Research on the Mechanism and Pathway of Digital Intelligence Technology Application in Collaborative Emission Reduction in the Chemical Industry

Lei Tian*

School of Business, Hohai University, Nanjing, China

*15002214515@163.com

Abstract. The integration of digital intelligence has become the core driving force of digitalization and sustainable green development. This convergence relies on data-centricity to achieve deep integration of data, intelligence, cloud computing and network technologies. In recent years, scholars at home and abroad have begun to pay attention to quantitative evaluation, but the relevant results are still insufficient in applying these evaluation methods to the chemical industry and carrying out specific quantitative research. Based on the panel data of 10 prefecture-level cities in Jiangsu Province from 2013 to 2022 (excluding the data of Huai'an, Taizhou and Suqian, the same below), this paper analyzes the spatiotemporal evolution characteristics of carbon emissions and the development of digital intelligence integration in the chemical industry in Jiangsu Province, and uses benchmark regression to analyze the impact of the development of digital intelligence integration on carbon emission reduction in the chemical industry, and draws corresponding conclusions and enlightenments, which provides a reference for the carbon emission reduction path of the chemical industry.

Keywords: Chemical Industry; Collaborative Emission; Intelligence Technology; Reduction Mechanism.

1 INTRODUCTION

In the current global environment, the chemical industry is an important part of the world economy, and the impact of its production activities on the environment has always been a hot issue. With the strengthening of environmental protection awareness and the implementation of sustainable development strategies, the chemical industry is facing unprecedented pressure to find effective ways to reduce emissions to achieve green development. In this context, the application of digital intelligence Technology has become the key to the transformation and upgrading of the chemical industry.

Digital intelligence technologies, including but not limited to big data, artificial intelligence, cloud computing, and the Internet of Things, offer unprecedented opportu

A. Haldorai et al. (eds.), *Proceedings of the 2024 3rd International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID 2024)*, Atlantis Highlights in Intelligent Systems 11,
https://doi.org/10.2991/978-94-6463-490-7_46

nities for the chemical industry. These technologies can help companies effectively collect and analyze data, optimize production processes, and improve resource efficiency to achieve their goal of reducing pollutant emissions. More importantly, digital intelligent technology can also promote information sharing and collaboration between industries and enterprises, break the traditional information island, and build a new efficient, transparent and collaborative environmental protection system.

The integration of digital intelligence is a key driving force for digitalization and greening. Digital intelligence integration refers to taking data as the core, intelligence as the guide, cloud as the foundation, and network as the link to realize the deep integration of data, intelligence, cloud, and network, and form a data-driven intelligent development model. The integration of digital intelligence can provide more efficient, safer, more reliable and more flexible solutions for the chemical industry, and promote the innovation, competitiveness and sustainability of the chemical industry. The core value of digital intelligence integration is to empower the collaborative emission reduction of the chemical industry, that is, to achieve collaborative optimization within the chemical industry through the application of digital intelligence technology, as well as the collaborative win-win situation between the chemical industry, upstream and downstream industries, and the social environment.

2 RELATED WORK

In recent years, numerous scholars have begun to pay attention to quantitative evaluation, but the results of quantitative research on combining the two and linking the chemical industry are still relatively lacking. The research on the development of the chemical industry mainly focuses on the evaluation of green efficiency, total factor production efficiency and the analysis of influencing factors, and then puts forward corresponding policy suggestions. Specifically, Li Hanzhi et al. (2022) [1] believe that in the context of the new era, green transformation has become an inevitable trend in the development of chemical enterprises, and digitalization is an important path to empower chemical enterprises to save energy, reduce emissions, costs and increase efficiency.

Additionally, researcher Yin Peiqi believes that the digital transformation of chemical enterprises first requires top-level design, followed by the overall architecture of digital transformation based on "unified and flexible" digital transformation, and the construction of infrastructure based on digital intelligence and informatization is the basic guarantee [2]. Zou Shaohui and Liu Bing (2021) [3] believe that CCUS technology is a key technology for carbon emission reduction in the new coal chemical industry, and the carbon neutrality goal of the new coal chemical industry should be achieved by adjusting the industrial structure, reducing the emission intensity, and increasing the forest carbon sink. Chen (2021) [4] empirically examines the impact of digitalization on carbon emissions using the ARDL method using BRICS countries as a sample, and long-term estimates show that digitalization has a significant inhibitory effect on carbon emissions in Brazil, India, and China.

