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Analyze the Impact Mechanism of Urban Planning on Traffic Carbon Emissions Based on Big Data

Ruijia Yuan[1], Liqin Zhao[2,*]

[1]*Faculty of Science and Engineering, University of Nottingham Ningbo China, Ningbo, 315000, China*
[2]*School of Management, Shijiazhuang Tiedao University, Shijiazhuang, 050043, China*
[*]*Corresponding author*

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Abstract: Since the United Nations Climate Change Conference shifted people's attention to the content of greenhouse gases in the atmosphere, more and more countries and cities have set their own carbon neutral targets. There is evidence that about 70% of greenhouse gas emissions are generated in cities. How to reduce carbon emissions in the process of urban development has become a primary concern. According to China's statistics in 2020, 15% of carbon emissions come from the transportation sector. About 90% of the carbon emissions generated in the field of transportation are from road traffic. This thesis used 11 indicator data of 35 cities in China about city size, traffic space, traffic time and public transport, and conducted bivariate correlation analysis and scatter correlation analysis through SPSS26.0 software. It was proved that urban population, urban area, commuting space radius, one-way commuting distance and one-way commuting time showed positive correlation with urban transport carbon emissions. The 2 indicators of workday vehicle peak speed and 5km commuting ratio showed negative correlations. The thesis then used the natural logarithm values of the seven correlation indicators to build a linear regression model, using a stepwise approach to exclude compounding and co-existence between indicators, and further calculated that the significant influencing factors of one-way commuting distance and workday vehicle peak speed had a significant linear relationship with urban carbon emissions. Finally the thesis proposed urban development planning recommendations for the integration of planning in new urban areas, strengthening road accessibility in old urban areas and vigorously developing public transport facilities based on the influencing factors of transport carbon emissions.

1. Introduction

1.1. The impact of Transportation on the Achievement of Cities' Carbon Neutrality Goals

In December 2015, countries committed in the Paris Agreement to control the global average temperature rise within 2°Ccompared with that before industrialization, and strive to control it within 1.5°C, and achieve the goal of global "carbon neutrality" by 2050-2100 [1]. There are two ways to achieve carbon neutrality: offsetting and reducing carbon emissions with reduced carbon emissions. The former can offset the reduced carbon emissions in other places with the carbon released by human activities through the carbon compensation mechanism, so as to achieve carbon neutral results, such as tree planting and carbon capture. The second approach focuses on reducing carbon emissions from various human activities as much as possible, for example, by using renewable energy to avoid carbon dioxide emissions into the atmosphere due to the combustion of fossil fuels. Compared with the former, the use of the second method is constantly mentioned in many fields. According to the statistics of the International Energy Agency (IEA, 2021), the carbon emissions of the transportation sector accounted for 24% of the global carbon emissions in 2019, becoming the second largest emission sector in the world [2]. Therefore, many scholars and institutions focus on how to reduce the huge carbon emissions brought by the transportation sector.

China has formulated a long-term strategy to achieve net zero emissions by 2060, and one of the specific goals is to reach the peak of carbon emissions by 2030. In order to achieve this commitment, it is necessary to discuss the reduction of carbon emissions in various fields. According to the report of China Energy Administration in 2020, about 15% of China's carbon emissions come from the transportation sector [3]. In this field, the carbon emissions generated by road traffic account for the largest proportion. Under the current policy scenario, the carbon dioxide emissions from road transportation will reach a peak of 1415.5 million tons in 2033 [4].

1.2. The transport Decarbonisation Dilemma

Transport, which includes the commuting of people and the transport of goods, plays an important role in the emission of carbon dioxide. In order to reduce carbon dioxide emissions in the future, on the one hand, transport policies need to be developed in such a way as to improve vehicle efficiency and increase the use of carbon-neutral alternative fuels. On the other hand, carbon dioxide emissions can be reduced through better transport planning, for example by reducing traffic congestion, lowering commuting times and avoiding more detours. Transport planning and its impact on carbon dioxide emissions can be examined by using detailed energy and emissions models and relating them to real-world driving patterns and traffic conditions. Many countries have conducted studies on how to reduce urban carbon emissions through better transport planning, and Barth et al. (2008), using a typical traffic situation in Southern California as an example, found that carbon dioxide emissions could be reduced by up to 20% through three different strategies [5]. Among these are the reform of urban traffic to reduce severe congestion, the use of congestion mitigation strategies to make vehicles move faster on average, and the use of shock wave suppression techniques to further reduce traffic-related acceleration and deceleration in congested road conditions where vehicles have to stop and go several times. It follows that the design of a new, improved, low-carbon urban transport system is a vital element in helping to reduce urban carbon dioxide emissions and achieve urban carbon neutrality targets, among other issues. After obtaining this result, in order to reverse this huge trend, IEA proposed the combination of technical and behavioral measures: avoidance, transfer, improvement and conversion (IEA, 2012) [6]. According to the proposal of IEA, comprehensive traffic planning should be carried out in urban planning to help avoid unnecessary vehicle travel, or example, by shortening the distance between home and workplace, or improving the integration of public transport, cycling and walking. Some of these measures may even be cheaper and easier to implement than developing electric vehicles or developing lighter materials. Instead of forcing residents to give up travelling by car through various policies, reasonable traffic planning can guide residents to choose a lower carbon travel mode by reducing congestion and facilitating travel. There is no doubt that this change will bring significant common benefits, such as more livable streets.

