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# Evolution and characteristics of Crossover Innovation Network of Emerging Technologies: a study based on patent data of the self-driving car technology

## *Evolução e Características da Rede de Inovação Cruzada em Tecnologias Emergentes: um estudo baseado em dados de patentes da tecnologia de carros autônomos*

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## Abstract

Along with the rapid development of a new round of scientific and technological revolution and industrial transformation, digital manufacturing, artificial intelligence, the Internet and other emerging fields marked by digitalization and intelligence are experiencing widespread penetration, cross-integration and constantly emerged crossover innovation. New technology development is a process of continuous increase of resource heterogeneity characterized by high fuzziness and uncertainty. However, it is difficult to meet the requirements of the development of emerging technologies only by the innovative resources and capabilities of the enterprises themselves. The limitation of innovation resources urges emerging technology enterprises to actively or passively exchange various innovation resources with other innovation subjects across organizational, technological or industry boundaries, and promotes the rapid rise of crossover innovation networks of emerging technologies, which has become an important way for emerging technology enterprises to avoid innovation risks and improve innovation efficiency. To explore the crossover innovation network of emerging technologies and its evolution path, this paper uses social network analysis to build the IPC co-occurrence network, patentee cooperative innovation network and patent citation network by stages by taking the invention patent data of self-driving car technology from 2006 to 2020 as samples, analyzes the subject cooperation, knowledge flow and technology convergence in the process of crossover innovation, explores the evolution process of crossover innovation network of emerging technologies and its characteristics in each stage, and then draws relevant enlightenment.

**Keywords**: Emerging Technologies. Crossover Innovation Network. Social Network Analysis. Network Structure.

**Resumo**

*Com o rápido desenvolvimento de uma nova fase de revolução científica e tecnológica, transformação industrial, fabricação digital, inteligência artificial, internet e outros campos emergentes marcados pela digitalização e inteligência estão experimentando ampla penetração e constante emergência de inovação cruzada. O desenvolvimento de novas tecnologias é um caminho constante de ampliação na diversidade de recursos, marcado por uma complexidade e incerteza significativas. No entanto, satisfazer as exigências do desenvolvimento de tecnologias emergentes apenas com os recursos inovadores e habilidades das próprias empresas torna-se uma tarefa desafiadora. A limitação de recursos inovadores instiga as empresas de tecnologia emergente a trocar ativamente ou passivamente diversos recursos inovadores com outros agentes de inovação, transcendendo limites organizacionais, tecnológicos ou industriais. Isso impulsiona o rápido surgimento de redes de inovação cruzada em tecnologias emergentes, tornando-se uma maneira crucial para as empresas de tecnologia emergente evitarem riscos inovadores e aprimorarem a eficiência da inovação. Este estudo emprega a análise de redes sociais para construir redes de coocorrência de códigos IPC, redes de cooperação entre detentores de patentes e redes de citação de patentes em estágios específicos. Utilizando dados de patentes de tecnologia de carros autônomos de 2006 a 2020 como amostras, analisa a cooperação entre os sujeitos, o fluxo de conhecimento e a convergência tecnológica no processo de inovação cruzada. Explora o processo evolutivo da rede de inovação cruzada em tecnologias emergentes e suas características em cada estágio, proporcionando insights relevantes.*

***Palavras-chave***: *Tecnologias emergentes. Rede de Inovação Cruzada. Análise de Redes Sociais. Estrutura da Rede.*

## Introduction

The concept of emerging technology was first developed in 1994 by the Wharton School's Hunstman Research Center's Emerging Technology Management Research Program, and is defined as a science-based technology that can create or change an industry (Day; Schoemaker, 2000). Emerging technologies, different from traditional ones, whose development is marked by major technological breakthroughs and convergent innovations, and is reflected in the continuous increase of various required resources, showing a high degree of fuzziness and uncertainty. As a result, emerging technology enterprises with limited innovation resources seek cooperation and innovation from external organizations, thus forming a crossover innovation network with various formal or informal connections among different organizations (Wang, 2006). Innovation network is an institutional arrangement of resource exchange, information transfer, knowledge exchange and cooperation among innovation subjects to achieve innovation goals (Freeman, 1991), and each participating subject can access and integrate the knowledge resources in the network, thus forming systematic technological innovation results (Dang; Zheng, 2011). Due to different resource conditions, innovation subjects adopt different combinations of crossover behaviors in the innovation process and exchange innovation resources actively or passively, leading to changes in the number of enterprises, relationships, rules and transactions in the network as well as the network location and resources of enterprises (Raffaelli, 2019), driving the evolution of crossover innovation networks. The expansion of network scale and the increase in the degree of node heterogeneity promote the effective exchange and integration of diverse external knowledge, enhance the ability of enterprises to absorb and apply knowledge, and facilitate the realization of crossover innovation (Choi; Sang-Hyun; Cha, 2013); the enhancement of network connectivity shortens the average path of information resource transfer, promotes the sharing and transfer of innovation resources such as knowledge, information and technology in the network, and enhances the possibility of crossover innovation (Hua; Wang, 2013); the increased frequency of cooperation and communication among subjects makes the strength of network connection increase, which can lead to the establishment and enhancement of mutual trust among subjects and thus is conducive to accelerating the acquisition of external knowledge, information and other resources, prompting enterprises to absorb and integrate knowledge more quickly and effectively, achieving rapid and low-cost development of new products and services, responding to environmental changes, and enhancing the speed of emerging technological innovation (Zhao *et al.*, 2022). Enterprises that are at the core of the network have greater network power, possess more critical information, knowledge, and technology resources, and enjoy higher status and reputation in the network structure, which makes it easier to win the conviction and reliance of other enterprises, and thus helps to reach crossover cooperative innovation with more enterprises (Shi *et al.*, 2020). In the process of dynamic evolution of crossover innovation networks of emerging technologies, different technologies, knowledge and information are continuously diffused and transferred, which promotes the integration of emerging technological knowledge with the original technological knowledge (Liu *et al.*, 2020), and thus promotes crossover innovation, giving rise to new technologies, which in turn form new products and eventually successfully enter the mainstream market (Muller, 2020). The research of Lee, Park and Kang (2018), Shao, Dang and Wang (2018), Feng *et al.* (2019), Mao *et al.* (2021), Safadi, Johnson and Faraj (2021) all confirmed that the crossover innovation network of emerging technologies plays an important role in promoting the development of emerging technologies.

