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A pathway linking smart growth neighborhoods to home-based pedestrian travel

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Land development patterns, urban design, and transportation system features are inextricably linked to pedestrian travel. Accordingly, planners and decision-makers have turned to integrated transportation-land use policies and investments to address the pressing need for improvements in physical activity levels via the creation of walkable communities. However, policy questions regarding the identification of smart growth indicators and their connection to walking remain unanswered, because most studies of the built environment determinants of pedestrian travel: (a) represent the built environment with isolated metrics instead of as a multidimensional construct and (b) model this transportation-land use relationship outside of a multidirectional analytic framework. Using structural equation modeling, this Portland, Oregon study identifies a second-order latent construct of the built environment indicated by land use mix, employment concentration, and pedestrian-oriented design features. Study findings suggest this construct has a strong positive effect on the household-level decision to walk for transportation and discretionary trip purposes.

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1. Introduction

Urban planners and transportation experts have pointed to smart growth development as a response to a pressing need for improving transportation-related physical activity levels and environmental quality (Saelens et al., 2003). The prevailing rationale is that land development patterns and urban design, which are impacted by transportation policies and investments, are inextricably linked to travel behaviors and outcomes (Handy, 2005). This connection underscores a desirability for smart growth communities, which bring residents closer to out-of-home activity destinations and improve their feasibility of reaching those locations by walking (Handy et al., 2002). Accordingly, smart growth and other integrated transportation-land use investment strategies must continue to be pursued in order to develop activity friendly, walkable environments that support increased physical activity (Frank and Kavage, 2009).

Smart growth neighborhoods exhibit compact development patterns with higher densities, land use diversity, and a pedestrian-friendly design aimed at minimizing automobile use for short trips (Downs, 2005). The formation of these sustainable communities was a policy goal in the 2014–2018 strategic plan of the US Environmental Protection Agency and previously envisioned within a suite of livability principles guiding its 2009 Interagency Partnership for Sustainable Communities with the US Departments of Transportation and Housing and Urban Development. However, questions regarding the identification of a set of built environment indicators and creation of commonly accepted standards for what constitutes a walkable, smart growth neighborhood largely continue to be unanswered (Clifton et al., 2007). An unlikely circumstance that exists despite a popularity in transportation-land use research rising from the potential to moderate travel behaviors and patterns by altering the physical environment in accordance with smart growth policy (Ewing and Cervero, 2010).

This policy discussion remains because past active travel behavior studies have adopted imperfect measures to reflect the interrelated dimensions characterizing the built environment (Handy et al., 2002). Although recent studies have used more sophisticated statistical methods to estimate the effects of more environmental factors (Ewing and Cervero, 2010), these studies tend to depict the built environment as a series of isolated measures rather than a comprehensive collection of synergistic indicators reflecting its multidimensionality. Factor analysis has gained approval as one method to derive generalized dimensions of neighborhood character from isolated measures that may display conceptual or empirical redundancy (Song and Knaap, 2007). The use of this method to

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recognize the built environment as a multidimensional concept can offer insight into measurement selection and the cumulative impact of altering interrelated land development pattern, urban design, and transportation system factors comprising this higher-order construct on travel behavior.

The impact of residing in a smart growth neighborhood on walking may also not be fully realized because the indirect effects of the various explanatory factors influencing one another and travel behavior have been inadequately examined (Van Acker et al., 2007). A host of individual, societal, and contextual factors is hypothesized to predict walking for both transportation and recreational purposes (Pikora et al., 2003). However, by not accounting for the indirect effects of these characteristics, which may diminish or confound the total effect of the built environment on pedestrian travel, studies may offer an incomplete picture of this transportation-land use connection. In all, the precise nature of residing in a smart growth community on travel behavior cannot be entirely understood without a conceptual and methodological framework specifying the many pathways to and determinants of travel (Bagley and Mokhtarian, 2002).

The objectives of this study are twofold. First, this study introduces a multidimensional concept of the physical environment reflecting several heralded tenets of smart growth policy. Second, this paper proposes a framework linking this second-order environmental construct and sociodemographic aspects to pedestrian travel and tests these complex interactions using structural equation modeling (SEM). By doing so, this paper offers a novel and robust measure of what constitutes a smart growth neighborhood and extended understanding of how this multidimensional concept influences household-level pedestrian travel.

2. Literature review

Of the existing studies linking a built environment construct to travel behavior using SEM techniques, the measurement of identified indicators has been either objective, perceived, or some combination (Ma et al., 2014). Further, once a construct has been confirmed, a number of travel outcomes and behaviors have been explored by using pathways illustrated in a variety of proposed conceptual frameworks. The following subsections review the SEM evidence base linking built environment constructs to travel and recommend a conceptual framework to guide this study's analysis of household-level pedestrian travel.

2.1. Structural equation models of the transportation-land use connection

While most transportation-land use studies focus on objective built environment measurement, several SEM applications have identified built environment constructs based on individual perceptions. These studies have explored themes of neighborhood accessibility (Cao et al., 2007; Cao, 2016), arrangement and aesthetic (Aditjandra et al., 2012; Aditjandra and Mulley, 2016; Banerjee and Hine, 2016) and sense of place (Deutsch et al., 2013) to recognize their influence on automobile ownership and travel mode choice. Other studies have identified residential environments as single constructs containing both perceived and objective indicators (Bagley and Mokhtarian, 2002) or as distinct constructs reflecting an individual's objective and perceived residential environment (Ma et al., 2014).

In a San Francisco Bay Area study, Bagley and Mokhtarian (2002) identified separate constructs for traditional and suburban environments to estimate the impact of neighborhood types, lifestyles, and attitudes on miles traveled via automobile, public transit, and active transport. The objectively measured indicators of the traditional environment included population density, grid-like street design, and speed limit of the road (Bagley et al., 2002). In a Portland-based study examining the effect of objective and perceived environments on monthly cycling rates, Ma et al. (2014) described an objective environment with built environment indicators including the number of business establishments, percent of connected streets, and miles of bike infrastructure near an individual's home. Consequently, the construct better represented an objective bicycling environment rather than a residential environment; underscoring the importance in selecting measurement variables that reflect a residence's overall built environment (de Abreu e Silva et al., 2012a).

