Abstract: Controlling carbon dioxide (CO₂) emissions is the foundation of China’s goals to reach its carbon peak by 2030 and carbon neutrality by 2060. This study aimed to explore the spatial and temporal patterns and driving factors of CO₂ emissions in China. First, we constructed a conceptual model of the factors influencing CO₂ emissions, including economic growth, industrial structure, energy consumption, urban development, foreign trade, and government management. Second, we selected 30 provinces in China from 2006 to 2019 as research objects and adopted exploratory spatial data analysis (ESDA) methods to analyse the spatio-temporal patterns and agglomeration characteristics of CO₂ emissions. Third, on the basis of 420 data samples from China, we used partial least squares structural equation modelling (PLS-SEM) to verify the validity of the conceptual model, analyse the reliability and validity of the measurement model, calculate the path coefficient, test the hypothesis, and estimate the predictive power of the structural model. Fourth, multigroup analysis (MGA) was used to compare differences in the influencing factors for CO₂ emissions during different periods and in various regions of China. The results and conclusions are as follows: (1) CO₂ emissions in China increased year by year from 2006 to 2019 but gradually decreased in the eastern, central, and western regions. The eastern coastal provinces show spatial agglomeration and CO₂ emission hotspots. (2) Confirmatory analysis showed that the measurement model had high reliability and validity; four latent variables (industrial structure, energy consumption, economic growth, and government management) passed the hypothesis test in the structural model and are the determinants of CO₂ emissions in China. Meanwhile, economic growth is a mediating variable of industrial structure, energy consumption, foreign trade, and government administration on CO₂ emissions. (3) The calculated results of the \( R^2 \) and \( Q^2 \) values were 76.3% and 75.4%, respectively, indicating that the structural equation model had substantial explanatory and high predictive power. (4) Taking two development stages and three main regions as control groups, we found significant differences between the paths affecting CO₂ emissions, which is consistent with China’s actual development and regional economic pattern. This study provides policy suggestions for CO₂ emission reduction and sustainable development in China.

Keywords: CO₂ emissions; ESDA; PLS-SEM; China

1. Introduction

Climate change is a major global challenge faced by humanity today and has attracted extensive attention from the international community [1]. Countries have committed to reducing greenhouse gases to address climate change caused by greenhouse gases such as carbon dioxide (CO₂) [2,3]. In 2016, 178 parties signed the Paris Agreement, which became the third landmark international legal text to tackle climate change, following the UN Framework Convention on Climate Change in 1992 and the Kyoto Protocol in 1997, shaping global climate governance patterns. The Paris Agreement obliges all parties to
commit to a long-term greenhouse gas emission reduction strategy for the mid-21st century until 2020 to promote early and significant reductions in global emissions. At the 75th UN General Assembly in September 2020, China proposed reaching its carbon peak by 2030 and striving to achieve carbon neutrality by 2060. A carbon peak is reached when carbon emissions (mainly CO$_2$) no longer increase. Carbon neutrality refers to a state of net-zero emissions after efforts to reduce or offset CO$_2$ emissions. China’s carbon peak and carbon neutrality targets are consistent with the Paris Agreement and key to achieving the 1.5 °C global temperature decrease target.

China is at a critical stage of industrialisation and urbanisation. CO$_2$ emissions are continuing to increase, and many energy conservation and emission-reduction activities could be implemented. China has made continuous attempts to construct low-carbon cities, establish a circular economy, conserve resources, encourage an environment-friendly society, and pursue other paths to green development, with some positive results [4,5]. During the 14th Five-Year Plan (2021–2025), China will enter a critical period in which the country will focus on CO$_2$ reduction, promote the synergy and efficiency of pollution and CO$_2$ reduction, facilitate a comprehensive green transformation in economic and social development, realise a qualitative change in the improvement of ecological and environmental quality, and promote major changes in the way society functions. China will pursue its long-term goals of peak carbon and carbon neutrality; promote economic and social transformation; and accelerate the building of a green, low-carbon economic system. It will also continue to play a positive and constructive leading role in the international community, promote the establishment of a new cooperation mechanism for global climate governance, and strive to build a community with a common future for humanity [6–8].

In 2020, China’s CO$_2$ emissions totalled 9894 billion tons, the highest in the world, and thus China came under great pressure to reduce emissions. China has a vast land area, and there are great differences between regions in the natural environment, development stage, population distribution, industrial structure, urbanisation, and other characteristics. The main factors that affect CO$_2$ emissions and their degree of influence are also different [9,10]. Therefore, it is of great theoretical and practical significance to explore the spatio-temporal patterns and driving factors of CO$_2$ emissions in different regions within China to formulate energy conservation and emission reduction policies to achieve the goals of peak carbon and carbon neutrality.

The determinants of CO$_2$ emissions are diverse, and the relationships between these driving forces are complex. Therefore, it is of great significance for China’s ability to further control CO$_2$ emissions in the future to identify the influencing factors of CO$_2$ emissions and further clarify the causal relationships between these driving forces. First, we identified the driving factors affecting CO$_2$ emissions and constructed a conceptual model. We then analysed the spatio-temporal evolution of CO$_2$ emissions in China by using exploratory spatial data analysis (ESDA). We analysed the effect paths of the driving factors affecting CO$_2$ emissions using partial least squares structural equation modelling (PLS-SEM) methods. Finally, we propose policy suggestions for China’s sustainable development.

2. Literature Review and Hypotheses

Increased CO$_2$ emissions result from economic growth, industrial structure, energy consumption, and other factors. Clarifying the key factors that affect CO$_2$ emission for research is of critical importance. However, most studies have focused on the relationship between specific factors and CO$_2$ emissions, while few studies have systematically explored the factors and their degree of influence on CO$_2$ emissions. Therefore, this study attempts to construct a theoretical framework concerning CO$_2$ emissions and explores the direction and intensity of each driving factor. We discuss the factors influencing CO$_2$ emissions in six dimensions: economic growth, industrial structure, energy consumption, urban development, foreign trade, and government management. We then hypothesise that these factors influence CO$_2$ emissions and construct a conceptual model (Figure 1).
2.1. Industrial Structure

With adjustments and developments of industrial structures, the CO$_2$ emissions of an economic system also change. The theory of industrial structural evolution holds that, during the process of economic development, the labour force shifts from primary industries dominated by agriculture to secondary industries dominated by factory production of goods, which is the main industry for CO$_2$ emissions. The higher the proportional contribution of the secondary industry to the total output value, the greater the threat to the environment and the higher CO$_2$ emissions. In particular, the higher the proportion of energy-intensive industries, the greater the CO$_2$ emissions. As the economy continues to expand, the labour force moves to tertiary industries dominated by services. In this process, the total CO$_2$ emissions will continue to increase, but the growth rate will decelerate. Additionally, different industrial structures have different impacts on CO$_2$ emissions. Some scholars have studied the influencing factors on CO$_2$ emissions in different industrial sectors, such as transportation, agriculture, industry, and tourism, and results vary from study to study [11,12]. Zheng et al. explored interregional differences in industry, construction, and transportation; warehousing industries had a significantly positive impact on interregional differences in CO$_2$ emissions from 2007 to 2016 [13]. Li et al. suggested that governments should increase the proportion of high-tech industries through technological progress, vigorously develop resource-saving and environment-friendly tertiary industries, and develop a low-carbon economy by promoting clean production technology [14]. Many scholars have found that industrial structure upgrading has a significant positive impact on economic growth, thereby promoting CO$_2$ emission reduction [15,16]. On the basis of the aforementioned literature, we propose the following hypothesis:

