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How Does Green Technology Innovation Affect Carbon Emissions? A Spatial Econometric Analysis of China's Provincial Panel Data

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Due to an increasing number of issues such as climate change, sustainable development has become an important theme worldwide. Sustainable development is inseparable from technological innovation. Only by making technological breakthroughs can we ensure the overall integration of economic development and environmental protection. Here, based on China's inter-provincial panel data from 2006 to 2019, we examine the relationship between green technological innovation and carbon dioxide (CO_2) emissions in 30 provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) and sub-regions (eastern, central, and western China) in China using a space panel econometric model based on the STIRPAT equation. Additionally, we use geographic information analysis methods to analyze the spatial pattern and evolution characteristics of CO_2 emissions. Our major finding is that, from the perspective of the whole country, green technology innovation has a negative correlation with carbon emissions, but the effect is not obvious. In addition, from the regional sample, green technology innovation in the eastern and central regions can effectively reduce carbon emissions, while in the western region, green technology innovation can promote carbon emissions in the province. At the same time, the research results show a strong spatial spillover effect of inter-provincial carbon dioxide emissions, and the progress of green technology in neighboring provinces has a negative impact on carbon emissions in their own provinces. Therefore, cross-province policies and actions for reducing carbon emissions are necessary. Additionally, our results show that carbon-emission driving factors, such as economic development, industrial structure, energy consumption structure, and population, have a significant positive effect on carbon dioxide emissions. Based on the above research results, we put forward corresponding policy recommendations.

Keywords: sustainable development, green technology innovation, carbon emissions, carbon emissions spatial effect, spatial panel model

1 INTRODUCTION

In recent years, the continuous accumulation of carbon dioxide emissions has produced a series of environmental problems, such as global warming and frequent outbreaks of extremely severe weather. Therefore, carbon emission reduction has become an important topic of concern to all countries globally, and green development has also become an important factor in promoting the transformation of the global economic structure (Shao and Zhong, 2021a).

The Chinese Government has realized the serious environmental problems caused by massive CO_2 emissions. It has not only introduced a series of relevant policies and measures but also promised at the Paris Climate Conference to reduce CO_2/GDP by 60–65% by 2030 compared with 2005 and peak carbon emissions around 2030 (Mi et al., 2017). The Chinese Government also attaches great importance to promoting the environmental society and Governance (ESG) system (Coleman et al., 2010; Blank et al., 2016), and issued the reform plan of the legal disclosure system of environmental information in 2021, clearly pointing out that the mandatory disclosure system of environmental information should be basically formed by 2025. In addition, at the Fifth Plenary Session of the Nineteenth Central Committee, "support for green technological innovation" was particularly emphasized. Hence, there is a need for innovation on the existing operations so that maximization of the growth can be achieved with the least possible cost to the environment (Li et al., 2020; Meirun et al., 2021). Therefore, green technological innovation makes economic activities more environmentally friendly and can be a potential solution for planned reduction of carbon emissions, which has attracted the attention of experts around the world (Nikzad and Sedigh, 2017; Shao and Zhong, 2021b). Additionally, how does green technology innovation affect CO_2 emissions? Can green technological innovation reduce CO_2 emissions in economies of scale? This is the focus of attention of governments at all levels and related scholars.

The concept of green technological innovation was first proposed by Braun and Wield (1994). They believed that green technological innovation refers to producing green products based on reducing environmental pollution, raw materials, and energy consumption through the use of technological processes. Based on existing literature research (Wang et al., 2021), our understanding of green technology innovation is that green technology innovation takes the promotion of energy conservation, environmental optimization, and economic development as its core concepts, and its results are mainly reflected in technological progress that contributes to energy conservation and emission reduction (Long et al., 2017; Sellitto et al., 2020). The fundamental difference between green technological innovation and traditional innovation is that environmental output is considered. The lower the pollution degree to the environment in the process of technological innovation, the higher the degree of green technological innovation.

Theoretically it is assumed that technology innovation can promote the transition toward environmentally oriented lifestyles and reduce carbon emissions. And it is frequently considered as the crucial way to achieve green growth (Albino et al., 2014; Cheng et al., 2018; Shao and Zhong, 2021a). However, scholarly evidence on the association between green technology and carbon emissions are mixed and even contradictory based on empirical analysis because of the different scenarios. For example, according to Braungardt et al. (2016), green technology effectively resolved the trade-off between economic growth and environmental protection, while, there may exist a rebound effect. That is, green technological innovation has a direct effect and scale effect on carbon dioxide emissions. One is that green technological innovation can effectively reduce carbon emissions by improving energy utilization efficiency, that is, the direct effect of green technological innovation on carbon emissions. The other is that green technology innovation promotes the expansion of economic scale and output level, which requires more energy consumption and indirectly causes the level of carbon emissions to rise, that is, the scale effect of green technology innovation on carbon emissions (Fisher-Vanden and Wing, 2008; Abdouli and Hammami, 2017; Khan and Su et al., 2021). Therefore, the direction of this combined effect is not clear. Just as Sinn (2008) argues, good intentions do not always lead to good behaviors. Here, this study uses empirical analysis to test the comprehensive effect of green technological innovation on CO_2 emissions and to judge whether China's green technological innovation has achieved its goal of energy saving and emission reduction.