In the European context, several studies have examined the impact of land development patterns on travel behavior. Van Acker et al. (2007) examined this path with a land use factor reflecting the distance to public transit and two categorical indicators of the residential environment in Flanders. Their results indicated land use had a positive direct effect on a travel behavior construct reflecting the total distance, duration, and number of trips originating from the home location. A second study by Van Acker and Witlox (2010) examined the mediating effect of auto ownership on the path connecting the built environment to automobile use. While this latter study had additional variables related to land development and patterns, the SEM application does not describe the residential environment as a multidimensional construct. Eboli et al. (2012) explored the land use-travel behavior link with latent factors for each, in southern Italy. Land use was indicated by only two objective measures: housing unit surface area and residential environment.

Using a more comprehensive set of built environment indicators, a series of papers addressed the impact of land patterns on short- and long-term travel behavior decisions in Lisbon (de Abreu e Silva et al., 2006), Seattle (de Abreu e Silva and Goulias, 2009), Montreal (de Abreu e Silva et al., 2012a), and Los Angeles (de Abreu e Silva et al., 2012b). In the first paper, a traditional urban land use factor largely driven by population density and public transit supply at the residence predicted an increase in distance traveled and trip frequency for nonmotorized travel modes. The authors then identified a residential environment construct with Montreal data reflective of land use entropy and automobile accessibility as well as a pair of home- and job-based constructs described as a central, denser, and accessible area. In the American context, this multidimensional construct describing a dense and centrally-located residential environment indicated by population, building, and intersection density as well as distance to the central business district was identified in Seattle. Finally, the Los Angeles study examined the link to trip scheduling from a residential land use construct with indicators representing the activity participation opportunity.

Overall, only a handful of SEM studies have exclusively represented the built environment as a set of objectively measured indicators reflecting a multidimensional latent construct. In contrary to perceived environmental measures, a construct composed of objective measurements is not subjected to reporting bias that may inflate the effect of residing in a smart growth community on pedestrian travel (Aditjandra and Mulley, 2016). Further, those SEM studies detailing a construct with objective indicators have tended to examine its influence on auto-related outcomes rather than pedestrian travel patterns and behaviors. While smart growth communities provide an alternative to auto-oriented neighborhoods, policies related to improving community livability via increased transportation-related physical activity levels are provided limited insight by past studies focused solely on auto travel (Handy, 2005).

2.2. Conceptual framework

A framework describing the built environment and transportation connection is provided in Fig. 1. The built environment is comprised of land development patterns, urban design, and transportation system features (Frank and Engelke, 2001; Handy, 2005). Land development patterns describe the land use mix (distance-based accessibility, intensity, and pattern) as well as the density of features in a defined spatial extent, while urban design features detail the arrangement and aesthetics of the built environment (Handy et al., 2002). The transportation system refers to both the physical infrastructure available to an individual and the performance or quality of any provision.

In the proposed framework, the built environment features are determined by sociodemographic attributes of an individual, household, and his/her neighborhood (Van Acker et al., 2007), which in turn have a direct effect on travel outcomes such as walk mode choice (Saelens et al., 2003). Sociodemographic and economic features may include, but are not limited to, a person's age, income, education, gender, or access to private transport options (Ma et al., 2014) in addition to the sociodemographic and economic composition of his/her household and neighbors. Contextual factors such as government policy and the natural environment also impact travel behaviors and patterns, but are considered to be external to the built environment and sociodemographic influences (Panter et al., 2008).

3. Data and methods

This section describes a methodology for adopting this framework to (a) provide a multidimensional construct reflecting three distinct built environment facets and (b) estimate the impact of a second-order construct representing a smart growth neighborhood on household-level, home-based pedestrian travel.

3.1. Study area and sample

This study examined the travel behaviors of residents in the three Oregon counties spanning the Portland metro region: Multnomah, Clackamas, and Washington. The decision to broaden the study area beyond the region's state mandated growth boundary enabled measurement of the transportation-land use connection in neighborhoods both impacted and not by the enactment of regional growth controls. Respondents of the Oregon Household Activity Survey (OHAS), a statewide transportation survey detailing weekday activity and travel patterns of randomly sampled households, completed a one-day travel diary for themselves and each member of their household. Survey participants also reported information about their activity locations, trip purposes, trip distances, and travel mode choices as well as sociodemographic and economic characteristics of each household member. Table 1 summarizes the descriptive statistics for the study sample of 4416 households surveyed in the three-county study area during 2011.

3.2. Built environment measurement

A one-mile areal buffer centered on the home location, which approximates the distance that an individual may travel on a 20-min walk originating from his/her home, was selected to delineate the residential neighborhood of sampled OHAS respondents. To understand the multidimensionality of the built environment measured at the home location and its connection to household-level pedestrian travel, an extensive set of 62 built environment indicators related to land development patterns, urban design features, and transportation infrastructure was assessed in both urban and non-urban contexts. Table 2 details this list of built environment measures from various regional and national datasets utilized in this study to identify a walkable, smart growth neighborhood.

Land use mix embodies a subset of land development pattern measures describing both the composition and configuration of land use types in a landscape (Gehrke and Clifton, 2016). Portland Metro's Regional Land Information System provided parcel-level data to calculate composition measures characterizing the percent of land area or patches of each land use type in a landscape and configuration measures explicitly accounting for the spatial arrangement, shape, and dissimilarity of the landscape patches (Li and Reynolds, 1994; Turner, 2005). Other measures considered the proportion of all or a reduced set of five (residential, retail, entertainment, education, and other) land use types, including the land use entropy index (Cervero, 1989) and measures of land use balance (Bhat and Gossen, 2004) and activity-related complementarity (ARC). The ARC measure represents the localized balance of land use types based on the derived demand for travel to these activity sites rather than their spatial equilibrium.

$$ARC = 1 - \sum_{i=1}^{n}\left[P_i * \frac{|P_i - F_i|}{1 - F_i}\right] \quad (1)$$

In Eq. (1), n is the number of land use types, P_i is the proportion of area dedicated to land use type i, and F_i is an activity factor associated with each land use type in a neighborhood. These activity factors measure the percentage of trip ends terminating at one of nine land use categories: $F_{RES} = 0.42$, $F_{RET} = 0.32$, $F_{IND} = 0.03$, $F_{UTI} = 0.01$, $F_{ENT} = 0.02$, $F_{EDU} = 0.16$, $F_{CON} = 0.01$, $F_{EXT} = 0.01$, and $F_{AGR} = 0.04$. For instance, in the study sample, 42-percent of all trips concluded at an activity location within a residential land use type. In the end, a score of zero indicates a neighborhood dominated by a single land use type; whereas, a score of one indicates a neighborhood where the spatial allocation of all land use types perfectly matches the observed attraction for activities at these sites.

