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Measuring the Direct and Indirect Effects of Neighborhood-Built Environments on Travel-related CO_2 Emissions: A Structural Equation Modeling Approach

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Abstract: Intervening in the built environment is a key way for land-use and transport planning and related policies to promote low-carbon development and low-carbon travel. It is of significance to explore and recognize the actual impact of the neighborhood built environment on travel-related CO_2 emissions. This study calculated the CO_2 emissions from four purposes of trips, which were within the urban region, using Travel O-D Point Intelligent Query System (TIQS) and 1239 residents' travel survey questionnaires from 15 neighborhoods in Guangzhou. It measured the direct and indirect effects of built environments on CO_2 emissions from different purposes of trips by developing structural equation models (SEMs). The results showed that for different purposes of trips, the effects of the neighborhood built environments on CO_2 emissions were inconsistent. Almost all built environment elements had significant total effects on CO_2 emissions, which were mainly indirect effects through mediators such as car ownership and trip distance, then affecting CO_2 emissions indirectly. Most of the direct effects of neighborhood built environments on CO_2 emissions were not significant, especially those from non-commuting trips. These findings suggest that in the process of formulating low-carbon oriented land-use and transport planning and policies, the indirect effects of the built environments should not be ignored, and the differences of the effects of the neighborhood built environments among different purposes of the trip should be fully considered.

Keywords: built environment; CO_2 emissions; indirect effect; different purposes of trips; structural equation model (SEM)

1. Introduction

The transportation sector is the world's second largest unsustainable energy user and contributor to carbon emissions, contributing 23.31% of global carbon dioxide (CO_2) emissions in 2014 [1]. Regarded as the most difficult sector in which to achieve carbon reduction, it has the fastest growth rate of CO_2 emissions and its global share is projected to rise to 30–50% by 2050 [2–4]. China surpassed the United States in 2007 and became the country with the largest total CO_2 emissions in the world [5]. Over the past two decades, China's urban development patterns have continued along the path of suburbanization and decentralized development, characteristic of the U.S.'s urban spread in the second half of the twentieth century. In the process of rapid urban expansion, the spread pattern of low density, decentralized development, and segregation of land-use has appeared in the urban fringe areas, which has greatly increased the distance of residents' travel and the use of cars [6,7]. In this context, private car ownership in China has expanded rapidly, with 123.39 million in 2014, and the average annual growth rate was as high as 23.26% from 1985 to 2014. With the continuous development of the economy and more private cars, China's carbon emissions from transportation will continue to grow [8].

Although the transportation sector is a large and diverse sector that includes air, land, and water transport, and the movement of both passengers and freight, people's daily travel by passenger vehicles is the primary source of CO_2 emissions [9]. Over the past two to three decades, numerous studies have examined the relationship between the built environment and travel behavior [10–13], focusing on trip frequencies, trip lengths, mode choices or modal splits, and person miles traveled (PMT), vehicle miles traveled (VMT), or vehicle hours traveled (VHT) [14,15]. However, little attention has been paid to travel-related carbon emissions, which can also be regarded as a travel behavior or an outcome of travel behavior [16,17]. Macro-level studies on CO_2 emissions from transport have mainly explored the influencing factors based on the aggregate data of country, region, or city, using decomposition methods [18–21], scenario analysis [22–24], panel data models [8], and Data Envelopment Analysis (DEA) models [25–27]. They have seldom examined the effects of urban forms or built environments on transport-related CO_2 emissions. Most studies on the neighborhood/local level have used questionnaires and disaggregate methods to investigate the impact of socio-demographics and built environments on residents' travel behavior and its related CO_2 emissions. Some research has focused on quantifying the effects of residents' socio-demographic attributes on travel-related CO_2 emissions and neglected to analyze the effects of built environment factors [28–31]. Others have primarily measured the direct effects of the built environment on travel-related CO_2 emissions with case studies of cities in North America, Europe, and Oceania [28,32–34], but ignored the indirect effects of the built environment, which ultimately affects CO_2 emissions through intermediary factors. Furthermore, they did not examine the differences in the effects of the built environments on CO_2 emissions in terms of different purposes of trips [17,35,36].

