Walking, Bicycling, and Urban Landscapes: Evidence From the San Francisco Bay Area

Some claim that car-dependent cities contribute to obesity by discouraging walking and bicycling. In this article, we use household activity data from the San Francisco region to study the links between urban environments and nonmotorized travel.

We used factor analysis to represent the urban design and land-use diversity dimensions of built environments. Combining factor scores with control variables, like steep terrain, that gauge impediments to walking and bicycling, we estimated discrete-choice models. Built-environment factors exerted far weaker, although not inconsequential, influences on walking and bicycling than control variables.

Stronger evidence on the importance of urban landscapes in shaping foot and bicycle travel is needed if the urban planning and public health professions are to forge an effective alliance against car-dependent sprawl. (*Am J Public Health.* 2003;93:1478–1483)

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URBAN PLANNERS AND PUBLIC health advocates alike decry sprawl for prodding Americans to drive their cars from anywhere to everywhere.[1,2] Car-dependent cities and suburbs, critics charge, spawn a sedentary lifestyle and associated health problems such as obesity, adding as much as $76 billion annually to US medical expenses by one estimate.[3] Eight-lane thoroughfares, serpentine roads, incomplete sidewalk networks, far-flung retail plazas, campus-style business parks, and other distinguishing traits of contemporary America are said to conspire against walking and bicycling. However, are their influences serious enough to warrant radical changes in how we design communities of the future?

Numerous studies have examined the effects of built environments on motorized travel; however, far less attention has been given to impacts on walking and bicycling.[4,5] Probing effects on nonmotorized transport requires a different analytic approach. For one thing, walking and bicycle trips are usually shorter than those made by car or public transit, requiring a finer analytic resolution. Geographic information system (GIS) tools help in this regard, especially if one knows the longitudinal-latitudinal coordinates of trip origins and destinations. Additionally, choice models of motorized travel normally include comparative highway travel times of competing modes in their utility specifications.[6] This is because trip durations often vary substantially between the private car and public transit. For nonmotorized transport, and especially walking, speeds tend to be so much slower than by car, train, or bus that travel-time differentials are meaningless. Because people of a similar age and stature usually walk at comparable speeds, and given that pedestrians perceive trip making mainly in spatial terms, distance is a more suitable measure of impedance.[7]

As important to the question of model specification is the inclusion of factors that represent potential barriers to walking or bicycling.[8] Besides distance, these include steep slopes, nightfall, precipitation, and less secure environs. Failure to include such factors can compromise the internal and construct validity of the research. For example, curvilinear and cul-de-sac street layouts that discourage walking are particularly common in hilly terrain.[9] Ignoring topography means that associated variables, such as road designs, that are included in a predictive model end up absorbing the influences of this omitted but relevant variable. Assigning health benefits to built environments necessitates a valid model specification that nets out impedance factors such as the presence of a steep terrain.

In this study, the influences of urban designs, land-use diversity, and density patterns on the choice to walk or bicycle, vis-à-vis other factors, are examined using year-2000 data for the San Francisco Bay Area. The work builds upon other research that has applied the "3D" principle (density, diversity, and design) to associate travel choices with built environments.[10–12] We close the article with a discussion of the public health and urban planning implications of the research findings.

DATA AND METHODS

The chief database used to carry out this research was the 2000 Bay Area Travel Survey (BATS), which contains up to 2 days of daily activity information for members of 15 066 randomly selected households in the 9-county San Francisco Bay Area.[13] Household activity surveys provide rich details on everyday activities of all household members, including travel and out-of-home activities. To narrow our investigation to trips that were potentially walkable or bikable, we limited the analysis to purposes that were unlikely to involve carrying significant amounts of items or goods, such as groceries. Accordingly, records for the following out-of-home activities were selected: socialize/visit friends; meals/eating; personal services (e.g., banking); recreation/entertainment; volunteer/civic/religious activities; and shopping away from home (under 15 minutes in duration). Because BATS did not reveal the exact nature of shopping, we imposed a 15-minute limit, as an upper bound, under the assumption this would correspond to a walkable convenience shop trip. One quarter of all sampled shop activities took fewer than 15 minutes, and 94%

of shop destinations reached by foot were below this benchmark. Also, only records for trips that did not begin at a workplace were selected; in most instances, trip origins corresponded to people's residences. A final refinement was the selection of trip records of less than 5 miles, a potentially walkable distance range that encompassed 88% and 96% of sampled bicycling and walking trips, respectively. These refinements yielded a sample frame of 7889 trip records.