Domestic and foreign scholars have widely focused the research on the formation and evolution of innovation networks, and a research paradigm on the impact of innovation networks on technological innovation has gradually been formed. Studies have been conducted to construct innovation networks through different data sources and analyze the networks' evolution. For example, the alliance agreement of professional database has been used to understand the cooperative relationship among innovation subjects (Narula; Santangelo, 2009), or the cooperative R&D has been grasped by collecting archives and literature and the main data of knowledge flow among innovation subjects, so as to study the evolution of innovation network (Karna; Taübe; Sonderegger, 2013). Some scholars have adopted questionnaires to explore the cooperative and innovative relationship among innovation subjects (Fitjar; Rodríguezpose, 2011). Patent data, one of the important carriers of technological information, can combine inventors with applicants to carry the dual functions of "knowledge production" and "knowledge utilization" (Mario; Teodora; Stefano, 2011). Compared with literature and scale surveys, patents can objectively reflect the technological innovation level of enterprises because of its novel and practical characteristics (Cantner; Meder; Wal, 2010). The construction of technological innovation network using patents can analyze the evolution of technology and reflect the trend of technological development (Liu; Jian, 2022). Cantner and Graf (2006) used the patent data from 1995 to 2001 related to Jena in DPMA to analyze the evolution process of the innovation network in Jena, Germany. Guan and Yam (2015) used the patent data in the energy field in USPTO to construct a cooperative innovation network based on the city and national level to explore the influence of different levels of networks on innovation.

Social Network Analysis (SNA) is a network scientific analysis method based on the knowledge of statistics, mathematics, graph theory, computer and other disciplines. It provides ideas for network analysis based on nodes, connectivity relationships and structure, and has been widely used in network-related research in academic circles. Thus, it can be used to effectively analyze emerging technological innovation networks. The social network analysis software Gephi and Ucinet are commonly applied by researchers for visual analysis and quantitative measurement of innovation networks because of their powerful functions. Therefore, they can be used to draw the network map to directly show the evolution of the innovation network, and analyze its influence by calculating the network structure characteristics (Kim; Song, 2013), thus guiding promoting the innovative production and R&D activities of enterprises and strategy formulation (Marra; Antonelli; Pozzi, 2017).

The technology of self-driving cars is rated as one of the most promising emerging technologies according to the Gartner Hype Cycle for Emerging Technologies. It has formed a crossover innovation network in corporate practice with the participation of many complementary players from upstream and downstream industries and different technologies and industries. This network shows a relatively complete and continuous dynamic evolution process from the initial exploration to the gradual improvement and value realization of the technology, which provides a good research context for this paper to explore the evolution and characteristics of crossover innovation networks of emerging technologies. Most existing studies on the evolution of technology innovation networks use simulation analysis method to simulate the network evolution process or case study method to capture the characteristics of networks of a few enterprises, which lack sufficient data support. Therefore, this paper starts from the characteristics of emerging technologies, adopts the social network analysis method by collecting patent data of self-driving car technologies from 2006 to 2020, uses the Ucinet software to draw network mapping to visualize the process of network evolution, and analyzes the stage characteristics of network evolution in depth by quantitative measurement of network structure characteristics to reveal the laws of network evolution.

This paper extends the study of innovation network evolution to the perspective of crossover innovation of emerging technologies, and deeply explores the crossover cooperation, knowledge flow and technology integration in the evolution process of the crossover innovation network of emerging technologies, and thus reveals the characteristics and main rules of network dynamic evolution in the process of crossover innovation of emerging technology enterprises, which complements and deepens the research on innovation network and crossover innovation of emerging technologies. The technology of self-driving cars is disruptive through crossover technology integration and is an emerging technology in the process of crossover innovation. The research in this paper has practical inspirational value for both the continuous innovation of this technology and the future crossover innovation of similar emerging technologies. It is of great theoretical value and practical significance to guide emerging technology innovation subjects to build crossover innovation networks, formulate feasible innovation cooperation strategies, and how the government builds innovation cooperation platforms.

## Research Design

### Research objects

Self-driving cars, also known as driverless cars, are intelligent cars developed based on computer technology, which was put into practice at the beginning of this century. The joint work of various technologies such as artificial intelligence and GPS system enables the cars to drive safely and automatically according to the instructions issued by the computer without driving. In China, the mass production and commercial operation of Hongqi EVs, the first batch of L4 self-driving passenger cars in September 2019 marked its self-driving technology entry into a stage of rapid development. Subsequently, enterprises have continuously modified and improved the automatic driving function through simulation testing, and increased the actual testing and demonstration application efforts to continuously promote the realization and promotion of the application of intelligent connected vehicles technology and products. On January 11, 2021, the Ministry of Industry and Information Technology released a draft in official website to speed up the development of autonomous driving technology in China and realize the commercial application of intelligent connected vehicles early. During the development of self-driving car technology, an informal cooperative innovation network has been formed among innovation subjects such as universities, research institutions and intermediaries to share and transfer knowledge, which has promoted the integration of different technologies, promoted the crossover innovation of self-driving car technology and promoted the development of crossover innovation networks. Therefore, this paper constructs a crossover innovation network of self-driving car technology by collecting the related patent data, and studies the network's evolution law and main characteristics.

## Data source and processing

There are three types of patents: Patent for Invention, Patent for Utility Model, and Patent for Design, of which the academic circle generally recognizes the Patent for Invention as it has high technical content and originality and can well measure the applicant's technological innovation ability. The content of the Patent for Invention includes the patentee (i.e. the innovation subject), technology association, cooperation relationship, citation information, etc. It has been widely applied to the empirical research on innovation network, technology diffusion and innovation performance.

The data in this paper were from Derwent Innovations Index (DII) database, commonly used by scholars in patent analysis containing relatively complete and authoritative patent data. They can query all kinds of information, including patent licensor, patent number, rating and so on. In addition, the database contained patent and citation information from six major patent agencies of the Patent Cooperation Treaty (PCT), in the United States, Europe, Germany, the United Kingdom and Japan, spanning the period from 1963 to the present, with high update frequency, which is of great help to various agencies and researchers in understanding the technological frontier and technological developments (Liu; Zhou; An, 2013).

DII provides a variety of retrieval methods. This paper used DII advanced retrieval to collect patent data from 2006 to 2021. Due to the time delay of patent data caused by patent application and its licensing, the patent data before 2020 was considered relatively novel and relatively complete to reflect the development trend of autonomous vehicle technology as a whole. The keywords related to self-driving car technology in the subject area (TS) was searched in this paper, with information retrieval expressions: TS = "autonomous vehicle *" OR "driverless car *" OR "self-piloting automobile" OR "self-driving car *". The symbol * was used as a wildcard to retrieve the basic variants of word cells. Up to the date of final retrieval in this paper, 10,339 pieces of patent information were collected, and finally 9,527 invention patents were obtained after screening and statistics.