1.3. Hypothesis, Aims and Objectives of the Study

There are many factors that influence urban transport carbon emissions. This thesis analysied factors related to urban planning and road planning to demonstrate the factors that influence urban commuting carbon emissions as well as the pathways of influence. The thesis hypothesised that the overall planning and road planning of cities of different sizes have an impact on the transport space, travel time and public transport choices of residents commuting to work, while the performance of urban commuting would also have a degree of influence on commuting carbon emissions. The aim of the study is to find the influencing factors that affect the carbon emissions of urban commuting, and then to use these factors to make appropriate recommendations for urban planning and transport planning.

2. Factors Influencing Urban Planning on Low Carbon

2.1. Spatial Autocorrelation Theory

Tobler (1970) pointed out that "the first law of geography is that everything is correlated with everything else, but what is near has a stronger correlation than what is far". Spatial autocorrelation refers to the potential interdependence between observations of a number of variables within the same distribution area(Getis, 2008)[7].In the study of the correlation between urban carbon emissions and urban planning, the theory of spatial autocorrelation could be understood as the idea that elements in space do not exist alone, but are influenced by each other and spatial interactions(Bautista-Hernández, D. 2019)[8]. Urban carbon emissions are affected by industrial structure, energy structure, population levels, the size of the built-up area, transport planning, distance to work and residence, commercial space and many other factors Li et al., 2022. [9] Among them, the factors related to urban space and road planning mainly include the distance between work and residence, traffic structure, road network density, public transport services, etc. Other factors about the industrial structure, commercial prosperity, energy structure and population size of the city are very weakly correlated with the carbon emissions caused by urban space and road layout. Therefore, the concept of carbon emissions related to urban planning can be narrowed down to urban commuting carbon emissions, which can more accurately reflect the influence of relatively stable index factors such as urban spatial planning, occupational and residential planning, road planning and public transport planning on urban carbon emissions.

Urban space interacts with the activities of the population and is divided into residential space and employment space in order to meet the occupational needs of the population. The employment structure involves the primary, secondary and tertiary sectors, which have huge spatial differences. In order to unify the treatment, it can be expressed in terms of commuter transport space, with specific indicators covering road network density, weekday peak vehicle speed, commuter space radius, one-way commuting distance, and separation between jobs and dwellings.

2.2. Urban land Use Theory

In the development of urban land use theory, Homer Hoye proposed the Sector Theory, which suggests that the influence of directional accessibility and directional inertia of urban transport routes will lead to the formation of commercial, industrial and educational land on their the influence of Directional Accessibility and Directional Inertia Beauregard, 2007) [10]. Hansen proposes a land use-transport interaction loop model to explain the interaction between land use and commuter travel. The different types of land use make it necessary for urban residents to overcome the cost of spatial distance to move around to meet their needs (commuting to work, school, etc.). In terms of urban transport, the choice of public transport routes and locations leads to differences in accessibility to different locations in urban space, which affects residents' choice of travel mode (Hansen, 1959) [11].

Residential commuter transport is generally reflected through the commuting time of urban workers and the stability of urban public transport facilities. The commuting time of urban workers can cover two indicators: one-way commuting time and 5km commuting ratio. Urban public transport facilities can be represented by two indicators: the proportion of commuting covered by 800 metres of rail and the proportion of 45-minute bus service capacity.

2.3. Factors Influencing Urban Commuting Carbon Emissions

According to the theory of spatial autocorrelation and urban land use theory, consideration of urban carbon emissions can be narrowed down to a relatively fixed range of urban commuting carbon emissions, and the impact of urban road planning on urban carbon emissions can be considered around the relatively stable traffic routes in the city [12-14]. Specific impact factors can be divided into four categories of secondary indicators 11 tertiary indicators, see the following Table 1.

