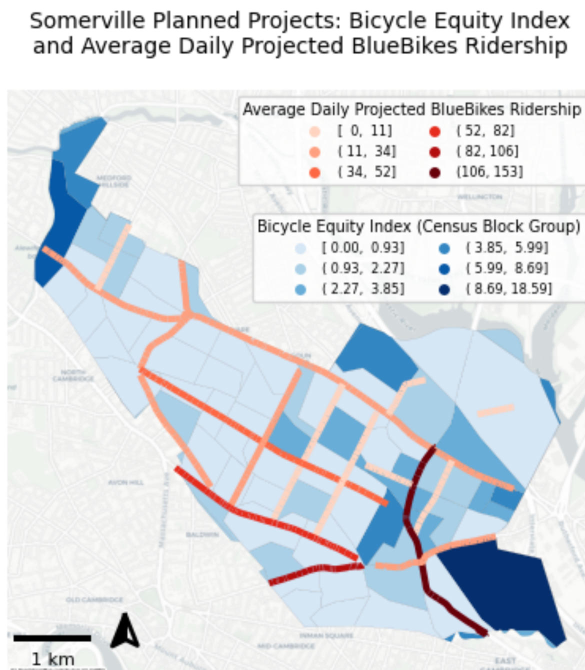


Figure 31: Somerville Planned Projects

Figure 32: Somerville Planned Projects by Average Daily Projected BlueBikes Ridership and Bicycle Equity Index

In Somerville, based on the results of the traffic flow assignment analysis, the McGrath Highway redesign project should be the highest priority, given its high degree of projected ridership and high-stress scores. It additionally serves several census block groups with high BEI index scores, like communities in East Somerville, the Inner Belt, and Prospect Hill. The Washington Street West and Somerville Avenue projects are the next highest ranked by centrality, likely because they serve as important connective routes with neighborhoods in Cambridge. While it has a lower traffic flow assignment score, the West Broadway project additionally serves as an important link to high BEI index neighborhoods in West Somerville. The map of selected projects, and their associated projected BlueBikes ridership are shown in Figures 31 and 32.

Chapter 5: Recommendations and Limitations

Planning new Cycling Infrastructure

The results of the traffic flow assignment and traffic stress analyses show that there exists a significant gap between the highest usage, most direct routes for bicycle share users, and the provision of safe infrastructure. When planners in the study cities consider the development of additional cycling infrastructure, using an initial spatial network analysis-based approach like the work done in this paper would provide valuable insight into the highest leverage corridors for investment. Doing so within the context of the bicycle share system would allow city planners to maximize investments made both in bicycle sharing and in city infrastructure. It would also allow planners to model potential bicycle behavior without expensive and time-consuming data collection projects, allowing the data collection process to be more targeted to the highest priority identified routes.

By including a consideration of the differential experiences of traffic stress, and the varying populations in the study area facing transportation disadvantages or particular needs in cycling infrastructure, this study also illuminated the large coverage gaps within the study area for bicycle sharing. Many communities facing significant transportation challenges in Dorchester, Roxbury, Mattapan, Charlestown, and East Boston are both lacking in connective, safe routes and in bicycle share stations. While this traffic flow assignment study provides key insights into where there are significant gaps in safe infrastructure for existing riders, it does not adequately address the needs of communities without significant cycling networks. To increase cycling mode share to the levels aspired to by comprehensive transportation plans in each of the study cities, both improving the connectivity of existing networks and building new extensions to the cycling network are necessary.

There are several potential reasons for the mismatch between cycling ridership, high stress levels and the areas of highest community socioeconomic need. In part, they represent a difficult mutually reinforcing set of negative incentives. Without adequate safe infrastructure in neighborhoods like Dorchester, levels of cycling will remain low, limiting the perceived demand for new investment in safe infrastructure and the expansion of the BlueBikes system. Conversely, if cycling as seen as an activity predominately for the wealthy, new cycling infrastructure will be seen with skepticism in communities facing the greatest needs. These headwinds, however, make choosing the right locations for new infrastructure even more important, given the greater difficulty in doing so with public buy-in. Using tools like the traffic flow assignment tool outlined in this paper can help in this regard, by ensuring that new infrastructure has an existing use base.

This thesis is intended to provide a tool for planners beginning the process of planning new transportation routes, and metrics by which to evaluate the potential impact of new investments. In using this traffic flow assignment tool, city planners can gain a better understanding of how cyclists use their road networks today, and build a case for the potential demand and effects of new investments.

Limitations

OpenStreetMap accuracy and data availability

This project and analysis were built upon the data available about street conditions through OpenStreetMap, which by its decentralized, community-driven nature, needs to be more consistent, and can be inaccurate. Through OpenStreetMap, there exists a limited set of information about street conditions, excluding many factors, like the presence of parking, intersection treatments, and road quality, that significantly impact bicycle stress levels. Cities looking to produce a more robust measure of existing street conditions will still need to compile more comprehensive data sources about road conditions. The primary benefit of the analyses done in this study are to provide quick estimates based on publicly available data, but will require local expertise and context to verify results given the underlying inaccuracies in OpenStreetMap.

