Bikeshare Use in Urban Communities: Individual and Neighborhood Factors

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Objective: Bicycling is an affordable way to increase access to employment, schooling, and services and an effective measure against obesity. Bikeshare programs can make bicycling accessible to diverse populations, but little evidence exists on their adoption in low-resource neighborhoods. Our study examined factors associated with bikeshare use in a metropolitan area in the southern United States.

Methods: We performed a retrospective cross-sectional analysis of a database of clients (N=815) who rented a bicycle from Zyp Bikeshare in Birmingham, Alabama between October 2015 and November 2016. Individual-level variables included bike use frequency, average speed, total miles traveled, total minutes ridden, bike type (traditional vs electricity-assisted pedelec), membership type, sex, and age. Area-level data aggregated to Census tracts, proxies for neighborhoods, were obtained from the 2010 US Census after geocoding clients' billing addresses. Using exploratory factor analysis, a neighborhood socioeconomic disadvantage index (SDI) was constructed. Bikeshare station presence in a tract was included as a covariate. Multivariate linear regression models, adjusted for clustering on Census tracts, were estimated to determine predictors of bikeshare use.

Results: In a multivariate regression model of individual and neighborhood characteristics adjusted for clustering, each decile increase in the SDI was associated with a 9% increase in bikeshare use (P<.001). Bikeshare use was also positively associated with speed (.1, P<.001), total miles (.008, P<.001), and pedelec use (1.02, P<.01).

Conclusion: Higher neighborhood socioeconomic disadvantage is associated with higher bikeshare use. Bikeshare is a viable

Introduction

Low-income urban communities have limited access to healthy food and physical activity opportunities and carry a disproportionate burden of obesity. They also have limited transportation options, which restricts community connectivity (access to employment, schooling, retail, and services) and negatively affects quality of life.[1] Active modes of transportation are an effective prevention measure against obesity and chronic diseases.[2] For example, bicycling decreases obesity rates,[3,4] lowers body weight,[5] decreases cardiovascular risks,[6] and improves well-being.[7] Bicycling is also an affordable way to improve community connectivity and livability.[8]

Public bicycle sharing systems, or "bikeshares," allow clients to use a smart card or a key fob to unlock a bicycle from one bikeshare station and return the bicycle to another station within a period of time usually ranging from 30 to 60 minutes. Wireless communication technology allows real-time monitoring of occupancy rates at stations, and the movement of bicycles is monitored through global positioning system (GPS) devices.

Due to their relatively low cost and convenience, bikeshare programs can make bicycling accessible to users of diverse socio-demographic profiles, including low-income people and racial/ethnic minorities. For example, discounted annual memberships paid in cash are typically available for income-qualifying individuals receiving public assistance. Bikeshare programs that include electricity-assisted bicycles (pedelecs) are particularly effective, as they make bicycling accessible in hot climates, on

transportation option in low-resource neighborhoods and may be an effective tool to improve the connectivity, livability, and health of urban communities. *Ethn Dis*. 2017;27(Suppl 1):303-312; doi:10.18865/ed.27.S1.303.

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hilly terrains, or to users with limited fitness,[9] who would otherwise use sedentary modes of transportation.[10] Bikeshare programs that include pedelecs could be a feasible alternative to a sedentary lifestyle and help enhance the health of communities.[11]

Despite significant expansion, bikeshare programs may not have reached the populations of highest need,[12] and the evidence for maximizing their potential in low-income urban areas is scarce. The goal of this study was to examine socioeconomic factors associated with bikeshare use in Birmingham, Alabama, a metropolitan area in the southern United States.

The study was informed by the Health Lifestyle Theory,[13] which correlates health lifestyles with structural determinants, such as class circumstances, age, sex, race/ethnicity, collectivities, and living conditions. Applying this theoretical framework, we hypothesized that bikeshare use would be associated with individual- and neighborhood-level social factors.

