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Direct demand modelling approach to forecast cycling activity for a proposed bike facility

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ABSTRACT

In the United States, planning and design efforts to generate bike-friendly environments through the greater provision of safe, low-stress bike infrastructure in our cities continue to advance. In Cambridge, Massachusetts, construction of the Grand Junction Pathway – an envisioned shared-use pathway – is at the heart of a citywide effort to enhance its active transportation system. However, a challenge – shared by many public agencies given that data on cycling activity are rarely frequently systematically gathered – is the creation of a baseline estimate of cycling demand for this planned network link. Using short-duration manual data supplemented with long-duration count data, this study employs a state-of-the-practice method for generating annual average daily bicycle trips for current bike network facilities. A statistical modelling strategy is then undertaken to forecast the volume of daily cyclists that the proposed off-street, shared-use path could expect to attract given its physical context and the socioeconomic attributes of nearby residents.

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Bicycling; cycling demand; bike infrastructure; non-motorized traffic modelling; built environment

1. Introduction

Meeting the challenge to plan and design cycling-friendly cities is essential to reducing inequities, improving traffic management, and producing co-benefits related to the economy, environment, and public health of a city's population (Giles-Corti et al. 2016). Urban planning and design efforts to generate bike-friendly environments characterized by a greater provision of bike infrastructure have been widely associated with increased rates of cycling activity (Pucher et al. 2011). However, while municipal governments in the United States have traditionally collected data on motorized traffic demand and roadway supply, public agencies have rarely systematically gathered data about cycling activity and the bike network (Buehler and Dill 2016). Standardization of this information is needed not only to improve measurement of cycling demand, but also to support a provision of the future bike infrastructure required to enhance both the sustainability and resiliency of an urban transportation system (Pucher and Buehler 2012).

In Cambridge, Massachusetts, construction of the Grand Junction Pathway (GJP) – an envisioned shared-use pathway for cyclists and pedestrians – is anticipated to produce

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direct economic, environmental, and health-related benefits to the residents, workers, and visitors of the Kendall Square neighbourhood. A requisite first step to determining the extent of the many intended non-transportation benefits, however, is an empirically driven estimation of the demand in cyclists the construction of this planned link in the regional bike network would attract. To date, active transportation planners, who often rely on the results from limited manual count programmes or regional travel demand models that are unresponsive to active travel modes, have not had access to directed planning tools that enable them to make informed decisions about the future demand associated with new bike infrastructure such as the GJP.

This study seeks to address this need in active transportation study to create or replicate direct demand models estimating local and regional demand for cycling associated with the introduction of a high-quality bike facility. To accomplish this stated objective, first, a state-of-the-practice method to translate short-duration manual bike counts to average daily cycling activity is introduced. Second, statistical modelling strategies are developed to define the neighbourhood-level determinants of the adjusted cycling demand metric for observed count sites. Informed by the model estimation results, a segment-level forecast of cycling demand is produced for the current and envisioned Cambridge bike network, including the proposed GJP. An implementation of this analytic approach is intended to offer a data-driven, decision-support tool for urban planners in jurisdictions with bike count programmes to develop context-specific direct demand models for cycling activity, with model findings then used to help evaluate the performance of a current bike network, support the creation of future bike infrastructure, and assess the expected non-transportation benefits associated with an expansion of the bike network.

2. Literature review

Cycling activity can be measured in a variety of ways, resulting in a range of determinants of its modelled demand (Chen, Zhou, and Sun 2017). Many methods for expressing cycling activity (e.g. mode share, trip frequency, trip duration, trip distance) traditionally rely on individual-level responses collected from household travel or intercept surveys, which are either resource intensive or produce statistically unrepresentative samples that distort quantitative analysis findings (Buehler and Dill 2016). In turn, the collection of traffic monitoring data on cycling activity, which is presently not collected by most urban municipalities (Chen, Zhou, and Sun 2017), is a data collection strategy that allows planners to develop and track performance metrics when making evidence-based decisions on future bike infrastructure investments (Hankey et al. 2017). The following paragraphs describe advancements in using data from local bike count programmes to produce measures of cycling activity and review recent studies examining the determinants of predicted cycling activity.

2.1. Measurement of cycling activity

In the past decade, efforts to collect cycling activity from manual traffic count programmes akin to traditional methods in motor vehicle traffic monitoring have emerged to assist planners with developing comparable performance metrics and modelling techniques to better understand cycling travel patterns (Hankey et al. 2017). In general, these methods seek to extend the utility of short-duration bike counts, which are rarely representative of the cycling activity associated with a particular facility, by incorporating continuous long-duration bike counting technology to produce an estimate more reflective of the average daily activity on a bike facility (Nordback et al. 2013). Notable advancements in this adaptation of traditional motor vehicle traffic monitoring strategies to model infrastructure-specific and system-wide cycling activity include the introduction of scaling factors and factor groups to estimate typical bike traffic patterns.

