Analysis of the Impact Measurement on RE Development in the Context of Artificial Intelligence

Xiang Sui
College of Finance, Harbin University of Commerce, Harbin, Heilongjiang 150000, China

Correspondence should be addressed to Xiang Sui; suix@s.hrbcu.edu.cn

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The research and application of artificial intelligence (AI) have changed the way people live and produce. This paper discusses the factors affecting the development of RE in the context of artificial intelligence, analyzes the industrial status of 31 provincial administrative regions in China from the three dimensions of industrial influence, industrial relevance, and industrial efficiency, and uses gray correlation analysis to evaluate the system and measure.

1. Introduction

AI products based on various machine learning algorithms have been improving their ability to solve practical problems. In commercial applications, AI technology uses computer learning algorithms to derive a set of intelligent decision rules for target machines and control systems from existing data so that AI products can simulate the thinking process of the human brain and replace human beings for automated operations. The commonly used neural network model is shown in.

\[ T = f(WA'b). \] (1)

Therefore, some scholars regard AI technology as a new factor of production, which will change the traditional economic growth model under its wide application. On the one hand, AI has a certain substitution effect on labor and capital factors; on the other hand, AI will also promote product and service innovation. This has an important driving effect on RE development. Take the current application of AI technology in the field of auto self-driving as an example. AI technology will change the economic growth model of the whole auto industry, as shown in Figure 1.

At present, the development of AI industry plays an irreplaceable and important role in the industrial transformation and upgrading of China’s regional economy. Like the previous technological revolution, the impact of AI on the economic development of the region focuses on promoting the improvement of labor productivity in the region. Some scientists have conducted research in 17 countries and regions, including the USA, the UK, and France. In view of the current trend, the impact of AI on the future economic development of the region will be more prominent (Table 1). Table 2 shows the changes in the scale and growth rate of China’s AI market.

Artificial intelligence (AI), by its connotation, is a set of computer systems with intelligent thinking required or a set of intelligent systems that solve complex problems requiring the adoption of rational decisions to achieve goals. AI is an important source of modern economic growth and an important engine for the sustainable development of China’s regional economy. The research and application of AI technology has changed people’s ways of life and production. In 2017, China incorporated the development of AI into the government work report for the first time, raised it to the national strategic level, and regarded it as part of economic development. The introduction of AI technology, through the formation of new growth points, creates industries with regional advantages, injects new impetus into the development of the regional economy, and promotes the development of the regional economy. Therefore, this paper discusses the influencing factors of RE development under...
the background of artificial intelligence and evaluates the factors affecting RE development and their significance by establishing a deep learning model.

2. Related Work

From the multiyear trend, the development of AI in China has experienced three stages: the embryonic period, the slow development period, and the rapid development period [1, 2] (Figure 2).

From the development of AI in different regions, AI in the eastern region started earlier, thus the current situation is that the eastern region is far ahead, the central region is developing slowly, and the western and northeastern regions are lagging behind on the whole in China [3–5]. First, from the development trend, the AI patent applications and the rapid development of AI in the eastern region since 2014 are consistent with the trend of AI development in China as a whole, while the development in other regions has been relatively slow [6, 7]; second, from the number, the number of AI patent applications in the eastern region in 2018 was 24,415, accounting for 70.12% of the national ratio reaching 70.12%, while the previous 2014–2017 eastern region also accounted for more than 65% of the country 7–9 (Figure 3).

