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Relationship Between Built Environment, Socio-economic Factors and Carbon Emissions from Shopping Trip in Shenyang City, China

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Abstract: Promoting active travel behavior and decreasing transport-related carbon dioxide (CO_2) emissions have become a priority in many Chinese cities experiencing rapid urban sprawl and greater automobile dependence. However, there are few studies that holistically examine the physical and social factors associated with travel CO_2 emissions. Using a survey of 1525 shoppers conducted in Shenyang, China, this study estimated shopping-related travel CO_2 emissions and examined how the built environment and individual socioeconomic characteristics contribute to shopping travel behavior and associated CO_2 emissions. We found that, firstly, private car trips generate nearly eight times more carbon emissions than shopping trips using public transport, on average. Second, there was significant spatial autocorrelation with CO_2 emissions per trip, and the highest carbon emissions were clustered in the inner suburbs and between the first and second circumferential roads. Third, shopping travel CO_2 emissions per trip were negatively correlated with several built environment features including population density, the quantity of public transport stations, road density, and shop density. They were also found to be significantly related to the individual socio-economic characteristics of car ownership, employment status, and education level using a multinomial logistic regression model. These empirical findings have important policy implications, assisting in the development of measures that contribute to the sustainability of urban transportation and meet carbon mitigation targets.
Keywords: transport carbon emission; travel behavior; built environment; socio-economic factors; shopping trips; China

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1 Introduction

There is clear scientific and political agreement on the need to reduce global CO_2 emissions in response to growing concerns about climate change over the past two decades (Lin, 2010; Alhorr *et al.*, 2014; Zahabi *et al.*, 2015). The transport sector is a major contributor of unsustainable energy use, currently contributing around 20%–25% of CO_2 emissions globally with this projected to increase to 30%–50% by 2050 (VandeWeghe and Kennedy, 2007; Brand *et al.*, 2013). Because of the rapid rise of motorization, energy consumption and CO_2 emissions in China's transport sector have been increasing at a phenomenal rate. From 1985 to 2013, the total energy consumption of China's transport sector increased from 3.7×10^7 t of standard coal equivalent (TCE) to 3.5×10^8 TCE. The CO_2 emissions in China's transport sector increased from 9.2×10^7 t to 8.7×10^8 t, with an average annual growth rate of 8.31%. As such, reducing energy consumption in the transport sector is regarded as an urgent matter in urban China that is attracting increasing attention worldwide (Xu and Lin, 2015).

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While the factors affecting the CO_2 emissions of industrial and power sectors are well understood, transport sector emissions and emission intensities have not been examined to the same extent, especially in the context of developing countries (Timilsina and Shrestha, 2009). The identification of factors that influence transport CO_2 emissions is important for promoting sustainable travel patterns and proposing effective climate change mitigation policies and strategies. A number of studies have used travel behavior attributes, such as travel mode and vehicle kilometers traveled, to estimate transport carbon emissions (He *et al.*, 2013; Ma *et al.*, 2015). Extensive literature has found that built environment characteristics, such as street design, population density, land use diversity, destination accessibility, and distance to transit, are important factors in determining household travel behavior and transport-related GHG emissions (Handy, 1996; Ewing, 2001; Cao *et al.*, 2006; Ewing and Cervero, 2010; Liu and Shen, 2011; Cao and Fan, 2012; Zahabi *et al.*, 2015). For instance, Newman and Kenworthy (1987) suggested that physical planning policies, particularly re-urbanization and a reorientation of transportation priorities, are key to reducing gasoline consumption and automobile dependence in U.S. cities. Baran *et al.* (2008) contributed to understanding the relationships between the syntactical properties of street design and walking behavior in New Urbanist and conventional suburban neighborhoods by establishing an association with the walking patterns of residents in these communities. Etminani-Ghasrodashti and Ardeshiri (2016) examined the relationships between land use attributes (such as density, design, diversity, and local access to transit) and travel behavior through the analysis of home-based work and non-work trips in the metropolitan area of Shiraz, Iran. Nonetheless, it has become increasingly apparent that built environment factors can not fully account for individual differences in travel behavior (Bagley and Mokhtarian, 2002). Other scholars have looked at individual factors such as socio-demographic characteristics, attitudes, beliefs, and lifestyle in influencing travel behavior (Stead, 2001; Anable and Gatersleben, 2005; Ory and Mokhtarian, 2009; Haybatollahi *et al.*, 2015; Etminani-Ghasrodashti and Ardeshiri, 2015). Beige and Axhausen (2008) showed that changes in residence, education, and employment decrease the probability of variations in the ownership of mobility tools. Joh *et al.* (2012) find that socioeconomic characteristics, such as race and ethnicity, gender, age, household income, employment status, children in the household, and foreign-born status, are associated with walking behavior. Mokhtarian and Salomon (2001) suggested that travel demand is largely influenced by individual attributes including attitude, habits, and lifestyle.

