Research on Technology Opportunity Identification Considering the Impact of Supply Chain Knowledge Spillover: A Case Study of New Energy Vehicles

Jiang Jingjing
Beijing Wuzi University, Beijing, China

Abstract: At present, the competition between enterprises has gradually transformed into the competition between supply chains, and the trend of technological innovation is fierce. According to the knowledge spillover theory, the technology R&D decisions of enterprises will be unconsciously influenced by their supply partners, technology partners and market competitors. Taking CATL as the empirical research object, the effectiveness of the model is verified.

Keywords: *Knowledge Spillover; Patent Mining; Technology Opportunity Identification*

I. INTRODUCTION

In the wave of globalization and the rapid development of technology, the iteration of new technologies has been accelerating, and the competition among enterprises has also become more intense[1]. In the fierce market competition, it is crucial for enterprises to maintain a high level of self-reliance in technological research and development. Technological innovation is the core driving force for enterprises to enhance their competitiveness, and the identification of technological opportunities is the starting[2] point of research and development activities. Technology opportunities usually refer to the potential opportunities for technological progress in a particular field. For enterprises, being perceptive in identifying and grasping the development trends of these new technologies is the key to gaining a competitive edge in the market. However, the risks involved in the actual investment and development of new technologies cannot be ignored. A deviation in the identification and selection of key technology directions in the process of identifying technology opportunities will not only result in missed opportunities but also cause a waste of enterprise resources. Therefore, it is crucial to grasp the breakthrough point of enterprise technology opportunity identification. At present, for the identification of specific enterprise technology opportunities, some scholars have identified technology opportunities in specific areas of an enterprise based on the enterprise's technology capabilities and research and development directions. However, research on specific enterprises only considers the internal characteristics of the enterprise and ignores the impact of the external environment on the enterprise's technology research and development.

In fact, every enterprise is part of a certain supply chain, and the enterprise's technology domain may involve multiple levels of the supply chain and can expand and transform[3] under both internal and external influences and drives. At a time when the global traditional fuel vehicle market is facing challenges, China's new energy vehicle market shows a strong momentum of development. Against this backdrop, enterprises in the upstream, midstream and downstream of the new energy vehicle industry chain have achieved a new model of enterprise technology diversification through cross-level technology cooperation and improved the efficiency of technological innovation in the supply chain. CATL leads the global market with its cutting-edge ternary lithium and lithium iron phosphate battery technologies. Currently, well-known new energy vehicle manufacturers such as SAIC Motor, Dongfeng Motor, GAC Group, FAW Group and Geely have formed a solid alliance with CATL dedicated to the innovative research and development, mass production and market promotion of new energy power battery systems. Byd has made a comprehensive strategic deployment in the new energy vehicle industry chain, closely integrating raw material supply, core component research and development and manufacturing, and terminal sales links to maximize the advantages of the vertical supply chain in terms of cost-effectiveness, technological innovation and capacity management. Due to knowledge spillover, technology at one level of the supply chain can be transferred to another[4]. However, there are few studies currently considering the technological relevance between different levels of the supply chain, which may overlook some technological opportunities and thereby affect enterprise R&D innovation.

This paper aims to identify technology opportunities for enterprises in the supply chain by considering the impact of knowledge spillover at different levels of the supply chain. Specifically, first, construct the International Patent Classification (IPC) multilayer network, where each layer in the IPC multilayer network represents the IPC co-occurrence relationship belonging to that layer. Secondly, use the association rule algorithm to explore the potential relationship between existing and undeveloped technologies of the enterprise, thereby obtaining the potential technology opportunities of the enterprise. This paper considers the impact of knowledge spillover on enterprise technology research and development, identifies knowledge spillover from three dimensions: enterprise technology cooperation, technology citation and supply relationship, and determines the final potential technology opportunity of the enterprise based on the technology combination of the spillover subject.