Regarding the influence of technological innovation and other factors on carbon emissions, scholars have conducted much research, mainly focusing on the following three aspects. The first one is focused on the relationship between technological innovation and CO_2 emissions. Sun et al. (2010) used the Laspeyres index decomposition method to analyze the influencing factors of carbon emissions and found that the increase in GDP was the main driving force, and technological progress was the main reason for the reduction in carbon emissions. Suki et al. (2022) found that, on the one hand, endogenous technological progress increases carbon emissions through economic scale effects, but on the other hand, it reduces CO_2 emissions through efficiency improvements. The overall environmental effects of technologies are uncertain in the short term. In addition, Erdoğan S, (2020) investigated the impact of innovation on CO_2 emissions based on the sectors for fourteen countries in the G20. The results showed that the carbon emissions in several sectors, such as energy sector, and transport sector is not significantly influenced by technology innovation in the long run. Ang (2009) found that technological innovation can curb CO_2 emissions. Meanwhile, Carrión-Flores et al. (2013) analyzed the impact of technological innovation on polluting gases in 127 manufacturing industries and found that there is a two-way causal relationship between technological innovation and polluting gases. However, some studies drew opposite conclusions. For example, Shen (2012) built technological progress on the basis of the endogenous growth model of Aghion and Howitt (1992). They showed that the degree of technological progress is not enough to achieve both economic growth and the dual goal of reducing CO_2 emissions. Similarly, Tobelmann and Wendler (2020) used data from the 27 EU countries and showed that environmental innovation can help reduce CO_2 emissions, while general innovation activities will not lead to a reduction in emissions.

The second one is focused on the timing difference of the impact of technological progress on carbon dioxide emissions. Li KJ (2012) used the vector error correction model to analyze the relationship between technological progress and carbon emissions and found that technological progress can reduce CO_2 emissions in the long run, but the short-term effect is not obvious. Similarly Shao and Zhong (2021b) found the negative and significant impact of green technology innovation with carbon emission in the long run in N-11 countries, but the short-run association of green technology innovation is not significant. Zhang W (2014) reached similar conclusions. They found that technological progress at different development stages has different effects on CO_2 emissions. Guan and Chen (2010) suggest that technological progress is the key to addressing climate change. Their research found that under the effect of technological progress, China's carbon emissions over time present three inverted U-shaped curves, and the driving factors of each stage are different.

The third focus of attention is the spatial difference in the impact of technological progress on carbon dioxide emissions. Research by many scholars found that ordinary panel data does not consider the possible spatial effects of CO_2 emissions, which is unreasonable. Therefore, some scholars have realized the importance of spatial correlation and heterogeneity on the research of carbon emission factors and have begun to use spatial measurement models for empirical testing (Hao et al., 2021; He and Zhang et al., 2021). Auffhammer and Carson (2008) used a spatial measurement model to predict China's carbon dioxide emissions and found that introducing a spatially dependent regression model makes the prediction more reliable. Gu and Chu (2020) discovered that technological innovation has spatial spillovers, and regional carbon emission intensity has an obvious spatial correlation.

On the whole, technological innovation is an important factor influencing carbon dioxide emissions, but related research mainly focused on the impact of technological innovation on CO_2 emissions, and few studies consider the impact on CO_2 emissions from the perspective of green technology innovation with the goal of energy saving and emission reduction. In addition, scholarly evidence on the association between green technology and carbon emissions are mixed and even contradictory because of the different scenarios. Also, most existing research ignores the spatial correlation between neighboring units and lacks spatial panel data analysis. In response to the abovementioned problems, this study extends previous research in three ways. First, the effect of green technology innovation on carbon emissions is investigated. Second, because of potential spatial correlations in carbon emissions, we analyze the spatial effect of this influence by using appropriate econometric models. Third, because the effect of green tech innovation on carbon emissions varies with the level of economic development, this study explores the impact of the former from multiple perspectives across China and the eastern, central, and western sub-regions. In summary, we use China's provincial panel data from 2006 to 2019 to analyze the temporal and spatial characteristics of CO_2 emissions and examine whether green technological innovation has played an environmentally friendly role. It helps us to have a comprehensive understanding of the influencing factors behind the evolution in China's CO_2 emissions.

2 THEORETICAL BACKGROUND AND METHODS

2.1 Theoretical Base

Most scholars use the IPAT model, the STIRPAT model, and the Kaya model for research to explore the relationship between human activities and carbon emissions, and **Figure 1** shows the relationship between human activities and carbon emissions (York et al., 2003). With accelerating urbanization and industrialization, rapid population growth and economic development may consume more energy and emit more environmental pollutants. However, with the development of technology and the economy, the impact of human activities on the environment may be mitigated. That is, environmental issues (I) are the result of the combined effects of the three key factors: population (P), affluence (A), and technology (T).

However, due to the irrationality of the same proportional changes among its variables, York et al. (2003) constructed the STIRPAT model based on the IPAT model, which can more reasonably analyze the non-proportional impact of human activities on the environment. Based on the STIRPAT model, this paper takes CO_2 emissions as the explanatory variable and green technology innovation level as an explanatory variable, and establishes a spatial panel measurement model to analyze the relationship between the two. In addition to technological innovation, many of previous studies have explored other drivers affecting carbon emissions. And some factors have been widely accepted, such as energy consumption structure (Dong et al., 2016), industry structure (Wang et al., 2016; Cheng et al., 2018), economic level (Huang, 2018; Shao and Zhong, 2021a), population (Zhang and Tan, 2016). Therefore, we introduce four control variables (economic level, population, industry structure, and energy consumption structure).

2.2 Calculating Carbon Emissions

Since carbon dioxide is mainly produced by fossil fuel combustion and cement production, we draw on the practice of most scholars, such as Wu ZX (2014) and Zhang W (2014), to calculate the CO_2 emissions from fossil fuel combustion and cement production.

First, we adopt the methods recommended by the IPCC to estimate carbon emissions from the burning of fossil fuels. The computing method is as follows:

$$EC_t = \sum_{j=1}^{8} E_{jt} \times NCV_j \times CEF_j \times COF_j \tag{1}$$

Here, CO_t represents the provincial carbon emissions produced by types of energy consumption at year t; E_j stands for the total energy consumption of type j at year t; according to the

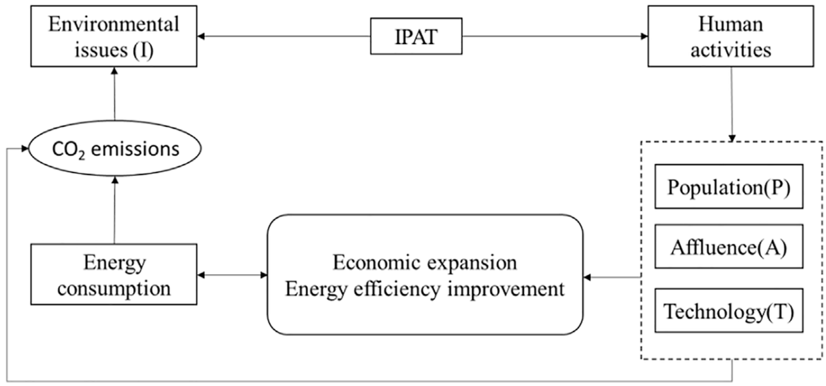

FIGURE 1 | Human activities and carbon emissions.