Table 1: Table of Factors Affecting Carbon Emission of Urban Commuting

One-level indicators	Two-level indicators	Three-level indicators
Urban spatial layout	Urban size	Urban population
		Urban area
	Transport space	Road network density
		Workday vehicle peak speed
		Commuter space radius
		One-way commuting distance
		Degree of separation between workplace and residence
	Commuting time	One-way commuting time
		5km commuting ratio
	Public transport facilities	Proportion of commuting covered by tracks
		Proportion of 45-minute bus service capacity

3. Methods and Data

3.1. Methods

3.1.1. Data Testing

In conducting the analysis of the factors influencing urban commuting carbon emissions, it was first necessary to verify that all panel data showed an overall normal distribution. The paper uses the "descriptive statistics-exploration-pp/qq plot" tool in SPSS 26.0 software to generate frequency plots (plus bell-shaped curves) for graphical analysis and to lay a viable data base for subsequent correlation and regression analyses.

3.1.2. Correlation Analysis

In the search for significant correlations between urban commuting carbon emissions and various factors of urban spatial layout, the thesis used Pearson Correlation Analysis in SPSS26.0 to analyse the correlation between various indicators of urban spatial layout and urban residents' commuting carbon emissions. The key indicators of interest are as follows.

Pearson correlation (R-value): reflects the degree of correlation between two variables, and takes a value between -1~ +1. If the value is greater than 0, the two variables are positively correlated, while if the value is less than 0, the two variables are negatively correlated. The closer the R-value is to 0, the weaker the correlation is. Generally speaking, a positive R-value of 0.2 or less indicates a very weak correlation, R-value of 0.2~0.4 indicates an average correlation, R-value of 0.4~0.7 indicates a strong correlation, and R-value of 0.7 or more indicates a very strong correlation.

Significance value (P-value): used to test whether the correlation coefficient is statistically significant. When the P-value is greater than 0.1, it means that its corresponding correlation is statistically insignificant because the pattern is not significant, it does not indicate that the two are correlated. When $0.05 \leq$ P-value ≤ 0.1, it means that its corresponding R-value is somewhat significant, which can be interpreted as 90% of the sample supporting the conclusion that the two are significant. When $0.01 \leq$ P-value ≤ 0.05, the corresponding R-value is highly significant, which can be interpreted as 95% of the sample supporting the conclusion that the two are significant. When the P-value is <0.01, it means that the corresponding R-value is highly significant and can be interpreted as 99% of the sample supporting the conclusion that the two are significant. Most studies use P-value of 0.05 as the threshold for significance.

The correlation analysis allows for the preliminary identification of urban spatial layout indicators that affect the carbon emissions of urban residents commuting, providing conditions for the subsequent establishment of regression equations and further research on the quantitative relationship between urban spatial layout and the intensity of stabbing in carbon emissions.

3.1.3. Regression Analysis

The purpose of modelling regression analysis is to further analyse the degree of influence of the independent variable (x) on the dependent variable (y). In this thesis, the model will be built using multiple regression analysis:

$y = b_1x+b_2x+b_3x+\cdots + b_nx+c$

"c" is the regression constant;

b_n (n=1,2,3, n) is the regression parameter;

The following indicators need to be looked at in the model:

First, in the model summary table, R denotes goodness of fit, which is a measure of how well the estimated model fits the observations. The goodness of fit statistic is the coefficient of determination 'R^2', and the closer the value is to 1 the better the model fits. For general bounds in the natural sciences, a goodness-of-fit-R of 0.1(R^2 of 0.01) is generally considered a small effect, 0.3 a medium (R^2 of 0.09) and 0.5 a large (R^2 of 0.25). Also of note in this table is the Durbin-Watson-value (DW-value), which is used to test for autocorrelation of the residuals in the regression analysis, the closer the value to 2 the better.

Secondly, in the Anova table, it is also important to look at the F-value and the sig-value, which reflect the usefulness of the overall regression equation. It is generally accepted that a regression equation is useful when the F-value corresponds to a sig-value of less than 0.05. In addition, the F-value is a significance test for the regression equation. If F>Fa, the original hypothesis is rejected, i. e. the explanatory variables included in the model combine to have a significant effect on the explanatory variables, and if not, there is no significant effect.

Again, VIF is the variance expansion factor, which is used to diagnose the presence of multicollinearity in the independent variables. When 0<VIF<10, there is no multicollinearity, then it will not affect the regression analysis results; when 10≤VIF<100, there is strong multicollinearity; when VIF≥100, there is severe multicollinearity and the regression analysis results are difficult to be established.

Finally, the coefficient tables present the results of the significance tests for the independent variables (using a one-sample t-test), i. e. the independent variables that have a significant effect on the dependent variable (P-value ≤ 0.05) are selected. As each independent variable has a different magnitude and range of values, B does not reflect the magnitude of the effect of each independent variable on the dependent variable, so the standardised coefficients are used. The value of the standardised coefficient Beta in the table is the final coefficient of influence, with larger values indicating a greater influence on the dependent variable.