Each trip record contained information on the purpose; mode; time of day; day of week; origin and destination longitudinal-latitudinal coordinates; and other features of the journey. Attributes of trip makers (e.g., gender) and their households (e.g., vehicle availability) were obtained from the BATS personal and household data files and linked to each trip record. Data on built-environment and control variables were collected for year 2000 to match up with BATS travel records. Average slope (rise/run) was calculated based on the elevations of trip origins and destinations. Recorded times of trip departures and arrivals, matched against sunrise and sunset information for the Bay Area, produced a dummy variable on whether trips occurred during nightfall. Information on neighborhood crime rates and social conditions would have been a preferred measure of "safety and security"; however the unavailability of geocoded data within a consistent 1-mile radius of trip origins and destinations precluded this. An admittedly less-than-ideal proxy for "neighborhood quality"—the proportion of households with annual incomes below $25 000 within a 1-mile radius of trip origins and destinations—was used instead.

Data on neighborhood attributes, such as median household incomes, were obtained from the 2000 census. Information on employment by occupations (used to gauge land-use mixture) was acquired from the Association of Bay Area Governments, stratified by census tract.[14]

For each trip record, density and land-use composition were imputed for 1-mile and 5-mile radii of origins and destinations using block-level data and GIS tools. Because many walking and bicycle trips are beyond 1 mile in length, we distinguished land-use attributes at both the origins and the destinations of trips. Variables related to street and urban design characteristics within 1-mile radii of trip origins and destinations, such as counts of 3-way intersections and lineal miles of local streets, were computed from 2000 census topologically integrated geographic encoding and referencing (TIGER) files. Having numerous 3-way intersections equates to neighborhoods populated by T-intersections, curvilinear streets, and cul-de-sacs, whereas areas with all 4-way intersections and small quadrilateral blocks have gridiron, usually pedestrian-friendly, street patterns.[15,16] We turned to discrete-choice logit modeling, of the following form, to estimate the probability Bay Area residents walked or bicycled:

$$(1)\ P_{niod} = \exp(V_{niod}) / [\Sigma_{j \in Cnod} \exp(V_{njod})],\ \forall\ V_{niod} = f(I_{od}, PH_n, BE_o, BE_d)$$

where

P_{niod}=probability of person n choosing mode i for traveling between origin o and destination d
C_{nod}=choice set of modes available to person n traveling between origin o and destination d
V_{niod}=utility function for person n traveling by mode i between origin o and destination d
V_{njod}=utility function for person n traveling by mode j between origin o and destination d
I_{od}=impedance vector for trips from origin o to destination d, including distance and slope
PH_n=personal and household characteristics vector for trip maker n (e.g., gender, vehicle availability)
BE_o=built-environment vector for 1- or 5-mile radius of origin o, representing measures of land-use intensity, land-use mixture, land-use accessibility, and walking quality
BE_d=built-environment vector for 1- or 5-mile radius of destination d, comparable to the vector for origin o

Our operative hypothesis is that BE_o and BE_d are significant explainers of the decision to walk or ride a bicycle, controlling for I_{od} and PH_n. Because of high intercorrelations among variables in these vectors, we turned to factor analysis to express BE_o and BE_d. The SAS software package (SAS Institute Inc, Cary, NC) was used for both discrete-choice modeling and factor extraction.

FACTOR ANALYSIS

The core dimensions of built environments—density, diversity, design—are not easily captured by a single variable. However, when multiple variables are used to express elements such as street design and land-use mixture, multicollinearity problems often contaminate model estimation. As in several previous studies of built environments and travel, we turned to factor analysis to resolve this problem.[10,17–19] Using variables on street supply, intersection configurations, city block sizes, and housing/employment characteristics within 1-mile radii of trip origins and destinations, we extracted 4 interpretable factors that exhibited Thurstone's "deep structure" (with eigenvalues above 1).[20] Principal components estimation and varimax rotation were used in deriving the results shown in Table 1. Together, these factors accounted for more than two thirds of the variance among the 18 variables listed in the table.

