The Impact of Built Environment on Low Carbon Travel: A Case Study from China

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Abstract: This study investigates the impact of the built environment on low-carbon travel behaviors in Panzhihua, a medium-sized city in China, using the Hierarchical Linear Model (HLM). The analysis, based on a survey of residents' travel patterns, reveals an significantly influences travel choices in land use and bus stop density by one standard unit, that is, the likelihood of residents to choose public transportation for commuting increases by 46.24%. Oppositely, residents in densely populated areas are less willing to choose cars in living trips. It suggests the balances between residential density and accessible public transit, which shows the necessary for urban planning. These findings provide valuable insights for public officials to reduce carbon emissions through sustainable urban development strategies.

Keywords: Built Environment, Low Carbon Travel, HLM, Travel Mode

1. Introduction

The rapid urbanization and motorization have led to significant environmental challenges, including traffic congestion and carbon emissions. While large cities have been the focus of numerous studies on travel behavior and low-carbon transportation, smaller urban areas have received less attention. This research aims to address this gap by examining the influence of the built environment on residents' travel choices in Panzhihua, a representative small to medium-sized city in Sichuan, China.

The importance lies in its potential to inform urban planning and policy-making, particularly in the context of promoting low-carbon travel modes. By understanding how urban density, land use mix, and public transportation accessibility affect travel behavior, we can better design cities to reduce reliance on private vehicles and lower carbon emissions [1-2].

We employ a Hierarchical Linear Model (HLM) to analyze data from a questionnaire survey, focusing on commuting, living, and entertainment trips. The results of this study are expected to provide a theoretical foundation for guiding low-carbon transportation choices, formulating urban land use policies, and optimizing urban transportation structures in smaller urban settings [3-4].

The following sections detail the methodology, including the variable design, data collection, and analysis approach, followed by the presentation of the empirical findings and their implications for urban planning and sustainable development.

2. Methods

The study employs a Hierarchical Linear Model (HLM) to investigate the influence of the built environment on residents' low-carbon travel behaviors in Panzhihua, China. The HLM is chosen for its capacity to analyze the nuanced effects of the built environment on travel choices across various travel purposes, including commuting, living, and entertainment trips.

2.1 Impact Mechanism of the Built Environment on Residents' Low-Carbon Travel

The interplay between land use and travel mode choice is characterized by a macro-level feedback loop between urban planning and transportation systems. Micro-level analyses focus on the built environment's impact on travel behavior, considering density, land use diversity, design, and accessibility [5-8]. Extensive research has identified commonalities in the relationship between the built environment and travel behaviors [9-10].

Residential and employment density are key determinants of travel behavior. High densities, indicative of concentrated land use, are theorized to improve public transport efficiency and accessibility, consolidating travel demands and potentially favoring non-motorized modes. This concentration may also lead to peak-hour congestion, reducing car travel appeal. Thus, increasing densities is suggested to decrease car dependency and encourage low-carbon travel.

Land use diversity, reflecting the variety and balance of land uses, affects travel patterns. A diverse mix of services can satisfy various social activities, potentially shortening trips and reducing car demand. Enhancing land use diversity is hypothesized to reduce car reliance and promote sustainable travel.

Design elements, including road networks, pedestrian infrastructure, and parking, influence travel preferences. While improved road density and connectivity may increase car travel, they can also improve public transport attractiveness. Pedestrian-friendly streets and bike lanes are expected to encourage walking and cycling.

Accessibility to public services, such as transit stops, is crucial. High accessibility is likely to increase public transport use and decrease car dependency, whereas poor accessibility may increase car reliance.

2.2 Hierarchical Linear Model Concerning the Impact of The Built Environment on Residents' Travel Mode

2.2.1 Hierarchical Linear Model

Hierarchical Linear Model (HLM), initiated by Lindley and Smith, is a flexible framework for analyzing nested data structures. Laird et al. enhanced the field with a robust covariance component estimation method [11-13].

