A Tale of Two Social Groups in Xiamen, China:

Travel Mode Choice of Migrants and Locals and Its Determinants

Abstract:

Across developing countries, there are billions of migrants in cities for any given moment. Meeting their travel demand is important but challenging. While many scholars have studied this in the West, little has been done in the context of China. This study, taking Xiamen, China as an example, investigates the migrants' and locals' trip frequencies by walking, cycling, public transport, and motor vehicle and their sociodemographic and built environment determinants. It finds that migrants depend more on non-driving-alone modes such as public transport and walking than locals. Both sociodemographic and built environment variables (e.g., population density, land use mix and distance to commercial centers) can significantly predict travel behavior of locals. Sociodemographic variables also significantly predict migrants' mode trip frequencies whereas the built environment indicators have significant but minor impacts. This study highlights the importance of contexts and population differentiation and calls for more in-depth research on migrants' travel behaviors and their determinants. The results and findings would help decision-makers to undertake more informed and tailored countermeasures to accommodate the travel demand of all residents in cities, regardless of they are migrants or locals.

Keywords:

Travel behavior; Determinants; Comparative study; Migrants and locals; Xiamen, China.

1. Introduction

Cities are composed of heterogeneous social groups (e.g., migrants and locals, youths and seniors), and one of the normative imperatives of urban development is to ensure all groups can have sufficient access to the infrastructures and public facilities, enjoy the benefits and welfare brought about by the development, and participate in activities that shape or re-shape the city. This is not only the essence of social justice (Rawls, 2009) but also the overtone of sustainable development. In particular, due attention should be given to the unprivileged and disadvantaged such as migrants, children and the elderly (see "vertical equity" by Litman (1999)). One important way to fulfill the above imperative is to make urban and transportation planning proactively and effectively respond to and accommodate the transportation needs of those people. In other words, planning, designing and building cities and transport systems in a way that even the unprivileged and disadvantaged can access basic facilities and conduct basic activities such as working, living, studying and recreating conveniently and comfortably (Chung et al., 2014). Nevertheless, this is a challenging task, since the unprivileged and disadvantaged are often marginalized and unvocal, and hence urban and transportation planners or policy makers are prone to base their decisions on the voices of the normal population and overlook the differences between the advantaged and disadvantaged sub-groups (Guo et al., 2018).

Thus, to address the aforementioned challenges and help migrants better fit into the urban life, there have been increasingly more researchers paying attention to migrants' travel behaviors, concerning their transportation demands, preferences, problems and determinants (Tal & Handy, 2010; Blumenberg & Song, 2008; Chung et al., 2014), as well as a distinctive process of "transportation assimilation" (Blumenberg & Shiki, 2007a). However, most of these studies focused on international migrants in developed countries. Comparatively, travel behaviors of internal migrants in developing countries are understudied, and thus some researchers have recommended that more empirical studies should be conducted to examine travel behaviors of migrants in different contexts (Guo et al., 2018). Even though the internal migration in developed countries (e.g., US) has slowed down and even ceased (Molloy et al., 2011), migrants in developing countries are still predominantly internal. Internal migrants in developing countries are more prone to be neglected since policy-makers therein may value growth and efficiency more than social justice. Whether internal migrants in developing countries undergo a similar process of "transportation assimilation" remains uncertain as well. Furthermore, there are few studies comparing travel behaviors of migrants and locals and their determinants. Comparative studies are necessary because without them, it would be hard to understand the differences between migrants' and locals' travel behaviors and how the same determinants (e.g., built environment) impact them differently.

It is particularly timely and necessary to study the travel behaviors of internal migrants in China and their determinants, because China faces the above-mentioned challenges to a larger degree, due to the following two facts. Firstly, the unbalanced urban and economic development has been giving rise to massive rural-urban and inland-coastal migrations in domestic China. Migrant workers usually work in low-salary and low-skilled positions and are excluded from quality medical service, education, housing and other social welfare due to a restricted household registration system (*hukou* in Chinese), which put them in a particularly disadvantaged position in cities (Gong et al., 2012; Shen, 2013). Secondly, even though internal migrants in China have long been referred to as "floating people" in China's official expression, more and more migrants are settling down in cities in recent years, especially the younger generation, for example, "born-after-1980s" generation (Connelly et al., 2011; Chen & Liu, 2016). This new trend has been exerting great challenges on the policy-making and infrastructure construction of China's cities. For example, urban and transportation planning, despite of their normative role in promoting environmentally and socially sustainable transportation (e.g., Ewing & Cervero, 2001, Ewing & Cervero, 2010), will fail to achieve their goals and deteriorate the quality of life of urban migrants, if they continue to be exclusively focused on the demands of the “privileged” (e.g., locals with local *hukou*) and overlook the differentiation of migrants and locals.

Therefore, using empirical data from Xiamen, China, this study attempts to examine the travel behavior and its determinants for two groups, namely, migrants and locals, and compare the results for the two groups wherever feasible. Specifically, it aims to answer two research questions: 1) what is the travel behavior of migrants and locals like respectively, and whether they are significantly different? 2) whether the determinants of the trip frequencies of four major modes of and migrants and locals different? It attempts to fill the aforementioned gap in existing studies. It will also generate relevant knowledge in support of urban and transport planning practitioners and policy-makers in developing countries like China.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the research materials and methods. Section 4 describes the research results. Section 5 presents a discussion of the results. Section 6 concludes with the contributions and limitations of this study.

2. Literature review

2.1 Travel behaviors of migrants

Migration (both international and internal) is a common phenomenon in the current era which is characterized by some phenomena such as increased globalization and unbalanced development (Massey et al., 1993). In the United States (US), which has long been one of the most popular destinations of international immigration, the travel behaviors of international immigrants have attracted lots of attention from scholars and decision-makers. In general, immigrants in the US are more dependent on alternative modes of private driving such as walking, cycling, carpooling and public transit than their native-born counterparts (Blumenberg & Song, 2008; Chatman & Klein, 2009). Most notably, nearly 50 percent of transit commuters were foreign-born immigrants (Blumenberg & Evans, 2007). The reasons underlying this are: (a) immigrants have a propensity to carry forward their original travel habitats in the US; (b) they are lacking in experience and/or capacity of operating a motor vehicle; and (c) perhaps more importantly, there are effects of “immigrant neighborhood”. As its name implies, “immigrant neighborhood” is a neighborhood with high concentrations of immigrants. Such a neighborhood can provide affordable housing, temporary jobs and familiar social connections, and hence many immigrants choose to reside and work there when they first arrived in the US (Smart, 2015; Blumenberg & Smart, 2014). However, “transportation assimilation” occurs when immigrants become accustomed to the new country/place and start adopting the dominant mode of travel (i.e., driving alone) among native-born residents (Blumenberg & Shiki, 2007a). Such assimilation, of course, takes some time to emerge. Tal & Handy (2010), for instance, found that (a) after controlling spatial and socio-demographic factors, immigrants’ travel behaviors were still significantly impacted by immigration period and place of birth and (b) most immigrants assimilate to the typical US travel pattern (i.e., private vehicle) after 5 years. The above means that the migration destinations’ characteristics won’t influence travel behaviors of migrants immediately upon their arrival and that instead, there is a temporal lag effect.

