Travel Behaviour and Society 17 (2019) 62–71

Contents lists available at ScienceDirect

Travel Behaviour and Society

journal homepage: www.elsevier.com/locate/tbs

Understanding stated neighborhood preferences: The roles of lifecycle stage, mobility style, and lifestyle aspirations

Steven R. Gehrke[a,*], Patrick A. Singleton[b], Kelly J. Clifton[c]

[a] Department of Geography, Planning, and Recreation, Northern Arizona University, PO Box 15016, Flagstaff, AZ 86011, United States
[b] Civil & Environmental Engineering, Utah State University, 4110 Old Main Hill, Logan, UT 84322, United States
[c] Civil & Environmental Engineering, Portland State University, PO Box 751 CEE, Portland, OR 97201, United States

ABSTRACT

Stated neighborhood preference is informed by a host of factors describing an individual's socioeconomic condition, current environmental context, recent transportation decisions, and future aspirations for certain housing and accessibility attributes. To date, travel applications and behavioral models investigating the residential location choice process have been parsimonious in differentiating decision-makers and the available neighborhood supply. This Portland, Oregon study used stated preference survey data and an integrated choice and latent variable modeling framework to provide a new awareness of the relationships between an individual's lifecycle stage, mobility style, lifestyle aspirations, and underlying preference in residential environment. Specifically, we found that aspirations regarding housing and accessibility were strong predictors of stated neighborhood preferences, while mobility style was also closely associated with these lifestyle aspirations. Also, consistent with a narrative of gentrification, high income households preferred more urban environments with better multimodal access.

1. Introduction

Added insight into the varying residential location preferences of different market segments is key toward refining an understanding of complex decision-making processes within integrated land use and travel demand analysis. Theory and empirical evidence suggest associations between travel behaviors and residential environments, but questions remain about directions of causality and time scales (Næss, 2015; Cao & Chatman, 2016). Transportation may be an important factor considered during the residential location choice process, especially for people whose residential and/or travel preferences do not match or who are dissatisfied with their current travel patterns and residential environment (De Vos et al., 2012). Similarly, changes in residential environments (due to residential relocation or neighborhood change) may be enough to stimulate travel behavior changes, but studies of travel effects of the built environment must account for self-selection biases due to travel and residential preferences (Bagley & Mokhtarian, 2002).

More practically, an improved understanding of the residential location choice process is also essential for identifying the drivers of future housing, land use, and transportation policies. As communities face a series of vexing challenges related to public infrastructure provision, climate change preparation, natural resource consumption, and sustainable development realization during these recent times of economic uncertainty, transportation and land use plans have become increasingly predicated on assumptions concerning the market for various types of residential environments and travel options. However, if planners lack faith in the estimates of these travel demand models, the long-range supply of housing stock, activity locations, and transportation facilities planned for these communities will likely be insufficient to meet future demands.

Preferences for residential environments are informed by an interdependent set of characteristics describing an individual's current sociodemographic and economic context, environmental setting, and travel behaviors (and satisfaction with those elements of one's life) as well as perceptions of and aspirations for future housing, accessibility, and transportation attributes (Schirmer et al., 2014). This connection is further complicated by variation in the (descriptive and/or behavioral) characteristics chosen to reflect the decision-maker and the bundling of housing, accessibility, and transportation features, which is understood to portray the spectrum of residential neighborhood supply. Travel demand applications and behavioral models tend to be relatively parsimonious in their specification of some of these key components of the residential location decision-making process. For instance, an adopted convention has been to distinguish decision-makers solely on descriptive sociodemographic and economic measures (Walker and Li, 2007) and to forecast their future residential location decisions based on the existing supply of neighborhood types. Consequently, these invaluable urban policy tools are generally unable to explain how emerging market segments and lifestyle aspirations may influence

* Corresponding author.
E-mail addresses: steven.gehrke@nau.edu (S.R. Gehrke), patrick.singleton@usu.edu (P.A. Singleton), kclifton@pdx.edu (K.J. Clifton).

https://doi.org/10.1016/j.tbs.2019.07.001
Received 19 September 2018; Received in revised form 28 June 2019; Accepted 4 July 2019

future housing, land use, and transportation decisions.

Drawing on a diverse and interwoven collection of social, spatial, and attitudinal factors, this study provides a holistic approach for identifying market segments and understanding the more subtle sources of heterogeneity in stated neighborhood preferences. It builds upon existing conceptual frameworks (Liao et al., 2015; Smith and Olaru, 2013; Walker and Li, 2007) examining lifecycle and lifestyle factors in the residential location choice process. Specifically, this study classifies individuals in terms of their lifecycle stage and mobility style, while also describing their expressed lifestyle aspirations based on their rated importance for certain bundles of housing, accessibility, and transportation attributes. It offers an important advancement from previous frameworks which were limited in their ability to parse out how an individual's long-term travel preferences and lifestyle aspirations influence their residential location decision-making process. Together, the latent classes and factors—along with observed attributes of the decision-maker—are integrated into our study's conceptual and modeling framework to offer new insight on the many tradeoffs and complexities inherent to the choice of a residential environment.

2. Literature review

2.1. Lifecycle stage

Household structure is an important determinant of residential location decisions, while a desire to adopt or preserve a certain lifestyle also facilitates a household's preference for a neighborhood type (Smith and Olaru, 2013). The evidence base commonly reflects the former residential location preference factor using a set of objective indicators describing influential life events and the latter factor with subjective indicators describing inter-household differences at these various stages (Liao et al., 2015). Although the formative research of Rossi (1955) long ago pointed to a shift in household structure, or lifecycle stage, as a major catalyst of residential mobility plans or desires, the operationalization of this mechanism in the literature has only slightly varied (McAuley and Nutty, 1982). In general, lifecycle stages are reflections of the sociodemographic features of a household that express how its configuration changes from formation to dissolution (Clark and Onaka, 1983).

Examining lifecycle and residential mobility, Speare (1970) constructed six stages differentiated by adult age, marital status, and household composition. Acknowledging that not all persons successively pass though or even experience the recognized stages (e.g., married with school age children), the author found considerable differences in mobility rates by lifecycle stage. Using a similar classification, McAuley and Nutty (1982) investigated the link between lifecycle stage and preference of residential characteristics if these features were available at a new location. Housing cost was rated as the most important predictor of residential mobility for all lifecycle stages; however, households without children rated convenience to medical and shopping facilities as well as the presence of culture in area as also being of high importance. Synthesizing other early topical contributions, Clark and Onaka (1983) theorized that voluntary household relocations are the result of adjustment (housing, neighborhood, and accessibility) or induced (lifecycle and employment) reasons. Defined by household formation, marital status, and household size factors, a change in lifecycle was found to strongly affect relocation decisions for a household closer to a formation or dissolution stage. A review by Schirmer et al. (2014) restated that both residential location and relocation decisions remain largely influenced by defining lifecycle stage events such as a change in marital status, employment status, or the birth of a child. Highlighting the influence of the last event on residential location decisions, a pair of studies (Kim et al., 2005; Chen and Lin, 2011) defined the presence of a child as a principal lifecycle stage indicator. Accounting for marital status, relationship among household members, and age of household head and youngest child, Smith and Olaru (2013) found that lifecycle stage had a determinant role in understanding residential location, but that household structure alone is not sufficient to account for dwelling and location preference heterogeneity.

