# The Technological Innovation Capability of The New Energy Vehicle Industry

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**Abstract**—Several subsidy programs are being implemented by nations all over the world in an effort to support the growth of the new energy vehicle industry and increase its capacity for innovation. In order to assess the sector's capacity for technical innovation, the innovation capability level of China's new energy vehicle industry from 2012 to 2017 was computed using a network DEA model. Technology development and innovation transformation were the two stages into which the sector was split. The findings demonstrate that a mismatch between the effectiveness of the technology development stage and the effectiveness of the innovation transformation stage is the cause of innovative technology's inability to support business operations. This mismatch also contributes to the new energy vehicle industry in China's overall low level of innovation capability. Based on the study's findings, significant policy suggestions are made in order to progress the new energy vehicle industry's technological capabilities within the constraints of China's present new energy policy.

## 1. Introduction

The COVID-19 outbreak has made it necessary to reevaluate the energy transition (Panarello & Gatto, 2023). The unexpected pandemic breakout has had a significant negative impact on society and the economy, and it has presented a significant challenge to the whole automobile sector (B. Sun & Ju, 2022). The automobile sector is a crucial pillar industry for the nation and a leading indicator of market economy growth. After the pandemic, China's macroeconomic trend is heavily influenced by the automotive sector's development (Y. Hu et al., 2022). As a result, the expansion of China's automobile sector has entered a phase of adjustment due to the demands of industrial development and energy transformation.

The global automotive industry is experiencing an era of upgrading from internal combustion engines to new energy sources led by pure electric and hybrid drives (Z. Hu & Yuan, 2018; Zeng et al., 2023). More and more countries in the world realize that a single energy structure is not conducive to national strategic security, especially for some countries that lack oil resources (B. Sun & Ju, 2022; Trost et al., 2017). At the same time, some emerging developing countries believe that there is still a large gap in internal combustion engine technology for their national automobile manufacturing enterprises to surpass the established automobile enterprises in developed countries, so these developing countries also regard the new energy automobile revolution as a historical opportunity to develop their automobile manufacturing industries (H. Sun et al., 2018; Y. Wang et al., 2023).

As for developed countries, the pressure brought by global warming and industrial progress has also prompted them to actively develop their own new energy vehicle industry (Stokes & Breetz, 2018). In short, many countries hope to gradually replace traditional fuel vehicles with new energy vehicles as the most important means of transportation and develop their automobile manufacturing industries. Technological innovation activities have a certain degree of revenue uncertainty and positive externalities, and under the spontaneous regulation of the market, enterprises are not motivated to innovate, and it is difficult to achieve the optimal allocation of innovation resources, which usually requires government intervention, guidance and support through subsidies and other means (Arent et al., 2022; Jiang & Liu, 2022). Therefore, some countries have introduced policies to support the development of the new energy vehicle industry.

The importance of technological innovation in the sustainable development of the new energy vehicle industry has been fully demonstrated by the fact that many countries have given priority to "improving technological innovation capacity" when formulating their policies (Cao et al., 2022). The manufacturing industry is an important part of the national economy

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and its development directly determines the development of the national economy. The epidemic has affected the development of many manufacturing industries since the outbreak. In addition to the long and extensive industrial chain of the manufacturing industry, the ongoing epidemic not only affects the development of the manufacturing industry itself, but also continues to affect the symbiotic ecology of employment, education, and even national security (Xie et al., 2022). It is worth discussing how to assess the innovation capacity of the new energy vehicle industry and promote its improvement.

In this paper, I hope to construct the innovation capability evaluation indexes of enterprises in the new energy vehicle industry, so as to reasonably measure the innovation capability.