Methods

Study Population

The project was implemented in the City of Birmingham (*N*=212,237), where 28% of all residents and 35% of African American residents live in households with income below the federal poverty level. Additionally, 17% of residents aged ≥ 25 years and 25% of African American residents aged ≥ 25 years are without a high-school diploma. Life expectancy in Jefferson County, where Birmingham is located, varies 20 years across Census tracts,

and tracts with high percentages of African Americans have some of the lowest life expectancies in the country.[14] Obesity and chronic diseases are major health issues in the area, with a significant differential disease burden by race.[15] Compounding these challenges is the fact that all of the US Department of Agriculture (USDA) food deserts in Jefferson County are in the City of Birmingham, concentrated in areas with high percentages of African Americans. A total of 39%

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of Birmingham's population lives in Census tracts designated as food deserts.[16] For residents with limited transportation options, this creates a major problem. The USDA found that 11,000 people in Jefferson County had no ready means of transportation and were more than a mile from a grocery store.[17] Public transportation in the area is limited, and until recently Alabama was one of only four states without a transit association.[18]

Bikeshare Program

Zyp Bikeshare, an initiative of REV Birmingham in partnership

with the Regional Planning Commission of Greater Birmingham and the City of Birmingham, is a program that includes 40 bikeshare stations and 400 bicycles (both traditional and pedelecs) accessible 24/7, year-round. Riders check out bicycles and pedelecs through daily, quarterly, or annual membership. Annual membership is available in three options: Annual ($75 for 1 year), Equity ($15 for 1 year, paid in cash, for income-qualifying individuals receiving public assistance), and Shyfter ($200 for 2 years, including event invitations and other benefits).

Zyp Bikeshare uses equipment from Bewegen Technologies, Inc. featuring BikeEmotion Module that contains Active Live GPS, boards, and a screen. Two types of bikes are available, both with a bright green aluminum frame and a basket: the regular pedal bike with an 8-speed internal gear hub, and the electric-assisted pedelec with a 250 watt nominal DynaMe motor. The pedelecs offer approximately 80% assistance in pedaling. Both bikes contain lithium ion batteries charged by solar power at the bike stations.

User data collected by Zyp include utilization history (eg, frequency, distance, speed, and time of rides; turn-by-turn routes and terrain; pick-up and drop-off stations) and billing history; Zyp does not collect socio-demographic data.

Study Design

We performed a retrospective cross-sectional analysis of bikeshare utilization data collected between October 15, 2015 and November 7, 2016. Only clients who had pur-

chased an annual membership, either prior to or during this time period, were included in the analyses. To obtain data about the clients' residential neighborhoods, we geocoded the clients' billing addresses, assumed to match their residential addresses, and assigned a Census tract identifier to each record. Census data at the Census tract level were obtained from the 2010 US Census and matched to individual clients based on their Census tract, with the exception of one variable (disability), which was obtained from the 2012 American Community Survey. The location of each bike rental station (available at https://www.zypbikeshare.com) was also geocoded, to determine which Census tracts had easy access to bikes. Ethical approval for this study was obtained from the UAB Institutional Review Board, Protocol X160613005.

Measures

Individual Characteristics

Each client had one record for each rental session, containing the time and location a bike was picked up and dropped off, the distance traveled, and the total amount of time for which the bike was rented. Rental session data were matched with personal data that included sex, age, membership type, length of membership in days, and Census tract identifier. Measures from each ride were added together to create a summary measure of each variable across all rides of a client. The total miles each client traveled were divided by the total renting hours of that client to create a measure of average speed. The total number of rides a client took on a pedelec was divided

by the total number of rides to create a ratio of pedelec use. Finally, for every client, we calculated an average number of rides per membership day by dividing the client's total number of rides by the total number of membership days within the data collection period. This was done to account for the varying lengths of memberships during the data collection period.

Individual characteristics included sex, age, type of annual membership (Annual, Equity, Shyfter), average number of rides per membership day, percentage of rides on a pedelec, average speed of rides, total distance traveled, and total minutes ridden. The dependent variable was average number of rides per membership day. Because it was not normally distributed in its untransformed form (mean=.978, standard deviation=8.96), it was log-transformed prior to inclusion in the analyses. Type of annual membership was included as a covariate because it may be indicative of individual income. Pedelec use, speed and distance were included as covariates to control for differences in riding styles.