HLM construction involves a random effects regression model with first-layer variables to screen for variability; and the introduction of second-layer variables to refine the model.

Compared with the random effects model, the complete model is incorporated with second-layer predictor variables, through which, how the variables of the first and second layers affect Y_{ij} can be detected. The basic formula is presented as follows:

The first layer:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + r_{ij} \tag{1}$$

The $second$ layer:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} W_{1j} + \mu_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} W_{1j} + \mu_{1j} \tag{3}$$

The subscript "0" represents the intercept; the subscript "1" represents the regression coefficient related to the first-layer predictor variable X_1; the subscript i stands for the research unit of the first layer; and the subscript j stands for the second layer unit subordinated to the first-layer individual. If there is more than one independent variable in the first-layer model, such as X_2 and X_3, accordingly, there will be β_{2j} and β_{3j}, and so on in a similar fashion. And in the second-layer equation, β_{0j}, γ_{00}, and μ_{0j} are the same as the null model. Specifically, β_{1j} is the slope of the first layer related to the second-layer unit j; γ_{10} represents the overall average of the slopes of all the second-layer units in the first layer.

W_{1j} represents the first predictor variable of the second layer. if there is a second predictor variable, it will be W_{2j}. The rest can be done in the same manner. γ_{01} and γ_{11} are the regression slopes of the Eq. (2) and the Eq. (3) respectively. The remaining parameters are the same as above.

2.2.2 Model Concerning the Impact of The Built Environment on Residents' Travel Mode

With reference to the formula described in section 2.2, the HLM concerning the impact of the built environment on residents' travel mode is constructed as follows:

First layer:

$$\begin{aligned} \varphi_{ij} = \beta_{0j+}\beta_{1j}(gender) + \beta_{2j}(age) \\ + \beta_{3j}(familys) + \beta_{4j}(kids) \\ + \beta_{5j}(income) + \beta_{6j}(bike) \\ + r_{ij}, \end{aligned} \tag{4}$$

Regarding gender, 0 present males while 1 present females. In terms of age, families means family size; kids are the number of children in the family; income shows the family salary per month; bike is the number of bicycles owned by the family; and car is the number of cars owned by the family. It is temporarily assumed that the above independent variables have an impact on residents' travel modes.

It is assumed that built environment variables are composed of population density, degree of land use mixture, road network density, distance to the downtown, and density of bus stops exert influences on residents' travel choice through affecting the household car-owning rate. The second-layer model is constructed as follows:

Second layer:

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \mu_{0j} \\ \beta_{1j} &= \gamma_{10} + \mu_{1j} \\ &\dots \\ \beta_{6j} &= \gamma_{60} + \mu_{6j} \end{aligned} \tag{5}$$

$$\beta_{7j} = \gamma_{70} + \gamma_{71}(density) + \gamma_{72}(diversity) + \gamma_{73}(road) + \gamma_{74}(dis\tan c\,e) + \gamma_{75}(stops) + \mu_{7j}$$

Where density represents the population density of the traffic zone where the residential area is located; diversity is the degree of land use mixture of the traffic zone where the residential area is located; road represents the traffic zone where the residential area is located; distance stands for the distance from the center of the traffic zone where the residential area is located to the downtown; and stops indicates the number of bus stops owned by the traffic zone where the residential area is located.

3. Experiment Design

The travel survey is carried out in Panzhihua, Sichuan, China, to analyze the influence of the residential area's built environment on low-carbon travel behaviors by a Hierarchical Linear Model (HLM). This comprehensive analysis encompasses variable design, model construction, data analysis, model calibration, and analysis.

3.1 Variable Design

3.1.1 Built Environment Variables

(1) Dependent Variable: Resident travel within a traffic zone, characterized by attributes such as distance, mode, bus stop distribution, and timing, significantly affects urban structure, transport efficiency, energy consumption, and carbon emissions. Carbon emissions are particularly influenced by these travel attributes, underscoring their importance in low-carbon travel characterization.

