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Do residential location effects on travel behavior differ between the elderly and younger adults?

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Abstract

The built environment affects individuals' travel behavior in a variety of dimensions, such as trip generation, mode choice, and travel duration. However, it is not well understood how these effects differ across different socioeconomic groups (e.g. the elderly versus younger adults) and how residential self-selection contributes to these differences. Using the 2013 Nanjing (China) Travel Survey data, this study estimates the differential responsiveness to the variation in residential location for different age groups. The two-step clustering method is applied to characterize two types of residential locations and the propensity score matching approach is utilized to address self-selection effects. We find that, after control for self-selection, residential location effects on travel behavior differ significantly between the elderly (60+ years old) and younger respondents (18-59 years old). Changes in the living environment play a more important role in influencing the elderly's travel frequency and travel duration than those of younger adults. When we compare the observed effects of residential location, self-selection effects are modest for the elderly while they matter to a great extent for younger adults. In addition, due to differences in residential self-selection, there is an underestimation of residential location effects on the elderly's travel behavior versus an overestimation of those for younger adults. These findings indicate that overlooking the variation of built environment effects between different age groups may lead to ineffective housing and transportation policy implications.

Keywords: Travel behavior; Residential self-selection; Built environment; Propensity score matching; Elderly; Younger adults

1 Introduction

A substantial number of studies have evidenced the influences of the built environment on people's travel behavior. Empirical studies show that elements such as residential location, land use, neighborhood design, population density, and transport accessibility are important factors in explaining travel behavior in terms of trip generation, travel mode choice, vehicle miles traveled, etc. (Cao et al., 2006; Cervero, 2002; Cheng et al., 2016; Dieleman et al., 2002; Handy et al., 2005; Van Acker and Witlox, 2011; Wang et al., 2011; Wang and Zhou, 2017). Overall, inhabitants of higher density, mixed use ('urban', 'traditional', or 'neo-traditional') neighborhoods are more likely to walk more and drive less than residents of lower-density, single-use residential ('suburban') areas (Cervero and Duncan, 2003; Crane and Crepeau, 1998; Frank et al., 2006, Zhang et al., 2012). These findings provide evidence that changing land use is an important way to reduce automobile dependency and the related consequences of air pollution, traffic congestion, energy consumption, and climate change. Younger adults' driving accounts for the majority of vehicle miles traveled (VMT). According to the 2017 US National Household Travel Survey (USDOT, 2017), the annual VMT of younger drivers constitutes 76% of the whole market, and the average annual VMT per younger adult is 1.6 times of the elderly's VMT. More recently, built environment–wellbeing research illuminates the strong connections between the built environment and an individual's quality of life through the mediating effects of activity participation and travel behavior (Hjorthol, 2013; Nordbakke and Schwanen, 2014). The demographic aging phenomenon stimulates related discussions as "aging in place" is a key strategy for coping with the challenges of an aging society (Figueroa et al., 2014; UN, 2015) – i.e. improving elderly's mobility and wellbeing through the interventions of living environment.

In order to propose tailor-made built environment interventions (for improving elderly's wellbeing and decreasing younger adults' VMT), one research question comes out: how does the built environment favor or restrict travel behavior of individuals in different age groups? In particular, how can neighborhood design adjustments be made to enhance the mobility of the elderly? Does the built environment exert a larger effect on driving behavior of younger adults than that of the elderly? Older and younger adults are confronted with different spatial and transportation opportunities and restrictions, resulting in different travel behaviors (Figueroa et al., 2014; Newbold et al., 2005). Older adults seem to have fewer options for residential choices (due to limited incomes) and are less likely to fulfill their preferences than younger adults.[1] That is, the elderly are more likely to experience a mismatch between the chosen living environment and the preferred living environment (i.e. less likely to self-select the place of residence than younger adults). Due to the different moderation effects of attitudes on the elderly and younger adults' travel behavior (Cao et al., 2010a; Cheng et al., 2019b), the influence of the built environment on travel behavior is most likely heterogeneous across age subgroups of the population – their response to the adjustment of the built environment would be different.

[1] In Chinese culture, it is common that older parents use their savings to financially help their adult children, buying houses or apartments (Deng et al., 2016).

This study makes an attempt to test the hypothesis that the effects of the built environment, in particular residential location, on travel behavior differ between the elderly and younger adults. In addition, we investigate to what extent self-selection effects differ in the observed travel behavior. This study contributes to the existing literature in two ways. First, by comparing the residential self-selection effects for older and younger adults, this study shows the differential responsiveness to variation in residential location among different subgroups of the population. Second, this paper feeds current debates on the role of self-selection in overstating or understating the effects of the built environment on travel behavior.

The remainder of this paper is structured as follows. Section 2 makes a literature review on the relationships between travel behavior, built environment and residential self-selection, in addition to heterogeneous travel behaviors across socio-economic groups. This is followed by the data collection and methodology adopted in Sections 3 and 4 respectively. Section 5 illustrates the model estimation results and discusses the effects of residential location for older and younger adults. Finally, in Section 6, our main conclusions are drawn and future avenues for research are suggested.

2 Literature review

2.1 Travel behavior, built environment and residential self-selection

The built environment can affect people's travel behavior in various ways, mainly through its density, diversity, design, destination accessibility and distance to public transport (often referred to as the 5Ds; Ewing and Cervero, 2010). A substantial literature now exists on the relationships between travel behavior and built environment. A comprehensive summary, reviewing a meta-analysis of over 50 studies, is made by Ewing and Cervero (2010). The built environment of different geographical levels is well documented as an important determinant of travel behavior. City- and district-level built environment, including urban structure, city size, and population density, is strongly related with modal split, car use, and travel distance (Dieleman et al., 2002). Neighborhood- and community-level built environment, including land use mixture, diversity, neighborhood design, public transport accessibility, and pedestrian/cycling facility, has important connections with travel frequency, vehicle miles traveled, walking and bicycling behaviors (Ewing and Cervero, 2010). Neighborhood type is also associated with the time allocation for out-of-home activity and associated travel (Yang et al., 2017).

A major challenge for the empirical research on the travel behavior-built environment relationships is to infer causality. For example, do residents of walk-friendly neighborhoods make more walking trips because the built environment itself causes them to walk more, or do these people choose to live in these neighborhoods because of its walk-friendly character? This example shows the hypothesis known as "residential self-selection", which evolves out of endogeneity (Chatman, 2009; Mokhtarian and Cao, 2008). Socio-demographics and attitudes towards travel and land use are the primary sources of residential self-selection (Cao et al., 2009; Mokhtarian and Cao, 2008). Most studies in the travel behavior-built environment analysis are on the basis of observational data, where individuals choose to dwell in, rather than being randomly distributed into, different neighborhoods. This sorting process, if not controlled for, may confound the estimation of the built environment effects on travel behavior. Because if variations in the built environment lead to residential sorting based on travel attitudes, then those attitudes would be highly correlated with built environment characteristics (Cao et al., 2009).