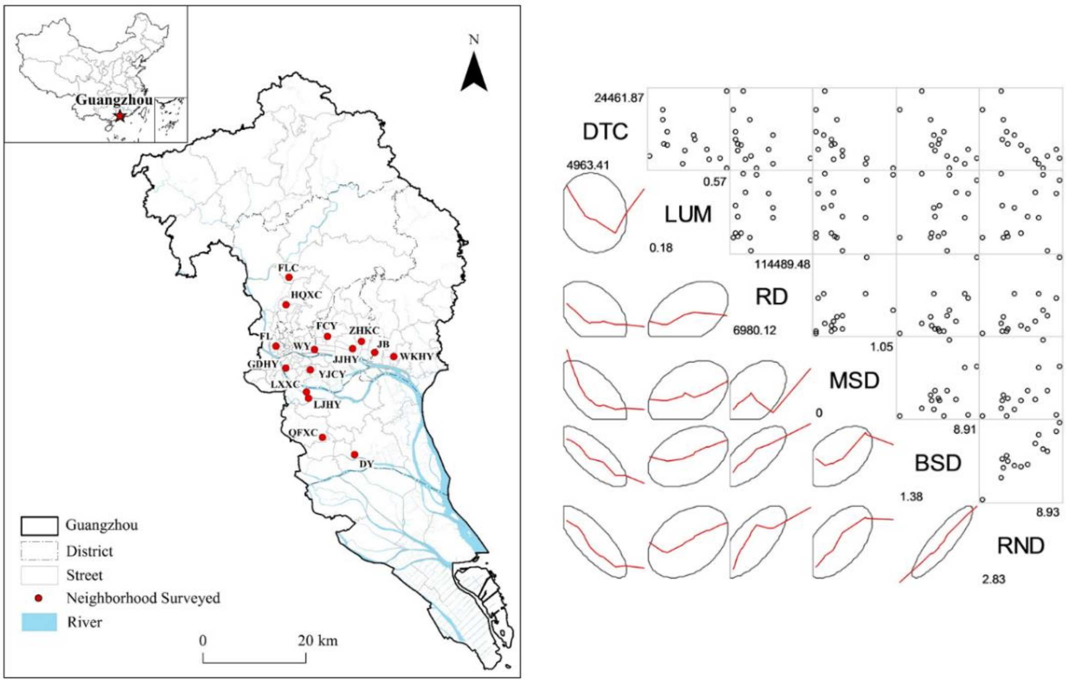
In this paper, taking Guangzhou as an example, we measured the direct and indirect effects of neighborhood built environments on CO_2 emissions from four purposes of trips based on survey data and structural equation modeling. It aimed to address the following two research questions: (1) How does the neighborhood built environment affect the travel-related CO_2 emissions of residents? For example, do they affect CO_2 emissions directly or indirectly by affecting other mediating variables?; (2) For different purposes of trips, are there any differences in the effects of neighborhood built environment elements on CO_2 emissions?

The rest of this paper is organized as follows. Section 2 introduces the methodology and data used in the analysis. Section 3 examines the estimation results of the models and analyzes the direct and indirect effects of neighborhood built environments on travel-related CO_2 emissions. Section 4 summarizes the primary conclusions and policy implications of the study.

2. Methodology and Data

2.1. Study Area and Neighborhoods Surveyed

This paper takes Guangzhou as the study area. It is the largest city in southern China and covers an area of 3647.43 km^2 and includes 2055 neighborhoods. Its total population was 14.04 million in 2016. In order to select the survey neighborhoods, we first used GIS technology to measure the built environment for all these 2055 neighborhoods, including the following six criteria: the distance to city public centers (DTC), residential density (RD), land-use mix (LUM), bus stop density (BSD), metro station density (MSD), and road network density (RND). Specifically, the distance to city public centers was measured through the average Euclidean distance from the center of the neighborhood to 16 urban public centers of different types. The residential density was calculated by dividing the neighborhood population by the area of the neighborhood. The land-use mix was calculated by methods similar to those used in previous studies [37,38] with 13 types of points of interest (POIs). The bus stop density and the metro station density were obtained by estimating the bus stop vector data and the metro station vector data, respectively, using the kernel density method. The road network density was measured by the method of line density with the road network vector data. And then, to ensure the statistical significance of the model fit, we specifically chose neighborhoods with large differences in the built environment to conduct the survey. Eventually, 15 neighborhoods from 7 districts were selected. They are Fuli (FL), Wuyang (WY), Yijingcuiyuan (YJCY), Guangdahuayuan (GDHY), Fangcaoyuan (FCY), Junjinghuayuan (JJHY), Zhonghaikangcheng (ZHKC), Huiqiaoxincheng (HQXC), Fulicheng (FLC), Jinbi (JB), Wankehuayuan (WKHY), Luoxixincheng (LXXC), Lijianghuayuan (LJHY), Qifuxincun (QFXC), and Dongyi (DY) (Figure 1a). In the scatter plot and the fitting curve between the built environment elements of these neighborhoods, almost all their confidence ellipses have a larger area, which indicates that there are significant differences in the built environment elements between the surveyed neighborhoods (Figure 1b).