In practice, scaling factors are computed to account for temporal variations in cycling activity associated with the time of day, day of week, and month of year that a short-duration count was observed (Miranda-Moreno et al. 2013; Nordback et al. 2013). The need for scaling factors stems from an intentional selection of manual count locations by planners at sites where infrastructure improvements or high levels of cycling activity are anticipated (Hankey et al. 2012); not necessarily the randomized selection of count locations required to understand system-wide variations in cycling activity. Following National Bicycle and Pedestrian Documentation Project protocol, these scaling factors – derived from continuous automated counters – tend to be applied to mid-week counts collected in the evening peak travel period (Nordback et al. 2013) in order to convert short-duration manual bike counts into an annualized average of daily cyclist activity accounting for temporal and seasonal variation (Miranda-Moreno et al. 2013).

Factor groups, which classify continuous count locations with similar traffic patterns, have been created to further account for temporal variation found across manual count locations and improve accuracy in modelling cycling activity. In a study by El Esawey et al. (2013), factor groups were developed for different functional road classes; however, the authors found this distinction did not significantly improve cycling activity estimates. Examining variation in traffic patterns specific to bike facilities, Miranda-Moreno et al. (2013) demonstrated differences in the hourly and daily patterns for facilities that attract utilitarian versus recreational cyclists. More recent studies have suggested the incorporation of spatial variables to create facility groups to compare and contrast traffic patterns at count locations in areas with different land use and demographic characteristics (Lu et al. 2017).

Additional efforts to refine the measurement of cycling activity expressed as traffic volume have examined the incorporation of variables to account for anomalies attributed to atypical events of heavy precipitation or inclement weather (Nosal, Miranda-Moreno, and Krstulic 2014), strong seasonal patterns (Fournier, Christofa, and Knodler 2017), or occlusion that occurs when multiple pedestrians or cyclists pass a detection zone of an automated counter at the same time (Lu et al. 2017). Other technology-related adjustments to cycling activity estimates include correction factors pertaining to the impact of light, rain, and temperature on the precision and accuracy of certain automated devices (Proulx, Schneider, and Miranda-Moreno 2016) and the ability to compensate for periodic malfunctions that lead to sporadic data collection gaps (El Esawey, Ibrahim Mosa, and Nasr 2015). Taken together, these and other studies have helped establish a state-of-the-practice approach to model cycling activity from data collected by local traffic monitoring programmes (FHWA 2016).

2.2. Determinants of cycling activity

Strategies for monitoring bike traffic are largely the result of increased pressure on government officials to document the demand and benefits of future investments in bike infrastructure (Lindsey, Nordback, and Figliozzi 2014). To estimate these outcomes, researchers have increasingly sought to use traffic monitoring count data to develop new methods to model cyclist activity as a function of various determinants (Hankey et al. 2017; Sanders et al. 2017). Kuzmyak et al. (2014) identified five types of cycling activity determinants: facilities, land use and the built environment, demographics, natural environment, and attitudes and perceptions. However, certain measurement categories are more applicable to analyses of traffic volumes, which rely more on aspects of the transportation network and other spatial features describing the environment and demographic context surrounding count locations (Wang et al. 2016).

In a review of studies investigating the effects of bike networks on cycling activity, Buehler and Dill (2016) noted a positive relationship between cycling activity and networks of bike-friendly facilities including bike lanes, bike paths, and cycle tracks. Using passively collected behavioural data, Dill (2009) found that cyclists preferred to ride on bike facilities rather than in mixed traffic without a dedicated bike facility. Examining observed count data, Hankey et al. (2012) reported cyclist activity was significantly higher on streets with bike facilities, including those with higher motor vehicle volumes but a dedicated bike lane. Estimating a direct demand model, Fagnant and Kockelman (2016) found an increase in the width of bike lanes and the provision of a separated shared-use path to significantly increase cyclist activity. In general, direct demand models have echoed other study designs revealing a beneficial nature of bike infrastructure provision to increasing cyclist traffic volumes (Wang et al. 2016); however, studies designed to measure the differential impact of bike lanes and paths have been less conclusive (Buehler and Dill 2016).