TABLE 1 | Net heating value and carbon emissions factor of every energy source.

	Coal	Coke	Gasoline	Kerosene	Diesel oil	Fuel oil	Natural gas
NCV_j	20908	28435	43070	43070	42652	41816	38931
CEF_j	95333	107000	69300	71500	74100	77400	56100

classification of the final energy consumption by the China Energy Statistical Yearbook, we know there are coal, coke, gasoline, kerosene, dieseluel oil, natural gas, and electricity. However, electricity is produced by other energy, so in order to avoid double-counting, we did not calculate carbon emissions that come from electricity. NCV_j stands for the net heating value(unit: *KJ/kg* or KJ/m^3) according to the China Energy Statistical Yearbook. CEF_j is carbon emissions factor (unit: *kg/TJ* or m^3/TJ); COF_j is energy carbon oxidation factor; furthermore, both CEF_j and COF_j are from IPCC (2006), shown in **Table 1**.

Second, regarding the CO_2 emissions in the cement production process, the calculation formula is:

$$CC_t = Q_t \times \partial \tag{2}$$

Here, CC_t represents the CO_2 emissions during the cement production process of the province in year t; Q_t represents the total cement production of the province in year t; ∂ represents the CO_2 emission coefficient of cement production, referring to Du (2010), with a value of $0.5270t\ CO_2/t$.

Therefore, the formula for calculating the total carbon dioxide emissions of China's 30 provinces from 2006 to 2019 is:

$$CO_{2t} = EC_t + CC_t \tag{3}$$

2.3 Green Technological Innovation Efficiency Measurement

Green technological innovation (GI) is an intangible variable and cannot be directly measured. Based on the difference in understanding of the connotation of green technology innovation, there are mainly three measurement methods. The first is the direct measurement of innovation achievements, which uses a single indicator of green technology patents to measure the green technology innovation (Jia J, 2014). The second is the factor analysis method, which builds an indicator system based on innovation output to evaluate the regional green technology innovation level (Wang, 2012). The third is based on the efficiency measurement method of green innovation input and output using the parametric method represented by stochastic frontier analysis (SFA) and the non-parametric method represented by data envelopment analysis (DEA) to measure the efficiency of green technology innovation. Thus, the efficiency of green technological innovation is used to characterize the green technological innovation (Guan and Chen, 2010). Efficiency is a relative indicator. Compared with direct output indicators, the level of efficiency can better reflect the innovation level of a region. Therefore, this paper uses the efficiency of green technology innovation to measure the green technology innovation of each province and uses the input-oriented DEA method to measure the efficiency of green technology innovation. The green technology innovation efficiency measurement indicators are selected as follows:

Two indicators of innovation investment are selected as R&D expenditure and the full-time equivalent of R&D personnel, which are, respectively, used as capital investment and human investment. The expected output indicators select the sales revenue of new products as the economic benefit and the number of patent authorizations as the innovation benefit, and the comprehensive utilization rate of solid waste and the harmless treatment rate of domestic garbage as the environmental benefits. Unexpected output mainly refers to environmental benefits, and the discharge of wastewater, waste gas, and solid waste in various regions is selected. Since the undesired output is a negative output, the environmental indicators are taken as the input part for measurement.

In addition, the measurement of several control variables is described as below. Energy consumption structure (*ES*) is measured by the proportion of the province's coal consumption in total energy consumption. Additionally, economic level (*GDP*) is measured by per capita GDP. Population (*P*) is measured by the province's proportion of the national population. The industrial structure (*IS*) is measured by the proportion of the output value of the secondary industry in the total output value of the province.

2.4 The Spatial Panel Models

According to the Geographic First Law, a spatial link exists between any two things, and the factors in different areas are spatial heterogeneity and spatial correlation. If we do not consider the space effect while building a model, there will be an estimation error. Thus, based on the improved STIRPAT model, we set up the following three spatial panel models to estimate the effects of green technology innovation on carbon emissions.

If there is an endogenous interaction effect between carbon dioxide emissions, that is, the carbon dioxide emissions of the local area depend on the carbon dioxide emissions of neighboring areas in some way, then the spatial lag panel data model (SLPDM) needs to be used:

$$\begin{aligned}\ln CO_{2it} &= \partial + \rho \sum_{j=1}^{N} w_{ij} CO_{2it} + \beta \ln GI_{it} + \gamma_1 \ln ES_{it} + \gamma_2 \ln GDP_{it} \\ &+ \gamma_3 \ln P_{it} + \gamma_4 \ln IS_{it} + \mu_i + \nu_t + \varepsilon_{it}\end{aligned} \tag{4}$$

where *i* is the different provinces of the cross-section (i = 1,2, . . . ,30), and *t* is the time series of the study (t = 1,2, . . . ,14). w_{ij} is an element of spatial weight matrix, and we used adjacency matrix to build the spatial weight matrix. We standardized the matrix at the same time.

The dependent variable CO_{2it} is identified as CO_2 emissions(tco_2), and the core interpretation variable GI_{it} is the efficiency of green technology innovation. The control variables (ES_{it}、GDP_{it}、P_{it}、IS_{it}) are defined as above. β is the coefficient of the control variable. ∂ is the constant term. ρ is the spatial lag coefficient, which reflects the influence degree of the observed value of adjacent region on the observed value of local region. Additionally, μ_i stands for the spatial effect. v_t stands for the time effect. ε_{it} is the stochastic error, and $\varepsilon it \sim i.i.d\ (0,\sigma^2)$.