(a) **(b)**

Figure 1. (**a**) The spatial distribution of the neighborhoods surveyed; (**b**) the scatter plots and fitting curves between built environment elements.

2.2. Survey Data

A pre-survey exercise was conducted in March 2015. After feedback and refinement, the formal survey began in May 2015 and lasted until July. The objects of our survey were residents aged 16 and above and below 60 years of age living in each neighborhood. We surveyed the respondents in the public spaces of the neighborhoods, using a face-to-face and random interception approach. A total of 1345 questionnaires were collected, of which, 1239 were valid (Table 1).

The residents' socio-demographic data and travel information were collected by a survey (Table 2). We obtained 1239, 726, 702, and 712 trip OD pairs of commuting trips, social trips, recreational trips, and daily shopping trips, respectively, with the specific address of their origins and destinations such as the name of the neighborhood, building, bus stop, and so forth. We performed spatial coding and vectorization of these OD pairs (a total of 3379 pairs) and used Travel O-D Point Intelligent Query System (TIQS) which was developed by us based on the Baidu map LBS (Location Based Service) open platform to calculate trip distance, travel time and other detailed travel information.

Table 1. The sample distribution and built environment characteristics of the neighborhoods surveyed.

Neighborhood	District	Sample	Distance to City Public Centers	Land-Use Mix	Residential Density	Bus Stop Density	Metro Station Density	Road Network Density
			km	-	Person/km^2	Unit/km^2	Unit/km^2	km/km^2
Fuli	Liwan	63	7.37	0.54	11,4489	8.91	0.68	8.93
Wuyang	Yuexiu	88	4.96	0.57	39,885	6.28	1.05	7.63
Yijingcuiyuan	Haizhu	75	7.23	0.48	24,695	6.89	0.23	6.99
Guangdahuayuan	Haizhu	102	8.04	0.18	32,147	6.09	0.36	7.97
Fangcaoyuan	Tianhe	39	5.93	0.35	63,200	7.72	0.67	7.28
Junjinghuayuan	Tianhe	109	9.34	0.36	13,827	4.85	0.36	6.43
Zhonghaikangcheng	Tianhe	69	10.71	0.27	17,580	4.56	0.21	5.86
Huiqiaoxincheng	Baiyun	121	9.49	0.47	56,825	8.07	0.02	8.68
Fulicheng	Baiyun	41	14.05	0.27	10,343	5.70	0.00	4.78
Jinbi	Huangpu	89	13.36	0.40	63,149	4.75	0.10	5.38
Wankehuayuan	Huangpu	34	17.12	0.25	29,717	4.45	0.29	4.48
Luoxixincheng	Panyu	109	11.00	0.25	13,938	5.15	0.25	4.81
Lijianghuayuan	Panyu	95	12.13	0.41	9989	5.32	0.21	4.42
Qifuxincun	Panyu	159	19.64	0.25	6980	1.38	0.00	2.83
Dongyi	Panyu	46	24.46	0.57	20,503	3.52	0.12	4.31
Total		1239	11.66	0.37	34,484	5.58	0.30	6.05

Table 2. The distribution of socio-demographic attributes for the sample population.

Variable	Level	Number of Samples	Percent
Gender	0 for male	694	56.01%
	1 for female	545	43.99%
Age	1 represents age 16–24	137	11.06%
	2 represents age 25–34	605	48.83%
	3 represents age 35–44	426	34.38%
	4 represents age 45–60	71	5.73%
Household size	1 represents 1 people	39	3.15%
	2 represents 2 people	140	11.30%
	3 represents 3 people	429	34.62%
	4 represents 4 people	355	28.65%
	5 represents $\geq$ 5 people	276	22.28%
Any child under 16	0 for no	414	33.41%
	1 for yes	825	66.59%
Education	1 represents senior high school and below	151	12.19%
	2 represents junior college	357	28.81%
	3 represents bachelor degree	551	44.47%
	4 represents master degree or above	180	14.53%
Hukou	0 for other cities	584	47.13%
	1 for Guangzhou	655	52.87%
Household monthly incomes per capita	1 represents income $\leq$ 3999 RMB	129	10.41%
	2 represents income 4000–5999 RMB	221	17.84%
	3 represents income 6000–7999 RMB	208	16.79%
	4 represents income 8000–9999 RMB	202	16.30%
	5 represents income 10,000–14,999 RMB	208	16.79%
	6 represents income $\geq$15,000 RMB	271	21.87%
Car ownership	0 for no	488	39.39%
	1 for yes	751	60.61%
Bicycle ownership	0 for no	429	34.62%
	1 for yes	810	65.38%

