Travel and the Built Environment

Insights Using Activity Densities, the Sprawl Index, and Neighborhood Types

Kelcie Ralph, Carole Turley Voulgaris, and Anne Brown

There are many ways to evaluate the built environment, including measures of observable individual characteristics (such as activity density), continuous composite measures (such as the sprawl index), and categorically measured variables (such as neighborhood types). However, a systematic comparison of how well each of these three measurement types captures the influence of the built environment on travel behavior has not yet been undertaken. This lack presents a quandary for both researchers and practitioners who seek to quantify and describe the effects of the built environment on travel behavior. This paper assesses whether continuous, composite, or categorical measures provide more information and better-fitting models compared with measures of observable individual characteristics across four travel behaviors: vehicle miles traveled, walk trips, transit trips, and trip length. For each travel variable, four multivariate regression models were estimated with various measures of the built environment: activity density, sprawl index, neighborhood type, and combined sprawl index and neighborhood type. Both the sprawl index and the neighborhood-type models outperformed the activity density model. Moreover, a combined model with both the sprawl index and neighborhood types provided the best fit for all four travel behavior variables. These results suggest that both continuous and categorical composite variables provide unique and complementary information about how the built environment influences travel behavior. These findings underscore the importance of researchers' decisions on how to represent the built environment quantitatively in models, because measurement decisions influence the understanding of how the built environment affects travel behavior.

Plans and policies for predicting or influencing travel behavior generally rely on an understanding of the relationships between travel behavior and the built environment, and thus these relationships are among the most studied topics in transportation planning (*1, 2*). However, to quantify such relationships, researchers must determine how to quantify or describe relevant characteristics of the built environment.

There are many ways to measure the built environment. This paper compares three types of variables: (*a*) single measures of observable characteristics (such as density); (*b*) composite measures that combine multiple characteristics into a single, continuous variable; and (*c*) categorical neighborhood types that use statistical classification methods to define distinct neighborhoods that share similar characteristics.

Are the latter two measures unnecessarily complex when density would be a sufficient predictor of travel behavior? Perhaps density and the other useful measures of the built environment covary to such a degree that multidimensional measurements of sprawl yield no additional benefits over use of density as a proxy for its many covariates. To answer such questions, several regression models predicting four travel behavior outcomes are estimated: (*a*) personal vehicle miles traveled (VMT), (*b*) trip length, and (*c*) the odds of making a trip by walking or (*d*) by transit. For each of these travel behavior outcomes, various measures of the built environment are included as explanatory variables and model fits are compared. This paper demonstrates that both the sprawl index and the neighborhood-type models perform better than does the activity density model and that a model that combines both the categorical neighborhood-type variable and a continuous composite variable provides the best fit for all four travel behavior outcomes. This result suggests that the composite variables provide unique and complementary information about how the built environment influences travel behavior. These findings underscore the importance of researchers' decisions about how to represent the built environment quantitatively in models, because measurement decisions influence an understanding of how the built environment affects travel behavior.

LITERATURE REVIEW

General Approaches to Measuring the Built Environment

Travel and transportation research has repeatedly found that the built environment affects travel behavior, even after the self-selection of individuals into neighborhoods that align with travel preferences is controlled for (*3, 4*). However, less attention has been paid to how to best measure the built environment, particularly its potentially synergistic effects that can alter travel behavior. This section discusses three types of variables for measuring and describing the built environment: (*a*) single measures of observable characteristics; (*b*) composite measures that combine multiple characteristics into a single, continuous variable; and (*c*) categorical neighborhood types that use statistical classification methods to define distinct neighborhoods that share similar characteristics.

This review is restricted to measures of the built environment and therefore does not define areas by other characteristics that may

K. Ralph, Edward J. Bloustein School of Planning and Public Policy, Rutgers University, 33 Livingston Avenue, New Brunswick, NJ 08901. C. T. Voulgaris and A. Brown, Institute of Transportation Studies, Meyer and Rence Luskin School of Public Affairs, University of California, Los Angeles, 3250 School of Public Affairs Building, Los Angeles, CA 90095. Corresponding author: K. Ralph, kelcie.ralph@ejb.rutgers.edu.

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affect travel patterns, such as household income, race or ethnicity, or neighborhood-level crime. Within the built environment domain, the measures reviewed are all objective measures of the built environment that are readily available from existing data sources. A review of audit tools for measuring the built environment and methodologies for collecting subjective measures of the built environment are available elsewhere (*5*).