Just as substantial literature that focus on the built environment do not typically account for social aspects, most social environment studies do not control for the effect of the built environment. In an attempt to improve existing knowledge on the impacts of the living environment on travel behavior, this study aims to examine simultaneously how social aspects of individual characteristics interact with built environment factors to affect travel behavior and the resulting carbon emissions. Furthermore, in contrast to most studies that consider travel behavior and CO_2 emissions from commuting to work (Cirilli and Veneri, 2014; Ma *et al.*, 2014; Andong and Sajor, 2015; Focas, 2016), this study focuses on shopping trips. This is because a particularly noteworthy trend globally is the increasing share of travel for personal business, recreational, social, and other non-work purposes, especially trips to shopping centers (Zhang, 2005). With economic and social development, retailing in China has entered into a period of rapid growth, especially seen in the rapid development of new commercial centers (Wang *et al.*, 2015). The density, size, and location of commercial centers influence both the retailers' performance and consumers' travel choices, which could also reflect the externalities associated with carbon emissions (Cachon, 2014). Within this context, this paper aims to fill this gap in the literature by exploring the interaction between built environment factors and individual socio-economic characteristics in shopping travel behavior and the related transport carbon emissions through a case study of the city of Shenyang, one of the largest metropolitan areas in China to propose effective policies to reduce transport CO_2 emissions.

2 Materials and Methods

2.1 Study area

Shenyang, the capital city of Liaoning Province, is one of China's oldest industrial bases and most developed metropolitan areas. Since the reform and opening up of China at the beginning of the 1980s, successful economic restructuring and transformation has seen the rapid growth of the tertiary sector and retail, which now plays an important part in the economic and urban development of Shenyang City (Qin and Zhang, 2011; Li *et al.*, 2015). By the end of 2014, urban retail sales of consumer goods reached 3.1×10^{11} yuan (RMB) with more than 163 000 commercial sites in Shenyang City. Motor vehicle ownership and utilization are growing rapidly as income increases in urban Shenyang: the number of private car ownership was 7.7×10^{5} and the average per capita income was 2423 yuan (RMB) in 2014. Our study area is the central urban area of Shenyang, which consists of nine urban districts (Heping, Shenhe, Dadong, Huanggu, Tiexi, Sujiatun, Hunnan, Yuhong and Shenbei). According to the 2010 census data, it has 5.6×10^{6} people and an area of 1040.28 km^2. There are 2 subway lines and 235 bus routes serving study area (Fig. 1).

2.2 Data collection

Data were collected through face-to-face interviews targeting shoppers in the eight commercial centers on both weekends and weekdays in August 2013 and again in October 2014. The questionnaire was essentially comprised of three parts. The first part collected specific travel data such as the origin and routing of the shopping trip, the mode of transport, travel time, and the frequency of trips. The second part collected information on the built environment of the shopper's place of residence, including the residence location, distribution of commercial facilities, subway stations, and bus stations. The third part collected personal socio-economic characteristics including car ownership, gender, age, education, occupation, income, and attitudes towards the development of public transport. A total of 1672 randomly selected shoppers were approached in eight commercial centers from 9:00 a.m. to 7:00 p.m., and 1525 shoppers completed our questionnaire (802 weekday shoppers and 723 weekend shoppers). The supplementary material details the demographic information from censuses in 2010 and the road and public transport network in Shenyang City.

