Original Research

The Influence of Technological Innovation on PM$_{2.5}$ Concentration in the Yangtze River Delta, China

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Abstract

PM$_{2.5}$ pollution seriously affects the environment, human health and socio-economic development, which has garnered wide-spread attention. Technological innovation plays a great role in PM$_{2.5}$ concentration. Thus, better understanding of the influence of technological innovation on PM$_{2.5}$ concentration is necessary. The Yangtze River Delta (YRD) was selected as the study area. This paper explored the spatial characteristic of PM$_{2.5}$ concentration and technological innovation. Then, bivariate Moran’s $I$ was applied to analyze the spatial correlation between technological innovation and PM$_{2.5}$ concentration. The geographically and temporally weighted regression (GTWR) model was applied to explore the spatial heterogeneity of the influence of technological innovation on PM$_{2.5}$ concentration, and geographical detector model was applied to reveal the interactive influence between technological innovation and other factors. The main conclusions were as follows. (1) No city’s PM$_{2.5}$ concentration fell below the standard which is considered harmless to human health. Cities in the northwest of the YRD had higher PM$_{2.5}$ concentration. (2) Cities in the core region of the YRD had relatively higher technological innovation. (3) There existed negative spatial correlation between technological innovation and PM$_{2.5}$ concentration, and three local spatial correlation types were found. (4) Technological innovation contributed to the decrease in PM$_{2.5}$ concentration. The interactive influence between technological innovation and natural factors was generally greater than that between technological factors and socio-economic factors. Comparing to other socio-economic factors, technological innovation and foreign investment had greater interactive influence on PM$_{2.5}$ concentration. Finally, some policy recommendations were drawn.

Keywords: PM$_{2.5}$ pollution, technological innovation, spatial heterogeneity, interactive influence, the YRD

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Introduction

Fine particulate pollutants have caused severe haze pollution in China, posing a significant threat to the environment, human health, and socio-economic development [1, 2]. PM$_{2.5}$ is the main cause of haze pollution in many Chinese cities [3]. Studies indicate that PM$_{2.5}$ can lead to respiratory diseases and cardiovascular diseases, weaken the human immune system and increase the mortality of exposed people [4]. Thus, the PM$_{2.5}$ issue has attracted widespread attention from the government and academia [5]. According to data released by China’s Ministry of Ecology and Environment, the number of days with PM$_{2.5}$ as the primary pollutant failing to meet the air quality standards was the largest, accounting for 39.7% of the total. Thus, it is crucial to investigate the forces of PM$_{2.5}$ pollution and provide decision-making basis for PM$_{2.5}$ control.

Current studies of PM$_{2.5}$ mainly focused on chemical composition and sources [6], transmission and diffusion [7], impact on human health [8], temporal-spatial distribution [9], and influencing factors [10]. It is widely recognized that both natural conditions and social-economic factors influences on PM$_{2.5}$ concentration. Thus, many scholars have studied the influence of natural conditions such as temperature, rainfall and humidity [11-13], as well as social-economic factors such as economic development, population density, technological innovation [14-16] on PM$_{2.5}$ concentration. Technological innovation is also regarded as an important factor that influences PM$_{2.5}$ concentration [17]. Therefore, to clarify the influence of technological innovation on PM$_{2.5}$ concentration is conducive to the formulation of PM$_{2.5}$ control policies.

The studies on the relationship between technological innovation and PM$_{2.5}$ concentration focused on whether technological innovation can reduce PM$_{2.5}$ concentration. Firstly, technological innovation reduced PM$_{2.5}$ concentration. These who hold this view deemed that technological innovation reduced the environmental impact of industrial production by improving productivity and resource utilization while reducing factor input. In addition, the application of clean technologies effectively reduced pollution emissions. Therefore, technological innovation was regarded as an important means to reduce PM$_{2.5}$ concentration by many scholars [18-20]. Secondly, technological innovation increased PM$_{2.5}$ concentration. These who hold this view deemed that the original intention of technological innovation was to improve productivity, not to solve pollution problems. Productivity improvement promoted the reproduction of enterprises and expanded the production scale, and fossil energy consumption also increased. And technological innovation might also lead to new sources of pollution. Thus, technological innovation played a role in increasing PM$_{2.5}$ concentration [21, 22]. Thirdly, the influence of technological innovation on PM$_{2.5}$ concentration was uncertainty. Some scholars deemed that technological innovation had different impacts on PM$_{2.5}$ concentration [23], and there existed N-shaped, inverted U-shaped or other nonlinear relationship [24, 25].