**Hypothesis 1 (H1):** Industrial structure contributes to more CO$_2$ emissions.

2.2. Energy Consumption

Economic growth heavily depends on energy consumption, which is a direct source of CO$_2$ emissions. Energy consumption quantity, intensity, and structure have some impact on CO$_2$ emissions. Economic development is inseparable from the use of all kinds of
energy. The larger the economy grows, the more energy is consumed, and the more CO\textsubscript{2} emissions rise. Wang et al. concluded that reducing energy intensity could, to a large extent, reduce CO\textsubscript{2} emission intensity. By optimising industrial structure, CO\textsubscript{2} emission intensity could also be inhibited \cite{10}. Energy intensity is the energy consumed per unit of output and is used to measure energy efficiency. The higher the level of technological progress, the less energy is wasted \cite{17}. The structure of energy consumption has an important impact on CO\textsubscript{2} emissions. The carbon content of energy used in economic construction determines CO\textsubscript{2} emissions; the higher the carbon content, the greater the CO\textsubscript{2} emissions, and vice versa \cite{18}. Xu et al. analysed the dynamic relationships between CO\textsubscript{2} emissions, economic growth, and the consumption of various fossil fuels in China and found that increasing coal and petroleum consumption significantly promoted CO\textsubscript{2} emissions. However, natural gas offers a cleaner substitute for other fossil fuels \cite{19}. Thus, the impact of energy consumption on CO\textsubscript{2} emissions is clear. China is in a period of highly industrialised development, and coal-fired power generation is still the main form of power generation. Coal-fired power plants burn much fossil fuel and emit a large amount of CO\textsubscript{2}, although the Chinese government has regulated the power industry as a key sector \cite{20}. However, compared with European and American countries, China still has a long way to go in terms of energy conservation and emission reduction. Therefore, the sustainable development of electric energy is the main path of a low-carbon economy. In this way, the following hypothesis is proposed:

**Hypothesis 2 (H2):** Energy consumption contributes to more CO\textsubscript{2} emissions.

2.3. Foreign Trade

Engaging in international trade may be a factor in changing CO\textsubscript{2} emissions. Foreign trade is one of the principal ways to transfer CO\textsubscript{2} emissions through an international division of labour \cite{21}. The expansion of foreign trade, as well as the structure and volume of foreign trade, may be factors in a country’s CO\textsubscript{2} emissions. It is undeniable that China’s foreign trade products are characterised by high energy consumption and low added value. The effect of import and export on CO\textsubscript{2} emissions is intuitively positive. However, relevant studies have found that the impact of foreign trade on CO\textsubscript{2} emissions may be positive \cite{22}, negative \cite{23}, or irrelevant \cite{24}, depending on both the foreign trade structure and trade volume \cite{25} and also to the research period and region. Nevertheless, industrial transfer is one way of transferring CO\textsubscript{2} emissions. According to the foreign direct investment (FDI) theory, to maximise profits and reduce environmental costs, investors implement cross-border pollution transfer to transfer high-emission industries to lower-income regions, thus realising CO\textsubscript{2} emissions transfer. China is in a period of rapid economic development and must introduce a large amount of foreign capital for economic construction, which has a significant impact on CO\textsubscript{2} emissions. As the energy price is low, and the regulation of polluting industries is lower than that of higher-income countries, many export industries with high energy consumption and carbon emissions rapidly develop and become production sites for capital investment countries to transfer pollution \cite{26}. Additionally, FDI has a technological spillover effect on CO\textsubscript{2} emissions that can improve the technical level of the region and reduce CO\textsubscript{2} emissions. Therefore, FDI affects the CO\textsubscript{2} emissions of the host country. On the basis of the aforementioned literature, we propose the following hypothesis:

**Hypothesis 3 (H3):** Foreign trade contributes to more CO\textsubscript{2} emissions.

2.4. Government Administration

Government intervention may be a key factor influencing CO\textsubscript{2} emissions. Related studies have found that governments affect CO\textsubscript{2} emissions in many ways. First, governments formulate corresponding energy transition and environmental policies to constrain the CO\textsubscript{2} emissions of enterprises and society \cite{17,27}. Second, governments can increase
financial expenditure on environmental governance [28] and scientific and technological investment, as well as collect pollution control fees and taxes from enterprises [29] to reduce levels of environmental pollution. Third, local governments may take the initiative to relax environmental regulations to achieve regional economic growth and thereby attract investment, which results in the deterioration of regional environmental quality and an increase in CO$_2$ emissions. Local government decision-making competition has three effects on CO$_2$ emissions: market distortion, investment bias, and a race to the bottom of environmental policies.

**Hypothesis 4 (H4):** Government administration contributes to reduced CO$_2$ emissions.

### 2.5. Urban Development

Urban development is an important factor affecting CO$_2$ emissions. First, a country’s level of urbanisation is closely related to its economic development. The larger the scale of urban development, the more CO$_2$ emissions increase. However, improvements in urbanisation levels can decrease CO$_2$ emissions and thus realise low-carbon development [30]. In the early stages of urban development, Sun found that the expansion of the scope of urbanisation promotes improvement in CO$_2$ emission efficiency. After the urbanisation level reaches a critical point, the economic growth rate falls behind the growth rate in CO$_2$ emissions [31]. Second, a large number of energy resources is necessary for infrastructure construction during the process of urbanisation, which leads to an increase in CO$_2$ emissions. Zhou et al. found that spatial urbanisation was positively associated with CO$_2$ emissions due to the new infrastructure construction and conversion of existing land [32]. Third, during urbanisation, many people migrate from rural to urban areas, and this substantial increase in the urban population also increases CO$_2$ emissions [33]. Improvements in economic development and urbanisation can help achieve low-carbon development in an urban agglomeration [34].

**Hypothesis 5 (H5):** Urban development contributes to more CO$_2$ emissions.

### 2.6. Economic Growth

Economic growth is an important index for measuring the economic development of a country or region. According to the environmental Kuznets curve (EKC), when a country has a low level of economic development and uses few energy resources, its CO$_2$ emissions are low. However, with the acceleration of industrialisation, more fossil energy is needed, the degree of environmental deterioration worsens, and CO$_2$ emissions rise. When economic development reaches a certain level, the degree of environmental pollution and CO$_2$ emissions gradually decrease. Dinda et al. analysed the EKC hypothesis and postulated an inverted-U-shaped relationship between different pollutants and per capita income; that is, environmental pressure increases up to a certain level as income increases and decreases thereafter [35]. Fang et al. verified the panel EKC between economic growth and CO$_2$ emissions in China from 1995 to 2016 and found that, as the economy developed and GDP per capita increased, more energy was consumed, and the amount of environmental pollution increased [36]. Mardani et al. further found that CO$_2$ emissions were stimulated at higher or lower levels as economic growth increased or decreased. Conversely, a potential reduction in emissions harms economic growth [37].

China faces the dual pressures of economic growth and environmental protection [36]. On the one hand, China needs to reduce CO$_2$ emissions to jointly cope with the global climate crisis with the international community. On the other hand, China should also pay attention to domestic economic growth and social progress to enhance its national strength and improve its resilience to external environmental changes. Economic growth is a task and goal that cannot be ignored. Therefore, economic growth plays a connecting role between industrial structure, energy consumption, trade growth, government management, and carbon emissions. In recent years, China has witnessed rapid economic growth,
increasing energy consumption, and a rapid increase in CO₂ emissions. In the future, China will need enough space for CO₂ emissions to reach the level of higher-income countries. Thus, as the economy continues to grow, CO₂ emissions will continue to accumulate.