3.2 Interpretation and Calculation of Indicators

In the thesis data, 2 indicators of urban scale refed to «China Urban Construction Statistical Yearbook 2020», and 3 secondary indicators of traffic space, traffic time and public transport and 9 tertiary indicators refer to the relevant research of «China Major Cities Road Network Density Monitoring Report 2020», which were based on the GPS data of taxis, some in-car navigation data, crowdsourcing track data, two passengers and one dangerous (referring to chartered buses engaged in tourism, class 3 or more buses and special road vehicles transporting dangerous chemicals, fireworks, firecrackers and civil explosives) in each city. In 2020, 25 million records of 3.7 million vehicles had been available every minute across China. The calculation methods and ranges for each indicator would been explained below.

3.2.1. Commuting Carbon Emissions

The commuting carbon emissions indicator is expressed in terms of carbon emissions from one-way commuting transport for 10,000 people in a city, and the formula takes into account four indicators: the one-way commuting distance per inhabitant of a city, the means of transport used, all the fuels used by the means of transport, and the carbon emissions per unit of each fuel.

3.2.2. Urban Size

Urban district (or main city) is a densely populated area of a city with a relatively developed industrial, commercial, service, transport, cultural, educational and health sector. Urban population is the number of people resident within the urban area and Urban area is the overall area within the urban area. These 2 data indicators are generally obtained through the statistical yearbooks of individual cities or the China Urban Construction Statistical Yearbook.

3.2.3. Transport Space

Road network density refers to the ratio of the total road mileage within a certain range to the area of that range. In order to ensure the comparability of road network density across cities and the consistency of statistical calibre, the thesis adopts the standards in the "Monitoring Report on Road Network Density in Major Cities in China 2020" and takes the built-up area of the central city of each sample city as the scope of index calculation, where roads are based on electronic map mapping data, including urban expressways, primary roads, secondary roads, feeder roads and major neighbourhood roads within the scope.

Workday vehicle peak speed is the average of the highest peak vehicle movement speed for each street in the urban area detected by the city for 24 hours a day during working hours from Monday to Friday, which is then aggregated and calculated on an annual basis. Generally raw statistics are obtained from crowdsourced data collection by the city's traffic management department and big data calculations are performed.

Commuter space radius is a spatial ellipse covering 90% of the urban commuting population's residential and employment distribution. The long axis of the ellipse is used to define the spatial radius of commuting as a measure of the spatial radiation range of urban commuting, the larger the spatial radius of commuting, the larger the spatial range of closely linked urban commuting.

One-way commuting distance is calculated using the shortest distance of the commuting road network from the 250m grid of the Internet map: the OD (Optical Distance) inter-road network distance, the length of the distance calculated based on the residents' single-directional pick-up and drop-off links.

Degree of separation between workplace and residence is the minimum commuting distance that can theoretically be achieved by exchanging places of employment under the conditions of the established employment and residence layout, without taking into account employment differences and human choices. Cities obtain data by fixing the location of each resident and measuring the average distance to the nearest place of employment. It is a measure of the spatial layout match of employment and residence in the city. The smaller the separation of employment and residence, the better the balance of the spatial supply of employment and residence in the city.

3.2.4. Commuting Time

One-way commuting time is the average of the time taken by different modes of transport to travel from their place of residence to their place of employment during the morning rush hour for commuters in the central city. It is generally calculated through a multi-level, large-scale questionnaire, and is an intuitive way of perceiving people's commuting experience, and is an important factor influencing the quality of life of residents.

5km commuting ratio refers to the proportion of commuters who travel less than 5km each way in the central city, and is used as an indicator to measure the balance of jobs and housing in the city.

3.2.5. Public Transportation Facilities

Proportion of commuters covered by tracks refers to the proportion of commuters in the central city who live and work within 1,000 metres of a rail station, reflecting the match between the rail network and the organisation of workplace space.

Proportion of 45-minute bus service capacity refers to the proportion of people who can commute to work within 45 minutes by rail, bus and other modes of public transport. It is a measure of the city's public transport service capacity and reflects the extent to which the public transport system fits in with the spatial organisation of jobs and housing.

3.3. Data

The paper mainly used 35 key cities in China, including 4 mega-cities with a permanent population of over 10 million; 10 mega-cities with a permanent population of over 5 million and under 10 million; 10 mega-cities with a permanent population of over 3 million and under 5 million; and 11 mega-cities with a permanent population of over 1 million and under 3 million. The values of their specific indicators were shown in the Table 2.