II. THEORETICAL BASIS AND RESEARCH REVIEW

A. *Technical opportunity identification*

At present, research on technology opportunity identification can be divided into two categories: qualitative analysis and quantitative analysis. Qualitative analysis includes Delphi, Analytic hierarchy process, scenario analysis, etc. These methods are highly dependent on expert experience. Although they can produce creative and visionary predictions, they are highly subjective and the methods and conclusions are often difficult to replicate. [5]With the development of big data and artificial intelligence, the methods for identifying technological opportunities have shifted from early qualitative approaches to quantitative ones. Typical quantitative analysis is based on patent data, and methods include text mining, link prediction, etc. For example, Chen Yue et al. used patent text[6] information to identify core technologies through co-occurrence analysis of subject terms. Xu Xin et al. used the link prediction[7] method to transform the task of identifying technology opportunities into a binary classification problem of whether there is a co-occurrence link between technology elements. Li Ganrui et al. proposed an [8]emerging technology industry opportunity identification model based on SAO[8] semantic analysis. Park et al. predicted technology [9]convergence by predicting the flow of underlying[9] technology knowledge in citation networks. Wu Jie et al. identified the technology opportunities of the target enterprise under the condition of considering the technology capabilities and[10] technology similarities of the competitors. Although the study can identify technology opportunities in specific areas of enterprises, it ignores the impact of knowledge spillover on enterprise innovation. When knowledge spillover occurs in the supply chain, enterprises will face more intense competition in the market. Ignoring knowledge spillover and blindly "working in isolation" is not conducive to enterprise research and development innovation and enhancing competitiveness.

B. Knowledge spillover effects

Knowledge spillover is an important concept for explaining agglomeration, innovation and regional growth in branches of economics such as endogenous growth theory and new economic geography. Knowledge spillover effect refers to the process of knowledge spreading and diffusing among different individuals, organizations or regions, which has a significant impact[11] on economic growth and technological innovation. Arrow[12] first proposed the concept of knowledge spillover, arguing that it is an externality of a company's R&D activities that has a positive impact on innovation and development in other organizations. [13]Based on this, Romer[13] pointed out that the non-competitiveness and partial exclusivity of technical knowledge are the fundamental causes of knowledge spillover and established an endogenous growth model of knowledge spillover. Introducing knowledge as an independent element into the growth function. According to endogenous growth theory, sustained economic growth mainly depends on technological progress, which is not only influenced by the investment in research and development and human resources within enterprises, but also closely linked to the richness of the public knowledge base and the externalities of knowledge. The flow and spillover of knowledge across enterprise boundaries play a crucial role in promoting technological innovation and productivity improvement. This, in turn, has a positive impact on growth rates.

With the continuous improvement of the theory of knowledge spillover, empirical research on knowledge spillover has gradually become a hot topic. At the enterprise level, the research literature mainly focuses on knowledge spillover among enterprises, including its identification, measurement, and mechanisms of impact on enterprises themselves. For example, Del Giudice et[14] al. examined the role of lateral knowledge spillover in the international growth of Chinese small and medium-sized enterprises; Pang Ruizhi et[15] al. examined the relationship between product market competition among enterprises and knowledge spillover, and how these factors affect the R&D activities of enterprises; Tu Xinyu et[16] al. explored the role of knowledge spillover in the process of digital transformation of enterprises to enhance total factor productivity, using data from listed manufacturing companies in China. Based on the literature review, the pathways of knowledge spillover are mainly classified into the following four categories: the flow of human resources, the dissemination of information, cooperation in technology research and development, and the relationship between suppliers and customers. The movement of talents across different spatial ranges and their interaction and communication with surrounding groups, on the one hand, promote the creation of new knowledge, and on the other hand, accelerate the dissemination of knowledge among different groups. The dissemination and flow of information itself is also a kind of knowledge spillover. From the perspective of knowledge flow theory[17], the flow of knowledge among knowledge nodes in a citation network shows the selection, utilization, inheritance and innovation[18] of knowledge. Formal or informal cooperative research and development activities are another key way[19] of knowledge spillover among enterprises. Through joint research and development, enterprises can learn from each other and utilize each other's technical knowledge, accelerating the process of technological innovation. Isaksson et[20] al. provided evidence of knowledge spillover in supply chains. Samsung learned A lot about operations and product promotion by supplying the so-called A-series chips used in Apple's iPhone and ipad, and released the Galaxy S, a very similar competitor to the iPhone, in 2010. An analysis of 521 suppliers in the high-tech industry revealed knowledge spillover in the supply chain.

Based on the sorting and review of the literature, this paper considers the impact of knowledge spillover under the approaches of enterprise technological cooperation, enterprise citation relationship and enterprise supply relationship. On this basis, potential technological opportunities are identified for enterprises.

