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Key Points:

- Variation in the land use environment (LUE) impacts the continuum of walkability to car dependency, which has effects on health outcomes
- We assessed measurement invariance of a land use construct across levels of urbanicity using multiple group confirmatory factor analysis
- We determined that measurement of the LUE does vary across urbanicity which can lead to place-based confounding

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Assessing Measurement Invariance of a Land Use Environment Construct Across Levels of Urbanicity

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Abstract Variation in the land use environment (LUE) impacts the continuum of walkability to car dependency, which has been shown to have effects on health outcomes. Existing objective measures of the LUE do not consider whether the measurement of the construct varies across different types of communities along the rural/urban spectrum. To help meet the goals of the Diabetes Location, Environmental Attributes, and Disparities (LEAD) Network, we developed a national, census tract-level LUE measure which evaluates the road network and land development. We tested for measurement invariance by LEAD community type (higher density urban, lower density urban, suburban/small town, and rural) using multiple group confirmatory factor analysis. We determined that metric invariance does not exist; thus, measurement of the LUE does vary across community type with average block length, average block size, and percent developed land driving most shared variability in rural tracts and with intersection density, street connectivity, household density, and commercial establishment density driving most shared variability in higher density urban tracts. As a result, epidemiologic studies need to consider community type when assessing the LUE to minimize place-based confounding.

Plain Language Summary A community's land use environment (LUE) describes its citizens ability to walk from place to place versus their reliance on vehicles for transportation. Some factors that might influence LUE include the street network, size of road blocks, density of walkable establishments (food stores, restaurants, schools, etc.), and the mixture of residential and commercial establishments. Existing objective measures of the LUE do not consider urbanicity, which can lead to differences due only to places being more or less rural. The Diabetes Location, Environmental Attributes, and Disparities (LEAD) Network created a national, census tract-level LUE measure and assessed whether the LUE construct differed across LEAD community type groups (higher density urban, lower density urban, suburban/small town, and rural). We found that the LUE construct does vary across LEAD community type. Future epidemiologic studies examining the LUE need to consider urbanicity to account for these differences.

1. Introduction

Humans have changed natural environments in a number of ways, for uses such as habitation, agriculture, transportation, industry, commerce, and recreation. These decisions about, and patterns of, land uses, have had dramatic impacts on ecosystems, ecosystem services, biodiversity, climate, pollution, and increasingly, human health (Markovchick-Nicholls et al., 2008; Seto & Shepherd, 2009; Su et al., 2009; Tilman & Clark, 2014). In the area of urban planning and the built environment, the land use environment (LUE) has been used to describe changes in development patterns and transportation networks over time. Previous work has described the evolution of transportation networks within the theory of three urban fabrics: walking, transit, and auto (Newman & Kenworthy, 2015). Cities in early history were connected by the walking urban fabric and were characterized by dense settlement, a mix of land uses, investment in public places, human-scaled design, and a clear distinction between city and country (Beatly & Manning, 1997; Gillham, 2002). In the United States (U.S.) in particular, the past 100 years have seen human development patterns dramatically change, with the advent of the automobile, public investment in high-speed road networks, closure of urban electric rail lines, home financing policy, and social and economic factors that resulted in white flight from cities (Beatly & Manning, 1997), consistent with the auto urban fabric theory. These factors created a landscape with a predominant horizontal form of development spreading out from urban cores in a pattern referred to as urban sprawl which is characterized by low density residential housing, single use zoning, low destination accessibility, automobile dependence, and lack of economic viability for public transit (Gillham, 2002). These changes made active transport increasingly difficult, co-occurred with the obesity epidemic in the U.S., and focused public health attention on ways of measuring these health-relevant features of land uses.

The features of settlement patterns now observed in the U.S. exist alongside a continuum of urbanicity which has been characterized by the U.S. Department of Agriculture's (USDA) Rural Urban Commuting Area (RUCA) codes ("Economic Research Service & USDA, 2020 Rural-Urban Commuting Area (RUCA) Codes,"2010). Additionally, the Diabetes Location, Environmental Attributes, and Disparities (LEAD) Network has developed a modification of the RUCA codes that is nationally applicable, of a geographic scale relevant to obesity and type 2 diabetes development, and that minimizes within-category distributional differences of key community features relevant to obesity and type 2 diabetes development (Hirsch, Moore, et al., 2020; McAlexander et al., 2022). The LEAD modification is referred to as LEAD community type.