The pure text document data was exported from the database, and the patentee names were cleaned and merged using the data analysis software Thomson Data Analyzer. SQL SERVER BI and VBA programming extracted the information including patent number, patent application date, title, applicant, abstract, classification number, patent citation and other fields. The data was cleaned and processed (Zhai *et al.*, 2013) to generate the data format accorded with the imported Gephi, and the visual network map was drawn. The characteristics and rules of network evolution were analyzed by calculating the network structure index.

## Network construction

1) IPC co-occurrence network. It analyzes the correlation degree and mutual influence relationship between different technical fields. Each node in the network represents a technical field, and the connection between nodes is a co-occurrence relationship, i.e. two connected IPC classification numbers simultaneously appear in the same patent. The more nodes, the more technical fields the technology involves. The more connections, the more co-occurrence. The co-occurrence intensity can reflect the degree of integration between different technical fields.

2) Cooperation network of patentees. The nodes in the cooperation network represent the innovation subjects, and the connections between the nodes represent the crossover cooperation relationship among the innovation subjects. The establishment of cooperation relationship is usually accompanied by the implicit heterogeneous flow of technological knowledge, which affects the integration of different technologies, and thus affects the crossover innovation.

3) Patent citation network. Patent citation reflects the mutual citation relationship between patent documents and between patent documents and non-patent documents, which can reflect the quality and influence of patented technology (Ma, 2015); Also, it reflects the knowledge flow and overflow contained in patents, as well as the direction, characteristics and process of information flow guiding technological innovation (Stolpe, 2002). The patent citation network used in this paper was constructed with the patentee organization as the node and the citation relationship among organizations as the connection line, which was used to analyze the knowledge flow relationship among patentee organizations. The citation relationship is divided into forward citation, which indicates the case where the patent is cited by another patent, and backward citation, which indicates where the patent cites another patent. Because the citations are directional, the citation network is a directed network.

## Indicators for network analysis

In this paper, the statistical indicators such as density, average degree, number of components, average path length, diameter and clustering coefficient proposed by Albert and Barabási (2002) that have been widely used to analyze the structure and properties of the network were adopted, as shown below.

1) Number of nodes: Total number of nodes in the network;

2) Number of connections: Total number of links in the network;

3) Network density: The ratio of actual links to all possible links in the network;

4) Average degree: Degree is the sum of connections between a node and its neighboring nodes, and the average degree is calculated by dividing the sum of all node degrees by the total number of nodes in the network;

5) Number of components: Component refers to the independent sub-networks in the network, and the number of components represents the number of independent sub-networks in the network;

6) Number of nodes in the maximum component: Total number of nodes in the maximum component;

7) Average path length: An average of path lengths between any pair of nodes in the network;

8) Diameter: The maximum path length in the network;

9) Cluster coefficient: The clustering coefficient of nodes is the ratio of the number of links between adjacent nodes to the maximum possible number of links between them. The clustering coefficient of the network is the average of the clustering coefficients of all nodes.

In this paper, the centrality analysis was performed using the indicators proposed by Freeman (1978) to test the value and importance of each node, as shown below.

1) Degree centrality: It is measured by the sum of nodes directly connected to a node, and the degree centrality of node i is expressed by the formula: $c(\mathrm{i})_d = \frac{\Sigma_{k=1}^{n} a(N_i, N_k)}{n-1}$, where $a(N_i \cdot N_k)$ =1 when and only when $\mathrm{i}(N_i)$ and are connected, otherwise, $a(N_i \cdot N_k)$=0; n is the total number of nodes in the network. In a directed network, degree centrality is divided into in and out-degree centrality.

2) Closeness centrality: It is measured by the sum of the shortest path lengths between one node and all other nodes. It has the significance of global centrality, including not only direct connections but also indirect connections. The formula for calculating the closeness centrality of node i is $C(\mathrm{i})_C = \frac{n-1}{\sum_{k=1}^{n} \mathrm{d}(N_i, N_k)}$, where, $\mathrm{d}(N_i, N_k)$ is the path length between nodes $\mathrm{i}(N_i)$ and ; $k(N_k)$ and n is the total number of nodes in the network. In a directed network, the closeness centrality is divided into the in-degree and out-degree closeness centrality.

3) Betweeness centrality: It measures the degree to which a node acts as a bridge or agent in the network, that is, the degree to which a node controls resources. The formula for calculating the betweeness centrality of node i is $c(j)_b = \frac{\Sigma_{j<k} g_{jk}(\mathrm{i}) / g_{jk}}{[(n-2)(n-1)/2]}$, where, $g_{jk}$ indicates the number of paths between nodes j and k, and $g_{jk}(\mathrm{i})$ indicates the number of paths between connecting nodes j and k through node i, and n is the total number of nodes in the network.

## Empirical Analysis

### Descriptive analysis

The change in the number of patent applications can be used to speculate on the market and research and development investment trends, reflecting the development process of self-driving car technology. Through the statistics of the total number of technical invention patents of self-driving cars from 2006 to 2020, it is found that the number of patent applications for inventions of self-driving car technology increased from 2006 to 2013 but with a relatively low growth rate, the total number of patent applications increased significantly from 2014, especially the total number of patents for inventions of self-driving car technology increased rapidly in the four years after 2016, with the average annual patent application volume remaining above a certain level. Figure 1 shows a case of a patent application containing at least two IPC main classification numbers in a joint invention patent application in the technical field of automatic driving vehicles. As the number of joint patent applications in that year should be regarded as the result of continuous crossover cooperation and innovation among innovation subjects, it should be calculated by taking 3 years as the duration of the cooperative relationship, which is based on the data of joint invention patents in the current year and the year before and after, concerning the research results of scholars Deeds and Hill (1999). According to the figure, the patent application volume showed an overall growth trend before 2014, but the growth rate was slow. Affected by the overall economic downturn in 2008, the number of patents decreased in 2009, and then began to climb slowly, with a slight decline in 2012-2013. However, in recent years after 2014, the total number of applications for invention patents has increased sharply, from 153 in 2014 to 2,926 in 2019, showing a trend of rapid and steady growth, indicating that the crossover integration effect of self-driving car technology has become increasingly prominent with the development of technology in recent years.

