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# Effects of rural built environment on travel-related $CO_2$ emissions considering travel attitudes

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ABSTRACT

This study contributes to the understanding of the impacts of the rural built environment on travel-related $CO_2$ emissions by considering the mediating effects of household car ownership, travel frequency, travel distance, and individual travel attitudes through structural equation modeling. The travel data were collected from an activity diary survey in rural Sichuan. Geographic information system technology, combined with on-site measurement, was used to obtain data on the built environment. After controlling the socio-demographic factors, the model results corroborate that all built environment variables had significant total effects on car ownership, travel distance, travel frequency, and travel emissions. Specifically, residents living in the village with more accessible markets, higher roads, and higher building density travel a shorter distance and emit less $CO_2$. Meanwhile, residents living in the village with centralized living style and higher transit and destination accessibility travel less frequently but emit more $CO_2$. Individual travel attitudes have a limited effect on travel behavior and $CO_2$ emissions. This study suggests that planners and policymakers should consider shortening the distance between destination/transit and residential areas and increasing road and building densities. Moreover, promoting the construction of bicycling facilities and separate bicycle lanes to encourage rural residents to ride electric bicycles, bicycles, and motorcycles will reduce transport $CO_2$ emission in Chinese rural areas.

## 1. Introduction

Accumulated scientific evidence shows that climate change is a real and daunting threat to global human development (Stocker et al., 2013). Global climate change caused by energy consumption from human activities and related $CO_2$ emissions has attracted widespread attention from the international community (Ou et al., 2013; Solomon et al., 2007). Transportation is the fastest growing sector in terms of global energy consumption and $CO_2$ emissions (Agency, 2009; Yan and Crookes, 2009). According to the International Energy Agency (IEA), the global transportation sector produced 7001.1 Mt of $CO_2$ in 2011, accounting for 22.3% of all emissions and making it the second largest source of $CO_2$ emissions. Road traffic accounts for around three-quarters of the total $CO_2$ emissions from transportation (73.9%). China's transportation has a relatively low proportion of $CO_2$ emissions but ranks second only to the United States (Statistics, 2011). This situation means that China faces enormous challenges in reducing carbon emissions from transport (Yang et al., 2015). By the end of 2015, China's energy production and energy consumption were 2.93 and 2.61 times that

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in 2000, respectively. Meanwhile, the number of car ownership per 100 rural households in China in 2016 was 13.18 times the number in 2000. Reducing $CO_2$ emissions from transport is the primary way to achieve climate change mitigation goals (Ma et al., 2015), and transportation is supposed to be the most challenging sector in terms of reducing $CO_2$ emissions (Brand et al., 2012; Marsden and Rye, 2010). Numerous studies have investigated the relationship between transport planning and individual travel behavior (Cao et al., 2009; Cao and Yang, 2017; Ding et al., 2017b; Handy et al., 2005; Li and Zhao, 2017; Liu et al., 2016; Sun et al., 2017). Several investigations related to mobility have demonstrated the validity and importance of these relationships through empirical research (Bamberg et al., 2003; Haustein and Hunecke, 2007; Heath and Gifford, 2002; Schoenau and Müller, 2017; Thorhauge et al., 2016). Scholars have affirmed that high population density, mixed land use, and pedestrian-friendly street designs are positively related to small numbers of vehicles, short travel distances, and reduced motor vehicle travel (Ewing and Cervero, 2010; Ewing et al., 2015; Khattak and Rodriguez, 2005; Krizek, 2003).

China is in a process of rapid urbanization and new rural construction. However, all studies in relation to the relationship among the built environment, travel behavior, and travel-related $CO_2$ emissions focused on large cities in China, such as Beijing, Guangzhou, Shanghai, and Nanjing (Cao and Yang, 2017; Liu et al., 2016; Ma et al., 2015; Yang et al., 2015). The scale of China's rural urbanization and new rural construction is unprecedented. The interrelationship among rural space reorganization, rural resident travel attitudes, travel behavior, and travel-related $CO_2$ has undergone profound changes. Exploring the relationship among them is crucial for the further establishment of a new ecological and low-carbon countryside and fills the abovementioned research gap.

Therefore, this study focuses on rural areas in Sichuan, China, and explores the direct and indirect impacts of China's rural built environment on travel $CO_2$ emissions. The residents' psychological factors are considered in this work. The structure of this paper is as follows. Section 2 explains the methodology used in this research, data collection, and variable specification. The results and discussion of the structural equation model (SEM) are presented in Section 3. The conclusions and policy implications are summarized in Section 4.

## 2. Literature review

Built environment exerts a significant influence on travel behavior and transport carbon emissions (Hankey and Marshall, 2010). The built environment is measured by the D variable. With the accumulation of relevant research, the built environment measurement indicator has developed from 2D to 4D and is now widely accepted as 6D (Ewing and Cervero, 2001, 2010; Ewing and Handy, 2009; Ewing et al., 2015; Vance and Hedel, 2007). The "6Ds" of the built environment, namely, density, diversity, design, destination accessibility, distance to transit, and demand management, have been widely utilized (Ewing and Cervero, 2001, 2010; Ewing and Handy, 2009; Ewing et al., 2015; Vance and Hedel, 2007). Travel behaviors are measured in many ways, including travel mode, distance, frequency, purpose, and time (Boarnet, 2011; Ewing and Cervero, 2001, 2010; Handy et al., 2005). Overall, scholars have found that high population density, mixed land use, and pedestrian-friendly street designs are positively related to small numbers of vehicles (Brownstone and Golob, 2009; Ewing and Cervero, 2010), short distances (Ewing et al., 2015; Khattak and Rodriguez, 2005), and reduced motor vehicle travel (Krizek, 2003; Modarres, 2013) because compact and high-density urban forms promote public transport development and reduce the use of private cars (Ewing, 1997; Kenworthy and Laube, 1996). For example, Ding et al. (2014) discovered that job density in urban centers is important in reducing travel $CO_2$ emissions compared with the situation in household dwelling areas. Hong (2017) found a nonlinear relationship between density and transport $CO_2$ emissions. However, the relationship between $CO_2$ emission and population density is not significant to some extent. In other studies, the correlation between residential density and transport $CO_2$ emissions is not significant (Barla et al., 2011; Jiang et al., 2011; Xiao et al., 2011). Moreover, increasing road capacity is a viable means to increase energy efficiency in transportation and reduce related emissions. However, Shim et al. (2006) revealed an inverse relationship between transport energy consumption and road density in their study of 61 small and medium-sized cities in South Korea. Improvements in road capacity may encourage rampant driving, which may increase $CO_2$ emissions. Ma et al. (2015) examined commuting travel data in Beijing and found that subway accessibility is negatively correlated with $CO_2$ emissions. Another study in China showed that the proportion of bus travel has a significant negative impact on $CO_2$ in transportation (Su et al., 2011). Ribeiro and Balassiano (1997) reported that $CO_2$ emissions from private cars used for daily commute are nearly eight times higher than those from public transport. Yang et al.'s (2015) study indicated that a significant negative relationship exists between urban public transportation and per capita $CO_2$ emissions from transportation. Therefore, public transport plays a key role in reducing carbon emissions. Zahabi et al. (2012) discovered that if density, transit accessibility, and land use mix index are increased by 10% separately, travel-related greenhouse gas emissions will decrease by 0.5%, 5.8%, and 2.5%, respectively. Zhao (2010) found that the urban sprawl in Beijing's urban borders increases travel distance and car use, leading to increased emissions. Moreover, parking service as the 6th D variable (demand management) has an impact on $CO_2$ emissions as well. Researchers have found that low-cost parking lots are correlated with high $CO_2$ emission due to car ownership (Guo, 2013; Tyrinopoulos and Antoniou, 2013).

However, most of the studies above focused on the urban built environment. Only a few researchers have investigated the rural household travel behavior associated with $CO_2$ emission. Dargay (2002) reported that car ownership by rural households is much less sensitive to car costs than car ownership by urban households. Therefore, measures to control travel-related $CO_2$ emissions in rural areas through car use cost are not necessarily appropriate for rural areas. Moreover, a study showed that Chinese rural residents have a strong desire to own a car due to the lower rate of household car ownership compared with urban dwellers, and this will lead to a rapid increase in the number of cars in rural areas (Zhu et al. 2012). Christie and Fone (2003) used data from Wales and found that although car ownership is related to household income level, no evidence indicates that low-income households in rural areas own fewer cars than those in urban areas. This result indicates that car ownership is minimally correlated with household income. Once rural residents have cars, they become increasingly dependent on their cars because of the few alternative transport modes available, which will increase travel-related $CO_2$ emissions in rural areas (Wang et al., 2011).

Meanwhile, a few studies have focused on travel mode analysis in rural China. As for the choice of travel mode, rural residents in different regions have slightly different choices. Rural residents in Haining, Zhejiang, prefer electric bicycles to cars and walking (Kong and Yao, 2015), whereas rural residents in northern Jiangsu prefer electric bicycles, followed by walking and motorcycles (Chen and Zhu, 2013). Children and elderly people with limited mobility needs are the major residents in rural areas because most of the young population are working outside the rural area. Therefore, rural residents have fewer trips and lower travel $CO_2$ emissions compared with urban residents (Yang et al., 2014). For rural households, literature has found that socio-demographic characteristics influence travel-related $CO_2$ emission, similar to the situation for urban households. Specifically, men, middle-aged individuals, and elderly people who live in rural areas and own bicycles have a significant but weak association with $CO_2$ emissions (Brand et al., 2013).

The studies above investigated the effects of the built environment on $CO_2$ emissions but did not consider psychological determinants, such as preference and personal attitudes. Only a few studies have considered these perspectives (Ao et al., 2019; Belgiawan et al., 2014). These studies have found that significant differences exist between developed and developing countries in terms of car purchase motivation. The expectation of others exerts substantial impacts on purchase intention in developing countries. Attitude is an essential determinant factor for driving and commuting intentions in developed countries. People view the car as a symbol of wealth, which may decide their travel mode. Environment attitudes may influence private car purchase decisions.

In summary, the studies above did not reach a consistent conclusion. This scenario indicates that the impacts vary from country to country, and this variation might be related to attitudes and preferences. Compared with Western countries, urban residents in China have particular travel-related attitudes and preferences (Wang and Lin, 2014). In addition, a massive difference in the built environment exists between urban and rural areas in China. For example, rural households cannot select residential locations according to their preferences because of the fixed homestead location, which is contrary to urban households in China. With the rapid development of new rural construction and urbanization, great changes have taken place in China's rural built environment. However, in China, all related studies on the relationship among the built environment, travel behavior, and travel $CO_2$ emissions were conducted in China's first-tier or second-tier cities, such as Shanghai, Nanjing, Guangzhou, and Beijing (Cao and Yang, 2017; Liu et al., 2016; Ma et al., 2015; Yang et al., 2015). Research on rural areas is lacking. The scale of China's rural urbanization and new rural construction is unprecedented. The interrelationship among rural space reorganization, rural residents' travel attitudes, travel behavior, and travel-related $CO_2$ emissions has undergone profound changes. Exploring the relationship among them has significant impacts on the further establishment of a new ecological and low-carbon countryside. In addition, most existing studies only considered the direct impact of the built environment on $CO_2$ emission from daily traveling; they ignored the indirect effects of the built environment, which may affect other variables and ultimately influence travel-related $CO_2$ emissions (Cao and Yang, 2017).