However, the possible shortcomings were shown as follows. Firstly, while most studies analyzed the influence of multiple factors on PM$_{2.5}$ concentration, few have specifically examined the influence of technological innovation alone. As a result, a deeper analysis of the influence of technological innovation on PM$_{2.5}$ concentration was lacking. Secondly, the spatial heterogeneity of the influence of technological innovation on PM$_{2.5}$ concentration was insufficient. The geographically weighted regression (GWR) model is often utilized, but it has limitations as it employs cross-sectional data and cannot adequately address spatial-temporal nonstationarity, despite considering spatial effects and heterogeneity [26, 27]. The GTWR model can effectively solve this problem. Thus, this paper applied GTWR model to analyze the spatial heterogeneity of influence of technological innovation. Thirdly, studies, further exploring the interaction between technological innovation and other factors, were still scarce. PM$_{2.5}$ concentration is influenced by multiple factors which interact with each other. Thus, identifying the interactive influence between different factors made it clear which two factors could be combined to reduce PM$_{2.5}$ concentration.

The YRD is the densest, richest and most urbanized area in China, but it also faces the sharpest contradiction between economic development and eco-environment in China [28]. PM$_{2.5}$ pollution is also an issue in the YRD [29]. However, the YRD is the prior region for achieving China’s strategic development with both economic and ecological goals [30]. Thus, it is necessary to take the YRD as the study area. In addition, the YRD is also a region with a relatively higher level of technological innovation in China, but there also exists imbalance among cities [31, 32]. Therefore, how to play the role of technological advantages in reducing PM$_{2.5}$ concentration according to local conditions is a topic worth discussing.

Overall, this study conducted the research using bivariate Moran’s $I$, GTWR model, and geographical detector model. The findings highlighted spatial heterogeneity in how technological innovation impacts PM$_{2.5}$ concentration and offered policy recommendations based on these results.

Methodology

Data Resources

PM$_{2.5}$ data from Atmospheric Composition Analysis Group, using NASA satellites, ground-based monitoring, and regression models, commonly used. Other Relative data was collected from China City
The Influence of Technological Innovation...

Statistical Yearbook, Shanghai Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook and statistical yearbook of each city. NDVI was collected from Resource and Environment Science and Data Center, Chinese Academy of Sciences. Economic data was converted in 2010 constant price.

This paper assessed technological innovation using input, output, and environment measures. A 3-level index system (3 first-grade indexes, 7 second-grade indexes) was used (Table 1). Entropy weighting determined indicator weights.

To identify the influence of technological innovation on PM$_{2.5}$ concentration, temperature, rainfall, humidity, vegetation coverage, economic development, industrial structure, population density, construction land and foreign investment was collected as control variables (Table 2).

### Table 1. Index system of technological innovation.

<table>
<thead>
<tr>
<th>First grade index</th>
<th>Second grade index</th>
<th>Explanations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation input</td>
<td>Financial expenditure on science and technology</td>
<td>The proportion of science and technology expenditure in GDP</td>
</tr>
<tr>
<td></td>
<td>Scientists</td>
<td>Number of staffs in universities and scientific research institutions</td>
</tr>
<tr>
<td>Innovation output</td>
<td>Patent for invention</td>
<td>The number of patents for innovation</td>
</tr>
<tr>
<td></td>
<td>Design patent</td>
<td>The number of design patents</td>
</tr>
<tr>
<td></td>
<td>Patent for utility models</td>
<td>The number of patents for utility models</td>
</tr>
<tr>
<td>Innovation environment</td>
<td>Universities</td>
<td>The number of Universities</td>
</tr>
<tr>
<td></td>
<td>Books in libraries</td>
<td>The number of books in libraries</td>
</tr>
</tbody>
</table>