While a positive connection between bike facilities and cycling activity is apparent, detailed metrics of the built environment and demographic composition near count locations is needed (Miranda-Moreno et al. 2013). To date, an assorted set of neighbourhood-level built environment and demographic determinants have been studied to model variations in bike volume (Chen, Zhou, and Sun 2017; Sanders et al. 2017). In terms of land development patterns, count locations in the vicinity of a greater diversity in land use types (Strauss and Miranda-Moreno 2013; Chen, Zhou, and Sun 2017; Hankey et al. 2017), intensity in commercial space (Griswold, Medury, and Schnieder 2011; Tabeshian and Kattan 2014), and population (Wang et al. 2014; Hankey and Lindsey 2016) or employment (Fagnant and Kockelman 2016) density have displayed higher levels of cycling activity. Less evidence exists modelling the neighbourhood effect of network connectivity on cycling activity (Schoner and Levinson 2014). Strauss and Miranda-Moreno (2013) discovered an increase in average street length was negatively associated with cycling activity, while Griswold, Medury, and Schnieder (2011) found connected node ratio to have a positive impact on cycling activity on weekdays. Regarding neighbourhood-level sociodemographic and economic determinants, a handful of studies (Strauss and Miranda-Moreno 2013; Wang et al. 2014) found average household income was positively related to cycling activity; a finding contradicted by other studies (Hankey et al. 2012; Hankey et al. 2017). More consistently, cycling activity has been positively associated with neighbourhoods composed of a higher percentage of residents with a college education (Hankey et al. 2012; Wang et al. 2014), which parallels individual-specific trends of cycling in the United States (Pucher et al. 2011). Likewise, count locations within neighbourhoods with a higher percentage of residents younger than six or older than 64 have been found to have lower levels of cycling activity (Wang et al. 2014). In all, while studies providing direct demand models of cyclist activity are emerging, research gaps still exist in the examination of how the built environment – chiefly, network connectivity metrics incorporating links and nodes – moderates the effect of bike-friendly facilities on increasing cycling activity.

3. Methods

3.1. Data

Count data used in the estimation of cycling demand associated with a proposed GJP were gathered from two sources. Visualized in Figure 1, short-duration manual counts were performed at 91 approaches across 19 intersections for one-hour peak period travel periods in September 2016 as part of the City of Cambridge's biannual bike count programme. These observed counts of cyclists using various facilities at a given time and location were complemented with long-duration automated counts collected for the 2016 calendar year by the Eco-Totem counter at Broadway near Kendall Square. In-ground loop detectors embedded under the pavement at this location permit the continuous tracking of the number of bikes passing by this automated counter, with these data being publicly shared in 15-minute time increments.

The 91 manual count locations were geocoded to the City's street network, which included corridor-level information (e.g. cycling facility type) related to the intersection approach as well as all street segments in the citywide study area. To measure the

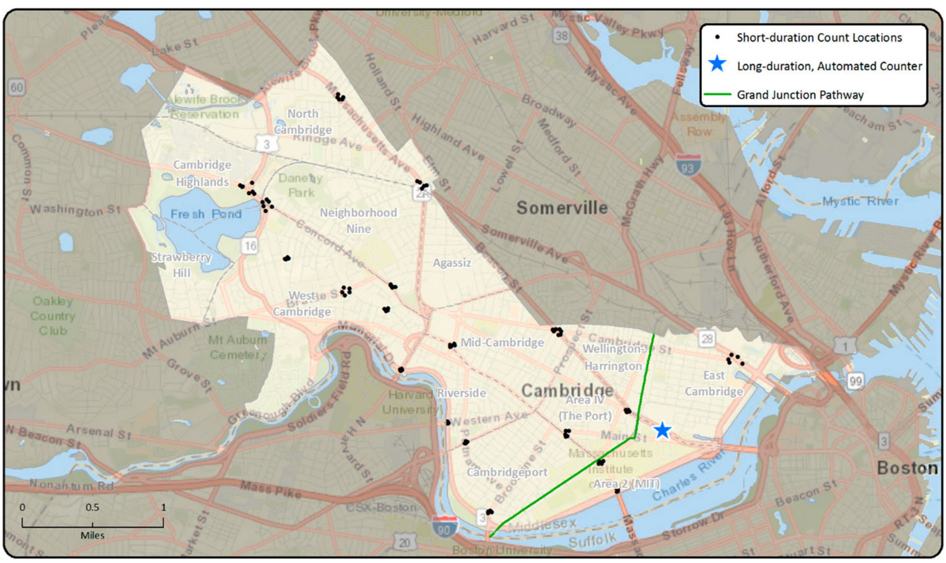

Figure 1. Manual and automated count locations in Cambridge, Massachusetts.

neighbourhood-level context surrounding the count locations and other street segments, the geographic midpoint of each transportation network link was determined and spatially associated with two zone-based systems. First, the study area was delineated into 344 250-meter grid cells, with a set of built environment measures (Gehrke and Welch 2017) describing the land development pattern and network connectivity calculated for each subunit that was then assigned to the relevant street segment. Second, the link-level midpoints were then spatially related to its surrounding United States Census block group; for which various neighbourhood-level socioeconomic features were calculated using 2012–16 American Community Survey's Five-year Estimates data.