## 2. Research Significance

When nations throughout the world realized the necessity of expanding the new energy vehicle industry, they made innovation capability a focal point of their industrial development and implemented key industrial subsidy programs to help the new energy vehicle industry grow. Previous studies, on the other hand, have typically focused solely on the impact of subsidy policies on innovation inputs, innovation outputs, and enterprise performance in enterprises' innovation activities, and the inconsistency of research backgrounds has often resulted in conflicting conclusions. Firm innovation capabilities must be considered in a systematic manner; otherwise, the research perspective will be limited. This study designs a two-stage network DEA model to measure the innovation capability of organizations, and decomposes the innovation capability into innovation development and innovation transformation stage, based on the innovation value chain perspective. I develop the innovation capability measurement indexes in an objective and systematic manner using the innovation value chain theory and DEA model, which to some extent corrects the subjectivity in previous similar studies and analyzes what is in the "black box" of innovation capability.

## 3. Theoretical framework

Hansen and Birkinshaw (2007) merged value chain theory and technological innovation theory to establish the innovation value chain theory, which describes innovation as a multistage process that involves idea creation, concept development, and dissemination via the innovation value chain. In this theoretical framework, the process of realizing the value of technological innovation in a company consists of a complex series of activities from research to development and then from development to transformation of economic results.

Innovation capability belongs to the intangible assets of an organization and at the same time is the ability of an organization to continue developing that asset in a continuous innovative manner. Past studies have mainly used traditional DEA methods such as SBM-DEA and DEA-MALMQUIST to measure the innovation capability of firms (Guan et al., 2006; W. Wang & Zhang, 2018). In general, it still decomposes innovation capability into innovation input, innovation output and firm performance in isolation, and fails to take a comprehensive perspective on firm innovation capability. At the same time, some scholars have assessed firms' innovation capability by means of questionnaires (Le & Lei, 2019; Saunila & Ukko, 2014). Although innovation capability can be measured by combining innovation inputs, innovation outputs, and firm performance, the questionnaire method can hardly overcome the problem of subjectivity. Therefore, an integrated perspective combined with objective measurement methods is needed to measure the innovation capability of firms.

In the innovation value chain perspective, innovation capability is an integrated indicator of innovation inputs, innovation outputs, and firm performance. Therefore, in order to assess innovation capability more comprehensively, the innovation value chain perspective should be introduced, and this study combines the study of DU et al. (2019) to structure the innovation capability of the new energy vehicle industry into a technology development stage and an innovation transformation stage (Du et al., 2019). The technology development stage refers to the process from the initial technology development input of enterprises through investing research funds and R&D personnel to obtaining the intermediate innovation output. Innovation transformation stage refers to the process of applying technology development results to produce marketable products, commercializing intermediate innovation results and forming enterprise economic benefits, which is the continuation of technology development stage and the key link between technology innovation results and market, and its core task is to realize the market value of intermediate innovation results output. As the intermediate product of the whole technological innovation activity, the intermediate innovation output is not only the initial result of the enterprise's initial R&D investment, but also the premise of applying to commercial production and forming economic benefits at a later stage, connecting and promoting the mutual promotion and coordinated development of each sub-stage. It is easy to see that the process of enterprise technology innovation value realization has obvious two-stage chain network characteristics. The specific process is shown in Figure 1.