2.2. Lifestyle and mobility style

Beyond the described lifecycle constraints, lifestyle preferences have also been hypothesized to affect household residential location decisions (Kim et al., 2005). In fact, Jansen (2012) suggests that traditional sociodemographic characteristics are insufficient predictors of residential neighborhood preferences in the presence of available lifestyle indicators. Yet, in contrast to lifecycle stage, the concept of lifestyle has no generally agreed upon definition (Jensen, 2007) and has subsequently been measured by adopting a multitude of approaches (Van Acker, 2015). In the residential location (Heijs et al., 2009) and travel behavior (Van Acker, 2015) literature, lifestyle has been operationalized with manifest (behavioral), latent (psychological), or a mix of measures from each category. These two streams of research, which comprise distinct lifestyle dimensions, are intertwined due to the likelihood that longer-term decisions of residential location have a synergistic relationship with short-term travel behavior decisions (Krizek and Waddell, 2002).

In an early study of lifestyles and travel behavior, Salomon and Ben-Akiva (1983) joined the lifecycle components of household formation and labor force participation with objective indicators of orientation toward leisure to define an individual's lifestyle. Examining activity patterns, Pas (1984) defined lifestyle using social status (household income and education level), mobility (auto ownership), and location (residential density) features. Krizek and Waddell (2002) introduced a framework using factor and cluster analyses to define lifestyle by travel pattern, activity participation, and neighborhood type indicators. The travel dimension of lifestyle has received attention in studies of mobility (Lazendorf, 2002) and modality styles (Vij et al., 2013). Mobility style describes longer-term transportation decisions (e.g., car ownership); whereas, modality style pertains to the short-term subcomponent of daily travel mode choice that may mirror an underlying long-term behavioral predisposition for a selected lifestyle (Vij et al., 2013). Such representations of lifestyle as a typology of travel behavior are valuable to transportation studies, but do not portray an individual's orientation or the values he or she holds (Kitamura, 1988).

Behavioral indicators, which may describe lifecycle stage or mobility style, are thought to be less predictive of an individual's residential preference than his or her lifestyle orientation when measured in the form of values (Jensen, 2007). Walker and Li (2007), employing a latent class choice model to examine residential environmental preference, discovered three lifestyle classes described by orientations toward housing, neighborhood, and transportation/access attributes. In their Portland study, lifecycle indicators predicted lifestyle preferences, which predicted a household's choice among five alternatives describing tenure and housing type. Smith and Olaru (2013) adopted a similar modeling approach to investigate the significance of four latent lifestyle classes and household structure characteristics on housing preferences along a new railway corridor in Perth. Like the prior study, the authors discovered that lifestyle distinctions were influential, but that lifecycle stage also played a significant role in stated housing preferences. Finally, Liao et al. (2015) extended this discrete choice modeling framework to examine the impact of two latent classes described by sociodemographic and attitudinal factors on residential preferences for compact development in Utah's Wasatch Front.

3. Analytic approach

3.1. Conceptual framework

Based on the studies and results of Walker and Li (2007), Smith and

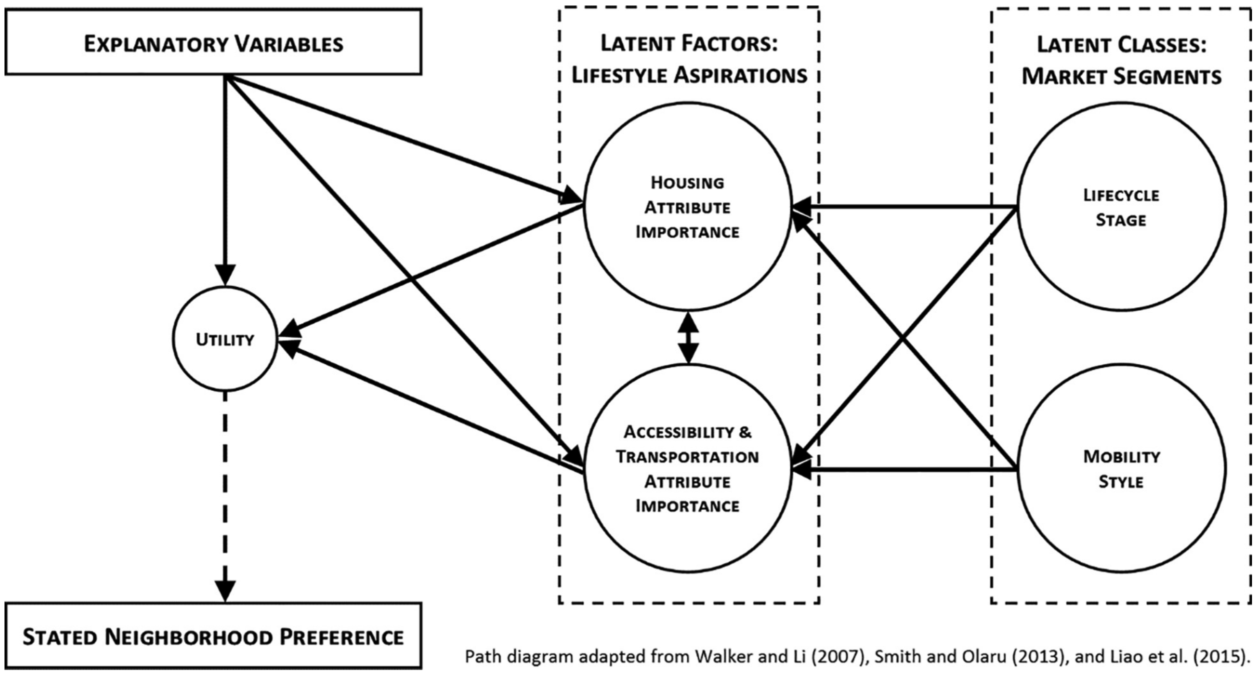

Fig. 1. Conceptual framework for examining lifecycle and lifestyle impacts on stated neighborhood preference.