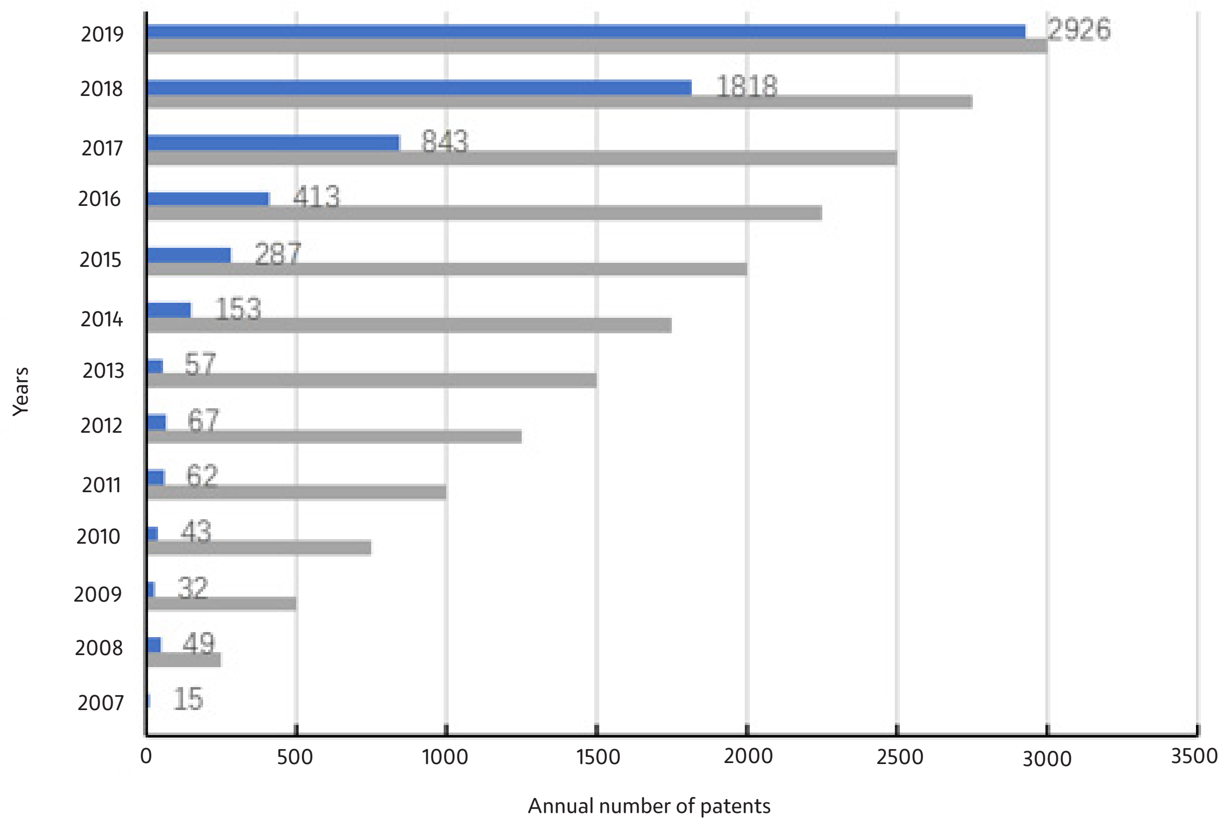


**Figure 1** – Application for invention patent of innovation network organization of self-driving car technology.
Source: Elaborated by authors (2021).

## Evolution and characteristic analysis of IPC co-occurrence network

The evolution stages of its innovation network were divided based on rolling method in this paper to analyze the development and evolution process of self-driving car technology. An enterprise often takes several years of continuous technological innovation to apply for an invention patent. Yan (2007) believed that a three-year period can effectively reflect the sustainability of innovation activities, and made an empirical study by building an enterprise's innovation network in that year with a rolling window of three years. Therefore, based on the relevant research results, the collected invention patents were divided into five window periods with every three years as a stage. The IPC co-occurrence network analysis indicators for each stage are shown in Table 1. Analysis of Table 1 reveals the,

**Table 1** – Analysis of IPC co-occurrence network indicators

| Stages | 2006-2008 | 2009-2011 | 2012-2014 | 2015-2017 | 2018-2020 |
|---|---|---|---|---|---|
| Number of nodes | 73 | 97 | 130 | 188 | 304 |
| Number of connections | 189 | 389 | 610 | 1514 | 3511 |
| Network density | 0.072 | 0.084 | 0.073 | 0.086 | 0.076 |
| Average degree | 5.178 | 8.021 | 9.385 | 16.106 | 23.099 |
| Proportion of maximum components (node) | 80.82% | 80.41% | 89.23% | 95.74% | 96.74% |
| Proportion of maximum components (edges) | 94.71% | 96.92% | 98.85% | 99.93% | 99.94% |
| Average path length | 2.623 | 2.315 | 2.429 | 2.21 | 2.209 |
| Average clustering coefficient | 0.778 | 0.796 | 0.78 | 0.775 | 0.708 |

Source: Elaborated by authors (2021).

1) Increasing number of technical fields. The number of nodes in the network kept increasing, from 73 in the first stage to 304 in the fifth stage. The network size increased more than fourfold and accelerated, with the growth rates of 32.88%, 34.02%, 44.62% and 61.7% in each stage respectively. Different nodes represent different technical fields, which indicates that the technology of self-driving cars gradually involves more and more different technical fields. The overall technical network is rapidly integrating, absorbing external knowledge and continuously expanding.

2) Increased technology crossover integration. The number of connections in the network increased rapidly, from 189 in the first stage to 3,511 in the fifth stage, an increase of nearly 18 times, and showed a large-scale accelerated growth state, which indicates that there were more and more co-occurrence types in the network, that is, there were more and more technical fields in which convergence occurred. The network density did not decrease with the expansion of the network scale. Still, it remained basically the same, which showed that once the new technology entered the network, it could quickly connect with other technology networks to produce technology convergence. The network average degree indicates the average number of each node connected to other nodes in the network. A significant increase in the average degree implies an increasing number of technical fields converging with a technical field, further indicating that crossover integration between different technologies is becoming more common.

3) Enhanced network connectivity. It is called a connected graph if all nodes in the network can be connected, otherwise a disconnected graph. The non-connected graph can be divided into a plurality of blocks based on the connection relationship of the nodes, and each block represents a connected component. As shown in the table, the proportion of nodes and edges in the maximum component of the network continued to increase. In particular, the proportion of the maximum component of the network had exceeded 95% in the past five years, indicating that the development of the self-driving car technology is a process of continuous convergence and integration of different technologies, which has gradually formed an overall large network. The continuous decrease of average path length and clustering coefficient indicates that the degree of single centralization of the network is weakening. The core of nodes is gradually decreasing, indicating that technology convergence is no longer limited to some specific key technical fields, and further indicating that network connectivity is enhanced. Crossover convergence between different technical fields is becoming more and more frequent.