Neighborhood Characteristics

Census tracts, which are small, socio-demographically homogenous geographic units, served as proxies for neighborhoods of residence. Fifteen variables obtained from the US Census were included in the analyses: 1) % adults aged >25 years without high-school diploma; 2) % adults aged >25 years with college degree; 3) median household income; 4) % households with interest, dividend, or rental income; 5) median value of owner-occupied housing; 6) % households on public assistance or food stamps; 7)

% households in poverty; 8) % cost-burdened households (with housing costs >30% income); 9) civilian unemployment rate; 10) % households without vehicles; 11) mean number of household vehicles; 12) % minority population; 13) % disabled population; 14) % households with seniors (age >65 years) living alone; and 15) % single-parent households with children. These variables reflect various aspects of income, wealth, education, occupation, housing, and family structure and are comparable to measures used previously to examine the effects of neighborhood disadvantage on health.[19-22] All data were obtained from the 2010 decennial US Census,[23] except disability data, which were not available on the Census tract level for 2010 and were therefore obtained for the next available year, 2012.

As done in previous studies,[20,24-27] we used exploratory factor analysis to construct an index of neighborhood socioeconomic disadvantage from the 15 candidate variables listed above. According to the Kaiser criterion,[28] factors with eigenvalues ≥1 were retained (n=2); they explained 86.9% and 13.0% of the total variance, respectively. Next, we used orthogonal VARIMAX rotation for factor extraction. Individual variables were retained if they had a factor loading (ie, standardized regression coefficient) ≥.5. The clustering of variables into two orthogonal factors is shown in Table 1. Factor 1, which was defined by eight variables, was identified as "socioeconomic disadvantage"; it explained 60.0% of neighborhood variability.

We then constructed a socioeconomic disadvantage index (SDI) by

Table 1. Orthogonal VARIMAX rotated factor patterns and loadings of neighborhood variables

	Variable	Factor 1 loading	Factor 2 loading
1	% adults age 25+ without high-school diploma	.79	.51
2	% adults age 25+ with college degree		
3	Median household income		
4	% households with interest, dividend, or rental income		
5	Median value of owner-occupied housing		
6	% households on public assistance or food stamps	.82	
7	% households in poverty	.82	
8	% cost-burdened households (housing cost >30% income)	.74	
9	Civilian unemployment rate, %		.67
10	% households without vehicles	.96	
11	Mean number of household vehicles		
12	% minority population	.59	.59
13	% disabled population	.83	
14	% households with seniors (age 65+) living alone	.66	
15	% single-parent households with children		.68

Cells without data represent factor loading <.5.

summing the mean standardized z-scores of the eight positive variables clustered in Factor 1 (Cronbach's alpha=.95), with higher scores indicating higher disadvantage (range -1.1 to 1.4, mean=0, SD=.9). The scores were then categorized into deciles to create a scale of 1 to 10, which was used continuously. Neighborhoods with scores in the bottom decile of the SDI were classified as least disadvantaged, while neighborhoods with scores in the top decile of the SDI were classified as most disadvantaged.

Statistical Analysis

Univariate statistics, including means, standard deviations, frequencies, and proportions, were obtained for all non-missing observations. Linear regression was used to estimate models of bikeshare utilization by individual and neighborhood characteristics. Because the majority (76.9%) of the Census tracts had <3 observations per tract, multilevel modeling was not

feasible. Instead, we accounted for clustering on Census tracts by adjusting for standard errors and the variance-covariance matrix of estimates to allow for intra-group correlation, relaxing the requirement of independence within clusters.[29] Statistical tests were two-sided and were performed using a 95% significance level (α=.05). Analyses were performed using Stata software, version 14.

RESULTS

Study Population

The dataset included 31,129 rides taken by 815 unique clients between October 15, 2015 and November 7, 2016. Employees (n=11) and non-annual members (n=37) were excluded from the analyses, as were clients (n=120) with missing data due to technical errors in recording distance and duration. Clients with incomplete Census data (n=12), those

without listed sex (n=1), and those without listed age (n=1) also were excluded. The final dataset included 24,048 unique rides by 633 unique clients residing in 117 Census tracts. Ninety Census tracts had three or fewer individuals per tract: 52 tracts had one individual each, 27 tracts had two individuals each, and 11 tracts had three individuals each. One Census tract included 152 individuals, or 24.0% of the sample. The implications of this are discussed later.