## 3. Methodology

### 3.1. Model specification

Two models were applied in this study. First, exploratory factor analysis (EFA) was used to reduce data to a small number of non-related comprehensive variables. EFA identified the structure of the relationship between the variables and obtained the important and common travel attitudes. Second, the EFA result was used in the structural equation model (SEM) to investigate the influence of travel attitudes on travel behavior and travel-related $CO_2$ emissions.

SEM is a research technique that has been used in its present form since the 1970s. This technique is widely utilized in the majority of qualitative research in psychology, sociology, biological sciences, education research, political science, and marketing (Van Acker et al., 2007). Recently, SEM was used to explore the complex effects of the built environment on travel behavior (Cao and Yang, 2017; Liu et al., 2016; Ma et al., 2015; Van Acker et al., 2007). SEM can solve endogeneity problems between variables, and it can analyze the indirect, direct, and total effects between exogenous and endogenous variables (Glaser, 2001; Jahanshahi and Jin, 2016; Jahanshahi et al., 2015; Kline and Santor, 1999). The variables used in this study were all observational. SEM without latent variables can be defined as follows:

$$y = By + \Gamma x + \xi$$

The definitions of the letters in the formula above are as follows:
$y$ – vector of endogenous variables;
$x$ – vector of exogenous variables;
$B$ – matrix of coefficients representing the effects of endogenous variables on each other;
$\Gamma$ – matrix of coefficients representing the effects of exogenous on endogenous variables;
$\xi$ – vector of errors.

The conceptual framework based on SEM is shown in Fig. 1. The socio-demographic attributes and built environment affect household car ownership, travel behavior (e.g., travel frequency and distance), and $CO_2$ emission from daily traveling. Several existing studies used travel frequency, travel distance, and car ownership as dependent variables to explore the effects of socio-demographic attributes and the built environment. In addition, studies on travel-related $CO_2$ emissions typically defined travel

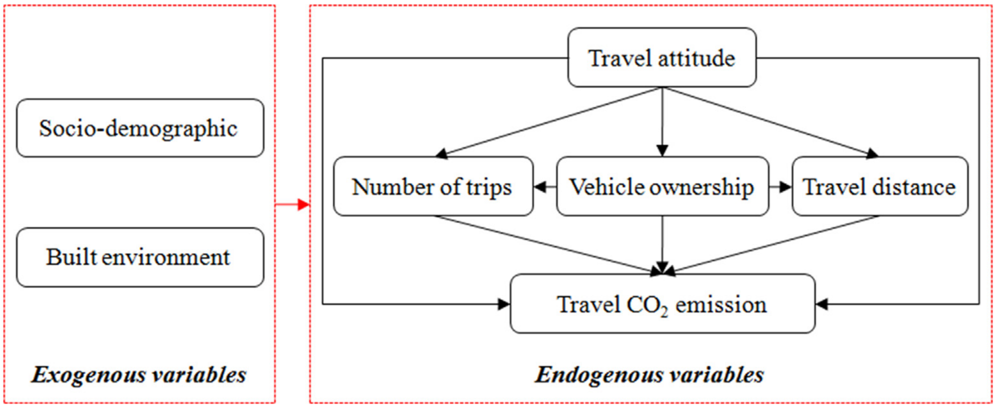


**Fig. 1.** Conceptual framework for SEM analysis.

frequency and distance, household car ownership, socio-demographic information, and built environment as exogenous variables but ignored their endogeneity. However, based on literature, we found that travel behavior and car ownership have a significant impact on $CO_2$ emissions from daily traveling. $CO_2$ emissions are affected by socio-demographic variables and the built environment as well (Van Acker and Witlox, 2010; Yang and Cao, 2018). Therefore, this study adopted travel frequency, travel distance, and car ownership as intermediary variables to explore the mediating effects of the built environment and socio-demographic characteristics on travel-related $CO_2$ emissions. Car ownership also affects travel frequency and travel distance (Van Acker and Witlox, 2010). People with different socio-demographic attributes choose various built environments due to residential self-selection. Many studies have considered the impact of socio-demographic attributes on the built environment (Ding et al., 2017a; Ma et al., 2015; Yang and Cao, 2018). However, Chinese rural residents have limited freedom to select their residential location because of the fixed homestead location in China. Therefore, this study did not consider the influence of socio-demographic attributes on the built environment but considered that travel attitudes directly affect travel behavior and travel emissions. Then, we assumed that different travel conditions and rural residents have unique travel preferences and attitudes in rural China. We also assumed that the built environment and socio-demographic attributes directly affect travel attitudes.

### 3.2. Sample selection and data collection

The data collection was implemented in Sichuan rural areas. Rural areas can be divided into three categories based on living places. The first category is scattered living places, which is the traditional way of living in Sichuan rural areas. The infrastructure has been dramatically improved in the last decades; however, the living places are still the same. The second category is new-style living spaces. The traditional residential patterns in the countryside have been changed by moving rural residents to concentrated living spaces in rural areas. They often occupy agricultural land as well. The third category is the mixture of traditional- and new-style living spaces. It is normally a transition stage from traditional living to new-style living spaces.

#### 3.2.1. Sample selection

Based on our experiences in data collection in Sichuan rural areas and the purpose of this research, we selected sample village areas that satisfy the following criteria. (1) The area should have the necessary road infrastructure that can be used by vehicles, including buses. A road should be connected to at least one highway/freeway/motorway, which can be used by personal vehicles. (2) The residents in the rural area should support the research and are willing to cooperate for a survey or interview. We found that if a person in our research team came from the village, then obtaining support from the residents would be easy.

Based on the two criteria, we organized the sample village selection in four steps (see Fig. 2) . First, we recruited volunteer students who are from Sichuan rural areas and interested in this research (1st Oct. 2017 to 31st Oct. 2017). To minimize knowledge barriers, we recruited students studying in the Environmental and Civil Engineering Department of Chengdu University of Technology. The purpose was to have at least one person in each sample village to set up communication with residents in the village. In total, 117 students submitted their applications. With the criteria mentioned above, a pre-selection was carried out, and 37 rural village areas were selected. Second, intensive training was organized for the recruited students (1st Nov. 2017 to 10th Nov. 2017). We held discussions with the students to determine if the pre-selected rural village areas are suitable for this research. After the training and examination, 14 pre-selected rural village areas were eliminated. Third, we established a connection with the village communities from the pre-selected rural village areas (10th Nov. 2017 to 120th Nov. 2017). We asked if the residents are willing to cooperate and whether the research team can approach them or not. After the discussion, only 10 pre-selected village communities provided consent. Lastly, we organized pre-interview groups for 1–2 residents living in each approved rural village area to understand the residents' willingness to cooperate (21st Nov. 2017 to 10th Dec. 2017). We found that residents were unwilling to assist and showed precaution from Helin Village (Chongren Town, Dongpo District, and Meishan City), Nanliu Community (Huangshui Town, Shuangliu District, and Chengdu City), and Shiguan Village (Sanshui Town and Guanghan City). In the end, seven rural village areas

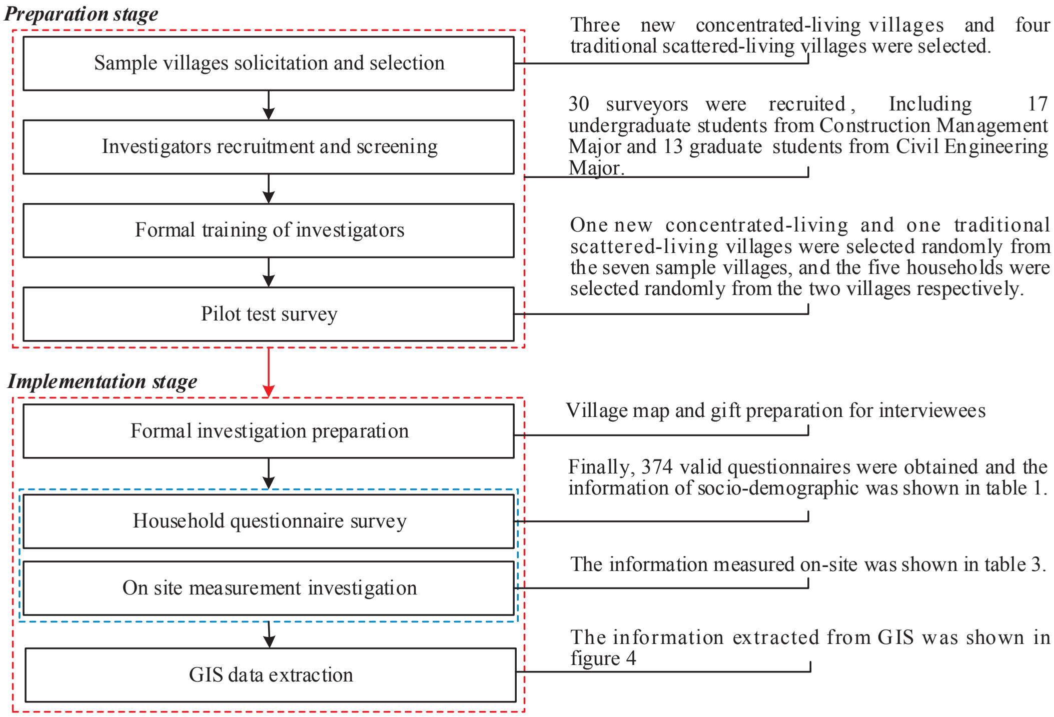


**Fig. 2.** Data and sample collection flowchart.

were selected for the data collection. The seven rural village areas covered 16,953 individuals and 5888 households.

#### 3.2.2. Data collection

Three types of data were collected in this study, and these are GIS, field measurement, and individual data. GIS and field measurement data were collected for built environment measurement. A huge difference exists between the built environment in rural and urban areas, especially traditional rural living areas. Therefore, we pre-defined a few rules to measure the built environment. For the new-style living spaces in rural areas, we measured the built environment by using the village committee office as the center point and with 1 km as the radius. For the traditional-style living areas, the village committee office was set at the center location. The built environment indicators were calculated based on the data on the natural boundary of the village. The main reason is that the scattered rural areas in Sichuan vary greatly. Using a 1 km radius to measure the area is impossible. Based on the definitions, we used Arcgis 10.2 to obtain building and road information. However, the GIS data for rural areas in China are very limited. Field measurement is necessary for collecting objective built environment information. All interviewees were equipped with the same Baidu navigation system. They used the navigation system to measure the driving distance between the center of the village and the nearest public transport stations (bus, coach, and train), main subway/freeway/motorway, open market/supermarket, school, hospital, and administration center of the city/town.