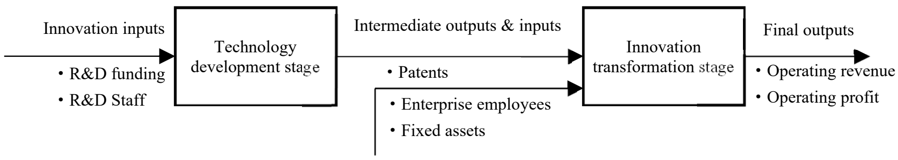


Fig. 1. Deconstruction of Innovation Capability of New Energy Vehicle Industry

## 4. Research Methodology

Traditional econometric techniques like regression analysis and simple ratio analysis are not as effective analytical approaches for assessing efficiency assessment activities as the Data Envelopment Approach (DEA). DEA is a mathematical methodology that transforms inputs into outputs using principles from linear programming in order to compare the effectiveness of similar businesses or goods. Each decision making unit (DMU) in DEA is allowed to select any set of inputs and outputs in order to optimize its comparative efficacy. The proportion of total weighted outputs to total weighted inputs is known as the relative efficiency or efficiency score (Zhu, 2009). DEA is a common method for estimating the efficiency of a system in a nonparametric framework, and since its first application in 1978, it has been popularized and widely accepted in several research areas (Tone & Tsutsui, 2009). However, the traditional DEA model can only assess the efficiency level of a process by putting the input indicators into a "black box" and considering the efficiency of the output indicators without considering what happens in the "black box", which was once an advantage for DEA models. This was once an advantage for DEA models, but as the problems considered by academics became more complex, the need to decompose the contents of the "black box" led to the development of network DEA models (Crepon et al., 1998). The innovation capability of the new energy vehicle industry covers the whole process from the technology development stage to the innovation transformation stage. Therefore, a two-stage network DEA model can help to open the "black box" of innovation capability evaluation. Under the network DEA model, referring to the study of DU et al. (2019) on innovation capability, the specific explanatory variables are shown in Table 1.

Table 1 Two-Stage Indicators for Deconstructing Innovation Capability

| Stage | Level 1 Indicators | Level 2 Indicators |
|---|---|---|
| Technology development stage | Innovation inputs | R&D funding (10000 yuan) |
| | | R&D staff (persons) |
| | R&D intermediate outputs | Patent applications (items) |
| | | Increase in value of intangible assets (10000 yuan) |
| Innovation transformation stage | Commercial inputs | Full-time equivalent of practitioners (persons/year) |
| | | Net value of fixed assets (10000 yuan) |
| | Commercial outputs | Revenue from main business (10000 yuan) |
| | | Operating profit (10000 yuan) |

The non-radial SBM two-stage network DEA model proposed by Tone is used to ensure the efficiency of the evaluation model to some extent because the network DEA model may cause the network DEA model to overestimate the efficiency level of the evaluation object if there is over-input or under-output in the network DEA model (i.e., there is non-zero slack). This is shown as follows.

For a set of n decision making units $DMU_s(j = 1, \dots, n)$ with $K$ nodes$(k = 1, \dots, K)$. Let $m_k$ and $r_k$ be the input and output amounts for node $k$ respectively. $(k, h)$ denotes the connection relation between nodes $k$ and h, and $L$ is the connection set. The observed data are $\{\mathrm{x}_j^k \in R_+^{m_\mathrm{k}}\}(j = 1, \dots, n; k = 1, \dots, K)$ ( $DMU_j$ input quantity at node), $\{\mathbf{y}_j^k \in R_+^{r_k}\}(j = 1, \dots, n; k = 1, \dots, K)$ ( $DMU_j$ output quantity at node $k$ ), and $\{\mathbf{z}_j^{(k,h)} \in R_+^{t_{(k,h)}}\}(j = 1, \dots, n; (k, h) \in L$. where $t_{(k,h)}$ is the connection relation $(k, h)$ variable number. In this paper, I adopt the assumption of variable payoffs of scale and define the set of production possibilities $\{(\mathbf{x}^k, \mathbf{y}^k, \mathbf{z}^{(k,h)})\}$ as:

$$\mathbf{x}^k \geq \sum_{j=1}^{n} \mathbf{x}_j^k \lambda_j^k \ (k = 1, \dots, K), \mathbf{y}^k \leq \sum_{j=1}^{n} \mathbf{y}_j^k \lambda_j^k \ (k = 1, \dots, K) \tag{1}$$

$$\mathbf{z}^{(k,h)} = \sum_{j=1}^{n} \mathbf{z}_j^{(k,h)} \lambda_j^k \ (\forall (k,h)) (\text{as the output of node } k) \tag{2}$$

$$\mathbf{z}^{(k,h)} = \sum_{j=1}^{n} \mathbf{z}_j^{(k,h)} \lambda_j^h \ (\forall (k,h)) (\text{as the input of node } h) \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j^k = 1 (\forall k), \lambda_j^k \geq 0 (\forall j, k) \tag{4}$$