### Table 2. Control variables and their explanations.

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Symbols</th>
<th>Explanations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>Temp</td>
<td>Average annual temperature</td>
</tr>
<tr>
<td>Rainfall</td>
<td>Rain</td>
<td>Average annual rainfall</td>
</tr>
<tr>
<td>Humidity</td>
<td>Humi</td>
<td>Average annual humidity</td>
</tr>
<tr>
<td>Vegetation coverage</td>
<td>Vege</td>
<td>Normalized Difference Vegetation Index (NDVI)</td>
</tr>
<tr>
<td>Economic development</td>
<td>PGDP</td>
<td>Per capital GDP</td>
</tr>
<tr>
<td>Industrial structure</td>
<td>Indu</td>
<td>Proportion of the secondary industry output value over the total GDP</td>
</tr>
<tr>
<td>Population density</td>
<td>Popu</td>
<td>Ratio of resident population to total area</td>
</tr>
<tr>
<td>Construction land</td>
<td>Cons</td>
<td>Ratio of urban built-up area to municipal area</td>
</tr>
<tr>
<td>Foreign investment</td>
<td>Fore</td>
<td>The proportion of actually utilized foreign capital in GDP</td>
</tr>
</tbody>
</table>

Spatial Autocorrelation Analysis Method

Firstly, the univariate Moran’s $I$ index was used to explore the spatial distribution characteristics of technological innovation and PM$_{2.5}$ concentration, respectively. The univariate Moran’s $I$ index can be calculated as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})^2}$$  \hspace{1cm} (1)

Where $I$ is the univariate Moran’s $I$ index; $n$ is the number of cities; $i, j$ represents the city $i$ or $j$; $x$ is the PM$_{2.5}$ concentration or technological innovation; $\bar{x}$ is the average value of $x$; $W$ is the spatial weight matrix.

Secondly, bivariate Moran’s $I$ index was applied to explore the spatial correlation between PM$_{2.5}$ concentration and technological innovation. The bivariate Moran’s $I$ index can be calculated as follows:

$$II = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \bar{x})(y_j - \bar{y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}$$  \hspace{1cm} (2)

Where $II$ is the bivariate Moran’s $I$ index; $x$ is the PM$_{2.5}$ concentration; $y$ is the technological innovation.

To identify the local spatial correlation between technological innovation and PM$_{2.5}$ concentration, bivariate local Moran’s $I$ index was also calculated as follows:
\[ II_i = Z_i^a \sum_{j=1}^{n} W_{ij} Z_j^b \]  

(3)

Where, \( II \) is the bivariate local Moran’s I index; \( Z_i^a \) is the standard variance of PM\(_{2.5}\) concentration; \( Z_j^b \) is the standard variance of PM\(_{2.5}\) concentration. For other details, please refer to Hu [33], Ge [34].

Geographically and Temporally Weighted Regression Model

By incorporating the temporal effect into the GWR model, the GTWR model can deal with both temporal and spatial non-stationarity [35]. Thus, Therefore, the GTWR model can capture the temporal-spatial heterogeneity by integrates temporal and spatial information in the spatial weighted matrix. The GTWR model is shown as follows:

\[ Y_i = \beta_0 (u_i, v_i, t_i) + \sum_k \beta_k (u_i, v_i, t_i) X_{ik} + \varepsilon_i \]  

(4)

Where, \( Y_i \) is the PM\(_{2.5}\) concentration; \( u_i, v_i \) is the dimension and longitude of the \( i \)th city; \( t_i \) is the year; \( (u_i, v_i, t_i) \) is the temporal-spatial coordinates of \( i \)th city; \( \beta_k (u_i, v_i, t_i) \) is the regression constant; \( \beta_k \) is the \( k \)th influencing factor’s regression coefficient of \( i \)th city; \( X_{ik} \) is the value of the \( k \)th influencing factor in the \( i \)th city; \( \varepsilon_i \) is the residual.