III. RESEARCH FRAMEWORK

A. Technical opportunity Identification based on Association Rules (ARM)

Association mining algorithms, as an unsupervised learning technique, are primarily aimed at extracting frequent item sets from a series of transaction data and revealing the association rules that exist among the items in the dataset in an "if-then" logical structure. [21]In this paper, the association rule algorithm is applied to the IPC classification numbers of patents obtained from upstream, midstream and downstream enterprises in the new energy vehicle supply chain to mine frequent item sets, explore the combination relationships and strong association rules among different technical fields, thereby identifying potential technology opportunities for enterprises.

This paper selects three indicators - confidence, support, and improvement - to measure the strong association rules of technology combinations, and sets an initial threshold to evaluate and screen the association rules. In the case of technology A→ Technology B, technology A is the former technology and technology B is the latter technology. Support quantifies the relative frequency with which the two technologies appear together in the patent collection; Confidence, on the other hand, reflects the conditional probability that technology B will appear simultaneously under the condition that technology A appears; The boosting degree is used to assess how much the occurrence of technology A enhances the probability of technology B. The higher the boosting degree is greater than 1 and the higher the value, the stronger the positive correlation between technology A and technology B.

This paper considers the impact of knowledge spillover on enterprise technology research and development, identifies the subjects that have A knowledge spillover impact on the target enterprise, and screens the enterprise technology opportunities by mining the existing technologies of the spillover subjects. If the enterprise has developed the preceding technology (A) in the rule but has not developed the subsequent technology (B), then the subsequent technology (B) is recognized as having no technology opportunity. If the latter technology (B) exists in the patent set of the knowledge spillover subject, according to the principle of knowledge spillover, the enterprise is more likely and more likely to develop the backward technology (B), at which point the latter technology (B) is identified as the technology opportunity of the target enterprise.

B. Knowledge spillover identification

1) Knowledge overflow identification based on the enterprise patent cooperation network

An enterprise patent cooperation network is a network of cooperative relationships formed by enterprises in the process of technological innovation, which reflects the exchange and sharing of knowledge resources among enterprises and is an important way of knowledge spillover. Some scholars have found that the strength of enterprise patent cooperation network relationships has a positive impact[22] on knowledge spillover. In this paper, degree centrality is selected as an indicator to measure the strength of enterprise cooperation relationships, and the calculation formula is as shown in Equation (1):

$$DC_i = \frac{k_i}{N-1} \tag{1}$$

Among them, represents the Quantity of existing edges connected to node k_i; $N-1$represents the Quantity of nodes i connected to other nodes.

2) Knowledge overflow identification based on the enterprise patent citation network

The backward reference of patents reflects the learning and absorption of technical knowledge in the process of research and development and innovation, and is an important way and form of knowledge spillover and technology flow in the process of innovation. The reference relationship between patents forms the patent reference network. In this paper, the centrality of nodes in the patent reference network is calculated. The higher the centrality, the more important the node is in the network. It also has a higher[23] priority in the process of patent citation mining. In-degree centrality indicates how many other nodes have referenced the node. In this paper, in-degree centrality is selected to measure the importance of knowledge spillover, and the calculation formula is as shown in Equation (2) :

$$C_{in(i)} = \frac{d_{in(i)}}{N_{nod}-1} \tag{2}$$

Where represents the number $d_{in(i)}$*of in-degree connections of node i*; N_{nod}Represents the total number of nodes.

Convert the centrality of nodes in the patent reference network to the centrality of the enterprise reference network by the formula shown in Equation (3) :

$$C_{en} = \sum_{n=1}^{N_{en}} C_{in(i)} \tag{3}$$

Where represents the number of all patent nodes of the enterprise.N_{en}

3) Knowledge overflow identification based on supply relationship

Upstream suppliers or downstream manufacturers in the supply chain can enhance their core competitiveness through supply network relationships. According to transaction cost theory[24] and social network theory[25], supply chain network relationships can provide innovative knowledge and information to supply chain members, which not only directly promotes technological progress but also indirectly creates market opportunities, bringing potential possibilities of technological innovation and market expansion to supply chain network members. Stable supplier-customer relationships facilitate the dissemination of innovative knowledge from upstream and downstream suppliers and promote technological innovation[26] in enterprises.