To get a snapshot picture of the accuracy of the analysis based on OpenStreetMap data alone, the results of the stress analysis can be compared to the Level of Traffic Stress analysis conducted by the Boston Transportation Department based on city and state street and land-use data shown in Figure 33 ("Bicycle Level of Traffic Stress Map | Boston.Gov" 2020). Overall, Boston's stress network is considerably more stressful, with LTS 4 ratings given to many of the main arterial corridors rated LTS 3 in this analysis of this thesis. Additionally, many of the residential streets are rated as LTS 3, rather than LTS 2 in the analysis of this thesis. In both cases, Boston identifies the compounding stress of more interactions with vehicle traffic, both by considering interactions with schools and other high vehicle turnover land uses, and with more direct consideration of vehicle traffic data. As a result, interventions like neighborways which seek to lower interactions with vehicle traffic without necessarily building dedicated cycling infrastructure will more visibly improve the stress conditions described by the Boston stress map. Nevertheless, the traffic of stress analysis conducted in this research follows similar logic as the one conducted in Boston, and does so using data that does not require specific municipal data sources, making it more extensible than the more detailed Boston analysis.

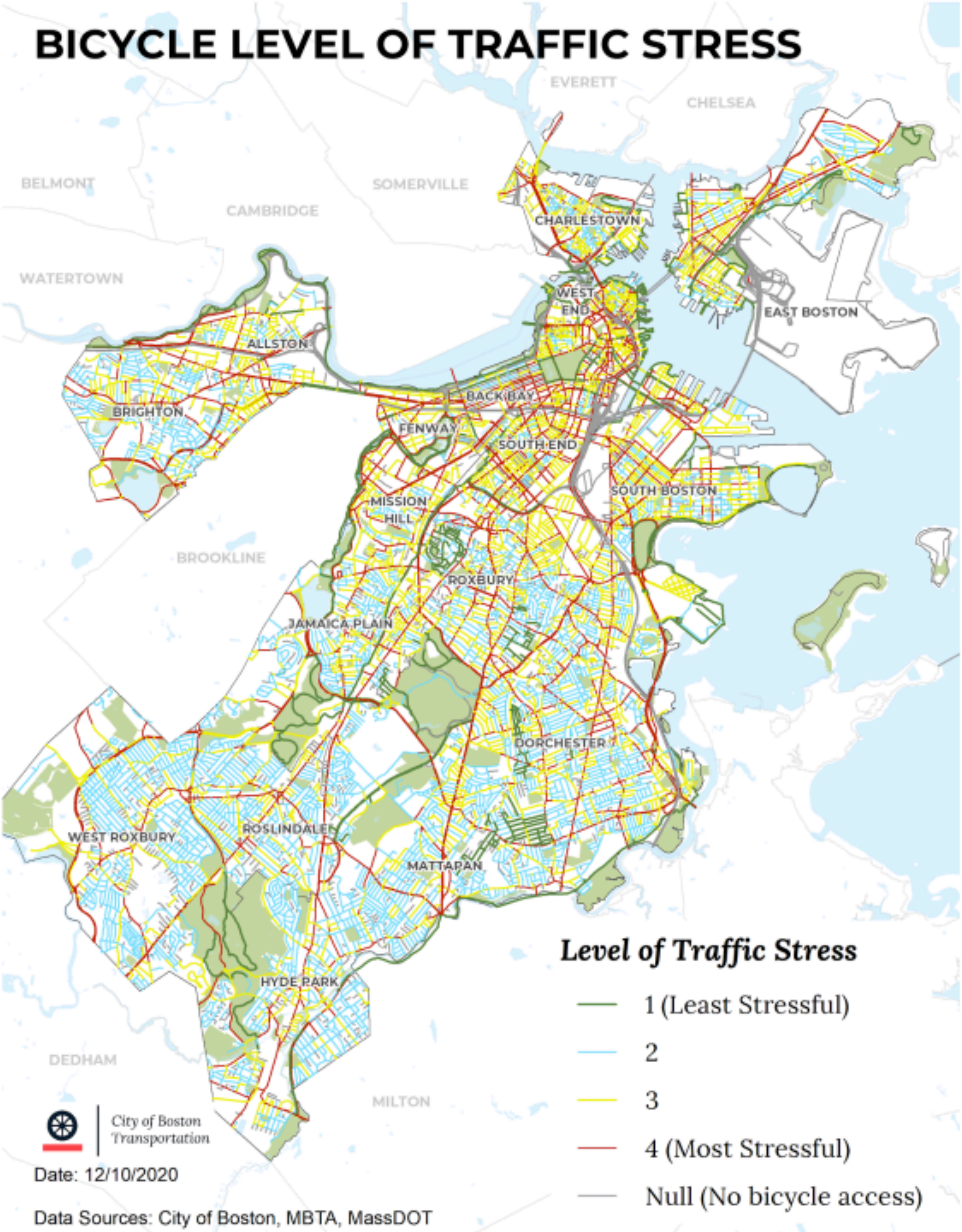


Figure 33: Boston Level of Traffic Stress, City of Boston 12/10/2020

Mobility Flow Modeling

To model the behavior of BlueBikes riders without access to detailed GPS traces, the traffic flow assignment analysis assumed that riders would take the shortest path between their origin and destination, regardless of the street conditions present. While riders have a demonstrated preference in the literature for shorter paths, this does not account for rider preferences for safer conditions or include any other reason why riders might choose a different path. Future analyses could be built upon more accurate sources of data, like GPS traces provided by private services like Strava, to compare and build upon this dataset. However, even if these results don't entirely match the ridership patterns of existing users, they do represent paths that are the most desirable given uniform stress conditions and thus provide key insights into paths key for increasing connectivity.