If the emissions in this area are to some extent impacted by the emissions errors in neighboring areas, the spatial error panel data model (SEPDM) needs to be used:

$$\begin{aligned}\ln CO_{2it} &= \partial + \beta \ln GI_{it} + \gamma_1 \ln ES_{it} + \gamma_2 \ln GDP_{it} + \gamma_3 \ln P_{it} \\ &+ \gamma_4 \ln IS_{it} + \phi_{it} \\ \phi_{it} &= \lambda \sum_{j=1}^{N} w_{ij} \phi_{2it} + \varepsilon_{it}\end{aligned} \tag{5}$$

Here, ϕit is the error term of spatial autocorrelation. λ is the coefficient of spatial error.

In addition to the spatial spillover effect and related error terms of emissions in adjacent regions, if exogenous interaction effects exist, that is, explanatory variables in adjacent regions also have an impact on regional emissions, the spatial Durbin panel data model (SDPDM) needs to be used:

$$\begin{aligned}\ln CO_{2it} &= \rho \sum_{j=1}^{N} w_{ij} \ln CO_{2it} + \beta_1 \ln GI_{it} + \beta_2 \ln ES_{it} + \beta_3 \ln GDP_{it} \\ &+ \beta_4 \ln P_{it} + \beta_5 \ln IS_{it} + \eta_1 \sum_{j=1}^{N} w_{ij} \ln GI_{it} \\ &+ \eta_2 \sum_{j=1}^{N} w_{ij} \ln ES_{it} + \eta_3 \sum_{j=1}^{N} w_{ij} \ln GDP_{it} \\ &+ \eta_4 \sum_{j=1}^{N} w_{ij} \ln P_{it} + \eta_5 \sum_{j=1}^{N} w_{ij} \ln IS_{it} + \mu_i + \nu_i + \varepsilon_{it}\end{aligned} \tag{6}$$

Here： $\sum_{j=1}^{N} w_{ij} \ln GI_{it}$、 $\sum_{j=1}^{N} w_{ij} \ln ES_{it}$、 $\sum_{j=1}^{N} w_{ij} \ln GDP_{it}$、 $\sum_{j=1}^{N} w_{ij} \ln P_{it}$, and $\sum_{j=1}^{N} w_{ij} \ln IS_{it}$ stand for spatial lag term of adjacent region's interpretation variables; $\beta_1 - \beta_4$ and η1 −η4 are the regression coefficients. The null hypothesis H0: η+ρβ = 0 can be used to test whether the model can be reduced to a spatial error model or the null hypothesis H0: η = 0 can be used to test whether the model can be reduced to a spatial lag model (YM, 2014; Belotti et al., 2017).

According to the research of Elhorst (2003), Elhorst (2014), it is necessary, first, to determine whether there is a spatial effect for the estimation of the spatial panel model; second, to select the type of model (SLPDM or SEPDM); and finally, to determine the individual effect or the period effect (fixed effect or random effect). Specifically, we use Morans' I test method for the spatial correlation test. Additionally, we use LM spatial lag, LM spatial error, Robust LM spatial lag, and Robust LM spatial error test methods to determine which model to use. In addition, we use Wald and likelihood ratio LR test to judge whether SDPDM can be simplified to SLPDM or SEPDM, and the Hausman test method is used to determine fixed effects or random effects.

2.5 Data Source

This paper selects a balanced panel dataset of 30 provinces in China over the period 2006–2019 (Hong Kong, Macao, Taiwan, and Tibet are not included due to lack of data). Because of 2006 is the first year of the Twelfth Five-Year Plan for national economic and social development of the People's Republic of China, we began to select sample data in 2006. In 2020, due to the epidemic, many companies and factories in China suspend work and production, which may affect the data indicators greatly. Therefore, this paper does not collect sample data for 2020 in order to avoid interference with research issues. Additionally, in the empirical process, the original data are processed by natural logarithm to eliminate the instability and heteroscedasticity of the data. The original data are derived from the China Statistical Yearbook, the China Energy Statistical