$\lambda^k \in R_+^n$ denotes the weight corresponding to node $k(k=1,\ldots,K)$ and $\mathrm{DMU}_o(o=1,\ldots,n)$ can be expressed by:

$$\mathbf{x}_o^k = \mathbf{X}^k \lambda^k + \mathbf{s}^{k-} \left(k=1,\ldots,K\right), \mathbf{y}_0^k = \mathbf{Y}^k \lambda^k - \mathbf{s}^{k+} \left(k=1,\ldots,K\right) \tag{5}$$

$$\mathbf{e}\lambda^k = 1\left(k=1,\ldots,K\right), \lambda^k \geq 0, \mathbf{s}^{k-} \geq 0, \mathbf{s}^{k+} \geq 0, \left(\forall k\right) \tag{6}$$

$$\mathbf{X}^k = \left(\mathbf{x}_1^k,\ldots,\mathbf{x}_n^k\right) \in R^{m_k \times n}, \mathbf{Y}^k = \left(\mathbf{y}_1^k,\ldots,\mathbf{y}_n^k\right) \in R^{r_k \times n} \tag{7}$$

where $\mathbf{s}^{k-}(\mathbf{s}^{k+})$ is the input (output) slack variable. For the constraints of the connecting variables, LF is used to connect the nodes, indicating that the connecting variables are free to decide to maintain the continuity of the input and output quantities at the same time, as expressed by the following equation:

$$\mathbf{Z}^{(k,h)} \lambda^h = \mathbf{Z}^{(k,h)} \lambda^k, \left(\forall \left(k,h\right)\right) \tag{8}$$

$$\mathbf{Z}^{(k,h)} = \left(\mathbf{z}_1^{(k,h)},\ldots,\mathbf{z}_n^{(k,h)}\right) \in R^{t_{(k,h)} \times n} \tag{9}$$

Considering the possible slackness of the input and output quantities, for more accurate assessment, the undirected network model is used in this paper, as shown in the following equation.

$$\rho_o^* = \min_{\lambda^k, sk-s^{k+}} \frac{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^k}{x_{i0}^k}\right)\right]}{\sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_t^{k+}}{y_{t0}^k}\right)\right]} \tag{10}$$

Here $\sum_{k=1}^{K} w^k = 1, w^k \geqslant 0(\forall k)$, where $w^k$ is the relative weight of node k to indicate the relative importance of that node. Meanwhile, $\rho_o^*$ is defined as the undirected efficiency of the decision unit $DMU_0$. If $\rho_o^* = 1$,it indicates the overall efficiency of the decision unit $DMU_o$, and the representation of each node is

$$\rho_k = \frac{1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{ii}^k}\right)}{1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_r^{k+*}}{y_{r0}^k}\right)} \left(k=1,\ldots,K\right) \tag{11}$$

Here, $\mathbf{s}^{k-*}$ and $\mathbf{s}^{k+*}$ are the slack variables for the optimal input and optimal output, respectively.

The initial sample is centered on companies that were listed on the Shanghai and Shenzhen stock exchanges prior to 2012 and whose primary industry is new energy vehicles. After eliminating ST and *ST stocks, as well as businesses with significant missing data, the balanced panel data of 39 publicly traded companies, including BYD and Shanghai Auto, is eventually chosen. The period span of the data is picked as 2012-2017 based on the comprehensiveness of the study and the availability of data. The data in this study comes from the same CHOICE database, CSMAR database, State Intellectual Property Office, and each company's annual reports, with the missing individual data estimated using the interpolation approach.

## 5. Finding and Conclusion

The data were generated and reported in Table 2 using DeaSolver 13.0 software and the network DEA model to estimate the comprehensive efficiency of 39 new energy vehicle industry enterprises from 2012 to 2017.