In countries where international immigrants are relatively fewer, social exclusion can emerge because the travel demand of immigrants is not appropriately accounted for and met. In South Korea, for instance, unskilled migrant workers did face such a phenomenon (Chung et al., 2014). In Norway, as compared to natives, non-western immigrants are suffering from higher mobility disadvantages (Priya Uteng, 2007). Thus, the travel-induced social exclusion exists in some contexts with fewer international immigrants.

In countries where international immigrants are heavily restricted and/or limited, travel behaviors of internal migrants also seem to have significant social and policy implications. In China, the massive rural-urban and inland-coastal migration has characterized the unprecedentedly rapid and massive urbanization. Particularly in recent years, as increasingly more migrants are settling down in cities, an increased number of studies have started unraveling the above implications. Migrants, for instance, could suffer from lower job accessibility and longer commutes as compared to their fellow residents in the same city (Zhao & Howden-Chapman, 2010). To overcome these issues, they could exchange inferior housing conditions for good job accessibility and short commutes. In Shenzhen, workers residing in urban villages enjoyed better job accessibility and relied more extensively on active and public transport at the cost of residential segregation (Zhu et al., 2017). Similarly, in the *Xiguan* Region of Guangzhou City, the migrants are faced with tenser financial limitations and hence choose to live closer to their places of employment and usually use walking as the most frequent commuting transport mode to cut commuting costs (Lau, 2013). In other words, such communities as urban villages in Shenzhen and dilapidated neighborhoods in *Xiguan*, Guangzhou, which are not uncommon across Chinese cities, indeed play a similar role as the “immigrant neighborhood” mentioned above in the west. Additionally, more interestingly, locals and migrants have different travel mode choice preferences even under the same or similar circumstances (e.g., income level). For instance, in a pioneering study in the domain in China, Guo et al. (2016b) found that compared to local residents with similar income levels, migrants are more likely to choose cheaper transport modes such as walking, cycling and motor cycle but use buses or automobiles less. They attributed the differences to the fact that migrants’ disposable income is much less than their earned income because they usually have a family to support in their hometown. Thus, the travel needs of locals and migrants might warrant different types of transportation infrastructures and transit services (Guo et al., 2018). As a whole, the aforementioned studies shed lights on the travel behaviors of migrants in China, and yet, they also reflect the importance of more in-depth studies for migrants' travel behaviors in different cities. The above-mentioned studies in Beijing and Shenzhen, for instance, indicate that travel behaviors of migrants can display different patterns even in the same country.

2.2 Determinants of travel behavior

2.2.1 Sociodemographic determinants

Numerous studies have identified individual- and household-level sociodemographic variables as affecting factors of residents' travel behavior. Individual-level variables include age, gender, educational attainment, occupation status, driving license possession, while household-level variables include income, residence tenure, residence size, household size, and automobile ownership. Arguably, studies on the impacts of sociodemographic variables on travel behaviors can be divided into two categories. First, scholars have intensively studied travel behaviors of diverse population subgroups (e.g., seniors, children, students, low-incomers, and migrants), which are divided based on different sociodemographic characteristics. The motivation of such research is that different population subgroups are usually characterized with different travel demands, constraints, needs, attitudes, and preferences, and differentiation of these characteristics may significantly impact travel behaviors or moderate the impacts of other determinants on travel behaviors. For instance, a study conducted in Portland found no associations at all between the built environment and older adults' likelihood of walking or not walking (Nagel et al., 2008), while another study confirmed children's (11-12 years old) active school travel (walking and cycling) were associated with travel distance, number of intersections with signals, and block density (Mitra & Buliung, 2012). Besides, it was reported that active travel modes were more prevalent among university students in McMaster University, in Hamilton, Canada than among the general population, and the students' probability of using motorized modes was positively associated with street network density and yet negatively with sidewalk density (Whalen et al., 2013). This study, looking into the differences between locals and migrants, can be considered among this category.

Second, with no population subgroups being identified, some researchers pay attention to the whole population and try to examine the impacts of sociodemographic variables on people's travel behaviors. For example, Gao et al. (2017) found that being woman, being an elder (50-79 years old), being native and/or with higher socioeconomic status can increase people's probability of walking and cycling. More such studies usually consider sociodemographic variables as control variables (see the numerous studies shown in Table 1.)

2.2.2 Built environment determinants

The association between built environment and people's travel behavior has long been a hot topic across disciplines, for example, urban and transport planning, public health, and urban geography (Wang & Zhou, 2017; Giles-Corti et al., 2016; Ewing & Cervero, 2010). Among the diverse findings, the 3Ds model (density, diversity and design) introduced by Cervero & Kockelman (1997a) has gained remarkable popularity and significance. The 3Ds epitomize how the built environment can be quantified and how we can examine corresponding indicators correlated to travel behavior. Afterward, the "3Ds" was expanded to "5Ds", with destination accessibility and distance to transit added (Ewing & Cervero, 2001; Ewing et al., 2009), then followed later by demand management as a sixth D and demographics as a seventh D (Ewing & Cervero, 2010).

Density is always measured as the amount of interest (e.g., residence, people, and occupation) per unit of area. Diversity refers to the degree of land use mix, which jointly considers the number of major land use types (e.g., residences, retails, business, entertainment, and education) and their proportions within a certain area. The entropy value is the most frequently used measurement of diversity (Ewing & Cervero, 2010). Design refers to the pedestrian-oriented design, including street connectivity (often measured by three-or-more-way intersection density), presence of shade, and block length (Frank et al., 2005). Destination accessibility measures the degree of ease of accessing the destinations of interests (e.g., CBD, city hall, or recreational facilities), and it can be measured by mobility and proximity to such destinations. Distance to transit is usually represented by the density of transit stops or (straight-line- or network-based) distance to them.

Table 1 presents the summarization of associations between 5Ds and travel behavior in both developed and developing contexts. More specifically, in developed contexts, the aforementioned Ds have widely been confirmed to have significant impacts on people's travel behaviors. For example, after controlling geographical scale or other confounding factors such as residential self-selection, accessibility, and access to transit stations, density is still found to significantly encourage non-motorized (walking and cycling) travel behavior and discourage motor vehicle use (Cao & Fan, 2012; Chen et al., 2008; Winters et al., 2010; Hong et al., 2014). More mixed-use development patterns are also found to be able to significantly reduce motor vehicle use and increase walking in US cities, according to Zhang et al. (2012). Besides, evidences are abundant that pedestrian-oriented design is correlated with more walking and/or cycling (Marshall & Garrick, 2010; Koohsari et al., 2014; Berrigan et al., 2010), and shorter distance to transit is associated with more active and public transport use (Besser & Dannenberg, 2005). (See Table 1)

However, on the other hand, some recent studies in developing regions (e.g., South America and Asia) have reported inconsistent findings on the built environment-travel behavior associations. For instance, Lu et al. (2017) found that in Hong Kong, neither diversity nor design (represented by street connectivity) was statistically significantly related to walking for transport or leisure, while population density was only positively correlated with transport walking, and that as for walking for leisure, an inverse U curve existed. Likewise, Salvo et al. (2014) paid attention to Mexican adults and found that their moderate-to-vigorous physical activity (including walking and cycling) was inversely related to walkability (a combined index of density, diversity and design (Frank et al., 2010)) and transit accessibility (See Table 1).