Numerous studies have addressed or quantified the self-selection effects using a range of methods (Cao et al., 2009; Mokhtarian and Cao, 2008; Næss, 2009), conducted worldwide including Europe, North America, Oceania, and Asia (Cao et al., 2006; Guan and Wang; 2019; Kamruzzaman et al., 2016; van Wee, 2009; Yang et al., 2017). Basically, all these studies found that after controlling for self-selection the built environment still exerts important influences on travel behavior. Nonetheless, empirical results on residential self-selection effects are inconclusive with regard to the existence, direction, and magnitude. Even though the majority of the research acknowledged the confounding effects of attitudes on travel behavior-built environment relationships, a few studies also revealed that there is no or quite limited residential self-selection effects (Scheiner, 2010; van de Coevering et al., 2016; Wang and Lin, 2017). For instance, De Vos et al. (2012) identified that in Flanders, Belgium, around 51% of residents show some degree of mismatch/dissonance between the neighborhood they live in and the type of neighborhood they prefer. The limited self-selection effects may be due to the fact that the residential location choice is affected by a variety of factors besides transport, such as neighborhood design and housing characteristics (De Vos et al., 2018). In addition, without controlling for self-selection effects, it causes either overestimation (Cao et al., 2009; Cao and Fan; 2012;) or underestimation (Lee et al., 2014; van Acker et al., 2011; Yang et al., 2017) of the built environment influences on travel behavior. Cao et al. (2009) reviewed 38 empirical studies employing different methods to control for self-selection. They found that the estimated effects are moderated after controlling for self-selection. Ewing and Cervero (2010) included 19 studies which address self-selection effects concluding opposite results, i.e. controlling for self-selection will increase the estimated effects. The estimated proportion of residential self-selection to the observed influences of the built environment on travel behavior varies from 2% to 66% across different research contexts (Cao et al., 2010b; Cao and Fan, 2012; Mokhtarian and van Herick, 2016). It can also be argued that self-selection effects confirm the influence of people's residential location on their travel behavior. If there were no such effect, then car lovers, for instance, would not have a preference for suburban-style neighborhoods in the first place (e.g. Chatman, 2009; Naess, 2009, 2014).

2.2 Behavioral heterogeneity

It is acknowledged that different socioeconomic and demographic groups are inclined to show heterogeneous travel behavior. For example, Schmöcker et al. (2008) and Cheng et al. (2019c) indicated that females depend more on public transport and less on car. Schmöcker et al. (2008) also showed that people living in high-income households are unlikely to take public transport. Similar conclusions have been drawn in studies among Norwegian, Swedish, Danish and Dutch residents, where Hjorthol et al. (2010) and Böcker et al. (2017) uncovered that persons with high incomes, as well as those having driving licenses, perform more trips by car. In regard to education level, Cheng et al. (2019a) and van den Berg et al.

(2011) reported that education level is strongly and positively related to public transit trips (particularly for discretionary activities). Lu and Pas (1999) found that employment status also has an effect – employed persons conduct fewer daily trips while travel longer time compared to unemployed persons.

Age is an important socio-economic factor that socially stratifies people with regard to travel behavior. As people age (after around 40 years old), the ability and willingness to travel decline, resulting in decreased activity participation, travel distance, and travel duration (Hjorthol et al., 2010). The observed trend becomes notable as soon as the retirement age is reached (Collia et al., 2003). Giuliano and Narayan (2003) uncovered that older adults perform fewer trips and travel shorter distances than younger adults in the UK and US. Cheng et al. (2016) found that the elderly, without work constraint, are inclined to allocate more time to leisure activities. It is additionally identified that the age effect is consistent across population segments by gender, income, and race (Szeto et al., 2017).

The important differences in travel behavior between older and younger adults are also explained by their different residential environment. The built environment often determines access to urban amenities, such as goods, services, and infrastructure. The spatial pattern of population subgroups is associated with the spatial distribution of urban amenities. The American Community Survey (US Census Bureau, 2016) indicates that the share of US seniors choosing to live in suburbs and exurbs increases from 83% in 2000 to 87% in 2016. Melia et al. (2018) also noted that in the US, Canada, and the UK younger adults, in particular millennials (i.e. those born in the 1980s and 1990s), are inclined to dwell in downtown with good access to social and recreational opportunities. However, the phenomenon is different in China. Xie et al. (2016) observed that in China older adults mostly concentrate in urban areas where land use is more mixed-use with high local accessibility (access to food market, shopping center, and parks, etc.). Three possible reasons might contribute to the concentration of Chinese aging population in urban areas. First, Chinese cities have witnessed rapid urban sprawl over the past decades (Schneider and Mertes, 2014). The old residential communities and villages where older adults originally lived in have now become urban areas. Second, due to historical reasons, many Chinese elderly's houses were provided as welfare and allocated by work unit (i.e. *danwei*) based on their job rank or job title (Wang and Lin, 2014). These *danwei* communities are traditionally located in urban centers. Third, Chinese elderly people are largely dependent on walking for conducting out-of-home activities (Cheng et al., 2019b). Older adults living in urban areas, where facilities and services are in close proximity, will more easily access social and recreational opportunities. Anyhow, the difference in spatial distribution of older and younger adults affects the spatial opportunities/constraints of their activity participation and travel behavior. On the other hand, travel attitudes – important explanatory variables of travel behavior – affect the elderly and younger adults' travel behavior in a different way. For example, Cao et al. (2010a) reported that the pro-bike/walk attitude is positively related to public transit frequency of the elderly while the relationship is negative for younger adults. Using activity-travel survey data of Nanjing, China, Cheng et al. (2019b) showed that preferences for active travel have significant and positive impacts on younger adults' active travel. However, these effects are modest in explaining the seniors' travel behavior.

Even though the built environment effects on the travel behavior are in general well documented, comparative analysis of these effects across age groups has not received much research attention until the 2010s. Cao et al. (2010a) identified that neighborhood design has distinct effects on travel behavior of elderly and younger adults. The improved accessibility has a much greater influence on older adults than on younger adults. Analyzing the active travel pattern of Chinese elderly, Feng (2017) and Cheng et al. (2019b) found that the built environment exerts larger effects on the active travel frequency and duration of the elderly than on that of younger adults. For instance, distance to chess/card room, the number of bus stops, and the number of bike-sharing stations significantly affect the elderly's active travel behavior. These variables, however, exert insignificant influences on younger adults. These findings indicate that the built environment affects travel behavior of older and younger individuals differently. Nevertheless, these studies did not address self-selection effects in the modeling process. As a result, their estimated effects might be biased.