Olaru (2013), and Liao et al. (2015), we developed a conceptual framework to guide our empirical analysis, shown in Fig. 1. Representing an advancement to these prior efforts, this framework is comprised of three key groups of latent constructs: market segments, lifestyle aspirations, and stated neighborhood preferences.

The market segments consist of two unobserved categorical variables representing lifecycle stage and mobility style. These constructs segment the sample into groups based on sociodemographic and transportation characteristics. Unlike Walker and Li (2007), Smith and Olaru (2013), or Liao et al. (2015), the latent class constructs do not directly enter into the utility equation as response heterogeneity sources. Instead, their effect on stated neighborhood preference is mediated by two latent factors that represent lifestyle aspirations related to features of the residential location decision-making process. These unobserved continuous variables represent the rated importance of various housing, accessibility, and transportation attributes that individuals consider when choosing their potential residence. These lifestyle aspirations, in turn, are hypothesized to directly influence stated neighborhood preferences through another latent construct: the utility equation. Borrowing from the previous studies, exogenous explanatory variables—such as household income—also predicted both lifestyle aspirations and stated neighborhood preference utility.

The adoption of this conceptual framework permits an assessment of how an individual's experiences, exemplified by their lifecycle stage and mobility style, predicts present housing and transportation tastes, which directly determine their stated neighborhood preference. The objective classification of individuals based on lifecycle stage attributes is customary in market segmentation strategies, while the identification of latent mobility styles provides an additional strategy for predicting class membership. Furthermore, the integration of two latent constructs that reflect potentially competing lifestyle aspirations adds behavioral complexity not found in previous frameworks, which underscore the important tradeoffs in housing versus access that individuals are likely to consider when stating their preference for a residential neighborhood. Taken together, this conceptual framework is an extension of previous efforts, which can provide fresh insight into how differences in these forward-looking lifestyle aspirations of current market segments may inform their future residential location decision-making processes.

3.2. Modeling framework

Following from the three latent components described above, a three-stage modeling process was employed. First, latent class cluster analysis (LCCA) was used to model the latent lifecycle stage and mobility style market segments. LCCA can be conceived in various statistically-equivalent ways: as a model-based form of clustering, as mixture modeling with a fixed number of class-based distributions, or as a subset of structural equation modeling with discrete latent variables (Vermunt and Magidson, 2002). The market segments were measured by sociodemographic and behavioral indicators. For lifecycle stage, classes were indicated by sociodemographic and economic characteristics: age, work status, and the number of household adults and children. For mobility style segmentation, classes were indicated by descriptive and behavioral transportation characteristics: driver's license, transit pass, carshare membership, primary travel mode, commute travel mode, and the numbers of cars and bikes per adult in the household. LCCA was conducted in R using the poLCA package (Linzer and Lewis, 2011).

Second, lifestyle aspirations, as indicated by importance ratings of housing, transportation, and accessibility characteristics, were constructed using confirmatory factor analysis (CFA). As a subset of structural equation modeling, CFA uses the covariances between item responses to test the data's consistency with a measurement model in which each continuous latent variable predicts multiple item responses. CFA was performed in R using the lavaan package (Rosseel, 2012). Given that the importance ratings were ordinal, the CFA employed a diagonally weighted least squares estimator with probit links to indicators and theta parameterization. To assess the statistical validity of the CFA model, typical goodness-of-fit statistics (Kline, 2016)—comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA)—were inspected.

Third, these concepts and constructs were combined into a discrete choice model predicting stated neighborhood preferences. Integrated choice and latent variable (ICLV) modeling (Ben-Akiva et al., 1999, 2002; Walker, 2001)—sometimes called hybrid choice modeling—links structural equation modeling with discrete choice analysis, allowing unobserved constructs (the latent variables) to predict choice utility while simultaneously accounting for measurement error in the indicators. Thus, ICLV models simultaneously estimate both measurement and structural latent variable model components, as well as a discrete choice model. Given the presence of two correlated latent variables, ICLV models were analyzed in Python Biogeme (Bierlaire, 2016) using maximum simulated likelihood estimation with C code for Flexible Sequential Quadratic Programming nonlinear optimization (Lawrence et al., 1994); the simulation involved 1000 random draws according to a Modified Latin Hypercube Sampling strategy (Hess et al., 2005). For simplified estimation purposes, latent class models were estimated separately, and predicted class membership probabilities entered the structural model predicting the latent variables. This structural model, in which the latent variables predict the items and are themselves predicted by other variables, is akin to a multiple indicators, multiple causes (MIMIC) framework.

The conceptual framework in Fig. 1 as represented by an ICLV model can be mathematically specified according to the following regression equations:

$$\text{Latent utility:}\quad U_{jn} = \mathbf{B_j X_n} + \mathbf{D_j}\boldsymbol{\eta}_\mathbf{n} + \varepsilon_{jn} \text{ or } U_{jn} = ASC_j + \sum_k B_{kj}\cdots X_{kn} + \sum_s D_{sj}\cdots\eta_{sn} + \varepsilon_{jn}$$

$$\text{Latent factor:}\quad \boldsymbol{\eta}_\mathbf{n} = \boldsymbol{\Gamma}\mathbf{X_n} + \mathrm{K}\boldsymbol{\pi}_\mathbf{n} + \boldsymbol{\zeta}_\mathbf{n} \text{ or } \eta_{sn} = \alpha_s + \sum_k \gamma_k\cdots X_{kn} + \sum_c \mathrm{K}_{cs}\cdots\pi_{cn} + \zeta_{sn}$$

where the indices j, n, k, s, and c refer to alternatives, individuals, explanatory variables $\mathbf{X}$, latent factors $\boldsymbol{\eta}$, and latent class membership probabilities π, respectively. The stochastic elements ε_{jn} and ζ_{sn} are assumed to be mutually independent. The typical distributional assumptions for ε_{jn} (IID Gumbel) yield the familiar discrete choice multinomial logit model; and ζ_{sn} are assumed to be normally distributed with zero mean and a covariance matrix Ψ.

3.3. Data source

An empirical application of the described analytic approach utilized data collected for the Neighborhood Transportation Study (NTS). Completed in November 2014, the NTS was an online, cross-sectional survey of 654 residents of the Portland, Oregon metropolitan region. For survey recruitment, a stratified sampling strategy—in which postcards with a link to the online survey instrument were mailed in two waves to housing units in objectively-defined neighborhood types (Currans et al., 2015)—was employed. The implementation of this survey instrument enabled the collection of background information, stated neighborhood preference, and importance levels that survey participants placed on items related to their residential location decision-making process. Further details about the NTS research design, sample recruitment, and survey instrument are described elsewhere (Gehrke et al., 2019).