Along the urbanicity continuum, communities which are often defined by census tract boundaries range from being primarily automobile-dependent to easily facilitating ways of active transport, including walking and cycling (Cervero & Kockelman, 1997; Dannenberg et al., 2003; Ewing & Cervero, 2001; Stowe et al., 2019). This is a result of unique combinations of the overlapping urban fabrics (Newman & Kenworthy, 2015). Studies have reported associations between both individual aspects and composite measures of a community's built environment with lower rates of vehicular travel (Cervero & Kockelman, 1997; Ihlanfeldt, 2020; Le et al., 2018; Mccann & Ewing, 2003), including increased population and household density, diversity of land use, compact design of neighborhoods and street networks, access to desirable destinations, and low distance to transit (Cervero & Kockelman, 1997; Ewing & Cervero, 2001), some components of which have been incorporated into proprietary measures such as Walk Score® ("Walk Score Methodology," 2021). Many measurement dimensions that promote active transport, such as land use mix and intersection density, have been associated with favorable health outcomes, including lower risks of obesity and hypertension (Chiu et al., 2015; Ewing et al., 2003; Frank et al., 2006; Mccann & Ewing, 2003; Stowe et al., 2019).

The Diabetes LEAD network sought to derive a LUE construct that could be used for the entire U.S., was more inclusive of rural areas, and was at a geographic scale relevant to the development of type 2 diabetes. In this paper, we first developed a measurement model for the contiguous U.S. at the census tract level using factor analysis to measure the LUE using measures of the road network, density of developed land, and desirable walking destinations. We next assessed whether the measure derived by the factor analysis incorporated the road network, density of developed land, and desirable walking destinations similarly across the four LEAD community types: higher density urban, lower density urban, suburban/small town, and rural (McAlexander et al., 2022). We hypothesized that measurement of the LUE varies in these four community types, requiring different measurement approaches by community category.

2. Materials and Methods

2.1. Unit of Measurement

We performed this analysis at the census tract level for the contiguous U.S. (n = 72,538) as represented in the 2016 Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line Geodatabase. Census tract is a geographic scale that has been commonly used in prior studies of the built environment and human health that were community-focused (Auchincloss et al., 2009; Sharp & Kimbro, 2021). While convenient in terms of necessary data, census tracts may not be experientially and behaviorally relevant (Moudon & Lee, 2003). While other studies have relied on egocentric buffers when evaluating community features relevant to utilitarian physical activity (Christine et al., 2015; Gebreab et al., 2017), the Diabetes LEAD network did not have the ability to share individual-level home addresses, necessitating an approach that relied on common geographic boundaries. By implementing the analysis at the census tract level, the resulting measures cover the entire range of the urban-rural continuum and are sharable by the Diabetes LEAD network with other research teams.

Table 1
Variables Used in Land Use Environment Composite Measure

Variable name	Derivation	Data source
Average block length	Sum of street miles[a] divided by intersection count[b]	Computed in ArcGIS Pro using 2016 TIGER/Line Geodatabase and 2009 Vintage Esri Data
Average block size	Represented by average census block area in squared kilometers[d]	2010 RECVD[c], which draws from U.S. census data
Intersection density	Intersection count divided by land area in square miles	Computed in ArcGIS Pro using 2016 TIGER/Line Geodatabase and 2009 Vintage Esri Data
Street connectivity	Intersection count divided by the sum of intersection count and dead end count	Computed in ArcGIS Pro using 2016 TIGER/Line Geodatabase and 2009 Vintage Esri Data
Percent developed land	Sum of low, medium, and high intensity percent developed land	2011 National Land Cover Data set via RECVD data
Commercial establishment density	Count of walkable commercial establishments in 2010 excluding food and physical activity venues divided by land area in square miles	2010 RECVD
Household density	The count of households divided by land area in square miles	RECVD data based on 2008–2012 ACS data

[a]Sum of street miles is the total length of streets within the tract boundary measured in miles. [b]Intersection count is defined as the count of three or more legged intersections within a census tract boundary. [c]Data from the Retail Environment and Cardiovascular Disease (RECVD) project which evaluated how access to healthy food sources, physical fitness, and medical facilities affect disparities in cardiovascular disease. [d]Because indicators were z-transformed (and thus unitless) we used the units of the native variables rather than converting to the same units across indicators (e.g., miles vs. kilometers).