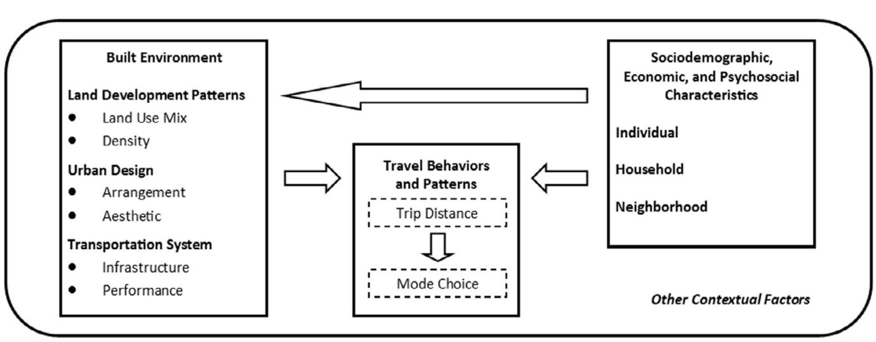

Fig. 1. Proposed conceptual framework linking the built environment to travel behaviors and patterns.

Table 1
Household-level descriptive statistics of study sample.

Indicator Name	n	%	Mean	St. Dev.	Min	Max
Sociodemographic and Economic Characteristics						
Number of children under 6 years	–	–	0.14	0.45	0.00	4.00
Number of children 6 years or older	–	–	0.32	0.71	0.00	5.00
Number of adults	–	–	1.95	0.79	1.00	7.00
Non-related household	129	0.03	–	–	0.00	1.00
Annual income: Under $25,000	505	0.12	–	–	0.00	1.00
Annual income: $25,000 to $49,999	823	0.20	–	–	0.00	1.00
Annual income: $50,000 to $99,999	1675	0.41	–	–	0.00	1.00
Annual income: $100,000 or more	1080	0.26	–	–	0.00	1.00
Household workers: 0	864	0.20	–	–	0.00	1.00
Household workers: 1	1800	0.41	–	–	0.00	1.00
Household workers: 2	1557	0.35	–	–	0.00	1.00
Household workers: 3 or more	195	0.04	–	–	0.00	1.00
Oldest adult: Under 30 years	127	0.03	–	–	0.00	1.00
Oldest adult: 30 to 44 years	892	0.21	–	–	0.00	1.00
Oldest adult: 45 to 64 years	2198	0.51	–	–	0.00	1.00
Oldest adult: 65 years or more	1131	0.26	–	–	0.00	1.00
Education: High school diploma or less	358	0.08	–	–	0.00	1.00
Education: Associate's degree or credits	982	0.22	–	–	0.00	1.00
Education: Bachelor's degree	1434	0.33	–	–	0.00	1.00
Education: Graduate degree	1635	0.37	–	–	0.00	1.00
Transportation Characteristics						
Vehicles per licensed driver	–	–	1.05	0.56	0.00	8.00
Transit passes per adult	–	–	0.16	0.31	0.00	1.00
Bikes per person 6 years or older	–	–	0.55	0.71	0.00	13.00
Home-based Travel Behaviors and Patterns						
Average trip distance (miles)	–	–	4.33	3.87	0.01	29.63
Walked for transportation purposes*	541	0.12	–	–	0.00	1.00
Walked for discretionary purposes*	232	0.05	–	–	0.00	1.00

Notes: Dash (–) indicates frequencies (n) were not provided for continuous measures. A star (*) indicates a binary measure of the household-level decision to make 0 vs. ≥1 walk trips.

The remaining composition measures in Table 2 describe the jobs-housing balance of a residential environment and its employment entropy, as measured by the diversity of office, retail, industrial, service, and entertainment jobs. In turn, land use configuration was measured by computing the maximum patch size for a specific land use in a neighborhood or by adopting the contagion index from landscape ecology, which measures the level of patch disaggregation and interspersion particular to all land use types (Li and Reynolds, 1994). A neighborhood's maximum patch size was calculated by determining the largest area of adjoining parcels for a chosen land use and normalizing this calculation by the overall landscape area. The contagion index differentiates landscapes with a small number of contiguous patches from areas with an intermixing of dissimilar patch types, which aptly characterizes a neighborhood with a higher level of land use integration (Clifton et al., 2008).

$$Contagion\ Index = 1 + \frac{\sum_i^n \sum_j^n [(P_{ij}) \ln(P_{ij})]}{2 \ln(n)} \tag{2}$$

The numerator in Eq. (2) is the entropy index adopted from information sciences (Shannon and Weaver, 1949), where P_{ij} is the probability of adjacent 66-foot grid cells in a landscape belonging to patch type i and j. As the cells in a landscape become increasingly fragmented, the contagion index score nears a value of zero. Although, calculation of the contagion index is complicated by the construction of a spatial dissimilarity matrix, this metric provides a unique depiction of the neighboring land use contrasts within a landscape (Li and Reynolds, 1994).