Therefore, we propose the following hypotheses:

**Hypothesis 6 (H6):** Economic growth contributes to more CO₂ emissions.

**Hypothesis 7 (H7):** Economic growth mediates the relationship between industrial structure and CO₂ emissions.

**Hypothesis 8 (H8):** Economic growth mediates the relationship between energy consumption and CO₂ emissions.

**Hypothesis 9 (H9):** Economic growth mediates the relationship between foreign trade and CO₂ emissions.

**Hypothesis 10 (H10):** Economic growth mediates the relationship between government administration and CO₂ emissions.

3. Materials and Methods

3.1. Study Area

This study selected 30 provinces, autonomous regions, and municipalities as the research areas to acquire relevant statistical data, excluding Hong Kong, Macao, Taiwan, and Tibet. These areas can be divided into three main regions: eastern, central, and western.

- Eastern region: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan.
- Central region: Shanxi, Henan, Anhui, Jilin, Heilongjiang, Jiangxi, Hubei, Hunan, and Inner Mongolia.
- Western region: Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang.

The CO₂ emissions of 30 provinces in China showed an overall upward trend from 2006 to 2019, increasing from 8.32 billion in 2006 to 13.92 billion in 2019, with an annual growth rate of 4.03%.

3.2. Data Collection

This study selected 420 data observations from 30 provinces, autonomous regions, and municipalities from 2006 to 2019 as research samples. The main data in this paper include CO₂ emissions and influencing factors. The former were calculated from fossil energy consumption data published in the China Statistical Yearbook of Energy (2006–2019), while the latter were mainly derived from the China Statistical Yearbook (2006–2019). Missing values were supplemented using linear interpolation with IBM SPSS Statistics 25.0 software (IBM Inc., Armonk, NY, USA).

(1) Data on CO₂ emissions. The estimates of CO₂ emissions of provinces in China are taken from the IPCC Guidelines for the National Greenhouse Gas Emission Inventory. According to China Energy Statistical Yearbook, primary energy consumption can be divided into eight categories: coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, and natural gas. As there are so many energy sources, the total CO₂ emissions from combustion should be the sum of the CO₂ emissions from each energy source.

\[ CE_{it} = \sum_{i=1}^{n} E_{ijt} \times \omega_j \]  

where \( CE_{it} \) represents the CO₂ emissions generated by energy combustion in province \( i \) in year \( t \), \( E_{ijt} \) represents the burned amount of energy \( j \) in province \( i \), and \( \omega_j \) represents...
the CO\textsubscript{2} emissions coefficient of energy \textit{j} combustion, and \( n \) represents the eight kinds of energy.

(2) Data for influencing factors. Following the principles of systematicity, representativeness, and availability of index selection, this study used 16 specific indicators from the six dimensions of economic development level, industrial structure, energy consumption, urban development, foreign trade, and government management, using the following specific descriptions:

(i) Economic growth. Gross domestic product (GDP) and per capita GDP represent the level of economic growth, which can measure the impact of the economy on CO\textsubscript{2} emissions. Household consumption level is selected to reflect the economic conditions of people’s lives, which is an important reflection of national economic growth.

(ii) Industrial structure. The proportion of the value added by the secondary industry to GDP can represent the industrial structure of the main source of CO\textsubscript{2}. The proportion of industrial added value in the GDP reflects that China is still in the development stage of industrialisation at present; its main industries have high energy consumption, and that consumption will not be significantly reduced in a short time.

(iii) Energy consumption. With China’s economic development and social progress, the production and consumption of electric energy are increasing. The power industry has become a major contributor to fossil fuel consumption and CO\textsubscript{2} emissions. Annual carbon emissions from electricity generation are close to 50% of the country’s total energy CO\textsubscript{2} emissions. Therefore, it is reasonable to take electric energy production and consumption as two indicators to measure CO\textsubscript{2} emissions.

(iv) Urban development. The urban employed population reflects the agglomeration of the urban population. Urban fixed-asset investment reflects the input of urban factors. Traffic is an important source of urban CO\textsubscript{2} emissions, and the number of civilian vehicles can be used as an indicator to measure the impact of traffic on CO\textsubscript{2} emissions.

(v) Foreign trade. The total FDI and number of FDI enterprises can reflect the investment in foreign capital; the total export–import volume is used to reflect foreign trade. As FDI and total export–import volume are denominated in U.S. dollars, the U.S. GDP deflator is used to calculate the real value for the year 2019.

(vi) Government management. The impact of the Chinese government’s intervention on CO\textsubscript{2} emissions can be considered from two perspectives: financial spending and administrative management. Scientific and technological input is selected as the financial index, reflecting the government’s ability to curb CO\textsubscript{2} emissions by improving scientific and technological levels. Administrative management indicators include the accepted number of domestic patent applications and the authorised number of domestic patent applications, which are used to measure the impact of government and enterprises on CO\textsubscript{2} emissions from the perspective of science and technology.

3.3. Methods

Quantitative studies of CO\textsubscript{2} emissions have been a hot topic in recent years. Previous studies widely used include the Kaya identity [38–40]; the IPAT model [41–43]; the arithmetic mean divisia index (AMDI); the logarithmic mean divisia index (LMDI) [44–47]; and the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model [48–51]. This study integrated ESDA and PLS-SEM to study the spatio-temporal differences and influencing factors of CO\textsubscript{2} emissions in China. The spatial correlation and hotspot analysis of the ESDA method intuitively reflected the spatial distribution and spatial agglomeration of CO\textsubscript{2} emissions. The PLS-SEM method was used to analyse the influence paths, intensity, and significance of the factors influencing CO\textsubscript{2} emissions.
3.3.1. ESDA

ESDA is an analytical method for exploring the spatial relevance of geographical phenomena from the perspective of spatial analysis; it is also suitable for studying the spatial agglomeration of CO$_2$ emissions [52,53].

Spatial Autocorrelation

Global and local autocorrelation can reveal the spatial connections and differences between research units, which are often expressed by Moran’s I. Global autocorrelation can describe the spatial correlation pattern of a whole research area; the local autocorrelation can reflect the spatial agglomeration characteristics of each unit within the region and identify high-value agglomeration and low-value agglomeration at different spatial locations. This method is suitable for representing the spatial agglomeration characteristics of CO$_2$ emissions in the research area [54,55]. The calculation formula is

\[
I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (2)
\]

\[
I_L = \frac{n(x_i - \bar{x}) \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (3)
\]

where $I$ represents the global Moran index, and $I_L$ represents the local Moran index. $n$ is the number of provinces, and $x_i$ and $x_j$ are the CO$_2$ emission values of province $i$ and province $j$, respectively. $w_{ij}$ is the adjacency matrix between province $i$ and province $j$. At the significance level, the value of the global Moran I index ranges from $-1$ to $1$. If the value of the index is greater than 0, there is a positive spatial correlation between the two provinces; if the value is less than 0, there is a negative spatial correlation; if it is equal to 0, there is no spatial correlation. The local spatial association mode can be divided into high–high (H-H), high–low (H-L), low–high (L-H), and low–low (L-L). The global Moran index statistics can only test the global spatial correlation but cannot determine the specific spatial agglomeration region, whereas the local Moran index and the Getis–Ord $G_i^*$ statistics can solve this problem.