Geographical Detector Model

Geographical detector model, proposed by Wang [36], can detect and explain the spatial heterogeneity of driving forces. It assumes that if an independent variable influences a dependent variable, their spatial distribution should be similar [37]. \( q \) value is used to measure the explanation of independent variable to dependent variable by geographic detector. By calculating and comparing the \( q \) value of each factor and the \( q \) value after the superposition of the two factors, the geographic detector can judge whether there is interaction between the two factors, as well as the strength, direction, linearity or nonlinearity of interaction. The \( q \) can be can be calculated as follows:

\[ q = 1 - \frac{\sum_{k=1}^{L} \sum_{i=1}^{N_h} (y_{ih} - \bar{Y}_h)^2}{\sum_{i=1}^{N} (y_i - \bar{Y})^2} = 1 - \frac{\sum_{k=1}^{L} N_h \sigma_k^2}{N \sigma^2} \]  

(5)

Where, \( q \) is the power of determinate, which reflects the influence of \( X \) on the spatial heterogeneity of \( Y \). The larger the \( q \) is, the larger the influence is. \( L \) is the number of strata; \( h \) is the \( h \) strata; \( N_h \) and \( N \) are the numbers of the units in the \( h \) strata and whole area, respectively; \( \sigma_k^2 \) and \( \sigma^2 \) are the variance of \( h \) strata and whole area, respectively.

Geographical detector model can detect whether different factors are independent in influencing the dependent variable, or evaluate whether the influence of one factor on the dependent variable is enhanced or weakened by another factor. Table 3 provides criteria for determining which type of interaction is involved.

Results and Discussion

The Spatial Evolution of PM\(_{2.5}\) Concentration

This paper analyzed PM\(_{2.5}\) concentration in 2003, 2011. In 2003, 36 cities exceeded the limit of 35 μg/m\(^3\), with Huaihai and Xuzhou having higher levels. By 2011, 37 cities exceeded the limit, and Xuzhou, Huaihai, and Fuyang had highly polluted air. However, by 2019, only 25 cities exceeded the limit, with Xuzhou being the most polluted city. No city met the WHO’s standard of an annual PM\(_{2.5}\) concentration below 10μg/m\(^3\). Cities in the northwest of the YRD had higher PM\(_{2.5}\) concentrations compared to those in the southeast.

The Spatial Characteristics of Technological Innovation

To analyze the spatial evolution of technological innovation, the spatial distribution of technological innovation in 2003, 2011, and 2019 had also been mapped (Fig. 2). The Natural Breaks Classification method was applied to classify technological innovation. By comparing distribution of technological innovation from 2003 to 2019, it found that cities in the core region of the YRD, such as Shanghai, Nanjing, Hangzhou and Hefei, had relatively higher technological innovation.

<table>
<thead>
<tr>
<th>Description</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>( PD(X1 \cap X2) &lt; \text{Min}(PD(X1), PD(X2)) )</td>
<td>Weak and nonlinear</td>
</tr>
<tr>
<td>( \text{Min}(PD(X1), PD(X2)) \leq \text{PD}(X1 \cap X2) &lt; \text{Max}(PD(X1), PD(X2)) )</td>
<td>Weaken and univariate</td>
</tr>
<tr>
<td>( PD(X1 \cap X2) &gt; \text{Max}(PD(X1), PD(X2)) )</td>
<td>Enhance and bivariate</td>
</tr>
<tr>
<td>( PD(X1 \cap X2) = PD(X1)+PD(X2) )</td>
<td>Independent</td>
</tr>
<tr>
<td>( PD(X1 \cap X2) &gt; PD(X1)+PD(X2) )</td>
<td>Enhance and nonlinear</td>
</tr>
</tbody>
</table>
Technological innovation had positive spatial autocorrelation but decreasing differences in spatial distribution from 2003 to 2019, while PM$_{2.5}$ concentration had positive spatial autocorrelation with growing differences in spatial distribution during the same period. Bivariate Moran’s I indicated negative spatial correlation between technological innovation and PM$_{2.5}$ concentration, meaning high technological innovation cities were adjacent to low PM$_{2.5}$ concentration cities or vice versa.

while cities in the peripheral regions, such as Suzhou and Bozhou, were relatively lower.