Referring to the calculation method of the stability index[27] of the top five suppliers, that is, the repetition number of the top five suppliers of the previous year in the current year divided by 5, this paper selects the repetition of the supply relationship from the beginning to the present to measure the stability of the supply relationship. The calculation formula is as shown in Equation (4) :

$$S_{en(i)} = \frac{\sum_0^{t_i} f_{en(i)}}{t_i} \tag{4}$$

Where represents the duration of the supply relationship (years); $t_i f_{en(i)}$To indicate the supply situation, the calculation formula is as shown in Equation (5) :

$$f_{en(i)} = \begin{cases} 0, & supplyrelationshipdidnotappear \\ 1, & supplyrelationshipdidnotappeared \end{cases} \quad \text{.....................(5)}$$

Based on the enterprise patent technology cooperation relationship, enterprise technology citation relationship and enterprise supply relationship, this paper conducts a three-dimensional mapping of the indicator results to identify the subjects of knowledge spillover in the supply chain, and mine the subject technology combinations. If the latter technology (B) exists in the patent set of the knowledge spillover subjects, according to the principle of knowledge spillover, The enterprise is more likely and easier to develop backward technology (B), at which point the latter technology (B) is identified as a technological opportunity for the target enterprise.

C. Technology Opportunity Assessment

For the identified technology opportunities, this paper selects indicators of technology maturity and technology impact to assess the developability and potential of the technology opportunities. Technology maturity refers to the level of maturity of a given technology, which is usually evaluated[28] by the S-curve model. The S-curve model divides technology development into six distinct phases: the initial introduction phase, the early growth phase, the growth phase, the early maturity phase, the maturity phase and the saturation phase. In this paper, Logistic model is used to fit the S-curve, and the calculation formula is as shown in Equation (6) :

$$\mathrm{y_{it}} = \frac{\mathrm{L}}{1+\mathrm{ae^{-bt}}} \tag{6}$$

Where represents the cumulative number of y_{it}*i-technology* patents in the supply chain over time t, L is the maximum value of yt, and a and b control the position and shape of the curve, respectively.

Accordingly, the calculation formula for technology maturity is as shown in Equation (7) :

$$TM_{it} = \frac{y_{it}}{L} \tag{7}$$

Where, the initial introduction period of technology: $TM<0.1$; Early growth period: $0.1\le TM<0.3$; Growth period: $0.3\le TM<0.5$; Early maturity: $0.5\le TM<0.75$; Maturity stage: $0.75\le TM<0.9$; Saturation stage: $TM\ge 0.9$.

Technology influence is an important measure of technology quality, which can be evaluated by the frequency of patent references. Citation frequency shows the influence of a patent on subsequent technological development activities, that is, the more times a patent is cited, the greater[28] its technological influence. In this paper, the average citation count of the technology is selected to assess the technological influence, and the calculation formula is as shown in Equation (8) :

$$TI_i=\frac{AC_i}{\sum_1^n AC_n} \quad (8)$$

Where represents the citation count AC_i *of technology i* and *n* represents the total number of technologies.

IV. EMPIRICAL ANALYSIS

To ensure the authenticity of the data, this paper selects the Patsnap global patent database as the data source for patent mining, referring to the "Development Plan for the New Energy Vehicle Industry (2021-2035)" issued by The General Office of the State Council. This paper first divides the supply chain of new energy vehicles into three layers, taking 2014-2024 as the cut-off point. Through simple family merging, 23,790 patents from the upstream of the new energy vehicle supply chain, 20,001 patents from the midstream, and 9,619 patents from the downstream were obtained. An IPC co-occurrence network was constructed and the strong correlation of technology combinations was mined through the association rule algorithm. This paper considers the impact of supply chain knowledge spillover, builds enterprise patent technology cooperation network and patent citation network, and combines supply chain supply relationship data published by Guotaian (CSMAR) database to identify knowledge spillover from multiple dimensions. This paper selects CATL New Energy Technology Co., Ltd. for empirical research. Specifically, the research framework of this paper is shown in the figure.