Table 2 Innovation Capacity of China's New Energy Vehicle Industry, 2012-2017

| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | Mean |
|---|---|---|---|---|---|---|---|
| Innovation capability | 0.2510 | 0.1952 | 0.2085 | 0.2044 | 0.2123 | 0.2419 | 0.2189 |
| Technology development stage | 0.2637 | 0.2564 | 0.2586 | 0.2304 | 0.1975 | 0.1870 | 0.2322 |
| Innovation transformation stage | 0.2969 | 0.2119 | 0.2257 | 0.2404 | 0.2567 | 0.2948 | 0.2544 |

Table 2 shows the three efficiency values (average efficiency from 2012 to 2017) of 39 listed new energy industry enterprises, which reflect the overall state of innovation capability as well as efficiency by stage of listed new energy vehicle industry enterprises in China over the last six years. The average value of China's enterprise innovation capability from 2012 to 2017 is 0.2246, which is a relatively low level of innovation capability overall, and the level of innovation capability varies somewhat from year to year. Although the change in innovation capability from 2015 to 2017 has increased, it has not yet achieved the level of innovation capability seen in 2012, showing that the Chinese new energy vehicle industry as a whole is still developing. There is definitely opportunity for improvement in terms of innovative capability.

The total efficiency of enterprises in China's listed new energy industry's innovation transformation stage exceeded the technological development stage from 2012 to 2017. The efficiency of the technology development stage is between 0.1870 and 2637, while the efficiency of the innovation transformation stage is between 0.2119 and 2969. Over the past six years, the efficiency of the innovation transformation stage has been about 12.1% higher than the efficiency of the technology development stage. In the past 6 years, it is easy to find that the listed Chinese enterprises in the new energy industry have emphasized the potential commercial value of enterprise technology innovation and insisted on direct market-oriented innovation transformation activities, and overall innovation transformation efficiency has remained stable. At the same time, there is a significant mismatch between the technology development stage and the innovation transformation stage of Chinese listed new energy industry enterprises, as well as a gap in efficiency between the two stages. Simultaneously, the efficiency level of the technology development stage has been steadily d ecreasing from 2012 to 2017, indicating that enterprise technology development activities have shifted away from solving actual technical problems and meeting market demand, lowering overall innovation capability.

## 6. Recommendation

According to this study, China's new energy vehicle sector has a limited overall capacity for innovation, and earlier subsidy programs did not help to improve this situation; they rather made it worse. Government subsidies, when compared to market-based income distribution, are a form of income redistribution that raises transaction costs in a variety of ways, including policy design, policy implementation, policy exit, and rent-seeking costs. Because of these transaction expenses, government subsidies are generally ineffective in promoting the industry's innovation capability.

To improve their innovation capability, it is necessary to curb enterprises' motivation to cheat on subsidies from the source, stimulate their independent innovation, guide them to increase their awareness of R&D investment, focus on the output of market-oriented technological innovation results, and improve the technology conversion rate. This is the key to effectively converting innovation inputs into innovation outputs.