The study by [10, 11] shows that the increase of income inequality between different groups may also lead to the increase of inequality between regions. High skilled professionals are concentrated in cities that create new jobs, which is often different from unemployed cities, leading to the increase of inequality between cities. [12, 13] suggests that the substitution of unskilled labor in developing countries by AI reduces the relative wage levels in these countries, which in turn affects the international distribution of output. The development of industrial automation triggered by AI will replace labor at a cheaper cost, and developing countries will gradually lose their cost advantage.

| Country         | Base growth rate (%) | AI stable contribution status (%) |
|-----------------|----------------------|-----------------------------------|
| United States   | 2.6                  | 4.6                               |
| United Kingdom  | 2.5                  | 3.9                               |
| Germany         | 1.4                  | 3.0                               |
| France          | 1.7                  | 2.9                               |
| Japan           | 0.8                  | 2.7                               |
| Sweden          | 1.7                  | 3.2                               |
| Italy           | 1.0                  | 2.8                               |

Table 2: China’s AI market size and growth rate changes in the past three years.

| Year | AI market size (billion yuan) | Growth rate (%) |
|------|------------------------------|-----------------|
| 2016 | 96.61                        | 37.9            |
| 2017 | 130.13                       | 40.7            |
| 2018 | 200.97                       | 54.4            |

Figure 1: AI drives economic growth model innovation in the automotive industry.

Figure 2: Patent application of AI in China from 2000 to 2018.

Figure 3: AI development in different regions.
Furthermore, industrial automation will mean that manufacturing will create fewer jobs where wages are relatively high [14, 15, 16]. Through the empirical analysis of interprovincial panel data from 2000–2016 in China, it is found that high-tech industrial agglomeration in China makes the income gap between regions widen by affecting the employment structure, industrial structure, and income structure of regions, and from different regions, in the national and eastern regions, high-tech industrial agglomeration can effectively suppress the regional income gap, while the opposite is true in the central and western regions.

Therefore, the relevant research results at home and abroad show that although domestic and foreign scholars have studied the impact of AI on RE growth, the impact degree of AI on RE growth and the progress and measures of its impact on RE growth are the measures taken to realize the impact of AI industry on RE growth. The relevant empirical analysis is even less. Therefore, this paper quantitatively analyzes the impact of AI on China’s RE development and establishes corresponding models for practical experiments [17, 18].

3. Methods

The application of AI in RE development requires full consideration of regional characteristics, climatic features, and types of typical industries. In the research process, the article mainly analyzes the industrial situation of 31 provincial administrative regions in China in three dimensions: industrial influence, industrial relevance, and industrial efficiency [19–22].

Industrial agglomeration reflects the status and role of an industry in the regional economy and explains the degree of specialization of an industrial sector in a specific region. A commonly used indicator to measure the influence of industry is location entropy. The calculation formula is

\[ LQ_{ij} = \left( \frac{q_{ij}}{q_i} \right) \]  

Gray correlation analysis is the measurement of the same degree of change trend between systems and systems and factors and factors in the process of development and change. The value added of industries in 31 provincial-level administrative regions of China is set as the reference series, which is set as \( X_0 \) in the process of model construction, as shown in

\[ X_0 = \left[ X_0(k) | k = 1, 2, \ldots, n \right] = \left[ X_0(1), X_0(2), \ldots, X_0(n) \right]. \]  

The values are set as comparative series, respectively, \( X_1, X_2, \ldots, X_6 \), as shown in

\[ X_i = \left[ X_i(k) | k = 1, 2, \ldots, n \right] = \left[ X_i(1), X_i(2), \ldots, X_i(n) \right], i = 1, 2, \ldots, m. \]

After dimensionless processing of the reference and comparison series, the correlation coefficient is calculated, as shown in

\[ \zeta_i(k) = \frac{\text{min}_k \min X_0(k) - X_i(k) + \text{max}_k \max X_0(k) - X_i(k)}{X_0(k) - X_i(k)} \]

\[ r_i = \frac{1}{n} \sum_{k=1}^{n} \zeta_i(k). \]

Industrial technical efficiency is used to measure the difference. DEA (Data Envelopment Analysis) is a commonly adopted method, and its formula is as follows.