Existing Network Limitations

As currently designed, the suite of tools created for analyzing potential cycling routes for street-scape improvements is limited to the existing road network, which may miss key opportunities to improve connectivity by creating new routes, including off-street paths. Projects in the study area that meet this criteria, and thus can not be analyzed as part of this analysis, include the Grand Junction path, a proposed bike route alongside a freight rail line in Cambridge, and the Fenway Multi Use Path in Boston. Similar limitations apply to contraflow bike lanes on one-way streets, which are not represented in the connectivity analysis. These projects can be particularly beneficial because they increase cycling connectivity by adding pathways on otherwise low-traffic streets, and can be used as part of a suite of traffic volume reduction tools.

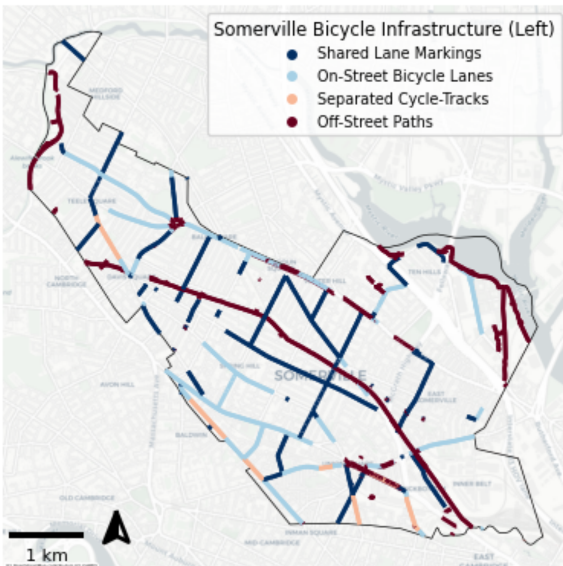
Boston has planned contraflow bike lanes on Eliot Street and Boylston Street in Jamaica Plain, and Hemenway Street in East Fenway.

Recommendations for future research

The core analysis of this thesis was to provide a new framework for quickly analyzing a city cycling network through the lens of bike-share users, to provide a window into where there exist discrepancies between demonstrated need and available safe infrastructure. While this research provides a model for understanding current travel patterns, it does not provide the ability to analyze the potential impacts of future cycling infrastructure construction. To expand upon the model introduced in this thesis, using the existing body of research for predicting cycling route choice, future researchers could include a predictive model of the impacts of introducing new cycling facilities, analyzing the changes in ridership patterns and the proportion of routes that are on safe infrastructure. In addition to expanding the scope of the model to include analyzing future impacts, the goal of this thesis was to produce a model that could be easily extrapolated to other cities and study areas, so that the tools described therein could be a low-cost option for beginning a project prioritization process. It is recommended that future researchers expand the scope of this research and test the results on other bike-share networks, to provide comparative insights about the performance of docked bike-share systems. Doing so could provide lessons about how different cities manage the relationship between bicycle-sharing and city bicycling infrastructure.

Appendix A: Bicycle Infrastructure Maps

Somerville



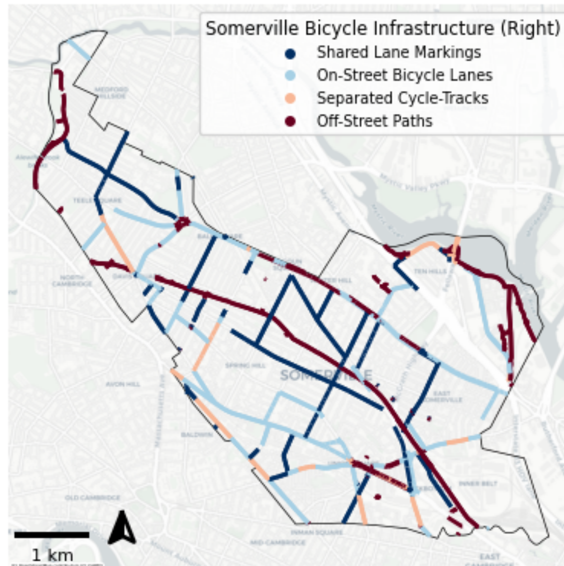
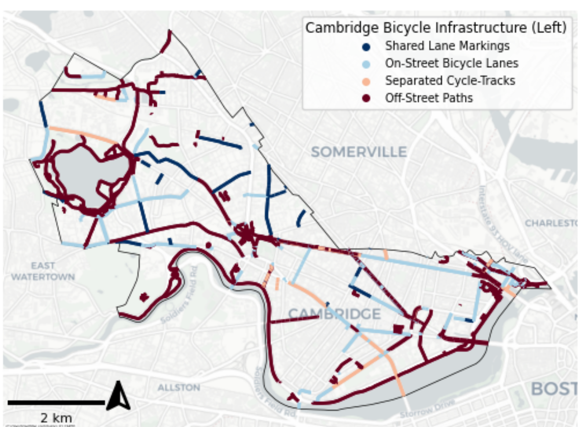


Figure 34: Somerville Bicycle Infrastructure - Left Direction (By Andrew Brieff)

Figure 35: Somerville Bicycle Infrastructure - Right Direction (By Andrew Brieff)