Hotspots Analysis

On the basis of the Getis–Ord $G_i^*$ value, ARCGIS software can be used to automatically draw a spatial clustering graph of high and low values with statistical significance, which reveals the hotspots and coldspots of regional CO$_2$ emissions [56]. The formulas are as follows:

\[
G_i^* = \frac{\sum_{i=1}^{n} \omega_{ij}x_j - \bar{X}\sum_{j=1}^{n} \omega_{i,j}}{S\sqrt{\frac{n}{i=1} \omega_{ij}^2 - \left(\frac{\sum_{j=1}^{n} \omega_{ij}}{n}\right)^2}} \quad (4)
\]

\[
S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2} \quad (5)
\]

\[
\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (6)
\]
where $x_j$ is the attribute value of province $j$, $\omega_{ij}$ is the spatial weight of province $i$ and province $j$, and $n$ is the total number of provinces. $G_i^*$ is the score of the $z$ value, which reflects the spatio-temporal agglomeration characteristics of high and low CO$_2$ emissions.

### 3.3.2. PLS-SEM

PLS-SEM is used to estimate a complex causal relationship model with latent variables; it is widely used in economics, sociology, and other fields [57]. Therefore, this study is a new attempt to explore the influence of various driving factors on CO$_2$ emissions using PLS-SEM. The PLS-SEM model has the following three advantages: first, multiple latent variables are introduced to better reflect the path, orientation, and intensity between latent variables and CO$_2$ emissions; second, the complex relationships between latent variables and their causal effects can be further clarified; third, comparative analyses between control groups better reflect the temporal difference and spatial heterogeneity. PLS-SEM must generally follow four steps: model construction, hypothesis formulation, confirmatory factor analysis, and structural model analysis [58–60]. We also adopted multigroup analysis to understand the differences between factors affecting CO$_2$ emissions in different periods and regions. As both the total sample and the control sample size exceeded 100, the PLS-SEM technology of SmartPLS 3.3.3 software was suitable for testing the causal relationships proposed in the conceptual model.

Multigroup analysis (MGA) allows for testing whether pre-defined data groups have significant differences in their group-specific parameter estimates (e.g., outer weights, outer loadings, and path coefficients) [61]. In recent years, the MGA method has also been widely applied in tourism [61,62], marketing [63,64], and other fields. This study adopted MGA to analyse the difference in the impact paths on CO$_2$ emissions in different periods and regions. SmartPLS 3.3.3 provides outcomes of four different approaches that are based on bootstrapping results from every group.

### 4. Results

#### 4.1. Spatio-Temporal Evolution Patterns and Agglomeration Characteristics of CO$_2$ Emissions

#### 4.1.1. Spatio-Temporal Patterns at Different Scales

At the national scale, CO$_2$ emissions have been rising steadily in China, from 277.43 million tons in 2006 to 463.97 million tons in 2019, with an annual growth rate of 4.03%. From the perspective of the development stage, CO$_2$ emissions grew rapidly from 2006 to 2011 but slowed from 2012 to 2019, with annual growth rates of 7.63% and 1.71%, respectively (Figure 2).

![Figure 2. Averages of CO$_2$ emissions in three main regions in China from 2006 to 2019.](image-url)
At the regional scale, the average CO₂ emissions of the eastern, central, and western regions were 334.95 million tons, 322.68 million tons, and 155.49 million tons, respectively, in 2006. The average CO₂ emissions of the eastern, middle, and western regions increased to 535.34 million tons, 515.03 million tons, and 304.43 million tons in 2019, with annual growth rates of 3.82, 3.66, and 5.30%, respectively. The order of mean CO₂ emission is eastern region > central region > western region (Figure 2).

At the provincial scale, CO₂ emissions in nine provinces were higher than the national average of CO₂ emissions (277.43 million tons) in 2006, and CO₂ emissions in 11 provinces were more than the national average of CO₂ emissions (463.97 million tons) in 2019. Shandong province has always ranked first in CO₂ emissions in China, whereas Qinghai province always ranked last from 2006 to 2019. The growth rate of CO₂ emission in Beijing decreased year by year, showing a negative growth rate. The growth rate of CO₂ emissions in Shanghai and Henan remained at relatively low levels, 0.69 and 1.31%, respectively, while the growth rates for Ningxia and Xinjiang, although they were located in the western region, were 10.82 and 10.05%, respectively (see Figure 3).

Figure 3. CO₂ emissions for 30 provinces in China from 2006 to 2019.

4.1.2. Spatial Agglomeration Characteristics

To display the spatial difference characteristics of the CO₂ emissions, we calculated the spatial correlation and hotspot analysis of CO₂ emissions for 30 provinces in China from 2006 to 2019, and the z values were divided into five levels using the natural breakpoint method.

The spatial correlation of CO₂ emissions in China was calculated with Geoda 1.18 software using Formulas (2) and (3) (see Figure 4).

The results show that the global Moran’s I was 0.087, and the statistical significance test at 5% indicated that the spatial distribution of CO₂ emissions in each province was significantly positive; that is, the regions with high CO₂ emissions were relatively concentrated in terms of their locations. Shandong, Hebei, Henan, Shanxi, Liaoning, Jiangsu, Zhejiang, and Inner Mongolia were H-H agglomeration areas, indicating that local CO₂ emissions and those of neighbouring provinces were high. Beijing, Shanghai, Tianjin, and Anhui were L-H agglomeration areas, indicating that local CO₂ emissions were low and those of the surrounding provinces were high. Xinjiang was an H-L agglomeration area, indicating that local CO₂ emissions were high and those of the surrounding provinces were low.
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To display the spatial difference characteristics of the CO\textsubscript{2} emissions, we calculated the spatial correlation and hotspot analysis of CO\textsubscript{2} emissions for 30 provinces in China from 2006 to 2019, and the \( z \) values were divided into five levels using the natural breakpoint method.

The spatial correlation of CO\textsubscript{2} emissions in China was calculated with Geoda 1.18 software using Formulas (2) and (3) (see Figure 4).

![Figure 4. Local autocorrelation of CO\textsubscript{2} emissions in China from 2006 to 2019.](image)

The results show that the global Moran's \( I \) was 0.087, and the statistical significance test at 5\% indicated that the spatial distribution of CO\textsubscript{2} emissions in each province was significantly positive; that is, the regions with high CO\textsubscript{2} emissions were relatively concentrated in terms of their locations. Shandong, Hebei, Henan, Shanxi, Liaoning, Jiangsu, Zhejiang, and Inner Mongolia were H-H agglomeration areas, indicating that local CO\textsubscript{2} emissions and those of neighbouring provinces were high. Beijing, Shanghai, Tianjin, and Anhui were L-H agglomeration areas, indicating that local CO\textsubscript{2} emissions were low and those of the surrounding provinces were high. Xinjiang was an H-L agglomeration area, indicating that local CO\textsubscript{2} emissions were high and those of the surrounding provinces were low.

The hotspots and coldspots of regional CO\textsubscript{2} emissions were plotted with ArcGIS 10.6 software using Formulas (4)–(6) (see Figure 5).

![Figure 5. Hotspots of CO\textsubscript{2} emissions in China from 2006 to 2019.](image)

The hotspots and coldspots of regional CO\textsubscript{2} emissions were plotted with ArcGIS 10.6 software using Formulas (4)–(6) (see Figure 5).