2.2. Data

A team of experts from the Diabetes LEAD network informed the choice of indicators included in the LUE construct a priori through extensive review of the literature and examination of available data. Twelve indicators that measured community design, land use, and street networks were investigated. Of those 12, five were excluded due to limited national data accessibility. The seven indicators examined, described in Table 1, included measures describing the road network (average block length, average block size, intersection density, and street connectivity) and land development (percent developed land, commercial establishment density, and household density). We excluded census tracts from analyses that had intersection count or land area equaling zero. Data sources for this study included ESRI 2009 Vintage Street data, 2016 Census TIGER/Line Geodatabase, and the Retail Environment and Cardiovascular Disease (RECVD) project (Hirsch, Moore, et al., 2020; Kaufman et al., 2015). Intersection density, average block length, and street connectivity utilized ESRI 2009 Vintage Street data and were computed in ArcGIS Pro. We removed freeways, ramps, and ferry connections from the street data set. Commercial establishment density excluded food and physical activity venues to avoiding double counting when examining the LUE measure in models with the food and physical fitness environment domains included in the LEAD network analyses (Hirsch, Moore, et al., 2020). After deriving each LUE variable, we log transformed average block size, average block length, intersection density, household density, and commercial establishment density, as well as standardized all seven indicators using z-score standardization to achieve normality. Variables were also standardized for direction so that an increase in any variable indicates more compact development.

We computed descriptive statistics for all LUE indicators, overall and stratified by LEAD community type, as mean and standard deviations. We computed Pearson correlations of the seven LUE indicators, stratified by LEAD community type. We then used factor analysis to elucidate how the LUE indicators differentially reflect the LUE construct across LEAD community type groups.

2.3. Identifying the Baseline Model

To assess measurement invariance by LEAD community type, we first needed to identify a baseline model with good fit among all community types. We thus used confirmatory factor analysis (CFA) to fit a one-factor model for the seven LUE indicators in which residual correlation was allowed among related or highly correlated indicators. Examples of these pairs of highly correlated indicators include block length with intersection density, household density with establishment density, and street connectivity with block size. Next, we used CFA to fit a two-factor model in which the road network indicators (average block length, average block size, intersection density, and street connectivity) were loaded onto the first factor and land development indicators (percent developed land, commercial establishment density, and household density) were loaded onto the second

Table 2
Levels of Measurement Invariance

Model	Level	Constraint	Result
Configural invariance	1	Same model structure	Indicates the construct is measured with the same model structure in each group
Metric invariance	2	Equal factor loadings	Allows for quantitative comparisons across groups
Scalar invariance	3	Equal item intercepts	Allows for latent mean comparisons
Strict invariance	4	Equal factor variances and covariances	Indicates equal factor covariances, correlations, and error variances

factor, allowing for covariance between the two factors and for residual correlation among related indicators. In all models, maximum likelihood estimation with robust standard errors was utilized. We assessed and compared model fit using the root mean square error of approximation (RMSEA) and Bayesian information criterion (BIC). RMSEA was chosen due to its lack of sensitivity to sample size; models were considered to have an acceptable fit when RMSEA was below 0.08 (Van de Schoot et al., 2012). To assess measurement invariance by LEAD community type, we chose the model with the lowest RMSEA and the lowest BIC.

2.4. Assessing Measurement Invariance of Land Use Environment by LEAD Community Type

Measurement invariance can be characterized as configural invariance, metric invariance, scalar invariance, and strict invariance, described in detail in Table 2 (Steinmetz et al., 2009). For the purposes of this analysis, achieving scalar invariance would be sufficient because it would allow for mean comparisons. To test for measurement invariance of LUE across community types, we utilized multigroup confirmatory factor analysis (MGCFA) to fit nested models that allowed us to assess configural, metric, and scalar invariance. Significant differences across the models were tested using a chi-square statistic with the Sattora-Bentler scaling correction factor (Satorra & Bentler, 2001). To conclude that scalar invariance existed across community types, it was necessary that both the chi-square test comparing the metric and configural models, as well as the test comparing the scalar and metric models were not statistically significant. However, if any of the sequence of nested models were statistically significantly different, we concluded that the LUE construct was different across groups, and could determine the degree to which the measure varies across community types.

3. Results

Of the 72,538 census tracts in the contiguous U.S., 323 (0.4%) census tracts were excluded due to their intersection count or land area equaling 0; thus 72,215 tracts were included in the analysis. Of the excluded tracts, 42% were rural and 53% had no LEAD community type designation due to not having a RUCA classification (which primarily coincides with tracts having no residential population). Average block length and average block size were smaller for more urban areas compared to more rural areas (Table 3). Intersection density, street connectivity, household density, percent developed land, and commercial establishment density were higher for more urban

Table 3
Summary Statistics, Mean (SD), of Land Use Environment Variables by Location, Environmental Attributes, and Disparities Community Type