Table 1 summarizes the sociodemographic, economic, and transportation characteristics of the study sample. Socioeconomic information pertaining to the respondent's age, work status, and household composition are a common but non-exhaustive set of lifecycle stage descriptors, whereas a respondent's mobility style may be derived from a set of transportation characteristics related to travel mode availability and choice. In terms of socioeconomic background, approximately three-quarters of the study sample were employed and had zero household children. A majority of survey respondents (54%) reported living with one other adult, while the largest age cohort was between 35 and 49 years old. As for travel mode availability, most individuals possessed a driver's license (95%), no transit pass (79%), and no carshare membership (86%). At the household-level, 44% of the study sample had access to one vehicle per household adult and 35% of respondents reported they did not have access to a household bike.

Additional sections of the NTS survey instrument collected residential location choice information concerning the study samples' stated neighborhood preference and the level of importance they placed on various housing, accessibility, and transportation attributes. First, survey participants examined four neighborhood types and selected the concept where they would most prefer to live. These neighborhood concepts were conveyed as collages of nine images that were accompanied by descriptive text of the type of dwelling units, level of accessibility to local services and regional centers, mix of renters and owners, and parking facilities inherent to the neighborhood concept (Fig. 2). Of the survey participants, 49 (9%) selected the central district concept, 98 (18%) preferred an urban residential district, 220 (40%) favored an urban neighborhood, and the remaining 181 (33%) stated a preference for a suburban neighborhood. In comparison, a little more than one half of the sample currently lived in an urban residential district (28%) or an urban neighborhood (29%), while 43% of the sample currently resided in a suburban neighborhood. No individuals in the study sample lived in a central district, since this concept is not currently found anywhere in the Portland metro region.

Next, survey respondents were asked to rate the importance of each attribute in their residential location decision-making process using a three-level classification: very important (must have or "deal breakers"), somewhat important (nice to have or "icing on the cake"), or not at all important (no bearing on their decision). The importance ratings of the following attributes were included in this NTS survey component:

Table 1
Descriptive statistics for study sample.

Indicator	Count (n)	Percent (%)
Sociodemographic and Economic Characteristics		
Respondent age: 18 to 34 years old	142	27
Respondent age: 35 to 49 years old	164	31
Respondent age: 50 to 64 years old	154	29
Respondent age: 65 years or older	72	14
Respondent work status: Full- or part-time	393	74
Respondent work status: Unemployed or retired	139	26
Household adults: 1	133	25
Household adults: 2	285	54
Household adults: 3 or more	114	21
Household children (under 18 years old): 0	400	75
Household children (under 18 years old): 1	65	12
Household children (under 18 years old): 2 or more	67	13
Transportation Characteristics		
Respondent driver's license	507	95
Respondent transit pass	110	21
Respondent carshare membership	73	14
Respondent typical travel mode(s)[a]: Car only	271	51
Respondent typical travel mode(s)[a]: Walk, bike, and/or transit only	105	20
Respondent typical travel mode(s)[a]: Car and walk/bike/transit	156	29
Respondent primary commute mode[b]: Car	238	45
Respondent primary commute mode[b]: Walk, bike, or transit	143	27
Respondent primary commute mode[b]: No commute	151	28
Household cars per adult: 0	68	13
Household cars per adult: Between 0 and 1	163	31
Household cars per adult: 1	235	44
Household cars per adult: 1 or more	66	12
Household bikes per adult: 0	187	35
Household bikes per adult: Between 0 and 1	89	17
Household bikes per adult: 1	159	30
Household bikes per adult: 1 or more	97	18
Neighborhood Characteristics		
Current neighborhood: Urban residential district	147	28
Current neighborhood: Urban neighborhood	154	29
Current neighborhood: Suburban neighborhood	231	43

[a] Respondents able to select multiple modes.
[b] Respondents limited to selecting one mode.

Fig. 2. Preferred neighborhood concepts in Neighborhood Transportation Study (Gehrke et al., 2019).

- Own my house/condo;
- Live in a home with a large living space;
- Live in a detached single-family home;
- Have a private yard;
- Have privacy from my neighbors;
- Living at the "center of it all";
- Being near high-quality public schools;
- Living near established, older homes;
- Access to highways/freeways;
- Having a variety of transportation options;
- Having a commute that takes 25 min or less;
- Walking to bus and/or rail stop;

- Having off-street parking at local destinations;
- Having dedicated parking at your residence;
- Access to parks and recreational areas;
- Walking to nearby places; and
- Biking to nearby places.

An examination of the importance ratings for these attributes—-whose classification was unconstrained (see Gehrke et al., 2019)—permitted an improved understanding of tradeoffs considered during the residential location decision process through the identification of latent lifestyle aspirations reflecting an importance for such housing, accessibility, and transportation attributes.

4. Results

Utilizing these NTS data, we sought to better explain the sources of heterogeneity in stated neighborhood preference through the application of a framework (see Fig. 1) accounting for the lifecycle stage, mobility style, and lifestyle aspirations of the survey participants. The estimation results for the distinct latent class cluster and confirmatory factor analysis components as well as the integrated choice and latent variable model are provided below.

4.1. Latent class cluster analysis

An appropriate number of lifecycle stage and mobility style classes was determined by comparing model information statistics. Table 2 summarizes the goodness of fit measures for three lifecycle stage models estimated with sociodemographic and economic characteristics of the study sample, and three mobility style models estimated by specifying the described set of transportation characteristics. The best fitting model, and subsequent optimal number of classes, was mainly guided by the selection of the tested model that produced the lowest Bayesian information criterion (BIC) value (Vermunt and Magidson, 2002). As a result, each survey participant was classified as a member of one of three identified lifecycle stage classes in addition to one of three mobility style classes.

Working adults, working families, and non-working adults were the naming conventions chosen to reflect the lifecycle stages estimated in the final three-class model. A majority of survey participants (59%) were categorized as working adults (Class 1), while approximately one-quarter (24%) of the sample belonged to a working family (Class 2) and the remaining 17-percent were classified as non-working adults (Class 3). Table 3 offers an overview of the characteristics associated with each lifecycle stage class.

While respondents who were identified as working adults were generally under 65 years of age, Class 1 membership was uniformly distributed across the other three age cohorts. Nearly one-half (49%) of Class 1 members had one other adult in the household, and each of these households had zero children.

In contrast, all Class 2 members had at least one child living at home, with one-half of these individuals reporting two or more household children. Aside from being employed (83%), the typical working family respondent was between 35 and 49 years old (59%) and resided in a household with two adults (65%). All members of the remaining lifecycle stage (Class 3) were either unemployed or retired. Moreover, the vast majority of Class 3 members were at least 50 years old (94%) and reported having zero household children (98%). Although not completely deterministic, membership to a lifecycle stage identified in the three-class model was largely predicated on an individual's work status and number of household children.