4.2. Measurement Model

4.2.1. Reliability Test

Reliability and construct validity are the keys to establishing the measurement model. Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were obtained using PLS algorithms [65]. Table 1 shows all factor loadings of Cronbach's alpha, CR, and AVE.

| Latent Variables | Indicators                  | Factor Loading | t-Value | Cronbach's Alpha | CR  | AVE  |
|------------------|-----------------------------|----------------|---------|------------------|-----|------|
| Economic growth  | EG1 GDP                     | 0.864          | 81.788  | 0.899            | 0.747 |      |
|                  | EG2 Household consumption   | 0.850          | 43.414  |                  |      |      |
|                  | EG3 Per capita GDP          | 0.879          | 54.032  |                  |      |      |
| Industrial structure | IS1 Industrial added value | 0.986          | 375.863 | 0.984            | 0.969 |      |
|                  | IS2 Secondary industry      | 0.983          | 297.067 |                  |      |      |
| Energy consumption | EC1 Electric energy production | 0.975        | 345.139 | 0.977            | 0.955 |      |
|                  | EC2 Consumption of electric power | 0.979    | 500.524 |                  |      |      |
| Urban development | 0.948                       | 0.967          | 0.906   |                  |      |      |
The results show that most of the hotspots were distributed in the eastern coastal areas. Liaoning and Inner Mongolia ranked highest, followed by the Beijing–Tianjin–Hebei and the Yangtze River Delta regions (Shanghai–Jiangsu–Zhejiang). Shandong, Shanxi, and Henan ranked in the central. Hainan, as an isolated province, was a coldspot for CO₂ emissions.

4.2. Measurement Model
4.2.1. Reliability Test

Reliability and construct validity are the keys to establishing the measurement model. Cronbach’s alpha, composite reliability (CR), and average variance extracted (AVE) were obtained using PLS algorithms [65]. Table 1 shows all factor loadings of Cronbach’s alpha, CR, and AVE.

Table 1. Factor loadings, Cronbach’s alpha, composite reliability (CR), and average variance extracted (AVE).

| Latent Variables       | Indicators                                      | Factor Loading | t-Value  | Cronbach’s Alpha | CR  | AVE  |
|------------------------|------------------------------------------------|----------------|----------|------------------|-----|------|
| Economic growth        | EG1 GDP                                         | 0.864          | 81.788   | 0.847            | 0.899| 0.747|
|                        | EG2 Household consumption level                  | 0.850          | 43.414   |                   |     |      |
|                        | EG3 Per capita GDP                               | 0.879          | 54.032   |                   |     |      |
| Industrial structure   | IS1 Industrial added value as a percentage of GDP | 0.986          | 375.863  | 0.968            | 0.984| 0.969|
|                        | IS2 Secondary industry as a percentage of GDP    | 0.983          | 297.067  |                   |     |      |
| Energy consumption     | EC1 Electric energy production                   | 0.975          | 345.139  | 0.953            | 0.977| 0.955|
|                        | EC2 Consumption of electric power                | 0.979          | 500.524  |                   |     |      |
| Urban development      | UD1 Total fixed-asset investment                 | 0.961          | 188.443  | 0.948            | 0.967| 0.906|
|                        | UD2 Urban employment                             | 0.925          | 96.994   |                   |     |      |
|                        | UD3 Number of civilian motor vehicles            | 0.968          | 235.794  |                   |     |      |
| Foreign trade          | FT1 Number of foreign-invested enterprises       | 0.983          | 227.454  | 0.965            | 0.977| 0.935|
|                        | FT2 Total volume of foreign trade                | 0.970          | 285.679  |                   |     |      |
|                        | FT3 Foreign direct investment                    | 0.948          | 123.828  |                   |     |      |
| Government administration| GA1 Accepted number of domestic patent applications | 0.987          | 413.46   | 0.975            | 0.984| 0.953|
|                        | GA2 Authorised number of domestic patent applications | 0.986          | 273.979  |                   |     |      |
|                        | GA3 Expenditures in science and technology of local government | 0.956          | 105.985  |                   |     |      |

Note: CR = composite reliability; AVE = average variance extracted.

(1) Cronbach’s alpha was calculated to ensure composite reliability. By convention, Cronbach’s alpha should be greater or equal to 0.800 for a good scale and 0.700 for an acceptable scale. Table 1 shows that all Cronbach’s alpha values ranged from 0.899 to 0.984, which indicates that the measurement indexes had high reliability. (2) The CR was used to examine internal consistency. The higher the CR value, the higher the internal consistency of the plane; 0.700 is an acceptable threshold. We found the model to be sufficiently reliable and internally consistent, as shown in Table 1. (3) The AVE reflected the average commonality of each latent factor and was used to establish convergent validity. The AVE should be above 0.500 for all latent variables, whereby at least 50% of measurement variance is explained. Table 1 shows that all AVE values ranged from 0.747 to 0.969. In conclusion, the model had high reliability and construct validity, as evidenced by the verification of Cronbach’s alpha, CR, and AVE.
4.2.2. Validity Test

Convergent and discriminant validities were utilised to examine the model’s construct validity [65]. (1) Factor loading measures convergent validity and must be greater than 0.500. The factor loadings were greater than 0.850 (see Table 1), indicating that the measured variables had high convergence validity. (2) The square root of each construct’s AVE was greater than the bivariate correlation with the other constructs, which shows that the model had high convergent validity. Table 2 shows the square roots of the AVEs and all the correlations. (3) The HTMT ratio is an important indicator used to evaluate discriminant validity by applying a PLS algorithm [66]. The HTMT ratio for the two latent variables was below 0.900. The HTMT values are shown in brackets in Table 3. In conclusion, the model has high convergent and discriminant validity, found through the verification of Cronbach’s alpha, CR, and AVE.

Table 2. Results of the hypothesis model.

| Hypothesis | Path         | Path Coefficient | t-Value | p-Value | 95% BCa Confidence Intervals | $f^2$ | Support |
|------------|--------------|------------------|---------|---------|-----------------------------|-------|---------|
| H1         | IS→$CO_2$    | 0.122 ***        | 4.661   | 0.000   | [0.080, 0.165]              | 0.048 | Yes     |
| H2         | EC→$CO_2$    | 0.995 ***        | 21.654  | 0.000   | [0.916, 1.066]              | 0.858 | Yes     |
| H3         | FT→$CO_2$    | −0.012           | 0.205   | 0.419   | [−0.116, 0.107]             | 0.000 | No      |
| H4         | GA→$CO_2$    | −0.528 ***       | 6.372   | 0.000   | [−0.639, −0.380]            | 0.130 | Yes     |
| H5         | UD→$CO_2$    | 0.001            | 0.011   | 0.496   | [−0.093, 0.102]             | 0.000 | No      |
| H6         | EG→$CO_2$    | 0.223 ***        | 4.013   | 0.000   | [0.133, 0.307]              | 0.058 | Yes     |
| H7         | IS→EG        | −0.157 ***       | 4.651   | 0.000   | [−0.229, −0.111]            | 0.068 | Yes     |
| H8         | EC→EG        | 0.279 ***        | 4.311   | 0.000   | [0.181, 0.399]              | 0.113 | Yes     |
| H9         | FT→EG        | 0.302 ***        | 4.660   | 0.000   | [0.200, 0.414]              | 0.068 | Yes     |
| H10        | GA→EG        | 0.334 ***        | 3.270   | 0.001   | [0.144, 0.472]              | 0.061 | Yes     |

Note: BCa: bias corrected and accelerated bootstrap. Significance level: *** $p < 0.001$. EG = economic growth; IS = industrial structure; EC = energy consumption; UD = urban development; FT = foreign trade; GA = government administration.