2.3. Calculation of Travel-Related CO_2 Emissions

In order to examine the relationship between the built environment and CO_2 emissions from travel, this paper measures the CO_2 emissions based on trip distance, like the methods proposed by existing studies in the field of travel research [28,35,36,39,40], which is different from studies of transportation engineering and energy sciences that mainly focus on accurate calculation of emission factors and CO_2 emissions through experimental methods, and studies of other disciplines such as environmental science that estimate CO_2 emissions based on the energy use. Moreover, based on the application of Travel O-D Point Intelligent Query System, we have data on all segments of each trip, which allows us to exclude the non-motorized trip distance from the total trip distance and make the calculation of CO_2 emissions relatively more accurate than most previous related studies. The calculation formula of CO_2 emissions for each trip is as follows:

$$TC_i = MTD_i \times EF_m, \tag{1}$$

$$MTD_i = TD_i - NTD_i, \tag{2}$$

where TC_i denotes the CO_2 emissions for trip i, TD_i denotes the total trip distance for residents that travel from O point to D point during trip i, and NTD_i is the non-motorized trip distance during this trip. We use Travel O-D Point Intelligent Query System to calculate the TD_i and NTD_i by entering the space coordinates of the trip OD point. MTD_i is the motorized trip distance for trip i, which is calculated by TD_i and NTD_i. EF_m is the emissions factor for the motorized travel mode m in the related trip, which can be found in Table 3.

Table 3. The specific energy consumption and CO_2 emissions factor for motorized travel modes.

Motorized Travel Modes	Final Energy Consumption (l/100 km, KWh/km)	Capacity (Persons)	Primary Energy Consumption (MJ/Pkm)	CO_2 (g/Pkm)
Passenger car	11.0	1.3	0.84	233.1
Urban bus	35.0	40	0.35	26.0
Coach	30.0	44.0	0.27	20.3
Metro	5.0	216	0.26	20.9

Note: According to the research of Entwicklungsbank on China's transportation CO_2 emissions [41]. MJ is an abbreviation of the unit of heat for megajoule. Pkm refers to person kilometer.

2.4. Structural Equation Model (SEM)

Structural equation model (SEM) is often used to explore the complex relationship between the built environment and the travel behavior [17,42,43]. It can effectively solve the endogenous problem between variables and can examine the direct, indirect, and total effects of exogenous variables on endogenous variables, as well as between endogenous variables [44–46]. Therefore, this paper measures the direct and indirect effects of neighborhood built environments on the travel-related CO_2 emissions of residents through constructing four SEMs for four purposes of trips and examines whether the influence mechanism has differences in these different purposes of trips.

The SEMs were constructed according to the following conceptual framework: set the socio-demographics and built environments as exogenous variables, and car ownership, trip distance, and travel-related CO_2 emissions as endogenous variables. Among them, taking into account that car ownership and trip distance are likely to have significant effects on travel-related CO_2 emissions, and these effects are not independent because they may also be affected by residents' socio-demographics and neighborhood built environments [43,44,47], we set these two variables as mediating variables (Figure 2).

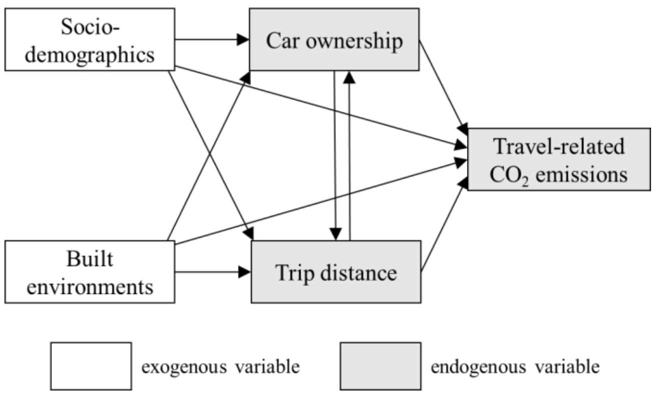


Figure 2. The conceptual framework for the structural equation models construction.

Since the variables estimated in this paper were observed variables rather than latent variables, the SEMs without latent variables constructed in this paper can be expressed as follows [44,48]:

$$y = By + \Gamma x + \zeta, \tag{3}$$

where y is the $N_Y \times 1$ vector of endogenous variables, x is the $N_X \times 1$ vector of exogenous variables, B is the $N_Y \times N_X$ matrix of coefficients representing the direct effects of endogenous variables on other endogenous variables, Γ is the $N_Y \times N_X$ matrix of coefficients representing the direct effects of exogenous variables on endogenous variables, and ζ is the $N_Y \times 1$ vector of errors in the equation. The ordered categorical variables in socio-demographic attributes, such as Age, Household size, Education, and Household monthly incomes per capita, were introduced directly into the models as continuous variables. The models were estimated using Amos 21.0 (IBM, Armonk, NY, USA). This paper used the Bollen-Stine bootstrap estimation method and the number of bootstraps was set to 2000, considering that the data of variables was not multivariate normal distribution [49,50].