According to the above analysis, the development and evolution of self-driving car technology accorded with the evolutionc haracteristics of emerging technology crossover innovation network, namely, the increasing number of technical fields, the improvement of the diversification degree of technical knowledge resources, the enhancement of heterogeneity and the increasingly common phenomenon of integration.

## Analysis on evolution and characteristics of patentees' crossover cooperation network

With the patentee of the self-driving car technology invention as the node and the cooperative relationship between the co-patentees as the connection line, a five-stage patentee cooperative innovation network was drawn by the rolling period of three years. Based on the calculation and comparison of the network structure characteristics of the five stages of the evolution of the crossover cooperative innovation network of the self-driving car technology, it is found that its overall structure has changed significantly with time, as shown in Table 2. The five stages of the evolution of the self-driving car technology's crossover cooperative innovation network conform to the evolution of the emerging technology crossover innovation network, characterized by the continuous expansion and openness of the network and the gradual fuzziness of the network boundary.

Table 2 further shows that the scale of crossover cooperative innovation network has gradually expanded, and the number of nodes and connections in the network has been increasing yearly. Although the network scale increased before 2015, the growth rate was relatively small. With the gradual development of crossover cooperative innovation activities, the number of subjects and cooperative relationships for crossover cooperative innovation in the field of self-driving car technology increased significantly in the two stages of 2015-2017 and 2018-2020, indicating that cooperation in the field of self-driving car technology has become increasingly common. The trend of technological innovation among innovation subjects through extensive crossover cooperation has promoted the rapid development of piloted driving technology in recent years. The crossover cooperative innovation network was gradually opening up, which was reflected in the facts that the network density was gradually decreasing from 0.046 to 0.003 on the one hand, suggesting the change from high density to low density of the crossover cooperative innovation network for self-driving care technology. The average clustering coefficient gradually decreased and the degree of network aggregation decreased. The average degree and average path length gradually increased after a slight decrease in 2012-2014 on the other hand. During the three stages of 2006-2008, 2009-2011 and 2012-2014, the vast majority of the subnet in the crossover cooperative innovation network took the form of complete graphs, with regular network structures and close membership within the subnets, which were usually established based on social or geographical connections. At this time,

**Table 2** – Indicators of self-driving car technology patent cooperation innovation network.

| Stages | 2006-2008 | 2009-2011 | 2012-2014 | 2015-2017 | 2018-2020 |
|---|---|---|---|---|---|
| Number of nodes | 39 | 39 | 76 | 202 | 568 |
| Number of connections | 34 | 33 | 57 | 164 | 495 |
| Average degree | 1.744 | 1.692 | 1.5 | 1.624 | 1.743 |
| Average density | 0.046 | 0.045 | 0.02 | 0.008 | 0.003 |
| Average clustering coefficient | 1 | 0.922 | 0.925 | 0.89 | 0.706 |
| Average path length | 1 | 1.108 | 1.034 | 1.155 | 2.832 |

Source: Elaborated by authors (2021).

there is a relatively stable interaction among the few. Still, highly aggregated innovation subjects in the network, and the long-term crossover cooperation is beneficial to accumulate the technological knowledge in a certain field in the innovation network, so that the technical knowledge is difficult to spread out of the network.

The network can build an initial technology chain once the technical knowledge has accumulated to a certain extent and a breakthrough innovation has taken place. Hence, the first three stages are the gestation stage of self-driving car technology. The two stages of 2015-2017 and 2018-2020 witnessed a further decrease in network density, a decrease in aggregation, and a gradual increase in average degree and average path length, indicating that crossover cooperation between different innovation subjects is becoming more frequent and common. The crossover cooperative innovation network of self-driving car technology is becoming more and more open. The further increase in the number of innovation subjects and the cooperative relationship is conducive to the birth of a large number of incremental innovations and the outward extension of the technology chain, which has accelerated the flow and diffusion of diversified technological knowledge in the network with the enhancement of the heterogeneity of innovation subjects in the network, promoted the crossover integration of different technologies and thus promoted the crossover innovation, and promoted the development and evolution of self-driving car technology. Therefore, the five stages of the evolution of the crossover cooperative innovation network of autonomous driving vehicle technology show that the crossover cooperative innovation network of emerging technologies is characterized by expansion, openness, the increasingly common crossover cooperative innovation among heterogeneous innovation subjects in the network, the richer and more diversified technological knowledge resources, and the fuzziness of network boundaries.

The maximum connected subgraph was extracted from the fifth stage of the patentee cooperative innovation network to get the crossover cooperative innovation network subgraph, as shown in Figure 2. Since this study was conducted at the enterprise level, individual patentees were excluded from the crossover cooperative innovation network diagram, and nodes in the network represented both enterprise and institutional patentees. Node size refers to the size of betweenness centrality, an indicator of how much a node controls resources, which can be understood as the degree to which a node acts as a bridge and a medium in a network. The larger node indicates that the larger betweenness centrality, the thickness of the connection represents the cooperation times, and the thicker connection indicates.

According to the types of network members, the crossover cooperative innovation network mainly includes enterprises, foundations, universities and research institutes. Enterprises include traditional car companies, such as Hyundai, Kia and Ford, as well as high-tech companies, such as Omron Electronics, General Motors Global and Ford Global, which have a close and direct cooperative relationship and focus on providing supporting solutions such as auto parts and technical services in the research and development direction of self-driving car technology. The members of the network also include many universities and research institutes, such as Stanford, Massachusetts Institute of Technology, Korea National University of Transportation, Toyota Research Institute, etc., which have a strong scientific research foundation and technological research and development strength, and are often in the forefront of the research on the technology of self-driving cars, thus with close ties with enterprises. In addition, several innovation foundations and business foundations have emerged in the network, serving as a bridge connecting different types of innovation subjects.