\[ \min \theta \]

\[ s.t. \sum_{j=1}^{n} \lambda_j x_j + s^+ = \theta x_0, \]

\[ \sum_{j=1}^{n} \lambda_j y_j - s^- = \theta y_0, \]

\[ \lambda_j \geq 0, j = 1, 2, \ldots, n. \]

\( \theta \) unconstrained, \( s^- \leq 0, s^+ \geq 0. \)

In order to overcome the shortcomings of using the nonindustrial value and Moore’s index to measure industrial transformation and upgrading, this paper, on the basis of the practice of Gan Chunhui, considers two dimensions of industrial structure advanced and rationalization and upgrading, with the weights of both taken as 0.5 to measure the speed as follows.

\[ TL = \sum_{i=1}^{n} \frac{Y_i}{L_i} - 1 = \sum_{i=1}^{n} \frac{Y_i}{L_i} - 1, \]

\[ TS = \frac{Y_3}{Y_2} \]

where \( Y, L \) denote the output value and employment number, respectively. The larger the structural deviation is, the less reasonable the industrial structure is. The larger the ratio of high-end technology to middle and high-end technology industries, the more high-end the industrial structure.

The rise of industrial transformation is affected by a series of factors. Existing studies show that the level of economic development, the degree of opening to the outside world, foreign direct investment, and government intervention have an impact on the modernization of industrial structure. Taking these indicators as benchmark variables can be called

\[ T_{ij} = c_j + \beta_1 \ln AI_{ij} + \beta_2 \ln pgd_{ij} + \beta_3 \ln \rho_{ij} + \beta_4 \ln \mu_{ij}. \]

When analyzing the impact of artificial intelligence on RE development, this paper selects the data of 31 provinces, cities, and autonomous regions in China from 2009 to 2018 as the research object, shown in Table 3.
The results show that in recent ten years, the rationality of China’s industrial structure is relatively poor, the market production has not reached the equilibrium state, and the rationality level of industrial structure varies greatly among provinces, cities, and autonomous regions. The average value of the ratio of the output value of the high-end technology industry to the output value of medium and the high-end technology industry is 1.371, and the standard deviation is 0.659, which is less than the average and has no abnormal value. China’s advanced industrial structure in the past decade is relatively low, and there are obvious differences in the advanced level of provinces, cities, and autonomous regions [23–25].

### 4. Experiments

From the results of AI and RE development shown in Figure 4, the higher the level of educational AI, the higher the level of economic development. On the contrary, the lower the level of AI, the lower the level of economic development.

At the same time, a similar relationship exists between AI and regional development gaps, and this is based on the data calculated above for AI and regional absolute gaps (Figure 5).

In terms of the difference in the absolute value, the gap between the eastern region and other regions in China, which got rich first, is generally widening (see Figure 6). At the same time, compared with other underdeveloped regions, the original advantages of the northeast relative to the central and western regions have gradually disappeared, and the gap between the northeast and the central and western regions has gradually narrowed.

In this paper, we use the two-step systematic GMM method to construct a dynamic panel data model to analyze 31 provinces, cities, and autonomous regions in China during the 10 years from 2009 to 2018, as shown in Table 4.

The results show that the first-order coefficient explaining the difference between the two regression equations is significant at the level of 1%, and the coefficient of the main explanatory variable is positive, which verifies the effectiveness of the dynamic panel model and the positive correlation between the development of artificial intelligence and its repetition. If the level of artificial intelligence is increased by 1%, its mastery rate will be increased by 0.035%, indicating that the impact of artificial intelligence on re-development is relatively small.
Absolute gap

Figure 6: Evolution of the absolute gap between eastern regions and other regions.