Table 1.

Summarization of associations between built environment and travel behaviors: representative studies in developed and developing contexts.

5Ds	References	Variables	Travel modes[1]				Study area	Control variables
			W	C	T	M		
Density	Chen et al. (2008)	Job & population density	+[2]	+	+	-	New York Metropolitan Region	SES[3], demographics, residential self-selection, access to transit
	Winters et al. (2010)	Population density		+		-	Metro Vancouver, Canada	SES, demographics
	Buehler (2011)	Population density				-	USA vs. Germany	N/A
	Cao & Fan (2012)	Population density			+	-	North Carolina	SES, demographics, Self-selection
	Hong et al. (2014)	Residence density	+			-	Seattle metropolitan region	SES, travel attitude, spatial autocorrelation
	Salvo et al. (2014)	Residential density	-				Nanjing, China	SES, sedentary behavior, green space
	Su et al. (2014)	Residential density	-				Hangzhou, China	SES, demographics
	Lu et al. (2017)	Population density	+/-				Hong Kong	Neighborhood SES
Diversity	Cervero (2002)	Entropy			+	-	Montgomery County, Maryland	SES, demographics travel cost
	Leck (2006)	Entropy	+		+	-	N/A	SES, demographics
	Winters et al. (2010)	Entropy		+		-	Metro Vancouver, Canada	SES, demographics
	Zhang et al. (2012)	Entropy				-	Seattle, Richmond-Petersburg and Norfolk-Virginia Beach, Baltimore, Washington, DC	SES, demographics
	Hong et al. (2014)	Entropy	+			-	Seattle metropolitan region	SES, demographics, travel attitude, spatial autocorrelation
	Lu et al. (2017)	Entropy	0				Hong Kong	Neighborhood SES
Design	Frank et al. (2007)	Street pattern (grid) & quality	+			-	Metropolitan Atlanta	Neighborhood selection & preference
	Winters et al. (2010)	Intersection density		+		-	Metro Vancouver, Canada	SES, demographics
	Berrigan et al. (2010)	Street connectivity	+	+			Los Angeles, San Diego	SES, demographics, health-related variables
	Marshall & Garrick (2010)	Intersection density, street connectivity, grid street pattern	+	+	+		24 California cities with populations of between 30,000 and 100,000	vehicle volumes, activity levels, income levels, and

								proximity to limited-access highways and the downtown area
	Koohsari et al. (2014)	Street connectivity	+				Adelaide, Australia	Individual and neighborhood SES
	Lu et al. (2017)	Street connectivity	0				Hong Kong	Neighborhood SES
Distance to transit	Kim & Kim (2004)	Access & distance to transit				+	USA	SES, demographics, number of licensed drivers, presence of children
	Besser & Dannenberg (2005)	Access to transit	-	-	-		USA	SES, demographics
	Hess (2009)	Walking distance to transit	-		-		California, New York	SES, demographics
	Shatu & Kamruzzaman (2014)	TOD (1: yes, 0: no)	+	+	+	-	Kelvin Grove Urban Village (TOD) vs. Annerley (non-TOD), both in Brisbane, Australia	SES, demographics
	Nasri & Zhang (2014)	TOD (1: yes, 0: no)	+	+	+	-	TOD vs. non-TOD areas in Washington DC & Baltimore	SES, demographics
	Salvo et al. (2014)	Transit station density	-				Mexico	SES, demographics
Destination accessibility	Cervero & Duncan (2006)	Job, retail/service accessibility				-	San Francisco Bay Area	SES, number of vehicles, license
	Zegras & Srinivasan (2007)	Distance to CBD				+	Chengdu, China, and Santiago, Chile	SES, demographics
	Cao et al. (2009)	Destination (library, business, etc.) accessibility	+	+		-	Northern California	SES, demographics, residential self-selection
	Ewing et al. (2015)	Destination (regional employment) accessibility	+	+		-	15 diverse US regions	SES, demographics
	Chudyk et al. (2015)	Destination (groceries/stores, malls, restaurants) accessibility	+			-	N/A	SES, demographics
	Lu et al. (2018)	Distance to CBD				-	Hong Kong	SES

Notes: [1]Among the travel modes, W: walking, C: cycling, T: public transit, M: motor vehicle; [2]"+" indicates significantly positive association, "-" indicates significantly negative association, "0" indicates no significant association, and being blank means the travel mode was not involved in the study; [3]SES is short for socioeconomic status variables; [4]Cells in grey represent studies in developing contexts.

3. Materials and methods

3.1 Study area

Xiamen, as a well-known tourism city and special economic zone located in southeastern China, is one of the most popular destinations for migrants, owing to its rapid economic and urban development and agreeable living environment. Xiamen has been undergoing a rapid growth of the migrant population in recent years. By the end of 2016, the migrants in Xiamen reached 2,998,091. Thus, Xiamen is a suitable laboratory for studying/comparing travel behaviors of migrants and locals.

By 2016, Xiamen has an area of 1,699 km^2, of which 334 km^2 is urbanized areas. It has a three-level administration hierarchy, namely city-district-community/village (referred to as community for short thereafter) (See Fig. 1). There are 6 districts, namely, *Siming* District, *Huli* District, *Haicang* District, *Jimei* District, *Tong'an* District and *Xiang'an* District (as shown from 1 to 6 successively in Fig. 1). *Siming* and *Huli* Districts occupy the whole Xiamen Island, separated from the other four districts by sea, and they are the most developed and urbanized districts in Xiamen. Besides, in the lower administration level, Xiamen is divided into 508 communities, and therefore, each community has an area of around 3.34 km^2 on average. The size of the community is similar to the area of a circle of radius of 1,000 meters, a common spatial analysis unit in the built environment-travel behavior domain (Feng, 2017; Marshall et al., 2009). Therefore, the community is appropriate to act as the analysis unit in this study.