3.2. Analytic design

In combination, the two observed bike count data sources and neighbourhood-level measurement of the physical and social context surrounding the City's street network were used to estimate the determinants of cycling demand and forecast cycling activity at unobserved locations, including the GJP. The first step in this methodologic approach was to develop a metric of cycling activity that more aptly reflected the demand at manual count locations and was less biased by the time of day or season in which the 91 one-hour snapshots of site-level cycling activity were collected. In subsequent steps, these activity estimates were then used to summarize the number of annual average daily bicycle trips (AADBT) for different bike facilities in the study area, model AADBT at manual count locations based on neighbourhood-level physical and demographic characteristics of the street segment's surrounding context, and then forecast AADBT for all street segments in Cambridge based on either facility type or a set of significant model parameters.

3.2.1. Measuring cycling activity at observed count locations

A central motivation of many manual bike traffic monitoring programmes, which are time and resource intensive, is to provide active transportation data to planning professionals seeking to best inform investments in new bike infrastructure, demonstrate the utility of past investments, and ultimately quantify cycling benefits that make active transportation projects more competitive in funding decisions (Alta Planning +Design 2016). Therefore, the decision of where to conduct manual counts tends to be deliberate with an aim to highlight a community's infrastructure-related successes and opportunities, which often leads to targeted counts during weekday peak travel periods in warmer months. Given the spatiotemporal biases inherent to these subjective decisions, researchers should seek to create a cycling activity metric reflecting average travel conditions.

The estimation of AADBT at manual count locations in this study was performed using methods similar to those defined for non-motorized travel modes in the *Traffic Monitoring Guide* (FHWA 2016). The formula-based method adjusts the short-duration bike counts with time-of-day, day-of-week, and month-of-year factors derived from the long-duration counts collected by the Broadway Eco-Totem.

$$\widehat{AADBT} = c_{itdm} \times \left[\frac{1}{T} \times \frac{1}{D} \times \frac{1}{M} \times L\right] \quad (1)$$

where c_{itdm} is the observed count of bikes observed at site i at 15-minute interval (time-of-day) t on day-of-week d in month-of-year m. T is the time-of-day factor (percent of the annual count of cyclists at the Broadway Eco-Totem for equivalent 15-minute interval), D is the daily factor (percent of the annual count of cyclists at the Broadway Eco-Totem for equivalent day-of-the-week), and M is the month factor (percent of the annual count of cyclists at the Broadway Eco-Totem for equivalent month-of-the-year). An additional local factor (L) is then applied to correct for discrepancies with the automated counter technology related to cyclists occasionally passing the Broadway Eco-Totem outside the bike lane where detection is recorded. This study adopts a local correction factor of 1.167 based on ground-truthing manual counts at the same location (Toole Design Group 2018).

3.2.2. Forecasting cycling demand at unobserved locations

After expanding the short-duration counts into AADBT calculations for the observed locations in the study sample, two strategies were employed to estimate cycling demand. In the first strategy, the 91 locations were assigned to the nearest corresponding segment in the street network, which was classified into five bike infrastructure-related categories: on-street, local; on-street, arterial; on-street bike lane; off-street shared-use; and off-street, cycle track. A mean AADBT for each facility type in the study sample was next determined, with the facility-specific value and its standard deviation then assigned to similarly classified streets in the study area to provide a confidence interval estimate of forecast segment-level demand.

A second strategy to forecast cycling demand sought to offer additional nuance to these segment-level estimates by accounting for the neighbourhood-level context surrounding these facility types. Since AADBT cannot be a negative value, two tobit censored regression models (Tobin 1958) with a lower limit set at zero were estimated. These models were iteratively specified using a dredging approach in which a base model with facility type was first estimated, with neighbourhood-level characteristics related to the built environment and socioeconomic composition then subsequently added in separate waves producing the model with lowest log-likelihood statistic and selected neighbourhood predictors significant at $p \leq 0.05$. In addition to the categorical variable for facility type, the second tobit model included a set of dummy variables describing the 13 City of Cambridge neighbourhood planning groups in the initial estimation of a base model. The specification of grouping variables in the second model sought to help assuage concerns of spatial autocorrelation and a violation of the independence in sample observations due to a clustering of manual count locations, which could not be addressed by multilevel modelling approaches because of the limited sample size. The coefficients produced by the two models were then used to predict segment-level AADBT for all unobserved facilities, including the GJP, by inserting the relevant spatial information.