Table 3. Discriminant validity.

|          | EG  | IS  | EC  | UD  | FT  | GA  |
|----------|-----|-----|-----|-----|-----|-----|
| EG       | 0.865 |     |     |     |     |     |
| IS       | −0.083 (0.300) | 0.984 |     |     |     |     |
| EC       | 0.641 (0.599)  | 0.294 (0.305) | 0.977 |     |     |     |
| UD       | 0.695 (0.662)  | 0.177 (0.188)  | 0.864 (0.900) | 0.952 |     |     |
| FT       | 0.756 (0.796)  | −0.012 (0.071)  | 0.586 (0.606)  | 0.566 (0.595) | 0.967 |     |
| GA       | 0.788 (0.809)  | −0.007 (0.070)  | 0.689 (0.710)  | 0.771 (0.803)  | 0.873 (0.900) | 0.976 |

Note: The square roots of AVEs are shown on the diagonal in bold. The HTMT ratios are in brackets. EG = economic growth; IS = industrial structure; EC = energy consumption; UD = urban development; FT = foreign trade; GA = government administration.

4.3. Structural Model

4.3.1. Path Coefficients and Significance

The bootstrapping method is a non-parametric statistical procedure that detects the statistical significance of various PLS-SEM results, including path coefficients, Cronbach’s alpha, HTMT, $R^2$ values, and the effect size $f^2$. Here, the number of sub-samples was set to 5000 and the $t$-test results were guaranteed to be significant at the level of 0.05 [65]. Table 2 shows the standardised path coefficients, $t$-values, and results. The results show that the path coefficients of the four latent variables (economic growth, industrial structure, energy consumption, and government administration) passed the significance test, and the four hypotheses were acceptable. This reveals that four factors had an impact on China’s total $CO_2$ emissions from 2006 to 2019. However, urban development and foreign trade did not pass the hypothesis test in this model, which does not mean that these two latent variables did not contribute to carbon emissions. On the contrary, these two variables had an impact on $CO_2$ emissions through the latent variable of economic growth. An $f^2$ above 0.02, 0.15,
or 0.35 is considered a small, medium, or large effect, respectively. Additionally, the direct and indirect effects were analysed to verify the multiple mediation model (see Figure 6).

![Diagram](image)

**Figure 6.** Results of PLS-SEM. Note: The dotted line indicates that the path fails the hypothesis test, and the solid line indicates that the path passes the hypothesis test. *** $p < 0.001$.

### 4.3.2. Direct, Indirect, Total, and Mediation Effects

Table 4 shows the direct, indirect, and total effects among latent variables and CO$_2$ emissions. Moreover, the positive effect of industrial structure on CO$_2$ emissions is more direct (0.122) than indirect ($-0.035$) through economic growth. The effect of energy consumption on CO$_2$ emissions is more direct (0.955) than indirect (0.060) through economic growth. The effect of foreign trade on CO$_2$ emissions is entirely indirect (0.067); the direct effect is not statistically significant. The effect of government administration on CO$_2$ emissions is also more direct ($-0.528$) than indirect (0.077).

**Table 4.** Results of direct, indirect, and mediating effects of economic growth.

| Path       | Direct Effect | Indirect Effect | t-Value | p-Value | 95% Bca Confidence Intervals | Mediation Effect         |
|------------|---------------|-----------------|---------|---------|------------------------------|-------------------------|
| IS→CO$_2$  | 0.122 ***     |                 |         |         |                              | Complementary            |
| IS→EG→CO$_2$ | 0.995 ***   | $-0.035$ ***    | 3.313   | 0.000   | $[-0.054, -0.019]$           | Complementary (partial mediation) |
| EC→CO$_2$  | 0.060 ***     |                 | 4.305   | 0.000   | $[0.400, 0.088]$             | Complementary (partial mediation) |
| FT→CO$_2$  | $-0.012$      |                 |         |         |                              | Indirect-only (full mediation) |
| FT→EG→CO$_2$ | 0.067 ***    |                 | 3.114   | 0.001   | $[0.035, 0.103]$             | Complementary (partial mediation) |
| GA→CO$_2$  | $-0.528$ ***  |                 |         |         |                              | Complementary            |
| GA→EG→CO$_2$ | 0.077 *      |                 | 1.955   | 0.025   | $[0.025, 0.138]$             |                         |

Note: Bca = bias corrected and accelerated bootstrap. Significance level: *** $p < 0.001$, * $p < 0.05$. IS = industrial structure; EC = energy consumption; FT = foreign trade; GA = government administration; UD = urban development; EG = economic growth; CO$_2$ = CO$_2$ emissions.
Economic growth is a mediating variable of the effect of industrial structure, energy consumption, foreign trade, and government administration on CO\textsubscript{2} emissions. Therefore, H7, H8, H9, and H10 are supported. Table 4 shows the mediation effects of economic growth in the model.

4.3.3. Predictive Power

R\textsuperscript{2} and Q\textsuperscript{2} are important metrics for evaluating the predictability of a model. The R\textsuperscript{2} value was obtained using a PLS calculation; Q\textsuperscript{2} was calculated using blindfolding [65].

(1) The determination coefficient R\textsuperscript{2} value was used as an indicator of the overall predictive strength of the model. Falk and Miller consider that R\textsuperscript{2} value should be greater than 0.100 [67]; Chin [68] recommends 0.670, 0.330, and 0.100 (substantial, moderate, and weak, respectively); while Hair et al. [65] consider 0.750, 0.500, and 0.250 (substantial, moderate, and weak, respectively). The R\textsuperscript{2} value (R\textsuperscript{2} = 0.763 > 0.750) indicated that 76.3% of CO\textsubscript{2} emissions could be explained by the causality of six latent variables, showing that the model had substantial explanatory power. In addition, the R\textsuperscript{2} value of economic growth was 0.682, indicating 68.2% of economic growth can be explained by industrial structure, energy consumption, foreign trade, and government administration. (2) The Stone–Geisser Q\textsuperscript{2} value is a criterion for evaluating construct cross-validated redundancy. The larger the Q\textsuperscript{2} value, the stronger the prediction correlation. The Q\textsuperscript{2} value of CO\textsubscript{2} emissions was 0.754, indicating that the model had high predictive relevance.

4.4. Multigroup Analysis

The PLS-MGA p-values revealed significant group differences in the MGA. Table 5 and Figure 7 show the MGA for different regions and periods in China.

On the basis of the analysis of the temporal and spatial evolution characteristics of CO\textsubscript{2} emissions, we divided the study period into two control groups: 2006–2011 was the first growth stage, and 2012–2019 was the second growth stage. For the growth stage groups, H3, H4, and H6 differed significantly, showing that the impact of foreign trade, government administration, and economic growth on CO\textsubscript{2} emission for the first stage compared to the second stage group. Meanwhile, H7, H9, and H10 differed significantly, indicating that the impact of industrial structure, foreign trade, and government administration on economic growth in the first stage is stronger than in the second stage.

The pairwise comparison of the three regions in China revealed differences in the influencing factors of CO\textsubscript{2} emissions between the regions.

(1) For the eastern and central groups, H3, H4, and H6 differed significantly, indicating that the impact of foreign trade, government administration, and economic growth on CO\textsubscript{2} emissions in the eastern region is stronger than in the central region.

(2) For the eastern and western groups, H1, H2, H3, and H5 differed significantly, indicating that the impact of industrial structure, energy consumption, foreign trade, and urban development on CO\textsubscript{2} emissions in the eastern region is stronger than in the western region. Meanwhile, H8 differed significantly.