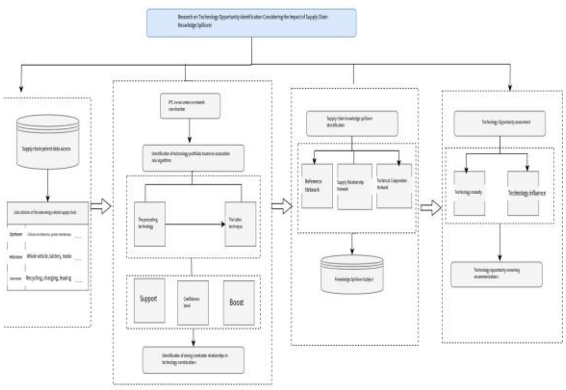

Fig. 1. Technology road map

A. *Identification of technology portfolio*

1) IPC co-occurrence network construction

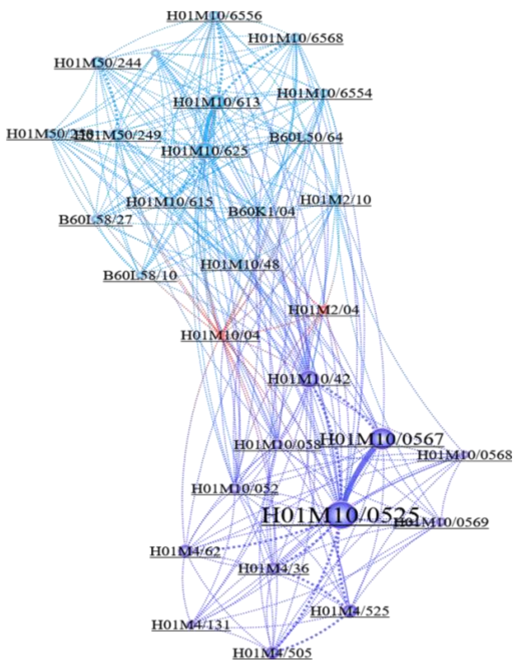

Fig. 2. Patent co-occurrence Network

Build an IPC co-occurrence network based on the patents obtained from the upstream, midstream and downstream of the new energy vehicle supply chain to analyze the overall situation of the new energy vehicle industry technology portfolio. The IPC co-occurrence network is shown in the figure, where nodes represent IPC classification numbers, edges represent co-occurrence relationships, and weights are the number of co-occurrences.

2) Identification of technical opportunities

Based on the association rule algorithm, this paper conducts frequent item mining of patent data in the field of new energy vehicles to calculate the association strength between technologies. When conducting the association analysis, it is necessary to set the minimum confidence and support thresholds. Different thresholds lead to different association results. In this paper, different thresholds are set and precision training is carried out. Finally, a support threshold of 0.2 and a confidence threshold of 0.5 are selected as the thresholds to output the technology opportunity association results. A total of 41 groups of associations were identified, and some of the identification results are shown in the table.

Table 1: Technical opportunity identification results

Prior technique	Latter technique	Support	Confidence	Boost
C01B25/45	H01M4/58	0.32	0.6	122.84
B60K1/04	H01M2/10	0.22	0.77	245.55
H02J7/00	B60L53/80	0.23	0.51	134.2
B60L11/18	H02J7/00	0.28	0.5	140.33
H01M4/131	C01G53/00	0.2	0.58	175.17

Take the first association rule as an example. IPC classification number C01B25/45→H01M4/58, the association rule support is 0.32, that is, the probability of simultaneous occurrence is 0.32; The confidence level is 0.6, that is, when C01B25/45 occurs, there is a 60% chance that H01M4/58 will also occur, indicating that the credibility of this association rule is relatively high; The boost was 122.84, meaning that when C01B25/45 occurred, the probability of H01M4/58 occurred increased by 122.84 times. A boost greater than 1 indicates that C01B25/45 had a positive effect on the occurrence of H01M4/58.

B. *Knowledge spillover subject selection*

This paper takes CATL New Energy Technology Co., LTD. (CATL) as the target enterprise. By analyzing the patent technology cooperation network, the patent citation network and the supply relationship network, and mapping the results in three-dimensional space, the knowledge spillover source subjects of CATL and the technology combinations contained in the knowledge spillover subjects are ultimately defined as potential technology opportunities of CATL.

1) Analysis of patent technology cooperation

In this paper, a patent technology cooperation network with "applicants (enterprises)" as nodes is constructed as shown in the figure, with edges as the number of cooperation times. The degree centrality of network nodes is calculated through equation (3-1) to measure the strength of cooperation among enterprises. The degree centrality of some enterprise nodes is shown in Table 2.