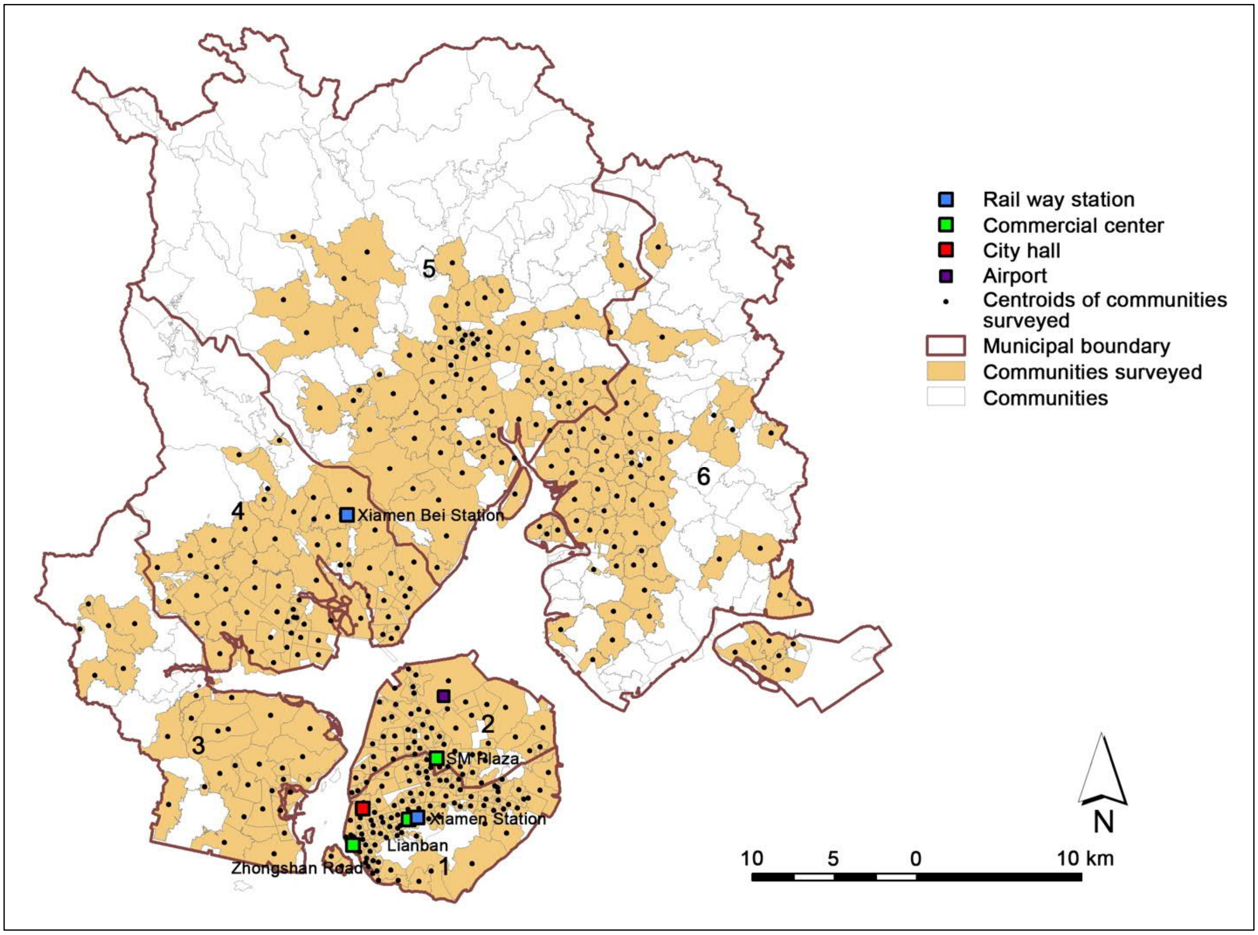

Fig.1. The study area-Xiamen City and the communities covered by the survey

3.2 Data

The data utilized in this study involve three categories: travel behavior data that indicates residents' travel trip frequencies, sociodemographic data that includes individual level and household level information, and built environment data that incorporates community as the spatial analysis unit.

Travel behavior data and respondents' sociodemographic data were extracted from the Travel Survey of Xiamen Residents 2015 (TSXR2015) Dataset. TSXR2015 was designed and jointly organized by the Department of Transportation of Xiamen, Xiamen Urban Planning and Design Institute, and China Urban Planning and Design Institute. It is a long-standing travel behavior survey conducted every 5 years. TSXR2015 determined its sampling strategy and method based on spatial distribution, household structure, age and gender structure of residents derived from the local census report, and it delivered 120,603 survey questionnaire forms and recovered 96,010, 93,812 out of which were valid. Among the 93,812 residents surveyed, there are 68,770 locals, whose *hukou* are registered in Xiamen and 25,042 migrants, whose *hukou* are registered in other places. The migrants are referred to as "floating people" in

China’s official expression. Given the sampling rate and response rate are 3.05% and 97.8%, respectively, the TSXR2015 well represents residents in Xiamen.

TSXR2015 recorded all the trips (n = 219,152) taken by all the 93,861 respondents during the whole 24 hours of the survey day, with travel modes, duration time, origins and destinations, and travel purposes included. The individuals were from 40,201 families, residing in 368 out of 508 communities in Xiamen (See Fig 1). The dataset also incorporated sociodemographic data of individuals (e.g., age and gender) and households (e.g., residence size and type). In the meantime, the information about which community each family was residing was recorded as well.

The built environment data were provided by Xiamen Urban Planning and Design Institute and Xiamen University, most of which were secondary data about land use, transportation infrastructure, and urban design features of the city.

3.3 Dependent variables

For both migrants and locals, there are four dependent variables respectively, which are the counts of the trips using the four major transport modes (i.e., walking, cycling, public transport and motor vehicle) of an individual during the survey day.

In the original TSXR2015, there are twelve travel modes concerned, namely, walking, cycling, electric cycling, bus, Bus Rapid Transit (BRT), taxi, private motor vehicle, carpooling, company shuttle, ferry, motorcycle, and others (motorized travel mode). To define and calculate the dependent variables, we aggregated the above modes into four new categories (as shown in Table 2). This categorization takes the motorization degree of each travel mode and the amount of physical activity into consideration. Afterwards, we added up the counts of trips of each category and created four dependent variables, i.e., walking (0, 1, 2, …, n), cycling (0, 1, 2, …, n), public transport (0, 1, 2, …, n) and motor vehicle (0, 1, 2, …, n). Walking (n) indicates a certain individual takes n trips by walking during the survey day, and the same applies to the other three variables.

Table 2.

Categorization of travel modes

New travel mode categories	Original travel mode categories in TSXR 2015
Walking	Walking
Cycling	Cycling and electric cycling
Public transit	Bus; Bus Rapid Transit (BRT); company shuttle; and ferry
Motor vehicle	Taxi; private motor vehicle; carpooling; motorcycle; and others

3.4 Independent variables

3.4.1 Sociodemographic variables

The individual demographic attributes include age, gender (male serving as the reference), education level (coded into three categories, namely, middle school and below, high school to junior college, undergraduate and above, with middle school and below serving as the reference), occupation class (coded into four categories, namely, blue-collars, students, white-collars, officials, and blue-collars serves as the reference, see Table 3).

Table 3.

Categorization of occupations (based on usual practice)

New occupation categories	**Original occupation categories in TSCR 2015**
Blue-collars (reference)	Commercial and service-related personnel; personnel of agriculture, forestry, animal husbandry, fishery and water conservancy; operators of production and transportation equipment; retired personnel; and others.
Students	Primary and secondary school students; and college students.
White-collars	Professionals; business personnel; and military personnel.
Officials	Governmental officials; and executives.

The family socioeconomic attributes include household size (coded into three categories, namely, small (1 -3 members), middle (4-7), and big (8-10), with small family as the reference), residence size (m^2), residence type (self-owned (serving as the reference), *danwei,* (i.e., former working units of China) residence, and rental residence), and motor vehicle availability. Unfortunately, TSXR2015 did not record the individual or household income, a frequently used variable for explaining people's travel behavior. However, such variables as residence type and size, amount of motor vehicle, and occupation class are usually significantly associated with income, and hence they can partly represent and substitute it.