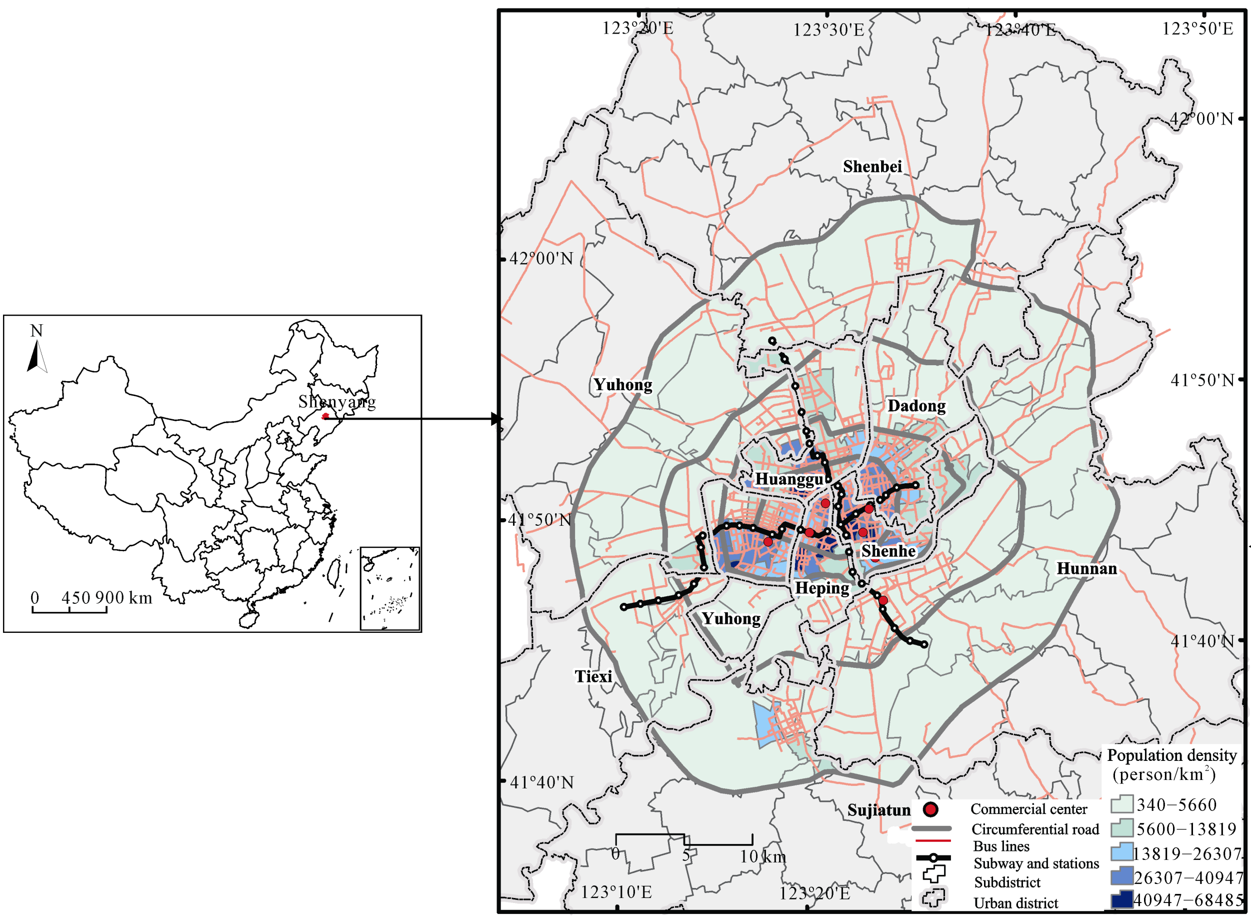

Fig. 1 Map of study area

2.3 Model

2.3.1 CO_2 emissions model

A bottom-up approach that creates a model to estimate CO_2 emissions from shopping trips according to detailed travel data was used in this study. The bottom-up approach estimates emissions from non-aggregated travel attributes, including trip frequency, mode choice, vehicle kilometers travelled (VKT), energy efficiency, and the CO_2 emissions factor for each trip (Wang *et al.*, 2007; Howitt *et al.*, 2010; Ma *et al.*, 2014; Dai *et al.*, 2016). The travel modes of shoppers were divided into five categories: 1) walking and cycling, 2) bus, 3) rail transit, 4) taxi, and 5) private car, among which walking and cycling generate zero carbon emissions. The carbon emissions per trip for bus, taxi, and private car were calculated using the following formula:

$$\mathrm{ECO}_{2i} = \frac{F_i \times \rho_i \times D_i \times EF_i}{AC_i} \tag{1}$$

where i represents the travel mode; ECO_2 is the estimated CO_2 emissions (g); F_i is the average fuel consumption rate of the travel mode i (m^3/100 km or L/100 km); ρ is the fuel density (kg/m^3); D is the travel distance (km); EF is the carbon emissions factor of fuel (t CO_2/1000 Nm^3 or t CO_2/t) and AC is the estimated transport capacity (Li *et al.*, 2016). Carbon emissions for rail transit are demonstrated as follows:

$$E\mathrm{CO}_{2p} = \frac{C_p \times D_p \times EF_p}{AC_p} \tag{2}$$

where p represents the travel mode; $E\mathrm{CO}_2$ is the estimated CO_2 emissions (g); C is the average power consumption (kWh/100 km); D is the travel distance (km); EF is the carbon emissions factor of power (kg/kWh) and AC is the estimated transport capacity (Li *et al.*, 2016).