	Higher density urban (n = 17,137)		Lower density urban (n = 25,714)		Suburban/Small town (n = 11,777)		Rural (n = 17,585)	
Average Block Length (mi)	0.14	(0.06)	0.17	(0.04)	0.25	(0.12)	0.57	(0.32)
Average block size (km^2)	0.03	(0.03)	0.07	(0.07)	0.22	(0.27)	0.91	(1.38)
Intersection density (per mi^2)	205	(98)	105	(50)	45	(49)	9	(12)
Street connectivity	0.89	(0.09)	0.80	(0.09)	0.75	(0.09)	0.72	(0.09)
Household density (per mi^2)	6,140	(8,329)	1,247	(684)	394	(445)	54	(80)
Percent developed land	0.87	(0.16)	0.60	(0.22)	0.24	(0.20)	0.04	(0.06)
Establishment density (per mi^2)	223	(457)	48	(44)	16	(30)	2	(4)

areas compared to more rural areas (Table 3). Correlations of the LUE indicators varied by LEAD community type (Table 4), with correlations generally strengthening for selected measures from higher density urban to rural. For example, in rural census tracts, correlations among household density, intersection density, commercial establishment density, and percent developed land all exceeded 0.75, while correlations in higher density urban areas did not exceed 0.53.

To find a baseline model, we fit several one and two factor models allowing for residual correlations between various related indicators and determined that the best fitting model was a one factor model allowing for residual correlation between average block length & intersection density, commercial establishment density & household density, and street connectivity & average block size, RMSEA = 0.063 (Table 5). This model structure was subsequently used to test for measurement invariance.

MGCFA was used to fit configural, metric, and scalar models. The configural model fit significantly better (χ^2(df) = 10,676(18), $p < 0.0001$) than the metric model, which constrains factor loadings to be equal across community type groups; thus, we conclude that measurement invariance does not exist across LEAD community type groups and while the model structure is the same, the factor loadings differ.

The variation in measurement of the LUE construct across LEAD community types was demonstrated by the variation in magnitude of the factor loadings of the seven LUE indicators across community types (Table 6). For example, factor loadings for average block length and intersection density increased as community type went from high density urban to rural (average block length loading increased from 0.179 to 0.769; intersection density loading increased from 0.236 to 0.618) (Table 6). Additionally, the factor loadings for average block size, household density, and commercial establishment density in suburban/small town and rural community types were higher compared to higher and lower density urban community types.

4. Conclusions

We used a measurement model approach to evaluate how to measure the LUE across a range of community types from rural to higher density urban. We found that a measurement model of the LUE at the census tract level across the U.S. must be stratified by community type because of the absence of measurement invariance but that the same single factor model structure was appropriate regardless of the community type. Specifically, we found that the LUE construct gradually becomes more strongly reflected by average block length and intersection density as community type shifts from higher density urban to rural. Additionally, average block size, household density, and commercial establishment density were more reflective of the LUE construct in suburban/small town and rural community types, compared to higher density and lower density urban community types.

The set of seven LUE indicators utilized in this paper were chosen based on the five D's of the built environment thought to influence utilitarian physical activity and automobile dependence (density, diversity, design, destination accessibility, and distance to transit) as well as data availability across the U.S., while minimizing high inter-correlations between variables (Cervero & Kockelman, 1997; Ewing & Cervero, 2001). Other variables considered but not included due to data availability at the national scale were land use mix, retail floor area ratio, vehicle miles traveled, and proximity to leisure amenities. Using these indicators, the LUE construct is able to measure a community's combination of walking, transit, and auto urban fabrics as described in the theory of urban fabric. After a long period of gravitating toward automobile dependence, cities are now using research based on these data to inform city planning to implement new policies that encourages the walking and transit urban fabrics (Newman et al., 2016). The concept of the five D's has been utilized in forming walkability indices in studies aimed to determine associations between the built environment and physical activity, walking, and health related outcomes, but primarily in urban areas. For example, aspects of the built environment including retail density, intersection density, and household density have been shown to have significant associations with walking time among adolescents (Carlson et al., 2015). Lower walkability scores, based on population density, household density, intersection density, and retail establishments, were associated with higher rates of hypertension and diabetes in a study of the CANHEART cohort in Ontario, Canada (Howell et al., 2019). The other end of the distribution of measures of the five D's in less developed areas would predict automobile dependence, not walkability, which is also supported by our research as intersection density, street connectivity, household density, percent developed land, and commercial establishment density were higher for more urban areas compared to those for more rural areas (Table 3). Interestingly, associations between walkability and health outcomes in youth