In addition to lifecycle stage assignment, individuals were also classified based on a mobility style. As noted in Table 4, the chosen mobility style model recognized three classes: private car-oriented drivers (Class A), captive transit users (Class B), and multimodal travelers (Class C). The transportation profile of most survey participants (60%) reflected an orientation toward private car use. All Class A members had a personal driver's license, while nearly all (98%) were not active participants of any carsharing program. Most private car-oriented drivers only selected the automobile as their typical mode of travel (72%) and primary commute mode (66%). Additionally, most Class A members (69%) reported at least one household vehicle per adult. In turn, one-third of surveyed individuals were identified as being captive transit users, who were characterized as generally having zero household cars per adult (90%). Many Class B members reported having a transit pass (54%), not having a driver's license (58%), and traveling via a non-auto mode if they commuted (58%). Likewise, most Class B members reported only non-auto modes as their typical methods of travel; whereas, nearly three-quarter (74%) of all captive transit

Table 3
Profiles of the three lifecycle stage classes.

Variable	Class 1: Working adults	Class 2: Working families	Class 3: Non-working adults
Class membership			
Estimated population shares	0.59	0.24	0.17
Predicted class memberships	0.58	0.24	0.18
Indicators			
Respondent age			
18–34 years old	0.35	0.22	0.06
35–49 years old	0.28	0.59	0.01
50–64 years old	0.31	0.19	0.36
65 years or older	0.06	0.00	0.58
Respondent work status			
Full- or part-time	0.92	0.83	0.00
Unemployed or retired	0.09	0.17	1.00
Household adults			
1	0.31	0.06	0.30
2	0.49	0.65	0.53
3 or more	0.20	0.29	0.17
Household children			
0	1.00	0.00	0.98
1	0.00	0.50	0.00
2 or more	0.00	0.50	0.02

Table 2
Comparison of latent class cluster analysis models for lifecycle stages and mobility styles.

	Lifecycle Stage Classes			Mobility Style Classes		
Information Statistics	2	3	4	2	3	4
Parameters	17	26	35	27	41	55
Max. log-likelihood	−1869.74	−1833.75	−1825.81	−2888.76	−2833.28	−2800.72
AIC	3733.48	3719.50	3721.63	5831.51	5748.56	5711.44
BIC	3846.18	3830.70	3.871.31	5946.98	5923.90	5946.66
Chi-square	136.04	57.95	41.82	1137.92	1193.55	1076.89
# classes < 10% share	0	0	1	0	1	1

Table 4
Profiles of the three mobility style classes.

Variable	Class A: Private car-oriented drivers	Class B: Captive transit users	Class C: Multimodal travelers
Class membership			
Estimated population shares	0.60	0.33	0.07
Predicted class memberships	0.61	0.32	0.07
Indicators			
Respondent driver's license			
Yes	1.00	0.42	1.00
No	0.00	0.58	0.00
Respondent transit pass			
Yes	0.06	0.54	0.37
No	0.94	0.46	0.63
Respondent carshare membership			
Yes	0.02	0.11	0.34
No	0.98	0.89	0.67
Respondent primary travel mode			
Car only	0.72	0.05	0.27
Walk, bike, or transit only	0.04	0.81	0.31
Multiple modes	0.24	0.14	0.43
Respondent commute travel mode			
Car	0.66	0.00	0.19
Walk, bike, or transit	0.00	0.58	0.64
No commute	0.34	0.42	0.17
Household cars per adult			
0	0.01	0.90	0.14
Between 0 and 1	0.29	0.10	0.38
1	0.52	0.00	0.41
Greater than 1	0.17	0.00	0.07
Household bikes per adult			
0	0.34	0.74	0.29
Between 0 and 1	0.22	0.12	0.09
1	0.30	0.11	0.34
Greater than 1	0.14	0.03	0.29

users resided in a household without access to a bike. The remaining mobility style, multimodal travelers, comprised the smallest share of individuals (7%). Akin to Class A, every Class C member possessed a driver's license; however, over one-third (34%) of all multimodal travelers also belonged to a carsharing program. Most multimodal travelers had one household car per adult (41%), one household bike per adult (34%), and selected both auto and non-auto mode as their typical travel modes (43%). Similar to the class of captive transit users, a majority of multimodal travelers commuted via a non-auto mode (64%). Overall, membership in one of the three mobility styles appears to be informed by various transportation indicators with an emphasis on possession of a driver's license, chosen commute travel mode, and household vehicle ownership.

4.2. Confirmatory factor analysis

Lifestyle aspirations related to the importance rating of certain residential location characteristics were identified by assessing both the theoretical soundness and empirical performance of a measurement model. This final measurement model consisted of two latent constructs describing the rated importance that survey participants placed on certain housing, transportation, and accessibility characteristics of the residential location decision-making process. The first latent construct measured the rated importance of a single-family dwelling lifestyle, while the second construct reflected the importance of non-auto access. Fig. 3 illustrates the indicators of these two lifestyle aspirations and their unstandardized (B) and standardized (β) loadings (all $p < 0.01$). Of the 17 attributes in the NTS survey, three statements were initially removed due to item misinterpretation and lack of response variation, with seven more items subsequently removed because of unacceptable loadings in either latent construct. Further technical details leading to the final CFA model selection, which supported an acceptable model fit to the sample data and sufficient loadings for all indicators, are described elsewhere (Gehrke et al., 2019).

The rated importance for single-family dwelling living (Factor A) was indicated by both housing and accessibility characteristics. Individuals with this residential lifestyle aspiration rated "living in a detached single-family home" and "having a private yard" as very important to their residential location choice, but were far less likely to rate "living at the center of it all" as an important indicator in this decision-making process. This latent construct was negatively associated with the other residential lifestyle aspiration that rated the bundle of attributes reflecting non-auto access (Factor B) as being important. Non-auto access importance was indicated by four transportation-related characteristics. Factor B was primarily reflective of a survey participant highly rating the importance of walking to nearby places, walking to transit stops or stations, and having a variety of transportation options with respect to a residential location decision. An indifference or lack of importance for a dedicated parking space at a residence was also indicative of this non-auto access importance latent construct, as noted by the reverse coding of this fourth indicator.

4.3. Integrated choice and latent variable analysis

The ICLV model consisted of several integrated models: a measurement model, using importance ratings to indicate the latent lifestyle aspirations factors; a structural model, using latent market segment classes and exogenous explanatory variables to predict these latent factors; and a discrete choice model, with stated preference neighborhood decision utility as a function of two lifestyle aspirations and other explanatory variables. The overall ICLV model, which estimated 69 parameters on a (complete-data) sample size of 512, had a log-likelihood of −3060.63. The results for the measurement model—see Table 5—were roughly similar to those shown in Fig. 3, with unstandardized loadings of similar relative magnitudes (although the latent factor correlation was diminished to −0.59).