Most studies point out that digitalization and intelligence have an impact on carbon emission reduction, but the final result is still uncertain whether carbon emissions increase or carbon emissions, and the results show that digital intelligence integration has certain potential in carbon emission reduction [5-6], and digital intelligence integration promotes carbon emission reduction through biased technological progress, optimization of energy structure [7], improvement of resource utilization and increase of environmental investment, but there are differences within different economic circles and regions[8]. At the same time, the "energy rebound effect" caused by the improvement of energy efficiency brought about by digitalization will also stimulate the increase of total energy consumption of enterprises, and the final result is that not only does not "reduce carbon" but "increases" emissions [9-10].

3 PRELIMINARIES

3.1 Data Descriptions

From 2013 to 2022, this paper selects the listed companies in the chemical industry in Jiangsu Province from 2013 to 2022 in Shanghai and Shenzhen A-shares, and carries out the following data processing:

(1) The enterprise samples of ST and ST* are excluded.

(2) To ensure the consistency of the data of each variable, the financial index data published in the annual consolidated statements of listed companies are used, and the samples of enterprises with obviously unreasonable financial indicators are excluded.

(3) To reduce the impact of outliers on the regression results, 1% and 99% are applied to all enterprise-level continuous variables Tail shrinkage.

Finally, 52 enterprises were identified as the research objects in this paper, with a total of 424 "enterprise-year" observation samples. Among them, the raw data at the enterprise level are mainly derived from the annual reports of enterprises, which are downloaded and processed from the official websites of the Shenzhen Stock Exchange and the Shanghai Stock Exchange, the data at the industry and regional levels are from the China Industrial Statistical Yearbook, and the regional carbon emission data are from the statistical yearbooks of cities at the local level in Jiangsu.

3.2 Analysis Methods

With the wide application of text big data in the field of economics and finance, recent literature studies have begun to try to use text analysis methods to describe the degree of digitalization of enterprises. Therefore, drawing on the research of Wu Fei et al. [11] and Zhao Chenyu et al. [12], this paper uses the logarithm of the total frequency of digitized keywords in the annual reports of listed companies to measure the degree of digitalization of enterprises, which is expressed in following Equation 1.

$$lnDi = In(1 + fre) \tag{1}$$

Where fre represents the frequency of key words in the integration of digital intelligence in enterprises. The higher the indicator $lnDi$ value, the higher the degree of digital intelligence integration of the enterprise.

When evaluating the carbon emission level of enterprises, this paper finds that few enterprises disclose carbon emission data in their annual reports, which is limited by the availability of enterprise carbon emission data, and this paper draws on the research method of Shen Hongtao et al [13] to estimate corporate carbon emissions by the proportion of operating costs, which is expressed in following Equation 2.

$$\mathrm{I}nce = In\left(1 + \frac{C_{opt}}{C_{bus} * C_{emi}}\right) \tag{2}$$

Where C_{opt} means the enterprise operating cost, C_{bus} is industry main business cost, and C_{emi} represents industry carbon emissions.

4 METHODOLOGIES

4.1 Spatiotemporal Analysis of Digital Intelligence Integration

Figure 1 shows that there is significant spatial heterogeneity in the level of digital intelligence integration in the chemical industry in Jiangsu Province from 2012 to 2022. The level of digital intelligence integration in different cities is increasing year by year, but there are great differences in the speed of improving the level of digital intelligence integration in different regions. The cities with the fastest development speed are Nanjing, Wuxi and Suzhou. The overall distribution characteristics of "low in the north and high in the south" are radiated to other cities with Nanjing, Wuxi and Suzhou as the center. At the same time, cities with a high level of digital intelligence integration are more consistent with cities with high GDP.

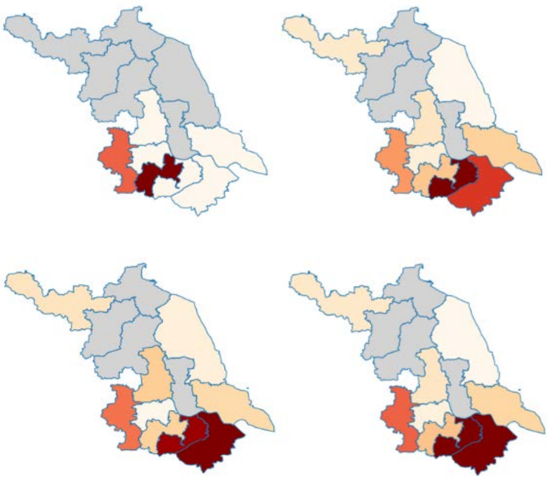

Fig. 1. Spatial distribution of digital and intelligent integration in Jiangsu Province.