4. Results

4.1. Neighbourhood context

Table 1 describes the built environment and socioeconomic neighbourhood-level measures tested in the specification of the direct demand models of segment-level

Table 1. Summary of neighborhood-level built environment and socioeconomic indicators.

Built Environment Indicators	Study Sample ($n = 26$)			Study Area ($n = 344$)		
Geography: 250-meter grid cell	Min	Mean	Max	Min	Mean	Max
Persons per acre	0.00	23.84	109.92	0.00	21.90	187.24
Jobs per acre	0.00	34.82	226.68	0.00	20.21	666.52
Activity (persons and jobs) per acre	0.00	58.65	242.02	0.00	42.11	675.91
Basic jobs per acre	0.00	6.35	105.05	0.00	2.67	141.97
Retail jobs per acre	0.00	4.26	24.74	0.00	1.92	112.05
Service jobs per acre	0.00	13.12	119.56	0.00	15.62	650.84
Employment entropy 1: 2-digit NAICS codes	0.00	0.50	0.85	0.00	0.37	0.85
Employment entropy 2: Basic, retail, service	0.00	0.45	0.93	0.00	0.30	0.99
Jobs-persons balance	0.00	2.14	19.35	0.00	11.72	1,707.69
Retail jobs-persons balance	0.00	0.22	1.69	0.00	0.40	50.90
Alpha index	0.00	0.78	1.00	0.00	0.67	1.00
Beta index	0.29	0.44	0.60	0.00	0.40	1.00
Gamma index	0.63	0.91	1.00	0.00	0.78	1.00
Connected node ratio	0.50	0.86	1.00	0.00	0.73	1.00
Rapid transit station within one-half mile	0.00	0.77	1.00	0.00	0.65	1.00
Sociodemographic and Economic Indicators	Study Sample ($n = 37$)			Study Area ($n = 88$)		
Geography: US Census block group	Min	Mean	Max	Min	Mean	Max
Age distribution						
Under 18 years	0.00	0.12	0.26	0.00	0.12	0.36
18–24 years	0.00	0.20	0.97	0.00	0.18	0.97
25–34 years	0.02	0.25	0.58	0.02	0.28	0.58
35–44 years	0.00	0.13	0.27	0.00	0.13	0.45
45–64 years	0.00	0.17	0.34	0.00	0.18	0.39
65 years and older	0.00	0.12	0.35	0.00	0.12	0.35
Educational attainment distribution						
Less than bachelor's degree	0.00	0.22	0.72	0.00	0.25	0.85
Bachelor's degree	0.17	0.29	0.59	0.15	0.30	0.59
Graduate degree	0.18	0.50	0.81	0.11	0.48	0.81
Annual household income distribution						
Under $15,000	0.00	0.11	0.55	0.00	0.11	0.55
$15,000 to $34,999	0.00	0.09	0.27	0.00	0.10	0.40
$35,0000 to $74,999	0.00	0.21	0.67	0.00	0.21	0.67
$75,0000 to $149,999	0.00	0.29	0.48	0.00	0.29	0.63
$150,000 and above	0.00	0.28	0.68	0.00	0.27	1.00
Race and ethnicity distribution						
White, non-Hispanic	0.38	0.67	0.95	0.08	0.66	0.95
Hispanic or Latino	0.00	0.07	0.21	0.00	0.08	0.22
Black or African American	0.00	0.08	0.45	0.00	0.08	0.53
Asian	0.00	0.14	0.34	0.00	0.14	0.34
Other distinctions	0.00	0.05	0.55	0.00	0.05	0.55
Primary commute travel mode						
Auto	0.08	0.32	0.59	0.00	0.32	0.62
Public transit	0.07	0.26	0.45	0.05	0.29	1.00
Bicycling	0.00	0.07	0.19	0.00	0.07	0.20
Walking	0.03	0.26	0.75	0.00	0.24	0.75
Other modes	0.00	0.09	0.21	0.00	0.08	0.21

cycling activity in the study sample and area. In general, the street segment midpoints associated with the study's observed count locations tended to be in neighbourhoods characterized by a higher employment concentration, more traditional street design, and greater balance of job opportunities to residential population than the average 250-meter grid cell in Cambridge. The residential population surrounding the manual count locations, in turn, was similar in its socioeconomic composition to the average US Census block group, with the workforce in neighbourhoods near count locations showing a comparable proclivity to cycle as the commuting population in the average citywide block group.