Cambridge



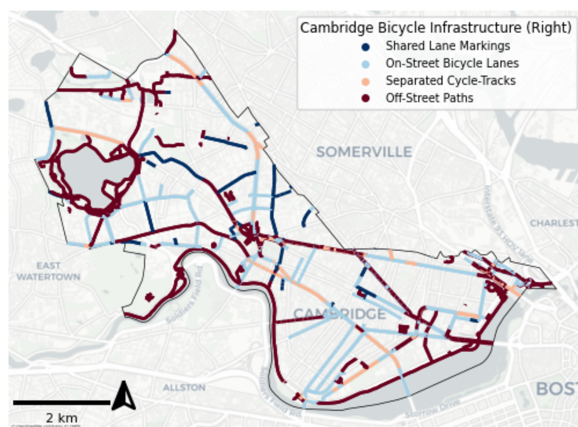
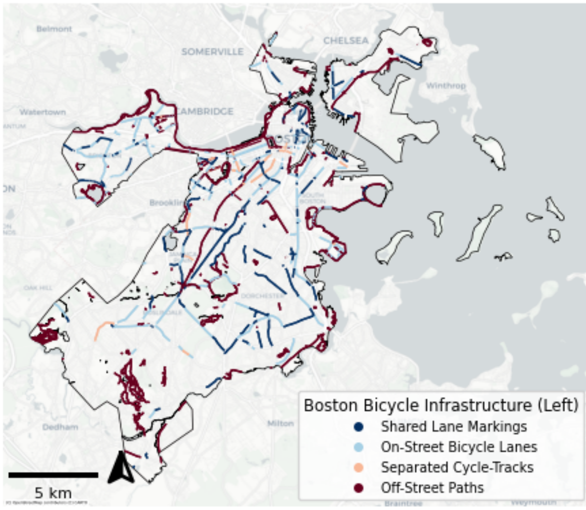


Figure 36: Cambridge Bicycle Infrastructure - Left Direction (By Andrew Brieff)

Figure 37: Cambridge Bicycle Infrastructure - Right Direction (By Andrew Brieff)

Boston



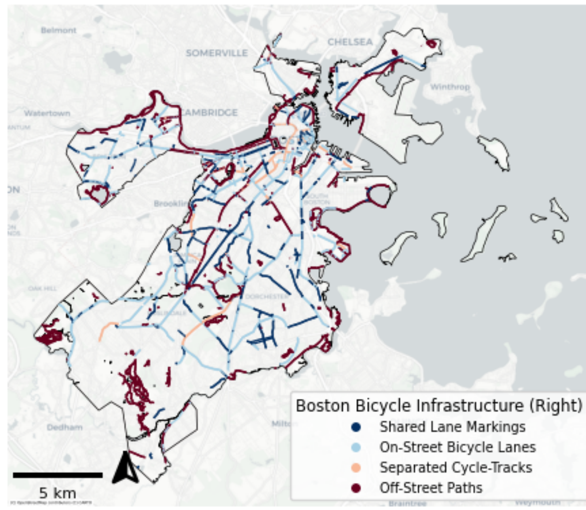
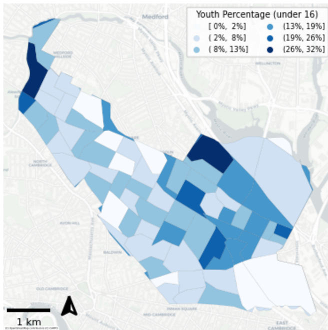


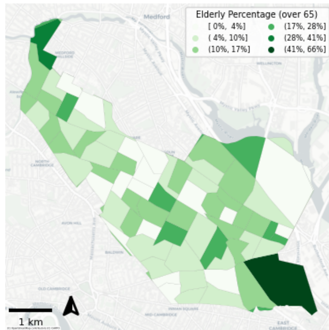
Figure 38: Boston Bicycle Infrastructure - Left Direction (By Andrew Brieff)

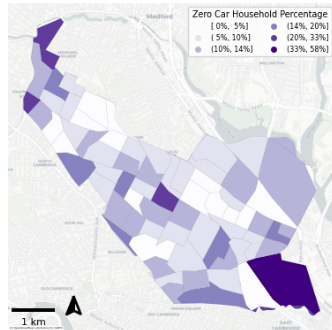
Figure 39: Boston Bicycle Infrastructure - Right Direction (By Andrew Brieff)

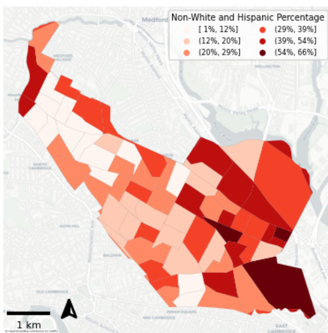
Appendix B: Equity Factor Maps

Somerville









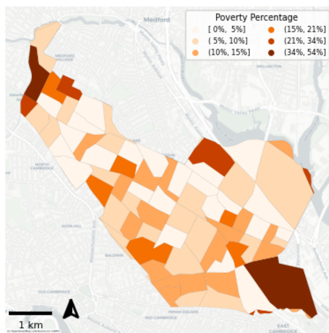


Figure 40: Youth Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff)