4.2 Spatiotemporal Analysis of Carbon Emission

The carbon emissions and changes of the chemical industry in Jiangsu Province from 2012 to 2022 are shown in Figure 2, which show similar changes to the level of digital intelligence integration. There is significant spatial heterogeneity in the carbon emissions of the chemical industry in Jiangsu Province, but the relative change is relatively stable. It can be seen from the figure that the carbon emissions of the chemical industry in Jiangsu Province are generally distributed in the north and high in the south. The outstanding performance is that the carbon emissions of Nanjing's chemical industry are significantly higher than those of other cities. At the same time, the total carbon emissions are on the rise.

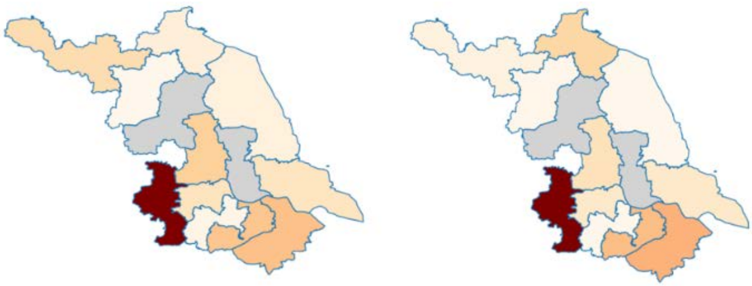

Fig. 2. Spatial distribution of carbon emissions in the chemical industry in 2012 and 2022.

4.3 Model Establishment

In order to study the impact of digital intelligence integration on carbon emissions, the following benchmark regression model is constructed, which is expressed in Equation 3.

$$lnCe_{it} = \alpha_0 + \alpha_1 lnDi_{it} + \alpha_2 Control_{it} + \gamma_i + \varepsilon_{it} \tag{3}$$

Where the $lnCe_{it}$ is the carbon emission index, and $lnDi_{it}$ is the digital intelligence integration development index and the $Control_{it}$ is the enterprise control variables. α_0, α_1, and α_2 represent the impact of the intercept term, the carbon emission index of the digital intelligence integration development enterprise, and the impact of other control variables on the synergy index, respectively. γ_i is an individual fixed effect, which represents a fixed effect at the firm level. ε_{it} is an unobservable random perturbation term that represents other possible influencing factors that are not taken into account in the model. The control variables refer to the research of Shi Yutang and Wang Xiaodan [14], Zeng Hao [15], Zhang Zeyu [16], Liu Xuexin et al. [17], and the following variables are controlled in this paper:

(1) The age of the enterprise. The difference between the natural year of the enterprise and the year of incorporation of the enterprise;

(2) Enterprise scale. The logarithm of the total assets of the enterprise;

(3) Asset-liability ratio. It is measured by the ratio of corporate liabilities;

(4) Net profit margin on total assets. It is measured by the ratio of the net profit of the enterprise to the average total assets of the enterprise;

(5) The shareholding ratio of the largest shareholder. It is measured by the ratio of the number of shares held by major shareholders of the enterprise at the end of the year to the total number of shares of the enterprise;

(6) Proportion of independent directors. It is measured by the ratio of the number of independent directors at the end of the year to the total number of directors of company;

(7) Growth rate of operating profit. It is measured by the ratio of the company's operating profit growth in the current year to the total operating profit

5 EXPERIMENTS

5.1 Benchmark Regression Results

Table 1 illustrates the benchmark regression results of digital intelligence fusion fitted according to Equation 3 on the carbon emission intensity in Jiangsu Province.

Table 1. Regression results.

Variables	Corporate carbon intensity (1)	Corporate carbon intensity (2)
Level of integration in enterprises	0.004(0.0084)	-0.0602**(0.0296)
The age of the business		0.7487***(0.0802)
The size of the enterprise		0.4436***(0.0137)
Debt-to-asset ratio		-0.9619***(0.1435)
Net profit margin on total assets		-2.9820***(0.3244)
Holding ratio of the largest holder		-0.0380**(0.0155)
Proportion of independent directors		3.6920***(0.4953)
Operating profit growth rate		0.0101(0.0066)
Time fixation effect	YES	YES
Individual fixed effects	NO	NO
Sample size	424	424
Goodness of fit	0.6775	0.9986

Note: The ***, **, and * in the table indicate that the significance levels of the measurement results are 1%, 5%, and 10%, respectively, and the values in parentheses are robust standard errors.