(2) First-Layer Independent Variables: Individual and family factors, including gender, age, economic status, lifestyle, environmental consciousness, family size, and household vehicle/bicycle ownership, shape residents' low-carbon travel choices.

(3) Second-Layer Independent Variables: Built Environment Factors

1) Population density: With the traffic zone as the analysis unit, the population density of the traffic zone can be obtained by dividing the number of people in each traffic zone by the area of the traffic zone, as shown in **Figure 1. (a).**

2) Degree of land use mixture: Urban land can be divided into residential and commercial land, per the urban land classification standard. On this basis, it is measured in line with the entropy model. **Figure 1. (b)** shows the result of dividing the proportion of land type by the total land types in the community.

3) Road network density: The road network density is used as an indicator of the design variable and obtained by dividing the total length of the road in the community by the community area, as shown in **Figure 1. (c).**

4) Distance to the downtown: The distance between each traffic zone and the traffic zone where the downtown is, as shown in **Figure 1. (d).**

5) Bus stop density: The bus stop density is adopted to characterize the distance variable to the bus stop, which can be obtained by dividing the number of bus stops in the community by the area of the community, as shown in **Figure 1. (e).**

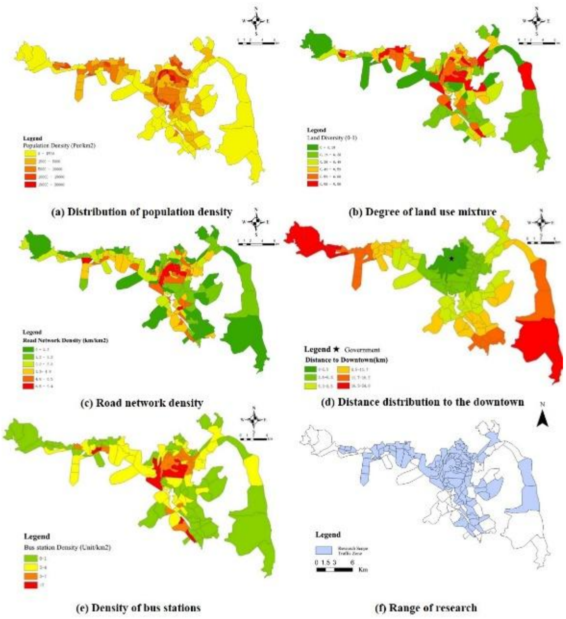

Figure 1. Variable Design, Data Statistics and Research Area

3.1.2 Research Area and Resident Travel Survey

This investigation centers on Panzhihua, Sichuan, China, covering an expanse of 7,440 square kilometers and accommodating approximately 640,000 residents, classifying it as a small to medium-sized city in China. The study focuses on 93 delineated traffic zones highlighted in **Figure 1. (f).**

Built environment metrics: Residential zone characteristics such as density, diversity, design, destination accessibility, and proximity to bus stops are assessed using population data, land use data, road network information, and bus stop data.

Personal and family data: Surveyed travel behavior data from Panzhihua residents, collected from September 13 to September 20, 2019, includes family demographics, personal details, and travel logs. The survey achieved an 88% effective response rate, with 1,765 households and 3,373 individuals' travel records analyzed.

3.2 Results

Data on commuting, living, and entertainment travel are solved with the HLM software, respectively. **Table 1.** presents regression coefficients showcasing the impact of diverse factor variables on residents' travel modes across different travel objectives. For instance, in commuting travel, the degree of land use mixture exhibits a negative coefficient of 0.4624. This value denotes a 46.24% reduction in the likelihood of residents opting for cars for commuting purposes per standard unit increase in land use mixture when other variables hold a value of 0. Similarly, the density of bus stops displays a negative coefficient of 0.4971 for commuting travel. It signifies a 49.71% increase in the likelihood of residents choosing cars for commuting travel per standard unit increase in bus stop density when other variables maintain a value of 0.