3.4.2 Travel purpose

A dummy variable (1/0) was introduced to roughly differentiate trip purposes during the survey day. Specifically, to simplify the analysis, we re-categorized the travel purposes in the original dataset into two categories, i.e., commuting (including going to school, working, and returning home from school/workplace) and non-commuting purpose (including shopping, entertainment, visiting friends or relatives, accompanying somebody, going to hospitals, etc.). We assume that if the number of commuting trips for an individual is bigger than non-commuting trips, his/her travel purpose has the "commuting propensity" (represented by 1), otherwise, his/her travel purpose has "non-commuting propensity" (represented by 0, acting as reference in the statistic models).

3.4.3 Community-level built environment variables

The community-level built environment variables are selected based on the review of empirical studies in the last section (see Table 1). All of the 5Ds variables are included. Single variables rather than comprehensive indices (e.g., walkability) are utilized because single variables can ensure us to single out the impacts of different components of built environment on residents.

Table 4 presents the description and formulas of the built environment variables. There are multiple formulas to calculate land use mix (diversity), e.g., . Entropy Index (Frank & Pivo, 1994; Turner et al., 2001) and Dissimilarity Index (Cervero & Kockelman, 1997b). In recent years, these indexes have been increasingly criticized, and some were adapted. Manaugh & Kreider (2013), for instance, proposed Interaction Method, which takes into account the extent to which complementary land use types adjoin one another. Guo et al. (2016a, 2017) created Generalized Dissimilarity Index, which can be considered to be an improvement and generalization to the traditional Dissimilarity Index. Moreover, Song et al. (2013) critically reviewed and compared a variety of land use mix indexes, and proposed an adapted Entropy Index. Specifically, the traditional Entropy Index is considered problematic since it assumes that land use is perfectly mixed when all land uses are occurring absolutely evenly. This assumption is not substantiated by any theories. In the adapted version, a well-balanced reference geography (usually a metropolitan district) is assumed, and the entropy index of a certain area is computed based on the comparison with the reference geography (Song et al., 2013). The computation process of Adapted Entropy Index are as follows: 1) Calculating the percentage of each land use type Zi within the reference district Z; 2) Calculating the percentage of each land use type Xi within a certain area X, and the quotient Pi of Xi divided by Zi; 3) Calculating the adapted entropy index value.

In consideration of the number of land use types involved and the analysis scale, the Adapted Entropy Index is adopted in this study.

Table 4.

Descriptions and formulas of the built environment variables

Variable	Description	Formula
Population density	The population density indicates the number of all residents within a certain unit of area.	$\frac{Counts\ of\ all\ residents\ within\ a\ community}{Area\ of\ the\ community\ (m^2)}$;
Job density	The job density indicates the number of all employment positions within a certain unit of area.	$\frac{Counts\ of\ \ job\ positions\ within\ a\ community}{Area\ of\ the\ community\ (m^2)}$;
Land use mix (Adapted Entropy Index)	We identified 14 major kinds of land uses, i.e., municipal administration, culture & sports, education, medicine, welfare	The whole Xiamen City acts as the reference geography Z;

	institution, relics & religion, business, public open space, non-construction land, transportation, industry, residence, urban village, and others.	$Z_i = \frac{Area\ of\ ith\ kind\ of\ land\ use\ type}{Total\ area\ of\ all\ 14\ kinds\ of\ land\ use\ type}$; For each community X, $X_i = \frac{Area\ of\ ith\ kind\ of\ land\ use\ type}{Total\ area\ of\ all\ 14\ kinds\ of\ land\ use\ type}$; $P_i = \frac{X_i}{Z_i}$; $LUM = \frac{(-1)(\sum_{i=1}^{n} P_i \ln(P_i))}{\ln(n)}$; n=14.
Intersection density	The intersection density indicates the number of all intersections (3 or more ways) within a certain unit of area.	$\frac{Counts\ of\ all\ intersections\ within\ a\ community}{Area\ of\ the\ community\ (m^2)}$;
Distance to the closest commerce center	The shortest distance from the centroid of the community to three centers of Xiamen (i.e., *Zhongshan Road*, *Lianban* and *SM Plaza*),	Formula: null; Unit: km.
Bus stop density	The bus stop density indicates the number of bus stops within a certain unit of area.	$\frac{Counts\ of\ all\ bus\ stops\ within\ a\ community}{Area\ of\ the\ community\ (m^2)}$.

3.5 Statistical analyses

Statistical analyses in this study are composed of descriptive analyses (e.g., ANOVA) and statistical modeling.

In terms of statistical models, we built four multilevel zero-inflated negative binomial regression models respectively for migrants and locals. The zero-inflated negative binomial regression model is selected because three reasons. First, the dependent variables are observed counts (0, 1, 2, …, n). Second, there exists over-dispersion in the dependent variables. We run over-dispersion test with the package "qcc" in R, which shows statistically significant over-dispersion, p<0.000). Third, there are excess zeros in the dependent variables (Yau et al., 2003). The formulas of the zero-inflated negative binomial regression model can be written as follows:

$$\Pr(Y_i = y) = \begin{cases} \pi + (1-\pi)(1+\kappa\lambda)^{-1/\kappa}, for\ y = 0; \\ (1-\pi)\frac{\Gamma(y+1/\kappa)}{\Gamma(y+1)\Gamma(1/\kappa)}\frac{(\kappa\lambda)^y}{(1+\kappa\lambda)^{y+1/\kappa}}, for\ y = 1, 2, 3, \dots \end{cases} \quad (1)$$

$$\lambda = \exp(ln\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n); \quad (2)$$

where Y_i is the counts of trips by certain travel mode of individual i; π is the zero-inflation parameter (i.e., probability of being an extra zero); κ is the over-dispersion parameter; x_n represents a vector of independent variables; and β the associated coefficients.

The utilization of the multilevel model is justified by the structure of the data used in this study. Specifically, in this study, individuals are nested within communities. Hence, the sociodemographic variables of individuals are processed in the first level, while the built environment characteristics of communities are processed in the second level. The formulas are as follows (Raudenbush & Bryk, 2002):

Level 1 (individual level):

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + \varepsilon_{ij}; \text{(3)}$$

where y_{ij} is the dependent variable (counts of trips by walking, cycling, public transit, and motor vehicle) for individual *i* living in community *j*; x_{ij} is the vector of sociodemographic variables; β_{0j} is the intercept of the dependent variable in community *j* (Level 2); β_{1j} is the slope for the relationship in community *j* between the Level 1 independent variables and the dependent variable; and ε_{ij} is the random error of the Level 1.

Level 2 (community level):

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\omega_j + \mu_{0j}; \text{(4)}$$

$$\beta_{1j} = \gamma_{10} + \mu_{1j}. \text{(5)}$$

where γ_{00} is the overall intercept, which is the grand mean of the values of the dependent variable across all the communities when all the independent variables are equal to 0; ω_j is the vector of independent variables in Level 2, namely, the community built environment variables; γ_{01} is the overall regression coefficient, between the dependent variable and the Level 2 independent variables; μ_{0j} is the random error component for the deviation of the intercept of a community from the overall intercept; and μ_{1j} is the error component for the slope. As equations (4) and (5) suggest, the multilevel model involves a random intercept and a fixed slope. The reasons that we do not set a random slope are (a) there is no theoretical hypothesis or a priori knowledge on the effects of level 1 variables (i.e., sociodemographic characteristics) on residents' travel behavior vary across level 2 groups (i.e., communities); (b) we are more interested in the associations between transport behavior of residents and their sociodemographic characteristics and the community built environment characteristics, rather than the interaction effects between the Level 1 and Level 2 variables; and (c) for the parsimony of model.