The literature review presented so far provides a strong academic background according to which we may propose the hypothesis underpinning our research. It is hypothesized that given the discrepancy of socio-demographics and travel attitudes – two major sources of residential self-selection effects – of older and younger adults, these two population subgroups may self-select place of residence to satisfy their travel preferences to a different extent. In fact, self-selection could vary across population groups with different socio-demographic characteristics (e.g. work type, income, and gender). Tran et al. (2016) showed that knowledge-intensive and labor-intensive workers show different responses to different types of land in work location choices. Wang and Cao (2017) noted that high-income residents are likely to self-select into the type of neighborhoods matching their travel preferences. Using the travel data from Nanjing, China, we investigate whether the residential location shows different influences on the travel behavior of older and younger adults, highlighting the differences in residential self-selection effects.

3 Data

There are two phases for the data collection. In the first phase, household surveys were carried out to get residents' socio-demographics and activity-travel information. In the second phase, built environment characteristics of the study area (i.e. the main city area) were obtained.

3.1 Sample and travel behavior data

To reveal travel behavior of older and younger adults, this study examines their travel frequency and travel duration based on the 2013 Nanjing Travel Survey data. Nanjing, the capital city of Jiangsu Province and around 300km to the east of Shanghai, China, has a population of 3.43 million in the main city in 2013. The main city area contains 316 traffic analysis zones (TAZs) and much of the area is located at the south bank of Yangtze River (Figure 1).

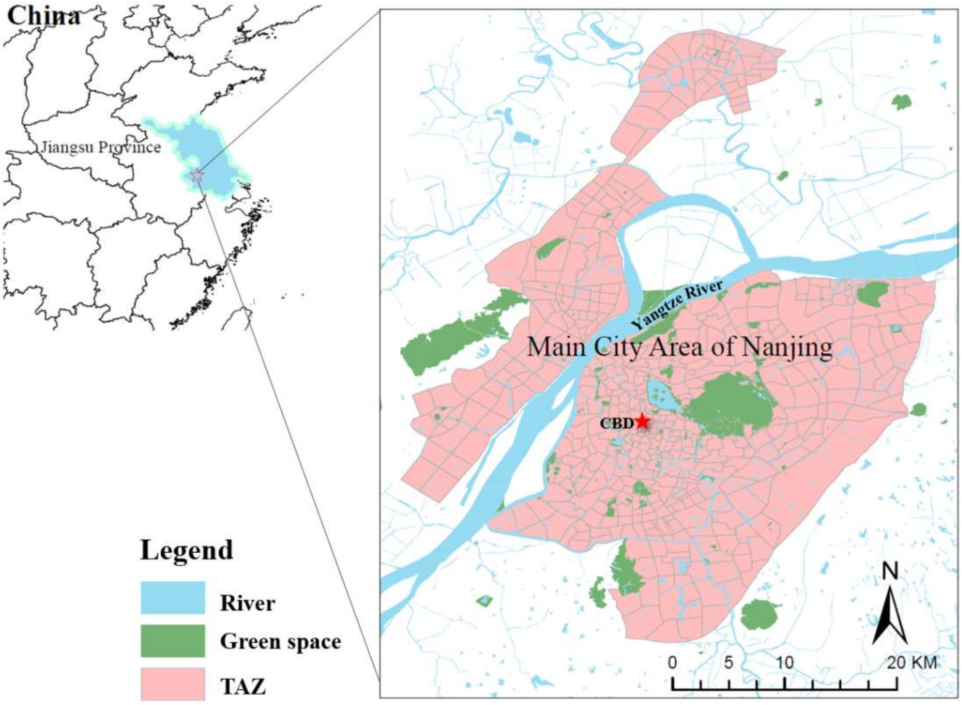

Figure 1 Map of the main city area of Nanjing

The survey was conducted by the local government on a normal weekday, that is Wednesday, October 30th, 2013. The questionnaire includes three sections: (i) socio-demographic characteristics, (ii) travel information of all trips performed on the previous day, and (iii) travel attitude, measured by three dummy variables representing individuals' travel mode preference – i.e. preference for private car, preference for public transit, and preference for walking. All the TAZs were selected for the survey. A random sample of households was drawn from the civil registries (i.e. with Nanjing *hukou*) of each TAZ according to their population – a TAZ with a higher population was targeted with a larger sample size. A structured household-based, face-to-face interview was applied to all persons aged more than six years old in the household. Initially, 5,562 individuals (2,000 households) were contacted and asked to participate in the survey. 5,172 completed questionnaires were obtained with the response rate of 93%. In this study, we consider the elderly those aged 60 or above, and respondents between 18 and 59 years old as younger adults.[2] After sample selection and data cleaning, we included 702 older persons and 3,772 younger persons for analysis. When compared to the Statistical Yearbook of Nanjing (Nanjing Municipal Bureau Statistics, 2014), the overall distribution of age, gender and household income groups corresponds to the census data, indicating that the survey data are representative. In China, men retire at an age of 60, while women retire at an age of 55. Respondents in the group of elderly are consequently all retired, while most younger adults are employed. As a result, differences in travel behavior and residential location choice can be expected (e.g. elderly do not have to live in the proximity of their job anymore, and they do not have to perform any commute trips anymore).

[2] Since we focus on the variations in responsiveness to the built environment for elderly people and non-elderly people, and we only found limited differences in travel behavior and attitudes within the group of younger adults, a deeper investigation on younger adults is not included in this study.

Table 1 Descriptive statistics by age group and tests of mean differences

	Variable	Description	Elderly	Younger	p-value (diff.)
Travel behavior variables	Walk frequency	Number of walking trips on the previous day	1.67	0.60	0.000
	PT frequency	Number of public transit trips on the previous day	0.52	0.37	0.000
	Car frequency	Number of car trips on the previous day	0.06	0.52	0.000
	Walk duration	The time spent on walking trips on the previous day (min)	39.94	11.37	0.000
	PT duration	The time spent on public transit trips on the previous day (min)	23.68	19.67	0.043
	Car duration	The time spent on car trips on the previous day (min)	1.55	19.37	0.000
Household characteristics	Size	Number of persons in the household	3.27	3.23	0.291
	High income	High annual household income (> 100,000 RMB) (0: no; 1: yes)	0.32	0.46	0.000
	Middle income	Medium annual household income (50,000-100,000 RMB) (0: no; 1: yes)	0.38	0.40	0.321
	Low income	Low annual household income (< 50,000 RMB) (0: no; 1: yes)	0.30	0.14	0.000
	Single generation	Household members of the same age group (0: no; 1: yes)	0.44	0.12	0.000
	Intergenerational with elderly	Elderly co-reside with adult children (0: no; 1: yes)	0.56	0.37	0.000
	Intergenerational without elderly	Younger adults with children (0: no; 1: yes)	NA	0.51	NA
	Child	Children under school age in the household (0: no; 1: yes)	0.14	0.16	0.040
	Car	Car ownership in the household (0: no; 1: yes)	0.36	0.56	0.000
	Bicycle	Bicycle ownership in the household (0: no; 1: yes)	0.71	0.69	0.337
Individual characteristics	Male	Gender (0: female; 1: male)	0.54	0.48	0.001
	High education	Highly educated respondent (0: no; 1: yes)	0.13	0.58	0.000
	Middle education	Medium educated respondent (0: no; 1: yes)	0.41	0.31	0.000
	Low education	Low educated respondent (0: no; 1: yes)	0.46	0.11	0.000
	Transit card	Transit discount card ownership (0: no; 1: yes)	0.86	0.83	0.126
	Driving license	Driving license ownership (0: no; 1: yes)	0.09	0.52	0.000
Travel attitudes	Walk preference	Preference for walking (0: no; 1: yes)	0.12	0.07	0.000
	PT preference	Preference for public transit (0: no; 1: yes)	0.33	0.36	0.233
	Car preference	Preference for car (0: no; 1: yes)	0.13	0.32	0.000

Note: p-value is derived from two-sample t-test; NA =not applicable.