Individual information was collected via a face-to-face interview. The household survey contained a list of socio-demographic variables, including individual and household information that may help explain travel behavior decisions. We executed the data collection via a household questionnaire survey. A total of 560 questionnaires were distributed, and 413 were collected back. Owing to the missing data, 39 out of the 413 questionnaires could not be used for the analysis. In the end, 374 valid questionnaires were used from the seven rural village areas. The survey covered 1758 individuals. The survey sample distribution matched the rural population in Sichuan and China well, as shown in Table 1. The socio-demographic distribution of the sample is listed in Table 2. The data of the on-site measurement are shown in Table 3. The sample area location is shown in Fig. 3, and the GIS data are presented in Fig. 4.

### 3.3. Calculation of $CO_2$ emissions

This study used Cao and Yang's (2017) formula to calculate travel-related $CO_2$ emissions, as shown below.

$$CE_{ij} = Distance_{ij} \times E\_factor_{ij}$$

where $CE_{ij}$ represents $CO_2$ emissions from a trip using mode $j$ for respondent $i$, $Distance_{ij}$ is the distance with mode $j$ for respondent $i$, and $E\_factor_{ij}$ is the emission factor of travel mode $j$ for respondent $i$.

The emission factor data of different transport modes are unavailable for rural areas. By referring to various studies and reports (more details can be seen in Table 4) (Entwicklungsbank, 2008; Proost et al., 2006; Yang et al., 2018; Cai and Xie, 2010; Xiao et al.,

**Table 1**
Sample vs. population characteristics.

| | Household[a] | Village[a] | Rural Sichuan[b] | Rural China[b] |
|---|---|---|---|---|
| Total population | 1758 | 16,953 | 419.6 2016:Billion | 5897.3 2016:Billion |
| Total number of households | 374 | 5888 | – | – |
| Average household size | 3.71 | 2.88 | 3.03 (2015) | 3.88 (2012) |
| Per capita income (10 k yuan) | 1.36 | – | 1.13 (2016) | 1.24 (2016) |
| Average household income (10k yuan) | 4.44 | – | – | – |

[a] Data from face-to-face household survey between 16th December 2017 and 5th January 2018.
[b] Source: China Statistical Yearbook (2013, 2016, and 2017).

**Table 2**
Distribution of socio-demographic information.

| Variables | Level | Number of sample | Percent |
|---|---|---|---|
| Male | 0 for female | 226 | 60.43 |
| | 1 for male | 148 | 39.57 |
| Age | 1 represent age 16–25 | 47 | 12.57 |
| | 2 represent age 25–40 | 65 | 17.38 |
| | 3 represent age 41–50 | 112 | 29.95 |
| | 4 represent age 51–60 | 80 | 21.39 |
| | 5 represent age 61–70 | 70 | 18.72 |
| Driving certificate | o for no driving certificate | 279 | 74.60 |
| | 1 for have driving certificate | 95 | 25.40 |
| Ride a motorcycle | 0 for cannot ride a motorcycle | 229 | 61.23 |
| | 1 for can ride a motorcycle | 145 | 38.77 |
| Ride a bicycle | 0 for cannot ride a bicycle | 108 | 28.88 |
| | 1 for can ride a bicycle | 266 | 71.12 |
| Ride electric bicycle | 0 for cannot ride an electric bicycle | 137 | 36.63 |
| | 1 for can ride an electric bicycle | 237 | 63.37 |
| Income (ten thousand yuan) | 1 represents 0 | 116 | 31.02 |
| | 2 represents 0–0.5 | 38 | 10.16 |
| | 3 represents 0.5–1 | 80 | 21.39 |
| | 4 represents 1–2 | 60 | 16.04 |
| | 5 represents 2–4 | 59 | 15.78 |
| | 6 represents > 4 | 21 | 5.61 |

**Table 3**
Data measured on-site.

| Name of villages | Distance to the nearest bus station (KM) | Distance to the nearest train station (KM) | Distance to the nearest public transportation station (KM) | Distance to the nearest main road (KM) |
|---|---|---|---|---|
| Dazhuang (DZ) | 18.20 | 19.90 | 2.50 | 2.50 |
| Wugang (WG) | 0.20 | 70.00 | 16.00 | 0.00 |
| Shuangyan(SY) | 16.30 | 13.40 | 0.50 | 0.50 |
| Xinlong (XL) | 13.40 | 13.40 | 1.20 | 0.80 |
| Dongxing (DX) | 3.90 | 16.40 | 3.90 | 0.50 |
| Shangten g(ST) | 22.40 | 24.80 | 0.69 | 0.69 |
| Yanjing (YJ) | 0.50 | 125.00 | 34.00 | 0.50 |

| Name of villages | Distance to the nearest market (KM) | Distance to the nearest school (KM) | Distance to the nearest hospital (KM) | Distance to the nearest city centre (KM) |
|---|---|---|---|---|
| Dazhuang (DZ) | 3.00 | 0.50 | 0.05 | 19.60 |
| Wugang (WG) | 3.50 | 2.50 | 0.20 | 16.00 |
| Shuangyan(SY) | 1.60 | 1.60 | 0.60 | 13.50 |
| Xinlong (XL) | 0.80 | 3.00 | 4.90 | 4.90 |
| Dongxing (DX) | 0.00 | 2.10 | 0.00 | 10.00 |
| Shangteng (ST) | 1.50 | 1.50 | 1.60 | 14.00 |
| Yanjing (YJ) | 1.50 | 0.50 | 1.70 | 35.00 |

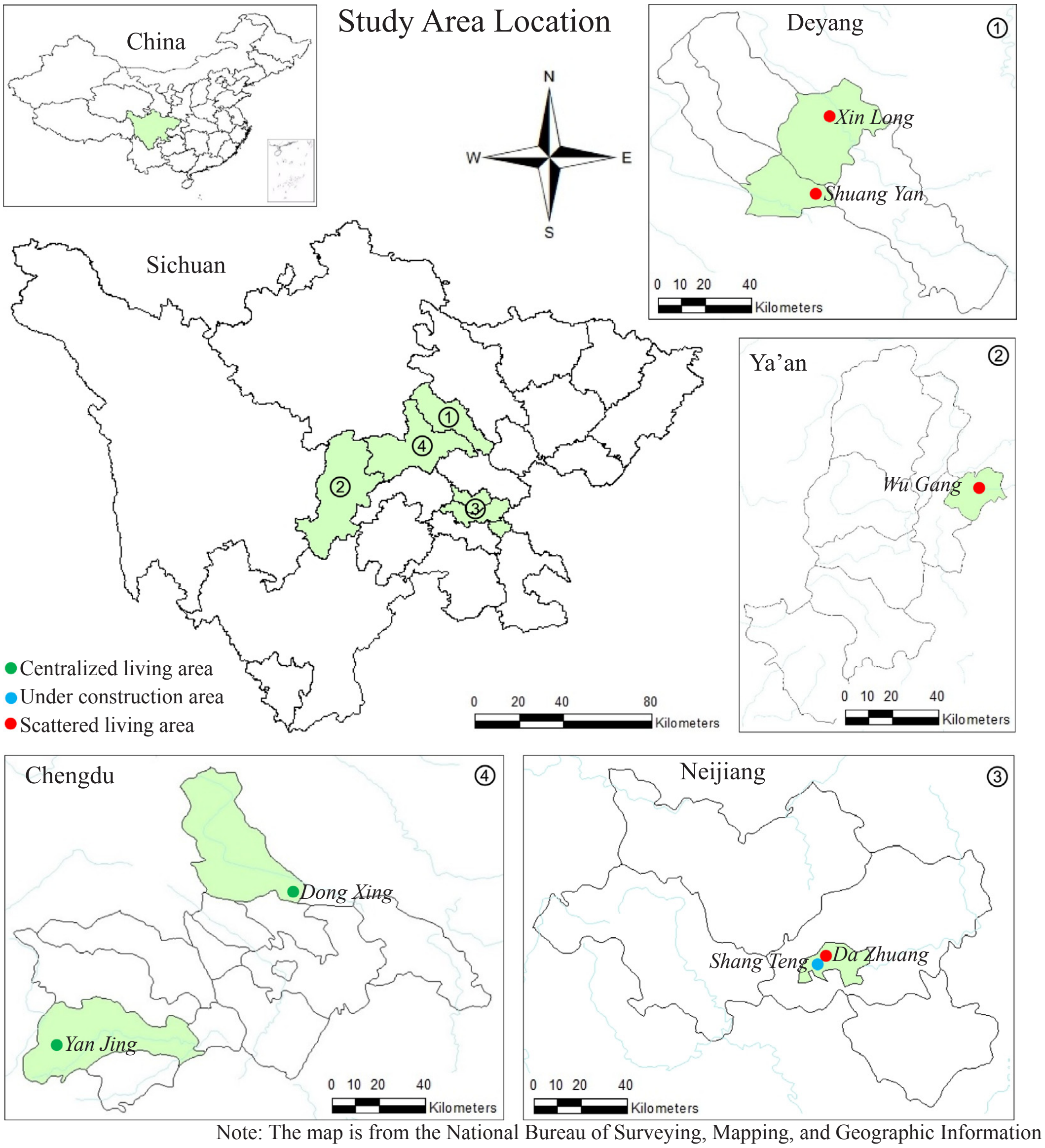


**Fig. 3.** Map of the study area's location.

2011) and in accordance with the relative intensity of energy consumption and carbon emission for each transport mode, we used the following emission factors in this study, as shown in Table 4.

### 3.4. Variable specification

#### 3.4.1. Socio-demographic variables

Travel behavior and travel-related $CO_2$ emissions are influenced by socio-demographic variables, as proven by literature. In this study, based on literature, eight variables were included in the final model. These variables are gender, age, income, driving license ownership, ability to drive a motorcycle, ability to drive an electric bicycle, and ability to ride a bike.

#### 3.4.2. Travel attitude variables

To explore the effects of travel attitudes on travel behavior and travel-related $CO_2$ emissions, 30 statements on travel attitudes were provided in the questionnaire (Cao et al., 2007; He and Thøgersen, 2017). A Likert scale ranging from 1 to 5 was used, wherein 1 signifies "completely disagree" and 5 means "completely agree." The respondents were asked to assess the 30 statements based on their attitudes. To identify the important broad attitudes, EFA was applied using SPSS 23.0. The Kaiser–Meyer–Olkin (KMO) measure was used to test the suitability for EFA, and Bartlett's test was applied to examine the factorability of individual attitude variables.