Data from the US Census and Longitudinal Employer-Household Dynamics allowed construction of the remaining density, urban design, and transportation system measures. Given the standardization in neighborhood unit of analysis, the nine density measures are simply continuous variables denoting the number of persons, housing units, or jobs surrounding a home location. Urban design features in Table 2 include common transportation planning measures such as the number of blocks, intersections, and cul-de-sacs as well as three network connectivity indices (Song et al., 2013). Finally, the seven transportation infrastructure measures describe the total length and percent of primary, secondary, and local roads in addition to the sidewalk coverage along these facilities.

A distillation process followed to reduce these built environment measures to a parsimonious set of indicators. The first step was to examine a correlation matrix and eliminate measures that were highly associated and pointed toward concept redundancy. A subsequent step was to perform an exploratory factor analysis (EFA) to identify an exclusive yet comprehensive collection of interrelated measures that reflect the land development pattern, urban design, and transportation system found within a residential environment. The EFA technique helped generate a theoretic understanding of the internal structure of how observed built environment measures may improve the construct measurement of a smart growth neighborhood. The assumption being that factors shaped by this exploratory technique may also be useful as operational descriptions of the three built environment dimensions.

The EFA was performed in sequential steps centered on three decisions related to selection of a factor model approach, extraction scheme, and rotation method (Ford et al., 1986). Principal axis factoring was used since this method has generally outperformed other methods in recovering factors with low loadings, providing solutions with stable loadings, and isolating correlated factors (de Winter and Dodou, 2012). The inspection of eigenvalues associated with each resulting factor and their scree plot display guided the factor extraction (Hayton et al., 2004). Finally, a promax rotation, which allows for correlation between the extracted factors, was chosen as a rotation method leading to the final three-factor model described in Table 3.

Table 2
Descriptive statistics of built environment indicators at home location.

Indicator Name	Mean	Median	St. Dev.	Min	Max
Land Use Mix: Composition Measures					
Land use percent: residential[a]	0.46	0.50	0.17	0.00	0.80
Land use percent: retail[a]	0.07	0.06	0.06	0.00	0.31
Land use percent: manufacturing[a]	0.04	0.01	0.05	0.00	0.37
Land use percent: utilities[a]	0.01	0.00	0.02	0.00	0.33
Land use percent: entertainment[a]	0.04	0.02	0.05	0.00	0.77
Land use percent: education[a]	0.06	0.06	0.05	0.00	0.29
Land use percent: construction[a]	0.00	0.00	0.00	0.00	0.05
Land use percent: extraction[a]	0.00	0.00	0.01	0.00	0.11
Land use percent: agricultural[a]	0.11	0.01	0.23	0.00	0.99
Activity-related complementarity (9 types)[a,b]	0.79	0.83	0.17	0.02	0.97
Activity-related complementarity (5 types)[a,b]	0.78	0.82	0.17	0.02	0.98
Land use entropy index (9 types)[a]	0.44	0.44	0.12	0.00	0.75
Land use entropy index (5 types)[a]	0.62	0.63	0.15	0.01	0.96
Land use balance (9 types)[a]	0.37	0.37	0.12	0.01	0.73
Land use balance (5 types)[a]	0.54	0.53	0.15	0.07	0.94
Employment entropy[c]	0.78	0.83	0.16	0.00	1.00
Employment-population balance[c,d]	0.47	0.28	0.57	0.00	5.05
Retail employment-population balance[c,d]	0.05	0.03	0.06	0.00	0.61
Land use patches: residential[a]	0.19	0.14	0.13	0.00	0.64
Land use patches: retail[a]	0.10	0.07	0.08	0.00	0.39
Land use patches: manufacturing[a]	0.02	0.01	0.02	0.00	0.17
Land use patches: utilities[a]	0.01	0.01	0.02	0.00	0.29
Land use patches: entertainment[a]	0.01	0.01	0.02	0.00	0.10
Land use patches: education[a]	0.05	0.04	0.05	0.00	0.26
Land use patches: construction[a]	0.00	0.00	0.00	0.00	0.03
Land use patches: extraction[a]	0.00	0.00	0.00	0.00	0.09
Land use patches: agricultural[a]	0.01	0.00	0.02	0.00	0.21
Land Use Mix: Configuration Measures					
Maximum patch size: residential[a]	0.12	0.08	0.12	0.00	0.76
Maximum patch size: retail[a]	0.02	0.01	0.02	0.00	0.16
Maximum patch size: manufacturing[a]	0.02	0.01	0.02	0.00	0.22
Maximum patch size: utilities[a]	0.01	0.00	0.02	0.00	0.27
Maximum patch size: entertainment[a]	0.02	0.01	0.04	0.00	0.51
Maximum patch size: education[a]	0.02	0.01	0.02	0.00	0.27
Maximum patch size: construction[a]	0.00	0.00	0.00	0.00	0.05
Maximum patch size: extraction[a]	0.00	0.00	0.01	0.00	0.10
Maximum patch size: agricultural[a]	0.08	0.00	0.19	0.00	0.99
Maximum patch size[a]	0.22	0.17	0.18	0.03	0.99
Contagion index[a]	0.57	0.56	0.09	0.42	0.98
Density Measures					
Population[d]	15,075	14,371	7655	48.26	38,944
Housing units[d]	6783	6189	4298	8.32	27,237
Employment[c]	7881	4188	14,230	0.00	115,360
Office jobs[c]	1468	355	4546	0.00	39,168
Retail jobs[c]	808	473	1070	0.00	6622
Industrial jobs[c]	1354	597	1901	0.00	12,487
Service jobs[c]	3198	1599	5433	0.00	40,272
Entertainment jobs[c]	922	434	1907	0.00	14,735
Total activity (population and employment)[c,d]	22,956	19,998	19,037	56.36	143,129
Urban Design and Transportation System Measures					
Census blocks[d]	300	214	224	1.00	1085
Street blocks[e]	243	146	216	0.00	918
Connected node ratio[e]	0.74	0.71	0.12	0.13	1.00
Alpha index[e]	0.23	0.19	0.12	-1.00	3.00
Beta index[e]	1.46	1.38	0.21	1.06	2.02
Gamma index[e]	0.49	0.46	0.08	0.37	3.00
Intersections[e]	432	391	228	1.00	1065
Cul-de-sacs[e]	126	117	68.59	0.00	330
Primary roads (miles)[e]	1.37	0.00	1.97	0.00	9.17
Secondary roads (miles)[e]	1.59	1.65	1.47	0.00	8.05
Local roads (miles)[e]	53.00	51.18	21.37	0.67	101
Percent of primary roads[e]	0.02	0.00	0.03	0.00	0.31
Percent of secondary roads[e]	0.03	0.02	0.04	0.00	0.75
Percent of local roads[e]	0.93	0.94	0.06	0.25	1.00
Sidewalk coverage[e]	0.45	0.46	0.27	0.00	0.98