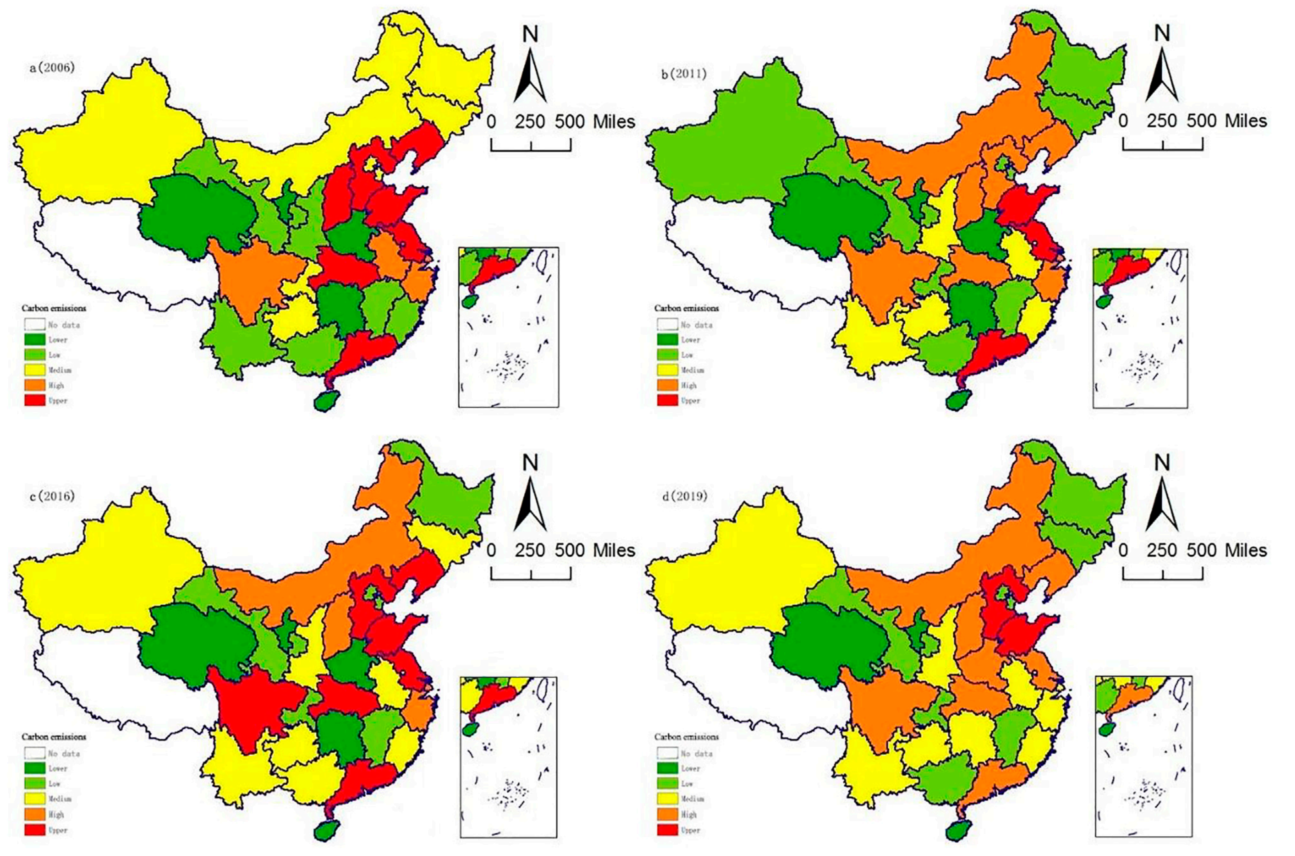

FIGURE 2 | Spatial distribution for 30 provinces in China between 2006 and 2019.

Yearbook, the China Environment Statistical Yearbook, and statistical yearbook of every province and IPCC, etc. We used sample interpolation method to supplement the missing values in some variables.

3 SPATIAL PATTERN OF CARBON EMISSIONS AND THEIR EVOLUTION

3.1 Evolution of Carbon Emission Types in China

To explore the distribution regularity of China's carbon emissions from time and space perspective, the provincial carbon emissions were divided into four grades by natural fracture method in this study: low carbon emissions, medium carbon emissions, high carbon emissions, and upper carbon emissions (**Figure 2**). According to the spatial distribution for 30 provinces, high carbon emission areas are mainly concentrated in the eastern and central areas. Over the period 2006–2019, the number of high carbon emissions reduced initially but then increased, and the high carbon emissions areas spread from the east to the middle. The medium-carbon emission regions gradually developed into the medium-high carbon emission type. Thus, the number of provinces of this type is decreasing year by year. Additionally, the number of low carbon emission provinces remains unchanged. On the whole, it has formed a pattern in which there are many provinces with high and medium-high carbon emissions, while provinces with medium and low carbon emissions are few, and there is a trend of shifting from the low carbon emission type to the high carbon emission type.

3.2 Three-Dimensional Trend Characteristics of Carbon Emissions

To reveal the overall spatial trend of China's carbon emissions, we conducted a trend analysis of China's carbon emissions to obtain a three-dimensional perspective based on the spatial coordinates and CO_2 emissions of each province, shown in **Figure 3**. The *X*-axis direction indicates the east–west direction, the *Y*-axis direction indicates the north–south direction, and the *Z*-axis indicates the amount of carbon emissions. Each vertical line in the figure represents the location of each province and its carbon emissions. All vertical lines are projected on the east–west and north–south orthogonal planes to obtain the projection point. We obtain the best-fitting curve through the projection point, which reflects the upward trend of CO_2 emissions from east to west and north to south.

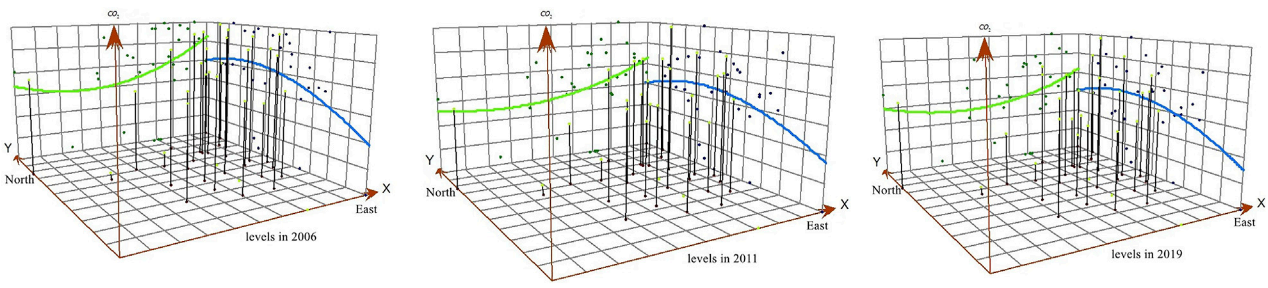

FIGURE 3 | Trend analysis of carbon emissions in China between 2006 and 2019.

TABLE 2 | Moran's I test results of provincial carbon emissions between 2006 and 2019.

	2006	2008	2010	2012	2014	2018	2019
Moran's I	0.3221	0.3250	0.3371	0.3435	0.3410	0.3351	0.3359
p-value	0.002	0.003	0.001	0.002	0.000	0.002	0.001

Specifically, from China's 2006 carbon emission fitting curve, we can find that CO_2 emissions increase in a curve from west to east, and in the north–south direction, the central part is larger than the northern part and the southern part. From the shape of the fitted curve, we can observe that the east–west projection line is approximately a straight line, while the north–south projection line is an inverted U-shaped curve. This means that, relatively speaking, the difference in carbon emissions between the northern and southern provinces is greater than the difference between the east and the west. From the perspective of time evolution, the fitting curve of China's carbon emissions in 2011 still showed a linear and slow growth trend from west to east. In the north–south direction, the central part is still larger than the northern part and larger than the southern part. However, compared with 2006, the east–west gap and the north–south gap has shown a narrowing trend. Judging from the fitting curve of CO_2 emissions in 2019, the spatial distribution of China's inter-provincial CO_2 emissions is similar to before. This shows that carbon emissions from 2006 to 2019 have a stable trend of being high in the east and low in the west, and high in the north and low in the south.