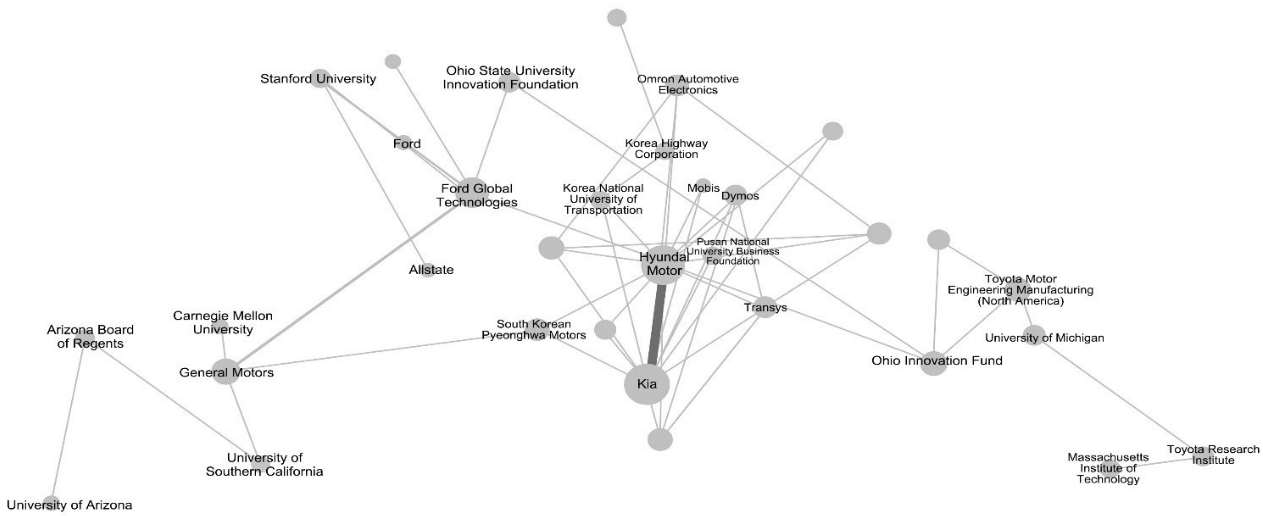


**Figure 2** – Subgraph of crossover cooperative innovation network.

Judging from the tie strength of network membership, the cooperation between Hyundai Motor and Kia Motor in Figure 2 is the strongest, because tacit knowledge is more complex and difficult to transfer and absorb. Therefore, it is easier for the same type of innovators to establish stronger ties that will promote the dissemination of tacit knowledge in the cooperation. In addition, there are many weak ties in the network, through which all kinds of innovative entities, especially car companies, establish contact and cooperate with universities, research institutes and foundations. As weak ties benefit the acquisition of diversified technological knowledge and heterogeneous innovation resources, enterprises as the main innovation subjects will establish weak ties with other types of organizations or institutions to acquire different resources needed for innovation to carry out continuous emerging technological innovation activities.

Judging from the geographical distribution of network members, most of the innovation subjects in this crossover cooperative innovation network are from South Korea or the United States, because the smaller the spatial distance between organizations, the smaller the differences in organizational structure, management model and organizational culture among the innovation subjects. Moreover, the smaller geographical distance can effectively reduce the cost of external knowledge search for the organization, which is beneficial to improving the efficiency of obtaining technical knowledge and promoting the communication and cooperation among each other, thus promoting the diffusion and transfer of technical knowledge and improving the innovation performance of crossover cooperation. However, knowledge distance plays a dual role in the diffusion and transfer of technical knowledge among innovation network subjects. The profit from knowledge transfer will be smaller and smaller when the knowledge distance between subjects in the whole network is too small, which weakens the willingness of knowledge transfer. With technological upgrading and technological development, the number of innovation subjects within the network has gradually increased, and the inter-subject crossover cooperative innovation network has established a connection between South Korea and the United States through joint patentees. As shown in the figure, General Motors Global and South Korean Pyeonghwa Motors both show a high degree of betweenness centricity, indicating that these organizations with strong mediating effect have narrowed the distance of knowledge flow between innovation subjects in the network, knowledge exchange and crossover technology cooperation are becoming closer. The network is gradually breaking through the geographical restrictions and industry or technology domain restrictions. The regional boundaries, industry and technology boundaries of the crossover cooperative innovation network of self-driving car technology will be further broken with the further improvement of the requirements for developing emerging technologies.

## Analysis of patent citation network

### The topology of the overall network

In the overall structure of the patent citation network, the nodes are represented by circles, representing the patentee, the edges are represented by straight lines, indicating the citation relationship, and the direction of the arrow indicates the direction of knowledge flow (if A cites B, the arrow points from B to A, if B cites A, the arrow points from A to B). The overall network contains 8,006 nodes and 25,845 connections, reflecting the strong knowledge mobility characteristic of the crossover innovation network of self-driving technology. The results of network topology analysis are shown in Table 3.

**Table 3** – Results of network topology analysis among kernel organizations that the more cooperation times.

| Indicators | Values |
|---|---|
| Number of nodes | 8006 |
| Number of connections | 25845 |
| Density | 0.000 |
| Average degree | 3.228 |
| Number of components | 4 |
| Number of nodes in the maximum component (as a percentage of the total number of nodes) | 7854 (98.1%) |
| Number of edges in the maximum component (as a percentage of the total number of edges) | 25730 (99.56%) |
| Average path length | 3.46 |
| Diameter | 8 |
| Average cluster coefficient | 0.135 |

Source: Elaborated by authors (2021).

The average path length of the cited network is 3.46, meaning it only takes about 3 steps from node to node on average, far less than the predicted value of 7.398 proposed by Erdos and Renyi. The diameter of the network representing the maximum path length of the network is only 8, which is far smaller than the predicted value of ER model 13, which fully shows that the small-world effect of the patent citation network of the patentee in the field of self-driving car technology is stronger than that of ER model, indicating that the network can flow, diffuse and transfer knowledge more quickly and efficiently. The average clustering coefficient is 0.135, greater than the theoretical prediction value of 0.006 by ER model, and is consistent with the proposal by Watts and Strogatz that networks reflecting the real world have greater clustering property than random networks. The above indicators show that the patent citation network of self-driving car technology has shorter average path length, diameter and larger clustering coefficient than the ER model of the same scale, fully showing that the crossover innovation network of self-driving car technology has faster and more efficient knowledge mobility. At the same time, the proportion of nodes and edges with the largest component in the network is more than 98%, which indicates that the overall network connectivity is strong, and further indicates that the flow of technical knowledge between different innovation subjects in the network is wide and close. The above analysis reveals that the patent citation network of self-driving car technology aligns with the characteristics of high knowledge heterogeneity, strong mobility and high network aggregation in the emerging technology crossover innovation network.

## Citation networks between core organizations

Due to too many nodes and connections in the overall network, the readability of the network mapping is greatly reduced and the detailed information cannot be displayed. Therefore, in this paper, the k-kernel decomposition method was adopted to perform visual analysis on the patent citation network, i.e. only the nodes in the original network graph with node degrees greater than or equal to k were retained, and the relationship between these core nodes was investigated. Degree centrality represents the degree to which a node is directly connected to other nodes. The degree of a node reflects the degree to which an organization is active in the technological innovation network. The greater the degree centrality of a node, the more organizations communicate knowledge with the organization.