Notes: Land use type taxonomy adopted from American Planning Association's Land-Based Classification Standards. Superscripts ([n]) indicate the measurement's data source: ([a]) 2011 Regional Land Information System, ([b]) 2011 Oregon Household Activity Survey, ([c]) 2014 Longitudinal Employer-Household Dynamic, ([d]) 2010 US Census, and ([e]) 2010 US Census Topologically Integrated Geographic Encoding and Referencing.

The results of this initial diagnostic step produced three built environment factors based on a set of smart growth indicators. Factor 1 comprises two composition and three configuration indicators of land use mix. Taken together, this land use dominance

Table 3
Exploratory factor analysis of built environment characteristics.

Built Environment Characteristics	Factor 1: Land use dominance	Factor 2: Employment concentration	Factor 3: Pedestrian-oriented design
Land use activity-related complementarity (9 types)	−**0.96**	0.00	−0.01
Employment entropy	−**0.52**	0.05	0.05
Employment-population balance	−0.03	**0.91**	−0.07
Land use patches: retail	0.10	0.15	**0.92**
Maximum patch size: agricultural	**0.90**	0.04	0.03
Maximum patch size	**0.97**	0.12	0.07
Contagion index	**0.86**	−0.19	−0.01
Office jobs	0.07	**0.93**	−0.02
Retail jobs	−0.06	**0.71**	0.20
Connected node ratio	0.04	−0.06	**0.95**
Sidewalk coverage	−0.19	−0.16	**0.69**
Eigenvalue	5.51	2.20	1.23
Percent of variance explained	50.09	19.96	11.22

Notes: Factor loadings >0.4 are in **bold**.

factor reflects a residential environment with a limited complementarity in land use types, imbalance of employment opportunities, and high patch aggregation or isolation, independent of the land uses in a neighborhood. Three land development pattern indicators were also found to strongly reflect Factor 2. The ratio of total employment-to-persons is a commonly adopted proxy measure for land use mixing; whereas, the number of office- and retail-related jobs within a one-mile radius around a residence also contributed to this employment concentration factor. The final factor was explained by two urban design and transportation system indicators, connected node ratio and sidewalk coverage, as well as a third indicator measuring the number of retail land use patches. Overall, the adoption of an EFA framework before estimating the structural model permitted an empirically-driven process for understanding the interrelationships between a collection of objective indicators, which may be supported by a priori theory to reflect potential underlying latent constructs (Brown, 2006).

3.3. Structural equation modeling

Application of an SEM method with latent constructs is a firmly established analytic strategy in which a set of specified equations containing measurement models for exogenous and endogenous variables are concurrently estimated with a structural model estimating the associations or pathways between (Golob, 2003). Using a two-step approach, the measurement models positing the relationship of observed variables to a latent construct were estimated by confirmatory factor analysis (CFA) before an assessment of a structural model with path assignments (Anderson and Gerbing, 1988). The application of this strategy offers several advantages over conventional multivariate regression methods, including the ability to: (a) develop latent constructs with multiple indicators, (b) correct for measurement error in the observed variables reflecting any latent construct, and (c) simultaneously test for both direct and indirect effects as well as any bidirectional relationships that exist between multiple variables across different paths (Golob, 2003; Van Acker et al., 2007; Aditjandra et al., 2012; de Abreu e Silva et al., 2012a). However, while this latter point constitutes a conceptual improvement over a single-equation approach, using cross-sectional data in any SEM application still does not infer the condition of time precedence needed to establish a causal relationship (Cao et al., 2007).

The pathways of greatest interest to this study are the direct and indirect effects of the latent construct reflecting a smart growth neighborhood on the household-level decision to conduct a walk trip for transportation (mandatory or subsistence) or discretionary trip purposes. Although, the use of SEM also allows for the simultaneous testing of the direct and total effects of several household-level measures on these two travel outcomes as well as the influence of these manifest variables on the smart growth neighborhood latent construct. By simultaneously estimating the different pathways leading to the two pedestrian travel outcomes, the proposed conceptual framework may be empirically tested to help inform policy actions such as the formation of walkable, smart growth neighborhoods, which may be adopted to guide an increase in home-based pedestrian activity.

4. Discussion of results

Estimation results of the final SEM are presented in Table 4. The model fit indices depict a reasonable, but not entirely good, fit to the sampled data (CFI = 0.85, TLI = 0.81, RMSEA = 0.08, and SRMR = 0.04). Indicators of the three first-order factors were all above an acceptable standardized loading ($\beta \geq 0.40$). Similarly, the standardized loadings for each of these latent factors on the second-order smart growth neighborhood construct were acceptable. The following discussion is separated based on the results of the measurement and structural models.

4.1. Smart growth neighborhood indicators

Fig. 2 visually displays the measurement models in the estimated SEM. The standardized loadings in the final SEM are similar to the estimation results of a second-order CFA, which produced comparative fit index (CFI) and Tucker-Lewis index (TLI) values of 0.85 and 0.81, respectively. Meanwhile, the three first-order latent constructs also have the same indicator structure of the final EFA model estimation. All measurement models in the final SEM have between three and five built environment indicators reflecting any given latent construct. Two first-order constructs represent the unique land development pattern aspects of land use mix ($\alpha = 0.90$) and density ($\alpha = 0.87$); whereas, two indicators of the remaining first-order construct ($\alpha = 0.73$) reflect a pair of urban design and transportation system characteristics.