Table 2: Index Value Table of China's 35 Cities in 2020

City name	commuting transport carbon emissions(t)	Urban size		Transport space					Commuting time		Public transport facilities	
		Urban population (Ton/10000people)	Urban area ($10000m^2$)	Road network density (Km/km^2)	Operating space during rush hour on workdays (Km/h)	Commuter space radius(km)	One-way commuting distance(km)	Degree of separation between workplace and residence	One-way commuting time(min)	5km commuting ratio	Proportion of commuting covered by tracks	Proportion of 45-minute bus service capacity
	Y	X12	X12	X21	X22	X23	X24	X25	X31	X32	X41	X42
Shenzhen	5.5	1343.88	1986.41	9.6	21.8	39	7.6	2.5	36	0.6	0.28	0.57
Shanghai	7	2428.14	6340.5	7.2	19.6	39	8.9	3.8	40	0.48	0.26	0.41
Guangzhou	6.7	719.14	2256.42	7.1	20.5	31	8.7	3.7	38	0.52	0.3	0.5
Beijing	8.7	1916.4	16410.54	5.7	19.6	41	11.1	6.7	47	0.38	0.2	0.31
Chengdu	6.7	760.63	1287.87	8.4	20.3	28	9	4.8	39	0.46	0.26	0.44
Hangzhou	5.9	415.93	2140.32	7.2	18.2	33	7.4	3.3	35	0.56	0.14	0.47
Chongqing	5.7	1213.56	7779.14	6.9	21.1	39	8.9	4	40	0.48	0.2	0.42
Zhengzhou	5.8	416.64	762.41	6.7	20.4	28	8	4.2	36	0.55	0.12	0.47
Tianjin	4.9	1174.44	2639.78	6.3	22.3	37	8.4	3.3	39	0.52	0.13	0.4
Wuhan	5.9	611.3	1452	6.2	22.1	29	8.3	3.8	39	0.5	0.27	0.44
Xi'an	5.6	643.5	942.53	5.8	19.4	27	8.1	4.1	34	0.52	0.12	0.5
Nanjing	4.8	644.84	4226.41	5.6	21.4	31	8.4	3.8	38	0.5	0.16	0.42
Qingdao	6.9	433.94	3089.18	5.4	18.8	25	8	4.5	39	0.52	0.14	0.47
Shenyang	4.6	457	1610	4.9	19.8	31	7.2	3.1	36	0.53	0.1	0.42
Xiamen	4.7	237.6	401.94	8.5	22.9	29	7.1	2.3	32	0.6	0.12	0.55
Hefei	4.1	241.34	1126.61	7	21.6	25	7.2	3	34	0.54	0.12	0.44
Kunming	5.9	406.31	1782.6	6.8	19.7	27	7.3	2.5	33	0.6	0.17	0.47
Changsha	7.1	396.52	1199.84	6.7	21.4	29	8.2	3.7	34	0.54	0.19	0.47
Dalian	5	347.83	1523	6.1	21.1	34	7.2	2.5	38	0.54	0.11	0.43
Taiyuan	2.9	301.93	1000	5.9	22.7	25	6.9	3.1	32	0.57	0.07	0.41
Changchun	6.5	362.09	3427.42	5.5	19.1	29	7.5	3.6	36	0.51	0.09	0.37
Harbin	5.2	395.96	473	5.1	18.3	33	7.2	2.8	35	0.55	0.03	0.46
Jinan	6.1	480.89	2419.15	4.9	18.1	31	7.7	3.6	34	0.56	0.01	0.43
Urumqi	6.1	225.65	842.09	3.5	23.6	29	6.9	2.6	34	0.55	0.03	0.37
Fuzhou	4	238.85	539.38	7.4	22.5	24	6.9	2.7	34	0.61	0.14	0.52
Nanning	4.1	252.56	865.08	7.4	22.1	21	6.8	2.7	33	0.55	0.18	0.47
Ningbo	5	217.53	1380.8	6.8	20	31	6.6	2.7	31	0.61	0.09	0.48
Nanchang	4.1	282.47	428.4	6.5	21.6	23	7.2	3.6	34	0.56	0.13	0.44
Guiyang	5.2	219.5	12330	6.3	21.1	26	7.5	3.1	34	0.57	0.04	0.46
Haikou	4.8	131	562.4	5.8	19.6	21	7	3.3	30	0.63	0.01	0.54
Xining	5.8	134.11	396.65	5.5	20.8	27	8.5	5.2	35	0.55	0.03	0.48
Shijiazhuang	4.5	331.65	518.81	5.4	22.9	27	8	5.3	35	0.55	0.09	0.43
Yinchuan	3.9	129.13	562.49	4.9	20.9	28	8.1	5.5	33	0.57	0.09	0.42
Hohhot	5.5	145	272.16	4.6	21.9	22	6.4	3.2	32	0.58	0.03	0.4
Lanzhou	3.5	196.04	342.38	4.3	19.6	28	7.2	3.7	33	0.63	0.07	0.47