4. Results

4.1 Travel behavior across groups

As a whole, each resident in Xiamen took 2.31 trips during the survey day averagely, and 31.8 percent of the trips during the survey day were taken on foot, slightly higher than those by motor vehicle (30.5%). Public transport is the third most popular travel mode (26.8%), and cycling seems to be the least popular mode, only taking up 10.9 percent of the trips.

Every local resident averagely took 2.32 trips during the survey day, more than migrant (2.28). As shown in Fig.2, the most popular travel mode for migrants is walking, followed by public transport. In contrast, the most popular travel mode for locals is the motor vehicle. Notably, locals are less likely to walk or cycle.

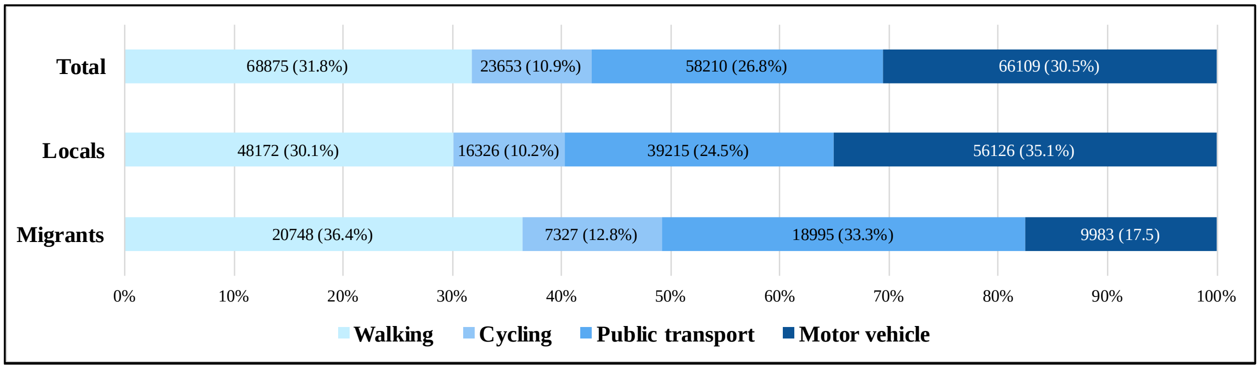

Fig.2. Counts and proportions of walking, cycling, public transport and motor vehicle by *hukou*. (Notes: Statistical significance assessed using Chi-square tests, p < 0.000.)

4.2 Descriptive analysis of probable determinants

Chi-square tests and ANOVA were used to compare probable determinants of locals' and migrants' travel behavior. Differences between the two groups in terms of the variables are statistically significant ($p < 0.000$) (See Table 5).

As presented, compared with locals, migrants in Xiamen are much younger, with relatively low educational attainment, and employed in lower-status jobs, and much fewer of them own motor vehicles. Moreover, migrants are residing in much smaller houses, in communities with higher population density and land use mix, yet lower job density, lower intersection density and smaller distance to commercial center.

Table 5.

Socioeconomic and demographic and built environment attributes between migrants and locals

Variables	**Mean (Standard deviation)/Percentage**			
	Total	**Migrants**	**Locals**	***p*-value**
Age	38.20 (16.02)	33.36 (12.78)	40.11 (16.76)	0.000

Residence area (m^2)	100.58 (63.74)	55.80 (43.87)	118.26 (61.67)	0.000
Community population density	161.67 (152.86)	167.90 (138.59)	159.21 (158.08)	0.000
Job density	3.67 (5.86)	3.14 (4.67)	3.88 (6.26)	0.000
Land use mix (Adapted Entropy Index)	0.58 (0.16)	0.62 (0.16)	0.56 (0.16)	0.000
Intersection density	0.19 (0.21)	0.18 (0.16)	0.20 (0.23)	0.000
Distance to the closest commercial center	10.00 (9.16)	7.64 (6.52)	10.94 (9.86)	0.000
Bus stop density	0.59 (0.69)	0.54 (0.57)	0.60 (0.73)	0.000
Travel purpose (%)				0.000
Commuting predominates	61.3	66.7	59.1	
Non-commuting predominates	38.7	33.3	40.9	
Gender (%)				0.000
Male	50.7	51.6	50.4	
Female	49.3	48.4	49.6	
Education (%)				0.000
Middle School and below	47.5	53.3	45.2	
High School to Junior College	37.9	37.7	38.0	
Undergraduate and above	14.6	9.0	16.8	
Occupation (%)				0.000
Blue-collars	65.5	71.6	63.2	
Students	11.3	9.4	12.1	
White-collars	20.1	16.7	21.4	
Officials	3.1	2.3	3.3	
Residence type (%)				0.000
Self-owned	69.1	17.0	89.7	
Danwei residence	1.0	0.9	1.0	
Rental residence	29.9	82.0	9.3	
Household size (%)				0.000
1 to 3	30.4	45.4	24.5	
4 to 7	66.4	52.9	71.8	
8 to 10	3.1	1.7	3.7	
Motor vehicle availability (%)				0.000
No vehicle	43.2	67.5	43.2	
At least one vehicle	56.8	32.5	56.8	

Notes: Statistical significance assessed using ANOVA tests for continuous variables and Chi-square tests for categorical variables.

4.3 Statistical modeling: Determinants of locals' and migrants' trip frequencies

Table 6 presents the results of the eight multilevel zero-inflated negative binomial regression models. All the models are statistically significant and with good performance.

As can be seen, for the locals, most of the sociodemographic and built environment variables are significant affecting factors for walking, cycling and motor vehicle trip frequencies. Concretely, the locals in Xiamen who are female or students, from relatively big families, or have no motor vehicles tend to walk, cycle or use public transport more while drive less. As expected, commuting purpose is positively related to walking and cycling while is negatively related to driving alone. In the meantime, communities with higher population density, higher land use mix, or shorter distance to commercial center encourage such active and public transport modes usage, while discourage motor vehicle use. More specifically, an increase of community population density from 0-100 residents per hectare to 100-300, 300-600, 600-900 residents per hectare would on average increase their walking by 21% ($e^{0.19}=1.21$), 35%, and 28%, respectively, while decrease their motor vehicle use by 4%, 10%, and 11%. Every one unit of rise of land use mix would increase locals' walking by 99%, while decrease their motor vehicle use by 5%. Additionally, living farther away from commercial center by 1 kilometer would decrease locals' walking by 1% while increase their motor vehicle use by 1%. In general, these results coincide with the prior findings and our intuition. However, discrepancies exist. On the one hand, such variables as job density, intersection density, and bus stop density confirmed to be significantly associated with travel behaviors in the existing studies are found to be insignificant in this study. On the other hand, counterintuitively, cycling is significantly negatively associated with job density and yet positively associated with distance to the closest commercial center.