An obvious path dependence exists in China's massive economy according to the stable spatial situation of carbon emissions. That is, if the region chooses a development path, then various economic activities in the region will adapt to this model in the longer development process. A strong exogenous shock is needed to change this development path in the short term. Therefore, if high-emission areas want to reduce carbon emissions and develop a green economy, the government should introduce strong regional economic policies. At the same time, the spatial differences in carbon emissions also indicate that China's energy conservation and emission-reduction measures must take regional differences into account.

4 EMPIRICAL RESULTS AND DISCUSSIONS

4.1 Spatial Correlation Test of Carbon Emissions

It is necessary to determine whether there is a spatial effect before using the spatial panel model. Based on the spatial weight matrix, we calculated the spatial correlation Moran'I index value of the provincial carbon emissions during 2006–2019, shown in **Table 2**. The results show that the Moran's I smoothly remain at around 0.33 between 2006 and 2019, and the significance level is still less than 5%. Thus, we can conclude that there are significant positive spatial correlations between provincial CO_2 emissions. That is, provinces with higher CO_2 emissions and provinces with lower CO_2 emissions tend to be close. Therefore, we need to consider spatial correlations when building a model.

4.2 Spatial Panel Model Estimation

We use MATLAB 2012a software to estimate models (4)–(6). First, we use the LMlag and LMerr and Robust LMlag and Robust LMerr tests to determine whether to use the spatial error model or the spatial lag model. The estimation results of the standard panel model (**Table 3**) show that the LM and Robust LM tests of the spatial lag panel model passed the 1% level of significance test and that the Robust LM of the spatial error panel model failed the 1% level of significance test. Therefore, the spatial lag panel model is better than the spatial error model. Second, the LR value of time-fixed effects was 122.0832 (p = 0.0000), and the LR value of individual fixed effects was 693.2063 (p = 0.0000). This indicates that the model has a double fixed effect of individual and period. Based on the above results, considering that the log-likelihood value of the individual fixed-effects model LogL is 225.4033, and the goodness of fit is relatively high (0.8575), we believe that it is more reasonable to use the individual fixed-effects spatial lag regression model (LeSage and pace, 2010).

Thirdly, we need to decide whether to use a random-effects model or a fixed-effects model. Since the Hausman test result was 10.0792 (p = 0.7183), it failed the 5% significance test and accepted the assumption that the spatial effect does not involve the explanatory variables. It means that the random-effects model is preferable (Elhorst, 2010). Finally, we use the

TABLE 3 | Standard panel estimation results of provincial carbon emissions.

Variables	No fixed effects	Spatial-fixed effects	Time-fixed effects	Spatial- and time-fixed effects
i	1.1657 (3.0024)***			
lnGI	−0.3123 (−5.1723)	−0.0714 (−2.6240)***	−0.2311 (−5.1944)***	−0.0389 (−1.4202)
lnES	0.0102 (0.8174)***	−0.0176 (−0.6944)	0.2072 (6.0658)***	0.1579 (6.5259)
lnGDP	0.5474 (22.0912)	0.6083 (35.3643)***	0.5136 (17.5249)***	0.2010 (3.2758)
lnIS	0.4687 (5.3576)***	0.6334 (5.7928)***	0.4039 (4.6275)***	0.5961 (5.65929)
lnP	0.6931 (35.0016)***	0.3498 (2.0124)**	0.7102 (37.0027)***	0.2417 (1.3843)
R^2	0.8652	0.8575	0.8126	0.2493
LogL	−81.0278	225.4033	−65.0761	279.9320
DW	1.0257	1.9918	1.4021	2.1995
LM test no spatial lag	7.5104***	12.9421***	10.8733***	9.1129***
Robust LM test no spatial lag	1.7687***	34.9780***	4.9654**	3.5681**
LM test no spatial error	11.1702***	0.0105	7.9018***	6.5121***
Robust LM test no spatial error	5.5070***	22.1029***	1.8973	0.8394

Notes*: The figures in brackets are* t *values. *, **, and *** stand for the significance levels of 10, 5, and 1%, respectively.*

TABLE 4 | SPDM estimation results of national/provincial carbon emissions.

	SLPDM		SDPDM
Variables	No fixed effects	Spatial-fixed effects	Random spatial effects of the SDPDM
lnGI	−0.0740 (−2.1808)**	−0.0712 (−2.3112)**	−0.0611(−0.7035)*
lnES	−0.0008 (−0.1203)	0.1332 (5.4575)***	0.1703 (6.80413)***
lnGDP	0.4270 (12.6951)***	0.2614 (4.5127)***	0.2418 (4.1310)***
lnIS	0.5975 (5.8219)***	0.7132 (6.6017)***	0.6701 (6.9043)***
lnP	0.2043 (1.1641)	0.1915 (0.9719)	0.5937 (9.214)***
W*lnGI		0.0633 (1.3162)	0.1896 (3.5312)***
W*lnES		−0.2136 (−5.8612)***	−0.0096 (−0.2564)
W*lnGDP		0.1713 (2.6809)***	−0.0531 (−0.4701)
W*lnIS		0.5501 (2.7140)***	−0.1727 (0.7038)*
W*lnP		0.6739 (1.5327)*	0.1837 (1.3326)*
W*dep.var	0.1593 (3.180350)***	0.0636 (1.0328)	−0.1713 (−2.8212)***
teta			0.1603 (5.4971)***
R2	0.9774	0.9801	0.9618
LogL	228.0837	259.2831	213.0713
Hausman_p		10.0792	

Notes*: The figures in brackets are* t *values. *, **, and *** stand for the significance levels of 10, 5, and 1%, respectively.*

Wald test and LR test of random effects to determine whether the spatial Doberman model can be simplified to a spatial lag model or a spatial error model. The results show that the values of the Wald_spatial_lag and LR_spatial_lag are 15.2712 ($p = 0.001$) and 13.9613 (p = 0.001)); the values of the Wald_spatial_error and LR_spatial_error are 14.2971 (p = 0.0210) and 13.3089 (p = 0.0015), respectively. Both Wald and LR tests pass the 5% significance test, indicating that the spatial Durbin model cannot be reduced to a spatial lag model or a spatial error model. Therefore, we chose the random-effect spatial Dubin model to analyze the impact of green technology innovation on carbon emissions.