Table 4: Regression results of the impact of RE development on AI.

| Variable   | (1)T        | (2)T        |
|------------|-------------|-------------|
| LT         | 0.739***    | 0.755***    |
|            | (114.252)   | (129.387)   |
| InAI       | 0.028***    | 0.039***    |
|            | (6.267)     | (3.859)     |
| Inpg dp    | −0.069***   | −2.872**    |
| open       | 0.182***    | (12.858)    |
| f di       | 0.273*      | (−1.782)    |
| gov        | 0.223***    | (3.798)     |
| cons       | 0.501***    | (44.023)    |
|            | (14.022)    |             |
| ar1 (p – value) | 0.029 | 0.049 |
| ar2 (p – value) | 0.197 | 0.198 |
| Hansen value | 0.292 | 0.279 |

Note. ar1, ar2 represent the first-order and second-order regression residual autocorrelation tests, respectively.

5. Conclusion

At the beginning of reform and opening up, in order to liberate and develop the productive forces, China implemented the strategy of taking the lead in the development of the eastern region, and before and after entering the 21st century, the country introduced a series of strategies for the development of specific regions in an attempt to achieve coordinated regional development. However, the rapid development of AI technology will bring new growth impetus to RE development, and we should also pay attention to the social problems that may be caused by AI replacing traditional occupations. By doing a good top-level design, accelerating technical research, and improving the quality level and innovation creativity of all people, we can provide guarantee for the stable development of AI industry and give full play to its economic driving effect [26, 27].

Data Availability

The dataset used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

[1] A. Zuiderwijk, Y. C. Chen, and F. Salem, “Implications of the use of artificial intelligence in public governance: a systematic literature review and a research agenda,” Government Information Quarterly, vol. 38, no. 3, Article ID 101577, 2021.
[2] S. Bag, J. H. C. Pretorious, S. Gupta, and Y. K. Dwivedi, “Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities,” Technological Forecasting and Social Change, vol. 163, Article ID 120420, 2021.
[3] T. Yigitcanlar, N. Kankanamge, M. Regona et al., “Altechnologies and related urban planning and development concepts: how are they perceived and utilized in Australia?” Journal of Open Innovation: Technology, Market, and Complexity, vol. 6, no. 4, p. 187, 2020.
[4] M. Obschonka and D. B. Audretsch, “Artificial intelligence and big data in entrepreneurship: a new era has begun,” Small Business Economics, vol. 55, no. 3, pp. 529–539, 2020.
[5] R. Vinuesa, H. Azizpour, I. Leite et al., “The role of Alin achieving the sustainable development goals,” Nature Communications, vol. 11, no. 1, pp. 1–10, 2020.
[6] X. Xiang, Q. Li, S. Khan, and O. I. Khalaf, “Urban water resource management for sustainable environment planning using artificial intelligence techniques,” Environmental Impact Assessment Review, vol. 86, Article ID 106515, 2021.
[7] J. Wang, W. Wang, Q. Ran et al., “Analysis of the mechanism of the impact of internet development on green economic growth: evidence from 269 prefecture cities in China,” Environmental Science and Pollution Research, vol. 29, no. 7, pp. 9990–10004, 2022.
[8] A. Clark, N. A. Zhuravleva, A. Siekelova, and K. F. Michalikova, “Industrial artificial intelligence, business process optimization, and big data-driven decision-making processes in cyber-physical system-based smart factories,” Journal of Self-Governance and Management Economics, vol. 8, no. 2, pp. 28–34, 2020.
[9] P. R. Jena, R. Majhi, R. Kalli, S. Managi, and B. Majhi, “Impact of COVID-19 on GDP of major economies: application of the artificial neural network forecast,” Economic Analysis and Policy, vol. 69, pp. 324–339, 2021.
[10] A. Jaiswal, C. J. Arun, and A. Varma, “Rebooting employees: upskilling for artificial intelligence in multinational corporations,” International Journal of Human Resource Management, vol. 33, no. 6, pp. 1179–1208, 2022.
[11] R. Radu, “Steering the governance of artificial intelligence: national strategies in perspective,” Policy and society, vol. 40, no. 2, pp. 178–193, 2021.
[12] N. Liu and F. Fan, “Threshold effect of international technology spillovers on China’s regional economic growth,” Technology Analysis & Strategic Management, vol. 32, no. 8, pp. 923–935, 2020.
[13] R. Dubey, D. J. Bryde, C. Blome, D. Roubaud, and M. Giannakis, “Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context,” Industrial Marketing Management, vol. 96, pp. 135–146, 2021.
[14] H. Chen, L. Li, and Y. Chen, “Explore success factors that impact artificial intelligence adoption on telecom industry in China,” *Journal of Management Analytics*, vol. 8, no. 1, pp. 36–68, 2021.