**Spatial Correlation Analysis**

Using GeoDa software, this paper calculated the univariate and bivariate Moran’s I values and significance of technological innovation and PM$_{2.5}$ concentration. According to Table 4, univariate and bivariate Moran’s I was statistically significant at least at 5% significance level. Technological innovation had positive spatial autocorrelation but decreasing differences in spatial distribution from 2003 to 2019, while PM$_{2.5}$ concentration had positive spatial autocorrelation with growing differences in spatial distribution during the same period. Bivariate Moran’s I indicated negative spatial correlation between technological innovation and PM$_{2.5}$ concentration, meaning high technological innovation cities were adjacent to low PM$_{2.5}$ concentration cities or vice versa.

**Table 4. Univariate and bivariate Moran’s I values of technological innovation and PM$_{2.5}$ concentration.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Moran’s I and P-value</th>
<th>2003</th>
<th>2011</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technological innovation</td>
<td>Univariate Moran’s I</td>
<td>0.3141</td>
<td>0.2998</td>
<td>0.1189</td>
</tr>
<tr>
<td>P-value</td>
<td>0.001</td>
<td>0.002</td>
<td>0.040</td>
<td></td>
</tr>
<tr>
<td>PM$_{2.5}$ concentration</td>
<td>Univariate Moran’s I</td>
<td>0.6543</td>
<td>0.7056</td>
<td>0.7147</td>
</tr>
<tr>
<td>P-value</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Technological innovation and PM$_{2.5}$ concentration</td>
<td>Bivariate Moran’s I</td>
<td>-0.2329</td>
<td>-0.1773</td>
<td>-0.1879</td>
</tr>
<tr>
<td>P-value</td>
<td>0.002</td>
<td>0.007</td>
<td>0.005</td>
<td></td>
</tr>
</tbody>
</table>
To further examine the local spatial correlation between technological innovation and PM$_{2.5}$ concentration, the study created Bivariate LISA cluster maps. The maps showed three types of local spatial correlation: low technological innovation-high PM$_{2.5}$ concentration, high technological innovation-low PM$_{2.5}$ concentration, and low technological innovation-low PM$_{2.5}$ concentration, as shown in Fig. 3.

Cities with low technological innovation-high PM$_{2.5}$ concentration were mainly distributed in the northwest of the YRD. According to the previous analysis, the technological innovation of these cities was indeed low, while PM$_{2.5}$ concentration was high. It indicates poor technology transfer and diffusion effect along with ineffective optimization effects of low technological innovation on air pollution. Much work is needed to control PM$_{2.5}$ pollution in these cities. Cities with low technological innovation-low PM$_{2.5}$ concentration were mainly in the south of the YRD. For these cities, low technological innovation cannot effectively control increasing PM$_{2.5}$ concentration. Cities with high technological innovation-low PM$_{2.5}$ concentration were mainly in the southeast of the Yangtze River, indicating a potential to leverage technological advantages for cleaner production and better resource utilization.

Mechanism Analysis of the Influence of Technological Innovation on Air Pollution

Spatial Heterogeneity Analysis

This study examined the spatial heterogeneity of technological innovation’s impact on air pollution while controlling for various factors such as temperature, rainfall, economic development, and population density. Collinearity tests were conducted, and the Variance Inflation Factor (VIF) values were all less than 10, indicating no collinearity. Diagnostic indexes of GTWR and GWR models were presented in Table 5, which indicated that the regression results of the GTWR model were more explanatory.

This paper focused solely on analyzing the impact of technological innovation on PM$_{2.5}$ concentration. Results showed that on average, technological innovation had contributed to reducing PM$_{2.5}$ concentration in 2003, 2011, and 2019, despite varying influence coefficients across cities (Fig. 9).