Neighborhood characteristics differed considerably between the most and the least disadvantaged neighborhoods as measured by the SDI. For example, compared with the least disadvantaged neighborhoods (bottom 30% of SDI), the most disadvantaged neighborhoods (top 30% of SDI) had more minority population (70.5% vs 16.8%), more poverty (37.9 vs 7.7%), more unemployment (5.8% vs 3.6%), more households without a vehicle (38.1% vs 2.7%), more cost-burdened households (50.8% vs 11.2%), and more households receiving public assistance or food stamps (31.7% vs 2.9%).

Descriptive and Bivariate Statistics

The characteristics of the final sample (N=633) are described in Table 2. The sample was 65.6% male, and the mean age was 40.9 (SD=12.7). The mean number of rides per client was 38.0 (SD=85.0). The mean number of membership days during the data collection period was 241.5 (SD=135.3), and the average number of rides per membership day was 1.0 (SD=9.0). Only 49 clients (7.7%) had used the bikeshare only once.

Figures 1 and 2 illustrate the distribution of bikeshare users (Figure 1) and SDI (Figure 2) by Census tracts in the Greater Birmingham region. As seen in the figures, while the bikeshare stations are concentrated in downtown Birmingham, clients reside throughout the entire metropolitan area.

Simple linear regression was used to examine bivariate associations between bikeshare use and age, sex, membership type, and neighborhood socioeconomic disadvantage. Because the dependent variable was logged, results are interpreted as a proportional increase: a coefficient of .08 relates to 8% increase of y with each unit increase of x, and a coefficient of 1 relates to a 100% increase of y with each unit increase of x.

In unadjusted bivariate analyses, bikeshare use, measured as average number of rides per membership day, was positively associated with younger age (.03, P<.001) and negatively associated with female sex (-.4, P<.01). Relative to standard annual membership, Shyfter annual membership was negatively associated with bikeshare use (-1.13, P<.001). Neighborhood SDI was positively associated with bikeshare use (.11, P<.001). That is, each decile increase in the neighborhood SDI was associated with an 11% increase in the number of rides per membership day.

Multivariate Statistics

Multiple regression was used to estimate the effect of individual and neighborhood characteristics on bikeshare use, measured as average number of rides per membership day. Three models were esti-

mated: Model 1 included only sex, age, and membership type; Model 2 added average speed, total miles, and pedelec use to account for difference in riding styles; and Model 3 added the neighborhood SDI (Table 3). The coefficients of the two models (Models 1 and 2) that included only individual-level characteristics were consistent in size and direction of the effect. The mean Variance Inflation Factor (VIF) of

all variables in Model 2 was approximately 1 (mean=1.08), indicating no multicollinearity concerns.