[15] A. N. Mk and M. A. V, “Role of energy use in the prediction of CO2 emissions and economic growth in India: evidence from artificial neural networks (ANN),” *Environmental Science and Pollution Research International*, vol. 27, no. 19, pp. 23631–23642, 2020.

[16] A. Dikshit, B. Pradhan, and A. M. Alamri, "Pathways and challenges of the application of artificial intelligence to geo-hazards modelling," *Gondwana Research*, vol. 100, pp. 290–301, 2021.

[17] J. Du, C. Jiang, Z. Han, H. Zhang, S. Mumtaz, and Y. Ren, "Contract mechanism and performance analysis for data transaction in mobile social networks," *IEEE Transactions on Network Science and Engineering*, vol. 6, no. 2, pp. 103–115, 2019.

[18] M. Chen, Q. Liu, S. Huang, and C. Dang, “COVID-19, cities and urban informal workers: India in comparative perspective,” *Indian Journal of Labour Economics: The Quarterly Journal of the Indian Society of Labour Economics*, vol. 63, pp. 41–46, 2020.

[19] O. I. Khalaf and G. M. Abdulsahib, "Design and performance analysis of wireless IPv6 for data exchange," *Journal of Information Science and Engineering*, vol. 37, pp. 1335–1340, 2021.

[20] X. Xie, W. Zhang, H. Wang et al., “Dynamic adaptive residual network for liver ct image segmentation,” *Computers & Electrical Engineering*, vol. 91, Article ID 107024, 2021.

[21] C. Magazzino, D. Porrini, G. Fusco, and N. Schneider, “Investigating the link among ICT, electricity consumption, air pollution, and economic growth in EU countries,” *Energy Sources, Part B: Economics, Planning and Policy*, vol. 16, no. 11-12, pp. 976–998, 2021.

[22] P. An, Z. Wang, and C. Zhang, “Ensemble unsupervised autoencoders and Gaussian mixture model for cyberattack detection,” *Information Processing & Management*, vol. 59, no. 2, Article ID 102844, 2022.

[23] R. Ali, A. Ali, F. Iqbal, A. Masood Khatak, and S. Aleem, "A systematic review of artificial intelligence and machine learning techniques for cyber security," in *Proceedings of the International Conference on Big Data and Security*, pp. 584–593, Springer, Singapore, August 2020.

[24] A. Ali, R. Ali, A. Masood Khatak, and M. Saqain Aslam, "Large scale image dataset construction using distributed crawling with hadoop YARN," in *Proceedings of the 2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)*, pp. 394–399, IEEE, Toyama, Japan, December 2018.

[25] S. C. Robinson, “Trust, transparency, and openness: how inclusion of cultural values shapes Nordic national public policy strategies for artificial intelligence (AI),” *Technology in Society*, vol. 63, Article ID 101421, 2020.

[26] B. C. Stahl, A. Andreou, P. Brey et al., “Artificial intelligence for human flourishing – beyond principles for machine learning,” *Journal of Business Research*, vol. 124, pp. 374–388, 2021.

[27] K. Chandra, A. S. Marcano, S. Mumtaz, R. V. Prasad, and H. L. Christiansen, “Unveiling capacity gains in ultradense networks: using mm-wave NOMA,” *IEEE Vehicular Technology Magazine*, vol. 13, no. 2, pp. 75–83, 2018.