Comparing travel behavior between older and younger adults (Table 1), we can see significant differences. The elderly show higher levels of walk and public transit use. Younger adults tend to travel more frequently by private car, around ten times as much as the elderly in terms of car frequency and car travel duration. Concerning socio-demographics, older respondents often live in low-income households, while the younger have a higher chance of living in high-income households. Elderly households are less likely to have children under school age and have fewer access to cars. Individually, the elderly tend to be less educated and a low proportion of them have driving licenses. They also tend to have a lower preference for car while a higher preference for walking, compared to younger adults. The variability in travel attitudes further consolidates the hypothesis that older and younger adults face different self-selection effects.

3.2 Built environment data

Built environment data of Nanjing in 2013 were obtained from the Nanjing Urban Planning Bureau. We applied the API service of Baidu Map to geocode the respondents' household addresses – collected in the Nanjing Travel Survey – into XY coordinates for projection on the map. In the analysis, the "buffer" function of the ArcGIS software was used to obtain relevant built environment variables around each household location.

First, population density is measured by the ratio of population and the area of the traffic analysis zone (TAZ). Land use mixture represents the diversity of different functions in the neighborhood. It is calculated as an entropy index: $s = -\sum_i \left(P_i ln\,(P_i)\right)/ln\,(I)$ within a 1,000m radius of the household, where P_i is the proportion of the ith land use type ($i = 1,2,\ldots,I$). Five land use types are included: residential, entertainment, commerce and business, education, and public services. Then, we measure indicators associated with transport provisions. These are road density (including arterial road and branch road), distance to the nearest metro station, and the number of bus stops, measured within a 500m radius of the household.

Table 2 Built environment characteristics of respondents' households

Variable	Group mean		
	Elderly	Younger adults	p-value (diff.)
Population density (persons/1000m^2)	2.15	1.96	0.001
Land use mixture	0.67	0.60	0.044
Road density (km/km^2)	8.23	8.06	0.192
Distance to the nearest metro station (km)	1.42	1.86	0.000
Number of bus stops	5.29	4.94	0.035

Note: p-value is derived from two-sample t-test.

Table 2 shows that households of older respondents exhibit differences in built environment characteristics compared to households of younger respondents. Older respondents have more access to potential destinations, urban amenities, and transport services. This is consistent with their spatial distribution differences – represented in Figure 3 and Figure 4 – indicating that elderly respondents reside more in urban areas. Specifically, the average population density and land use mixture of older respondents' neighborhoods are significantly higher than that of younger respondents' neighborhoods. Likewise, older respondents' households tend to have greater access to metro stations. A considerable difference also exists in the average number of bus stops within 500m: 5.29 bus stops in older respondents' neighborhoods versus 4.94 in younger respondents' neighborhoods.

4 Methodology

4.1 Two-step clustering method for neighborhood classification

Some studies define a respondent's residential location simply according to the distance between the place of residence and the city center (Cao et al., 2010b; Lin et al., 2017). We argue that the classification of residential location based on the simple distance may not take account of the broad variation of neighborhood features – e.g. a particular neighborhood far from the city center may be more walkable than some neighborhoods in the downtown area. Thus, it is more appropriate that neighborhoods are classified based on their local characteristics – i.e. measurement indicators included in Table 2.

We apply the two-step clustering method to classify respondents' neighborhoods. The method involves two stages (Kaufman and Rousseeuw, 2009). The first stage groups original cases into pre-clusters via constructing a cluster feature tree. In the second stage, the standard hierarchical clustering algorithm on these pre-clusters is applied. Identifying clusters hierarchically gives the researcher an opportunity to investigate possible solutions with different numbers of clusters. The optimal clustering result is then obtained based on the indicator of the Bayesian information criterion (BIC). Two-step clustering has extensive use in transportation research for segmentation. It has the following desirable features: dealing with continuous and categorical variables, automatically determining the number of best clusters, and producing reliable results by using both distance measures and statistical standards.

4.2 Propensity score matching for controlling for self-selection effects

As discussed above, our respondents, older and younger adults, may purposely choose their residential locations rather than be randomly distributed to their neighborhoods. Consequently, the observed travel behavior differences (in Table 1) might result from relative residential locations (e.g. urban versus suburban) and/or might due to observed household and individual characteristics and unobserved travel attitudes (e.g. preference for a certain travel mode). Figure 2 presents the 'residential self-selection' hypothesis – people self-select their residential environments in line with their travel attitudes. In order to derive the unbiased estimates of residential location effects, we need to control for these confounding factors.

Among the various approaches, one alternative is the propensity score matching (PSM) method. This method essentially tries to address the influence of socio-demographic and attitudinal characteristics which may cause self-selection by mimicking randomization among the respondents. PSM has been broadly used in the social program assessment to address self-selection effects (Boer et al., 2007; Cao et al., 2010b; Cao and Fan, 2012; Nasri et al., 2018; Yang et al., 2017). Different from the statistical control method or sample selection method, PSM is a prediction model in which multicollinearity evaluation and statistical significance of covariates are not required (Cao et al., 2010b). To address self-selection effects among sampled individuals, PSM is employed as a tool for (i) matching respondents by recognizing almost "identical" individuals in the control group (i.e. suburban respondents) for each individual in the treatment group (i.e. urban respondents), and afterwards (ii) calculating the difference in travel behavior (e.g. travel frequency and travel duration) between the matched respondents. Compared to multivariate regression (MVR) models, PSM method tries to control for all the confounding effects of socio-demographics and travel attitudes in order to infer causality. However, MVR just models effects from the built environment to travel behavior (linkage 1 in Figure 2), and effects from travel attitudes to travel behavior (linkage 2), ignoring the effects from travel attitudes to the built environment (linkage 3). In other words, MVR does not address the moderation effects of travel attitudes on travel behavior through the built environment. As a result, sources of residential self-selection (i.e. travel attitudes) could still exist and confound the results.