The first 2 factors pertain to street and city block characteristics—one factor for the trip origin, the other for the destination. We call these *pedestrian-/bicycle-friendly* factors because positive signs on loadings reflect urban design characteristics that are conducive to walking and bicycling. The block-size/intersection attributes of trip origins had the highest commonality among factors (eigenvalue of 3.86), accounting for 21.5% of total variance. Factor loadings reveal that areas with large city blocks are not pedestrian-/bicycle-friendly environs. Neither are neighborhoods with large shares of 3-way intersections and dead-ends, signs of nongrid street patterns. On the other hand, areas dotted with 4-way intersections (denoting gridiron street patterns) as well as intersections with 5 or more converging streets (suggesting even higher levels of connectivity) were positively associated with the pedestrian-/bicycle-friendly factor.

The third and forth factors reflect land-use diversity of trip origins and destinations. Neighborhoods with heterogeneous

TABLE 1—Factor Analysis Loadings and Summary[a]

	Pedestrian-/Bike-Friendly Design Factor, Origin	Pedestrian-/Bike-Friendly Design Factor, Destination	Land-Use Diversity Factor, Origin	Land-Use Diversity Factor, Destination
Square meters per block within 1 mile, average; origin	−0.480			
Square meters per block within 1 mile, average; destination		−0.327		
Three-way intersections, proportion of total intersections within 1 mile; origin	−0.942			
Three-way intersections, proportion of total intersections within 1 mile; destination		−0.952		
Four-way intersections, proportion of total intersections within 1 mile; origin	0.933			
Four-way intersections, proportion of total intersections within 1 mile; destination		0.943		
Five-or-more–way intersections, proportion of total intersections within 1 mile; origin	0.690			
Five-or-more–way intersections, proportion of total intersections within 1 mile; destination		0.677		
Dead ends as proportion of total intersections within 1 mile; origin	−0.890			
Dead ends as proportion of total intersections within 1 mile; destination		−0.873		
Mixed use entropy (within 1 mile), at origin[b]			0.826	
Mixed use entropy (within 1 mile), at destination[b]				0.828
Employed residents–to–jobs balance index (within 1 mile of origin)[c]			0.871	
Employed residents–to–jobs balance index (within 1 mile of destination)[c]				0.802
Employed residents–to–retail/services balance index (within 1 mile of origin)[d]			0.884	
Employed residents–to–retail/services balance index (within 1 mile of destination)[d]				0.873
"Residentialness" index, origin[e]				−0.879
"Residentialness" index, destination[e]				−0.773
Summary statistics:				
Eigenvalue	3.86	3.51	2.54	2.39
Percentage of variance	21.47	19.50	14.11	13.27
Cumulative percentage of variance captured by factors = 68.34%				

[a]Only loadings > 0.20 are shown.
[b]Mixed use entropy (within 1 mile) = $-1*\{[\Sigma_i (p_i)(\ln p_i)]/\ln k\}$, where p = proportion of total land uses; k = category of land use (single-family housing units, multifamily housing units, retail/service employment, office employment, manufacturing/trade/other employment); ln = natural logarithm.
[c]Employed residents–to–jobs balance index (within 1 mile of origin) = 1 − {[ABS(ER − JOBS)] /(ER + JOBS)}, where ABS = absolute value; ER = number of employed residents; JOBS = number of workers.
[d]Employed residents–to–retail/services balance index (within 1 mile of origin) = 1 − {[ABS(ER − RS)]/(ER + RS)}, where ABS = absolute value; ER = number of employed residents; RS = number of retail/service jobs.
[e]Where "residentialness" index = housing units as proportion of total employment and housing units.

mixes of single-family and multifamily housing as well as jobs spread across the retail/service, office, and manufacturing/trade/other sectors scored high on these factors (based on the 0–1 entropy index, wherein 1 represents maximal heterogeneity). So did areas with a balance of employed residents and jobs within 1-mile radii (based on the 0–1 balance index, wherein 1 represents perfect balance). Indexes reflecting a balance of retail/service activities relative to employed residents within 1-mile radii of origins and destinations also scored high on the diversity factor. These indexes are considered to be particularly relevant because they reflect the relative availability of retail shops and consumer services within 1-mile (and thus plausibly walkable) radii of origins and destinations. Lastly, indexes denoting the degree to which neighborhoods are residential in character loaded negatively onto the diversity factor. This accounts for the fact that bedroom communities (predominantly residential places) are usually not land-use–rich settings, whereas areas with higher shares of nonresidential activities often are.