2.3.2 Spatial analysis

Moran's I statistics were used to assess if there was any clustering of carbon emissions per trip for shopping in Shenyang City. The Spatial Autocorrelation (Global Moran's I) tool measures spatial autocorrelation based on both feature locations and feature values, simultaneously. Given a set of features and an associated attribute, it evaluates whether the pattern expressed is clustered, dispersed, or random. Moran's I values range between –1 (perfect dispersion) and +1 (perfect clustering), which are used in conjunction with G statistics to allow for better insight into local spatial patterns (Legendre and Fortin, 1989; Getis and Ord, 1992; Weimann *et al.*, 2016). A Getis-Ord Gi* statistic was applied to identify statistically significant hot and cold spots of carbon emissions per shopping trip. In our study, a hot spot was defined as a clustering of high carbon emissions while a cold spot represented the clustering of low carbon emissions. The Hot Spot Analysis tool calculates the Getis-Ord Gi^* statistic for each feature in a dataset. The Getis-Ord Gi^* statistic generates a z-score and corresponding P-value for each data point, where z-scores greater than –1.96 indicate a significant 'hot spot' and z-scores lower than 1.96 indicate a significant 'cold spot' ($P < 0.05$) (Getis and Ord, 1992; Rossen *et al.*, 2014; Maina *et al.*, 2016). The distributions of carbon emissions per trip for shopping were subsequently mapped for any clustering using Geographic Information Systems (ESRI ArcGIS 10.3 desktop).

2.3.3 Multinomial logistic regression model

Logistic regressions are widely used in various fields to assess the likelihood of certain events. The multinomial logistic regression (MLR) is a statistical tool used to assess and predict the impact of independent variables on a dependent variable, which is an appropriate technique when the dependent variable is categorical and the explanatory variables are continuous or categorical (Ng *et al.*, 2013; Nesheli *et al.*, 2016). We used an MLR modeling approach to examine the major determinants of travel behavior during shopping trips. The MLR model was run by the SPSS 22.0. The outcome probability is defined as follows (Omrani, 2015; Nesheli *et al.*, 2016):

$$P(y_i = j) = \frac{\exp\left(x_i \beta_j\right)}{\sum_{j=1}^{n} \exp\left(x_i \beta_j\right)} \tag{3}$$

where P ($y_i = j$) is the probability of belonging to group j; x_i is a vector of explanatory variables and β_j is the coefficients, which are estimated using the maximum likelihood estimation.

3 Results

3.1 Sample characteristics

Table 1 presents a description of the built environmental factors and individual socio-economic characteristics

Table 1 Descriptive statistics for variables

Factors	Variables	Variable groups	Level	Number	Percent (%)
Travel	Travel mode	Walking/cycling	1	289	18.95
		Bus/subway	2	952	62.43
		Taxi	3	88	5.77
		Private car	4	196	12.85
Built environment	Population density	<8021 person/km^2	1	422	27.67
		8021–18253	2	275	18.03
		18253–28491	3	212	13.90
		28491–40947	4	445	29.18
		>40947	5	171	11.21
	Bus station	<38 bus stations within 1 km	1	510	33.44
		38–79	2	393	25.77
		79–123	3	367	24.07
		123–180	4	198	12.98
		>180	5	57	3.74
	Subway station	Have subway stations within 1 km	0	1015	66.56
		No subway station within 1 km	1	510	33.44
	Road density	<1.91 km/km^2	1	209	13.70
		1.91–3.58	2	414	27.15
		3.58–5.44	3	296	19.41
		5.44–7.79	4	388	25.44
		>7.79	5	218	14.30
	Shop density	<726 unit/km^2	1	339	22.23
		726–1627	2	303	19.87
		1627–2590	3	313	20.52
		2590–3637	4	355	23.28
		>3637	5	215	14.10
Individual socio-economic characteristics	Car ownership	No	0	973	63.80
		Yes	1	552	36.20
	Age	<=18 years	1	30	1.97
		19–25	2	429	28.13
		26–35	3	531	34.82
		36–50	4	282	18.49
		>=51	5	253	16.59
	Education level	Below High school	1	399	26.16
		High school	2	225	14.75
		Undergraduate degree	3	835	54.75
		Master's degree or higher	4	66	4.33
	Occupation	Public	1	234	15.34
		Business	2	548	35.93
		Self-employed	3	267	17.51
		Unemployed	4	276	18.10
		Retirement	5	200	13.11
	Per capita monthly income	<2000 yuan (RMB)	1	228	15.00
		2000–3000	2	432	28.30
		3000–5000	3	470	30.80
		>5000	4	395	25.90
	Gender	Male	1	571	37.40
		Female	2	954	62.60