Note: Data from《ina Urban Construction Statistical Yearbook 2020》, hina Major Cities Road Network Density Monitoring Report 2020

4. Results

4.1. Test for Normal Distribution of Data

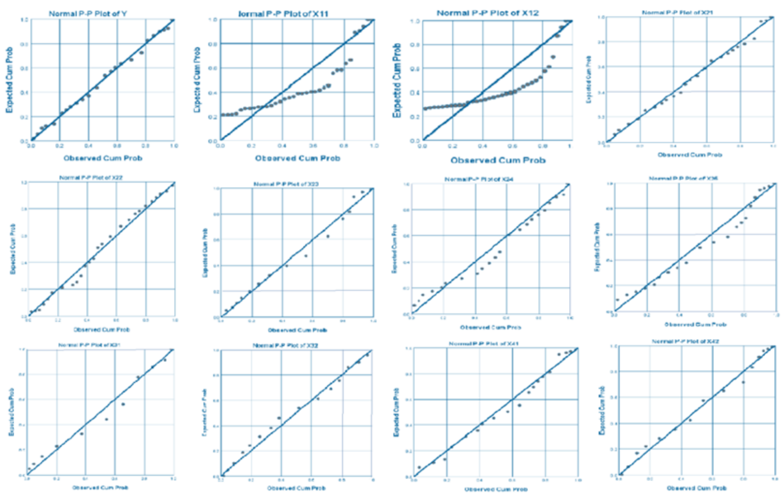

Figure 1: Statistical Chart of Level III Indicator Data Description

According to statistical requirements, all statistical data samples should be tested for overall normal distribution. Used the "Descriptive Statistics" function in SPSS software, the 13 statistics for the dependent and independent variables were tested and, as shown in Figure 1, the data for all three levels of indicators were generally normally distributed, proved that subsequent statistical analysis would been carried out.

Table 3: Descriptive Statistics

Classification	Indicator	N	Minimum	Maximum	Mean	Std. Deviation
Commuting carbon emissions	Y	35	2.9	8.7	5.39	1.19
Urban size	X11	35	129.13	2428.14	538.67	510.21
	X12	35	272.16	16410.54	2437.65	3439.30
Transport space	X21	35	3.5	9.6	6.23	1.25
	X22	35	18.1	23.6	20.77	1.45
	X23	35	21	41	29.34	5.13
	X24	35	6.4	11.1	7.75	.91
	X25	35	2.3	6.7	3.61	.98
Commuting time	X31	35	30	47	35.49	3.31
	X32	35	.38	.63	.55	.05
Public transport facilities	X41	35	.01	.30	.13	.08
	X42	35	.31	.57	.45	.05

The final statistical description of the overall data included frequency analysis, concentration trend analysis, dispersion analysis, etc. The results are shown in Table 3.

4.2. Indicator Correlation Analysis

4.2.1. Bivariate Correlation Analysis

The SPSS26.0 bivariate method of correlation function was applied to analyse whether the 11 independent variable indicators showed significant correlation for urban transport carbon emissions. After calculation, the following results were obtained in Table 4.

Table 4: Ln (Xn) and Ln Y correlation Analysis Table

LnY	Pearson Correlation	1	.526**	.521**	.081	-.397*	.448**
	Sig. (2-tailed)		.001	.001	.643	.018	.007
	N	35	35	35	35	35	35
		LnX24	LnX25	LnX31	LnX32	LnX41	LnX42
LnY	Pearson Correlation	.598**	.325	.589**	-.594**	.187	-.233
	Sig. (2-tailed)	.000	.057	.000	.000	.281	.178
	N	35	35	35	35	35	35

*. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The correlation coefficient for Ln (urban population) was 0.526, with a significant behaviour of 0.001<0.01, indicated that the higher the urban population, the higher the urban transport carbon emissions. Similarly, the correlation coefficient for Ln (urban area) was 0.521, with a significant behaviour of 0.001<0.01, indicated that the larger the urban area, the higher the urban transport carbon emissions.

The correlation coefficient of Ln (Workday vehicle peak speed) was -0.397, with a significant behaviour of 0.018<0.05, indicated that the smaller the weekday vehicle peak speed in urban areas, the higher the urban transport carbon emissions. The correlation coefficient of Ln (Commuter space radius) was 0.448, with a significant behaviour of 0.007<0.01, indicated that the larger the spatial radius of commuting in urban areas, the higher the urban transport carbon emissions. the correlation coefficient of Ln (One-way commuting distance) was 0.598, with a significant behaviour of 0.000<0.01, indicated that the larger the one-way commuting distance in urban areas, the higher the urban transport carbon emissions.