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Table 4
Pearson's Correlation Matrices of Land Use Environment Variables by Location, Environmental Attributes, and Disparities Community Types

a) In higher density urban census tracts

	Average Block Length	Average Block Size	Intersection Density	Street Connectivity	Household Density	% Developed Land	Establishment Density
Average Block Length	1.00	0.23	-0.49	-0.15	-0.02	-0.13	-0.04
Average Block Size		1.00	-0.37	-0.32	-0.17	-0.31	-0.14
Intersection Density			1.00	0.29	0.26	0.27	0.22
Street Connectivity				1.00	0.24	0.31	0.22
Household Density					1.00	0.20	0.53
Percent Developed Land						1.00	0.17
Establishment Density							1.00

b) In lower density urban census tracts

	Average Block Length	Average Block Size	Intersection Density	Street Connectivity	Household Density	% Developed Land	Establishment Density
Average Block Length	1.00	0.46	-0.68	-0.29	-0.44	-0.35	-0.31
Average Block Size		1.00	-0.46	-0.32	-0.37	-0.40	-0.27
Intersection Density			1.00	0.44	0.66	0.60	0.53
Street Connectivity				1.00	0.23	0.40	0.30
Household Density					1.00	0.57	0.46
Percent Developed Land						1.00	0.46
Establishment Density							1.00

c) In suburban/small town census tracts

	Average Block Length	Average Block Size	Intersection Density	Street Connectivity	Household Density	% Developed Land	Establishment Density
Average Block Length	1.00	0.64	-0.53	-0.37	-0.47	-0.50	-0.35
Average Block Size		1.00	-0.41	-0.35	-0.39	-0.47	-0.29
Intersection Density			1.00	0.55	0.83	0.79	0.75
Street Connectivity				1.00	0.47	0.58	0.44
Household Density					1.00	0.78	0.72
Percent Developed Land						1.00	0.67
Establishment Density							1.00

d) In rural census tracts

	Average Block Length	Average Block Size	Intersection Density	Street Connectivity	Household Density	% Developed Land	Establishment Density
Average Block Length	1.00	0.60	-0.58	-0.05	-0.52	-0.47	-0.43
Average Block Size		1.00	-0.29	-0.11	-0.28	-0.27	-0.23
Intersection Density			1.00	0.24	0.82	0.76	0.77
Street Connectivity				1.00	0.25	0.34	0.28
Household Density					1.00	0.83	0.82
Percent Developed Land						1.00	0.76
Establishment Density							1.00

Table 5
Model Fit Statistics for One and Two Factor Multiple Group Confirmatory Factor Analysis (MGCFA) Models Representing the Land Use Environment (LUE)

	BIC[c]	RMSEA[c]
One factor		
Model	[a]	[a]
With residual correlation between average block size and average block length	454,376	0.115
With residual correlation between average block length and intersection density	433,473	0.098
With residual correlations between average block length and intersection density; intersection density and household density	432,863	0.103
With residual correlations between average block length and intersection density; commercial establishment density and household density	414,186	0.075
With residual correlations between average block length and intersection density; commercial establishment density and household density; street connectivity and average block size	408,864	0.063
Two factors (road network and land development)[d]		
With residual correlation between average block length and intersection density	424,258	0.099
With residual correlations between average block length and intersection density; commercial establishment density and household density	[b]	[b]
With residual correlations between average block length and intersection density; commercial establishment density and household density; street connectivity and average block size	[b]	[b]

[a]Warning due to negative estimated residual variance of intersection density. [b]Warning due to factor correlation greater than one in suburban/small town and rural community types. [c]Bayesian Information Criterion (BIC) and Root Mean Square Error Approximation (RMSEA). [d]In this model, the road network factor includes average block length, average block size, intersection density, and street connectivity. The land development factor includes percent developed land, commercial establishment density, and household density.

populations have been found to vary across community types (Molina-García et al., 2020; Stowe et al., 2019). However, it is unknown if these differences were due to the application of the same approach to LUE measurement across a range of community types.

Neighborhood composition of land use, commercial establishments, and road networks differ across community types. This motivated the hypothesis among members of the LEAD Network that there may not be measurement invariance of LUE by community type (McAlexander et al., 2022). By examining the LUE construct with

Table 6
Factor Loadings by Community Type Group

	Higher density urban	Lower density urban	Suburban/Small town	Rural
Factor Loadings				
Average Block Length	0.179	0.236	0.530	0.769
Average block size	0.329	0.367	0.637	0.611
Intersection density	0.236	0.319	0.592	0.618
Street connectivity	0.393	0.391	0.470	0.161
Household density	0.284	0.269	0.407	0.556
Percent developed land	0.221	0.436	0.459	0.128
Establishment Density	0.287	0.276	0.504	0.623
Residual Correlation Loadings				
Average Block Length with Intersection Density	0.060	0.028	0.043	0.086
Average Block Size with Street Connectivity	0.033	0.059	0.056	0.063
Establishment Density with Household Density	0.126	0.042	0.047	0.110