We revised the SEMs according to the Modification Indices (M.I.) provided by Amos 21.0. The links between the variables and the covariance between errors that can improve the model fit were added in a revised model [51]. Meanwhile, the links that were not statistically significant ($p > 0.1$) were removed from the models. The models were re-estimated after each modification, until the table of M.I. no longer prompted that the model needed to be modified, and the significance level of each link was above 10%. The ratios of sample size to the number of observed variables in the SEMs constructed for commuting trips, social trips, recreational trips, and daily shopping trips are 1239/17 (≈73), 726/17 (≈43), 702/17 (≈41) and 712/17 (≈42), respectively, which are much greater than the large sample reference value (15). Therefore, the sample size can be considered to be large enough to meet the model construction and statistical requirements [52].

3. Results and Discussion

3.1. Goodness-of-Fit for SEMs

Based on the above conceptual framework, four SEM models were constructed and fitted for commuting trips, social trips, recreational trips, and daily shopping trips, respectively. All the goodness-of-fit indices for SEMs in Table 4 shows that the models fit well with the data.

Table 4. The model fit indices for the structural equation models.

Model Fit Indices	Reference Value	Model-Based Value			
		Commuting	Social	Recreational	Daily Shopping
Chi-square (χ^2)		55.940	63.407	70.981	54.887
Degrees of freedom (df)		68	73	72	73
Bollen-Stine bootstrap *p*-value	>0.05	0.861	0.755	0.493	0.929
Goodness of Fit Index (GFI)	>0.9	0.992	0.990	0.988	0.991
Adjusted Goodness of Fit Index (AGFI)	>0.9	0.981	0.979	0.975	0.981
Comparative Fit Index (CFI)	>0.9	1.000	1.000	1.000	1.000
Normed Fit Index (NFI)	>0.9	0.990	0.988	0.986	0.989
Non-Normed Fit Index (NNFI)	>0.9	1.004	1.003	1.000	1.007
Root Mean Square Error of Approximation (RMSEA)	<0.05	0.000	0.000	0.000	0.000

Figure 3 shows the SEM path relationship between residents' socio-demographics, the neighborhood built environments, car ownership, trip distance, and travel-related CO_2 emissions for the four purposes of the trips. Although the path relationship between the variables in these models was similar, there were still some differences: for the different purpose of trips, the factors and mechanisms that affect the travel-related CO_2 emissions of residents are likely to be different, which difference needs to be measured and explored separately.

Table 5 shows the direct effects, indirect effects, and total effects of six neighborhood built environment variables on car ownership, trip distance, and travel-related CO_2 emissions. Since the effects of socio-demographic attributes have been explored comprehensively and richly in existing studies, this paper focused on examining the direct effects and indirect effects of neighborhood built environments on the travel-related CO_2 emissions of residents, aiming at providing a scientific basis for land-use planning, transport planning, residential district planning, and related policy development.

Table 5. The standardized total, direct, and indirect effects of variables on endogenous variables.