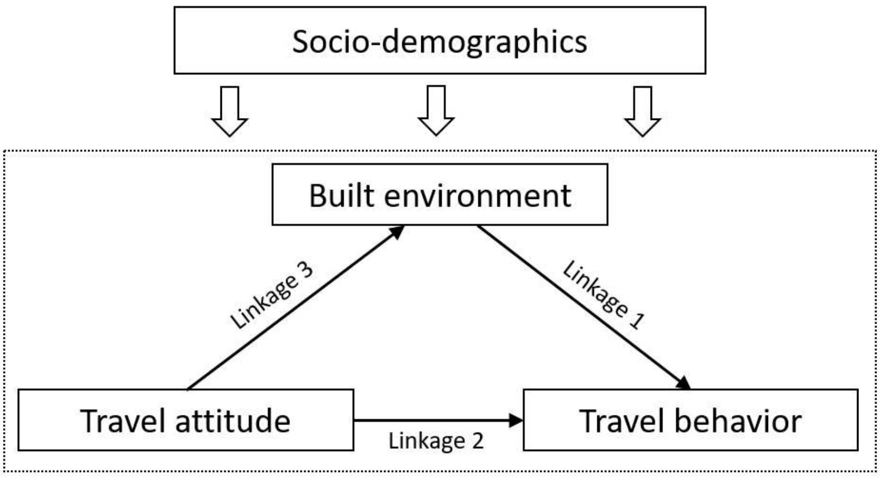

Figure 2 Illustration of residential self-selection hypothesis

Matching observations face the issue of dimensionality – i.e. the problem of recognizing the identical or similar persons with all covariates matched. Rosenbaum and Rubin (1983) suggested matching respondents via the propensity score – the conditional probability of an individual receiving treatment (e.g. living in the urban area) given the relevant covariates (e.g. socio-demographics and travel attitude). PSM deals with dimensionality by matching on the basis of a single indicator (i.e. propensity score) rather than the whole set of covariates. It should be noted that matching on the propensity score and matching on the entire covariates are equivalently effective (Rosenbaum and Rubin, 1983). In practice, the propensity score could be estimated using any binary discrete choice model, such as logit and probit (Caliendo and Kopeinig, 2008). After matching, the average treatment effect (ATE) – i.e. the "true" causal effect of dwelling in urban neighborhood, compared with the suburb neighborhood, on travel behavior – is calculated. It is the mean travel behavior difference between the matched treatment and control groups.

$$p(x) = Pr\,(D = 1 \,|\, x) \quad (1)$$

$$ATE = E(\Delta \,|\, p(x), D = 1) = E(y_1 \,|\, p(x), D = 1) - E(y_0 \,|\, p(x), D = 0) \quad (2)$$

where $p(x)$ is propensity score; $Pr\,(D = 1 \,|\, x)$ is the probability of an individual living in an urban neighborhood; x is the vector of an individual's socio-demographic and attitudinal attributes; D is a binary treatment variable (D=1 means living in urban neighborhoods; D=0, otherwise); ATE is the average treatment effect; y is the outcome variable (e.g. travel frequency or travel duration).

The observed effect (OBE) of the residential location on travel behavior is the difference of mean travel behavior between the original treatment group and control group before matching. The residential self-selection effect (SSE) could be obtained by calculating the difference between the OBE and the ATE.

$$OBE = E(\Delta^{'} | D = 1) = E(y_1^{'} | D = 1) - E(y_0^{'} \,|\, D = 0) \quad (3)$$

$$SSE = OBE - ATE \quad (4)$$

where OBE is the observed effect of the residential location on travel behavior; SSE is the residential self-selection effect.

5 Results

5.1 Neighborhood classification

As shown in Figures 3 and 4, the locations of older and younger respondents are automatically clustered into two groups. The Silhouette value is used to validate the clustering result (Rousseeuw, 1987). This indicator measures how similar an object is to its own cluster compared to other clusters, ranging from -1 (entirely cohered) to +1 (entirely separated). The Silhouette value in our analysis is 0.5, indicating our result can be regarded as acceptable.

The comparison of the two clustered built environment patterns is represented in Table 3. Relating to the spatial distribution of clusters in Figures 3 and 4, the first cluster is referred to as the "urban" area which is more densely populated, with greater land use mix and higher transport accessibility. The second cluster is referred to as the "suburban" area which is developed with inadequate urban amenities and services. In addition, Figures 3 and 4 show that the elderly tend to choose urban areas while younger adults are inclined to live in suburbs – the proportion of urban respondents is 54.0% and 46.7% for older and younger respondents, respectively. A Chi-squared test was carried out, showing that the residential location distribution of these two age groups is statistically different ($\chi^2 = 12.741$, $p < 0.001$). This result reinforces earlier findings of Xie et al. (2016) and reflects that Chinese elderly are more concentrated in urban settings.