In this paper, Gephi was used for k-kernel decomposition. By comparing and analyzing the results of k-kernel decomposition and considering the representation of node organization and the readability of network diagram, a 34- kernel decomposition network was finally selected, and a subnet with a total of 49 nodes and 1,226 edges were obtained, as shown in Figure 3. The circle's size represents the node's degree, and the edge's thickness represents the edge's weight. The weight is the number of patent citations between organizations, reflecting the intensity of knowledge flow between two connected organizations. The greater the weight of the edge, the greater the knowledge flow. A dense knowledge flow network was composed of 49 kernel organizations, and some organizations had a high proportion of self-citation (in the figure, some nodes had semicircular curves), that is, incremental innovation was carried out based on their original technology and knowledge. Another possibility was to realize disruptive crossover innovation by organically integrating externally acquired knowledge into existing technologies to change the "genes" of existing technologies.

To further analyze the role of each kernel organization in the network, in this paper, the outflow-inflow index, namely O-I index, proposed by Choe *et al.* (2016) was adopted to specifically measure whether an organization is a knowledge producer or a knowledge absorber in the patent citation network by referring to related research. O-I index is specifically calculated as:

O-I index=(out-degree centrality-in-degree centrality)/(out-degree centrality +in-degree centrality).

Where, the out-degree centrality indicates the outflow and diffusion of knowledge, the in-degree centrality indicates the absorption of knowledge, and the value of O-I index is between -1 and 1. If the O-I index is greater than 0, the outflow of knowledge is greater than the inflow; if it is less than 0, it is greater. The closer the O-I index value is to 1, the more knowledge flows out,

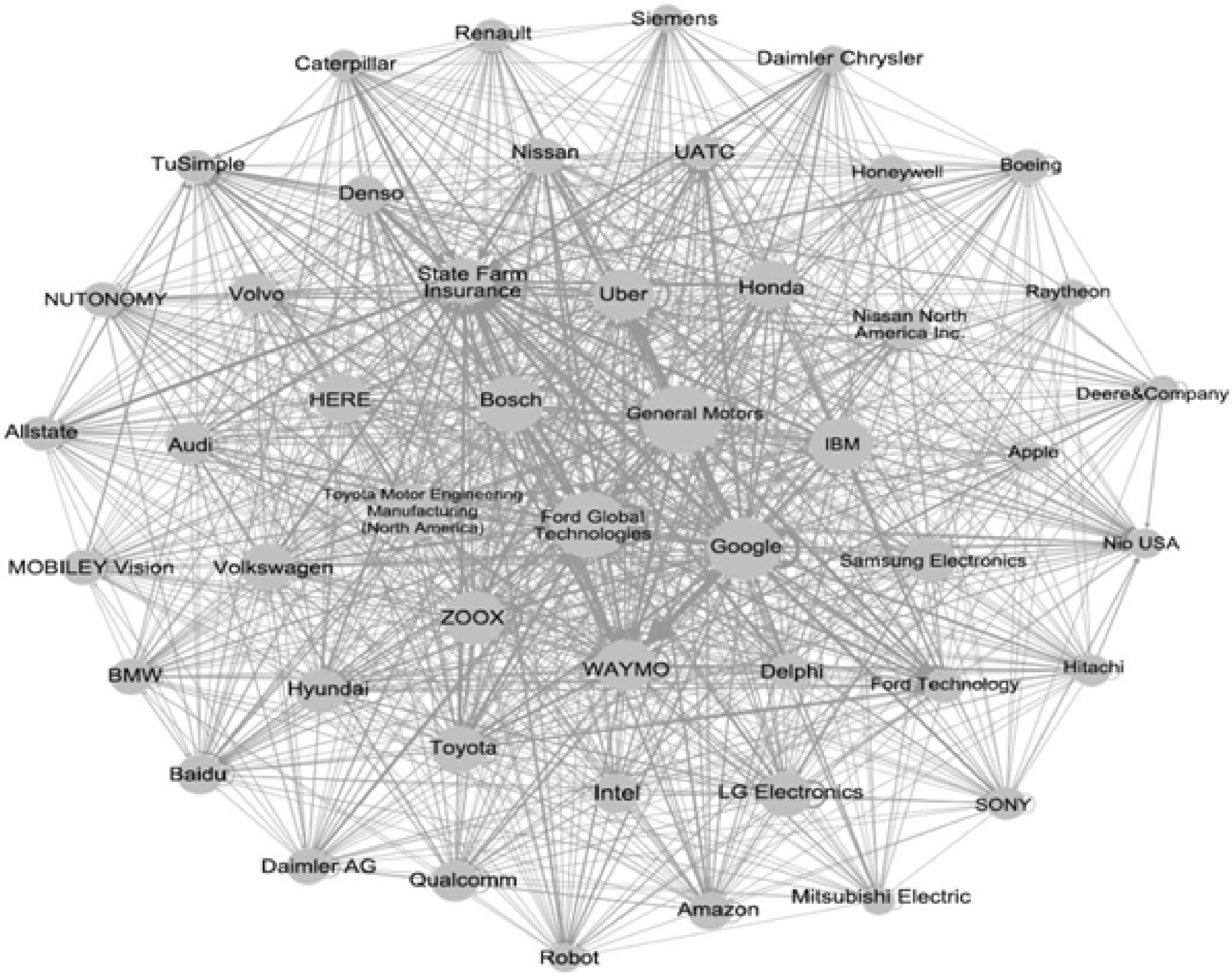


**Figure 3** – Citation network.
Source: Elaborated by authors (2021).

the higher the cited frequency, and the higher the quality of invention patents and the importance of knowledge. The closer the value is to -1, of the more the organization is absorbing a lot of external knowledge.

Calculating the O-I index of all kernel organizations, the top 15 one were obtained, as shown in Table 4, and were analyzed in combination with the closeness centrality of nodes. Closeness centrality refers to the sum of the shortest distances between a node and other nodes in the network, and is an indicator of how close a node is to other nodes in the network. Hence, a larger closeness centrality indicates that the node is closer to other nodes and needs fewer intermediate nodes, making it easier to spread and absorb technical knowledge. In the network, the average closeness centrality of nodes is large, and there is little difference between the top 15 organizations, which indicates that the technical knowledge flows widely and efficiently among organizations in the whole network.