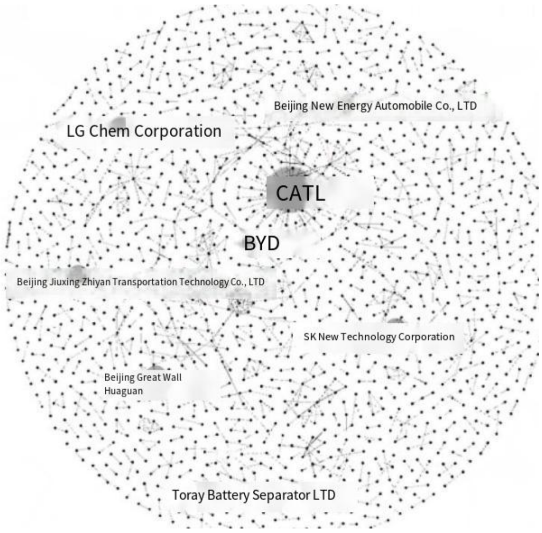

Fig. 3. Enterprise cooperation network

Table 2: Enterprise point degree Centrality

Serial Number	Node name	Degree centrality
1	CATL New Energy Technology Co., LTD	0.61
2	LG Chem Corporation	0.59
3	BYD Company Limited	0.7
4	Zhejiang Geely Holding Group Limited	0.67

2) Analysis of patent citation relationships

Based on the obtained citation relationships and citation frequency of new energy vehicles, this paper constructs an enterprise patent citation network with the "patent publication number" of the enterprise as the node, measures the importance of knowledge spillover by the node in-centrality index, and then converts it into a patent citation network with the "enterprise" as the node as the figure to calculate the importance of the enterprise knowledge spillover, as shown in Table 4-2.

Table 3: Importance of enterprise knowledge spillover (in-degree centrality)

Serial Number	Node name	In-degree centrality
1	Fengchao Energy Technology Co., LTD	0.52
2	Huawei Technologies LTD	0.72
3	Guangzhou Xiaopeng Automotive Technology Co., LTD	0.65
4	BYD Company Limited	0.75

3) Supply Relationship analysis

This paper uses the CSMAR database as the data source to retrieve the supply relationship data of CATL New Energy Technology Co., LTD. Some of the supply relationships are shown in the figure, and the supplier concentration is selected to measure the stability of the supply relationship as shown in Table 4-3, in order to identify stable sources of knowledge spillover for CATL.

Table 4: Stability of Supply Relationship

Category	Name	Supply relationship stability
Customers	BMW China	1
	Saic Volkswagen	0.9
	Beijing Benz	0.7
Suppliers	Cordali	0.9
	Peking University leads the way	0.6
	Greentech	0.8

C. Knowledge Spillover Subject Identification Analysis

The results of the indicator calculation were mapped in three dimensions, and the three-dimensional coordinate system was divided into four quadrants according to the interval [0,1]. The average value of each indicator was taken, and enterprises with indicators greater than the average value were selected as the knowledge spillover source subjects of CATL as shown in Table 4-4. The technologies mastered by the subjects were identified as potential technological opportunities.

Table 5: Knowledge spillover source entities of CATL

Enterprise name	Strength of cooperation	Citation intensity	Supply relationship stability
SaicVolkswagen Automotive LTD	0.61	0.3	0.9
Zhejiang Geely Holding Group Limited	0.67	0.6	0.8
Huawei Technologies LTD	0.52	0.72	0.8
BYD Company Limited	0.7	0.75	/
Shenzhen Kedali Industry Co., Ltd.	0.63	0.58	0.9

D. Analysis of the results of technology opportunity identification

Based on the association rule algorithm, this paper excavates possible technology combinations and further screens potential technology opportunities that can be developed for CATL through the identification of knowledge spillover source subjects. For the former technology that CATL has mastered, if the knowledge spillover subject has mastered the latter technology, the latter technology is identified as a potential technology opportunity for CATL. First, this paper selects patents filed by CATL from 2014 to 2020 (test set) for technology opportunity identification and calculates technology maturity and technology influence. Secondly, it uses patents filed by CATL from 2020 to 2024 (verification set) to verify whether CATL has developed technology opportunities, taking the technology combination identified in Table 4-1 as an example. The identified technology opportunities were evaluated, and some of the results are shown in Table 4-5.

Table 6: Validation of technology opportunity identification results

Technical opportunities	Technology maturity	Technology influence	Will it be developed from 2020 to 2024
H01M4/58	Early maturity	high	Y
H01M2/10	Early maturity	high	Y
B60L53/80	Growth period	high	Y
H02J7/00	Mature stage	high	Y
H01M8/1041	Growth period	low	N

As can be seen from the table, the identified technologies that are in the unsaturated stage and have high influence basically conform to CATL's technology development rules. To further verify the effectiveness of considering the influence of knowledge spillover on enterprise R&D decisions, this paper further compares and analyzes the identification accuracy of the test set and the verification set. The accuracy curve is shown in the figure. As can be seen from the graph, the technology opportunity identification that takes into account the influence of knowledge spillover has significantly higher identification accuracy. Based on this, this paper continues to identify technology opportunities for the patents applied for by CATL from 2020 to 2024, screens technology opportunities considering the impact of knowledge spillover, and evaluates technology opportunities in combination with technology maturity and technology influence.