From the random-effect spatial Dubin model estimation results (**Table 4**), it can be seen that the elasticity coefficient of national green technology innovation is significantly negative, which negates the view that green technology innovation has a dual impact on carbon emissions from the beginning of this paper. This shows that the current level of China's overall green technology innovation has a direct effect on carbon emissions greater than the scale effect. That is, the improvement of green technology innovation can reduce carbon emissions. However, we found that the effect of green technological innovation on reducing carbon emissions is not obvious. This may be because China's extensive economic growth has caused a substantial increase in carbon dioxide emissions, and the industrial structure dominated by the secondary industry and the energy consumption structure dominated by coal are not conducive to reducing carbon dioxide emissions. Since the reform and opening, the focus of China's technological innovation has been to increase productivity and expand the scale of the economy. Therefore, the emphasis on green technology innovation is insufficient, which has led to a relatively low level of overall green technology innovation. It can be seen that the improvement of technology plays a very limited role in reducing carbon emissions, and the final result is a continuous increase in carbon emissions.

In addition, it can be found that the elasticity coefficients of the control variables, such as industrial structure, economic growth, energy consumption structure, and population, are all positive values, which means that the control variables all have a positive effect on carbon emissions. The possible reason is that the secondary industry is the main sector of energy consumption, and high energy consumption and high emissions are still the main characteristics of China's industry. Therefore, secondary industry has become the main production sector of carbon dioxide. However, during the period 2006–2019, the proportion of the output value of the secondary industry in GDP dropped from 49.7 to 39.1%, and the tertiary industry rose from 38.9 to 53.7% (NBSC, 2007-2020a). Thus, the industrial structure has been significantly optimized. Although in the short term, the optimization and upgrading of the industrial structure cannot reduce carbon dioxide emissions immediately, in the long run, adjusting the industrial structure and gradually reducing the excessive dependence of economic development on the secondary industry is an important measure to reduce carbon emissions. In addition, the coefficient of energy consumption structure is significantly positive, which indicates that the current energy structure does not play a positive role in reducing carbon emissions. During 2006–2019, the proportion of coal in primary energy consumption remained stable between 65 and 70% (NBSC, 2007-2020b). Although the proportion of coal consumption has declined, the energy structure dominated by coal is still the basic feature of China's energy consumption. Such an energy consumption structure still promotes CO_2 reduction. The coefficient of the population is significantly positive, which shows that the population has a promoting effect on carbon emissions. Similarly, economic levels also have a positive effect on carbon emissions.

Among the interaction terms of each explanatory variable and the explained variable, green technology innovation in the neighboring area has a positive effect on the increase in carbon emissions in the region according to the results of the random effects space Dubin panel model. It shows that when the efficiency of green technology innovation in neighboring areas increases, it will promote the increase in CO_2 emissions in the focused region. This may be because the improvement of the efficiency of green technology innovation in the neighboring area will give the region a comparative advantage in certain industries. Thereby, neighboring will attract advantageous resources of these industries in the focused region, which in turn promotes the improvement of green technology innovation in the neighboring region. Eventually, the region's investment in these industries will shrink, technological innovation efficiency will decline, and carbon dioxide emissions will increase.

Furthermore, the industrial structure has a negative effect on the increase in carbon emissions in the region. This may be because the development and growth of the secondary industry in the neighboring areas prompt the agglomeration of resource-based industries in the neighboring areas. Additionally, the high-energy-consuming industries in the region are gradually shifting to neighboring areas. Thus, the industrial structure shows a negative spillover effect. At the same time, the population also shows a negative spatial spillover effect. The spatial effect of energy consumption structure and economic level on carbon emissions is not statistically significant.

TABLE 5 | SLPDM estimation results of the eastern, central, and western carbon emissions.

Variables	Eastern region	Central region	Western region
	Time-fixed effects	Time-fixed effects	Time-fixed effects
lnGI	−0.5675***	−0.2064***	0.0037*
lnES	0.0441	0.4970***	0.1733***
lnGDP	0.4816***	1.0635***	0.4795***
lnIS	0.6448***	0.9635***	2.1132***
lnP	0.5825***	0.5470***	0.8919***
W*lnGI	−0.1325		0.2702
W*lnES	0.0522***		0.1335*
W*lnGDP	0.4045***		−0.1371**
W*lnIS	0.7918***		−0.3960*
W*lnP	−0.1518***		−0.3462

4.3 Analysis of Regional Results

An empirical test of the national provinces suggests that green technology innovation for carbon emissions is negative; namely, innovative efficiency can reduce carbon dioxide emissions. Given the large differences in regional economic level and industrial structure, this paper does further sub-regional research on the impact of green technology innovation in carbon emissions. The selection criteria of the sub-regional spatial panel model are consistent with the national study of the province. **Table 5** shows the estimation results of the eastern, middle, and western panel models.

Table 5 shows the elastic coefficient of regional green technology innovation level to carbon emissions. The elastic coefficient is, respectively, −0.5675 in the east, −0.2064 in the middle region, and 0.0037 in the west. Obviously, it is negative in the east and middle and positive in the west. That is to say, both in the east and middle region, the improvement of green technology innovation efficiency can reduce CO_2 release, and innovation in the eastern region has the most obvious effect on carbon emission reduction. This result was not as expected, and the possible reasons might be as follows.