The land use mix construct describes a set of complementary indicators of land use composition and spatial configuration. A mixed-use residential environment was most strongly reflective of a balanced measurement in the ARC of local land use types in which the nine land uses were distributed as disparate land use patches. A neighborhood receiving a high land use ARC score signifies a home environment where land use types are spatially balanced to reflect those activity locations that generate passenger travel demand. By reverse coding the configuration index, a positive construct value reflects an environment with smaller, interspersed patches. Similarly, a home environment without a single, large homogenous landscape patch or a large patch devoted to agricultural land were found to reflect a higher level of land use mixing. A high construct value was also reflective of a neighborhood with a diverse set of nearby job opportunities. Together, these five indicators revealed a residential environment with the compositional and spatial heterogeneity of land uses required to produce greater transportation efficiencies through an intermingling of complementary non-residential land uses.

A second construct, employment concentration, consisted of two observed density measures and a composition measure. The density measures represented the number of retail and office jobs within a one-mile buffer surrounding the home location. These

Table 4
Structural equation model results with unstandardized (B) and standardized (β) coefficients.

Parameter Estimates	B	SE (B)	β	p-Value
Measurement Models				
Land use mix				
Land use activity-related complementarity (9 types)	1.00	–	0.97	–
Maximum patch size*	0.99	0.02	0.86	0.00
Maximum patch size: agricultural*	0.91	0.01	0.87	0.00
Contagion index*	0.51	0.00	0.94	0.00
Employment entropy	0.51	0.02	0.54	0.00
Employment concentration				
Retail employment	1.00	–	0.83	–
Office employment	0.73	0.03	0.91	0.00
Employment-population balance	0.70	0.03	0.87	0.00
Pedestrian-oriented design				
Sidewalk coverage	1.00	–	0.72	–
Connected node ratio	0.55	0.01	0.91	0.00
Land use patches: retail	0.39	0.01	0.92	0.00
Smart growth neighborhood				
Pedestrian-oriented design	1.00	–	0.85	–
Land use mix	0.66	0.02	0.63	0.00
Employment concentration	0.44	0.03	0.53	0.00
Structural Models				
Smart growth neighborhood ~				
Number of children 6 years or older	−0.02	0.00	−0.08	0.00
Number of adults	−0.04	0.00	−0.19	0.00
Annual income: $25,000 to $49,999	0.00	0.01	−0.01	0.69
Annual income: $50,000 to $99,999	−0.04	0.01	−0.11	0.00
Annual income: $100,000 or more	−0.05	0.01	−0.14	0.00
Non-related household	0.04	0.02	0.04	0.01
Household workers: 1	0.02	0.01	0.05	0.03
Household workers: 2	0.02	0.01	0.06	0.03
Household workers: 3 or more	0.03	0.02	0.03	0.10
Education: Associate's degree or credits	0.01	0.01	0.03	0.28
Education: Bachelor's degree	0.04	0.01	0.11	0.00
Education: Graduate degree	0.06	0.01	0.17	0.00
Vehicles per licensed driver	−0.09	0.01	−0.30	0.00
Transit passes per adult	0.06	0.01	0.11	0.00
Bikes per person 6 years or older	0.03	0.01	0.14	0.00
Average trip distance ~				
Smart growth neighborhood	−9.17	0.61	−0.40	0.00
Number of children under 6 years	−0.51	0.10	−0.06	0.00
Number of children 6 years or older	−0.96	0.07	−0.18	0.00
Number of adults	−0.40	0.09	−0.08	0.00
Annual income: $25,000 to $49,999	0.28	0.22	0.03	0.20
Annual income: $50,000 to $99,999	0.45	0.22	0.06	0.04
Annual income: $100,000 or more	0.26	0.24	0.03	0.26
Household workers: 1	1.11	0.17	0.14	0.00
Household workers: 2	1.40	0.19	0.17	0.00
Household workers: 3 or more	1.87	0.32	0.10	0.00
Education: Associate's degree or credits	0.40	0.26	0.04	0.13
Education: Bachelor's degree	−0.17	0.25	−0.02	0.49
Education: Graduate degree	−0.50	0.25	−0.06	0.05
Transit passes per adult	1.40	0.20	0.11	0.00
Walked for transportation purposes ~				
Average trip distance	−0.01	0.00	−0.10	0.00
Smart growth neighborhood	0.44	0.05	0.22	0.00
Number of children under 6 years	0.04	0.01	0.05	0.01
Number of children 6 years or older	0.07	0.01	0.16	0.00
Number of adults	0.04	0.01	0.09	0.00
Annual income: $25,000 to $49,999	−0.02	0.02	−0.02	0.31
Annual income: $50,000 to $99,999	−0.03	0.02	−0.05	0.11
Annual income: $100,000 or more	−0.04	0.02	−0.06	0.03
Household workers: 1	0.01	0.01	0.01	0.81
Household workers: 2	0.01	0.02	0.01	0.84
Household workers: 3 or more	−0.06	0.03	−0.04	0.04
Vehicles per licensed driver	−0.03	0.01	−0.05	0.00
Bikes per person 6 years or older	0.02	0.01	0.04	0.02
Walked for discretionary purposes ~				
Average trip distance	−0.01	0.00	−0.06	0.00
Smart growth neighborhood	0.21	0.03	0.16	0.00
Number of children 6 years or older	0.02	0.01	0.06	0.00
Number of adults	0.02	0.01	0.07	0.00
Household workers: 1	−0.02	0.01	−0.03	0.11
Household workers: 2	−0.02	0.01	−0.04	0.07
Household workers: 3 or more	−0.04	0.02	−0.04	0.04
Education: Associate's degree or credits	−0.01	0.01	−0.02	0.33

Table 4 (*continued*)

Parameter Estimates	B	SE (B)	β	p-Value
Education: Bachelor's degree	0.02	0.01	0.03	0.19
Education: Graduate degree	0.03	0.01	0.05	0.03
Transit passes per adult	−0.02	0.01	−0.03	0.04

Notes: Dashes (–) indicate standard error was not estimated. A star (*) indicates the measure was reverse-coded. Sample size (n) = 4035. χ^2 (247) = 6522, p = 0.00. Goodness-of-fit measures: Comparative Fit Index (CFI) = 0.853, Tucker-Lewis index (TLI) = 0.812, Root Mean Squared Error of Approximation (RMSEA) = 0.079, and Standardized Root Mean Squared Residual (SRMR) = 0.038.