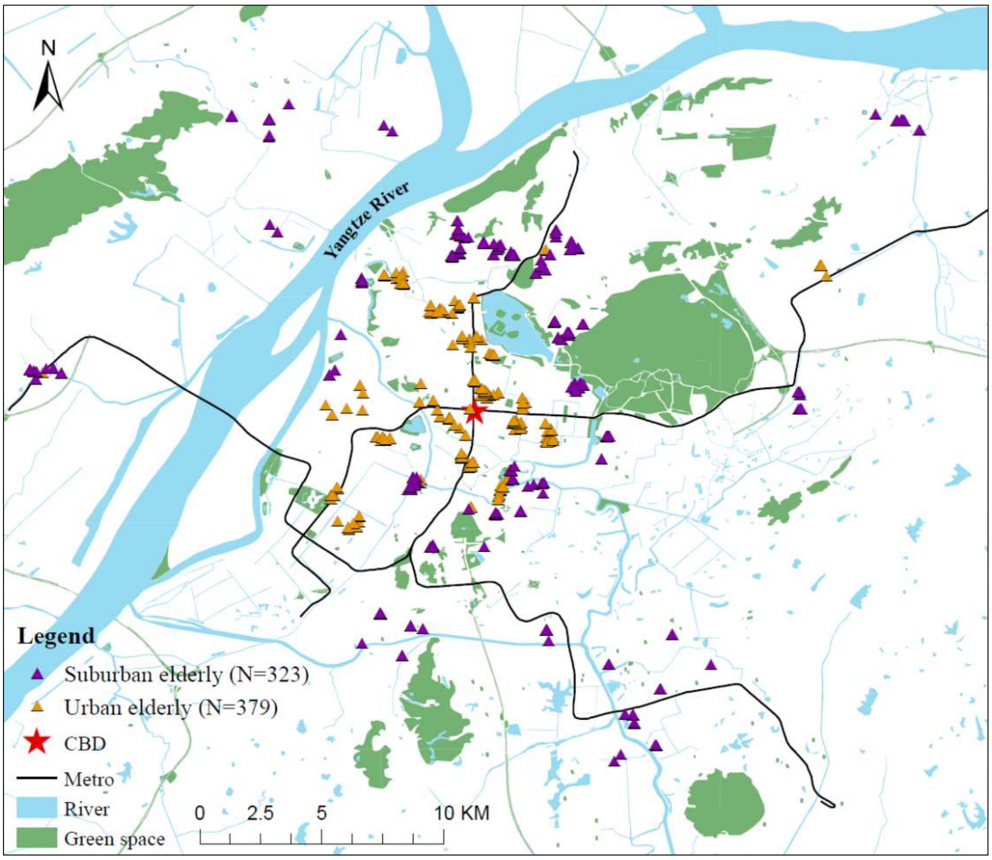

Figure 3 Location map of older respondents

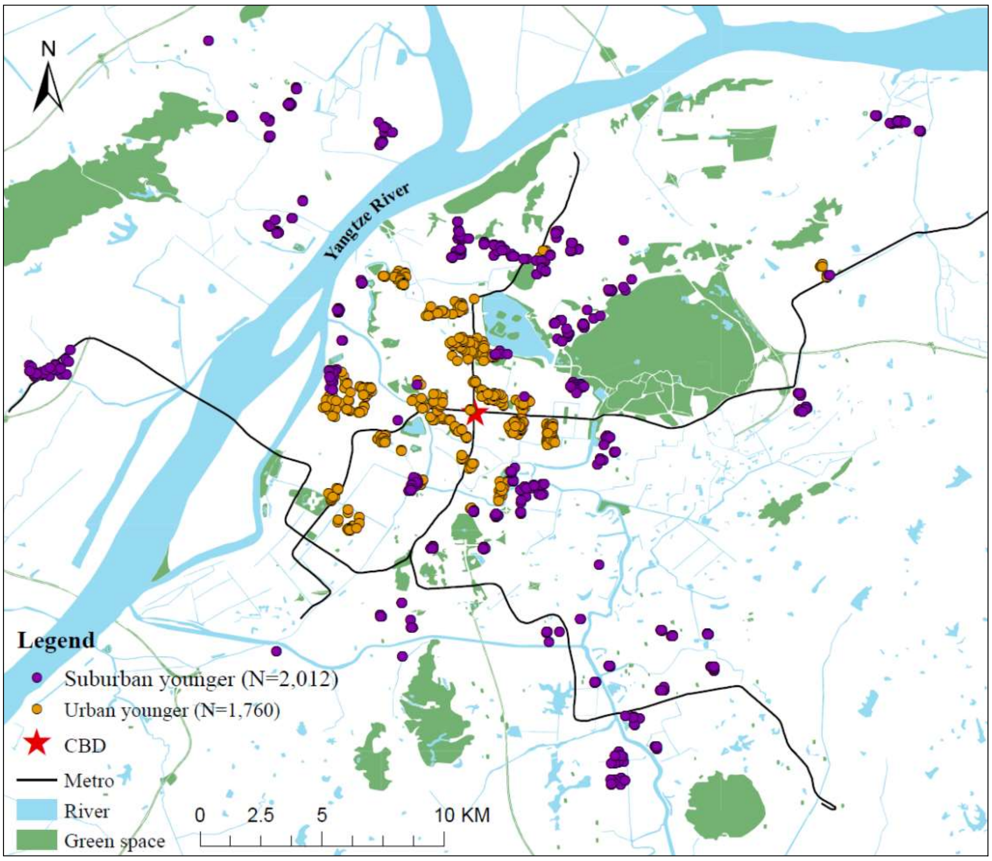

Figure 4 Location map of younger respondents

Table 3 Built environment characteristics of the clustering result

Variable	Cluster mean		
	Cluster 1	Cluster 2	p-value (diff.)
Population density (persons/1000m^2)	2.95	1.17	0.000
Land use mixture	0.71	0.56	0.000
Road density (km/km^2)	10.74	5.82	0.000
Distance to the nearest metro station (km)	0.91	2.50	0.000
Number of bus stops	6.88	3.59	0.000

Note: p-value is derived from two-sample t-test.

5.2 Propensity score matching estimation

Based on the clustering result, the location of residents is classified into urban areas and suburbs. Accordingly, individuals in the urban area are the treatment group and suburbanites are the control group. We implemented the propensity score matching in Stata 15. First, the propensity score – the probability of an individual living in urban neighborhoods – is estimated using a binary logit model. The model includes socio-demographics and travel attitudes as independent variables. Second, a "psmatch2" module is used to match a respondent in the treatment group to one in the control group, looking for respondents with propensity scores within 0.01 of each other. This caliper width is regularly adopted in similar empirical studies (Cao and Fan, 2012; Yang et al., 2017). Third, we evaluated if the chosen individuals in urban areas systematically vary from those in suburbs. The standard difference δ is calculated to assess if socio-demographics and travel attitudes of matched respondents are balanced (D'Agostino, 1998). It is calculated as $\delta = \frac{100(\overline{x_T} - \overline{x_C})}{\sqrt{\frac{s_T^2 + s_C^2}{2}}}$, where $\overline{x_T}$ and $\overline{x_C}$ are the mean value of variables for the treatment and control groups while s_T^2 and s_C^2 are the standard deviation of variables for the treatment and control groups. As a rule of thumb, Oakes and Johnson (2006) stated that a $|\delta| \leq 10\%$ is an acceptable criterion.

Table 4 compares the socio-demographics and travel attitudes between urban and suburban respondents. For the elderly, 293 pairs of respondents are matched, while younger group has 1,506 pairs of matched respondents. After propensity score matching, the standard differences of all covariates are below 10%, suggesting that characteristics of respondents in the matched groups are similar. Overall, sources of residential self-selection effects – socio-demographics and travel attitudes – are not statistically different. Therefore, the self-selection between the matched groups has been controlled for to a certain extent. Since car/bicycle/transit card ownership are used as covariates, their endogenous relationships with the built environment might merit discussion. In this study, we did not model the interactions between car/bicycle/transit card ownership and the built environment, but rather treated these two variables independently. In the application of the propensity score matching method, car/bicycle/transit card ownership are just regarded as control factors for obtaining quasi-randomization of treatment.

Table 4 Standard differences of observed covariates after matching

Variables	Matched mean (elderly)			Matched mean (younger adults)		
	Urban	Suburban	δ	Urban	Suburban	δ
Socio-demographics						
Size	3.246	3.272	-2.0	3.233	3.201	5.7
High income	0.357	0.323	4.8	0.460	0.451	2.0
Middle income	0.381	0.380	0.1	0.396	0.384	2.6
Low income	0.290	0.313	-7.4	0.155	0.164	-3.1
Single generation	0.448	0.437	6.5	0.126	0.138	-7.3
Intergenerational with elderly	0.569	0.573	-1.9	0.380	0.372	2.6
Intergenerational without elderly	NA	NA	NA	0.512	0.515	-0.7
Child	0.153	0.148	1.4	0.221	0.250	-8.3
Car	0.330	0.345	-4.2	0.551	0.563	-2.6
Bicycle	0.771	0.735	7.4	0.642	0.656	-3.5
Male	0.549	0.530	3.5	0.481	0.480	0.2
High education	0.134	0.129	1.9	0.580	0.556	5.9
Middle education	0.459	0.437	1.0	0.319	0.319	0.0
Low education	0.384	0.392	-1.7	0.107	0.125	-8.0
Transit card	0.890	0.884	0.5	0.804	0.782	3.3
Driving license	0.081	0.089	-1.4	0.465	0.485	-4.5
Travel attitude						
Walk preference	0.124	0.097	5.5	0.070	0.061	3.6
PT preference	0.380	0.363	3.7	0.347	0.352	-1.6
Car preference	0.089	0.103	-5.2	0.270	0.277	-2.4

Note: NA = not applicable.