As for migrants, the majority of the sociodemographic variables are statistically significant predictors of their travel behaviors, similar to locals. Commuting purpose expects significantly fewer walking and cycling trips and has no significant effects on public transit or motor vehicle trips. Moreover, in terms of associations between built environment variables and migrants' travel behaviors, things get complicated. Specifically, distance to the closest commercial center can encourage motor vehicle usage while discourage walking and public transport (one kilometer increment of the distance to commercial center would decrease migrants' walking and public transport use by 1% while increase their motor vehicle use by 2%). Migrants' cycling trip frequencies are influenced by job density negatively and yet by distance to closest commercial center positively, the same as locals. Different from the locals, the community population density has no significant impacts on migrants' travel behaviors, neither do intersection density and bus stop density.

In a nutshell, there are consistencies and discrepancies between the results of this study and prior studies. Moreover, comparatively, the impacts of built environment variables on locals' travel behaviors are more significant than those of built environment variables on migrants'. The aforementioned consistencies and discrepancies and the underlying causes will be further discussed latter.

Table 6.

Multilevel zero-inflated negative binomial regression modeling results: Locals' and migrants' travel behavior

Variables	Locals				Migrants			
	Model 1 Walking Coef. [z]	**Model 2 Cycling Coef. [z]**	**Model 3 Public transport Coef. [z]**	**Model 4 Motor vehicle Coef. [z]**	**Model 5 Walking Coef. [z]**	**Model 6 Cycling Coef. [z]**	**Model 7 Public transport Coef. [z]**	**Model 8 Motor vehicle Coef. [z]**
Level 1 variables								
Age	0.01***[16.54]	0.00[0.83]	-0.01***[-4.23]	-0.01***[-21.76]	0.01***[4.05]	0.01*[2.44]	-0.01***[-6.54]	-0.01***[-8.05]
Gender								
Female	0.36***[23.99]	0.10***[4.77]	0.14***[11.10]	-0.50***[-33.51]	0.24***[13.58]	-0.01[-0.27]	0.05***[2.97]	-0.90***[-26.74]
Education								
High School to Junior College	-0.29***[-15.61]	0.01[0.47]	0.19***[12.20]	0.05***[3.52]	-0.18***[-8.91]	0.01[0.26]	0.14***[6.87]	0.09*[2.47]
Undergraduate and above	-0.58***[-19.10]	-0.28***[-6.10]	0.19***[9.70]	0.10***[4.55]	-0.38***[-8.45]	-0.30**[-3.59]	0.15***[4.76]	0.16**[3.12]
Occupation								
Students	1.18***[37.01]	0.05[1.33]	0.17***[6.83]	-1.03***[-31.49]	0.44***[13.19]	-0.00[-0.4]	0.10**[2.62]	-1.27***[-15.41]
White-collars	-0.22***[-8.03]	0.05[1.74]	0.03[1.70]	0.12***[8.06]	-0.10**[-3.05]	-0.04[-0.80]	0.04[1.69]	0.09*[2.40]
Officials	-0.40***[-6.46]	-0.40***[-4.19]	-0.16***[-3.98]	0.28***[11.06]	-0.10*[-1.97]	-0.01[-0.05]	-0.22**[-3.13]	0.33***[5.58]
Residence area (m^2)	-0.01***[-3.48]	-0.00[-0.80]	-0.01***[-3.83]	0.01***[7.40]	-0.00[-1.12]	0.00[1.14]	-0.00[-0.77]	0.01***[3.39]
Residence type								
Danwei residence	0.03[0.58]	0.16[1.43]	0.07[1.32]	-0.03[-0.38]	0.11[1.19]	0.33*[2.27]	-0.03[-0.34]	-0.07[-0.46]
Rental residence	0.01[0.46]	-0.01[-0.21]	0.01[0.62]	-0.03[-1.09]	-0.01[-0.04]	0.10*[1.89]	-0.08**[-2.64]	0.04[1.10]
Household size								
4 to 7	0.03*[2.09]	0.16***[6.25]	0.03*[2.15]	-0.05***[-3.54]	0.07***[3.64]	0.19***[6.08]	-0.01[-0.64]	-0.07*[-2.24]
8 to 10	0.02[0.53]	0.28***[5.40]	0.01[0.30]	-0.13***[-4.27]	0.12*[2.05]	0.12[0.89]	-0.01[-0.04]	-0.26*[-2.57]
Motor vehicle								
At least one vehicle	-0.18***[-10.72]	-0.09***[-4.05]	-0.31***[-20.92]	2.31***[76.96]	-0.14***[-6.94]	-0.24***[-5.32]	-0.35***[-14.15]	2.43***[60.94]
Travel purpose								
Commuting dominates	-0.70***[-34.00]	-0.08***[-3.58]	-0.00[-0.30]	0.09***[6.06]	-0.18***[-8.96]	-0.15***[-5.32]	0.00[0.07]	0.04[1.05]
Level 2 variables								
Community population density								
100-300 per ha	0.28**[2.96]	0.03[0.53]	0.12[1.80]	-0.05[-1.44]	0.07[1.15]	0.02[0.30]	0.08[1.28]	-0.01[-0.13]
300-600 per ha	0.38***[3.46]	0.02[-0.40]	0.08[1.08]	-0.10**[-2.67]	0.08[1.18]	0.08[0.89]	-0.02[-0.47]	-0.09[-1.29]
600-900 per ha	0.35**[2.66]	0.03[0.36]	0.05[0.54]	-0.09**[-2.65]	-0.02[-0.29]	-0.07[-0.66]	-0.01[-0.08]	-0.15[-1.94]
Job density	0.00 [0.18]	-0.02***[-3.20]	-0.00[-0.54]	-0.00[-0.06]	0.01[1.14]	-0.02**[-2.84]	-0.00[-0.28]	-0.01[1.52]
Land use mix (Adapted Entropy)	0.60**[2.99]	0.47***[3.99]	0.06[0.51]	-0.17*[-2.42]	0.18**[2.91]	0.25[1.18]	-0.05[-0.36]	-0.30*[-2.04]
Intersection density	0.08[0.55]	-0.17[-1.66]	-0.10[-1.01]	-0.10[-1.48]	0.04[0.51]	0.39**[2.85]	0.06[0.68]	-0.16[-1.05]
Distance to closest commercial center	-0.02***[-4.70]	0.01***[4.45]	-0.03***[-9.07]	0.01***[9.71]	-0.01*[-1.97]	0.01**[2.96]	-0.01***[-3.62]	0.02***[5.76]
Bus stop density	0.07[1.25]	0.05[1.52]	-0.01[-0.09]	-0.03[-1.49]	-0.03[-0.86]	0.06[1.13]	-0.00[-0.10]	0.06[1.56]

Over-dispersion parameter (κ)	1.997	1.001	1.001	1.488	1.001	1.001	1.001	1.924
Zero-inflation (π)	0.256	0.880	0.546	0.195	0.507	0.836	0.461	0.133
AIC	120234	54998.2	111235.2	123593.6	53340	26397.8	51768.8	28859.2
Log-likelihood	-60091	-27473.1	-55591.6	-61770.8	-26644	-13172.9	-25858.4	-14403.6

Notes: Coef. = coefficient; [z] = z value; * for $p < 0.05$, ** for $p < 0.01$, *** for $p < 0.001$.