4.2. Cycling activity at observed count locations

The expansion of observed manual bike count data at 90 sampled locations into AADBT by using long-duration automated counter information resulted in a cycling activity estimate that better accounted for temporal and seasonal variations in cycling activity. The bike-related infrastructure of one observation was not obtained. Table 2 summarizes the AADBT at these manual bike count locations by facility type as well as the confidence interval (CI) bounds used to produce range estimates of other street segments.

In the study sample, 11 manual counts were conducted along local streets without a designated bicycling facility. The estimated cycling demand for street segments of this bike-related infrastructure description ranged between 22.65 and 86.78 AADBT, while arterial roadways without a dedicated bicycling facility in the study sample could expect between 256.84 and 404.95 AADBT. Of the three off-street infrastructure categories, sampled shared-use facilities – not including the proposed GJP – were estimated to have the lowest average AADBT. Conversely, off-street, cycle tracks were estimated to generate the highest activity levels; between 199.10 and 782.88 AADBT. Observed bike count locations along approaches with an on-street, bike lane were estimated to have an approximate AADBT of 603.44; less than one-half of the 1,223 (1,048 without the local correction factor) average daily bicyclists that passed by the Broadway Eco-Totem and its adjacent bike lane in 2016.

4.3. Modelled cycling demand forecasts

The estimation results of the direct bike demand model without neighbourhood grouping variables are shown in Table 3. The log-likelihood of this model specification with facility type and neighbourhood-level indicators reflected a significant improvement over the null model, which had a log-likelihood of −643.10. Modelled cycling demand – represented by AADBT – at the observed manual count locations was likely to be lower along local streets without any designated bike facility than off-street, shared-use paths. In regard to neighbourhood-level determinants of cycling demand, street segments in a physical context with more jobs than residents and a residential population earning between $75,000 and $150,000 (the median annual household income in Cambridge from 2012 to 16 was $107,897) were more likely to generate higher values of AADBT. Conversely, an increase in the average age of residents between 45 and 64 years in block groups surrounding a street segment resulted in a decrease in AADBT. This latter finding parallels evidence that neighbourhoods with a younger population are likely to have higher bike mode shares.

Table 2. Summary of annual average daily bicycle trips (AADBT) at observed manual bike count locations.

Bike-related infrastructure designation	*n*	Median	Mean	SD	Lower CI	Upper CI
On-street, local functional class	11	58.11	54.71	47.73	22.65	86.78
On-street, arterial functional class	35	252.92	330.90	215.58	256.84	404.95
On-street, bike lane	31	464.09	603.44	459.32	434.96	771.92
Off-street, shared-use facility	8	261.26	259.45	138.66	143.53	375.37
Off-street, cycle track	5	490.30	490.99	235.08	199.10	782.88

Table 3. Estimation results of the preferred direct bike demand model.

Indicators	Coef.	Std. Error	*p*-value	Lower CI	Upper CI
Intercept	515.70	139.70	0.01	241.87	789.50
Intercept (log standard deviation)	5.51	0.08	0.01	5.35	5.67
Bike-related infrastructure designation					
On-street, local functional class	−251.50	121.90	0.04	−490.45	−12.63
On-street, arterial functional class	−74.72	101.80	0.46	−274.34	124.90
On-street, bike lane	113.50	105.70	0.28	−93.71	320.80
Off-street, cycle track	−89.87	150.50	0.55	−384.92	205.19
Jobs-persons balance	24.69	7.82	0.00	9.37	40.01
Age: 45–64 years	−1,944.00	337.60	0.00	−2,605.57	−1,282.19
Household income: $75,0000 to $149,999	694.60	271.70	0.01	162.11	1,227.09

Notes: Log-likelihood = −610.32, *df* = 173.

An alternative bike demand model including neighbourhood grouping indicators was next estimated, with results provided in Table 4. This tobit model, which produced a log-likelihood statistic of −603.31, had a different specification to the prior direct demand model because its inclusion of neighbourhood grouping variables produces multicollinearity effects with certain built environment and socioeconomic indicators. Of note, the Area IV neighbourhood – including Kendall Square – is the reference case of this model, with Agassiz (neighbourhood 8) and Strawberry Hill (neighbourhood 13) not isolated in this specification because manual counts were not performed within these boundaries. While street segments located within the second neighbourhood experienced higher cycling demand than the Area IV neighbourhood, segments in five of the other nine neighbourhoods were likely to experience lower AADBT, ceteris paribus. Additionally, while facility type was not a significant determinant of AADBT in this alternative model, street segments in 250-meter grid cells with strong street network connectivity were negatively associated with cycling demand. A counterintuitive finding that may be related to a conceivable barrier to cycling presented by frequent intersection crossings and the increased possibility of conflicting vehicle turning movements. Finally, as

Table 4. Estimation results of direct bike demand model with neighborhood planning groups.