Cities with positive effects of technological innovation were mainly located in southern Anhui, southern Jiangsu, Shanghai, and northeastern Zhejiang. The number of such cities increased between 2003-2009, and compared to 2003, some cities including Shanghai and Suzhou had a positive effect on PM$_{2.5}$ concentration through technological innovation. Since the 1990s, the YRD had established high-tech industrial development zones, such as the Nanjing Economic-Technological Development Zone, and attracted foreign companies, leading to accelerated heavy and high-tech industry growth. The YRD had entered a period of accelerated development of heavy industry and high-tech industry. For these cities, technological innovation aimed at increasing production efficiency rather than addressing environmental concerns, which resulted in it contributing more to increasing PM$_{2.5}$ than inhibiting it. Although technological innovation helped decrease PM$_{2.5}$ levels, it could not fully address the increase caused by economic development.

The cities with negative influence of technological innovation were mainly distributed in central and northern Jiangsu province, central and northern Anhui

![Fig. 3. Bivariate LISA cluster maps of technological innovation and PM$_{2.5}$ concentration in YRD.](image)
Province, and southwestern Zhejiang Province. While the number of such cities decreased from 2003-2009, mean negative effect increased from –13.45 to –21.44, indicating that technological innovation had gradually enhanced its inhibitory effect on PM$_{2.5}$ concentration. Local governments paid more attention to haze control, leading to the formulation of relevant policies such as Xuzhou’s measures for air pollution prevention and control. Technological innovation became an important means for local governments to solve environmental problems. Additionally, better natural environments, such as those found in cities like Lishui and Wenzhou with low PM$_{2.5}$ concentrations and strong environmental self-purification abilities, made it easier for technological innovation to decrease PM$_{2.5}$ concentrations.

**Interaction Detections**

The GTWR model is limited to analyzing the independent effect of technological innovation, with other factors acting as control variables. Since PM$_{2.5}$ concentration is influenced by various factors, this study used a geographical detector model to analyze their interactive influence. Technological innovation and other factors were classified into five categories using the Natural Breaks Classification method, and the results are presented in Table 6.

There were two types of interactive influence between technological innovation and other factors on PM$_{2.5}$ concentration, which were nonlinear enhancement and bivariate enhancement. It indicated that the interactive influence between technological innovation and other factors was greater than the influence of technological innovation itself. The spatial heterogeneity of PM$_{2.5}$ concentration was more influenced by the interaction between technological innovation and other factors. As shown in Table 4, the interactive influence between technological innovation and natural factors was generally greater than that between technological

![Fig. 4. Spatial distribution of regression coefficient of technological innovation.](image)

**Table 6. Results of the interaction detections between technological innovation and other factors.**

<table>
<thead>
<tr>
<th></th>
<th>2003</th>
<th>2011</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$q$</td>
<td>Types</td>
<td>$q$</td>
</tr>
<tr>
<td>Tech ∩ Temp</td>
<td>0.689</td>
<td>EN</td>
<td>0.726</td>
</tr>
<tr>
<td>Tech ∩ Rain</td>
<td>0.580</td>
<td>EB</td>
<td>0.575</td>
</tr>
<tr>
<td>Tech ∩ Humi</td>
<td>0.415</td>
<td>EN</td>
<td>0.835</td>
</tr>
<tr>
<td>Tech ∩ Vege</td>
<td>0.399</td>
<td>EB</td>
<td>0.634</td>
</tr>
<tr>
<td>Tech ∩ PGDP</td>
<td>0.433</td>
<td>EN</td>
<td>0.325</td>
</tr>
<tr>
<td>Tech ∩ Indu</td>
<td>0.420</td>
<td>EN</td>
<td>0.429</td>
</tr>
<tr>
<td>Tech ∩ Popu</td>
<td>0.503</td>
<td>EN</td>
<td>0.353</td>
</tr>
<tr>
<td>Tech ∩ Cons</td>
<td>0.395</td>
<td>EN</td>
<td>0.475</td>
</tr>
<tr>
<td>Tech ∩ Fore</td>
<td>0.541</td>
<td>EN</td>
<td>0.806</td>
</tr>
</tbody>
</table>

Notes: EN denotes enhance and nonlinear; EB denotes bivariate enhance and bivariate
factors and socio-economic factors. Therefore, a good ecological environment was conducive to the improvement of PM$_{2.5}$ concentration by technological innovation. Compared to other socio-economic factors, technological innovation and foreign investment had greater interactive influence on PM$_{2.5}$ concentration. While attracting foreign investment, strengthening management and environmental regulations was conducive to the improvement of technological innovation on PM$_{2.5}$ concentration.