5.3 The effects of residential location on travel behavior

Once the matching is finished, we can identify the “true” residential location effects for elderly and younger adults. Table 5 shows the observed effect (OBE), the estimated average treatment effect (ATE), the self-selection effect (SSE), as well as the ratio of “true” effect (ATE%). It should be noted that only results with a statistical difference of ATE at the 0.1 significance level are reported. Overall, after controlling for self-selection, the residential location tends to have the similar effects on travel behavior for older and younger respondents. For example, compared to suburban (older and younger) respondents, urban respondents tend to make more walking and PT trips, fewer car trips, and spend more time on walking and PT, but less time on car. These are in line with previous studies (Lee et al., 2014; Wang and Cao, 2017).

Nevertheless, the magnitude of residential location effects differs between older and younger respondents. For the older group, the estimated ATE of dwelling in urban locations on walk frequency is 0.595, suggesting that, after addressing self-selection, urban elderly are inclined to perform 0.595 more walking trips per day than suburban elderly. This effect is almost ten times as much as for younger respondents. Urban younger respondents make 0.061 more walking trips than suburban younger respondents. Urban elderly will take 0.158

trips/day more and 3.515 minutes/trip longer on public transit than suburban elderly. Despite the residential location exerts no significant effect on younger respondent's public transit frequency, their duration of public transit trips increases by 2.602 minutes per trip. In terms of car use, younger adults living in urban neighborhoods tend to conduct fewer trips as well as travel fewer minutes than those in suburban neighborhoods. However, none of these differences are significant for the elderly. This result can be explained by the low share of elderly's car use (i.e. 0.06 trips and 1.55 minutes on average (Table 1)).

Table 5 The effects of residential location on travel behavior

	OBE	ATE	SSE	ATE%
Elderly				
Walk frequency	0.524	0.595	-0.071	113.5%
PT frequency	0.163	0.158	0.005	96.9%
Car frequency	/	/	/	/
Walk duration	7.602	8.819	-1.217	116.0%
PT duration	3.733	3.515	0.218	94.2%
Car duration	/	/	/	/
Younger adults				
Walk frequency	0.080	0.061	0.019	76.3%
PT frequency	/	/	/	/
Car frequency	-0.133	-0.069	-0.064	51.9%
Walk duration	2.771	2.050	0.721	74.0%
PT duration	3.960	2.602	1.358	65.7%
Car duration	-3.558	-2.068	-1.490	58.1%

Note: OBE = the observed effect; ATE = average treatment effect; SSE = self-selection effect; ATE% = ATE/OBE, the proportion of the observed effect which is attributable to the residential location itself; "/" = non-significant result of ATE at the 0.1 significance level.

Our results suggest that residential location has a dominant effect on the travel behavior of the elderly, as shown in the last column of Table 5. The ratio of ATE (ATE%) indicates significant differences in travel frequency and travel duration due to the residential location itself. For example, it accounts for 96.9% and 94.2% of the observed effects in terms of public transit frequency and public transit duration. The remainder is attributable to their residential self-selection (3.1% and 5.8%). The effects of SSE for the elderly's walking behavior are negative. This implies that among older individuals, quite a limited share meets their travel preferences when making residential location choices. In other words, the elderly are less likely to realize their expected travel patterns because they are less able to live in their preferred neighborhood. On the contrary, for younger respondents this ratio indicates relatively strong self-selection effects. The ATE% ranges from 51.9% to 76.3%, meaning that the remaining 23.7% to 48.1% of the observed effects result from self-selection. These results indicate that both environmental determinism and residential self-selection are possible. In our results, the built environment itself has a determinant role on elderly's travel behavior and self-selection effects are modest, while residential self-selection is important for younger adults.

Interestingly, we might underestimate or overestimate the effects of residential location on travel behavior. For the elderly, the ratio of ATE is greater than one, indicating that – without addressing self-selection – an underestimation of residential location effects might occur. This suggests a mismatch between the elderly's preference for walking and their living environment (i.e. a certain proportion of elderly people who prefers walking but lives in suburbs). Suburban neighborhoods suppress older people's desire to walk. As a result, the treatment (an urban elderly) will perform more walking trips and spend more time walking than the observed difference (i.e. ATE is larger than OBE). Several possible reasons might contribute to the elderly's residential mismatch. First, given that most elderly are retired, they do not have to perform any commute trips anymore. Travel-related preferences do not seem very important for the elderly's residential location choice. Other prioritizing factors, such as safety, proximity to health centers, and proximity to children's house, lower their probability of choosing a (travel) preferred neighborhood. Second, limited housing affordability of the elderly constrains the freedom of residential choices. Table 1 shows that low- and medium-income groups consist of 68% of older respondents, making it often difficult for them to afford their preferred residential environment. Third, due to historical reasons in China, many elderly's houses were provided as welfare and allocated by work unit (*danwei*) based on their job rank or job title (Wang and Lin, 2014). Thus, the elderly's choices on residential location and housing type were often limited. Another possible reason related to the underestimation of residential location effects on elderly's travel behavior is that many older urban residents do not prefer walking and thus walk less despite living in urban areas. On the other hand, the ratio of ATE for travel behavior of the younger is smaller than one, suggesting an overestimation. As a result, the change of walking, public transit and car use due to residential location effects is likely to be overstated.

To illustrate the capability of the PSM method to control for confounding effects, MVR models are estimated as baseline comparisons. In these MVR models, the dependent variables are characteristics of travel behavior (i.e. walk frequency, PT frequency, car frequency, walk duration, PT duration, and car duration), while the explanatory variables are household and individual socio-demographics, travel attitudes, and residential location (suburban = 0, urban = 1). In total, 12 models are specified for older and younger respondents. Ordinary least squares methods are used to estimate these models. In order to enhance readability, we only show the estimated coefficients regarding the effects of residential location on travel behavior (Table 6). Percent deviations are calculated to measure the extent to which the results of MVR deviate from the results of PSM. It is clear that both models produce similar results in terms of residential location effects on elderly's travel behavior. However, the effects on younger adults' travel behavior are quite different. MVR does not address the moderation effects of travel attitudes on travel behavior through the built environment (Figure 2). As a result, sources of residential self-selection (i.e. travel attitudes) could still exist and confound the results. For older adults, self-selection effects are modest and residential location determines their travel behavior. Thus, the estimation results of MVR are similar to those of PSM. However, for younger adults, self-selection is significantly affecting their travel behavior. MVR shows its incapability and its estimation results are closer to the observed effects of residential location (the second column of Table 6) when compared to the results of PSM.