As seen in Table 3, Model 1, older age (-.02, P<.01), female sex (-.4, P<.01), and Shyfter annual membership (-.9, P<.001) are negatively associated with bikeshare use. That is, a client's rides per membership day decrease 2% for each additional year of age, 40% for women vs men, and 90% for Shyfter
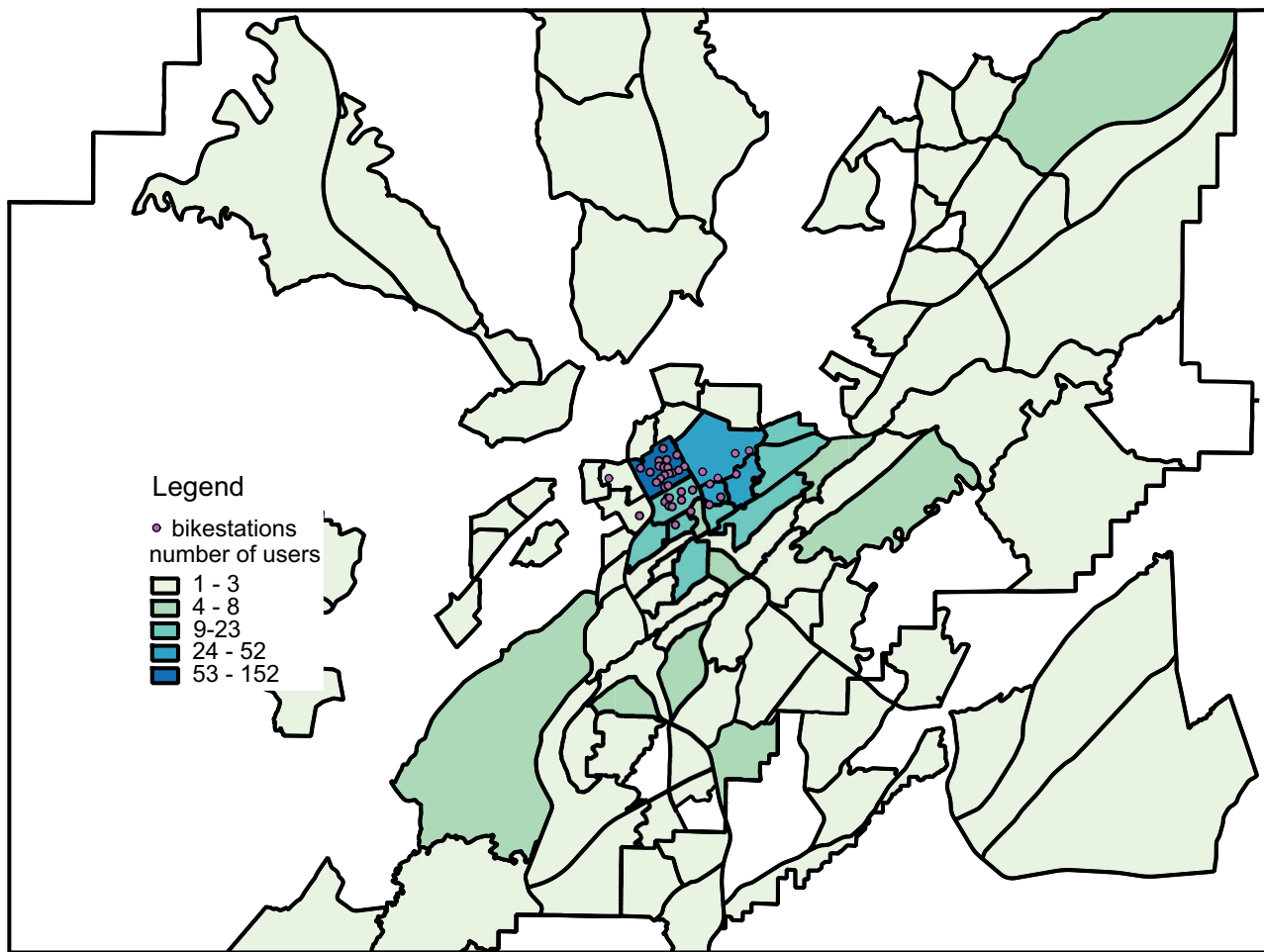
Table 2. Characteristics of the sample

Variables	Overall
Individual, N=633	
Number of rides	37.9 (85.0)
Age, mean (SD)	40.9 (12.7)
Female sex	215 (34.0)
Membership days	241.5 (135.3)
Membership, mean (SD)	
Annual	538 (85.0)
Equity	23 (3.6)
Shyfter	72 (11.4)
Rides per day, mean (SD)	1.0 (9.0)
Average speed	5.4 (1.8)
Total miles	45.9 (101.2)
Total minutes	521.7 (1,291.4)
% pedelec use	36.6 (26.3)
Zyp station in tract	
Yes	346 (54.7)
No	287 (45.4)
Neighborhood, Census tracts, N=117	
% College degree	40.4 (22.4)
% No high-school diploma	14.1 (11.8)
Median household income, $	46,012.17 (29,953.5)
% Households with interest, dividend, or rental income	22.3 (16.5)
Civilian unemployment rate, %	5.3 (3.1)
% Households without vehicle	15.6 (15.6)
Mean number of household vehicles	1.5 (0.5)
Median value of owner-occupied housing, $	232,948.7 (116,493.3)
% Seniors living alone	11.2 (5.6)
% Single parents with children	7.1 (5.2)
% Households with public assistance or food stamps	13.7 (13.5)
% Households in poverty	20.8 (15.8)
% Cost-burdened households	29.4 (23.4)
% Minority population	41.7 (27.7)
% Disabled population	15.8 (9.1)
SDI, deciles	4.8 (3.05)

Data are mean (SD) for continuous variables, n (%) for categorical variables.
SDI, Socioeconomic Disadvantage Index.