Endogenous Variables	Effect	Commuting			Social			Recreational			Daily Shopping		
		CAR	TD	TC	CAR	TD	TC	CAR	TD	TC	CAR	TD	TC
Distance to city public centers	Total	−0.240 ***	0.374 ***	0.094 **	−0.339 ***	0.231 ***	0.029	−0.335 ***	0.274 ***	0.056	−0.307 ***	0.028 **	−0.051 ***
	Direct	−0.240 ***	0.374 ***	-	−0.339 ***	0.231 ***	-	−0.335 ***	0.237 ***	-	−0.307 ***	-	-
	Indirect	-	-	0.094 **	-	-	0.029	-	0.037 ***	0.056	-	0.028 **	−0.051 ***
Residential density	Total	0.175 ***	−0.134 **	−0.008	0.221 ***	-	0.054 ***	0.217 ***	−0.119 **	−0.005	0.193 ***	−0.018 **	0.032 ***
	Direct	0.175 ***	−0.134**	-	0.221 ***	-	-	0.217 ***	−0.095 *	-	0.193 ***	-	-
	Indirect	-	-	−0.008	-	-	0.054 ***	-	−0.024 ***	−0.005	-	−0.018 **	0.032 ***
Land-use mix	Total	-	-	−0.077 **	-	-	-	-	-	-	-	-	-
	Direct	-	-	−0.077 **	-	-	-	-	-	-	-	-	-
	Indirect	-	-	-	-	-	-	-	-	-	-	-	-
Bus stop density	Total	−0.318 ***	0.416 ***	0.311 ***	−0.432 ***	-	−0.105 ***	−0.419 ***	0.399 ***	0.100 *	−0.388 ***	−0.184 ***	−0.176 ***
	Direct	−0.318 ***	0.416 ***	0.222 ***	−0.432 ***	-	-	−0.419 ***	0.352 ***	-	−0.388 ***	−0.219 ***	-
	Indirect	-	-	0.090 *	-	-	−0.105 ***	-	0.047 ***	0.100 *	-	0.036 **	−0.176 ***
Metro station density	Total	−0.152 ***	-	−0.045 ***	−0.192 ***	-	−0.047 ***	−0.201 ***	0.022 ***	−0.042 ***	−0.190 ***	−0.125 ***	−0.104 ***
	Direct	−0.152 ***	-	-	−0.192 ***	-	-	−0.201 ***	-	-	−0.190 ***	−0.143 ***	-
	Indirect	-	-	−0.045 ***	-	-	−0.047 ***	-	0.022 ***	−0.042 ***	-	0.017 **	−0.104 ***
Road network density	Total	-	−0.313 ***	−0.274 ***	-	−0.175 ***	−0.085 ***	-	−0.399 ***	−0.137 *	-	-	-
	Direct	-	−0.313 ***	−0.136 *	-	−0.175 ***	-	-	−0.399 ***	0.077 **	-	-	-
	Indirect	-	-	−0.138 ***	-	-	−0.085 ***	-	-	−0.214 ***	-	-	-
Car ownership	Total	-	-	0.296 ***	-	-	0.244 ***	-	−0.111 ***	0.211 ***	-	−0.092 **	0.165 ***
	Direct	-	-	0.296 ***	-	-	0.244 ***	-	−0.111 ***	0.271 ***	-	−0.092 **	0.212 ***
	Indirect	-	-	-	-	-	-	-	-	−0.059 ***	-	-	−0.047 **
Trip distance	Total	-	-	0.441 ***	-	-	0.485 ***	-	-	0.536 ***	-	-	0.508 ***
	Direct	-	-	0.441 ***	-	-	0.485 ***	-	-	0.536 ***	-	-	0.508 ***
	Indirect	-	-	-	-	-	-	-	-	-	-	-	-

Note: links that are not included in the model are indicated by '-'. CAR refers to car ownership; TD refers to trip distance; TC refers to travel-related CO_2 emissions. *** Significant at the 0.01 level; ** Significant at the 0.05 level; * Significant at the 0.1 level.