Measures of Observable Characteristics

Building on the so-called 3Ds classification of built environment characteristics by Cervero and Kockelman (*2*), Ewing and Cervero identified five directly observable and quantifiable characteristics that have been tested for relationships with travel behavior outcomes: density (including household density, population density, and employment density), diversity (including measures of jobs–housing balance and land use mix), design (including intersection density and measures of street network nodal degree), destination accessibility (including distance to the central business district and numbers of jobs that can be reached by a particular mode within a given commute time), and distance to transit (including transit stop density, transit service density, and average distance to a transit stop) (*1*). Of these, Ewing and Cervero found that the most commonly studied characteristics are land use mix and some form of density.

Density is widely used in travel and built environment research because the density value is both readily available and easy to compute. Although ubiquity facilitates comparisons between studies, the widespread use of density belies many underlying complexities that have implications for interpretation of results. For example, is it more appropriate to measure residential or employment density? Perhaps it is best to measure both, but if so, is a combined measure such as activity density best, or is it better to include residential and employment density separately? Likewise, for residential density, should researchers measure housing units or residents?

Just as pressing is what the appropriate scale is for measuring density. Can administrative boundaries serve as a unit of analysis, and, if so, is it most appropriate to measure the built environment of the block, the block group, the census tract, or the metropolitan area or that of something in between these? As an alternative to administrative boundaries, the built environment may be measured within some distance radius. If that is the case, how large should the radius be?

The other so-called D variables share similar methodological and measurement issues. For example, there are challenges in measuring job accessibility, which indicates the number of jobs that are reachable by a given mode in a specified amount of time. Analysts must select not only which modes to analyze but also the travel time threshold. Is it more appropriate to measure the number of jobs available within 20, 30, or 60 min travel time or to apply a decay function to weight destinations by proximity? Just as important, given variations in transit service and congestion, at what time of day should job accessibility be analyzed? The morning peak period? an off-peak period? an average for the entire day?

Because of these and other methodological issues, there is much variation in how the D variables are operationalized in travel behavior studies (*5*). Differences in operationalization can influence results in significant ways and can muddy comparisons between studies.

Another pressing methodological issue is that often many of the D variables are strongly correlated with one another (*6–10*). For example, a location with a high population density is likely also to have high densities of intersections, jobs, and transit service. Thus, including many D variables in a single regression model could introduce problems of multicollinearity and make it difficult to isolate the individual effects of each variable. To address this issue, researchers may use a single measure as a proxy for many factors that tend to vary together. For example, Barrington-Leigh and Millard-Ball use street network connectivity as a proxy for a broader measure of overall sprawl (*11*).

Continuous Composite Measures

As an alternative to the use of individual characteristics as proxies for the collective effect of many closely related characteristics, researchers can use a composite score or index that incorporates several characteristics of the built environment into a single, continuous measure. For example, researchers have studied the relationship between walking mode choice and walkability indexes (*12–14*)—the best known of which is the commercially available Walk Score, which incorporates both intersection density and distances to a variety of destination types (*12*).

Another well-known composite measure is the sprawl index, which was created by Ewing et al. (*15*) and refined by Hamidi et al. (*8*) to improve on previous measures of sprawl that lacked complexity. Existing measures relied on only one or two variables and failed to capture the multiple dimensions of sprawl. A research team could introduce additional built environment measures, one or more for each of the dimensions of sprawl. Instead, Ewing et al. combined the multiple dimensions of sprawl into a readily interpretable index (*15*).

Composite measures are intuitive and readily understandable, yet this simplicity belies methodological complexity. When developing a composite measure, the research team must determine how many built environment components to include, how to measure each component, and how to combine data to create broader comprehensive components. More fundamentally, the team must collect and organize all the data, a time-consuming process that requires considerable expertise (*5*). Moreover, issues of scale and scope that arise in measuring observable characteristics are compounded in construction of a composite measure.

Rather than make such methodological decisions on their own, scholars or practitioners may use an existing composite measure of the built environment. Here, too, analysts must consider many factors to determine which type of measure will be most appropriate for their work.