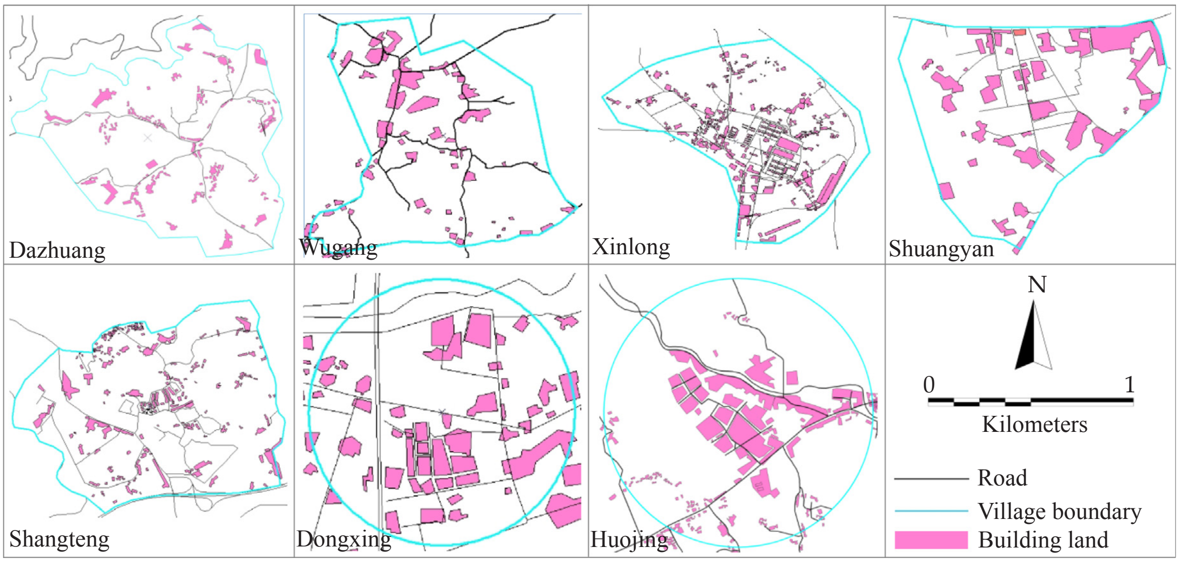


**Fig. 4.** GIS information on road and building land.

**Table 4**
Emission factors of different travel modes (kg $CO_2$/person·km).

| Walk, bike | Electric bike | Bus | motorcycle | car | Coach | references |
|---|---|---|---|---|---|---|
| – | – | 0.026 | – | 0.0606 | 0.0203 | Entwicklungsbank (2008) |
| 0 | – | 0.0738 | 0.01136 | 0.01786 | – | Proost et al. (2006) |
| 0 | 0.008 | 0.035 | – | 0.126 | – | Yang et al. (2018) |
| 0 | 0.008 | 0.035 | – | 0.135 | – | Xiao et al. (2011) |
| – | – | – | 0.0472 | – | – | Cai and Xie (2010) |
| 0 | 0.008 | 0.035 | 0.0472 | 0.126 | – | Selected in this research |

**Table 5**
Travel attitude component analysis.

| Statements | Component | | | | | |
|---|---|---|---|---|---|---|
| | pro_wb | pro_Eb | pro_Ab | less_out | use_cost | buy_cost |
| Cycling exercises your body | 0.762 | | | | | |
| Cycling is a low-carbon, environmentally friendly travel mode | 0.767 | | | | | |
| Bicycle parking is convenient | 0.738 | | | | | |
| The low cost of bicycle purchase and use poses no economic burden at all | 0.588 | | | | | |
| Quick and easy to walk | 0.602 | | | | | |
| Walking exercises your body | 0.742 | | | | | |
| Walking is a low-carbon and environmentally friendly travel mode | 0.724 | | | | | |
| It is quick and easy to ride electric bicycles | | 0.769 | | | | |
| It is safe and environmentally friendly to ride electric bicycles | | 0.828 | | | | |
| The low cost of electric bicycle purchase and use poses no economic burden at all | | 0.591 | | | | |
| Electric bicycle parking is convenient | | 0.586 | | | | |
| It is safe and environmentally friendly to ride motorcycles | | | 0.523 | | | |
| The low cost of motorcycle purchase and use poses no economic burden at all | | | 0.771 | | | |
| Motorcycle parking is convenient | | | 0.696 | | | |
| I often make reasonable arrangements to minimize the number of outings | | | | 0.726 | | |
| For problems that can be resolved by the telephone or the Internet, they will not be resolved on site. | | | | 0.793 | | |
| The price of gasoline affects my choice of travel mode | | | | | 0.739 | |
| Parking costs are high everywhere, and driving is not worthwhile | | | | | 0.754 | |
| There is no economic pressure to buy a car | | | | | | 0.811 |
| Eigen value | 5.181 | 1.930 | 1.474 | 1.285 | 1.176 | 1.079 |
| Proportion of variance explained | 20.311 | 11.500 | 10.185 | 8.623 | 7.274 | 5.922 |
| Cumulative variance explained | 20.311 | 31.811 | 41.996 | 50.618 | 57.892 | 63.814 |

**Table 6**
Built environment variables used in this study.

| Variable | Calculation method |
|---|---|
| Road density | Total length of roads (m)/total surveyed area (hectares) |
| Building density | Building land area ($m^2$)/total surveyed area ($m^2$) |
| Transit accessibility | $\sum_k [1/(d_k + 1)]$, where $k$ = 1, 2, 3, 4 and $d_k$ represents the distance from the village center to the nearest bus station, train station, public transportation station, and main road |
| Destination accessibility | $\sum_k \left[\frac{1}{d_k+1}\right]$, where $k$ = 1, 2, 3, 4 and $d_k$ represents the distance from the village center to the nearest market, school, health center (hospital), and city (county) center |
| Living style | Respondents living in traditional scattered areas were measured at 0, whereas those in centralized areas were measured at 1 (only two types of living style existed in the sample villages) |
| Number of accessible markets | The number of accessible markets was obtained from the face-to-face questionnaire survey according to actual statistical data; this variable is expressed in ordinal numbers |

The final result of KMO was 0.806, and the P value of 0 confirms that high correlations exist among the attitude variables. EFA must be used to identify the main factors. The results of EFA are shown in Table 5. We eliminated the variables with a factor loading below 0.5. Finally, six travel attitude factors were identified, and they accounted for 63.814% of the variance. That is, only 36.186% loss in information was incurred by the 80.0% reduction in the number of variables. Accordingly, the obscure concepts of “travel attitude” can be interpreted and represented well.

#### *3.4.3. Built environment variables*

Six built environment variables were calculated and selected in this study according to the actual situation in rural Sichuan; these variables are road density, building density, transit accessibility, destination accessibility, living style, and number of accessible markets. Road and building density were calculated from the GIS extraction data, which are shown in Fig. 4. Transit and destination accessibility were calculated from the on-site measurement data used the Baidu navigation application, which is shown in Table 3. The calculation methods of road density, building density, transit accessibility, and destination accessibility are presented in Table 6 and can also be found in our previously published papers (Ao et al., 2018, 2019). The living style of rural residents is defined as the spatial form of different villages in this study according to the actual situation in rural Sichuan. The living style of rural residents is categorized into two types, which are scattered and centralized living styles. The shift from traditional scattered living style to centralized living style occurs gradually due to urbanization in China. It directly influences rural residents’ decisions on travel behavior and travel-related $CO_2$ emissions. Therefore, based on the current living situation, we set the living style for the seven sample villages as 0 for the traditional scattered living style and 1 for the centralized living style. Markets are the center of transactions in rural areas. Therefore, it is important to determine if the number of accessible markets has an impact on rural travel behavior and travel-related $CO_2$ emissions. The number of accessible markets was obtained from the face-to-face questionnaire survey. The actual built environment of the seven villages photographed by the researchers is shown in Fig. 5.

#### *3.4.4. Travel-related variables*

All travel-related data were collected from an activity diary survey, in which respondents were asked to record two entire days of activity from 30th December 2017 to 5th January 2018. We considered three travel-related variables, namely, frequency, distance, and travel-related $CO_2$ emissions. Then, we obtained 1042 trips with average frequency, distance, and $CO_2$ emissions of 1.393 times, 6.359 km, and 0.343 kg per person per day, respectively. On the average, each household has 0.540 cars (Table 7). Compared with the average travel-related $CO_2$ emissions of 1.91 kg/person · day in Chinese urban areas (Liu et al., 2016), the average $CO_2$ emissions of rural residents was lower.

Out of the 1042 trips collected in this study, 49.81% were conducted by walking. The electric bike was the second most commonly used transport mode (17.18%). Car trips accounted for 9.88% of the total trips. Motorcycles and bicycles accounted for 8.16% and 5.85% of all trips, respectively (Table 8). The current sample is similar to that of Kong and Yao (2015), who reported that electric bikes are more preferred than cars.

## 4. Results and discussions

### *4.1. Goodness-of-fit for SEM*

Amos 21.0 was used to estimate the conceptual SEM. This study adopted the Bollen–Stine bootstrap estimation method, and the number of bootstraps was set to 1000 (Yang and Cao, 2018). Links with no statistical significance ($P > 0.1$) were removed, and the model was re-estimated. The model was modified and improved according to the modification indices (MI). Table 9 presents the goodness-of-fit statistics of the final model and the corresponding reference values. The degree of freedom in the final model is 120, whereas the minimum fit function $\chi^2$ is 167.555. All indicators suggest that the model fits the data well.