(3) For the central and western groups, H1, H2, and H5 differed significantly, indicating that industrial structure, energy consumption, and urban development have stronger impacts on CO\textsubscript{2} emissions for the central than for the western region. Meanwhile, H7, H8, and H10 differed significantly. Likewise, we analysed the confidence intervals that allow us to verify if a path coefficient is significantly different from 0 as another way to assess the significance.
### Table 5. Results of multigroup analysis on different periods and regions in China.

| Hypothesis | Diff. | p-Value | Part (A): First Stage (n = 180) vs. Second Stage (n = 240). | Part (B): Eastern Region (n = 168) vs. Central Region (n = 140). | Part (C): Eastern Region (n = 168) vs. Western Region (n = 112). | Part (D): Central Region (n = 140) vs. Western Region (n = 112). |
|------------|-------|---------|-----------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
|            |       |         | PC Mean | t-Value | p-Value | 95% BCa CI | PC Mean | t-Value | p-Value | 95% BCa CI | PC Mean | t-Value | p-Value | 95% BCa CI | PC Mean | t-Value | p-Value | 95% BCa CI |
| H1         | −0.022| 0.478   | 0.007   | 2.475   | 0.007   | [−0.028, 0.129] | 0.080** | 2.421   | 0.008   | [0.026, 0.132] |
| H2         | −0.022| 0.411   | 0.956   | 9.454   | 0.000   | [−0.797, 1.133] | 0.978*** | 18.685  | 0.000   | [0.888, 1.057] |
| H3         | −0.449| 0.001   | −0.307  | 3.216   | 0.001   | [−0.499, −0.174] | 0.134   | 1.172   | 0.121   | [−0.029, 0.333] |
| H4         | 0.299 | 0.036   | −0.446  | 3.651   | 0.000   | [−0.626, −0.252] | −0.741***| 6.097   | 0.000   | [−0.93, −0.545] |
| H5         | −0.016| 0.453   | 0.083   | 0.706   | 0.240   | [−0.113, 0.237] | 0.095   | 1.391   | 0.082   | [−0.013, 0.2] |
| H6         | 0.201 | 0.025   | 0.420   | 5.481   | 0.000   | [−0.292, 0.54] | 0.227***| 3.432   | 0.000   | [0.121, 0.327] |
| H7         | 0.134 | 0.029   | 0.052   | 0.923   | 0.178   | [−0.045, 0.126] | −0.082* | 1.776   | 0.038   | [−0.179, −0.016] |
| H8         | −0.143| 0.109   | 0.031   | 0.499   | 0.309   | [−0.088, 0.172] | 0.171* | 2.166   | 0.015   | [0.055, 0.327] |
| H9         | −0.314| 0.011   | 0.207   | 2.139   | 0.016   | [−0.049, 0.368] | 0.541***| 5.442   | 0.000   | [0.381, 0.696] |
| H10        | 0.483 | 0.001   | 0.667   | 6.046   | 0.000   | [−0.466, 0.819] | 0.172   | 1.325   | 0.093   | [−0.065, 0.359] |

Note: BCa CI = bias corrected and accelerated bootstrap confidence intervals. Significance level: *p < 0.05, **p < 0.01, ***p < 0.001. Bold font: PLS-MGA p-value below 5% and above 95% indicate significant values. Diff. = path coefficient differences; PC = path coefficient; N.A. = not available. IS = industrial structure; EC = energy consumption; FT = foreign trade; GA = government administration; UD = urban development; EG = economic growth; CO2 = CO2 emissions.
5. Discussion

5.1. Theoretical Implications

First, Figures 2–4 show that spatio-temporal differences in China’s CO₂ emissions have a spatial scale effect. On the national scale, China’s total CO₂ emissions show a trend of gradual and steady growth. This is because China is in a period of rapid economic growth, and its CO₂ emissions are thus increasing rapidly. At the regional scale, the CO₂ emissions of the three main regions show decreasing distribution in the east, central, and west regions, which is consistent with the actual situation of China’s regional economic development [10]. At the provincial scale, provinces with high CO₂ emissions were mainly distributed in the eastern coastal region, indicating that provinces with high CO₂ emissions tend to be clustered together. Therefore, when formulating policies and development plans, the government should consider the spatial spillover effects of CO₂ emissions and the relevant influencing factors between neighbouring provinces.

Second, through confirmatory and structural model analyses, we found that the measurement model of the influencing factors for CO₂ emissions in China had high reliability and validity. Economic growth, industrial structure, energy consumption, and government management had a significant impact on carbon emissions. However, urbanisation development and foreign trade fail to pass the hypothesis test. These two latent variables had an impact on CO₂ emissions through the mediating effects of economic growth. The $R^2$ was
76.3%, and the Q^2 value was 75.4%, indicating that the structural equation model had a substantial explanatory and high predictive power.

Third, the path coefficients and significance of the six latent variables on CO₂ emissions were analysed. The results are as follows:

(1) H1: Industrial structure contributes to more CO₂ emissions, which is consistent with the research results of Long et al. [69]. China is at the central stage of an industrialised economy; the development of secondary industries requires energy and resources. The proportion of secondary industries in China is larger than that of higher-income countries. Secondary industries have a high energy demand, and therefore their CO₂ emissions are also high.

(2) H2: Energy consumption contributes to more CO₂ emissions, which is consistent with the results of Meng et al. [20]. With China’s economic development, the production and consumption of electric energy are growing, and the electric power industry has become the main sector of fossil fuel consumption and CO₂ emission. China’s energy consumption has always been based on coal; thermal power generation has long been the main component of power energy products, which will inevitably lead to the increase of CO₂ emissions.

(3) H3: Foreign trade fails to pass the hypothesis test. With the acceleration of China’s integration into economic globalisation, China’s foreign trade volume increases, and a large number of foreign-funded enterprises enter into China, resulting in the rapid development of the local economy and thus contributing more CO₂ dioxide. This result supports hypothesis H9.

(4) H4: Government administration contributes to reduced CO₂ emissions, which is consistent with the research results of Zheng et al. [70]. Government intervention reduces CO₂ emissions. The Chinese government can effectively reduce CO₂ emissions by implementing a variety of measures that are consistent with the national goal of energy conservation and emission reduction. Meanwhile, the government encourages enterprises to innovate independently and improve energy efficiency to reduce their CO₂ emissions. Therefore, the Chinese government has a restraining role in CO₂ emissions.

(5) H5: Urban development fails to pass the hypothesis test. China is in a period of rapid urbanisation development, and the contribution of increased urbanisation to CO₂ emissions exists. As a matter of fact, with the influx of migrants into cities, the construction of infrastructure, such as buildings and transportation, is accelerating, which will bring about the rapid development of the urban economy and inevitably increase CO₂ emissions.

(6) H6: Economic growth has a positive impact on CO₂ emissions, which is consistent with the findings of Cui et al. [16] and Li et al. [71]. China is currently at the central stage of economic development and undergoing large-scale economic growth and rapid development. Therefore, energy consumption and CO₂ emissions are high. This is consistent with the spatio-temporal evolution pattern of China’s CO₂ emissions.

Economic growth is an important intervening variable in the model. The mediation of economic growth is complementary (partial mediation) between industrial structure and CO₂ emissions; the mediation of economic growth is complementary (partial mediation) between energy consumption and CO₂ emissions; the mediation of economic growth is indirect-only (full mediation) between foreign trade and CO₂ emissions; the mediation of economic growth is complementary (partial mediation) between government administration and CO₂ emissions. These results are consistent with China’s multiple goals of pursuing both environmental protection and economic and social progress.