Categorical Neighborhood Types

Rather than creating a continuous built environment variable, some researchers have combined measures of the built environment to classify neighborhoods into distinct categorical types (*9, 16–20*). An advantage of neighborhood types over continuous index variables is that the categories may better represent discontinuities in the effects of the built environment on travel behavior. In a meta-analysis of 60 studies, Ewing and Cervero found that a 1% increase in population density decreases the VMT value by 0.04% (*1*). However, travel responses to changes in density are likely to vary considerably by the initial density (*21*). Increasing density by 1% in a rural or low-density suburban area may do little to change behavior because accessing destinations would still require long car trips. However, the same increase in density in a more urban setting could tip the scales and reduce the VMT value. For example, some people may forgo an automobile trip and make the trip by another mode, or transit service frequency may increase.

Following classification methods developed by researchers categorizing neighborhoods by sociodemographic characteristics (*22, 23*), researchers classifying neighborhoods by built environment characteristics (*9, 16–20*) first used factor analysis to reduce many variables to fewer factors, then used cluster analysis to identify groups of neighborhoods that had similar sets of factor scores.

Most neighborhood classification studies have addressed a specific region or metropolitan area, such as Baltimore, Maryland (*20*); Portland, Oregon (*19*); Charlotte, North Carolina (*18*); Boston, Massachusetts (*16*); and Atlanta, Georgia (*16*). Others have categorized neighborhoods within broader geographies: Salon classified neighborhoods throughout California (*17*), and Voulgaris et al. classified neighborhoods throughout the United States (*9*).

Three Specific Built Environment Measurements

This paper compares how effectively three built environment measures—one from each of the three categories described in the previous section—predict travel behavior outcomes. The single observable measure analyzed is activity density. The continuous, composite measure used is the sprawl index developed by Ewing et al. (*15*) and refined by Hamidi et al. (*8*). The categorical neighborhood-type variable assessed is the neighborhood types developed by Voulgaris et al. (*9*). These composite measures were selected because they have been validated against a wide variety of travel behavior outcomes (in contrast to walkability indexes that primarily have been evaluated against walking rates and mode shares) and are available for metropolitan areas throughout the United States. The remainder of this section discusses each of the three measures and then compares and contrasts the methodologies used to compute the two composite measures.

Activity Density

Activity density is calculated as the sum of population and employment density. This measure was selected because both employment and population density are commonly used descriptors of the built environment. Activity density was preferred to other single measures of the built environment because it is the most commonly used built environment variable, and—unlike for destination accessibility and design, for example—there is consensus on how to measure and calculate activity density, and it is easily obtained for the entire United States from the census. In addition, density often covaries with other so-called D variables; for example, increased land use mix and percentage of four-way intersections—which can be used to measure diversity and design, respectively—covary with density. In this way, density is a proxy for other D variables. If density provides a good proxy for the other variables, it should perform nearly as well as would the composite measures that explicitly incorporate additional measures of the built environment.

Sprawl Index

The sprawl index is a continuous composite measure of the built environment developed by Ewing et al. (*15*) and refined by Hamidi et al. (*8*). To construct the sprawl index, both Ewing et al. and Hamidi et al. began by identifying four broad components of sprawl: developmental density, land use mix, degree of centering (the degree to which activity is concentrated in one or more locations instead of being evenly dispersed throughout an area), and street connectivity. Each component included many input variables: eight measures of density, three of land use mix, five of centering, and five of street connectivity. Within each domain, the authors used principal components analysis—a statistical method that identifies linear combinations of input variables—to translate the input values into a single component score. Each score explains most of the variance of the input variables. The density score, for example, explains 73% of the variance in the eight density variables.

The authors computed the overall sprawl score by summing the values for the four broad components, each receiving equal weight (*8, 15*). The authors did not want the sprawl score to be correlated with population size, so they adjusted the scores by dividing by the natural log of metropolitan area population. Finally, the summed scores were converted into an index with a mean of 100 and a standard deviation of 25. Higher scores indicate that the area is more compact (less sprawling), and lower scores indicate that the area is less compact (more sprawling).

Neighborhood Types

The neighborhood-types variable is a composite categorical variable that combines multiple built environment measures into a cohesive neighborhood typology. To identify a small-scale neighborhood typology, Voulgaris et al. selected two data sources that provided built environment data at the census tract level across the entire United States: the U.S. Environmental Protection Agency's Smart Location Database and the U.S. census (*9*). From these sources, the authors selected 20 variables relevant to describing an area's built form and transportation system characteristics. The variables included housing density, share of rented housing units, age of the housing stock, number of jobs within 45 min, share of metropolitan employment in a census tract, jobs–housing balance, and a transit service index.