The correlation coefficient of Ln (One-way commuting time) is 0.589, with a significant behaviour of 0.000<0.01, indicating that the longer the one-way commuting time in urban areas, the higher the urban transport carbon emissions. Similarly, the correlation coefficient for Ln (5km commuting ratio) is -0.594, with a significant behaviour of 0.000<0.01, indicating that the greater the proportion of commuting within 5 km in urban areas, the lower the urban transport carbon emissions.

4.2.2. Scatter Correlation Analysis

Based on the results of the above bivariate correlation analysis, seven indicators, namely urban population (X11), urban area (X12), workday vehicle peak speed (X22), commuting spatial radius (X23), one-way commuting distance (X24), one-way commuting time (X31) and 5km commuting ratio (X32), which were significantly correlated with urban transport carbon emissions, were screened and correlated with urban transport carbon emissions indicators respectively Scatter correlation analysis was conducted to verify the accuracy of the bivariate correlation. The graphical function of SPSS 26.0 was applied to form the Figure 2.

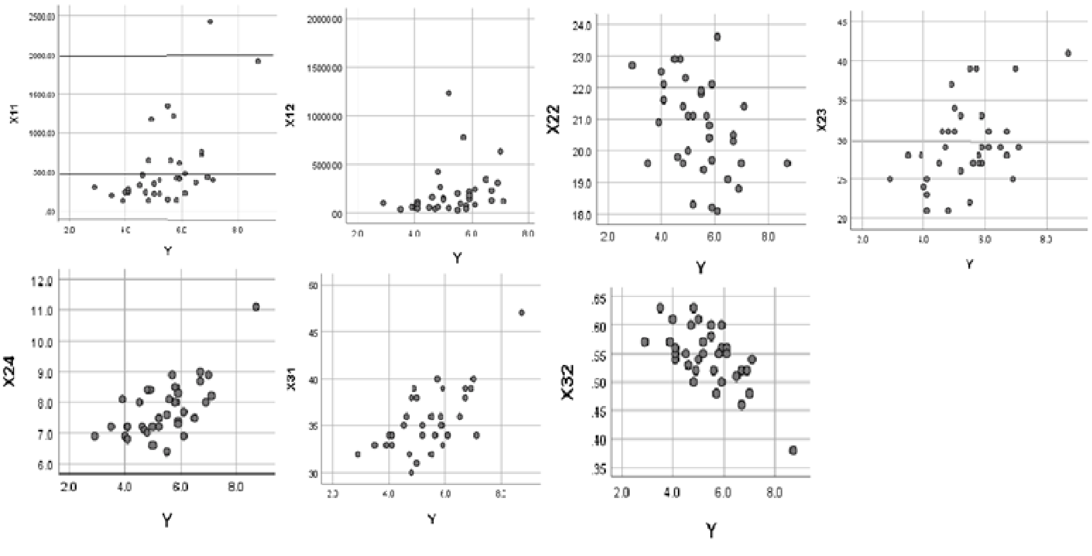

Figure 2: Ln (Xn) and Ln Y scatter correlation analysis diagram

From the scatter plot, it could be verified that urban population (X11), urban area (X12), commuting spatial radius (X23), one-way commuting distance (X24) and one-way commuting time (X31) show a relatively obvious positive correlation with urban transport carbon emissions, while workday vehicle peak speed (X22) and 5km commuting ratio(X32) showed a negative correlation, and the indicator X22 is more scattered and shows a weaker correlation compared to the other 6 indicators. The scatter plot showed results consistent with the bivariate correlation analysis above.

4.3. Regression Analysis of Indicators and Urban Transport Carbon Emissions

Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	0.598a	0.358	0.339	0.18348	0.358	18.409	1	33	0.000	
2	0.665b	0.443	0.408	0.17361	0.085	4.861	1	32	0.035	2.519

a. Predictors: (Constant), LnX24
b. Predictors: (Constant), LnX24, LnX22
c. Dependent Variable: LnY

Using the natural logarithm values of the correlation indicators, a linear regression model was established using SPSS26.0 software's, and a stepwise approach was used to exclude the compounding and co-existence of the 7 influencing indicators to further explore the common influence relationship of multiple indicators on urban transport carbon emissions.

The results showed that 2 regression models were established (see Table 5), with the first step indicator Ln (one-way commuting distance) entering the regression model to form Model 1, and the second step indicator Ln (workday vehicle peak speed) joining Model 1 to form Model 2. The adjusted R^2 for Model 2 was the highest, reaching 0.408, indicated that the independent variables can explain a total of 40.8% of the variation in the dependent variable, with Durbin-Watson value reached 2.519, indicated that the proposed model had some convincing power.