The study found two types of interactive influence between technological innovation and other factors, namely nonlinear enhancement and bivariate enhancement. These interactions were greater than the influence of technological innovation alone, suggesting that PM$_{2.5}$ concentration was heavily influenced by their interaction. Ecological factors had a stronger effect on PM$_{2.5}$ concentration than socio-economic factors, with technological innovation and foreign investment showing the greatest influence. Strengthening management and environmental regulations during foreign investment could improve the effects of technological innovation on PM$_{2.5}$ concentration.

**Discussion**

Haze pollution is a significant environmental and development obstacle that must be addressed for sustainable development [38, 39]. However, PM$_{2.5}$ pollution in the Yangtze River Delta remains serious. Solving haze pollution in the Yangtze River Delta is not only essential for the area but also to the entire country, given its role as a model for China’s social-economic development. Based on our findings, technological innovation is conducive to the reduction of PM$_{2.5}$ concentration in YRD. Therefore, enough attention should be paid to the role of technological innovation in the reduction of PM$_{2.5}$ concentration.

The role of technological innovation in PM$_{2.5}$ pollution control should be brought into play in light of local conditions. Technological innovation can reduce PM$_{2.5}$ concentration by promoting clean technologies and energy efficiency but may also increase it through productivity improvements. Therefore, it’s crucial to assess the impact of technological innovation on PM$_{2.5}$ concentration in different cities. According to our findings, the influence of technological innovation on PM$_{2.5}$ is spatially heterogeneous in the YRD. In some cities with high level of technological innovation, such as Shanghai, technological innovation promoted the increase of PM$_{2.5}$ concentration. Compared with other cities in the YRD, these cities were characterized by relatively lower PM$_{2.5}$ concentration and higher level of technological innovation (In sub-section 3.3, the local spatial correlation of these cities was not significant, because we calculated it apply Geodata software, and it only detected a significant level of 5%). Many of these cities fall under China’s major function zoning as optimized or key development zones aimed at promoting industrialization and urbanization. As a result, technological innovation is mainly geared towards improving productivity rather than addressing environmental concerns. To effectively reduce PM$_{2.5}$ concentration, it’s necessary for these cities to implement additional measures alongside technological innovation.

The loss of self-purification function of natural ecosystems is one of the major causes of haze pollution. When the functions of natural ecosystems are perfect, a large number of air pollutants are absorbed by various water bodies and forest systems. Urbanization and industrialization have seriously damaged natural ecosystems. This paper found that technological innovation had a stronger interaction with natural factors than with socio-economic factors. Therefore, protecting natural ecosystems can enhance the effectiveness of technological innovation in controlling haze pollution. However, many natural factors are inelastic, such as average annual temperature and precipitation, which are hard to change greatly. Although the interaction between socio-economic factors and technological innovation is smaller, it is more operational. Furthermore, this paper also finds that socio-economic factors can also increase the influence of technological innovation on PM$_{2.5}$ concentration. To maximize the effectiveness of technological innovation in controlling PM$_{2.5}$ pollution, it’s essential to consider natural and socio-economic factors comprehensively.

Compared to other socio-economic factors, this paper found that the interactive influence between technological innovation and foreign investment was greater. Some scholars believe that foreign investment will bring high-polluting enterprises, and open trade policies will make developing countries produce more pollution [40, 41]. Some scholars hold the point that foreign investment brings advanced production technology and management experience, which helps to improve the environment [42, 43]. The impact of foreign investment on environmental pollution is uncertain. But, we found that foreign investment increased the influence of technological innovation on PM$_{2.5}$ concentration. Therefore, when introducing foreign investment, it is necessary to increase the threshold of environmental access and reject the introduction of enterprises with low efficiency, high consumption and high pollution. Instead, it should strengthen the influence of technological innovation on PM$_{2.5}$ concentration by introducing green, clean and energy-saving enterprises.