5. Discussion

Similar to what happened in the US cities, the majority of the migrants in Xiamen rely more on active and public transport than locals. However, it can be different causes contributing to the reliance in two contexts. In the US, migrants are predominantly from abroad. The reliance can be due to factors such as original travel habits, lack of experience and/or driving skills, and sheltering effects of “immigrant neighborhood” (Smart, 2015; Blumenberg & Smart, 2014). In Xiamen, the reliance is probably due to the financial and institutional limitations of migrants. They tend to be employed in lower-paid jobs, and they usually have to use a fairly large portion of their incomes to support their families in their hometown, which can further reduce their disposable income. In addition, they are even not eligible to register a private car locally because they do not have a local *hukou*. Understandably, the reliance presents both a challenge and an opportunity for urban planners and policy-makers to achieve sustainable transportation. On the one hand, most of the migrants choose active and/or public transport because they have to do so, and hence the infrastructures supporting active and public transport are vital for their quality of life and determine to a large extent whether they can fit into the city well or not. On the other hand, if urban planners and policy-makers can make responsive and proactive planning to accommodate migrants’ travel demands, the proportion of active and public transport will be steadily high.

The results presented in Table 6 shows the mixed impacts of the same variable on locals’ walking and driving. Specifically, after controlling for sociodemographic characteristics, locals from the communities with higher population density, higher land use mix value and/or shorter distance to commercial center tend to walk more but drive less. This is consistent with the results from elsewhere, such as Zhang et al. (2012), Hong et al. (2014), Winters et al. (2010), Chen et al. (2008), and Cao & Fan (2012). This outcome implies that in countries like China where population density and land use mix of cities are already much higher than those of western cities, increasing density and land use mix can still promote active and public transport while decreasing motor vehicle use, at least for locals. However, job density, intersection density, and bus stop density, which used to be proved significant affecting factors of walking and driving, are not significantly associated with locals’ walking or motor vehicle use frequency. It may serve as one more evidence for the significance of context. Xiamen resembles many other cities in China and differs from typical western cities in urban form and distribution and structure of urban functions and infrastructures. For example, jobs in Xiamen may be distributed much more evenly than those in western cities where jobs are largely concentrated in central areas (downtown), and hence the geographic variation of job opportunities in Xiamen may not be big enough to significantly impact local residents’ travel behaviors. Additionally, intersection density and bus stop density in Xiamen are far bigger than those of the western cities. Hence the geographic variation of the densities in urban area and suburbs are not big enough to significantly impact locals' walking and driving. Besides, after controlling for sociodemographic attributes, locals' cycling frequency is negatively associated with job density but positively correlated with distance to the closest commercial center. This finding echoes the results of Kemperman & Timmerman (2009) that people use their bicycles more often in less urbanized areas. It can be also due to the lack of infrastructure suitable for cycling (e.g., standard cycling lanes and parking space) in the central city, which is more densely populated and infrastructure supply per capita for users of various modes is comparatively low. Moreover, due to the fact that electric cycling usage is strictly restricted in *Siming* and *Huli* Districts according to the policy by Xiamen government.

Similar to locals, certain variables affect migrants' walking and motor vehicle use frequencies in the opposite direction. However, unlike that of locals, travel behavior of migrants, in general, is affected by their individual and household socioeconomic and demographic variables to a larger extent than the built environment variables. While age, gender, education background, occupation, and automobile ownership can well predict migrants' travel trip frequencies, the built environment variables seem to have only marginal impacts. On the one hand, this discrepancy between locals and migrants can be partly due to the fact that migrants have been in Xiamen for a much shorter period than locals, and the impacts and molding effects of Xiamen's built environment (urban form, structure, and distribution of infrastructure) on their lifestyle and travel preferences can be much less pronounced, settled and evident than those on locals. This finding, more or less, echoes the "transportation assimilation" process and the time lag effect (Blumenberg & Shiki, 2007b; Tal & Handy, 2010). On the other hand, most of the migrants are in the relatively lower socioeconomic status, with 71.6% of them employed by blue-collar jobs and more than two-thirds of them having no motor vehicle. Therefore, the constraining effect of the lack of transportation resources may outweigh the molding effect of the built environment in affecting the travel behavior of the migrants. Moreover, 82% of the migrants do not own an apartment in Xiamen (as presented in Table 5). Hence, a large proportion of the migrants are facing a tradeoff between housing rents and commuting costs (in terms of both time and money), and it is probably this kind of tradeoff that moderates the impacts of the built environment on migrants' travel behaviors.

The results also confirm the impacts of travel purposes on travel behavior. Both locals and migrants were less likely to commute on foot or by cycling. This indicates that as a transport mode, walking or cycling tend to be associated with non-commuting trips, which have fewer strict time constraints. Additionally, commuters who are locals are more likely to drive alone whereas this is not true for commuters who are migrants. This might imply that most migrants do not have access to private cars and thus .

This study builds on the findings of several prior studies, and it's worth discussing the differences and consistencies between this study and the prior ones. For example, a pioneer study by Guo et al. (2018) exploring the impacts of internal migration on the travel mode choice in China, inspires the authors to look into the differences of travel behaviors of migrants and locals in China. What distinguishes this study and Guo et al. (2018) is that this study focus more on the impacts of community built environment. Both studies find that migrants' families are characterized by relatively low motor vehicle ownership, forcing migrants to rely on walking and/or cycling. Guo et al. (2018) found that transit accessibility plays an important role in travel behavior whereas our study does not find this.

6. Conclusions

As a whole, this study contributes to the current literature by shedding some light on the significant differences between the travel behaviors of migrants and locals and their determinants, by using Xiamen, China as the empirical case and employing diverse statistical methods.

We confirmed that migrants are obviously in a relatively lower socioeconomic status than locals. Meanwhile, migrants made fewer trips than locals and were far more dependent on active and public transport. This implies that providing more desirable infrastructures for active and public transportation can not only promote the sustainability of the transportation system but also can better accommodate migrants' transportation demands and help them better fit into the city and thus mitigate the transport injustice against them.

In terms of the determinants of the travel behavior, locals and migrants are found to be different to a large extent. As for locals, most of the socio-demographic variables and built environment variables are significant determinants. However, when it comes to migrants, the travel behavior is more affected by the sociodemographic variables than the community built environment variables, probably due to the "transportation assimilation effect". Hence, urban and transportation planners and policy-makers should take the differences and discrepancies between locals and migrants into consideration and endeavor to make targeted policy interventions and avoid making decisions based on the voice of locals only.

Without any doubt, this study has some limitations. First, concerning the data. The travel data this study utilized were self-reported, and hence errors or inaccuracies may exist. Some frequently used variables such as income and dwelling density are not included due to the limitation of data. Fortunately, they can be partly represented and substituted by variables like occupation category and/or residence type and size or population density respectively. Also, psychological variables were not involved due to the lack of data. Second, trips by manual bikes and electric bikes were combined given a small number of observations in the raw data. Although electric bike usage also involves physical activity to a certain extent, similar to the manual bike, it is important to look into the respective influencers of these two travel modes. Third, this study is a cross-sectional study. It can only infer correlation rather than causality. In future studies, longitudinal or panel data about travel behaviors of migrants and locals can be utilized to deeply look into the impacts of the built environment on travel behaviors and derive corresponding causal relationships, and in the meantime, to further explore the "transportation assimilation process" and "time lag effects" of migrants in the context of developing countries such as China.

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