Results for the structural model are shown in Table 6. All estimates are standardized coefficients, thus yielding estimated associations in terms of standard deviation changes in the latent dependent variables. Several variables significantly predicted the two latent residential lifestyle aspiration factors, including the market segments. Working families rated single-family dwelling attributes as much more important (nearly one standard deviation) than did working and non-working adults. Compared to working adults, working families rated non-auto access attributes as less important factors; these attributes were more important considerations for non-working adults. Differences with respect to mobility style were more pronounced. Both captive transit users and multimodal travelers rated single-family dwelling attributes as less important than did auto-oriented drivers. Members of these groups also considered non-auto access attributes to be much more important considerations (by nearly two standard deviations or more). Respondents' current neighborhood type also was a significant predictor. Residents of urban residential districts had much lower (around two standard deviations) importance ratings for single-family dwelling attributes than did urban and suburban neighborhood residents. On the other hand, suburban neighborhood dwellers had lower importance ratings for non-auto access attributes than residents of urban neighborhoods and especially urban residential districts. After accounting for these other factors, there were no significant differences in importance ratings by household income.

ICLV model results for the discrete choice portion are displayed in Table 7. The approximate log-likelihood for the discrete choice model portion was –387.85, representing (as measured by McFadden's pseudo

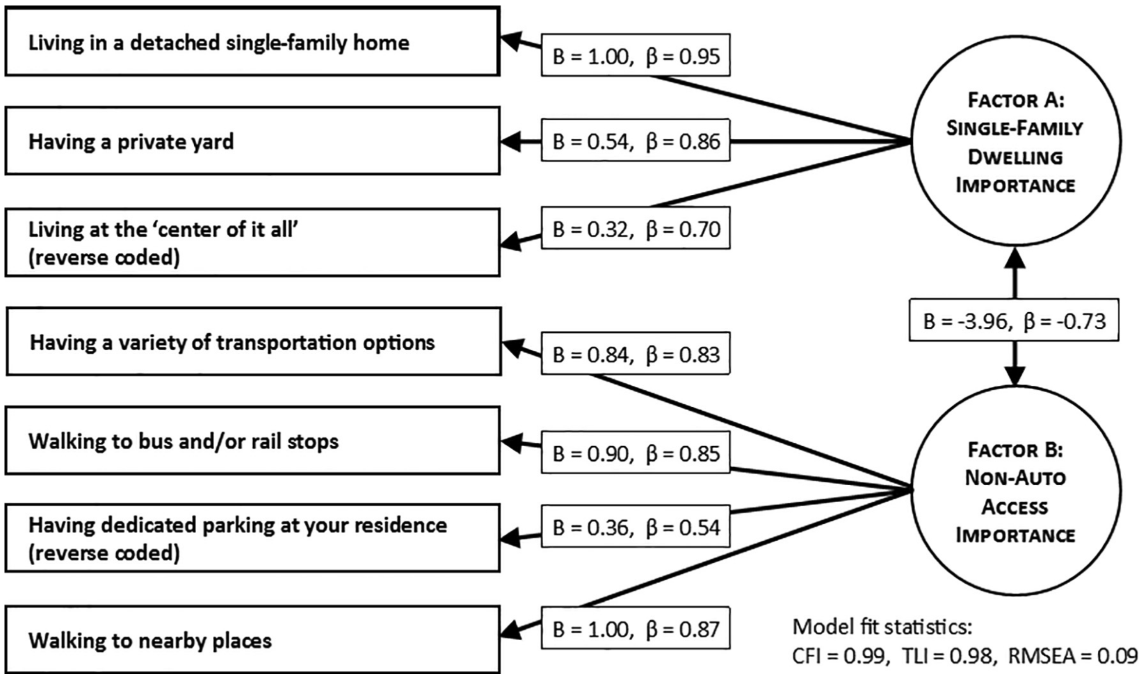

Fig. 3. Final measurement model for latent constructs reflecting residential lifestyle aspirations.

Table 5
Results from the measurement component of the ICLV model.

Variable	B	SE	p
Loadings: Factor A			
Living in a detached single-family home	1.00		
Having a private yard	0.70	0.09	0.00*
Living at the 'center of it all' (reverse coded)	0.38	0.07	0.00*
Loadings: Factor B			
Having a variety of transportation options	0.72	0.12	0.00*
Walking to bus and/or rail stops	0.86	0.15	0.00*
Having dedicated parking at your residence (reverse coded)	0.43	0.07	0.00*
Walking to nearby places	1.00		
Variances/Correlation			
Variance (Factor A)	1.71	0.25	0.00*
Variance (Factor B)	1.19	0.15	0.00*
Correlation(Factor A, Factor B)	−0.59	0.06	0.00*

Statistical significance: * = $p < 0.05$.

Table 6
Results from the structural component of the ICLV model.

Variable	Factor A: Single-family Dwelling Importance			Factor B: Non-auto Access Importance		
	Beta	SE	p	Beta	SE	p
Lifecycle stage[b]						
1: Working adults[a]	0.00			0.00		
2: Working families	0.98	0.212	0.00*	−0.31	0.156	0.05~
3: Non-working adults	−0.12	0.216	0.57	0.41	0.191	0.03*
Mobility style[b]						
A: Private car-oriented drivers[a]	0.00			0.00		
B: Captive transit users	−0.85	0.218	0.00*	1.91	0.292	0.00*
C: Multimodal travelers	−0.73	0.363	0.04*	2.66	0.503	0.00*
Household income						
$0–35,000	0.21	0.216	0.33	0.11	0.193	0.56
$35,000–75,000[a]	0.00			0.00		
$75,000–150,000	0.01	0.181	0.95	−0.22	0.155	0.16
$150,000 or more	−0.28	0.210	0.18	−0.14	0.201	0.49
Not reported	−0.19	0.430	0.66	−0.74	0.408	0.07
Current neighborhood						
Urban residential district	−2.11	0.300	0.00*	0.96	0.226	0.00*
Urban neighborhood	−0.14	0.169	0.40	0.56	0.174	0.00*
Suburban neighborhood[a]	0.00			0.00		

Statistical significance: * = $p < 0.05$, ~ = $p < 0.10$.
[a] Reference category.
[b] Variables entered the model as class membership probabilities (0–1).