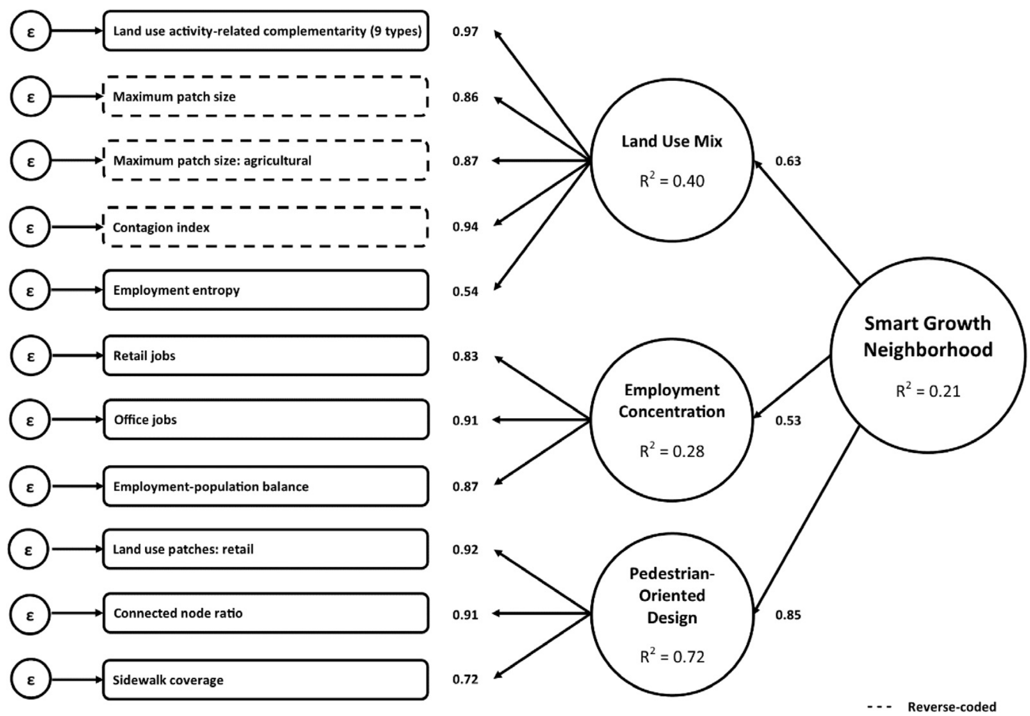

Fig. 2. Second-order latent construct reflecting a smart growth neighborhood.

density indicators signify the benefit of increased access to daily life activities related to subsistence (e.g., work, school) or maintenance (e.g., shopping, health care) activities. A higher intensity of these out-of-home activities near a residence has a conceptual link to an increased feasibility of walking for activity engagement. The third indicator of this density-related construct, an increased ratio of jobs-to-persons, also signified the positive value of residing in a neighborhood with an increased intensity of nearby work-related activity locations.

The third first-order construct reflects elements of each built environment dimension including urban design and the transportation system. Specifically, each of the three indicators are associated with the provision of a street design conducive to a highly walkable residential environment. This construct is reflected by a high percentage of four-way intersections, which create a traditional street network design, and a high percentage of streets with strong sidewalk coverage. Although listed as a composition measure, a positive value for the indicator of retail land use patches denotes the importance of a patchier landscape with smaller block sizes to this identified pedestrian-oriented design construct.

A second-order smart growth neighborhood was strongly reflective of a positive value in each of these described first-order latent constructs. The factor describing a home environment with a walkable and traditional street network design was the strongest predictor of a smart growth neighborhood ($\beta = 0.85$), followed by the land development pattern constructs of land use mix ($\beta = 0.63$) and density ($\beta = 0.53$). In sum, these three first-order constructs indicate a home environment characterized by a compact and complex land development pattern with a high intensity of nearby non-residential activity locations and a pedestrian-oriented street network design.

4.2. Path analysis of home-based pedestrian travel

An examination of the structural model reveals that residing in a smart growth neighborhood has a strong positive direct effect on the household-level decision to participate in one or more home-based walk trips for transportation ($\beta = 0.22$) or discretionary ($\beta = 0.16$) purposes. Furthermore, residing in a smart growth neighborhood had a negative direct influence on the average home-based trip distance for all household travel ($\beta = -0.40$). In fact, these paths from the second-order construct to the three home-based travel behaviors represented the largest standardized direct effect of any modeled determinant; however, caution must be stressed when providing conclusions based solely on the magnitude of direct effects (Van Acker et al., 2007; de Abreu e Silva et al., 2012a). Accordingly, Table 5 provides an overview of the direct, indirect, and total effects of the second-order smart growth construct as well as exogenous sociodemographic and transportation characteristics on the two modeled binary home-based walk trip outcomes.

Following the proposed conceptual framework, the observed sociodemographic and economic characteristics were directly predictive of the residential environment in addition to the average

Table 5
Standardized direct, indirect, and total effects of the structural equation model.