Tables 10 and 11 present the results of SEM, which indicate that all socio-demographic attributes and built environment variables significantly influenced travel behavior and travel-related $CO_2$ emissions. However, only three of the six travel attitude variables had


**Fig. 5.** Actual built environment of the seven villages.

**Table 7**
Information on travel behavior variables and $CO_2$ emission for the sample villages.

| Name of villages | Mean values | | | |
|---|---|---|---|---|
| | number of trips (Number) | distance traveled (KM) | Car ownership (Number) | $CO_2$ emission (kgce) |
| Dazhuang | 1.482 | 6.648 | 0.333 | 0.285 |
| Wugang | 1.277 | 6.364 | 0.702 | 0.419 |
| Shuangyan | 0.858 | 7.525 | 0.447 | 0.425 |
| Xinlong | 2.148 | 5.577 | 0.328 | 0.106 |
| Doxing | 0.957 | 3.713 | 0.862 | 0.122 |
| Shangteng | 1.092 | 3.640 | 0.490 | 0.140 |
| Yanjing | 1.988 | 12.751 | 0.675 | 1.142 |
| All samples | 1.393 | 6.359 | 0.540 | 0.343 |

**Table 8**
Information on the 1042 trips.

| | Car | Motorcycle | Electric bike | Bicycle | Walking | The others |
|---|---|---|---|---|---|---|
| Travel frequency | 103 | 85 | 179 | 61 | 519 | 95 |
| Frequency ratio | 9.88% | 8.16% | 17.18% | 5.85% | 49.81% | 9.12% |

**Table 9**
Goodness-of-fit statistics of the SEM model.

| Model fit indices | Values of our model | Reference value |
|---|---|---|
| Chi-square | 167.555 | |
| Degress of freedom (df) | 120 | |
| Probability level | 0.003 | < 0.05 |
| Goodness of Fit Index (GFI) | 0.962 | > 0.9 |
| Adjusted Goodness of Fit Index (AGFI) | 0.92 | > 0.9 |
| Comparative Fit Index (CFI) | 0.987 | > 0.9 |
| Normed Fit Index (NFI) | 0.958 | > 0.9 |
| Non-Normed Fit Index (NNFI) | 0.976 | > 0.9 |
| Root Mean Square Error of Approximation (RMSEA) | 0.033 | < 0.05 |

significant impacts on travel behavior and travel-related $CO_2$ emissions.

### *4.2. Effects of the rural built environment on endogenous variables*

Fig. 6 indicates that destination accessibility had significantly positive and direct effects on motorcycle riding attitude (0.932), travel distance (0.349), and rural household car ownership (1.14). Furthermore, it negatively and indirectly affected travel frequency (−0.515) and travel-related $CO_2$ emissions (−0.059). Destination accessibility had positive and indirect impacts on travel frequency through motorcycle riding attitude (0.068) and household car ownership (0.136), which weakened the direct negative impact of destination accessibility on travel frequency. However, the total effect remained negative (−0.311). Similarly, destination accessibility had an indirectly negative effect on travel-related $CO_2$ emissions through “motorcycle riding attitudes → travel frequency” (−0.010) and “household car ownership → travel frequency” (−0.020). Destination accessibility also exerted an indirectly positive effect on travel-related $CO_2$ emissions through travel frequency (0.075), household car ownership (0.09), and travel distance (0.265). This effect ultimately weakened the directly negative effect of destination accessibility on travel $CO_2$ (−0.059), which made the total effect of destination accessibility on travel-related $CO_2$ emissions positive (0.342). The total positive effect of destination accessibility on travel distance, household car ownership, and $CO_2$ emission from daily traveling is in contrast to the conclusions of a previous study on Chinese urban areas (Ma et al., 2015). China is undergoing rapid rural urbanization and new rural construction. Although this unprecedented development speed has increased destination accessibility in rural areas, the distance from residential areas to the main destinations (nearest hospital, school, city or county center, and market) remains large. The improvement of rural road capacity increased rural household car ownership and driving distance, which ultimately increased travel-related $CO_2$ emissions. However, rural residents’ daily travel-related $CO_2$ emissions remain significantly lower than those of urban residents (Liu et al., 2016).

Road density had significantly direct and positive effects on motorcycle riding attitude (0.28) and household car ownership (0.223), but travel distance (0.159) had a negatively and directly impact on travel frequency (−0.269). In addition, road density indirectly and negatively affected travel-related $CO_2$ emissions through “motorcycle riding attitude → trip frequency” (−0.003), “household car ownership → trip frequency” (−0.004), and travel distance (−0.121). In addition, it exerted an indirect and positive effect on $CO_2$ emission from daily traveling through frequency (0.039) and household car ownership (0.018). Moreover, the total effect of road density on travel $CO_2$ emissions was negative (−0.071) (Table 10). The effects of road density on travel behavior and

**Table 10**
Standardized effects of exogenous variables on endogenous variables.

| Variable | Effect | male | age | income | cert | R_autobike | R_ebike | R_bicycle | markets | tran | r_densi | b_densi | style | access |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| use_cost | Total | – | – | – | – | $-0.094^{c}$ | – | – | – | – | – | – | – | – |
| | Direct | – | – | – | – | $-0.094^{c}$ | – | – | – | – | – | – | – | – |
| | Indirect | – | – | – | – | – | – | – | – | – | – | – | – | – |
| pro_Ab | Total | – | – | $0.151^{a}$ | – | – | – | – | $-0.873^{b}$ | $0.542^{a}$ | $0.280^{a}$ | $-1.050^{a}$ | $0.514^{b}$ | $0.932^{a}$ |
| | Direct | – | – | $0.151^{a}$ | – | – | – | – | $-0.873^{b}$ | $0.542^{a}$ | $0.280^{a}$ | $-1.050^{a}$ | $0.514^{b}$ | $0.932^{a}$ |
| | Indirect | – | – | – | – | – | – | – | – | – | – | – | – | – |
| pro_Eb | Total | $-0.098^{c}$ | $0.203^{a}$ | – | – | – | $0.310^{a}$ | – | – | – | – | – | – | – |
| | Direct | $-0.098^{c}$ | $0.203^{a}$ | – | – | – | $0.310^{a}$ | – | – | – | – | – | – | – |
| | Indirect | – | – | – | – | – | – | – | – | – | – | – | – | – |
| less_out | Total | – | – | – | – | – | $0.129^{a}$ | – | $-0.491^{c}$ | – | – | $-0.415^{b}$ | $0.388^{a}$ | $0.522^{a}$ |
| | Direct | – | – | – | – | – | $0.129^{a}$ | – | $-0.491^{c}$ | – | – | $-0.415^{b}$ | $0.388^{a}$ | $0.522^{a}$ |
| | Indirect | – | – | – | – | – | – | – | – | – | – | – | – | – |
| pro_wb | Total | – | – | – | – | – | – | $0.118^{c}$ | $-0.268^{a}$ | $-0.303^{a}$ | $0.138^{b}$ | $0.158^{a}$ | – | – |
| | Direct | – | – | – | – | – | – | $0.118^{c}$ | $-0.268^{a}$ | $-0.303^{a}$ | $0.138^{b}$ | $0.158^{a}$ | – | – |
| | Indirect | – | – | – | – | – | – | – | – | – | – | – | – | – |
| car | Total | $-0.114^{b}$ | $0.111^{b}$ | $0.278^{a}$ | $0.262^{a}$ | $-0.150^{a}$ | – | $0.208^{a}$ | $-1.359^{a}$ | $0.524^{a}$ | $0.223^{a}$ | $0.163^{a}$ | $0.817^{a}$ | $1.114^{a}$ |
| | Direct | $-0.114^{b}$ | $0.111^{b}$ | $0.278^{a}$ | $0.262^{a}$ | $-0.160^{a}$ | – | $0.208^{a}$ | $-1.359^{a}$ | $0.524^{a}$ | $0.223^{a}$ | $0.163^{a}$ | $0.817^{a}$ | $1.114^{a}$ |
| | Indirect | – | – | – | – | 0.011 | – | – | – | – | – | – | – | – |
| Distance | Total | – | $-0.117^{b}$ | $0.119^{b}$ | $0.136^{b}$ | – | – | – | $-0.645^{b}$ | – | $-0.159^{a}$ | −0.432 | $0.308^{b}$ | $0.349^{c}$ |
| | Direct | – | $-0.117^{b}$ | $0.119^{b}$ | $0.136^{b}$ | – | – | – | $-0.645^{b}$ | – | $-0.159^{a}$ | −0.432 | $0.308^{b}$ | $0.349^{c}$ |
| | Indirect | – | – | – | – | – | – | – | – | – | – | – | – | – |
| Trips | Total | $-0.028^{a}$ | $0.044^{a}$ | $0.045^{a}$ | $0.140^{b}$ | $-0.018^{b}$ | $0.046^{a}$ | $0.026^{b}$ | $-0.230^{a}$ | $-0.750^{a}$ | $-0.222^{a}$ | $0.215^{c}$ | −0.109 | −0.311 |
| | Direct | – | – | – | $0.108^{b}$ | – | – | – | – | $-0.854^{a}$ | $-0.269^{a}$ | $0.433^{a}$ | $-0.247^{a}$ | $-0.515^{a}$ |
| | Indirect | $-0.028^{a}$ | $0.044^{a}$ | $0.045^{a}$ | $0.032^{b}$ | $-0.018^{b}$ | $0.046^{a}$ | $0.026^{b}$ | $-0.230^{a}$ | $0.104^{a}$ | $0.048^{a}$ | $-0.219^{a}$ | $0.137^{a}$ | $0.204^{a}$ |
| CE | Total | −0.005 | $-0.091^{a}$ | $0.111^{a}$ | $0.244^{a}$ | −0.004 | $-0.007^{a}$ | $0.013^{b}$ | $-0.566^{b}$ | $0.157^{a}$ | $-0.071^{c}$ | $-0.369^{b}$ | $0.316^{b}$ | $0.342^{b}$ |
| | Direct | – | – | – | $0.135^{a}$ | – | – | – | – | – | – | – | – | $-0.059^{c}$ |
| | Indirect | −0.005 | $-0.091^{a}$ | $0.111^{a}$ | $0.109^{a}$ | −0.004 | $-0.007^{a}$ | $0.013^{b}$ | $-0.566^{b}$ | $0.157^{a}$ | $-0.071^{c}$ | $-0.369^{b}$ | $0.316^{b}$ | $0.401^{a}$ |

Note: – means there is no link in the SEM model.
"Markets" represents the number of convenient markets, "tran" represents transit accessibility, "r_densi" represents road density, "b_densi" represents building density, "style" represents living style, and "access" represents destination accessibility.

[a] Refer to the significance level at 0.01, respectively.
[b] Refer to the significance level at 0.05, respectively.
[c] Refer to the significance level at 0.10, respectively.

**Table 11**
Standardized effects of endogenous variables on one another.

| Variable | Effect | use_cost | pro_Ab | pro_Eb | car | Distance | Trips |
|---|---|---|---|---|---|---|---|
| Car | Total | $-0.114^{b}$ | – | – | – | – | – |
| | Direct | $-0.114^{b}$ | – | – | – | – | – |
| | Indirect | – | – | – | – | – | – |
| Distance | Total | – | – | – | – | – | – |
| | Direct | – | – | – | – | – | – |
| | Indirect | – | – | – | – | – | – |
| Trips | Total | $-0.014^{b}$ | $0.073^{c}$ | $0.148^{a}$ | $0.122^{b}$ | – | – |
| | Direct | – | $0.073^{c}$ | $0.148^{a}$ | $0.122^{a}$ | – | – |
| | Indirect | $-0.014^{b}$ | – | – | – | – | – |
| CE | Total | $-0.070^{b}$ | $-0.011^{b}$ | $-0.022^{a}$ | $0.063^{c}$ | $0.795^{a}$ | $-0.146^{b}$ |
| | Direct | $-0.063^{b}$ | – | – | $0.081^{b}$ | $0.795^{a}$ | $-0.146^{a}$ |
| | Indirect | $-0.007^{b}$ | $-0.011^{b}$ | $-0.022^{a}$ | $-0.018^{b}$ | – | – |

Note: – means there is no link in the SEM model.
[a] Refer the significance level of 0.01, respectively.
[b] Refer the significance level of 0.05, respectively.
[c] Refer the significance level of 0.10, respectively.