Figure 1. Census tracts by number of bikeshare users.

members vs regular annual members. However, this model explains only 7% of variance (R^2=.0749).

The effects of age and sex on bikeshare use disappear when adding speed, distance, and pedelec use (Model 2). In Model 2, bikeshare use is positively associated with speed (.1, P<.001), distance (.008, P<.001), and percent pedelec use (1.07, P<.01) and remains negatively associated with Shyfter annual membership (-.9, P<.001). That is, a client's rides per membership day increase 10% for each mile-per-hour

faster speed, .08% for each additional mile of travel, and 107% for each percent increase in pedelec use. Relative to regular annual members, Shyfter members continue to have 90% fewer rides per day. Additionally, Model 2 has much better explanatory power than Model 1 (R^2=.3595).

Model 3 adds neighborhood-level variables to the individual-level variables from the first two models, explaining 38% of variance (R^2=.3754). As seen in Table 3, Model 3, each decile increase in the neighborhood SDI is associated with a 9% increase

in the number of rides a client takes. Bike station presence in a Census tract is not a statistically significant predictor of bikeshare use. All other results remain statistically the same.

Because one Census tract had a large concentration of clients (n=152), we also examined all associations without this particular tract. In supplemental analyses (available upon request), the removal of these users resulted in a SDI coefficient of .07 (P=.065). Next, we recalculated the SDI without this Census tract and obtained a coefficient of .06
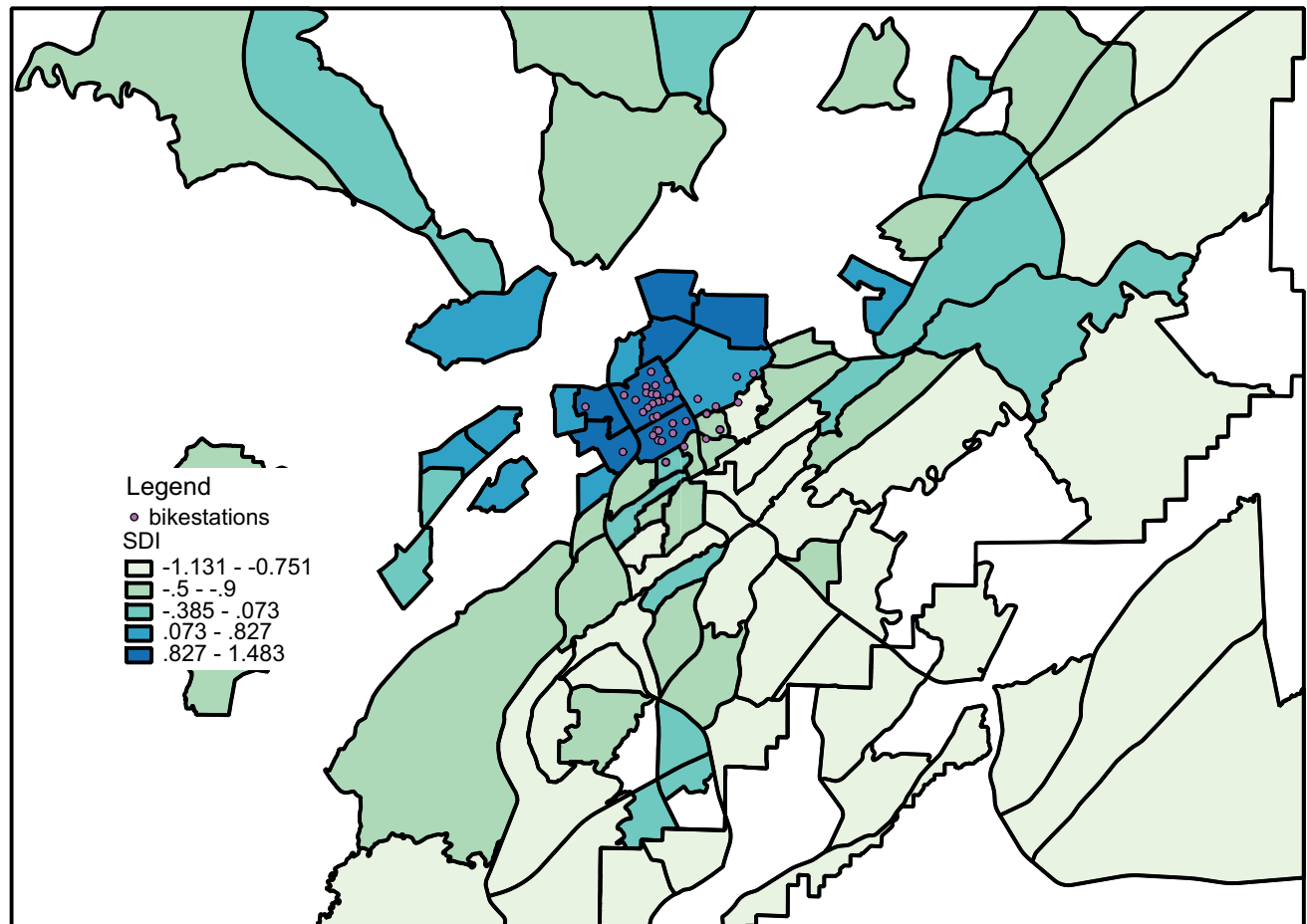
Figure 2. Census tracts by socioeconomic disadvantage index (SDI).