We note that other extracted factors (not shown in Table 1 because of low eigenvalues) captured some aspects of land-use intensity, such as population and employment densities; however, loadings on these factors were fairly small and not always interpretable. To a significant extent, density attributes of neighborhoods are captured in what we are calling the *design and diversity factor*s, that is, neighborhoods with small blocks, grid street patterns, and mixed uses also tend to be fairly dense.

RESULTS

Walking-Choice Model

Walking constituted 12.5% of surveyed BATS trips that were 5 miles or less for the trip purposes studied. Far more common was travel by automobile, van, or motorcycle, constituting 82.6% of the total. Even for trips under 1 mile, the car dominated, making up 60.7% of the total (compared with 34.3% for walking).

The best-fitting walking-choice model, shown in Table 2, presents the estimated coefficients that appear in the variables of each vector in equation 1. The coefficients reflect the direction in which each variable influences the walking-choice—positive values denote that a variable increases the probability of walking whereas negative values indicate the opposite. Table 2 reveals that control variables had appreciably stronger predictive powers than built-environment factors in explaining whether Bay Area residents traveling under 5 miles walked or not. Trip purpose weighed in heavily, with social and recreation/entertainment activities, in particular, increasing the likelihood that people walked. Weekends also favored walking. Personal attributes likewise mattered. Predictably, those with physical disabilities and numerous cars in the household were less likely to walk. More surprising was the ethnic/racial dimension. Even after controlling for a socioeconomic factor like vehicle ownership levels, African Americans were more likely to walk than were Whites or Asian Americans. (This is consistent with 2000 census results showing higher shares of African Americans [3.2%] walked to work than the typical American worker [2.9%][21]; for all trip purposes, African Americans averaged 82% more walking trips in 1995 than Whites.[22]) Further, males tended to walk more than females, all else being equal.

TABLE 2–Walking-Choice Model for Predicting the Probability That a Trip Will Be Made by Walking

	Coefficient	Standard Error	Probability
Constraints/deterrents			
Trip distance (miles)	–1.970	0.074	.000
Slope (rise/run)	–4.109	2.090	.049
Rainfall day of trip (inches in 24 hours)	–0.729	0.330	.027
Dark (1 = yes, 0 = no) (before sunrise or after sunset)	–0.158	0.112	.159
Low-income neighborhood (proportion of households within 1 mile of origin and destination with annual incomes < $25 000)	–0.766	0.523	.143
Personal/household attributes			
Disability (1 = yes, 0 = no)	–0.480	0.275	.081
Gender (1 = male, 0 = female)	0.161	0.083	.051
African American (1 = yes, 0 = no)	0.788	0.278	.005
Asian American (1 = yes, 0 = no)	–0.286	0.192	.136
White (1 = yes, 0 = no)	–0.310	0.118	.008
Number of vehicles in household	–0.695	0.050	.000
Trip characteristics			
Weekend trip (1 = yes, 0 = no)	0.246	0.100	.013
Recreation/entertainment purpose (1 = yes, 0 = no)	0.809	0.120	.000
Eating/meal purpose (1 = yes, 0 = no)	0.688	0.127	.000
Social purpose (1 = yes, 0 = no)	0.886	0.144	.000
Shopping purpose (1 = yes, 0 = no)	0.623	0.165	.000
Built-environment characteristics			
Employment accessibility: number of jobs (in 10 000s) within 1 mile of origin	0.068	0.042	.104
Pedestrian-/bike-friendly design factor, origin	0.037	0.048	.441
Pedestrian-/bike-friendly design factor, destination	0.035	0.047	.465
Land-use diversity factor, origin	0.098	0.042	.021
Land-use diversity factor, destination	0.023	0.042	.590
Constant	1.217	0.198	.000
Summary statistics:			
No. of cases = 7836			
χ^2 = 2 010.5 (probability = .000)			
ρ^2: 1 – $L(1)/L(0)$ = 0.429			

Five impedance factors entered the model, reflecting walking disutilities in the logit formulation. Even within a 5-mile distance band, the likelihood of walking eroded steadily with the length of the trip. Steep terrain, rain, and nightfall also deterred walking. The model further suggests that pedestrians tended to shy away from lower-income settings, presumably because of safety concerns.