variables we examined as predictors of shopping travel mode. We found that, of the 1525 participants, 952 (62.43%) took a bus or the subway to get to a commercial center; 289 (18.95%) walked or cycled, most of whom lived within 2 km of the visited commercial center; 196 (12.85%) travelled by private car, and only 88 (5.77%) took a taxi. These data show that public transit (bus and subway) is still the main shopping travel mode in Shenyang whereas taxi is the least popular travel mode for shopping. In total, 63.80% of the 1525 respondents had no private car at home and 62.60% of the participants were female. The respondents were primarily young (63.00% were 35 years of age or younger). Most of them have average monthly income of around 3000–5000 yuan (RMB) (30.8%), received a tertiary education (59.1%), and were employed in business (35.9%).

Among the built environment variables, population density is defined as population number divided by the area for each sub-district. Bus station is defined according to the number of stations within 1 km of the shopper's home. Subway station is a dummy variable where 0 means there is a subway station within 1 km of the participant's home and 1 means there is not. Road density is the length of the road divided by the area for each sub-district. Shop density is the number of shops within each sub-district.

3.2 Carbon emissions per trip for shopping

Based on the above mentioned bottom-up approach, the carbon emissions per shopper were calculated. Our results demonstrated that, on average, shoppers in Shenyang travelled 7.13 km and produced 226.04 g of carbon emissions. With regard to the mode of transport, the average travel distance by public transport (bus and subway) and associated CO_2 emissions were 8.44 km and 111.53 g, respectively. Respondents travelled, on average 6.28 km to their shopping destination by taxi. CO_2 emissions per trip when using taxi were five times higher than when using public transport. Shoppers travelled an average of 8.43 km by private car. Private car emissions were nearly eight times higher than that of public transport. The average travel distance by walking or cycling was 2.21 km.

3.3 Global Moran's I and hot spot analysis (Getis-Ord Gi*)

Results from the spatial autocorrelation analysis show that Global Moran's I is 0.097 with a z-score of 2.37, suggesting that there is significant spatial autocorrelation and spatial clustering of carbon emissions for shopping at the individual level ($P < 0.05$).

Detailed spatial clusters at the local level were further examined using G-statistics to measure the presence of concentrations of high or low values. Fig. 2 shows the spatial distribution of hot and cold spots of carbon emissions among shoppers at the individual level in our study. Cold spots are mainly distributed within the first circumferential road and the southern parts of the city between the first and second circumferential roads, with an average urban population density of approximately 2.92×10^4 person/km^2. Hot spot locations can be classified into two groups. The first group of hot spots is located beyond the second circumferential road, mainly clustered in the inner suburbs of Shenbei Region, Hunnan Region, Sujiatun Region and Yuhong Region. The other aggregated hot spots are located between the first and second circumferential roads, where urban population density is very high (2.14×10^4 person/km^2).

3.4 Multinomial Logistic Regression model results

To test the impact of various built environment and socio-economic variables, we selected we selected MLR to analyze which factors influence shopping travel mode. Among the factors in our analysis are five built environment variables and six individual socio-economic characteristics variables. Using the 95% significant level criterion, we found six variables statistically affected shopping travel mode significantly. Table 2 shows the results of the regression model analysis. The MLR is statistically significant (Chi^2 = 732.11, Sig. < 0.001). According to Nagelkerke R^2, the model explained 72.8% of the variance in the shoppers' choices of travel mode. Goodness-of-fit tests = 0.992 indicated that the model is appropriate for analyzing the data. The six variables that are significant in the model are: population density, bus station, road density, shop density, private car ownership, and education level. The results suggest that built environmental factors and individual socio-economic variables both played a major role in explaining variances. Subway station and occupation are not significant for the model as a whole; no improvement of the model is achieved with or without these two factors. As unexpected, compared with other trip purposes, occupation is not strongly correlated with for