(P=.05). Finally, we recalculated the SDI based on the data set without the Census tract in question. This time, the SDI included 6 instead of 8 variables, and the SDI coefficient was .04 (P=.085). These supplementary results show that while the Census tract that is a home of 24% of the clients plays an important role in the results, the trend remains the same even when this tract is excluded from analyses. Thus, the magnitude of the SDI effect in Model 3 may be liberal on the account of this tract, but the pattern is maintained even without it.

Discussion

We identified individual and neighborhood factors associated with bikeshare use in Birmingham, Alabama, a metropolitan area in the southeastern United States. Findings showed that higher level of neighborhood socioeconomic disadvantage is associated with increased bikeshare use. The negative effects of older age and female sex disappeared when controlling for average speed, total miles, and pedelec use.

The finding that neighborhood socioeconomic disadvantage is positively associated with bikeshare use needs to be examined more closely. Previous studies have reported that bikeshare users tend to be younger, educated, and affluent Caucasian males.[30-35] Disparities by race have been reported, with African Americans being less represented as membership holders.[30] Studies from the United Kingdom also document that residents of deprived areas are underrepresented as bikeshare users.[36] Overall, the evidence suggests that, in countries with low bicycling levels

Table 3. Multiple regression of bikeshare use, rides per membership day

Variables	Model 1			Model 2			Model 3		
	Coefficient	95% CI		Coefficient	95% CI		Coefficient	95% CI	
Individual level									
Age	-.02[b]	-.04	-.007	-.01	-.3	.1	-.007	-.3	.1
Female	-.4[b]	-.6	-.1	-.1	-.02	.002	-.1	-.02	.006
Membership type									
Annual	reference category			reference category			reference category		
Equity	-.2	-1.0	.6	-.2	-.8	.3	-.4	-1.0	.2
Shyfter	-.9[c]	-1.4	-.5	-.9[c]	-1.3	-.5	-.9[c]	-1.2	-.5
Average speed				.1[c]	.06	.2	.1[c]	.07	.2
Total miles				.008[c]	.004	.01	.008[c]	.004	.01
% pedelec				1.07[c]	.4	1.7	1.02[b]	.4	1.6
Neighborhood level									
SDI, deciles							.09[c]	.05	.1
Bike station in tract							-.2	-.5	.07
Intercept	-1.3	-1.9	-.7	-3.4[a]	-4.3	-2.5	-4.0[c]	-4.7	-3.2
Model F	12.08[c]			12.08[c]			47.5[c]		
R²	.0749			.3595			.3754		