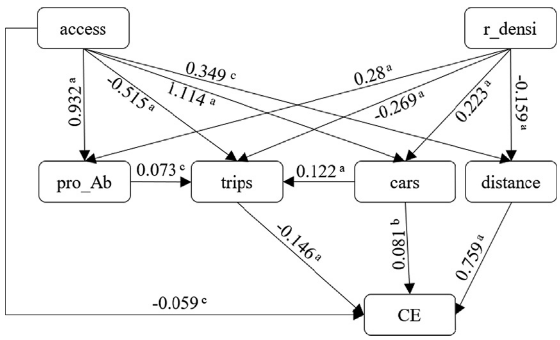


**Fig. 6.** Direct effects of destination accessibility and road density on endogenous variables.

travel $CO_2$ emissions are not completely consistent with the conclusions of similar research on Chinese cities. For instance, the higher the road density is, the better the road connectivity is, and small blocks and dense intersections can provide further alternative modes, such as biking and walking. Hence, the high level of road density reduces the probability of a household owning a car (contrary to the conclusions of this study) and the probability of traveling long distances (consistent with the conclusions of this study) (Ding et al., 2017a). Overall, increasing the road density indirectly reduced travel-related $CO_2$ emissions by reducing travel distance. This notion is consistent with the conclusions of research on commuting travel energy consumption (Ding et al., 2017a).

Fig. 7 shows that transit accessibility had a significantly positive and direct effect on the motorcycle riding attitude of rural residents (0.542) and household car ownership (0.524) and directly and negatively influenced travel frequency (−0.854). Transit accessibility exerted indirect and negative impacts on travel $CO_2$ emissions through “travel attitude → frequency of travel” (−0.0006) and “household car ownership → frequency of travel” (−0.009). In addition, $CO_2$ emission from daily traveling was

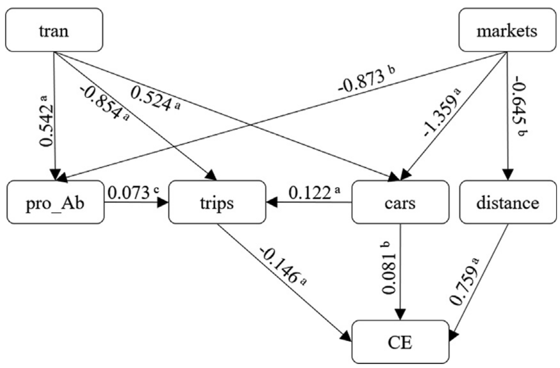


**Fig. 7.** Direct effects of transit accessibility and accessible markets on endogenous variables.

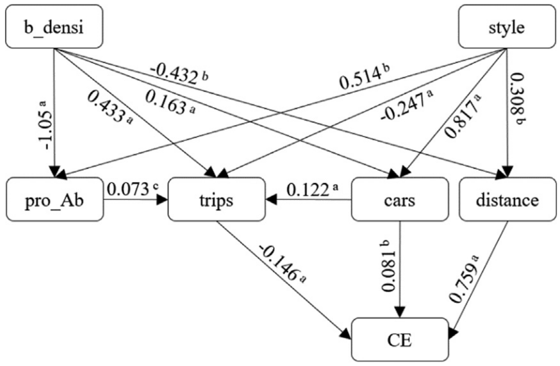


**Fig. 8.** Direct effects of building density and living style on endogenous variables.

indirectly and positively affected through travel frequency (0.125) and household car ownership (0.042). Transit accessibility had a completely positive effect on travel-related $CO_2$ emissions (0.157). Liu et al. (2016) conducted a research in Beijing which found that the distance to the subway from a residential location is positively correlated with travel $CO_2$ emissions. The finding is consistent with our research result. However, our intermediary variable differs.

The number of accessible markets had direct and negative effects on motorcycle riding attitude (−0.873), household car ownership (−1.359), and travel distance (−0.645). It did not directly affect travel $CO_2$ emissions significantly, but it indirectly and positively affected travel-related $CO_2$ emissions through "travel attitudes → travel frequency" (0.009) and "household car ownership → travel frequency" (0.024). Meanwhile, it exerted an indirect and negative impact on $CO_2$ emissions through car ownership (−0.11) and travel distance (−0.490). Finally, the number of accessible markets had a total negative effect on travel-related $CO_2$ emissions (−0.566). For rural areas, markets are trading centers. This means that increasing the number of accessible markets can effectively reduce travel-related $CO_2$ emissions, which is consistent with the conclusions of studies on Chinese cities (Ma et al., 2015; Qin and Han, 2013).

The significant direct effects of building density and living style on endogenous variables are shown in Fig. 8. Building density directly and negatively affected motorcycle riding attitude (−1.05) and travel distance (−0.432). It had direct and positive effects on travel frequency (0.433) and household car ownership (0.163). Building density did not directly affect travel-related $CO_2$ emissions significantly, but it indirectly and positively influenced travel-related $CO_2$ emissions through "travel attitude → travel frequency" (0.011) and household car ownership (0.013). Furthermore, it had an indirect and negative effect on travel-related $CO_2$ emissions through travel frequency (−0.063), "household car ownership → travel frequency" (−0.003), and travel distance (−0.328). Ultimately, it exerted a total negative effect (−0.369) on $CO_2$ emission from daily traveling, as shown in Table 10.

Centralized living style directly and positively influenced rural motorcycle riding attitude (0.514), household car ownership (0.817), and travel distance (0.308). It had a direct and negative impact on travel frequency (−0.247). Centralized living style had an indirect and negative effect on travel $CO_2$ emissions though travel attitude → travel frequency (−0.005) and household car ownership → travel frequency (−0.015). Furthermore, it exerted indirect and positive effects on travel $CO_2$ emissions through travel frequency (0.036), household car ownership (0.066), and travel distance (0.234). Finally, centralized living style had a total positive effect on travel-related $CO_2$ emissions (0.316), as shown in Table 10. This result confirms that a change in living style during rural urbanization and new rural construction increases travel distance and travel $CO_2$ emissions.

The abovementioned analysis indicates that travel distance is the main mediating variable that affects the impacts of the rural built environment on travel $CO_2$ emissions. Thus, effectively reducing travel distance is a key factor in controlling the travel-related

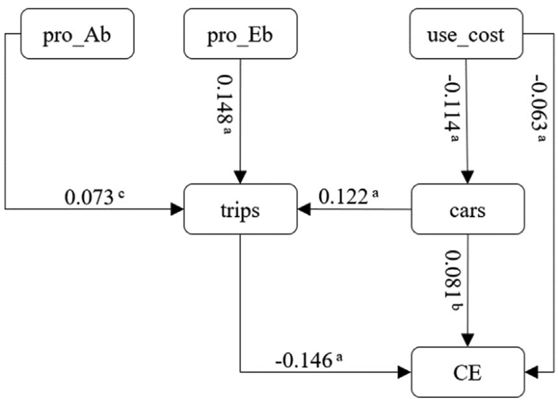


**Fig. 9.** Direct effects of individual travel attitudes on endogenous variables.

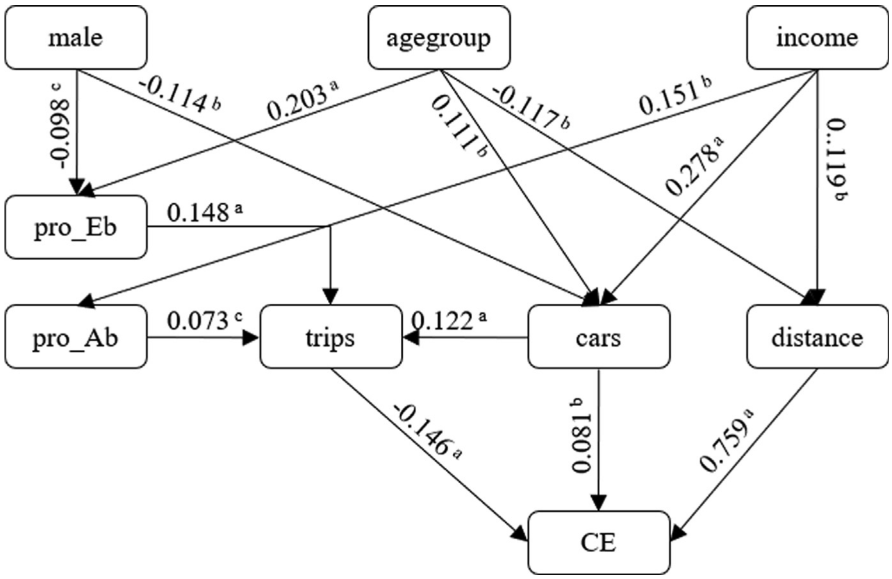


**Fig. 10.** Direct effects of basic socio-demographic variables on endogenous variables.

$CO_2$ emissions of rural residents.