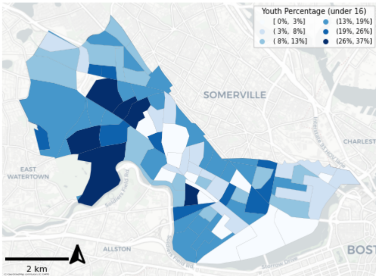
Figure 41: Elderly Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff

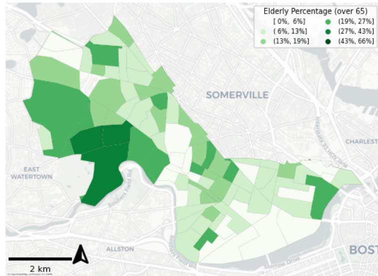
Figure 42: Zero-Car Household Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff)

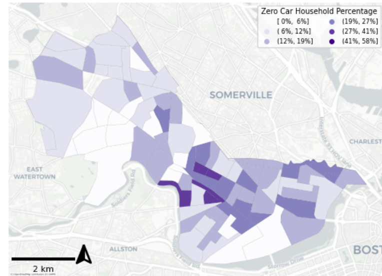
Figure 43: Non-white or Hispanic Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff)

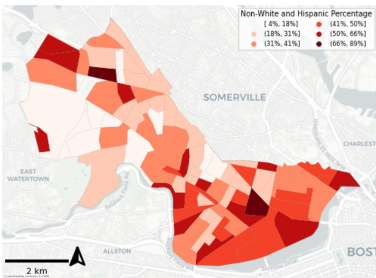
Figure 44: Population in Poverty Percentage – Somerville Census Block Groups (ACS 2021) (By Andrew Brieff)

Cambridge









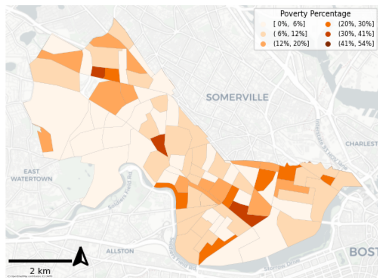


Figure 45: Youth Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff)

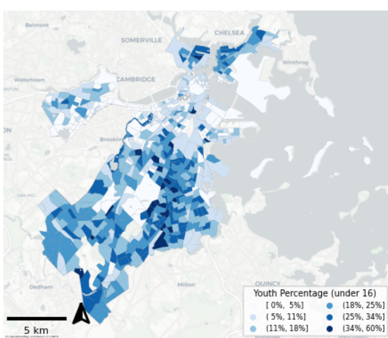
Figure 46: Elderly Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff)

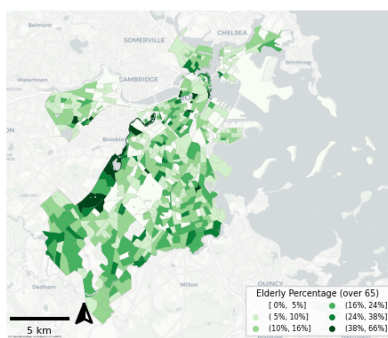
Figure 47: Zero-Car Household Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff)

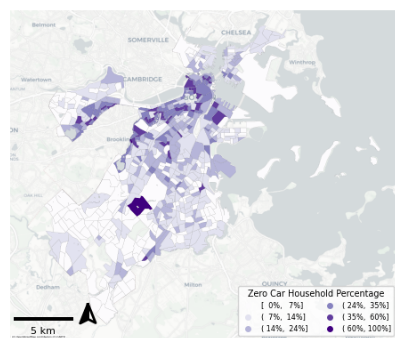
Figure 48: Non-white or Hispanic Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff)

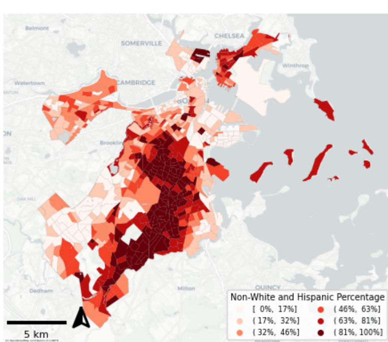
Figure 49: Population in Poverty Percentage – Cambridge Census Block Groups (ACS 2021) (By Andrew Brieff)

Boston









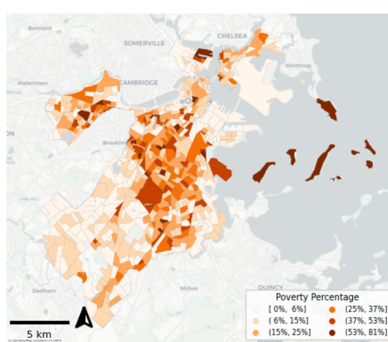


Figure 50: Youth Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff)

Figure 51: Elderly Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff)

Figure 52: Zero-car Household Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff)

Figure 53: Non-white or Hispanic Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brief

Figure 54: Population in Poverty Percentage – Boston Census Block Groups (ACS 2021) (By Andrew Brieff)

References

Abad, Lorena, and Lucas Van der Meer. 2018. "Quantifying Bicycle Network Connectivity in Lisbon Using Open Data." *Information* 9 (11): 287. https://doi.org/10.3390/info9110287.

Aldred, Rachel, and Sian Crosweller. 2015. "Investigating the Rates and Impacts of near Misses and Related Incidents among UK Cyclists." *Journal of Transport & Health* 2 (3): 379–93. https://doi.org/10.1016/j.jth.2015.05.006.