Voulgaris et al. used factor analysis to collapse the initial 20 variables into a set of five factors, which they defined as representing the degree to which a neighborhood is (*a*) dense, (*b*) diverse, (*c*) transient, (*d*) established or stable, and (*e*) accessible. Finally, the five factors were input into a cluster analysis for identifying the neighborhood types (*9*). Applying several statistical stopping criteria, the authors selected a seven-cluster solution. The resulting neighborhood types are one rural type, three suburban types, and three urban types.

Comparing Composite Measures of the Built Environment

The sprawl index and neighborhood types differ in several respects. These differences are discussed below.

Unit of Analysis

A key difference between the sprawl index and the neighborhood types is that they are constructed at different scales. The neighborhood types are measured at the census tract level, whereas the sprawl index is constructed at the metropolitan level. As a result, the sprawl index includes many metropolitan area–wide variables, but neighborhood types do not include any. Despite the focus on describing the built environment at the metropolitan level, the sprawl index includes scores for individual census tracts. As discussed in greater detail below, the scale of analysis likely influenced the selection of input variables. For example, the sprawl index, with its metropolitan focus, emphasizes centering and regional accessibility to a greater degree than the neighborhood types, which are more locally oriented.

Selecting Variables for Measuring the Built Environment

Both sets of authors set out to measure the built environment, but there is great diversity in the variables chosen for analysis. Just three variables are shared between the sprawl index and neighborhood types: employment density, intersection density, and jobs–housing balance.

Development density features prominently in both the sprawl index and the neighborhood types, but the precise measurement varies. Whereas the sprawl index includes population density, the neighborhood types include housing density. In addition to density, there are considerable differences in how roadways contribute to the sprawl index and neighborhood types. When constructing the neighborhood types, Voulgaris et al. included three roadway measures: intersection density and separate measures of car- and pedestrian-oriented road network densities (*9*). Each of these roadway variables loaded onto the density factor rather than a separate roadway factor. By contrast, street connectivity was identified as one of four distinct components of sprawl. In this way, the road network contributes more directly to the sprawl index than to the neighborhood types.

Many of the differences between the sprawl index and neighborhood types stem from differences in metropolitan versus local orientation, that is, their units of analysis or scale. The sprawl index includes measures of density across the entire metropolitan region (weighted average population and employment densities), likely a result of the metropolitan scale of analysis. By contrast, neighborhood types do not include any information about density in nearby tracts or for the region as a whole. Differences in scale also likely explain why the neighborhood types do not include any measure of centering, a foundational concept for the sprawl index. The degree of centering is a well-recognized feature for characterizing the built environment of a metropolitan area. Conversely, the degree of centering may appear less important when a census tract is used as a unit of analysis.

Different scales likewise affected road variables used in each composite measure. The street connectivity component of the sprawl index includes variables that use average values for the metropolitan area as a whole, including average block length, average intersection density, share of blocks smaller than 1/100 mi^2, and share of intersections of four or more ways. Although these measures vary immensely across a metropolitan area, the sprawl index holds them constant for tracts within the same metropolitan area.

Inclusion of such metropolitanwide measures in the sprawl index means that tracts share more of the input values, which smooths the differences between adjacent tracts. Although the neighborhood types do not include information about the metropolitan region as a whole, they do include some information about nearby tracts, such as the number of jobs within a 45-min drive. Because most census tracts can be traversed in fewer than 45 min, this variable includes information on job access in nearby tracts. Another neighborhood-type measure that incorporates metropolitanwide information is the share of total metropolitan-area jobs within a census tract. A high score on this measure indicates that the tract is an employment center.

Definitions of sprawl emphasize the separation of land uses, and concepts of mixed use and diversity feature prominently in both the sprawl index and the neighborhood types. In contrast to the metropolitan area–wide measures for the road network, land use mix variables were measured at the scale of a census tract (or smaller) for both the sprawl index and neighborhood types. Jobs–housing balance, for example, must be measured at a small scale because an entire metropolitan area should have relative balance between jobs and housing.