### 4.3. Effects of individual travel attitudes on other endogenous variables

Fig. 9 and Table 11 provide the direct, indirect, and total effects of travel attitude on travel behavior and travel-related $CO_2$ emissions. Only three of the six travel attitude indicators were statistically significant on travel behavior and travel-related $CO_2$ emissions. In particular, the attitudes of motorcycle riding (0.073) and electric bicycle riding (0.148) had direct and positive effects on travel frequency, whereas attitudes exerted indirect (total) and negative effects on travel-related $CO_2$ emissions (coefficients are −0.011 and −0.022, respectively; Table 11). This result indicates that rural residents who believe that riding motorcycles or electric bicycles is safe, convenient, and environmentally friendly with zero economic pressure emit less $CO_2$. Therefore, the preference for riding electric bicycles has a significant impact on travel-related $CO_2$ emissions. Meanwhile, car use cost had a direct and negative effect on household car ownership (−0.114) and travel-related $CO_2$ emissions (−0.063), but it exerted an indirect and negative impact on travel $CO_2$ emissions through household car ownership (−0.009). Car use cost indirectly and positively affected travel $CO_2$ emissions through "household car ownership → travel frequency" (0.002). However, all indirect effects were very small, and the total effect of car use cost on travel-related $CO_2$ emissions was negative (−0.070). Thus, expensive gas prices and parking costs can

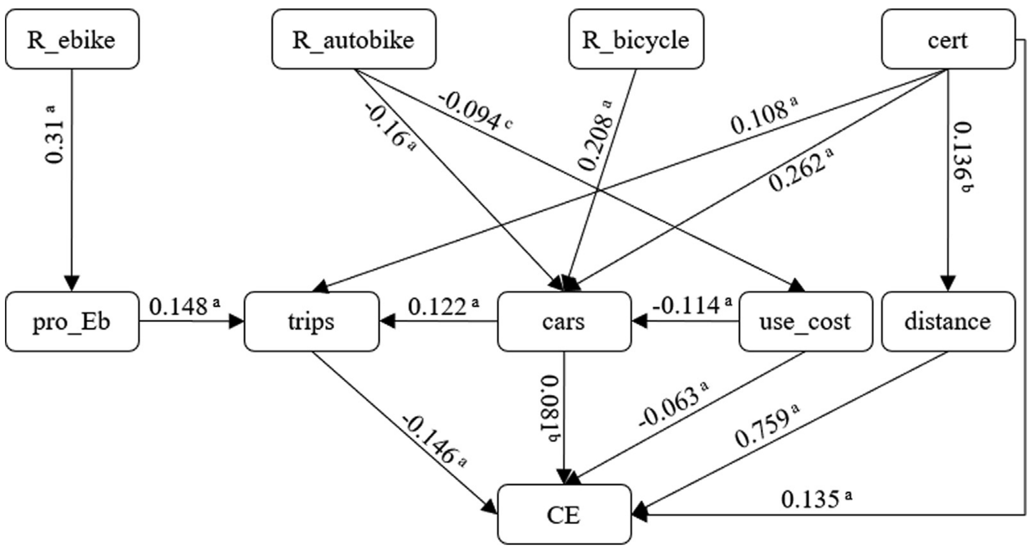


**Fig. 11.** Direct effects of respondents' driving skill on endogenous variables.

significantly reduce $CO_2$ emission from daily traveling in Chinese rural areas.

### 4.4. Effects of socio-demographic attributes on endogenous variables

Figs. 10 and 11 show the significant direct effects of socio-demographic attributes on endogenous variables. The results indicate that men are unwilling to own cars and ride electric bicycles, so they emit less travel-related $CO_2$. This result is in complete contrast to the conclusions of existing research on Chinese cities (Cao and Yang, 2017; Ding et al., 2017a; Ma et al., 2015). This huge difference between urban and rural areas is mainly due to the fact that the rural male segment of the labor force migrates for work. Thus, women and the elderly are the mainstays of the rural population. Moreover, income had a total positive effect on travel-related $CO_2$ emissions, but age exerted an opposite impact. These results are consistent with those of previous studies, which indicated that income and age significantly affect travel behavior and travel-related $CO_2$ emissions (Ding et al., 2017a; Ma et al., 2015).

The respondents' driving skills exerted significant direct or indirect impacts on $CO_2$ emission from daily traveling. Holding a driver's license had the highest positive impact on $CO_2$ emission from daily traveling. Rural residents who rode motorcycles and electric bicycles emitted less travel $CO_2$ (total effect coefficients of $-0.004$ and $-0007$, respectively; Table 10). An interesting result is that the skill of riding bicycles had a total positive effect on travel $CO_2$ emissions, although bicycling is a zero-carbon travel mode. This result is mainly due to the positive correlation between bicycling skills and household car ownership (0.208; Fig. 11). Thus, encouraging cycling and controlling the amount of household car ownership are effective measures to reduce travel-related $CO_2$ emissions in Chinese rural areas.

## 5. Conclusions and policy implications

This study adopted Sichuan rural areas a case study and considered the travel attitudes of rural residents. We proposed a causal model to explain the effects of built environment indicators on $CO_2$ emission from daily traveling. Data from the daily activity diary survey, on-site measurement, and GIS-based land use were utilized to estimate the SEM conceptual model. The following conclusions and planning implications were established. First, six elements of the built environment had significant total effects on travel-related $CO_2$ emissions, but only one (destination accessibility) of the six indicators had a significantly direct effect. Built environment indicators indirectly influenced $CO_2$ emission from daily traveling through mediating variables (travel attitude, car ownership, travel frequency, and travel distance). If only direct effects are considered, then the model would underestimate the impact of the built environment on $CO_2$ emission from daily traveling and thus misguide planning and policy formulation. Second, destination and transit accessibility had total positive effects on $CO_2$ emission from daily traveling. Therefore, shortening the distance from the residential area to the main destination and major public transport facilities is an effective measure for reducing travel-related $CO_2$ emissions of rural residents. Third, increasing road and building densities can effectively reduce travel-related $CO_2$ emissions. Although the road infrastructure in China's rural areas has greatly improved in the past decade, a large gap remains between urban and rural areas. Therefore, further strengthening rural road infrastructure investment is necessary. Moreover, the building density of centralized residential areas in new rural construction should be appropriately increased. Fourth, the number of accessible markets had a total negative effect on travel-related $CO_2$ emissions. Compared with the other built environment indicators, it exerted the greatest impact. Thus, the establishment of local market centers should be encouraged in rural areas to reduce travel-related $CO_2$ emissions. Fifth, household car ownership exerted a direct positive effect on travel-related $CO_2$ emissions. Rural residents should be encouraged to ride electric bicycles and motorcycles to reduce their daily travel-related $CO_2$ emissions. Therefore, further investing in cycling facilities and riding lanes and promoting low-carbon travel behavior are necessary. Sixth, travel attitudes had a limited impact on travel behavior and travel-related $CO_2$ emissions in rural areas. By contrast, the effects of the built environment were obvious and considerable. Therefore, low-carbon-oriented rural planning is particularly important for the development of ecological rural areas and affects the sustainable development of such areas.

Although the impacts of many built environment attributes on travel-related $CO_2$ emissions in rural Sichuan area were similar to the effects on urban areas, we have to emphasize that several calculation methods of built environment indicators in rural areas are different from the ones used in urban areas. For example, transit accessibility and destination accessibility are calculated as comprehensive indicators without considering multiple transport modes and various destinations. Although we found that transit accessibility and destination accessibility positive influence travel-related $CO_2$ emissions, which is different from what has been observed in urban environments, we cannot compare these results. Moreover, we found that centralized living style directly and positively influenced rural household car ownership and travel distance. The positive effects on travel-related $CO_2$ emissions indicated that a change in living style during rural urbanization and new rural construction increases travel-related $CO_2$ emissions. This finding is consistent with our expectation considering the considerable infrastructure gap between urban and rural areas in China. In the process of China's rural urbanization, the living style of rural residents gradually changed from the traditional scattered living style to the centralized living style with urban characteristics. In addition, only three of the six travel attitude indicators significantly influenced travel-related $CO_2$ emissions in rural China. In developed countries, such as the Netherlands (Ettema and Nieuwenhuis, 2017), residents' travel attitudes are important factors to predict travel-related $CO_2$ emissions. The difference indicates that in the case of limited economic development and infrastructure construction level, Sichuan rural residents' travel attitude exerts a limited impact on travel-related $CO_2$ emission.

This study is the first to investigate the relationship between the rural built environment and travel-related CO2 emissions in China while considering the daily traveling behaviors of rural residents. It collected data from different rural areas in Sichuan, China, which covered both traditional living style (scattered living) and new countryside style (centralized living). The results provide insights into the residents' travel behavior and theoretical guidance for the planning and construction of new rural areas in China.

## Declaration of Competing Interest

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication. All authors above would like to declare that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

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## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.07.004.

## References

Agency, I.E., 2009. Transport Energy and $CO_2$: Moving Towards Sustainability. OECD Publishing.
Ao, Y., Chen, C., Yang, D., Wang, Y., 2018. Relationship between rural built environment and household vehicle ownership: an empirical analysis in rural Sichuan China. Sustainability 10 (5), 1–18.
Ao, Y., Yang, D., Chen, C., Wang, Y., 2019. Exploring the effects of the rural built environment on household car ownership after controlling for preference and attitude: evidence from Sichuan, China. J. Transp. Geogr. 74, 24–36.
Bamberg, S., Ajzen, I., Schmidt, P., 2003. Choice of travel mode in the theory of planned behavior: the roles of past behavior, habit, and reasoned action. Basic Appl. Soc. Psychol. 25 (3), 175–187.
Barla, P., Miranda-Moreno, L.F., Lee-Gosselin, M., 2011. Urban travel $CO_2$ emissions and land use: a case study for Quebec City. Transp. Res. Part D Transp. Environ. 16 (6), 423–428.
Belgiawan, P.F., Schmocker, J.D., Abou-Zeid, M., Walker, J., Lee, T.C., Ettema, D.F., Fujii, S., 2014. Car ownership motivations among undergraduate students in China, Indonesia, Japan, Lebanon, Netherlands, Taiwan, and USA. Transportation 41 (6), 1227–1244.
Boarnet, M.G., 2011. A Broader context for land use and travel behavior, and a research agenda. J. Am. Plan. Assoc. 77 (3), 197–213.
Brand, C., Goodman, A., Rutter, H., Song, Y., Ogilvie, D., Consortium, i., 2013. Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorised passenger travel. Appl. Energy 104, 158–169.
Brand, C., Tran, M., Anable, J., 2012. The UK transport carbon model: an integrated life cycle approach to explore low carbon futures. Energy Policy 41, 107–124.
Brownstone, D., Golob, T.F., 2009. The impact of residential density on vehicle usage and energy consumption. J. Urban Econ. 65 (1), 91–98.
Cai, H., Xie, S., 2010. Determination of emission factors for different emission standards in China. J. Peking Univ. (Natural Science Edition) 46 (3), 319–326 (in Chinese).
Cao, X., Mokhtarian, P.I., Handy, S.I., 2007. Cross-sectional and quasi-panel explorations of connection between the built environment and auto ownership. Environ. Plan. A 39, 830–847.
Cao, X., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. Transp. Rev. 29 (3), 359–395.
Cao, X., Yang, W., 2017. Examining the effects of the built environment and residential self-selection on commuting trips and the related $CO_2$ emissions: an empirical study in Guangzhou, China. Transp. Res. Part D: Transp. Environ. 52, 480–494.
Chen, Y., Zhu, Y., 2013. Trip characteristics and traffic countermeasures analysis on rural resident in Northern of Jiangsu Province. Transp. Standardization 07, 17–23.
Christie, S.M.L., Fone, D.L., 2003. Does car ownership reflect socio-economic disadvantage in rural areas? A cross-sectional geographical study in Wales, UK. Public Health 117 (2), 112–116.
Dargay, J.M., 2002. Determinants of car ownership in rural and urban areas: a pseudo-panel analysis. Transp. Res. Part E Logist. Transp. Rev. 38 (5), 351–366.
Ding, C., Liu, C., Zhang, Y., Yang, J.W., Wang, Y.P., 2017a. Investigating the impacts of built environment on vehicle miles traveled and energy consumption: differences between commuting and non-commuting trips. Cities 68, 25–36.
Ding, C., Wang, D., Liu, C., Zhang, Y., Yang, J., 2017b. Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. Transp. Res. Part A: Policy Pract. 100, 65–80.
Ding, C., Wang, Y.W., Xie, B.L., Liu, C., 2014. Understanding the role of built environment in reducing vehicle miles traveled accounting for spatial heterogeneity. Sustainability 6 (2), 589–601.
Entwicklungsbank, K. 2008. Transport in China: Energy Consumption and Emissions of Different Transport Modes.
Ettema, D., Nieuwenhuis, R., 2017. Residential self-selection and travel behaviour: what are the effects of attitudes, reasons for location choice and the built environment? J. Transp. Geogr. 59, 146–155.
Ewing, R., 1997. Is Los Angeles-style sprawl desirable? J. Am. Plan. Assoc. 63 (1), 107–126.
Ewing, R., Cervero, R., 2001. Travel and the built environment – a synthesis. Land Develop. Public Involvement Transp. (1780), 87–114.
Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plan. Assoc. 76 (3), 265–294.
Ewing, R., Handy, S., 2009. Measuring the unmeasurable: urban design qualities related to walkability. J. Urban Des. 14 (1), 65–84.
Ewing, R., Tian, G., Goates, J.P., Zhang, M., Greenwald, M.J., Joyce, A., Kircher, J., Greene, W., 2015. Varying influences of the built environment on household travel in 15 diverse regions of the United States. Urban Stud. 52 (13), 2330–2348.
Glaser, D., 2001. A first course in structural equation modeling. Struct. Eq. Model. Multidiscipl. J. 8 (2), 316–323.
Guo, Z., 2013. Does residential parking supply affect household car ownership? The case of New York City. J. Transp. Geogr. 26, 18–28.
Handy, S., Cao, X., Mokhtarian, P., 2005. Correlation or causality between the built environment and travel behavior? Evidence from Northern California. Transp. Res. Part D: Transp. Environ. 10 (6), 427–444.
Hankey, S., Marshall, J.D., 2010. Impacts of urban form on future US passenger-vehicle greenhouse gas emissions. Energy Policy 38 (9), 4880–4887.
Haustein, S., Hunecke, M., 2007. Reduced use of environmentally friendly modes of transportation caused by perceived mobility necessities: an extension of the theory of planned behavior. J. Appl. Soc. Psychol. 37 (8), 1856–1883.