MGCFA, we found statistical evidence suggesting that while the factor structure of the LUE measure is the same across community types, the factor loadings differ across LEAD community type groups (higher density urban, lower density urban, suburban/small town, and rural). Others have examined measurement invariance of perceived walkability within neighborhoods of senior women from the Nurses' Health Study cohort using the Abbreviated Neighborhood Environment Walkability Scale (NEWS-A) across levels of population density (low, medium, and high) (Starnes et al., 2019). NEWS-A incorporated 20 indicators measuring factors including infrastructure for walking, access to destinations, street connectivity, traffic safety, personal safety, and aesthetics. Starnes et al. (2019) found that the NEWS-A measure was not scalar invariant across population density groups and that researchers should use caution when using the score across different communities. While our study likely included more rural communities with lower population density, our findings were consistent with the NEWS-A study.

Our results highlight the importance of accounting for community type when constructing and analyzing LUE measures at the tract level within the U.S. In higher density urban areas, higher levels of the factors represent increasing walkability whereas, in rural areas, lower levels represent increasingly stronger automobile dependence. These findings also suggest that other epidemiological studies should test and account for measurement invariance by community type when constructing LUE measures to represent the construct more accurately in each community. In turn, these analyses can help develop more targeted public health interventions and policies, developed with the understanding of the unique attributes of different community types.

A primary strength of this analysis was that it examined a consistent set of land use indicators at the community level across the contiguous U.S., which, to our knowledge, has not yet been done. This approach facilitated the development of LUE measures that can be replicated in other studies of U.S. based cohorts. This study also used LEAD community types which have been previously shown to have better distributional separation between community types on key community measures relevant to obesity and type 2 diabetes as compared to other methods of community type classification.

Since the LUE construct was developed at the census tract level, applying this measure in analyses at the individual level may present issues related to the modifiable areal unit problem (MAUP). MAUP is a common issue in many health outcome studies and is often addressed by considering multiple spatial contexts (James et al., 2014; Parenteau & Sawada, 2011). Further, the LUE construct would likely benefit from the addition of measures quantifying walking infrastructure, pedestrian safety, and access to public transportation. These measures may be particularly insightful in suburban/small town and rural community types where walking may be more likely to occur on off-road walking paths connecting neighborhoods to other amenities. However, such measures are not currently available on a national level across the U.S. Similarly, a limitation of this analysis is that measures of land use mix was not available to be included. Future work may include combining the LEAD network's objective measure with survey data aimed at quantifying sidewalk access and safety.

In conclusion, the measurement of the LUE construct varied across community types; factor loadings of the indicators were not consistent in different community types with average block length, average block size, and percent developed land driving most shared variability in rural tracts and with intersection density, street connectivity, household density, and commercial establishment density driving most shared variability in higher density urban tracts. Future studies should carefully consider how to incorporate the LUE in studies evaluating a range of community types.

Disclaimer

The findings and conclusions are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data for the land use environment components were (a) computed in ArcGIS Pro (a licensed software available through esri.com) using 2016 Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line Geodatabase and 2009 Vintage Esri Data or (b) were developed by the Retail Environment and Cardiovascular Disease (RECVD) project with support from the National Institute of Aging (Grants R01AG049970, R01AG049970-04S1, R01AG072634), National Heart, Blood, and Lung Institute (Grant R01HL14843), National Institute on Alcohol Abuse and Alcoholism (R01AA028552), Commonwealth Universal Research Enhancement (C.U.R.E) program funded by the Pennsylvania Department of Health—2015 Formula award—SAP #4100072543, the Urban Health Collaborative at + University, and the Built Environment and Health Research Group at Columbia University. The land use components that were computed in ArcGIS Pro, the final LUE construct, and the Diabetes LEAD Network's community type variable is available through the Diabetes LEAD Network's data page: https://sites.google.com/view/diabetes-lead-network/data. The land use components that were developed by the RECVD project contain proprietary information and cannot be shared.

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References

Auchincloss, A. H., Roux, A. V. D., Mujahid, M. S., Shen, M., Bertoni, A. G., & Carnethon, M. R. (2009). Health care reform neighborhood resources for physical activity and healthy foods and incidence of type 2 diabetes mellitus the multi-ethnic study of atherosclerosis. *Archives of Internal Medicine*, *169*(18), 1698–1704. https://doi.org/10.1001/archinternmed.2009.302

Beatly, T., & Manning, K. (1997). *The ecology of place: Planning for environment, economy, and community*. Island Press.

Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., et al. (2015). Association between neighborhood walkability and GPS-measured walking, bicycling and vehicle time in adolescents. *Health & Place*, *32*, 1–7. https://doi.org/10.1016/j.healthplace.2014.12.008

Cervero, R., & Kockelman, K. (1997). In *Travel demand and the 3Ds: Density, diversity, and design* (Vol. 2, pp. 199–219). Pergamon Press.