Neighborhood types contain some information not included in the sprawl index. Most prominently, neighborhood types incorporate housing tenure variables, which dominate two of the five factors clustered to create neighborhood types. With one exception (share of homes that are single family), these variables are not invoked in discussions of travel behavior and the built environment.

Combining Variables into Built Environment Components

Both the sprawl index and neighborhood type use individual built environment variables to create broad composite measures: four components of sprawl and five built environment factors, respectively. Hamidi et al. drew on the literature to identify four components of sprawl (developmental density, land use mix, centering, and street connectivity) (*8*). They then selected data corresponding to each component and conducted principal components analysis for each component. Voulgaris et al. did not identify specific neighborhood types ahead of time. Instead, they drew on the literature to identify relevant variables and then, through factor analysis, identified five broad components (density, diversity, transience, stability, and accessibility) (*9*). This approach allowed the number of relevant factors to vary, and Voulgaris et al. estimated multiple solutions ranging from five to eight factors. They selected a five-factor solution because it was the most interpretable.

Using Contracting Approaches to Combine Components into a Single Composite Variable

Contrasting approaches were used to combine information from each broad component into a final measure. Hamidi et al. summed the scores for the four sprawl components to create a composite sprawl index (*8*); Voulgaris et al. used cluster analysis to combine their five built environment factors (*9*). In cluster analysis, the analyst uses several so-called stopping rules to compare solutions with various numbers of clusters. Voulgaris et al. (*9*) computed statistics for 14 stopping criteria by using the R package clusterCrit (*24*) to determine that seven clusters yielded the most optimal criteria.

An advantage of the latter approach is that particular combinations of the five factors can reveal differences between tracts in a way that is not possible with composite scores. For example, two tracts with the same composite sprawl score could have quite different built environments. A tract that is dense but not diverse could produce the same composite sprawl score as that for a tract with low density but high diversity. Although the sprawl index scores likely would be similar for the two tracts, the scores likely would be assigned to different neighborhood types. This effect is especially important when the measures are used to predict travel behavior because the two tracts likely would be associated with different travel outcomes.

DATA AND METHODS

The study addressed in this paper was intended to determine how well an example of each of three types of built environment measures—activity density, the continuous composite sprawl index, and categorical composite neighborhood types—contribute to understanding travel behavior.

Data

The three measures were assessed with data from the 2009 National Household Travel Survey (NHTS), a survey commissioned by FHWA (*25*). Each survey respondent completed a detailed travel diary for a 24-h period, during which they recorded the purpose, mode, duration, and distance of each trip. In addition to disaggregate travel patterns, the survey collected data on personal and household characteristics. The confidential version of the NHTS, which includes residential location data for each household, allowed identification of the activity density, sprawl score, and neighborhood type of each respondent's home. The NHTS includes respondents living in rural, suburban, and urban areas across all 50 states, which enables analysis of the relationship between travel and the built environment in a variety of geographic settings. The analysis was limited to survey respondents age 18 years and older.

Built environment data were downloaded from the following locations: activity density (U.S. census), sprawl index (https://gis.cancer.gov/tools/urban-sprawl/), and neighborhood types (http://www.its.ucla.edu/publication/synergistic-neighborhood-relationships-with-travel-behavior-an-analysis-of-travel-in-30000-u-s-neighborhoods/). Values for all three variables were recorded at the census tract. Analysis was limited to the 53,438 census tracts (97% of all U.S. census tracts in metropolitan areas) in which NHTS respondents lived.

Descriptive Analysis

The descriptive analysis has two aims: to determine how the three measures of the built environment relate to one another and to determine how travel patterns vary across each of the three built environment measures. To facilitate these comparisons, 53,438 census tracts were separated into quintiles of roughly 10,700 tracts according to their values for activity density and the sprawl index. Tracts in each quintile share broadly similar built environment characteristics, and individuals in each quintile were assumed to share similar travel patterns. To assess this expectation, summary statistics were computed (mean and median) for activity density and the sprawl index within each of the density quintiles, the sprawl quintiles, and the neighborhood types.

Summary statistics were then computed (mean and median) for four travel variables: (*a*) VMT value on the survey day, (*b*) odds that a trip is by walking, (*c*) odds that a trip is by transit, and (*d*) trip length. These travel variables were selected for analysis because they are policy relevant; reducing the VMT value and increasing trips by walking and transit are policy aims for many transportation professionals.