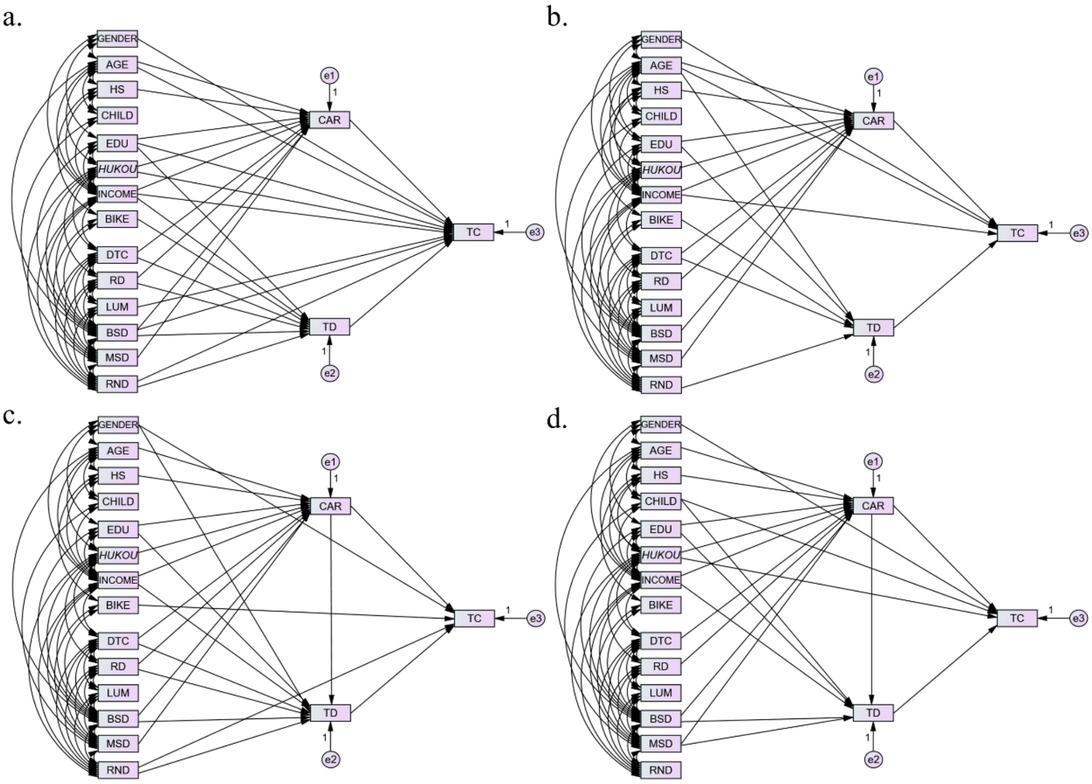


Figure 3. The SEM path diagram for commuting trips (**a**), social trips (**b**), recreational trips (**c**), and daily shopping trips (**d**).

3.2. The Interaction between Car Ownership, Trip Distance, and Travel-Related CO_2 Emissions

The path diagram (Figure 3) and model results (Table 5) show that, for different purposes of trips, the relationship between car ownership and trip distance was different. For example, car ownership had an impact on trip distance for recreational and daily shopping trips but had no significant impact on trip distance for commuting and social trips. This effect of the car ownership would further indirectly affect the CO_2 emissions. In general, both car ownership and trip distance have a significant positive direct effect and total effect on CO_2 emissions from trips (significant level was 1%), which meant residents with cars or those traveling longer distances emit more CO_2. Specifically, the effects of car ownership on travel-related CO_2 emissions were the largest for commuting trips and the smallest for daily shopping trips, while the effects of trip distance on travel-related CO_2 emissions were the largest for recreational trips and the smallest for commuting trips. This indicated that residents tended to use high-carbon modes for recreational trips but tended to use low-carbon modes for commuting trips, and residents with cars tended to emit more CO_2 during commuting trips than during other trips. This showed that the relationship between car ownership, trip distance, and travel-related CO_2 emissions would become very complex if we specifically explore them for different purposes of trips.

3.3. The Direct Effects of Neighborhood Built Environments on Travel-Related CO_2 Emissions

Overall, half of the neighborhood built environment elements that we studied had no significant direct effect on CO_2 emissions from commuting trips, while almost all of the elements had no significant effect on CO_2 emissions from other purposes of trips. In other words, the neighborhood built environments produced more pronounced effects for commuting trips than for other purposes of trips. For commuting trips, the land-use mix, bus stop density, and road network density had a significant level of 5%, 1%, and 10% of the direct effect on travel-related CO_2 emissions, respectively, while they had no significant direct effect for social and daily shopping trips. Moreover, for recreational trips, the road network density had the opposite effect. This shows that the impact of the built environment on carbon emissions for different purposes of trips is not consistent. Some built environment elements may have a direct effect for some purposes of trips but have no significant direct effect for other purposes of trips, and some may even have the opposite effect for different purposes of trips.

Specifically, the standardized coefficient of the direct effect of the land-use mix and road network density on CO_2 emissions from commuting trips were -0.077 and -0.136, respectively, which meant that the more diversified the neighborhood land-use, and the denser the neighborhood road network, the less CO_2 the residents emit during commuting trips. However, bus stop density had a significant direct effect on CO_2 emissions from commuting trips, which indicated that providing high-density bus services did not necessarily encourage residents to choose low-carbon modes for commuting trips, especially in cities like Guangzhou, where the supply of buses is already very high. As can also be seen from Table 1, there is no obvious difference in the bus stop density of the neighborhoods located in different locations. Therefore, for the neighborhoods with an adequate supply of bus services, attempts to add more bus stops or bus lines to reduce the residents' CO_2 emissions from commuting would probably not achieve the intended effect.

Although the vast majority of built environment elements have no direct impact on CO_2 emissions from other purposes of trips, it does not imply that planning intervention for the built environment is useless. If the direct effect is concerned only, the policy implications of the study are likely to be biased, because the actual impact (called the total effects) of the built environment may come from the indirect effect.

3.4. The Indirect Effects of Neighborhood Built Environments on Travel-Related CO_2 Emissions

Indirect effects are a major source of the impact of neighborhood built environments on travel-related CO_2 emissions, which come from intermediary variables such as car ownership and trip distance. From Table 5, we can see that the variables of distance to city public centers and metro station density had significant indirect effects on CO_2 emissions from commuting trips, and for CO_2 emissions from other purposes, many built environment variables also had significant indirect effects, which made them have significant total effects on CO_2 emissions.