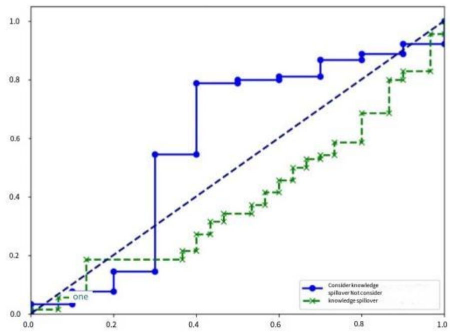

Fig. 4. Comparison of algorithmic utility

E. *Technology Opportunity prediction*

Based on the selected combinations of technology opportunities, this paper conducts association rule mining on CATL's patent application data from 2020 to 2024, identifies knowledge spillover entities to further screen technology opportunities, and predicts the final potential technology opportunities in combination with technology maturity and technology influence. Ultimately, 18 potential technology opportunities that CATL can develop in the future are obtained. Combined with the IPC subcategory, this paper divides the technology opportunities into two aspects: vehicle traction power units (B60L) and electrical energy conversion units (H01M).

CATL has strong existing strength and high self-attention in the H01M technology field. As shown in the figure, CATL's total patent applications for H01M accounted for almost more than 80% from 2014 to 2023. Therefore, CATL has the ability to further explore the H01M technology field. Meanwhile, it needs to have a clear insight into the market direction. Among them, H01M12/06 (metal electrode or gas electrode technology) can be a key innovation technology, which can improve battery performance by using non-cycling aluminum-air battery cells, etc., which is conducive to improving production efficiency and the utilization efficiency of multiple energy sources.

CATL has not paid enough attention to the B60L technology field, but through the association rule algorithm, it was found that the B60L53/00 (electric vehicle energy storage charging technology) it has mastered performs well in terms of support, confidence and improvement indicators for B60L15/00 (on-board traction, charge and discharge control technology), and in contrast, the knowledge spillover subjects Byd Co., LTD., as the leading company in the new energy vehicle industry, can rank 8th in the country in terms of the Quantity for B60L15/00 (on-board traction, charge and discharge control technology) (102 cases). CATL is already a leader in electric vehicle battery technology. Effective power device control not only helps optimize battery usage, but also helps to consolidate its market position from the perspective of market competitiveness by enhancing its innovation ability in power system control technology.

References

[1] Xu, T., Yang, J., Zhang, F., & Guo, W. (2021). Interfirm coopetition, interfirm knowledge creation, and collaborative innovation performance: The moderating roles of environmental competitiveness and dysfunctional competition. Industrial Marketing Management.

[2] Yoon, B., & Magee, C.L. (2018). Exploring technology opportunities by visualizing patent information based on generative topographic mapping and link prediction. Technological Forecasting and Social Change.

[3] Schmitt, A. J., & Singh, M. (2012). A quantitative analysis of disruption risk in a multiechelon supply chain. International Journal of Production Economics, 139(1), 22–32.

[4] Isaksson, O. H., Simeth, M., & Seifert, R. W. (2016). Knowledge spillovers in the supply chain: Evidence from the high tech sectors. Research Policy, 45(3), 699–706.

[5] Ren Haiying, Wang Qian. Research status, trends and problems of technology opportunity discovery methods [J]. Journal of Intelligence, 2020, 39(4): 51-59.

[6] Chen Yue, Tan Jianguo, Wang Zhiqi, et al. Analysis of technology opportunities in the Field of industrial robots from a patent perspective [J]. Science Research Management, 2018, 39(4) : 144-156.

[7] Xu Xin, Li Qian, Yi Chunbo, et al. A study on technology opportunity identification based on link prediction: A Case study of patent data in Privacy protection [J]. Library journal, 2023, 42 (9) : 103-112 + 128 + 136-137. The DOI: 10.13663 / j.carol carroll nki lj. 2023.09.013.

[8] Li Ganrui, Guo Junfang, Zhu Donghua. Research on Methods for Identifying Opportunities in Emerging Technology Innovation [J]. China Soft Science, 2018(11) : 138-147.