## References

1. Arent, D. J., Green, P., Abdullah, Z., Barnes, T., Bauer, S., Bernstein, A., Berry, D., Berry, J., Burrell, T., Carpenter, B., Cochran, J., Cortright, R., Curry-Nkansah, M., Denholm, P., Gevorian, V., Himmel, M., Livingood, B., Keyser, M., King, J., … Turchi, C. (2022). Challenges and opportunities in decarbonizing the U.S. energy system. *Renewable and Sustainable Energy Reviews*, *169*, 112939.
2. Cao, L., Deng, F., Zhuo, C., Jiang, Y., Li, Z., & Xu, H. (2022). Spatial distribution patterns and influencing factors of China’s new energy vehicle industry. *Journal of Cleaner Production*, *379*, 134641.
3. Crepon, B., Duguet, E., & Mairessec, J. (1998). Research, Innovation And Productivi[Ty: An Econometric Analysis At The Firm Level. *Economics of Innovation and New Technology*, *7*(2), 115–158.
4. Du, J., Liu, Y., & Diao, W. (2019). Assessing Regional Differences in Green Innovation Efficiency of Industrial Enterprises in China. *International Journal of Environmental Research and Public Health*, *16*(6), 940.
5. Guan, J. C., Yam, R. C. M., Mok, C. K., & Ma, N. (2006). A study of the relationship between competitiveness and technological innovation capability based on DEA models. *European Journal of Operational Research*, *170*(3), 971–986.
6. Hansen, M. T., & Birkinshaw, J. (2007). The Innovation Value Chain. *Harvard Business Review*, 15.
7. Hu, Y., Qu, S., Huang, K., Xue, B., & Yu, Y. (2022). The Chinese plug-in electric vehicles industry in post-COVID-19 era towards 2035: Where is the path to revival? *Journal of Cleaner Production*, *361*, 132291.
8. Hu, Z., & Yuan, J. (2018). China’s NEV market development and its capability of enabling premium NEV: Referencing from the NEV market performance of BMW and Mercedes in China. *Transportation Research Part A: Policy and Practice*, *118*, 545–555.
9. Jiang, C., & Liu, D. (2022). Effects of venture capital on green technology innovation in new energy vehicle industry in China. *Energy & Environment*, 0958305X221130135.
10. Le, P. B., & Lei, H. (2019). Determinants of innovation capability: The roles of transformational leadership, knowledge sharing and perceived organizational support. *Journal of Knowledge Management*, *23*(3), 527–547.
11. Panarello, D., & Gatto, A. (2023). Decarbonising Europe – EU citizens’ perception of renewable energy transition amidst the European Green Deal. *Energy Policy*, *172*, 113272.
12. Saunila, M., & Ukko, J. (2014). Intangible aspects of innovation capability in SMEs: Impacts of size and industry. *Journal of Engineering and Technology Management*, *33*, 32–46.
13. Stokes, L. C., & Breetz, H. L. (2018). Politics in the U.S. energy transition: Case studies of solar, wind, biofuels and electric vehicles policy. *Energy Policy*, *113*, 76–86.
14. Sun, B., & Ju, Z. (2022). Research on the promotion of new energy vehicles based on multi-source heterogeneous data: Consumer and manufacturer perspectives.
15. Sun, H., Geng, Y., Hu, L., Shi, L., & Xu, T. (2018). Measuring China’s new energy vehicle patents: A

social network analysis approach. *Energy*, *153*, 685–693.

16. Tone, K., & Tsutsui, M. (2009). Network DEA: A slacks-based measure approach. *European Journal of Operational Research*, *197*(1), 243–252.
17. Trost, T., Sterner, M., & Bruckner, T. (2017). Impact of electric vehicles and synthetic gaseous fuels on final energy consumption and carbon dioxide emissions in Germany based on long-term vehicle fleet modelling. *Energy*, *141*, 1215–1225.
18. Wang, W., & Zhang, C. (2018). Evaluation of relative technological innovation capability: Model and case study for China's coal mine. *Resources Policy*, *58*, 144–149.
19. Wang, Y., Fan, R., Lin, J., Chen, F., & Qian, R. (2023). The effective subsidy policies for new energy vehicles considering both supply and demand sides and their influence mechanisms: An analytical perspective from the network-based evolutionary game. *Journal of Environmental Management*, *325*, 116483.
20. Xie, X., Ramakrishna, S., & Manganelli, M. (2022). Smart Building Technologies in Response to COVID-19. *Energies*, *15*(15), Article 15.
21. Zeng, B., Li, H., Mao, C., & Wu, Y. (2023). Modeling, prediction and analysis of new energy vehicle sales in China using a variable-structure grey model. *Expert Systems with Applications*, *213*, 118879.
22. Zhu, J. (2009). *Quantitative models for performance evaluation and benchmarking: Data envelopment analysis with spreadsheets* (Vol. 2). Springer.