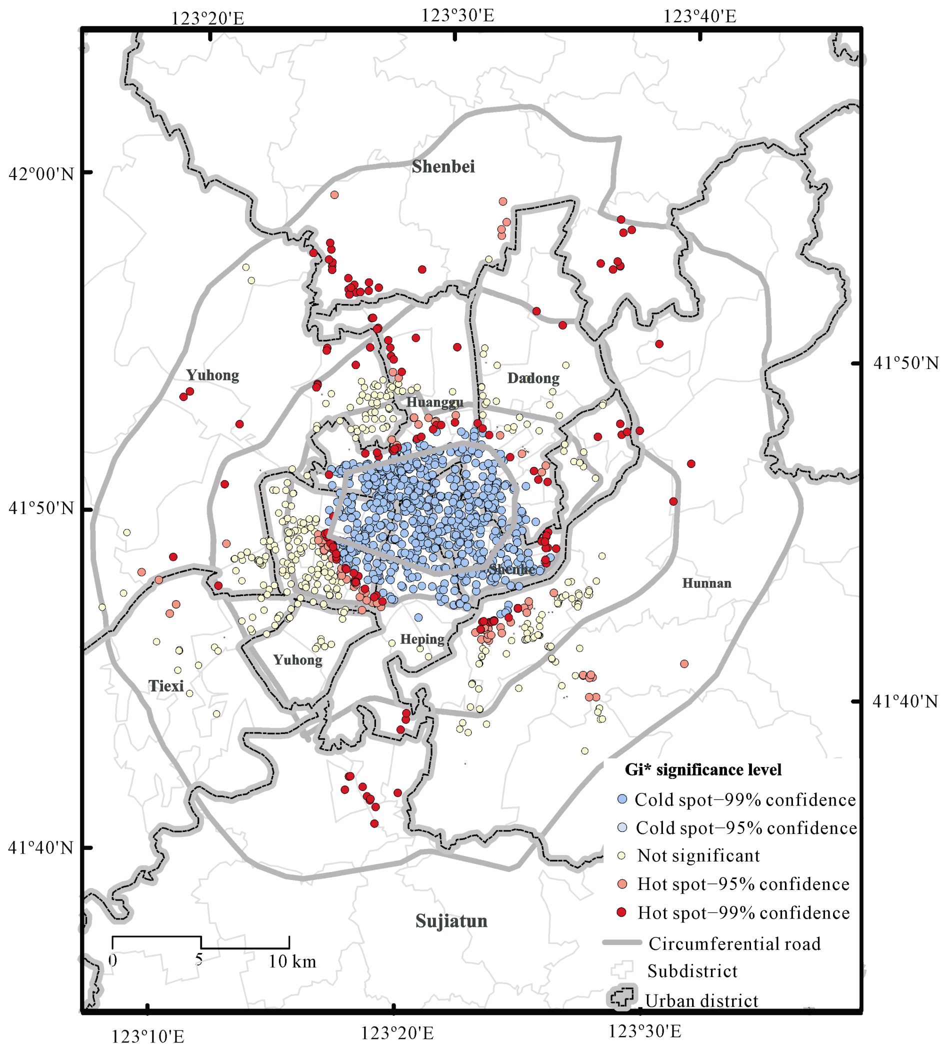

Fig. 2 Hot spot analysis of carbon emissions of overall shoppers

Table 2 Likelihood ratio tests of logistic regression

Model analysis		Chi^2	df	Sig.
Model likelihood ratio tests		732.11	78	0.000
Goodness-of-fit of the model (Pearson)		3527.79	3732	0.992
Parameter likelihood ratio tests	Population density	34.44	12	0.001
	Bus station	34.29	12	0.001
	Subway station	4.21	3	0.240
	Road density	27.34	12	0.007
	Shop density	22.88	12	0.029
	Car ownership	329.86	3	0.000
	Education level	23.37	9	0.005
	Occupation	13.91	12	0.306

Notes: R^2 = 0.709 (Cox & Snell), R^2 = 0.728 (Nagelkerke), R^2 = 0.440 (McFadden), n = 1525 (valid) cases

shopping. In the same way, subway station is not significant in the full model as the development of subway-based mass transit systems are under development in Shenyang and access to subway station is comparatively low for most shoppers.

Table 3 summarizes the MLR model's results, which show the estimated coefficients and the related statistics. The combination of a constant and the statistically significant variables identified in the MLR model that was developed for each of the shopping travel modes is also presented in Table 3. From our data and analysis, we found that shoppers having no private car are 44, 41, and 28 times more likely to go shopping by walking or cycling, public transit and taxi, respectively. Shoppers employed in businesses including private enterprise, state-owned enterprises, and foreign companies show a higher likelihood of using private car (2.8 and 2.1 times higher likelihood than walking/cycling and using public