The only built-environment factor significant at the 5% probability level was land-use diversity at the trip origin (which in most instances corresponded to a 1-mile radius of a person's residence). Balanced, mixed-use environs with retail services significantly induced walking, other things being equal. Similarly, land-use diversity at the destination generally encouraged walking; however, this relation was statistically weak. On the other hand, pedestrian-/bicycle-friendly designs at neither the origin nor destination had much bearing on mode choice. Evidently, the microdesign elements of neighborhoods examined in this study, such as intersection configurations and block sizes, exerted fairly inconsequential influences on walking. Only slightly more important, although still statistically insignificant, was employment density within 1 mile of a person's residence (reflected by the isochronic measure of job accessibility).

These results are consistent with those of previous studies suggesting that density (as reflected by the employment accessibility variable) and land-use diversity exert stronger pressures than urban design on the decision to walk.[5,10,12] This is even after introducing far more control variables that account for walking impedances than in the case of previous studies. The findings also align with earlier studies that show that travel choices depend as much, if not more, on the degree of land-use mixing as urban densities.[5,23] Perhaps most notably, these results parallel other research findings that show that land-use factors exert fairly modest influ-

TABLE 3—Bicycle-Choice Model for Predicting the Probability That a Trip Will Be Made by Bicycle

	Coefficient	Standard Error	Probability
Constraints/deterrents			
Trip distance (miles)	−0.291	0.084	.001
Slope (rise/run)	−7.796	5.930	.187
Dark (1 = yes, 0 = no) (before sunrise or after sunset)	−0.721	0.314	.022
Low-income neighborhood (proportion of households within 1 mile of origin and destination with annual incomes < $25 000)	−1.657	1.221	.175
Personal/household attributes			
Gender (1 = male, 0 = female)	0.588	0.194	.002
African American (1 = yes, 0 = no)	0.854	0.472	.071
Number of vehicles in household	−0.629	0.120	.000
Number of bicycles in household	0.345	0.037	.000
Trip characteristics			
Weekend trip (1 = yes, 0 = no)	0.226	0.219	.301
Recreation/entertainment purpose (1 = yes, 0 = no)	0.602	0.225	.001
Social purpose (1 = yes, 0 = no)	0.861	0.281	.002
Shop purpose (1 = yes, 0 = no)	0.443	0.389	.256
Built environment characteristics			
Employment accessibility: number of jobs (in 10 000s) within 5 miles of origin	−0.017	0.011	.106
Retail/service density: number of retail/service jobs per net commercial acre within 1 mile of origin	0.005	0.003	.114
Pedestrian-/bike-friendly design factor, origin	0.234	0.151	.122
Pedestrian-/bike-friendly design factor, destination	0.193	0.113	.088
Land-use diversity factor, origin	0.156	0.098	.112
Land-use diversity factor, destination	0.056	0.099	.570
Constant	−3.773	0.392	.000
Summary statistics:			
No. of cases = 7836			
χ^2 = 152.8 (probability = .000)			
$\rho^2 = 1 - L(1)/L(0) = .131$			

ences on travel behavior in comparison to the demographic characteristics of trip makers and impedances factors like distance and travel time.[4]

Bicycle-Choice Model

Only 1.5% of BATS trips 5 or fewer miles (for the subsampled nonwork trip purposes) were by bicycle. (For trips beyond 5 miles, the share was nearly identical.) For recreation/entertainment trips of 5 miles or less, bicycling captured a higher market share, 2.3% of all journeys. Bicycling is generally more popular in the Bay Area than in other parts of the United States. In 1995, just 0.9% of US trips were by bicycle.[24]

The binomial choice mode for bicycle trips, shown in Table 3, produced results that were fairly similar to those of the walking-choice model, although built-environment factors emerged as generally stronger predictors. The influences of control variables were akin to those of the walking-choice model with a few exceptions: weekend and shopping trips were more weakly related to bicycling; the only reasonably significant ethnic/racial variable was African Americans; the slope was less and nightfall was more of a deterrent to bicycling; rainfall generally did not dissuade people from bicycling; and, predictably, the likelihood of bicycling increased with the number of bicycles in a person's household (just as studies show that driving increases with car ownership). This relationship is likely circular—that is, a desire to bicycle no doubt increases bicycle ownership.