Fourth, through the MGA of different stages and regions, we found differences in the effect intensity of different influencing factors on CO₂ emissions at different development stages and different regions. Compared with the second stage, the impact of foreign trade, government administration, and economic growth on CO₂ emissions in the first stage was significantly different. This is because of China’s accession to the World Trade
Organization in the early 21st century, which significantly accelerated China’s participation in economic globalisation and opening-up and increased its import and export trade. During the 11th Five-Year Plan period (2006–2010), the central government promulgated the implementation of energy-saving target responsibility and evaluation, which has achieved some results. Progress has also been made toward the overall goal of building a resource-conserving and environment-friendly society, as proposed in the 12th Five-Year Plan (2011–2015) and 13th Five-Year Plan (2016–2020).

Fifth, through an MGA of different regions, we found differences in the effect intensity of various influencing factors on CO$_2$ emissions in different regions; this result is consistent with the current state of China’s regional economic development [46].

(1) The impact of foreign trade (H3), government administration (H4), and economic growth (H6) on CO$_2$ emissions in the eastern region was stronger than that in the central region. The eastern coastal region took the lead in implementing the reform and opening-up strategy, and its economy started early and developed rapidly. In addition, the eastern region is a densely populated urban area of China; as such, it is also the core region for CO$_2$ emissions. In recent years, the eastern region has taken the lead in implementing the energy conservation and emission reduction strategy. For example, the CO$_2$ emissions for Beijing showed negative growth, while those for Shanghai and Tianjin showed low growth.

(2) The impact of industrial structure (H1), energy consumption (H2), foreign trade (H3), and urban development (H5) on CO$_2$ emissions in the eastern region was stronger than in the western region. Compared with the eastern region, there is a huge gap in economic development, industrial structure, and urban development in the western region, which is also consistent with the actual situation of China’s regional development. The western region is a relatively backward region regarding economic development and has lower CO$_2$ emissions than the eastern and central regions. However, with the implementation of development and the opening-up strategy in recent years, emissions in the western region have rapidly increased, especially in Ningxia and Xinjiang, where the growth rates of CO$_2$ emissions are among the highest in the entire country. The current development in the western region still follows the model for inefficient, blind, and energy-intensive development; thus, the growth rate of CO$_2$ emissions is accelerating. Additionally, the western region is a key and difficult area in China’s ecological construction due to its vast territory and fragile environment. Overall, CO$_2$ emissions in the west are problematic.

(3) The impacts of industrial structure (H1), energy consumption (H2), and urban development (H5) on CO$_2$ emissions in the central region were stronger than that in the western region. The central region is the main energy- and resource-producing area in China, and its industrial structure is dominated by secondary industries. Faced with prosperity in the east and development in the west, the central region has experienced economic collapse. In recent years, the central region has taken over industries with excess capacity from the east, and the rise of urban clusters has led to continuous CO$_2$ emissions.

5.2. Practical Implications

Given the above analysis, China’s energy conservation and emission reduction measures can be proposed in six dimensions.

- China should improve the quality of economic growth through industrial upgrading, energy restructuring, and technological progress to change the economic growth model; it should also realise an extensive development model to intensify development model change.
- Per the law of industrial structure development at the present stage, China should strive to develop tertiary industries, promote the upgrading of secondary industries, advocate a circular economy, and encourage the development of green and environmental protection industries.
• China should continue to increase the proportion of clean energy in energy consumption; develop clean energy, such as wind power, solar energy, hydropower, and nuclear energy; and develop clean energy technologies and improve energy efficiency.

• China should remain on the path of green urbanisation and raise people’s awareness about green consumption.

• The Chinese government should formulate a strict environmental access system, improve environment-related rules and regulations, and control high pollution and high energy consumption projects.

• The government has increased investment in science and technology and environmental protection and has adopted preferential policies to encourage local enterprises to engage in independent innovation.

• Energy conservation and emission reductions are gradual processes that should be based on actual economic growth stages and regional patterns to promote the transformation and sustainable development of different regions.

6. Conclusions

This study analysed the spatial and temporal pattern of CO$_2$ emissions in China and clarified the determinants of CO$_2$ emissions and their internal relationships. First, six driving factors that affect CO$_2$ emissions were clarified, including economic growth, industrial structure, energy consumption, urban development, foreign trade, and government management, and a conceptual model was constructed. Second, mathematical statistics, spatial autocorrelation, and hotspot analysis were used to analyse the spatial and temporal patterns of CO$_2$ emissions in China. Third, the reliability, validity, path coefficient, and prediction ability of the structural equation model for CO$_2$ emissions were tested using 420 samples from 30 provinces in China during 14 years from 2006 to 2019. Fourth, multi-group analysis was used to analyse the differences between the impact paths of different regions and stages. Finally, we propose targeted policy suggestions for China’s future CO$_2$ emission reduction to provide a reference for achieving the goals of peak carbon and carbon neutrality. The main conclusions are as follows:

First, China’s CO$_2$ emissions have different spatial and temporal patterns. On the national scale, China’s total CO$_2$ emissions show a trend of gradual and steady growth. At the regional scale, the CO$_2$ emissions of the three main regions show a decreasing distribution pattern of east, central, and west. At the provincial scale, the eastern coastal area is a hotspot for high CO$_2$ emissions. These results are consistent with the actual status of China’s regional economic development.

Second, this study constructed a structural equation model on drivers of CO$_2$ emissions, including economic growth, industrial structure, energy consumption, urban development, foreign trade, and government management. The conceptual model was tested with 420 samples from 30 provinces in China from 2006 to 2019. We found that the R$^2$ value was 76.3% and the Q$^2$ value was 75.4%, indicating that the proposed model had a substantial explanatory power and a high predictive power.

Third, through path coefficient analysis and hypothesis testing, we found that latent variables had different degrees of influence on CO$_2$ emissions. As China’s secondary industries still occupy an important position in GDP and consume a large amount of energy, the industrial structure contributes to more CO$_2$ emissions. Because coal has always been the main energy consumption in China, electricity consumption and production burn a large amount of fossil fuel and emit a large amount of CO$_2$. Therefore, energy consumption contributes to higher CO$_2$ emissions. Government administration can effectively control CO$_2$ emissions through positive and effective measures. Foreign trade does not pass the hypothesis test but has an impact on CO$_2$ emissions through the mediating role of economic growth. Urban development does not pass the hypothesis test, but China’s urbanisation is an important factor that cannot be ignored. As China’s current economic development is still on the rise, the impact of economic growth on CO$_2$ emissions is significantly positive.
Meanwhile, economic growth is a mediating variable of the impact of industrial structure, energy consumption, foreign trade, and government administration on CO₂ emissions. Fourth, through the calculation of the MGA methods, we found that latent variables in different development stages and regions have different effects on CO₂ emissions. By comparing the two development stages, we found significant differences in the impact of foreign trade, government administration, and economic growth on CO₂ emissions. By comparing the three main regions, we found that the impact of foreign trade, government administration, and economic growth on CO₂ emissions in the eastern region was stronger than that in the central region; the impact of industrial structure, energy consumption, foreign trade, and urban development on CO₂ emissions in the eastern region was stronger than that in the western region; and the impact of industrial structure, energy consumption, and urban development on CO₂ emissions in the central region was stronger than that in the western region. These calculation results are consistent with the actual situation of China’s regional economic development.

There are some limitations in this paper, and further research suggestions are proposed. First, the factors that affect CO₂ emissions are diverse, and more latent variables should be considered, such as renewable energy production, macro-control policies, technological progress, and residents’ consumption awareness. Second, the selection of indicators has an impact on the intensity of CO₂ emissions, and therefore other indicators should be considered in the future. Third, more causal relationships between latent variables and their mediating effects should be explored in depth.

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