The eastern region has absorbed foreign advanced technology relatively early and has a developed economy. Therefore, it has the necessary capital and talents for green technology innovation. The eastern region has become China's main low-carbon-technology innovation area. Due to the pressure of economic development in the central and western regions, the government often sets lower environmental protection standards to prioritize economic development. Additionally, the degree of environmental regulation and investment in green technology innovation is naturally weaker than those in the eastern region.

Due to the early transformation of the economic structure, the eastern region closed down and transferred some high-energy and high-emission enterprises (Wang and Xiong et al., 2021), and they continued to introduce international environmental protection technologies to enhance the ability of green technology innovation. Moreover, the eastern region attaches great importance to the development of environmentally friendly products to meet the demand for green products in foreign trade. For the central region, most production still relies on traditional technology, and its technological innovation is mainly focused on increasing productivity. Furthermore, the improvement of green technology is slightly insufficient. Therefore, the effect of green technology innovation in the central region on carbon emission reduction is not as good as that in the eastern region. The western region takes development as its main task. The western region has not paid enough attention to green technological innovation and ecological civilization construction, which are conducive to long-term development. Additionally, the industrial structure of the western region is dominated by the energy industry. In high-energy-consuming industries, technological innovation may have an energy-rebound effect in the short term. That is to say, although green technological innovation can improve energy efficiency and save resources, the improvement of energy efficiency will reduce the production cost and price of products, which will promote product consumption and production. Thus, it will lead to a further increase in energy demand. From this point of view, the final result is that the reduction effect of green technological innovation on CO_2 emissions is not enough to offset the increased effect of additional energy consumption on carbon dioxide emissions in the western region. Therefore, it is not surprising that the efficiency of green technology innovation has increased carbon dioxide emissions in the western region.

From the perspective of the characteristics of technological innovation, due to the location-locking effect of innovation, innovation capability itself also depends on the original innovation capability. After the continuous accumulation of technological innovation in the eastern region, it is easier to form a technological innovation center. In addition, technological innovation has the characteristics of exclusivity and competitiveness, so the eastern region will not be easily transferred as a technological innovation center. In addition, technological innovation has the characteristics of exclusivity and competitiveness, so the eastern region will not easily transfer as a technological innovation center. Naturally, the green technological innovation capabilities of the central and western regions are far weaker than those of the eastern region, and their green technology innovation in reducing CO_2 emissions is also far weaker than that of the eastern region.

5 DISCUSSION

Based on the STIRPAT model, this study confirms that green technology innovation is an effective means of reducing carbon emissions. Additionally, for regions at different stages of economic development, green technological innovation has different effects in reducing carbon emissions. Specific conclusions of this study are presented below.

The empirical results show that the spatial pattern of China's inter-provincial carbon emissions is relatively stable. It shows obvious regional characteristics of being high in the east and north and of being low in the west and south from the spatial perspective. Moreover, the gaps between the east and the west and between the south and the north tend to narrow. From the timing point of view, during the period 2006–2019, the number of high-carbon emission provinces decreased first and then increased, the medium-high carbon emission provinces gradually increased, and the medium carbon emission provinces decreased year by year, while the number of low carbon emission provinces was relatively stable. Therefore, the overall trend is to shift from low carbon emissions to high carbon emissions. The stable state of this spatial trend reflects the obvious path-dependence characteristics of China's regional economy.

Furthermore, the direct effect of green technology innovation in China's 30 provinces (autonomous regions and municipalities) from 2006 to 2019 on carbon dioxide emissions is greater than the scale effect. Therefore, the overall effect is that the improvement of green technology innovation can help reduce carbon emissions, but the effect is not significant. Control variables, such as industrial structure, energy consumption structure, per capita GDP, and population, all have a significant positive role in promoting CO_2 emissions. However, due to the large differences in regional development in China, there are significant regional differences in the impact of green technological innovation on CO_2 emissions. Specifically, the improvement of green technology innovation in the eastern and central regions helps to reduce CO_2 emissions, and the degree of influence in the eastern region is higher than that in the central region. However, improvements in green technology innovation in the western region will increase carbon dioxide emissions.

At the same time, China's inter-provincial carbon dioxide emissions have a strong spatial spillover effect. The carbon emissions in this region not only are related to their own factors but also are affected by the factors of neighboring regions. Specifically, the green technological innovation and the improvement of the industrial structure in the neighboring regions have a depressing effect on the carbon emissions of the region. However, the population has a positive role in promoting carbon emissions in the region. The impact of energy consumption structure and economic level is not statistically significant.

Based on the analysis results, this study emphasized the policies related to carbon emission reduction from several aspects. For instance, the present study fully highlights the need for green technology innovations to reduce CO_2 emissions in China. Since economic development and energy consumption in western China, carbon emissions are not reduced adequately in despite of energy savings through green technology innovation. In western China, subsidies need to be given to encourage green technology innovation. Taking the spatial spillover effect of carbon emissions into account, it is necessary to establish a regional carbon-emission-reduction linkage mechanism and to conduct cross-regional governance of carbon emission reduction.

Although this paper investigates the spatial correlation of the factors influencing carbon emissions in China, there are still significant shortcomings. First, the construction of a green technology innovation-level calculation system is not comprehensive enough to consider more specific green innovation outputs and more undesired outputs. Also, this research has observed the general background of green technology innovation without specific divisions of it to understand better which type of innovation is more conducive to reducing China's carbon emissions. However, the current data are not sufficiently comprehensive, and the amount of publicly available data cannot yet support the establishment of a more comprehensive green technology innovation measurement system, so other methods are not used in this paper at this time. In addition, this research is only exploring the impact of green technology innovation on carbon emissions from the perspective of the region as a whole, while ignoring the impact between sectors, such as transportation sector. A detailed interpretation of the data is needed in subsequent studies.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

LC and SZ led the conceptual design of the manuscript, AC wrote the initial drafts, HY and UC advised the data model and all authors reviewed the manuscript and provided comments and feedback.

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