[9] Park, I., & Yoon, B. (2018). Technological opportunity discovery for technological convergence based on the prediction of technology knowledge flow in a citation network. Journal of Informetrics, 12, 1199 - 1222.

[10] Wu Jie, Liu Ziyu, Xie Xiaodong, et al. Research on Enterprise Technology Opportunity Identification considering Competitor Technology Similarity and technology capability [J/OL]. Intelligence magazine, 1-9 [2024-09-23]. http://kns.cnki.net/kcms/detail/61.1167.G3.20240814.1723.010.html.

[11] Bernstein J I. Costs of Production, Intra-and Interindustry R&D Spillovers: Canadian Evidence[J]. The Canadian Journal of Economics, 1988, 21(2): 324-347.

[12] Arrow, K. J., H. B. Chenery, B. S. Minhas, and R. M. Solow, " Capital-Labor Substitution and Economic Efficiency," Review of Economics and Statistics, 43 (1961): 225–250.

[13] Romer P M. Increasing Returns and Long-Run Growth[J]. Journal of Political Economy, 1986, 94(5): 1002-1037.

[14] Del Giudice M, Scuotto V, Garcia-Perez A, Petruzzelli A M. Shifting Wealth II in Chinese economy. The effect of the horizontal technology spillover for SMEs for international growth [J]. Technological Forecasting and Social Change, 2019, 145: 307-16.

[15] Pang Ruizhi, Tu Xinyu, Yan Xiaoling. How do product market competition and knowledge spillover affect enterprise research and development? -- Empirical identification based on multi-dimensional spatial proximity [J]. Industrial Economics Research, 2021, (02): 1-14+29.

[16] Tu Xinyu, Yan Xiaoling. Digital Transformation, knowledge spillover and Total factor Productivity of enterprises - Empirical evidence from

listed manufacturing companies [J]. Industrial Economics Research, 2022, (02): 43-56.
[17] Ikujiro Notanaka, Hirotaka Takeuchi. Enterprises that create knowledge: The driving force for continuous innovation in Japanese and American enterprises [M]. Beijing: Intellectual Property Publishing House, 2006.
[18] Liu Chen. Research on the Impact of Knowledge Spillover on R&D Strategies of Enterprises in Supply Chain [D]. Xi 'an Technological University, 2014.
[19] Li Zhiguo, Wang Wei. Knowledge spillover and enterprise clusters: A literature review [J]. Technology Economics,2013,32(08):21-26.
[20] Olov H.D. Isaksson, Markus Simeth, Ralf W. Siifert, 2016, Knowledge Spillovers in the Supply Chain: Evidence from the High Tech Sectors, Research Policy, 3(45): 699-706.
[21] Huang Z, Lu X, Duan H. Mining association rules to support resource allocation in business process management [J] . Expert Systems with Applications, 2011, 38(8) : 9483-9490.
[22] Tian Yifan. Research on the Impact of Patent Cooperation networks in the Electric Vehicle Industry on spillover of Common technologies [D]. Lanzhou University of Technology, 2023.
[23] Ding Zhaoqi, Zhang Jianhui, Xu Chenhui. Construction of a demand-driven cross-domain patent technology mining method [J]. Journal of Science and Technology Management Research, 2024, 44 (14): 154-163.
[24] Burt R S. The Contingent Value of Social Capital[J]. Administrative Science Quarterly, 1997, 42(2): 339-365.
[25] Pisano G P. The R&D Boundaries of the Firm: An Empirical Analysis[J]. Administrative Science Quarterly, 1990, 35(1): 153.
[26] Li Shuo, Li Qing. Research on Enterprise Innovation Performance from the Perspective of Supply Chain Shared Audit [J]. Economic Issues, 2023, (12): 115-122.
[27] Fu Li-Li, Chen Zhen, Wu Fengyun. Major shareholders' equity pledge and supply chain risk [J]. Journal of Zhongnan University of Economics and Law,2022,No.252(03):74-85.
[28] Yuan, X., & Cai, Y. (2021). Forecasting the development trend of low emission vehicle technologies: Based on patent data. Technological Forecasting and Social Change, 166, Article 120651.
[29] Criscuolo P, Narula R, Verspagen B. Role of home and host country innovation systems in r&d internationalisation: A patent citation analysis[J] . Economics of Innovation and New Technology, 2005, 14(5) : 417-433.