Indicators	Coef.	Std. Error	*p*-value	Lower CI	Upper CI
Intercept	921.20	263.90	0.01	403.90	1,438.51
Intercept (log standard deviation)	5.43	0.08	0.01	5.27	5.59
Bike-related infrastructure designation					
On-street, local functional class	−230.80	131.00	0.08	−487.56	26.06
On-street, arterial functional class	−50.97	110.40	0.64	−267.35	165.42
On-street, bike lane	166.10	116.60	0.15	−62.55	394.67
Off-street, cycle track	−54.73	140.80	0.70	−330.75	221.28
Neighborhood Planning Groups					
1: East Cambridge	−602.40	147.60	0.01	−891.56	−313.16
2: Area 2 (MIT)	289.20	128.10	0.02	38.02	540.31
3: Wellington-Harrington	−86.73	161.20	0.59	−402.72	229.27
5: Cambridgeport	−296.60	117.80	0.01	−527.52	−65.71
6: Mid-Cambridge	−282.10	133.00	0.03	−542.85	−21.44
7: Riverside	−273.40	132.00	0.04	−532.05	−14.75
9: Neighborhood 9	−138.50	141.00	0.33	−414.74	137.80
10: Neighborhood 10	−203.20	116.80	0.08	−432.08	25.73
11: North Cambridge	−142.10	123.30	0.25	−383.69	99.51
12: Cambridge Highlands	−387.20	158.20	0.01	−697.29	−77.17
Beta index	−1,249.00	435.80	0.01	−2,102.87	−394.42
Age: 25–34 years	738.60	340.60	0.03	71.06	1,406.23

Notes: Log-likelihood = −603.31, *df* = 164.

hypothesized, a street segment located in a block group with a higher residential demographic between 25 and 34 years of age was found to have an increased level of modelled cycling demand.

Due to the incomplete spatial representation of manual count locations, only estimation results from the first direct demand model are recommended to forecast cycling activity on citywide street segments. Figure 2 visualizes this forecast AADBT described in the model results of Table 3, using mean estimates and convenient breakpoints.

4.4. Cycling demand forecasts for the grand junction pathway

Figure 3 visualizes the cycling demand forecast for the proposed GJP using the single-point estimate from the facility-based summaries, preferred direct demand model (Model 1), and direct demand model with neighbourhood grouping variables (Model 2). The GJP is designed as a shared-use facility, which were projected to have an AADBT estimate of 259.45 using an aggregated summary by facility approach. This forecast is higher than the average cycling activity resulting from the second direct demand model for both the GJP segment north of Main Street (145.08 AADBT) and its southern section (264.90 AADBT). Estimated activity for the northern section in the preferred model was 447.05 AADBT, with the southern section that parallels the cycle track along Vassar Street having an average forecast demand of 742.68.

Extrapolating the AADBT estimates of the preferred model and utilizing the fixed Broadway Eco-Counter cyclist counts, it is possible to provide a peak hour volume estimate based on 2016 conditions and activity patterns of an on-street, bike lane. Given these caveats and others discussed in the subsequent section, a reasonable expectation is for the northern section of the GJP to have a morning and evening peak period

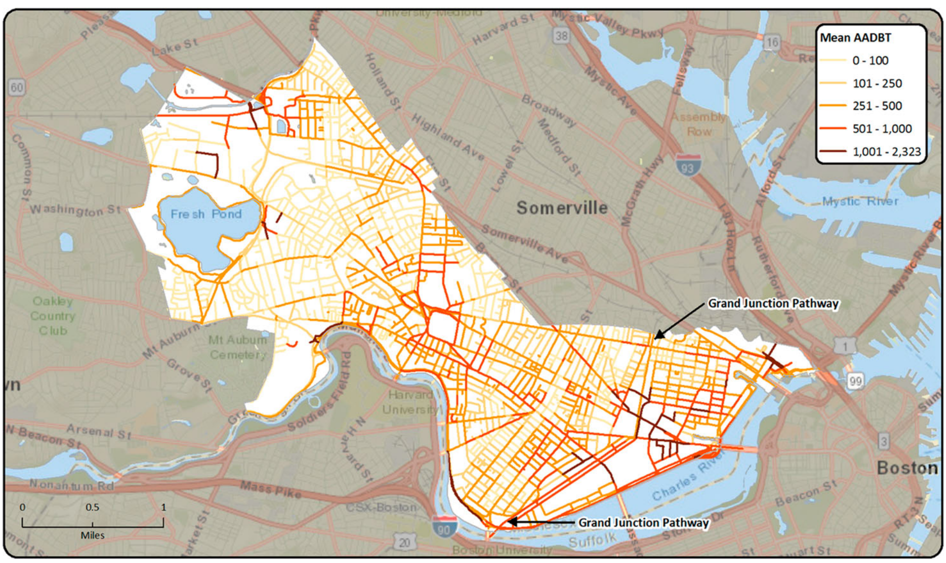

Figure 2. Forecast cycling demand as annual average daily bicycle trips (AADBT).