Chiu, M., Shah, B. R., Maclagan, L. C., Rezai, M.-R., Austin, P. C., & Tu, J. V. (2015). Health Reports Walk Score ® and the prevalence of utilitarian walking and obesity among Ontario adults: A cross-sectional study. *Health Reports*, *26*, 3–10.

Christine, P. J., Auchincloss, A. H., Bertoni, A. G., Carnethon, M. R., Sánchez, B. N., Moore, K., et al. (2015). Longitudinal associations between neighborhood physical and social environments and incident type 2 diabetes mellitus: The multi-ethnic study of atherosclerosis (MESA). *JAMA Internal Medicine*, *175*(8), 1311–1320. https://doi.org/10.1001/jamainternmed.2015.2691

Dannenberg, A. L., Jackson, R. J., Frumkin, H., Schieber, R. A., Pratt, M., Kochtitzky, C., & Tilson, H. H. (2003). The impact of community design and land-use choices on public health: A scientific research agenda. *American Journal of Public Health*, *93*(9), 1500–1508. https://doi.org/10.2105/AJPH.93.9.1500

Economic Research Service & USDA. (2020). 2010 Rural-urban commuting area (RUCA) codes. Retrieved from https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/documentation/

Ewing, R., & Cervero, R. (2001). Travel and the built environment: A synthesis. *Transportation Research Record*.

Ewing, R., Schmid, T., Killingsworth, R., Zlot, A., & Raudenbush, S. (2003). Relationship between urban sprawl and physical activity, obesity, and morbidity. *American journal of health promotion*, *18*(1), 47–57. https://doi.org/10.4278/0890-1171-18.1.47

Frank, L. D., Sallis, J. F., Conway, T. L., Chapman, J. E., Saelens, B. E., & Bachman, W. (2006). Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. *Journal of the American Planning Association*, *72*(1), 75–87. https://doi.org/10.1080/01944360608976725

Gebreab, S., Hickson, D. A., Sims, M., Wyatt, S. B., Davis, S. K., Correa, A., & Diez-Roux, A. V. (2017). Neighborhood social and physical environments and type 2 diabetes mellitus in African Americans: The Jackson Heart Study. *Health & Place*, *43*, 128–137. https://doi.org/10.1016/j.healthplace.2016.12.001

Gillham, O. (2002). *The limitless city: A primer on the urban sprawl debate*. Island Press.

Hirsch, A. G., Carson, A. P., Lee, N. L., McAlexander, T., Mercado, C., Siegel, K., et al. (2020). The diabetes location, environmental attributes, and disparities network: Protocol for nested case control and cohort studies, rationale, and baseline characteristics. *JMIR research protocols*, *9*(10), e21377. https://doi.org/10.2196/21377

Hirsch, J. A., Moore, K. A., Cahill, J., Quinn, J., Zhao, Y., Bayer, F. J., et al. (2020). Business data categorization and refinement for application in longitudinal neighborhood health research: A methodology. *Journal of Urban Health*, *98*(2), 271–284. https://doi.org/10.1007/s11524-020-00482-2

Howell, N. A., Tu, J. V., Moineddin, R., Chen, H., Chu, A., Hystad, P., & Booth, G. L. (2019). Interaction between neighborhood walkability and traffic-related air pollution on hypertension and diabetes: The CANHEART cohort. *Environment International*, *132*, 104799. https://doi.org/10.1016/j.envint.2019.04.070

Ihlanfeldt, K. (2020). Vehicle miles traveled and the built environment: New evidence from panel data. *Journal of Transport and Land Use*, *13*(1), 23–48. https://doi.org/10.5198/jtlu.2020.1647

James, P., Berrigan, D., Hart, J. E., Aaron Hipp, J., Hoehner, C. M., Kerr, J., et al. (2014). Effects of buffer size and shape on associations between the built environment and energy balance. *Health & Place*, *27*, 162–170. https://doi.org/10.1016/j.healthplace.2014.02.003

Kaufman, T. K., Sheehan, D. M., Rundle, A., Neckerman, K. M., Bader, M. D. M., Jack, D., & Lovasi, G. S. (2015). Measuring health-relevant businesses over 21 years: Refining the National Establishment Time-Series (NETS), a dynamic longitudinal data set. *BMC Research Notes*, *8*(1), 507. https://doi.org/10.1186/s13104-015-1482-4

Le, H. T. K., Buehler, R., & Hankey, S. (2018). Correlates of the built environment and active travel: Evidence from 20 US metropolitan areas. *Environmental Health Perspectives*, *126*(7), 077011. https://doi.org/10.1289/EHP3389