Multivariate Analysis

Multivariate analysis expands on the descriptive analysis by adding control variables drawn from the built environment travel literature. Multivariate analysis is used to compare model fit for each of the measures of the built environment: density, sprawl index, and neighborhood type.

Four separate models were estimated for each dependent travel variable. Table 1 shows the independent trip characteristics, individual characteristics, and household characteristics used in each of the models. All four models control for the same set of independent variables but differ by which of the three built environment measures they include. One model describes the built environment

TABLE 1 Independent Variables

Variable	95% Confidence Interval for Average (continuous) or Share (categorical)
Trip Level	
Trip length (mi, log transformed in model)[a]	9.0 to 9.8
Trip purpose (%)	
Home-based work (base)	13 to 14
Home-based shopping	22 to 23
Home-based social or recreation	12 to 13
Home-based other	19 to 20
Non-home-based	31 to 32
Person Level	
Age (years, included in model as age + age^2)	44.8 to 45.4
Sex (%)	
Male (base)	49 to 50
Female	50 to 51
Race or ethnicity (%)	
Non-Hispanic white (base)	64 to 66
Non-Hispanic black	12 to 14
Non-Hispanic Asian	3 to 4
Hispanic	15 to 17
Non-Hispanic other	2 to 3
Employment (%)	
Employed (base)	70 to 72
Not employed	28 to 30
Internet use (%)	
Daily (base)	63 to 65
Less than daily	35 to 37
Education level (%)	
Less than high school (base)	8 to 9
High school	25 to 27
Some college	29 to 30
Undergraduate degree	21 to 22
Graduate degree	15 to 16
Household Level	
Income ($, log transformed in model)	63,956 to 65,670
Number of adults	2.0 to 2.0
Number of children	0.7 to 0.8

[a]Trip length is not included as an independent variable in model predicting trip length.

exclusively in terms of activity density, the second describes it only in terms of neighborhood type, the third describes it only in terms of the sprawl index, and the fourth describes it in terms of both the sprawl index and neighborhood type. In total, 16 models were estimated (four dependent variables × four model specifications). The VMT value and trip length were log transformed. The VMT value was modeled at the person level; mode choice and trip length were modeled at the trip level.

Goodness of fit was assessed with the Akaike information criterion (AIC), which is similar to the likelihood ratio test but can be used to compare nonnested models. AIC values incur a penalty for model complexity. A lower AIC score indicates a better fit.

DISCUSSION OF RESULTS

Descriptive Results

Table 2 includes descriptive data comparing the neighborhood types to activity density and the sprawl index. As expected, activity density was extremely low in rural neighborhoods, increased through the suburban neighborhoods, peaked in old urban neighborhoods, and then dropped slightly in job centers. The sprawl index followed a similar pattern; compactness scores were lowest in rural neighborhoods and peaked in old urban neighborhoods.

For most of the activity density quintiles, the mean and median values for activity density were very similar. In the fifth (highest) quintile, by contrast, the mean density value was much higher than the median, which suggests that there are few very-high-density tracts. Indeed, the 15 highest-density tracts in the United States all have more than 1,000 jobs and residents per acre. There is much less difference between the mean and median values for the sprawl index, since the sprawl index was constructed to have a normal distribution with a mean of 100 and a standard deviation of 25.

For neighborhood type, activity density was very low in rural neighborhoods and steadily increased through the suburban neighborhoods. Density increased further in urban residential neighborhoods and then was much higher in old urban neighborhoods and job centers.

Travel behavior outcomes parallel the trends for density and the sprawl index. Higher densities and lower sprawl indexes are associated with lower VMT values, shorter trip lengths, and higher shares of walk and transit trips.

Multivariate Results

Full model results for the 16 estimated models are not reported here; Tables 3 through 5 summarize the model results. All built environment variables were significant at a 99.9% confidence level for all 16 models, indicating that even when the personal characteristics described in Table 1 are controlled for, a statistically significant relationship between travel and the built environment remains.

Tables 3 and 4 compare the estimated difference between new development neighborhoods (the most common neighborhood type) and old urban neighborhoods (the most distinctive neighborhood type) for each travel behavior outcome, as estimated by each of the four models. The neighborhood-type model, the sprawl index model, and the combined model produce similar estimates for the difference in VMT, for the odds that a trip is by transit, and for trip length. For the odds that a trip is by walking, the sprawl index model underpredicts the odds that one walks, relative to the model that includes both the sprawl index and neighborhood type and the model that includes neighborhood type alone.