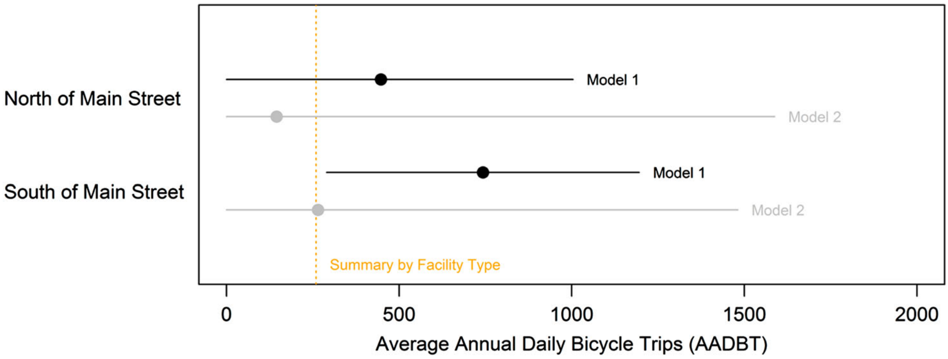

Figure 3. Forecast cycling demand for Grand Junction Pathway using three methods.

volume of up to 468 cyclists (1.95 bikes per minute) and the portion south of Main Street to have 558 cyclists (2.33 bikes per minute).

5. Conclusions

The contributions of this research are twofold. First, by complementing previous manual bike count efforts with archived automated bike counter data, one-hour observed counts were expanded into an average daily cycling demand estimate, adjusted for temporal and seasonal variation. Second, after translating annual average daily bicycle trips (AADBT) to a segment-level estimate, three methods were then undertaken to forecast cycling activity for all streets and paths in the study area. Of note, the two specified direct demand models offered a requisite ability to predict bicyclist demand on an off-street, shared-use facility such as the Grand Junction Pathway (GJP).

In all, our study findings offer public agencies a potential decision-support tool to quantitatively identify the demand associated with proposed bike-infrastructure investments and evaluate the cycling activity generated by past investments or programmatic interventions. This ability to generate a defensible forecast of cycling activity given the unique context of the GJP or any other proposed bike facility is critical for planning agencies given the growing competition amongst active transportation investments for limited local and state financial resources. However, any estimation of bicycle volume associated with the planned construction of a low-stress bike facility remains a challenging task for several reasons. Those new cycling trips generated by travellers who prefer riding along an off-street facility such as the GJP and existing trips that will be diverted to the GJP from present bike facilities are not captured in this study's modelled demand estimates. As such, our cycling demand estimates are considered a conservative baseline expectation that can be surpassed given a likelihood for the GJP to unlock a latent demand among risk-averse cyclists, re-route current travel patterns, and be accompanied by other local and regional bike infrastructure investments.

While offering value to ongoing and future active transportation planning processes, this study also has several notable limitations and opportunities for advancement. Foremost, the manual counts were likely conducted at locations that were predetermined by agency staff in an effort to underscore new opportunities or existing barriers to increasing cycling activity; as a result, introducing an upward bias to AADBT estimates based on observed counts. Future collection efforts of the bike count programme may consider a random assignment of manual count locations, with more observations and greater spatial variation. The small sample of short-duration counts limited the ability of this study to statistically control for spatial clustering of sites in its two direct demand models, which could be better addressed applying a multilevel modelling approach. Given a need to also offer greater variation in the time-of-day that counts are performed – only peak period cycling was measured in this study sample, manual efforts to obtain short-duration counts could be transitioned toward strategies using continuous automated technologies that are redistributed on a short-term schedule. A shift to this automated approach would allow time-of-day variation to be calculated at a randomly-assigned count location rather than capturing this 15-minute increment variation using the fixed Broadway Eco-Counter that likely has a different associated travel pattern. Finally, an extension of this proposed data collection effort would permit improvements to the bike direct demand models by incorporating precipitation- and temperature-related variables, which are known to impact cycling activity. Yet, despite these limitations and likely others, this research offers new insight into the cycling activity expected from introducing an off-street bike-friendly facility to cyclists.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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