Table 1. Logistics Regression Coefficient Conversion Table

Variable	Commuting Travel		Living Travel		Recreational Travel	
	Regression Coefficient	Reduction Coefficient	Regression Coefficient	Reduction Coefficient	Regression Coefficient	Reduction Coefficient
Gender	-0.1244	0.4689	—	—	—	—
Age	—	—	-0.0039	0.4990	-0.0044	0.4989
Income	0.0687	0.5172	0.0588	0.5147	0.0453	0.5113
Familys	—	—	-0.0197	0.4951	—	—
Kids	-0.0086	0.4979	-0.0607	0.4848	—	—
Bike	—	—	-0.0115	0.4971	-0.0559	0.4860
Car	0.3868	0.5955	0.1499	0.5374	0.1438	0.5359
Density	0.0001	0.5000	-0.0001	0.5000	0.0001	0.5000
Diversity	-0.1505	0.4624	0.0280	0.5070	0.1728	0.5431
Road	-0.0110	0.4973	0.0234	0.5058	-0.0394	0.4902
Stops	-0.0116	0.4971	-0.0495	0.4876	-0.0775	0.4806
Distance	0.0107	0.5027	-0.0156	0.4961	0.0013	0.5003

In small and medium-sized cities, the positive correlation between residential population density and car usage for commuting challenges conventional research, potentially due to insufficient public transit services in densely populated areas. This leads to a preference for car travel among residents. However, population and bus stop densities significantly influence car usage for living-related trips, while land use diversity, road network density, and central city proximity have negligible effects on travel mode preferences. Interestingly, population density negatively correlates with living travel mode choices, contrasting with commuting patterns. This could be attributed to the availability of walkable amenities and public transit in high-density regions. These results may vary across urban structures in different countries, and the built environment's components show minimal impact on entertainment travel mode selection.

4. Discussion

Firstly, small and medium-sized cities ought to adhere to a high-density and compact development model, ensuring a harmonized distribution of residential population and workplaces to curtail residents' commuting distances, consequently diminishing reliance on car travel. Secondly, a commitment to diversified land use development, steering clear of single land development, is imperative. Thirdly, a rationalized planning of the urban road network system can bolster road accessibility and expand the coverage of bus stops, thereby fostering the expansion of urban

public transportation services. However, these outlined policy measures negatively impact entertainment travel, and their efficacy may face challenges.
Hence, policy implementation must comprehensively consider factors influencing residents' entertainment-related travel and harmonize with other planning and travel guidance policies. This could involve augmenting bus routes to tourist destinations, enhancing the service network of public transportation dedicated to tourists, and augmenting specialized buses for tourist sites. Residents should be encouraged to adopt low-carbon travel modes for entertainment purposes, thereby reducing urban residents' reliance on cars. This approach aims to optimize the travel patterns of urban residents, mitigating carbon emissions and air pollution to foster a sustainable urban environment.

5. Conclusions

The research reveals that in densely populated areas with high bus station densities, residents favor public transport for living trips, while car use is prevalent for commuting in dense residential zones. These insights contribute to urban and transportation planning, aiming to promote low-carbon travel and optimize urban travel patterns.
(1) The study elucidates the impact mechanism of the built environment on low-carbon travel by examining the interplay between land use and transportation.
(2) Categorizing travel purposes into commuting, living, and entertainment highlights how modifying the built environment can reduce car dependence , and encourage low-carbon transport.
(3) Population density, land use mixture, and bus stop density significantly influence commuting mode preferences. Higher residential density correlates with increased car use for commuting, while a higher degree of land use mixture and bus stop density reduce car preference. The likelihood of choosing public transport increases with land use mix and bus station density, by 46.24% per standard unit increase.
(4) In living travel, population and bus stop densities discourage car use, favoring walking and public transport. Bus stop density also negatively affects living travel distances, while road network density has a similar impact. However, entertainment travel is less influenced by built environment factors, with travelers showing greater independence in their choices.
Future research could expand on built environment factors using big data and consider the impact of spatial scale selection on research outcomes, enhancing model accuracy across different scales.

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