Table 3 MLR model results

Dependent variable	Variable group	B	SE	Wald	df	Sig.	Exp(B)
Walking/cycling	Constant	6.15	1.26	23.75	1	0.000	
	Population density = 1	–1.95	0.80	5.97	1	0.015	0.15
	Population density = 2	–2.02	0.64	10.06	1	0.002	0.14
	Bus station = 1	–2.53	0.96	7.00	1	0.008	0.08
	Bus station = 2	–2.73	0.92	8.85	1	0.003	0.07
	Bus station = 3	–2.43	0.88	7.59	1	0.006	0.09
	Road density = 1	–1.43	0.74	3.75	1	0.050	0.24
	Road density = 2	–1.81	0.65	7.84	1	0.005	0.16
	Road density = 3	–1.41	0.55	6.57	1	0.010	0.24
	Shop density = 1	–2.00	0.84	5.62	1	0.018	0.14
	Shop density = 2	–1.17	0.43	7.38	1	0.007	0.31
	Car ownership = 0	3.78	0.32	136.43	1	0.000	43.96
	Occupation = 2	–1.04	0.39	7.27	1	0.007	0.35
Bus/subway	Constant	2.60	1.17	4.93	1	0.026	
	Bus station = 1	–1.70	0.88	3.71	1	0.050	0.18
	Shop density = 2	–.91	0.38	5.62	1	0.018	0.40
	Car ownership = 0	3.71	0.29	158.81	1	0.000	40.85
	Occupation = 2	–0.76	0.34	5.05	1	0.025	0.47
Taxi	Constant	–34.25	3007.40	0.00	1	0.991	
	Car ownership = 0	3.35	0.36	84.29	1	0.000	28.36
	Education = 1	16.86	0.34	2491.80	1	0.000	254.87
	Education = 2	17.13	0.43	1570.58	1	0.000	165.87

Notes: B: B-coefficient; SE: standard error; Wald: Wald chi-square test; df: degrees of freedom

transport, respectively). Consumers living in the outskirts of the city where population density is low, there are fewer bus stations, and lower shop density are more likely to go by private car to go shopping than walk or cycle. In comparing public transit and private car, we found that the number of bus stations and shops serving residents in the surrounding areas also influenced shoppers' choices of travel mode. Shoppers with none or few bus stations within 0.8 km of their residence preferred to travel by private car rather than by bus or subway for shopping. People living further away from shopping areas have a higher tendency to drive to shop (about 2.5 times more likely to use automobiles than public transit modes). Education levels also affected travel mode choice of taxi and private car. Compared with those with a master's degree or higher, shoppers with high school level education or below are more likely to take a taxi than go by private car.

4 Discussion

4.1 Built environment and transport carbon emissions

The study aims to identify which urban built environmental determinants affect travel mode for shopping and the related transport carbon emissions. The findings suggest that several built environment features, including population density, the quantity of public transport stations, road density, and shop density, within the home area are influential factors. Suburban areas where population density is lower usually have better road conditions but poorer infrastructure in terms of public transport and commercial facilities, and these factors are associated with increased private car use and higher shopping travelling CO_2 emissions. In Shenyang, shoppers living beyond the second circumferential road have the highest emissions. This is mainly because one in five shoppers residing outside the second circumferential road choose private car for shopping, which is nearly twice as many as those living within the second circumferential road.

Our findings align with previous studies, which show that population density had statistically significant and negative effects on personal car use and car distance traveled, thereby lowering household carbon emissions (Kotval-K and Vojnovic, 2015; Zahabi *et al.*, 2015). In general, studies have shown that convenient access to public transportation is the key factor influencing transport-related emissions (Frank *et al.*, 2000; Yang *et al.*, 2015). In terms of the effect of transport infrastructure on travel behavior, it was confirmed that an increase in road density positively contribute to road transport demand and transit-oriented urban development (Badland *et al.*, 2008; Choi and Ahn, 2015). Recent research has supported the notion that people living closer to shopping areas and leisure facilities tend to be more likely to walk or cycle, whereas those driving may tend to do so because they live further from these key destinations (King *et al.*, 2005; Sallis *et al.*, 2009; Carse *et al.*, 2013). Overall, the sprawling and decentralized urban form associated with low density and segregated land use has greatly increased traffic volume and reliance on cars, resulting in high fossil fuel consumption, increased carbon emissions and air pollution, and poses threats to pedestrian safety (Frumkin, 2002; Brand *et al.*, 2014; Haybatollahi *et al.*, 2015). Therefore, urban planning policy measures aiming to influence travel behavior should be proposed by the government through developing high density and compact built environments, with high roadway street density, a diverse land use mix, and robust provision of public transit and non-motorized mode access/facilities. This would help in promoting active modes of travel, reducing motorized vehicle miles, and lowering carbon emissions in order to attain sustainable urban transport (Carse *et al.*, 2013; Bhat *et al.*, 2014). Another strategy is to control development intensity in central urban areas through a polycentric urban development strategy (Wang *et al.*, 2016).