Asadi-Shekari, Zohreh, Mehdi Moeinaddini, and Muhammad Zaly Shah. 2013. "Non-Motorised Level of Service: Addressing Challenges in Pedestrian and Bicycle Level of Service." *Transport Reviews* 33 (2): 166–94. https://doi.org/10.1080/01441647.2013.775613.

"Bicycle Level of Traffic Stress Map | Boston.Gov." 2020. December 3, 2020. https://www.boston.gov/departments/transportation/bicycle-level-traffic-stress-map.

"Bike Score Methodology." n.d. Accessed February 11, 2023. https://www.walkscore.com/bike-score-methodology.shtml.

Board, National Research Council (U S.) Transportation Research. 2005. *Research on Women's Issues in Transportation, Report of a Conference: Technical Papers*. Transportation Research Board.

Boeing, G. 2017. "OSMnx: New Methods for Acquiring, Constructing, Analyzing, and Visualizing Complex Street Networks." *Computers, Environment and Urban Systems*. 65, 126-139.

Boisjoly, Geneviève, Ugo Lachapelle, and Ahmed El-Geneidy. 2020. "Bicycle Network Performance: Assessing the Directness of Bicycle Facilities through Connectivity Measures, a Montreal, Canada Case Study." *International Journal of Sustainable Transportation* 14 (8): 620–34. https://doi.org/10.1080/15568318.2019.1595791.

Broach, Joseph, Jennifer Dill, and John Gliebe. 2012. "Where Do Cyclists Ride? A Route Choice Model Developed with Revealed Preference GPS Data." *Transportation Research Part A: Policy and Practice* 46 (10): 1730–40. https://doi.org/10.1016/j.tra.2012.07.005.

Brown, Charles T., and James Sinclair. 2017. "Removing Barriers to Bicycle Use in Black and Hispanic Communities." In . https://trid.trb.org/view.aspx?id=1438326.

Buehler, Ralph, and Jennifer Dill. 2016. "Bikeway Networks: A Review of Effects on Cycling." *Transport Reviews* 36 (1): 9–27. https://doi.org/10.1080/01441647.2015.1069908.

Caulfield, Brian, Elaine Brick, and Orla Thérèse McCarthy. 2012. "Determining Bicycle Infrastructure Preferences – A Case Study of Dublin." *Transportation Research Part D: Transport and Environment* 17 (5): 413–17. https://doi.org/10.1016/j.trd.2012.04.001.

Chen, Li, Cynthia Chen, Raghavan Srinivasan, Claire E. McKnight, Reid Ewing, and Matthew Roe. 2012. "Evaluating the Safety Effects of Bicycle Lanes in New York City." *American Journal of Public Health* 102 (6): 1120–27. https://doi.org/10.2105/AJPH.2011.300319.

"Community Structure in Social and Biological Networks | PNAS." n.d. Accessed February 2, 2024. https://www.pnas.org/doi/abs/10.1073/pnas.122653799.

Cooper, Crispin H. V. 2018. "Predictive Spatial Network Analysis for High-Resolution Transport Modeling, Applied to Cyclist Flows, Mode Choice, and Targeting Investment." *International Journal of Sustainable Transportation*, November. https://www.tandfonline.com/doi/abs/10.1080/15568318.2018.1432730.

Cripton, Peter A., Hui Shen, Jeff R. Brubacher, Mary Chipman, Steven M. Friedman, M. Anne Harris, Meghan Winters, et al. 2015. "Severity of Urban Cycling Injuries and the Relationship with Personal, Trip, Route and Crash Characteristics: Analyses Using Four Severity Metrics." *BMJ Open* 5 (1): e006654. https://doi.org/10.1136/bmjopen-2014-006654.

Dill, Jennifer, and Nathan McNeil. 2013. "Four Types of Cyclists?: Examination of Typology for Better Understanding of Bicycling Behavior and Potential." *Transportation Research Record* 2387 (1): 129–38. https://doi.org/10.3141/2387-15.

———. 2016. "Revisiting the Four Types of Cyclists: Findings from a National Survey." *Transportation Research Record* 2587 (1): 90–99. https://doi.org/10.3141/2587-11.

Elvik, Rune, and Torkel Bjørnskau. 2017. "Safety-in-Numbers: A Systematic Review and Meta-Analysis of Evidence." *Safety Science* 92 (February): 274–82. https://doi.org/10.1016/j.ssci.2015.07.017.

Félix, Rosa, Paulo Cambra, and Filipe Moura. 2020. "Build It and Give 'em Bikes, and They Will Come: The Effects of Cycling Infrastructure and Bike-Sharing System in Lisbon." *Case Studies on Transport Policy* 8 (2): 672–82. https://doi.org/10.1016/j.cstp.2020.03.002.

Ferster, Colin, Jaimy Fischer, Kevin Manaugh, Trisalyn Nelson, and Meghan Winters. 2020. "Using OpenStreetMap to Inventory Bicycle Infrastructure: A Comparison with Open Data from Cities." *International Journal of Sustainable Transportation* 14 (1): 64–73. https://doi.org/10.1080/15568318.2018.1519746.

Fishman, Elliot, and Paul Schepers. 2016. "Global Bike Share: What the Data Tells Us about Road Safety." *Journal of Safety Research* 56 (February): 41–45. https://doi.org/10.1016/j.jsr.2015.11.007.