Table 5 provides information on model fit, the heart of the analysis. For all four travel behavior outcomes analyzed here, the models that include both a continuous index variable (the sprawl index) and a categorical variable (neighborhood type) provide the best model fit, which suggests that each variable contributes unique information to an understanding of the relationship between travel behavior and the built environment. The categorical variable for neighborhood type accounts for discontinuities and threshold effects that cannot be captured through a continuous variable alone. At the same time, travel within a particular neighborhood type is not homogeneous, and the sprawl index captures variations within each neighborhood type as well as differences in metropolitan area level between neighborhoods.

The sprawl index provided the second best model fit for three of the four travel behaviors analyzed here. The sole exception was walking mode choice, for which the neighborhood typology model provided a better fit than did the sprawl index model, which suggests that discontinuities and threshold effects in the relationship between the built environment and travel may be more central in the decision to walk than in the other examined travel behaviors.

CONCLUSION

Newly developed built environment measures generate new questions and challenges for quantifying built environment characteristics and pose alternatives to traditionally used single measures such as density. Some of these new measures are composite measures that combine multiple built environment characteristics into a single, continuous variable. Others create categorical neighborhood types by using statistical classification methods to define distinct groups of neighborhoods that share built environment traits. Should practitioners and scholars use these new measures? Are the new measures unnecessarily complex, or can they help quantitatively capture the synergistic effects of built environment characteristics?

This research found that both continuous composite measures and categorical measures provide important additive information in travel behavior models. Both are stronger predictors of travel behaviors than are traditional simplistic measures of density, as shown by their consistently better model fits. Moreover, the best-fitting model was a combined model that included both the sprawl index and the neighborhood types as explanatory variables.

The combined model best fits travel behavior variables because each built environment variable contributes unique aspects of the built environment. Neighborhood types are measured categorically and, unlike the sprawl index, can measure discontinuities and threshold effects that cannot be captured through a continuous variable alone. At the same time, the sprawl index provides information that the neighborhood types do not, namely, metropolitan-level context and fine-grained graduated values. Models that combine the sprawl index and neighborhood types may better reflect both local and metropolitan area–wide geographical contexts and characteristics. Future refinements to both the sprawl index and the neighborhood types used in this analysis or alternative indexes and typologies may perform even better than do those tested in this study. For example, this study identified thresholds in neighborhoods. It is possible that these thresholds do not align precisely with thresholds for travel behavior. It may be more appropriate to identify neighborhood types according to travel patterns and then to observe the built environment and socioeconomic characteristics that are prevalent there.

TABLE 2 Travel Behavior Outcomes and Built Environment Characteristics by Density and Sprawl Quintiles and by Neighborhood Type

	Prevalence		Built Environment Characteristics		Travel Behavior Outcomes			
Data by Category	Number of Census Tracts	Share of Census Tracts (%)	Activity Density[a] (mean/median)	Sprawl Index (mean/median)	VMT per Person (mean/median)	Walk Trips (%)	Transit Trips (%)	Trip Length[b] (mean/median)
Full sample	53,438	100	15/7	100/100	22/14	11	3	9/4
Activity density quintiles								
Q1	10,747	20	1/1	68/69	28/21	6	1	12/5
Q2	10,687	20	4/4	90/89	24/17	8	1	10/4
Q3	10,688	20	7/7	102/101	21/14	9	1	9/3
Q4	10,687	20	12/12	111/110	20/13	10	2	8/3
Q5	10,688	20	51/29	129/128	13/6	23	9	7/2
Sprawl index quintiles								
Q1	10,700	20	1/1	65/68	28/21	6	1	12/5
Q2	10,699	20	5/4	88/88	23/16	8	1	10/4
Q3	10,699	20	9/8	100/100	22/15	9	2	9/4
Q4	10,699	20	13/11	112/112	19/12	11	2	8/3
Q5	10,700	20	46/24	135/131	13/6	23	9	7/2
Neighborhood type								
Rural	3,142	6	1/<1	61/61	29/22	6	1	12/6
New development	13,692	26	4/3	83/83	26/19	7	1	11/5
Patchwork	9,922	19	8/6	99/99	22/14	9	1	9/3
Established suburb	9,896	19	12/9	109/109	20/13	10	3	9/3
Urban residential	9,642	18	14/11	112/111	17/11	12	3	8/3
Old urban	3,118	6	77/57	138/140	11/1	35	16	6/2
Job center	4,026	8	40/15	113/109	18/10	16	4	9/3

[a]Density in the number of jobs and residents per acre.
[b]Trip length in miles.