4.2 Individual socio-economic characteristics and transport carbon emissions

Besides built-environmental determinants, we found that individual socio-economic characteristics of car ownership, employment status, and education level are strongly associated with travel modes of shoppers and CO_2 emissions. Among these factors, private car ownership had the largest impact on shopping CO_2 emissions. Nearly 90% of car-driving shoppers have at least one vehicle. The results indicate that, as the number of vehicles available to a household increased, the likelihood of choosing non-motorized transport decreased (Lawson *et al.*, 2013). The literature on car ownership has reported similar results, suggesting that car ownership has a strong and negative association with non-motorized travel and public transport usage (Rubin *et al.*, 2014; Fairnie *et al.*, 2016). Furthermore, employment status was strongly associated with transport carbon emissions, especially workers employed in business. There was a higher percentage of workers in enterprises shopping by private car (36.2%) compared to shoppers employed in public sectors, or who are self-employed, unemployed, and retired. This is mainly because employment status affects people's ability and need to buy a car. These results are also consistent with previous studies in which employment is correlated with higher percentages of car availability due to long commuting distance (Carlsson-Kanyama and Lindén, 1999; Brand and Boardman, 2008; Susilo and Stead, 2009; Brand *et al.*, 2013; Wang *et al.*, 2016). Regarding education level, associations with travel mode have been supported by (Schwanen *et al.*, 2002), who provided empirical evidence that the likelihood of shopping by private car increased with education. This association may be partially explained by the fact that shoppers with higher education levels usually live in suburban areas. A correlation analysis conducted in our study indicates that education levels have a negative correlation with bus stations (R = –0.052, $P < 0.05$), road density (R = –0.048, $P < 0.05$) and shop density (R = –0.078, $P < 0.01$). This association is also related to the higher income levels enjoyed by more educated people. Consistent with earlier findings, education is a known proxy for latent income effects, which determine increased car availability and automobile use (Axhausen and Gärling, 1992; Ben-Elia and Ettema, 2011).

The results regarding the relationship between individual socio-economic characteristics and shoppers' travel mode choices may be beneficial in developing important policy measures for curbing the sharply increasing car ownership rates in developing countries, including sales control, fuel taxes, parking regulations, the rationing of car usage, and congestion pricing (Etminani-Ghasrodashti and Ardeshiri, 2016; Li *et al.*, 2016). This should be coupled with technological measures through the development of new cleaner fuel and fuel efficient vehicles for reducing the adverse effects of pollution in cities in a context of relatively high car ownership and use (Andong and Sajor, 2015). It is also suggested that the provision of cycle facilities and the promotion of walking and cycling by the government can play a key role in reducing car use (Raha and Taweesin, 2013). Improvement of underfunded and inefficient public transport systems in terms of convenience, speed, frequency, reliability, comfort, and accessibility is urgently needed, especially rail-based mass transits connecting the central city to suburban and rural areas to encourage high emitters to take public transit and be less car-dependent (Andong and Sajor, 2015; Li *et al.*, 2015; Yang *et al.*, 2015; Nesheli *et al.*, 2016). In addition, it is also necessary to use clean energy and fuel-efficient vehicles in public transport modes as part of low-carbon urban transportation development. Finally, government agencies should work together to inform the public of the negative environmental effects of cars and promote the use of active travel modes, as the effectiveness and legitimacy of low-carbon policies depend on the public perceptions of sustainable development.

5 Conclusions

This research is based on a questionnaire survey of shoppers conducted in Shenyang, China. It estimated individual shopping-related travel carbon emissions, analyzed the spatial clustering of carbon emissions, and examined the important built environment and individual socio-economic factors affecting carbon emissions and shopping travel behavior. Our findings suggest that shopping travel CO_2 emissions are strongly associated with particular built environment features including population density, the quantity of public transport stations, road density, and shop density. Our study also provides clear evidence that individual socio-economic characteristics including car ownership, employment status, and education level are significant factors in determining the travel modes of shoppers and the associated CO_2 emissions. The empirical findings have important policy implications firstly urban planners should seek to the efficacy of compact and polycentric urban development to make it possible to reduce automobile dependence and associated carbon emissions. Furthermore, it will be important for these policy proposals to be highlighted including private vehicles control interventions, technological measures, providing good public transit operations and service levels and promoting the public of low carbon consumption behaviors to develop low-carbon and efficient transport system.

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