Also, from the ANOVA coefficient table (see Table 6), it could be concluded that the established regression model had a significance Sig value <0.01 and could be considered significantly reasonable.

Table 6: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0.620	1	0.620	18.409	0.000[b]
	Residual	1.111	33	0.034		
	Total	1.731	34			
2	Regression	0.766	2	0.383	12.712	0.000[c]
	Residual	0.964	32	0.030		
	Total	1.731	34			

a. Dependent Variable: LnY
b. Predictors: (Constant), LnX24
c. Predictors: (Constant), LnX24, LnX22

Finally, SPSS26.0 software calculated the regression analysis coefficients of the 2 indicators X24 and X22 and urban transport carbon emissions Table 7 to form a multiple regression equation.

Table 7: Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics VIF
2	(Constant)	2.279	1.513		1.507	0.142	
	LnX24	1.107	0.274	0.544	4.049	0.000	1.035
	LnX22	-0.950	0.431	-0.296	-2.205	0.035	1.035

a. Dependent Variable: LnY

The ANOVA resulted from Table 6 and Table 7, F=12.712, indicated that its test corresponded to a value of P=0.005 and the covariance statistic VIF=1.035<5, indicated that there was no variance chi-square problem between the indicators of the independent variables and that the hypothesis of the existence of a regression between urban transport carbon emissions (Y) and the indicators of the independent variables holds. The multiple linear regression equation could be obtained according to the coefficient table.

$$\ln Y = 2.279 + 0.544\ln(X24) - 0.296\ln(X22) \qquad (1)$$

Where: Y represents urban transport carbon emissions.

X24 represents one-way commuting distance.

X22 represents workday vehicle peak speed

As could be judged from the regression equation, combined with Beta, it could be seen that one-way commuting distance had the greatest impact on urban transport carbon emissions, with a positive correlation; workday vehicle peak speed had the next greatest impact, with a negative correlation.

5. Conclusions and Recommendations

5.1. Conclusion

This work adopted relevant data from 35 large and medium-sized cities in China for correlation and regression analysis, aiming to assess the relationship between urban transport carbon emissions and certain factors affecting travel in urban planning, such as road network density, commuting speed, commuting radius, separation of jobs and housing, commuting time, rail and bus installation, urban population and area. The following conclusions could be drawn from the analysis.

First, urban planning had a significant role in urban population, urban area, commuting space radius, commuting distance, commuting time and commuting speed factors in transport commuting for urban transport carbon emissions. It indicated that in the urban planning process, the layout of urban living space and working space, the distance between the two and the ease of access had significant significance on the carbon emissions in commuting.

Secondly, through regression analysis, it was concluded that among the significant influencing factors, commuting distance and commuting speed had a significant linear relationship with urban carbon emissions. This suggests that urban planning should pay more attention to reducing the distance between residents' places of residence and work, and effectively strengthen urban street planning to increase the accessibility of streets and the smoothness of traffic, effectively increasing residents' commuting speed.

5.2. Urban Planning Proposals

This work, despite the limitations of adopting only 12 indicator factors for 35 cities in China, was considered effective in linking travel variables due to urban planning to urban transport carbon emissions. This effort has implications for both the upgrading of existing urban roads and the construction of new urban areas.

Firstly, for new urban areas it is important to develop an integrated mindset. From the above analysis, it is clear that the factors affecting urban transport carbon emissions are not independent of each other, but influence each other. For example, the separation of jobs and housing affects factors such as commuting radius and commuting time, and the density of the road network plays a significant role in commuting time and commuting speed. In countries and regions around the world where carbon emissions from transport are producing impressive results, the future of cities will be an integrated process. Better urban planning will mean that the specific division of work, leisure and recreation in cities will be broken down, which will on the one hand improve the commuting experience of residents and on the other hand gradually reduce unnecessary carbon emissions from transport.

Secondly, for older urban areas, road accessibility improvements should be enhanced, as well as the construction of feeder roads between houses and work areas, effectively reducing the number of commuting vehicles on main roads and effectively reducing commuting times. At the same time, increasing the installation of bicycle lanes and footpaths and increasing the frequency of non-motorised commuting for residents within a 3km commuting radius will effectively reduce urban transport carbon emissions.

Thirdly, public transport facilities should be developed vigorously. Especially for mega and large cities, the separation of jobs and housing in old urban areas cannot be changed. The government should plan transportation lines underground and in the air, speed up the construction of metro and light rail, increase the convenience of residents' travel, effectively reduce the distance and time of private car commuting, and improve the speed of road commuting, all of which will play a good role in reducing urban transportation carbon emissions.

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