Corporate carbon intensity (1) is the regression result with only the core explanatory variables, and it can be found that the impact of digital intelligence integration on the carbon emission intensity of chemical enterprises in Jiangsu Province is positive, but the results are not statistically significant. Corporate carbon intensity (2) is the regression result after adding a series of enterprise-level control variables, and the coefficient of the level of enterprise digital intelligence integration is significantly negative, which means that the digital intelligence integration inhibits the carbon emission intensity of chemical enterprises in Jiangsu Province. After analyzing the regression results of the control variables, except for the coefficient of operating profit growth rate, the other control variables have a significant impact on the carbon emission intensity of enterprises.

5.2 Robustness Results Analysis

To verify the impact of digital intelligence integration towards carbon emission reduction, the following robustness tests are concluded in Table 2.

Table 2. Robustness results.

Variables	Corporate carbon emission intensity (1)	Corporate carbon emission intensity (lag period) (2)	Corporate carbon emission intensity 2017 short period (3)
Level of integration in enterprises	-0.0380**(0.018)	-0.0630**(0.0323)	-0.0534**(0.0339)
The age of the business	1.2239***(0.0767)	0.8850***(0.0802)	0.9801***(0.1099)
The size of the enterprise	-0.0377*(0.0198)	0.3892***(0.0149)	0.3806***(0.0171)
Debt-to-asset ratio	0.2577***(0.0935)	0.0020(0.0048)	0.0036(0.0048)
Net profit margin on total assets	-0.8024***(0.1531)	-1.2200***(0.3450)	-1.5319***(0.3673)
Holding ratio of the largest holder	-0.0025 (0.0046)	-0.0506***(0.0120)	-0.0830*** (0.0239)
Proportion of independent directors	0.3794 (0.3136)	4.4192***(0.5444)	4.3198***(0.6209)
Operating profit growth rate	-0.0030(0.0025)	0.0007 (0.0013)	-0.00007(0.0013)
Time fixation effect	YES	YES	YES
Individual fixed effects	YES	NO	YES
Sample size	424	424	307
Goodness of fit	0.6595	0.9984	0.9984

Note: The ***, **, and * in the table indicate that the significance levels of the measurement results are 1%, 5%, and 10%, respectively, and the values in parentheses are robust standard errors.

Corporate carbon emission intensity (1) is the regression result of the control variable that controls for both individual fixed effect, time fixed effect and enterprise is added. The results show that the level of enterprise digital intelligence integration significantly inhibits the increase of enterprise carbon emission intensity at the 5% confidence level. Corporate carbon emission intensity (2) replaces the explanatory variable. Considering that the changes in carbon emission intensity of listed companies have a certain lag characteristic, in order to verify the medium- and long-term changes in the impact of enterprise digital intelligence integration on enterprise carbon emission intensity, the carbon emission intensity index with the explanatory variable is replaced by Hu Yuhao's practice [18] and regressed.

In order to explore the impact of different degrees of digital intelligence integration on corporate carbon emissions, this paper classifies the digital intelligence integration level of each city, divides them into high digital intelligence integration level and low digital intelligence integration level, and regresses the two sets of data separately. The regression results are shown in Table 3.

Table 3. Group regression results.

Variables	Corporate carbon intensity (1)	Corporate carbon intensity (2)
Level of integration in enterprises	0.0117(0.0082)	-0.0414*(0.0238)
The age of the business	0.0946***(0.0286)	0.7852***(0.1112)
The size of the enterprise	-0.0101(0.0111)	0.4538***(0.0167)
Debt-to-asset ratio	0.0041***(0.0007)	-1.3240*** (0.1528)
Net profit margin on total assets	-0.8910***(0.1231)	-2.6457***(0.4006)
Holding ratio of the largest holder	0.1105(0.1008)	-0.0408***(0.0099)
Proportion of independent directors	0.2462 (0.2101)	3.3442***(0.5024)
Operating profit growth rate	-0.0002 (0.0002)	0.0054(0.0077)
Time fixation effect	YES	YES
Individual fixed effects	NO	NO
Sample size	424	424
Goodness of fit	0.8878	0.9987

Note: The ***, **, and * in the table indicate that the significance levels of the measurement results are 1%, 5%, and 10%, respectively, and the values in parentheses are robust standard errors.