Fishman, Elliot, Simon Washington, and Narelle Haworth. 2014. "Bike Share's Impact on Car Use: Evidence from the United States, Great Britain, and Australia." *Transportation Research Part D: Transport and Environment* 31 (August): 13–20. https://doi.org/10.1016/j.trd.2014.05.013.

Fitch, Dillon T., James Sharpnack, and Susan L. Handy. 2020. "Psychological Stress of Bicycling with Traffic: Examining Heart Rate Variability of Bicyclists in Natural Urban Environments." *Transportation Research Part F: Traffic Psychology and Behaviour* 70 (April): 81–97. https://doi.org/10.1016/j.trf.2020.02.015.

Furth, Peter G., Maaza C. Mekuria, and Hilary Nixon. 2016. "Network Connectivity for Low-Stress Bicycling." *Transportation Research Record* 2587 (1): 41–49. https://doi.org/10.3141/2587-06.

Furth, Peter G., Theja V. V. K. Putta, and Paul Moser. 2018. "Measuring Low-Stress Connectivity in Terms of Bike-Accessible Jobs and Potential Bike-to-Work Trips:

A Case Study Evaluating Alternative Bike Route Alignments in Northern Delaware." *Journal of Transport and Land Use* 11 (1): 815–31.

Geller, Roger. 2009. *Four Types of Cyclists*. PortlandOnline.

Ghekiere, Ariane, Jelle Van Cauwenberg, Bas de Geus, Peter Clarys, Greet Cardon, Jo Salmon, Ilse De Bourdeaudhuij, and Benedicte Deforche. 2014. "Critical Environmental Factors for Transportation Cycling in Children: A Qualitative Study Using Bike-Along Interviews." *PLOS ONE* 9 (9): e106696. https://doi.org/10.1371/journal.pone.0106696.

Götschi, Thomas, Jan Garrard, and Billie Giles-Corti. 2016. "Cycling as a Part of Daily Life: A Review of Health Perspectives." *Transport Reviews* 36 (1): 45–71. https://doi.org/10.1080/01441647.2015.1057877.

Grisé, Emily, and Ahmed El-Geneidy. 2018. "If We Build It, Who Will Benefit? A Multi-Criteria Approach for the Prioritization of New Bicycle Lanes in Quebec City, Canada." *Journal of Transport and Land Use* 11 (1): 217–35.

Kellstedt, Debra K., John O. Spengler, Margaret Foster, Chanam Lee, and Jay E. Maddock. 2021. "A Scoping Review of Bikeability Assessment Methods." *Journal of Community Health* 46 (1): 211–24. https://doi.org/10.1007/s10900-020-00846-4.

Kim, Joon-Ki, Sungyop Kim, Gudmundur F. Ulfarsson, and Luis A. Porrello. 2007. "Bicyclist Injury Severities in Bicycle–Motor Vehicle Accidents." *Accident Analysis & Prevention* 39 (2): 238–51. https://doi.org/10.1016/j.aap.2006.07.002.

Kon, Fabio, Éderson Cássio Ferreira, Higor Amario de Souza, Fábio Duarte, Paolo Santi, and Carlo Ratti. 2021. "Abstracting Mobility Flows from Bike-Sharing Systems." *Public Transport*, March. https://doi.org/10.1007/s12469-020-00259-5.

Larsen, Jacob, and Ahmed El-Geneidy. 2011. "A Travel Behavior Analysis of Urban Cycling Facilities in Montréal, Canada." *Transportation Research Part D: Transport and Environment* 16 (2): 172–77. https://doi.org/10.1016/j.trd.2010.07.011.

Lowry, Michael B., Daniel Callister, Maureen Gresham, and Brandon Moore. 2012. "Assessment of Communitywide Bikeability with Bicycle Level of Service." *Transportation Research Record* 2314 (1): 41–48. https://doi.org/10.3141/2314-06.

Lowry, Michael B., Peter Furth, and Tracy Hadden-Loh. 2016. "Prioritizing New Bicycle Facilities to Improve Low-Stress Network Connectivity." *Transportation Research Part A: Policy and Practice* 86 (April): 124–40. https://doi.org/10.1016/j.tra.2016.02.003.

Lu, LongJason, and Minlu Zhang. 2013. "Edge Betweenness Centrality." In *Encyclopedia of Systems Biology*, edited by Werner Dubitzky, Olaf Wolkenhauer, Kwang-Hyun Cho, and Hiroki Yokota, 647–48. New York, NY: Springer. https://doi.org/10.1007/978-1-4419-9863-7_874.

Misra, Aditi, and Kari Watkins. 2018. "Modeling Cyclist Route Choice Using Revealed Preference Data: An Age and Gender Perspective." *Transportation Research Record* 2672 (3): 145–54. https://doi.org/10.1177/0361198118798968.