R^2 values) 40% and 45% reductions in the deviances of the constants-only and null models, respectively. The latent lifestyle aspiration factors were significantly associated with stated neighborhood preferences in expected directions. Those respondents rating greater importance to single-family dwelling attributes were more likely to prefer a suburban neighborhood to all other more-urban neighborhood types. In fact, a one standard deviation increase in single-family dwelling importance ratings was associated with at least an 80% ($1 - e^B$) reduction in the odds of preferring an urban residential or central district to a suburban neighborhood. Similarly, placing a greater importance on non-auto access attributes was associated with preferring more urban neighborhood types to a suburban neighborhood, by an odds ratio of at least 1.5:1 (e^B). However, this difference was only significant for the urban neighborhood: a one standard deviation increase in the non-auto access importance ratings more than doubled ($e^B = 2.21$) the odds of selecting an urban neighborhood over a suburban one. There was a marginally significant and monotonic association between the highest income bracket ($150,000 or more) and stated neighborhood preference (other household income parameters were not statistically significant): these highest-income respondents had stronger preferences for denser neighborhood types. Direct effects of residents' current neighborhood also appeared to be present. Respondents living in an urban residential district preferred such neighborhoods, while residents of urban neighborhoods preferred living in the same type of area.

5. Conclusions

Conceptual and empirical advancements leading toward a more refined representation of the residential location decision-making

Table 7
Results from the discrete choice component of the ICLV model.

	Central District			Urban Residential District			Urban Neighborhood		
Variable	B	SE	p	B	SE	p	B	SE	p
Constant	−7.48	1.36	0.00*	−5.14	1.07	0.00*	−1.09	0.34	0.00*
Lifestyle aspiration factors									
A: Single-family dwelling	−1.97	0.59	0.00*	−1.75	0.50	0.00*	−0.39	0.16	0.02*
B: Non-auto access	0.58	0.42	0.16	0.40	0.32	0.21	0.79	0.18	0.00*
Household income									
$0–35,000	0.59	0.96	0.54	−0.67	0.79	0.40	−0.65	0.47	0.17
$35,000–75,000 [a]	0.00			0.00			0.00		
$75,000–150,000	0.82	0.84	0.33	0.38	0.68	0.58	0.72	0.36	0.04*
$150,000 or more	1.81	0.95	0.06~	1.46	0.76	0.05~	1.05	0.46	0.02*
Not reported	−0.71	1.51	0.64	−0.18	1.26	0.88	−0.02	0.99	0.98
Current neighborhood									
Urban residential district	1.25	1.05	0.23	1.74	0.93	0.06~	0.95	0.65	0.14
Urban neighborhood	−1.00	1.33	0.45	1.10	0.74	0.14	1.13	0.34	0.00*
Suburban neighborhood [a]	0.00			0.00			0.00		

Statistical significance: * = $p < 0.05$, ~ = $p < 0.10$.
[a] Reference category.

process are put forward in this study. Foremost, this work builds upon previous frameworks (Liao et al., 2015; Smith and Olaru, 2013; Walker and Li, 2007) to offer a model of stated neighborhood preference that incorporates latent factors reflecting a person's lifecycle stage, mobility style, and lifestyle aspiration. The added grouping of individuals based on their penchant to travel in a certain way (mobility style) marked an important theoretic extension of this work, as was the inclusion of lifestyle aspirations—latent constructs resulting from a confirmatory factor analysis—as predictors of residential neighborhood preference. By examining the roles of lifecycle and lifestyle factors in residential choices, researchers can better understand lifestyle aspirations throughout the life course, thus offering planners critical insights into the provision of neighborhoods of various types that may be needed to match the demand of new or emerging segments in the future. For instance, urban neighborhoods could be in particularly high demand given strong preferences among people placing a high importance on non-auto access and only slightly lower preferences (than suburban neighborhoods) among people who value single-family housing attributes.

This study's integration of lifecycle and lifestyle latent factors in a choice modeling framework also provided new awareness of the various mechanisms that underlie an individual's stated preference in residential environment. Of note, the mobility style of an individual was a stronger predictor of lifestyle aspirations than membership to a lifecycle stage. This finding highlights an understood need for travel demand and land use allocation models to utilize policy-sensitive measures for explaining heterogeneity in decision-makers. It also suggests that previous studies, which focused more on lifecycle characteristics than on mobility styles, may have missed an important determinant of the lifestyle aspirations that inspire residential preferences. Yet, this study's depiction of lifecycle stage, which does not ascribe to any preset or linear progression across the modeled latent classes, could be bolstered with the inclusion of other social indicators (e.g., employment status) found in the literature and practice. In this study, lifestyle aspirations were also stronger predictors of neighborhood preference than other modeled explanatory variables. Compared to a constants-only ICLV model, adding just lifestyle aspiration explained 37% of the variation (model deviance reduced), which was more than either latent class membership (12%) or household income and current neighborhood (20%) individually. In the full ICLV model, lifestyle aspiration contributed as much as 93% of the reduced deviance. These results help to support the idea that in forecasting the demand for various neighborhood types, it is paramount to not only know who individuals are (e.g., lifecycle stage, mobility style), but also be able to discern what it is that they want and value (e.g., lifestyle aspiration) in a residential environment.

Our findings regarding the role of household income also offer important implications. The lack of significance of income on lifestyle aspirations is consistent with earlier research on residential preferences suggesting the relative importance of psychosocial factors like attitudes and perceptions over more objectively defined socioeconomic characteristics. In contrast, the significant and marginally significant associations of income with stated neighborhood preference suggest that people with higher incomes (at least those in the highest income bracket) seem to prefer living in more densely developed neighborhoods. This finding is consistent with a narrative of gentrification, in which people with higher incomes have the ability to value accessibility and the means to bid up property values in denser and more centrally-located neighborhoods. Although this could be the result of market trends unique to Portland, it seems likely that this higher-income preference for more urban living may also be present in other "in-demand" cities. One could use the results of our models—specifically, the statements about lifestyle aspirations related to non-auto access—and tie them to objective measures of the transportation system (such as walkability, transit accessibility, and parking availability) to help planners identify specific areas of urban neighborhoods that could be particularly susceptible to gentrification.

Overall, study results point to the relative consonance between current neighborhood, lifestyle aspiration, and stated neighborhood preference. Unsurprisingly, individuals were more likely to state a preference for a neighborhood concept that was similar to their current neighborhood. Supporting this finding of relative consonance were the significant associations between an individual's current neighborhood and their rated importance for the residential location-related items concerning housing and neighborhood access: as expected, suburban residents cared more about dwelling characteristics and less about having good non-auto access to destinations. It should be noted that current neighborhood choice is also likely an expression of preferences; however, directionality of the connections between current or stated neighborhood types and other modeled attributes cannot be adequately understood with the cross-sectional data used in this study. Additionally, although the framework modeled lifestyle aspirations as a function of lifecycle stage and mobility style, lifestyles may also influence lifecycle or mobility choices in the opposite direction. Future extensions should explore alternative theoretic frameworks or advance this study's adapted structure and undertake longitudinal data collection efforts with more robust survey instruments in which neighborhood dissonance and the stability of residential preferences, lifestyle aspirations, and the segmentation of markets can be more appropriately assessed. Despite these and other limitations, this work has provided a rounded approach for identifying market segments and examining how their aspirations for a particular lifestyle impact their stated preference for a residential environment.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2019.07.001.