He, S.Y., Thøgersen, J., 2017. The impact of attitudes and perceptions on travel mode choice and car ownership in a Chinese megacity: the case of Guangzhou. Res. Transp. Econ. 62, 57–67.
Heath, Y., Gifford, R., 2002. Extending the theory of planned behavior: predicting the use of public transportation. J. Appl. Soc. Psychol. 32 (10), 2154–2189.
Hong, J., 2017. Non-linear influences of the built environment on transportation emissions: focusing on densities. J. Transp. Land Use 10 (1), 229–240.
Jahanshahi, K., Jin, Y., 2016. Trend-breaking influences of built form on travel in UK cities: evidence from new quantifications of within-and between-built-form variations. Transp. Res. Rec. J. Transp. Res. Board 2564, 31–40.
Jahanshahi, K., Jin, Y., Williams, I., 2015. Direct and indirect influences on employed adults' travel in the UK: new insights from the National Travel Survey data 2002–2010. Transp. Res. Part A: Policy Pract. 80, 288–306.
Jiang, Y., He, D., Christopher, Z., 2011. Study on the influence of urban block form on residents' energy consumption. Urban Traffic 42 (3), 78–85 (in Chinese).
Kenworthy, J.R., Laube, F.B., 1996. Automobile dependence in cities: an international comparison of urban transport and land use patterns with implications for sustainability. Environ. Impact Assess. Rev. 16 (4–6), 279–308.
Khattak, A.J., Rodriguez, D., 2005. Travel behavior in neo-traditional neighborhood developments: a case study in USA. Transp. Res. Part A Policy Pract. 39 (6), 481–500.
Kline, R.B., Santor, D.A., 1999. Principles & practice of structural equation modelling. Canadian Psychol. 40 (4), 381.
Kong, R., Yao, Z., 2015. Haining city and rural residents travel characteristics comparison. Transp. Enterprise Manage. 09, 17–22.
Krizek, K.J., 2003. Neighborhood services, trip purpose, and tour-based travel. Transportation 30 (4), 387–410.
Li, S., Zhao, P., 2017. Exploring car ownership and car use in neighborhoods near metro stations in Beijing: does the neighborhood built environment matter? Transp. Res. Part D: Transp. Environ. 56, 1–17.
Liu, Z., Ma, J., Chai, Y., 2016. Neighborhood-scale urban form, travel behavior, and $CO_2$ emissions in Beijing: implications for low-carbon urban planning. Urban Geogr. 38 (3), 381–400.
Ma, J., Liu, Z.L., Chai, Y.W., 2015. The impact of urban form on $CO_2$ emission from work and non-work trips: the case of Beijing, China. Habitat Int. 47, 1–10.
Marsden, G., Rye, T., 2010. The governance of transport and climate change. J. Transp. Geogr. 18 (6), 669–678.
Modarres, A., 2013. Commuting and energy consumption: toward an equitable transportation policy. J. Transp. Geogr. 33, 240–249.
Ou, J.P., Liu, X.P., Li, X., Chen, Y.M., 2013. Quantifying the relationship between urban forms and carbon emissions using panel data analysis. Landscape Ecol. 28 (10), 1889–1907.
Proost, S., De Ceuster, G., Van Herbruggen, B., Logghe, S., Ivanova, O., Carlier, K., 2006. TREMOVE 2 Service contract for the further development and application of the TREMOVE transport model—Lot 3. Final Report Part, 4.
Qin, B., Han, S.S., 2013. Emerging polycentricity in Beijing: evidence from housing price variations, 2001–05. Urban Stud. 50 (10), 2006–2023.
Ribeiro, S.K., Balassiano, R., 1997. $CO_2$ emissions from passenger transport in Rio de Janeiro. Transp. Policy 4 (2), 135–139.
Schoenau, M., Müller, M., 2017. What affects our urban travel behavior? A GPS-based evaluation of internal and external determinants of sustainable mobility in Stuttgart (Germany). Transp. Res. Part F: Traffic Psychol. Behav. 48, 61–73.
Shim, G.-E., Rhee, S.-M., Ahn, K.-H., Chung, S.-B., 2006. The relationship between the characteristics of transportation energy consumption and urban form. Ann. Reg. Sci. 40 (2), 351–367.
Solomon, S., Qin, D., Manning, M., Averyt, K., Marquis, M., 2007. Climate Change 2007-the Physical Science Basis: Working Group I Contribution to the Fourth Assessment Report of the IPCC. Cambridge University Press.
Statistics, I. 2011. CO2 emissions from fuel combustion-highlights. IEA, Paris http://www.iea.org/co2highlights/co2highlights.pdf. Cited July.
Stocker, T., Qin, D., Plattner, G., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P., 2013. IPCC, 2013: Summary for Policymakers in Climate Change 2013: The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, New York, USA.
Su, T., Zhang, J., Li, J., Ni, Y., 2011. Empirical study on the influencing factors of urban transportation carbon emissions——evidence from Beijing-Tianjin-Hubei panel data. Ind. Eng. Manage. 5, 127–135 (in Chinese).
Sun, B., Ermagun, A., Dan, B., 2017. Built environmental impacts on commuting mode choice and distance: evidence from Shanghai. Transp. Res. Part D: Transp. Environ. 52, 441–453.
Thorhauge, M., Haustein, S., Cherchi, E., 2016. Accounting for the theory of planned behaviour in departure time choice. Transp. Res. Part F: Traffic Psychol. Behav. 38, 94–105.
Tyrinopoulos, Y., Antoniou, C., 2013. Factors affecting modal choice in urban mobility. Eur. Transp. Res. Rev. 5 (1), 27–39.
Van Acker, V., Witlox, F., 2010. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. J. Transp. Geogr. 18 (1), 65–74.
Van Acker, V., Witlox, F., Van Wee, B., 2007. The effects of the land use system on travel behavior: a structural equation modeling approach. Transp. Plan. Technol. 30 (4), 331–353.
Vance, C., Hedel, R., 2007. The impact of urban form on automobile travel: disentangling causation from correlation. Transportation 34 (5), 575–588.
Wang, D., Chai, Y., Li, F., 2011. Built environment diversities and activity–travel behaviour variations in Beijing, China. J. Transp. Geogr. 19 (6), 1173–1186.
Wang, D.G., Lin, T., 2014. Residential self-selection, built environment, and travel behavior in the Chinese context. J. Transp. Land Use 7 (3), 5–14.
Xiao, Z., Cai, Y., Liu, Z., 2011. Quantitative distribution and influencing factors of daily carbon emissions of residents in Beijing. Urban Develop. Res. 18 (9), 104–112 (in Chinese).
Yan, X., Crookes, R.J., 2009. Reduction potentials of energy demand and GHG emissions in China's road transport sector. Energy Policy 37 (2), 658–668.
Yang, Q., Yuan, H., Feng, S., 2014. Travel characteristics of rural residents under different economic condition. J. Chang'an Univ. (Natural Science Edition) 34 (01), 76–83.
Yang, W., Cao, X., 2018. Examining the effects of the neighborhood built environment on $CO_2$ emissions from different residential trip purposes: a case study in Guangzhou, China. Cities 81, 24–34.
Yang, W., Li, T., Cao, X., 2015. Examining the impacts of socio-economic factors, urban form and transportation development on $CO_2$ emissions from transportation in China: a panel data analysis of China's provinces. Habitat Int. 49, 212–220.
Yang, Y., Wang, C., Liu, W., 2018. Urban daily travel carbon emissions accounting and mitigation potential analysis using surveyed individual data. J. Cleaner Prod. 192, 821–834.
Zahabi, S.A.H., Miranda-Moreno, L., Patterson, Z., Barla, P., Harding, C., 2012. Transportation greenhouse gas emissions and its relationship with urban form, transit accessibility and emerging green technologies: a Montreal case study. In: Proceedings of EWGT 2012 – 15th Meeting of the Euro Working Group on Transportation, vol. 54. pp. 966–978.
Zhao, P., 2010. Sustainable urban expansion and transportation in a growing megacity: consequences of urban sprawl for mobility on the urban fringe of Beijing. Habitat Int. 34 (2), 236–243.
Zhu, C., Zhu, Y.L., Lu, R.Z., He, R., Xia, Z.L., 2012. Perceptions and aspirations for car ownership among Chinese students attending two universities in the Yangtze Delta, China. J. Transp. Geogr. 24, 315–323.