TABLE 3 Summary of Multivariate Model Results: Coefficients

Dependent Variable	VMT per Person (log transformed)	Odds That a Trip Is by Walking	Odds That a Trip Is by Transit	Trip Length (log transformed)
Old Urban Neighborhood Type Coefficient[a,b]				
Neighborhood type only	–0.457	1.611	2.923	–0.769
Combined model	–0.107	1.247	1.276	–0.279
Sprawl Index Coefficient[a]				
Sprawl index only	–0.008	0.009	0.038	–0.010
Combined model	–0.007	0.006	0.029	–0.009
Density Coefficient[a]				
Density only	–0.134	0.010	0.009	–0.005

[a]All coefficients shown have p-values < 2 E–16.
[b]These coefficients represent differences relative to the New Development neighborhood type, which was the base category.

TABLE 4 Summary of Multivariate Model Results: Predicted Percentage Difference Between Old Urban Neighborhoods and New Development Neighborhoods

	Predicted Percentage Difference Between Old and New Neighborhoods by Travel Behavior Outcome[a]			
Dependent Variable	VMT (log transformed)	Odds That Trip Is by Walking	Odds That Trip Is by Transit	Trip Length (log transformed)
Neighborhood type only	–46	161	292	–77
Sprawl index only	–45	50	212	–56
Density only	<–99	17	16	–9
Combined model	–50	158	289	–78

[a]Results are based on average densities and sprawl indices.

TABLE 5 Summary of Multivariate Model Results: AIC Scores

	AIC Score by Travel Behavior Outcome			
Dependent Variable	VMT (log transformed)	Odds That Trip Is by Walking	Odds That Trip Is by Transit	Trip Length (log transformed)
Neighborhood type only	415,024[a]	*224,754*[b]	74,418	2,467,307
Sprawl index only	*413,523*[b]	226,460[a]	*73,178*[b]	*2,459,928*[b]
Density only	413,948	224,826	76,481[a]	2,472,937[a]
Combined model[c]	**413,273**	**224,353**	**72,420**	**2,459,007**

[a]Entry indicates worst model fit.
[b]Italic entry indicates second-best model fit.
[c]Boldfaced entry indicates best model fit.

Nevertheless, the best-performing models likely will incorporate both continuous and categorical variables to describe the built environment. An improved ability to reflect and measure the built environment quantitatively is necessary for understanding its influences on travel behavior and for designing policies that reflect these influences.

Two improvements to future neighborhood typologies and built environment indexes would be useful to researchers, planners, and policy makers. First, tools allowing planners and policy makers to determine easily how proposed changes to the built environment would affect a neighborhood's type or sprawl index would help in determining how such built environment changes may affect travel behavior. For example, if built environment changes led to a shift in neighborhood type, what types of travel behavior changes could policy makers expect to observe? Second, longitudinal data for both built environment and travel behavior variables could be used by researchers to understand the effects of neighborhood change on changes in travel behavior over time.

A trade-off exists between maintaining continuity of the built environment measures over time and continually refining and improving the measures. The former allows for longitudinal studies of like variables, and the latter enables researchers to measure better the built environment's effects on travel behavior. This challenge is exacerbated for composite indexes and typologies. With these measures, identifying and removing unnecessary variables or adding omitted variables is more difficult than adding or removing independently measured variables such as the five so-called D variables.

Because of the complexity of the built environment and the multifaceted nature of travel behavior decisions, the creation of a single, comprehensive built environment measure—whether continuous or categorical—may be neither advisable nor possible. However, the combination of a continuous composite variable and a categorical neighborhood type indicator is a promising approach to estimating parsimonious models with strong predictive power for a variety of travel behavior outcomes. Such models may also allow researchers to capture unobservable ways in which the built environment affects travel behaviors, such as synergisms between elements like street design and mixed-use development that are not fully captured by isolated built environment variables. Whether through continuous, categorical, or composite measures, research should continue to quantify better the dynamic relationships between the built environment and travel behavior to inform transportation policy decisions more accurately.

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