References

Bagley, M.N., Mokhtarian, P.L., 2002. The impact of residential neighborhood type on travel behavior: a structural equations modeling approach. Ann. Reg. Sci. 36 (2), 279–297.

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., Polydoropoulou, A., 1999. Extended framework for modeling choice behavior. Market. Lett. 10 (3), 187–203.

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. In: Mahmassani, H.S. (Ed.), In perpetual motion: Travel behavior research opportunities and application challenges. Pergamon, Amsterdam, NL, pp. 431–470.

Bierlaire, M., 2016. PythonBiogeme: A Short Introduction (Report TRANSP-OR 160706). Ecole Polytechnique Fédérale de Lausanne, Lausanne, CH.

Cao, X., Chatman, D., 2016. How will smart growth land-use policies affect travel? A theoretical discussion on the importance of residential sorting. Environ. Plan. B: Plan. Des. 43 (1), 58–73.

Chen, C., Lin, H., 2011. Decomposing residential self-selection via a life-course perspective. Environ. Plan. A 43, 2608–2625.

Clark, W.A.V., Onaka, J.L., 1983. Life cycle and housing adjustment as explanations of residential mobility. Urban Stud. 20, 47–57.

Currans, K.M., Gehrke, S.R., Clifton, K.J., 2015. The use of images in transportation surveys: Testing respondents perceptions of housing, transportation and built environment chsaracteristics. Paper presented at the annual meeting of the transportation research board, Washington, DC.

De Vos, J., Derudder, B., Van Acker, V., Witlox, F., 2012. Reducing car use: changing attitudes or relocating? The influence of residential dissonance on travel behavior. J. Transp. Geogr. 22, 1–9.

Gehrke, S.R., Currans, K.M., Clifton, K.J., 2019. Assessing the importance of housing, accessibility, and transportation characteristics on stated neighbourhood preference. Int. J. Urban Sci. 23 (1), 49–66.

Heijs, W., Carton, M., Smeets, J., van Gemert, A., 2009. The labyrinth of life-styles. J. Hous. Built Environ. 24, 347–356.

Hess, S., Bierlaire, M., Polak, J.W., 2005. Estimation of value of travel-time savings using mixed logit models. Trans. Res. Part A: Pol. Pract. 39 (2), 221–236.

Jansen, S.J.T., 2012. What is the worth of values in guiding residential preferences and choices? J. Hous. Built Environ. 27, 273–300.

Jensen, M., 2007. Defining lifestyle. Environ. Sci. 4 (2), 63–73.

Kim, T.-K., Horner, M.W., Marans, R.W., 2005. Life cycle and environmental factors in selecting residential and job locations. Housing Stud. 20 (3), 457–473.

Kitamura, R., 1988. Life-style and Travel Demand. Special Report 220: A Look Ahead: Year 2020. Transportation Research Board, Washington, DC, pp. 149–189.

Kline, R.B., 2016. Principles and Practice of Structural Equation Modeling, 4th ed. The Guilford Press, New York, NY.

Krizek, K.J., Waddell, P., 2002. Analysis of lifestyle choices: Neighborhood type, travel patterns, and activity participation. Trans. Res. Rec.: J. Trans. Res. Board 1807, 119–128.

Lawrence, C.T., Zhou, J.L., Tits, A.L., 1994. User's guide for CFSQP Version 2.0: AC code for solving (large scale) constrained nonlinear (minimax) optimization problems, generating iterates satisfying all inequality constraints (Report TR-94-16). University of Maryland, College Park, MD.

Lazendorf, M., 2002. Mobility styles and travel behavior: application of a lifestyle approach to leisure travel. Trans. Res. Rec.: J. Trans. Res. Board 1807, 163–173.

Liao, F.H., Farber, S., Ewing, R., 2015. Compact development and preference heterogeneity in residential location choice behaviour: a latent class analysis. Urban Stud. 52 (2), 314–337.

Linzer, D.A., Lewis, J.B., 2011. poLCA: an R package for polytomous variable latent class analysis. J. Stat. Softw. 42 (10), 1–29.

McAuley, W.J., Nutty, C.L., 1982. Residential preferences and moving behavior: a family life-cycle analysis. J. Marr. Family 44 (2), 301–309.

Næss, P., 2015. Built environment, causality and travel. Trans. Rev. 35 (3), 275–291.

Pas, E.I., 1984. The effect of selected sociodemographic characteristics on daily travel-activity behavior. Environ. Plan. A 16, 571–581.

Rosseel, Y., 2012. lavaan: an R package for structural equation modeling. J. Stat. Softw. 48 (2), 1–36.

Rossi, P.H., 1955. Why families move. Free Press, Glencoe.

Salomon, I., Ben-Akiva, M., 1983. The use of the life-style concept in travel demand models. Environ. Plan. A 15, 623–638.

Schirmer, P.M., van Eggermond, M.A.B., Axhausen, K.W., 2014. The role of location in residential location choice models: a review of literature. J. Trans. Land Use 7 (2), 3–21.

Smith, B., Olaru, D., 2013. Lifecycle stages and residential location choice in the presence of latent preference heterogeneity. Environ. Plan. B 45, 2495–2514.

Speare, A., 1970. Home ownership, life cycle stage, and residential mobility. Demography 7 (4), 449–458.

Van Acker, V., 2015. Defining, measuring, and using the lifestyle concept in modal choice research. Trans. Res. Rec.: J. Trans. Res. Board 2495, 74–82.

Vermunt, J.K., Magidson, J., 2002. Latent class cluster analysis. In: Hagenaars, J.A., McCutcheon, A.K. (Eds.), Applied latent class analysis. Cambridge University Press, New York, NY, pp. 89–106.

Vij, A., Carrel, A., Walker, J.L., 2013. Incorporating the influence of latent modal preferences on travel mode choice behavior. Transp. Res. Part A 54, 164–178.

Walker, J.L., 2001. Extended discrete choice models: Integrated framework, flexible error structures, and latent variables (doctoral dissertation). Massachusetts Institute of Technology, Cambridge, MA Retrieved from http://hdl.handle.net/1721.1/3270.

Walker, J.L., Li, J., 2007. Latent lifestyle preferences and household location decisions. J. Geogr. Syst. 9, 77–101.