Judging from the O-I index, knowledge producers include industry-leading automobile manufacturers such as Daimler-Chrysler, Nissan, Toyota and Volkswagen, and the world's top suppliers of parts and components for automobile systems such as Denso and Mitsubishi Electric. Not only that, they also involve many technical fields such as energy, transportation systems,

**Table 4** – Ranking of O-I index- closeness centrality of nodes.

| Ranking | O-I index | | Closeness centrality |
|---|---|---|---|
| | Knowledge production | Knowledge absorption | |
| 1 | Nippon Denso (0.803) | Ford (-1.000) | Google (0.514) |
| 2 | Daimler-Chrysler(0.729) | UATC (-0.993) | Toyota (0.505) |
| 3 | Nissan (0.703) | NIO US (-0.900) | Bosch (0.487) |
| 4 | Hitachi (0.670) | TuSimple (-0.820) | General Motors (0.479) |
| 5 | Siemens (0.576) | Waymo (-0.792) | Ford global (0.476) |
| 6 | Mitsubishi Electric (0.469) | nuTonomy (-0.719) | Honda (0.474) |
| 7 | Toyota (0.449) | Baidu (-0.693) | Nippon Denso (0.472) |
| 8 | Volkswagen (0.401) | Robot (-0.690) | Nissan (0.463) |
| 9 | Daimler (0.393) | Ford Global (-0.686) | Hitachi (0.462) |
| 10 | Caterpillar (0.374) | Uber (-0.638 ) | Volkswagen (0.455) |
| 11 | Sony (0.342) | Toyota (-0.598) | Hyundai (0.450) |
| 12 | Audi (0.270) | Mobileye (-0.564) | Samsung Electronics (0.448) |
| 13 | BMW (0.255) | Statefarm insurance (-0.516) | IBM (0.446) |
| 14 | Bosch (0.246) | HERE (-0.502) | Sony (0.441) |
| 15 | Honda (0.213) | General Motors (-0.494) | BMW (0.440) |
| Mean of population | 0.437 | -0.477 | 0.408 |

Source: Elaborated by authors (2021).

electricity and electronics, among which Hitachi, Siemens and Sony are representative enterprises with high patent quality and strong ability to spread technological knowledge in the network. Knowledge absorbers include Internet technology companies such as Ford (Global) Technology, Baidu and Uber, traditional automobile manufacturers such as Toyota and General Motors, as well as NIO, Tucson Future, Waymo and NuTomomy which are engaged in the layout of smart cars, involving many technical fields such as aircraft transportation, artificial intelligence, vision technology and map services. UATC, Robotics, Mobileye, HERE and other outstanding enterprises are also active technology knowledge absorbers in the network. Unexpectedly, an insurance company- Statefarm Insurance, an excellent automobile insurance company in the United States, has also appeared among the top knowledge absorbers, and has close cooperation with car networking manufacturers. Nevertheless, with the wide application of self-driving cars, all kinds of traffic accidents will be greatly reduced, thus greatly impacting the traditional auto insurance market. In addition, the existing car companies have begun to lay out auto insurance business, forcing traditional insurance companies such as Statefarm Insurance to set foot in the field of automatic driving, strengthening cooperation and communication with car companies, and making strategic layout in advance to resist the impact of technological changes on the future market. It shows that the emergence of self-driving cars poses a threat and impact on the traditional markets of auto insurance, auto finance and other related industries. It further illustrates that the rapid development of emerging technologies will bring destructive or subversive changes to the original technologies or industries. The above analysis of the patent citation network among the kernel organizations in the technical field of self-driving cars further indicates that the development of emerging technologies depends on the knowledge flow and crossover integration among different technical fields. The innovative subjects of emerging technology change the original technology network structure and link mode through information collision and knowledge interaction, so that emerging technology knowledge is gradually integrated into the original one, and different technologies are integrated across borders to promote crossover innovations and promote the development and evolution of emerging technologies.

## Conclusions and Enlightenment

In this paper, the characteristics and evolution path of crossover innovation network of emerging technologies were analyzed by collecting driving car technology patent data and using social network analysis to construct IPC co-occurrence network, patent holder crossover cooperative innovation network and patent citation network. The research results show that the crossover innovation of emerging technologies essentially embodies the crossover integration of different technologies in the process of the development of emerging technologies. The cooperation and innovation network formed by crossover cooperation among innovation subjects can promote the communication and exchange between them, accelerate the dissemination and diffusion of new technologies, knowledge and information, promote the flow and integration of knowledge, and then create new technological knowledge, and promote the development of emerging technologies. Therefore, attention should be paid to the construction of innovation network in the process of emerging technology development, and the larger the network scale, the higher the diversity of nodes, the higher the relationship strength and the more perfect the network structure, which will help each other to form a closer communication and cooperation relationship, because the smoother the circulation of knowledge and information, the easier it is to stimulate more creativity and ideas, thus enhancing the possibility of crossover innovation and speeding up the development of emerging technologies. In addition, most of the innovation subjects in the crossover cooperative innovation network are foreign-funded enterprises. And there are a few core nodes with competitive advantages and strength, such as Ford, Google, GM and a few other companies occupying the most center of knowledge flow in the patent citation network, which indicates that these enterprises have a solid foundation of technological knowledge resources and research and development conditions, play a vital role in the development of emerging technologies and the enhancement of the overall competitiveness of the industry, and provide a direction for domestic autonomous vehicle technological innovation subjects to learn international advanced knowledge and technology. Therefore, in the development process, Chinese emerging technology enterprises should attach importance to crossover technical cooperation with different external enterprises, universities and research institutes, unite to overcome technical difficulties and develop emerging technologies with independent intellectual property rights. At the same time, in different stages of the development of emerging technologies, enterprises with R&D strength and competitive advantages should be guided to build crossover innovation networks with different structures, to break down technical barriers, improve the overall technical level and competitiveness, and promote the development of emerging technologies.

This paper uses patent data to analyze the evolution and characteristics of crossover innovation network of the self-driving car technology, but patent data itself has patents protect limitations, not all inventions, patents only reflect part of the results of technological innovation, and patent information has a time lag as well. Therefore, future research can combine with the analysis of non-patent literature to conduct a more in-depth and systematic analysis of the evolution and characteristics of crossover innovation networks of emerging technologies. In addition, this paper only selects self-driving car technology as the research object, which has strong technical and industry characteristics. Future research can include different emerging technologies and conduct comparative analysis of multiple technologies to obtain richer research results. This is more conducive to summarizing the characteristics and evolution laws of the evolution of crossover innovation networks of emerging technologies.

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## Contributors

X. Cao and Y. Jin contributed to conception and design of the study. H. Ma organized the database. Y. Jin performed the statistical analysis, wrote the first draft of the manuscript and wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.