Among built-environment features, the urban design and land-use diversity factors were positively associated with the decision to ride a bicycle. Although the relationships were not significant at the 5% probability level, design had a far stronger influence on bicycling than on walking choice. Block size, gridiron streets, and other design attributes were slightly more important to the decision to bicycle at the destination than the origin. Mixed land uses and balances of residences, jobs, and retail services also worked in favor of bicycling, although only to a notable degree at the origin of trips. The influence of density was less straightforward. Having appreciable retail/service activities within a 1-mile radius of a person's origin generally encouraged that person to bicycle. This isochronic metric of retail/service density captured the availability of nearby convenience retail outlets. Within a larger 5-mile radius of a trip origin, higher overall employment densities (as reflected by the employment-accessibility variable) deterred bicycle travel. Presumably this is because dense employment settings, like urban job centers and edge cities, often create numerous roadway conflict points and safety hazards for bicyclists.

DISCUSSION

Previous research on how urban landscapes shape travel behavior can be faulted on a number of grounds, though none more so than questionable construct and internal validity of research designs. Many factors conspire against walking and bicycling in contemporary urban American, and car-dependent landscapes is just one of those factors. Unless factors like weather conditions or topography are controlled for, our understanding of how built environments influence travel will remain murky.

Our research reveals that urban landscapes in the San Francisco Bay Area generally have a modest and sometimes statistically insignificant effect on walking and bicycling. Although well-connected streets, small city blocks, mixed land uses, and close proximity to retail activities were shown to induce nonmotorized transport, various exogenous factors, such as topography, darkness, and rainfall, had far stronger influences. Other control variables, such as demographic characteristics of trip makers, were also far stronger predictors of walking and bicycling choice than built-environment factors. From a public-policy standpoint, this suggests that a greater public health benefit might accrue from designing walkable neighborhoods that appeal to the niche-market characteristics of different demographic groups versus microdesigning places in hopes of swaying travel behavior. That is, pedestrian-friendly places suited to the taste preferences of sociodemographic groups might induce more physical activity over the long run through the process of residential self-selection than overt efforts to create compact, mixed-use, gridded-street neighborhoods throughout the cityscape. Market-responsive planning and zoning would help in this regard.

Among the built-environment factors in the models, land-use diversity in and around a person's neighborhood (e.g., the presence of neighborhood retail) was the strongest predictor of walking. Bicycling, on the other hand, was equally influenced by density, diversity, and design, especially at the origin (i.e., the residential end) of a trip. Because of the stronger statistical fits, our results hint that built environments exert bigger impacts on walking and bicycling in and around a person's residential neighborhood than do destinations. The evidence is suggestive although hardly compelling.

Might these results be generalizable beyond the Bay Area? We suspect so. Although factors like a hilly topography and Mediterranean climate are unique to the San Francisco region, given that these and other factors were controlled for in this study, the marginal impacts of built-environment elements, we suspect, are likely similar in other settings.

We do not rule out that the absence of strong statistical relationships in this study could reflect the use of imperfect variables to capture the myriad features of built environments. Although GIS tools enable physical attributes of neighborhood streets and blocks to be defined, other microdesign attributes of built environments, such as the presence of landscaping or street furniture (e.g., benches, light posts, bus shelters), were not examined because of data limitations. Other research suggests that such features generally exert minor influences on mode choices.[5,10,25,26] Still, statistical analyses like ours should be supplemented by microlevel analyses, including qualitative case studies and quasi-experimental comparisons, that account for possible influences of street-scale design elements.[27,28]

Although their motives are different, urban planners and public health officials form a potentially powerful alliance in the fight against car-dependent sprawl and the promotion of healthy cityscapes. However, more research is needed that clarifies the potential environmental benefits—whether cleaner air or healthier citizens—of altering urban landscapes if this alliance is to gain legitimacy. ■

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This article was accepted April 3, 2003.

Contributors

R. Cervero designed and directed the research, carried out the statistical analyses, and wrote the article. M. Duncan constructed the database and assisted with some of the data analyses.

Acknowledgments

This research was supported by a grant from the University of California Transportation Center.

Human Participant Protection

No protocol approval was needed for this study.

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