6 CONCLUSION

Based on the spatiotemporal evolution analysis of carbon emissions and the level of digital intelligence integration in prefecture-level cities in Jiangsu Province, this paper selects listed companies in the chemical industry in Jiangsu Province from 2013 to 2022 as the research object, and uses benchmark regression to explore the impact of digital intelligence integration on carbon emissions. The results show that the level of carbon emission and digital intelligence integration in Jiangsu Province shows a trend of "low in the north and high in the south" and increases year by year, and the level of digital intelligence integration has an inhibitory effect on the carbon emissions of chemical enterprises, and the characteristics of enterprises also have an impact on carbon emissions. In addition, there is a nonlinear relationship between digital intelligence integration and enterprise carbon emissions, which has an inhibitory effect on enterprises with a high level of integration, and may promote carbon emissions for enterprises with a low level of integration.

REFERENCES

1. Hanzhi L, Sha L, and Huanzheng D. Problems and countermeasures of green transformation of digital empowerment of small and medium-sized chemical enterprises.Zhejiang Chemical Industry 53.11(2022):50-54.
2. Peiqi Y. A Preliminary Study on the Digital Transformation of Chemical Enterprises (Groups) in the New Era.Chemical Management.34(2021):37-40.
3. Shaohui Z, and Bing L. Research on Carbon Emission Reduction Path of New Coal Chemical Industry under the Background of Carbon Neutrality.Finance and Economics, 09(2021):60-67.
4. Chen L. How CO 2 emissions respond to changes in government size and level of digitalization? Evidence from the BRICS countries. Environmental Science and Pollution Research, 2022, 29: 457-467.
5. Wang Q, Sun J, Pata U K, et al. Digital economy and carbon dioxide emissions: examining the role of threshold variables[J]. Geoscience Frontiers, 2024, 15(3): 101644.
6. Delanoë P, Tchuente D, Colin G. Method and evaluations of the effective gain of artificial intelligence models for reducing CO2 emissions[J]. Journal of Environmental Management, 2023, 331: 117261.
7. Ahmad T, Zhang D, Huang C, et al. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities[J]. Journal of Cleaner Production, 2021, 289: 125834.
8. Li Z, Wang J. The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China[J]. Journal of Cleaner Production, 2022, 351: 131570.
9. Lange S, Pohl J, Santarius T. Digitalization and energy consumption. Does ICT reduce energy demand?. Ecological economics, 2020, 176: 106760.
10. Goodman-Bacon A. Difference-in-differences with variation in treatment timing. Journal of Econometrics, 2021, 225(2): 254-277.
11. Fei W, Huizhi H, Huiyan L, et al. Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity.Management World,2021,37(07):130-144+10.
12. Chenyu Z, Wenchun W, Xuesong L. How Digital Transformation Affects the Total Factor Productivity of Enterprises.Finance & Trade Economics,2021,42(07):114-129.)
13. Hongtao S, Nan H. Can Carbon Emission Trading Mechanism Improve Enterprise Value?Finance & Trade Economics,2019,40(01):144-161.)
14. Yutang S, Xiaodan W. Can the Establishment of Big Data Comprehensive Pilot Zone Drive Enterprise Digital Transformation?– – An Empirical Study Based on Quasi-Natural Experiments.Science of Science,1-18[2024-02-23].2053.20230615.008.
15. Hao Z. Do Tax Incentives Promote the Digital Transformation of Enterprises?– – Based on Empirical Evidence of Forward-looking Effective Tax Rates.Journal of Tianjin University of Finance and Economics,2022,42(10):38-55.)
16. Zeyu Z. Bargaining Power, Commercial Credit and Firm Performance: An Analysis Based on the Perspective of Financing Constraints.Journal of Shanxi University of Finance and Economics,2023,45(03):98-111.)
17. Xuexin L, Xiaoxu K, Kai. W Party Organization Governance and Board Dissent in State-owned Enterprises: Evidence Based on the Voting of Board Resolutions of Listed Companies.Management World,2020,36(05):116-133+13.

18. Yuhao H, Chaoxian G. Research on the Impact of Digitalization on Carbon Emission Intensity of Manufacturing Enterprises: Theoretical Modeling and Mechanism Testing.Journal of Beijing University of Technology(Social Sciences),2023,23(05):153-168.)