Markovchick-Nicholls, L., Regan, H. M., Deutschman, D. H., Widyanata, A., Martin, B., Noreke, L., & Ann Hunt, T. (2008). Relationships between human disturbance and wildlife land use in urban habitat fragments. *Conservation Biology*, *22*(1), 99–109. https://doi.org/10.1111/j.1523-1739.2007.00846.x

McAlexander, T., Algur, Y., Schwartz, B., Rummo, P., Lee, D., Siegel, K., et al. (2022). *Categorizing community type for epidemiologic evaluation of community factors and chronic disease across the United States*. Press Social Sciences & Humanities Open.

Mccann, B. A., & Ewing, R. (2003). *Measuring the health effects of SPRAWL a national analysis of physical activity*. Obesity and Chronic Disease.

Molina-García, J., Campos, S., García-Massó, X., Herrador-Colmenero, M., Gálvez-Fernández, P., Molina-Soberanes, D., et al. (2020). Different neighborhood walkability indexes for active commuting to school are necessary for urban and rural children and adolescents. *International Journal of Behavioral Nutrition and Physical Activity*, *17*(1), 124. https://doi.org/10.1186/s12966-020-01028-0

Moudon, A. V., & Lee, C. (2003). Walking and bicycling: An evaluation of environmental audit instruments. *American Journal of Health Promotion*, *18*(1), 21–37. https://doi.org/10.4278/0890-1171-18.1.21

Newman, P., & Kenworthy, J. (2015). *The end of automobile dependence: How cities are moving beyond car-based planning*. Island Press.

Newman, P., Kosonen, L., & Kenworthy, J. (2016). Theory of urban fabrics: Planning the walking, transit and automobile cities for reduced automobile dependence. *Town Planning Review*, *87*(4), 429–458. https://doi.org/10.3828/tpr.2016.28

Parenteau, M. P., & Sawada, M. C. (2011). The modifiable areal unit problem (MAUP) in the relationship between exposure to NO_2 and respiratory health. *International Journal of Health Geographics*, *10*(1), 58. https://doi.org/10.1186/1476-072X-10-58

Satorra, A., & Bentler, P. M. (2001). A scales difference chi square test statistic for moment structure analysis. *Psychometrika*, *66*(4), 507–514. https://doi.org/10.1007/bf02296192

Seto, K. C., & Shepherd, J. M. (2009). Global urban land-use trends and climate impacts. *Current Opinion in Environmental Sustainability*, *1*(1), 89–95. https://doi.org/10.1016/j.cosust.2009.07.012

Sharp, G., & Kimbro, R. T. (2021). Neighborhood social environments, healthy resources, and adult diabetes: Accounting for activity space exposures. *Health & Place*, *67*, 102473. https://doi.org/10.1016/j.healthplace.2020.102473

Starnes, H. A., McDonough, M. H., Wilson, J. S., Mroczek, D. K., Laden, F., & Troped, P. J. (2019). Factorial Invariance of the abbreviated neighborhood environment walkability scale among senior women in the nurses' Health Study Cohort. *Measurement in Physical Education and Exercise Science*, *23*(2), 135–147. https://doi.org/10.1080/1091367X.2018.1554577

Steinmetz, H., Schmidt, P., Tina-Booh, A., Wieczorek, S., & Schwartz, S. H. (2009). Testing measurement invariance using multigroup CFA: Differences between educational groups in human values measurement. *Quality and Quantity*, *43*(4), 599–616. https://doi.org/10.1007/s11135-007-9143-x

Stowe, E. W., Hughey, S. M., Hallum, S. H., & Kaczynski, A. T. (2019). Associations between walkability and youth obesity: Differences by urbanicity. *Childhood Obesity*, *15*(8), 555–559. https://doi.org/10.1089/chi.2019.0063

Su, J. G., Jerrett, M., & Beckerman, B. (2009). A distance-decay variable selection strategy for land use regression modeling of ambient air pollution exposures. *Science of the Total Environment*, *407*(12), 3890–3898. https://doi.org/10.1016/j.scitotenv.2009.01.061

Tilman, D., & Clark, M. (2014). Global diets link environmental sustainability and human health. *Nature*, *515*(7528), 518–522. https://doi.org/10.1038/nature13959

Van de Schoot, R., Lugtig, P., & Hox, J. (2012). A checklist for testing measurement invariance. *European Journal of Developmental Psychology*, *9*(4), 486–492. https://doi.org/10.1080/17405629.2012.686740

Walk Score Methodology. (2021). https://www.walkscore.com/methodology.shtml