"Motor Vehicle Speed & Volume Increase Stress." 2017. National Association of City Transportation Officials. December 6, 2017. https://nacto.org/publication/urban-

bikeway-design-guide/designing-ages-abilities-new/motor-vehicle-speed-volume-increase-stress/.
"Multiuser Perspectives on Separated, On-Street Bicycle Infrastructure." n.d. Accessed January 26, 2024. https://doi.org/10.3141/2314-04.
Oja, P., S. Titze, A. Bauman, B. de Geus, P. Krenn, B. Reger-Nash, and T. Kohlberger. 2011. "Health Benefits of Cycling: A Systematic Review." *Scandinavian Journal of Medicine & Science in Sports* 21 (4): 496–509. https://doi.org/10.1111/j.1600-0838.2011.01299.x.
"PeopleForBikes BNA." n.d. Accessed October 11, 2021. https://bna.peopleforbikes.org/#/methodology.
Peters, Jonathan, and Cameron Gordon. 2014. *The Bike Share Gender Divide: Preliminary Analysis of Evidence from Bike Share Data in Three Cities*. https://doi.org/10.13140/RG.2.2.18388.35208.
Prabhakar, Ranjani, and R. Alexander Rixey. 2017. "Impacts of Level of Traffic Stress on Bikeshare Ridership in the Case of Capital Bikeshare in Montgomery County, Maryland." *Transportation Research Record* 2662 (1): 168–78. https://doi.org/10.3141/2662-19.
Pritchard, Ray, Yngve Frøyen, and Bernhard Snizek. 2019. "Bicycle Level of Service for Route Choice—A GIS Evaluation of Four Existing Indicators with Empirical Data." *ISPRS International Journal of Geo-Information* 8 (5): 214. https://doi.org/10.3390/ijgi8050214.
Pucher, John, Jennifer Dill, and Susan Handy. 2010. "Infrastructure, Programs, and Policies to Increase Bicycling: An International Review." *Preventive Medicine* 50 (January): S106–25. https://doi.org/10.1016/j.ypmed.2009.07.028.
Skov-Petersen, Hans, Bernhard Barkow, Thomas Lundhede, and Jette Bredahl Jacobsen. 2018. "How Do Cyclists Make Their Way? - A GPS-Based Revealed Preference Study in Copenhagen." *International Journal of Geographical Information Science* 32 (7): 1469–84. https://doi.org/10.1080/13658816.2018.1436713.
Teixeira, João Filipe, Cecília Silva, and Frederico Moura e Sá. 2021. "Empirical Evidence on the Impacts of Bikesharing: A Literature Review." *Transport Reviews* 41 (3): 329–51. https://doi.org/10.1080/01441647.2020.1841328.
Teschke, Kay, M. Anne Harris, Conor C. O. Reynolds, Meghan Winters, Shelina Babul, Mary Chipman, Michael D. Cusimano, et al. 2012. "Route Infrastructure and the Risk of Injuries to Bicyclists: A Case-Crossover Study." *American Journal of Public Health* 102 (12): 2336–43. https://doi.org/10.2105/AJPH.2012.300762.
Thomas, Beth, and Michelle DeRobertis. 2013. "The Safety of Urban Cycle Tracks: A Review of the Literature." *Accident Analysis & Prevention* 52 (March): 219–27. https://doi.org/10.1016/j.aap.2012.12.017.
Tilahun, Nebiyou Y., David M. Levinson, and Kevin J. Krizek. 2007. "Trails, Lanes, or Traffic: Valuing Bicycle Facilities with an Adaptive Stated Preference Survey." *Transportation Research Part A: Policy and Practice* 41 (4): 287–301. https://doi.org/10.1016/j.tra.2006.09.007.
Tustin, Kelsey. 2022. "Evaluating the Equity of Complete Streets in Massachusetts - ProQuest." Tufts University. https://www.proquest.com/docview/2672021961?pq-

origsite=gscholar&fromopenview=true.
Van Cauwenberg, Jelle, Peter Clarys, Ilse De Bourdeaudhuij, Ariane Ghekiere, Bas de Geus, Neville Owen, and Benedicte Deforche. 2018. “Environmental Influences on Older Adults’ Transportation Cycling Experiences: A Study Using Bike-along Interviews.” *Landscape and Urban Planning* 169 (January): 37–46. https://doi.org/10.1016/j.landurbplan.2017.08.003.
Vengroff, Darren Erik. (2022) 2023. “Censusdis.” Python. https://github.com/vengroff/censusdis.
“Who Is the ‘All Ages & Abilities’ User?” 2017. National Association of City Transportation Officials. December 6, 2017. https://nacto.org/publication/urban-bikeway-design-guide/designing-ages-abilities-new/ages-abilities-user/.
Winters, Meghan, and Kay Teschke. 2010. “Route Preferences among Adults in the near Market for Bicycling: Findings of the Cycling in Cities Study.” *American Journal of Health Promotion* 25 (1): 40–47. https://doi.org/10.4278/ajhp.081006-QUAN-236.
Yu, Wenya, Chen Chen, Boshen Jiao, Zafar Zafari, and Peter Muennig. 2018. “The Cost-Effectiveness of Bike Share Expansion to Low-Income Communities in New York City.” *Journal of Urban Health* 95 (6): 888–98. https://doi.org/10.1007/s11524-018-0323-x.
Zhao, Qiao, and Kevin Manaugh. 2023. “Introducing a Framework for Cycling Investment Prioritization.” *Transportation Research Record* 2677 (7): 265–77. https://doi.org/10.1177/03611981231152241.
Zuo, Ting, and Heng Wei. 2019. “Bikeway Prioritization to Increase Bicycle Network Connectivity and Bicycle-Transit Connection: A Multi-Criteria Decision Analysis Approach.” *Transportation Research Part A: Policy and Practice* 129 (November): 52–71. https://doi.org/10.1016/j.tra.2019.08.003.