Indicator Name	Walk Transportation Purposes			Walk Discretionary Purposes		
	Direct	Indirect	Total	Direct	Indirect	Total
Built Environment Characteristics						
Smart growth neighborhood	0.22	0.04	0.27	0.16	0.02	0.18
Sociodemographic and Economic Characteristics						
Number of children under 6 years	0.05	0.01	0.05			
Number of children 6 years or older	0.16	0.05	0.21	0.06	0.04	0.10
Number of adults	0.09	0.08	0.18	0.07	0.08	0.15
Annual income: Under $25,000	–	–	–	–	–	–
Annual income: $25,000 to $49,999	−0.02	0.00	−0.02			
Annual income: $50,000 to $99,999	−0.05	0.04	−0.01			
Annual income: $100,000 or more	−0.06	0.05	−0.01			
Household workers: 0	–	–	–	–	–	–
Household workers: 1	0.01	−0.04	−0.03	−0.03	−0.03	−0.06
Household workers: 2	0.01	−0.04	−0.04	−0.04	−0.03	−0.08
Household workers: 3 or more	−0.04	−0.02	−0.06	−0.04	−0.02	−0.06
Education: High school diploma or less	–	–	–	–	–	–
Education: Associate's degree or credits				−0.02	−0.01	−0.03
Education: Bachelor's degree				0.03	−0.04	−0.01
Education: Graduate degree				0.05	−0.06	−0.01
Transportation Characteristics						
Vehicles per licensed driver	−0.05	−0.07	−0.11			
Transit passes per adult				−0.03	−0.05	−0.08
Bikes per person 6 years or older	0.04	0.03	0.07			

Notes: Dash (–) indicates the reference case. Empty cell indicates pathway between variables was not specified.

home-based trip distance for all travel modes and decisions to walk for transportation or discretionary purposes. Therefore, the total effect of all household-level socio-economic and transportation characteristics also included the potential mediating impacts of the home built environment and average trip distance on the two pedestrian travel outcomes. Likewise, the total effect of a smart growth neighborhood on walking behaviors accounted for the indirect path through average home-based trip distance, which is theorized to directly influence the modal decision to walk.

In terms of a household making one or more walk trips for either subsistence or maintenance activities, the total effect of residing in a neighborhood characterized by smart growth features had the greatest standardized impact in the final SEM estimation. Household composition factors related to the number of children over six years of age and adults also had a strong positive effect on conducting at least one home-based walk trip for transportation purposes, which may include either school- or work-related travel. An increase in the number of children under six years old had a marginally significant positive effect on walking for subsistence or maintenance activities. In contrast, a household with an increase in the number of workers or annual income were less likely to walk for transportation purposes, with the former predictor having a stronger total effect. As expected, the number of household vehicles per licensed driver had a significant, negative direct and total effect on non-discretionary walking; whereas, an increase in the number of bikes per individual six years of age or older had a positive total standardized effect.

The total standardized effect of residing in a smart growth neighborhood on the household-level choice to participate in at least one walk trip for discretionary purposes was also positive, albeit smaller in magnitude than the paths to non-discretionary walking. An increase in the number of household adults and children six years of age or older also had positive direct, indirect, and total standardized effects on the decision to participate in at least one daily walk trip for discretionary purposes. In contrast, an increase in the number of household workers had a significant, negative direct and total effect on walking. While the direct effect of having at least one household member with a graduate degree had a positive impact on discretionary walking, the total effect of this indicator became negative once the indirect effects were modeled. Finally, households with a higher proportion of transit passes per adult were less likely to have taken at least one walk trip for discretionary activities.

5. Conclusions

This study introduced a second-order latent construct reflecting three key tenets of smart growth land development and established its link to pedestrian travel in a conceptual model. While planning literature has long hypothesized this transportation-land use connection, prior studies have inadequately addressed the multicollinearity of many built environment indicators and further misunderstood the contribution of these spatial phenomenon in a multidirectional modeling structure. To the first point, this study utilized latent factor analyses in finding that development patterns related to land use diversity and employment density as well as features related to pedestrian-oriented design together explain variation in residential environments. Therefore, a neighborhood characterized by a traditional street network design with strong sidewalk coverage and local retail, mixed land development patterns represented by complementary and spatially interspersed land use patches, and compactness exhibited by a high employment intensity were found to be indicative of a smart growth neighborhood. When measured at the residential location, this latent construct had a stronger direct and total effect on increasing home-based, household-level pedestrian travel than those socio-economic characteristics tested in the theoretical model. Findings from this SEM analysis corroborate generalizations within the transportation-land use literature stating that trip distance is largely a function of the built environment, while mode choice is a function of both sociodemographic and built environment characteristics (Ewing et al., 2015).

Evidence from this study may be used to help inform pedestrian planning policy and guide practice away from contentious land development debates. Analysis of residential built environments both within and outside of Portland and its metropolitan region resulted in the creation of a smart growth construct accounting for the variation in urban, suburban, and rural communities. To combat urban sprawl with urban infill and suburban retrofitting policies, this study has provided planners with an identified set of indicators that may be toggled to improve built environment efficiencies and consequently encourage physically active modes of travel. Of further interest, the density-related latent construct was the weakest indicator of a smart growth neighborhood and had the notable omission of any population density measure. While increasing the level of employment opportunities in a community presents its own set of difficulties, the strength of the other first-order factors suggests planners may achieve smarter growth by framing land development debates toward a dialogue of how development may be spatially configured and designed to promote walkability. Moreover, study findings support urban infill policies aimed at siting residential developments in existing employment districts as a favorable smart growth strategy.

While this study has several exciting implications for policy and practice, research extensions should also address its limitations to offer further direction on how residential environments may be developed to encourage transportation-related physical activity. Foremost, the study's cross-sectional research design limits the ability to establish causal inference and adequately control for residential self-selection bias in which a household chooses where to reside based on its travel preferences (Cao and Chatman, 2016). Yet, topic overviews have found that built environment characteristics influence active travel after accounting for any residential sorting (Cao, 2015). Additional sociodemographic variables, which may be assessed as a formative construct (e.g., Banerjee and Hine, 2016), and contextual factors (e.g., slope, weather) should be explored in alternative model specifications. Although the table of built environment indicators is extensive, the absence of psychosocial variables describing individual perceptions of the built environment and travel bias our findings. Relatedly, while a household-level analysis explains some inter-household dynamics, an adoption of a hierarchical SEM framework would enable an understanding of this transportation-land use connection at the level of the decision-maker. Further, while this SEM application measured the built-environment at a pedestrian scale, more work is needed to understand the impact of alternative spatial scales for both operationalizing the proposed smart growth construct and measuring its contribution to travel behavior. Nevertheless, while some methodological limitations are inherent to any modeling application, this study delivers an empirical analysis in a multidirectional framework that highlights the continued prospect for smart growth land use policies to positively affect pedestrian travel outcomes.

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