Table 6 Comparisons between PSM and MVR models

	OBE	PSM	MVR	Percent
		ATE	Coeff. (residential location)	deviation
Elderly				
Walk frequency	0.524	0.595	0.577	-3.03%
PT frequency	0.163	0.158	0.148	-6.33%
Car frequency	/	/	/	NA
Walk duration	7.602	8.819	8.810	-0.10%
PT duration	3.733	3.515	/	NA
Car duration	/	/	/	NA
Younger adults				
Walk frequency	0.080	0.061	0.072	18.03%
PT frequency	/	/	/	NA
Car frequency	-0.133	-0.069	-0.098	42.03%
Walk duration	2.771	2.050	2.367	15.46%
PT duration	3.960	2.602	/	NA
Car duration	-3.558	-2.068	-2.894	39.94%

Note: "/" = non-significant result of ATE at the 0.1 significance level; NA = not applicable.

6 Conclusions

Making unbiased estimates of treatment effects is a common objective of scientific research. Researchers have achieved great progress on understanding the independent casual influences of built environment on travel behavior, addressing residential self-selection. Nonetheless, these estimates of causal effects are lacking important variations in responsiveness to the built environment for different subgroups of the population. With better estimates which accounts for this variation, our study aims to test whether the built environment has different influences on travel behavior of different age groups. In particular, using the 2013 Nanjing Travel Survey data, we compared the effects of residential location on travel frequency and travel duration of the elderly (60+ years old) and younger adults (18-59 years old).

In order to avoid crudely distinguishing the treatment and control groups, and account for the large variation in the neighborhood characteristics, the two-step clustering method is employed to classify the respondents' neighborhood. The urban (treatment) and suburban (control) neighborhoods are identified based on their living environment characteristics (i.e. density, land use, and transport accessibility). The spatial distribution demonstrates that in China, the elderly are inclined to choose urban neighborhoods while younger adults tend to live in suburbs.

Our study illuminates the associations among residential location, travel behavior, and self-selection of older and younger adults. The propensity score matching approach is used to balance the systematic differences of socio-demographics and travel attitudes in the comparisons. Generally, urban settings stimulate walking trips and the use of public transit while decrease car use. These findings are in line with existing travel behavior-built environment literature. However, elderly's responses to variation in residential location are significantly different from those of younger adults. For the elderly, residential location determines their travel behavior and self-selection effects are modest. The proportion of SSE is smaller than 20% of walking behavior and smaller than 10% of public transit use for older respondents. In addition, we tend to underestimate residential location effects on elderly's walking behavior, indicating a mismatch between their travel preferences and living environment. However, for younger respondents, self-selection plays an important role in affecting their travel behavior, especially car use. It accounts for 48.1% of car frequency and 41.9% of car travel duration.

Basically, the results of our study help to propose insightful policy implications. For the elderly, our results could be viewed considering the expected suburban residential relocation of the aging population in China. An increasing proportion of older adults are moving to suburban areas. Xie et al. (2016) suggest that suburbanization will be a trend for Chinese elderly in the forthcoming decades. As our findings indicate that the residential location has a dominant effect on elderly's travel behavior, spatial and land use strategies will effectively influence their mobility. In other words, built environment interventions are a good way to shape/structure travel patterns of the elderly. For example, a pedestrian-friendly environment in the newly-developed area will successfully encourage active travel for the aging population. Improving public transit services including fixed route, demand responsive transit and shared ride shuttles in suburban areas will allow older residents to access distant destinations. In addition, making their suburban neighborhoods more "urban" (e.g. increasing density, land use mixture and transport accessibility) or building affordable housing for the elderly close to the district centers, in an attempt to generate consonant elderly travelers (i.e. travel preferences matching the living environment), also seems a favorable measure to improve their travel satisfaction. This travel satisfaction, in turn, is likely to enhance life satisfaction through the performance of valuable activities at trip destinations (De Vos et al., 2013). Furthermore, with the evidence that among younger adults relatively significant self-selection effects for car use exist, potential transit-oriented transportation and housing strategies in reducing auto-dependency might not have the intended effects. Younger adults' car use might not be very sensitive to the built environment adjustments. Built environment effects could be attenuated due to their residential self-selection. Younger adults seem to have a high level of freedom in residential location choices, resulting in travel preferences matching the chosen neighborhood. If car use curbing interventions are in place, they may move out and relocate to other neighborhoods conducive to car travel. Therefore, in order to reduce excessive car use and alleviate traffic congestion in China, travel demand management measures, including automobile purchase restriction, congestion pricing during peak hours, and driving restriction zones, also seem necessary. In addition, some advertising or educational measures would be helpful to reduce younger urban dissonants' car use by adapting their attitudes. Yoon and Kim (2016) found that green advertising is important in the persuasion process leading to the formation of eco-friendly behavioral intentions.

This study compared the influence of residential location on travel behavior between the elderly and younger adults. Different age groups have different responsiveness to variations in the built environment, represented by distinct residential preferences. The current study has some limitations. First, we only identified two groups with the threshold of 60 years old. A detailed segmentation of respondents (e.g. millennials, middle-aged, and seniors) may reveal more comprehensive behavioral differences due to age difference and the era within which people grew up. Second, although the propensity score matching method can be used to estimate treatment effects, it is not a panacea for addressing selection bias. The approach assumes that all variables affecting treatment assignments are measured through observed characteristics, and the hidden bias might be a potential concern. If self-selection effects come from other observable/unobservable characteristics (e.g. health conditions, non-travel-related preferences including neighborhood safety, proximity to urban amenities), the propensity score matching method cannot compensate for that. Future studies proposing/adopting more advanced approaches will lead to more conclusive causal inferences. For example, true panel studies of relocated residents or natural experiments of built environment adjustments in certain neighborhoods. Furthermore, the cohort effect (or mobility biography) is an important dimension in terms of individuals' residential and travel choices (Beige and Axhausen, 2012). The principal idea is that people's daily choices at major moments (e.g. residential choices) that can only be understood by considering the full trajectory of a person's life including marriages, child-births, and changes in education or employment. A zoom lens is useful when we want to know how people behave at a particular time and place; a panoramic view explains what motivated that behavior in the first place. On the basis of panel data or retrospective surveys, future studies could investigate whether the elderly make their residential and travel decisions in a similar way as when they were young. Nonetheless, this study provides valuable insights on elderly's interrelationships among the built environment, travel behavior, and travel attitudes, and how these differ compared to younger adults.

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