Specifically, the distance from the neighborhood to city public centers had a positive indirect effect and total effect on CO_2 emissions from commuting trips at the significance of 5%, which came from influencing the mediating variables of car ownership and trip distance. This indicated that although the distance between the neighborhood and city public centers was negatively correlated with car ownership, it was positively correlated with commuting distance (with a greater standardized coefficient than car ownership) so that the distance to city public centers had a positive indirect effect and total effect on CO_2 emissions from commuting trips. However, for daily shopping trips, it had a significant negative indirect effect and total effect on CO_2 emissions. This implied that residents who lived far from city public centers were likely to make their daily shopping trips in the vicinity of their neighborhood with little CO_2 emissions, especially for neighborhoods with well-developed commercial facilities. Although residential density had no significant direct effect on CO_2 emissions for all purposes of trips, it had a significant positive indirect effect and total effect on CO_2 emissions from social trips and daily shopping trips. This implied that the effect of residential density on travel-related CO_2 emissions in Chinese cities is likely to be different from that in Western countries, most of which usually have a significantly negative effect [28,32]. A study on the influence factors of transportation CO_2 emissions in China also demonstrated that urban population density was positively correlated with CO_2 emissions from transportation [8]. Therefore, in order to promote low-carbon travel and achieve low-carbon development goals, increasing neighborhood residential density is not an effective method for Chinese cities. A similar situation also occurred with bus stop density, which had a positive indirect effect on CO_2 emissions from commuting trips and recreational trips at a 10% significant level, and its total effect on them was positive (significant level was 1% for commuting trips and 10% for recreational trips). This result was inconsistent with that of many studies in Western countries.

Meanwhile, for social trips and daily shopping trips, the bus stop density had a significant negative indirect effect and total effect at a 1% significant level. This indicated that although improving the neighborhood bus service supply did not necessarily encourage residents to emit less CO_2 during commuting and recreational trips, it helped to reduce the CO_2 emissions from social trips and daily shopping trips. Metro station density had no direct effect on CO_2 emissions, but it had a significant indirect effect on them from four purposes of trips, which mainly came from the intermediary role of car ownership. Although both metro station density and bus stop density were negatively related to car ownership, the bus stop density often had a positive correlation with trip distance, for example, during commuting trips and social trips, as bus travel was likely to result in longer trip distances. Therefore, increasing the neighborhood's subway service is more effective than increasing the bus service in promoting low-carbon travel, which is consistent with an existing study on Guangzhou [53]. Meanwhile, road network density had negative indirect and total effects on CO_2 emissions from commuting, social, and recreational trips. Its indirect effects resulted from the mediating effect of trip distance, which indicated that the denser the neighborhood road network, the shorter the residents' trip distance would be, resulting in smaller emissions of CO_2. Land-use mix only had a direct effect on CO_2 emissions from commuting trips but had no significant indirect effect on emissions from commuting trips and other purposes of trips.

4. Conclusions and Policy Implications

This paper used neighborhood survey data and the Travel O-D Point Intelligent Query System to calculate residents' CO_2 emissions from commuting trips, social trips, recreational trips, and daily shopping trips and measured the direct and indirect effects of neighborhood built environments on them by building structural equation models. It drew the following conclusions and planning implications: first, most of the neighborhood built environment elements had a significant total effect on CO_2 emissions, which mainly came from an indirect effect through affecting the mediators, such as car ownership or trip distance, and then indirectly affecting the travel-related CO_2 emissions. Therefore, it would probably underestimate the effects of neighborhood built environments on travel-related CO_2 emissions and thus, mislead land-use and transport planning and its related policy development if only their direct effects were considered and their indirect effects were ignored. Second, the effects of neighborhood built environments on CO_2 emissions from different purposes of trips were not consistent. Low-carbon oriented land-use and transport planning needed to fully consider the difference of the effects of the built environment on CO_2 emissions for different trip purposes [54]. Third, narrowing the distance between neighborhoods and city public centers is an effective way to reduce CO_2 emissions from commuting. At the same time, the commercial facilities in neighborhoods far from city public centers should also be improved, which would be beneficial for reducing the CO_2 emissions from daily shopping. Meanwhile, the neighborhood's residential density should be controlled at a livable level instead of blindly increasing its density, which has little effect on shaping the low-carbon land-use pattern. The diversification of neighborhood land-use is worth advocating. It will be helpful to reduce travel-related CO_2 emissions, especially for reducing emissions from commuting trips [55,56]. For neighborhoods with a higher density of bus stops, further addition of bus stops may not effectively reduce the CO_2 emissions from commuting trips and recreational trips. Instead, increasing the number of metro stations around the neighborhood and its road network density, abandoning the large blocks and wide roads, and building a good non-motorized travel environment will play a greater role in promoting residents' low-carbon travel and travel behavior changes.

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