CI, confidence interval; SDI, socioeconomic disadvantage index.
a. P<.05.
b. P<.01.
c. P<.001, two-tailed tests.

such as the United States, bikeshare programs reflect the uneven participation patterns in bicycling in general, with visible disparities by sex, race/ethnicity, and socioeconomic status.[37]

Interpreted in the context of this evidence, our results may indicate that, while Zyp bikes have an increased use among residents of disadvantaged neighborhoods, high utilizers may not be as socioeconomically disadvantaged as their neighborhood of residence. This interpretation seems plausible considering the visible gentrification of the area served by Zyp. It is possible that the increased use of Zyp bikes in disadvantaged neighborhoods results from a disproportionate uptake of bikeshare services by students and young professionals who increasingly occupy traditionally disadvantaged neighborhoods in the city. Similar findings have been reported previ-

ously, suggesting that bikeshare membership may not equitably reflect the composition of communities where bikeshare programs are operating.[30]

Various explanations for the socio-demographically skewed composition of bikeshare users have been proposed, from membership cost,[38] to barriers imposed by use of debit/credit cards,[33,38] to marketing and communication practices.[30] According to Steinbach et al,[37] the visible absence of African American bikeshare users exacerbates the racial disparity in membership by reducing the chances of African Americans to see bikeshare as a viable transportation option. Barriers to bicycling among racial/ethnic minorities reported in other studies include fear of a traffic collision, fear of robbery and assault, pavement condition, fear of being stranded with a broken bicycle, and fear of being profiled by the police.[39]

As shown by previous research, bikeshare use in socioeconomically disadvantaged areas can increase if programs provide convenient stations, resolve safety issues, ensure affordable membership, and address the perceived lack of diversity in age and ethnicity of users.[40] In fact, Ogilvie and Goodman[36] report that, after adjusting for such factors, bikeshare rates are higher among residents in poorer areas compared with residents of more affluent neighborhoods. The results of our study corroborate these findings. The study also shows that pedelecs can help ameliorate the negative effects of older age and female sex on bicycling.

With an exponential growth in cities[41-44] and a positive health impact on weight,[35,42] stress,[35] and mortality,[11] bikeshare programs are a potential solution for improved quality of life in low-income urban communities.

Limitations

This study has several limitations. First, an assumption was made that a client's billing address matches his or her residential address. Second, neighborhood-level socio-demographic measures, although reasonably correlated with individual-level measures, are not a perfect substitute for individual data. To the extent possible, future studies should aim to collect socioeconomic and

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Findings showed that higher level of neighborhood socioeconomic disadvantage is associated with increased bikeshare use.

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sociodemographic measures from bikeshare users, including race/ethnicity. Third, our data featured a sparsely populated cluster structure that ruled out multilevel modeling. Instead, we accounted for clustering on Census tracts by adjusting for standard errors and the variance-covariance matrix of estimates. Fourth, we could not capture all nuances of bicycling that may have influenced the results, such as stopping time or repeated checkouts for the same trip. Finally, the cross-sectional design of the study limits our ability to make causal inferences about the observed relationships.

Conclusion

Neighborhood socioeconomic disadvantage is positively associated with bikeshare use. Bikeshare provides viable transportation options to residents of disadvantaged urban neighborhoods and may be an effective tool to improve the connectivity, livability, and health of urban communities. Future research should explore barriers to bikeshare use, especially among racial/ethnic minorities, and test solutions effective in specific socio-demographic subgroups. Additionally, the short- and long-term health benefits and risks of bikeshare programs in urban settings must be investigated.

Conflict of Interest

No conflicts of interest to report.

Author Contributions

Research concept and design: Oates, Fouad; Acquisition of data: Oates, Hamby, Norena, Hart; Data analysis and interpretation: Oates, Hamby, Bae, Hart, Fouad; Manuscript draft: Oates, Hamby, Bae, Norena, Hart, Fouad; Statistical expertise: Oates, Hamby, Bae; Acquisition of funding: Oates, Fouad; Administrative: Norena, Hart; Supervision: Oates, Fouad

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