**Conclusions and Recommendations**

Some conclusions were drawn as follows.

(1) No city’s PM$_{2.5}$ concentration fell below the standard which is considered harmless to human health. By comparing distribution of PM$_{2.5}$ concentration in different years, it found that cities with higher PM$_{2.5}$
concentration were mainly located in the northwest of the YRD, while cities with lower PM$_{2.5}$ concentration were located in the southeast.

(2) Cities in the core region of the YRD, such as Shanghai, Nanjing, Hangzhou and Hefei, had relatively higher technological innovation, while cities in the peripheral regions, such as Suzhou and Bozhou, were relatively lower.

(3) Technological innovation showed positive spatial autocorrelation, but the differences in spatial distribution were decreasing. PM$_{2.5}$ concentration also exhibited positive spatial autocorrelation, and its differences in spatial distribution were growing. There existed negative spatial correlation, that is, cities with high technological innovation were adjacent to low PM$_{2.5}$ concentration, or vice versa. There were three local spatial correlation types, including low technological innovation-high PM$_{2.5}$ concentration, high technological innovation-low PM$_{2.5}$ concentration and low technological innovation-low PM$_{2.5}$ concentration.

(4) Technological innovation had been contributing to the decline in PM$_{2.5}$ concentration. The influence coefficient of technological innovation presented obvious spatial differentiation characteristics. There were two types of interactive influence between technological innovation and other factors on PM$_{2.5}$ concentration, which were nonlinear enhancement and bivariate enhancement. The interactive influence between technological innovation and natural factors was generally greater than that between technological factors and socio-economic factors. Comparing to other socio-economic factors, technological innovation and foreign investment had greater interactive influence on PM$_{2.5}$ concentration.

Some policy recommendations were drawn.

Firstly, promoting the development of green technology is necessary. Green technology is an environment-friendly technology with the characteristics of recycling, low energy consumption and cleanliness. This paper also found that technological innovation in some cities with higher technological innovation increased the PM$_{2.5}$ concentration. For these cities, the technological level is relatively higher, but clean innovation is still needed in products, production processes and other links.

Secondly, in view of the spatial heterogeneity of influence of technological innovation on PM$_{2.5}$ concentration, formulating the PM$_{2.5}$ pollution control plan according to local conditions is necessary. Fully understanding the conditions of different cities can ensure that technological innovation controls PM$_{2.5}$ pollution without compromising steady socio-economic development. Lower technological innovation in cities like Xuzhou has led to a reduction in PM$_{2.5}$ concentration. Incentive policies for technological innovation and source control should be given priority. While end-of-pipe treatment is an option, it’s expensive, incomplete, and produces waste residue. Therefore, future technological innovation in Xuzhou should focus on source control to improve resource utilization and reduce waste.

Thirdly, attention must be paid to the interaction of other factors and technological innovation on PM$_{2.5}$ concentration. Natural factors played a significant role in exerting the influence of technological innovation on PM$_{2.5}$ concentration. It is necessary to improve the eco-environment to play its self-purification function. Meanwhile, adaptive strategies need to be developed, such as reasonable design of urban air duct, industrial location optimization, reasonable layout of green belt. However, the formulation of socio-economic countermeasures is more operable. Some regulatory policies, such as the adjustment of industrial structure and the relief of overloaded population, need to be formulated.

Fourthly, cities should strengthen technical cooperation and jointly control PM$_{2.5}$ pollution. Technological innovation can be supported through taxation and other means to improve resource utilization and reduce pollutant emissions. The YRD also should promote cooperation among cities in technical personnel exchanges, joint laboratory construction and technology transfer. Besides, the spatial correlation of PM$_{2.5}$ pollution is strong. Cities can share PM$_{2.5}$ detection data and establish joint prevention and control mechanisms.

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Conflict of Interest

The authors declare no conflict of interest.

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