WEP Warwick Evans Publishing

International Journal of Global Economics and Management

ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 10, Number 2, Year 2026
DOI: https://doi.org/10.62051/ijgem.v10n2.02
Journal homepage: https://ijgem.org

An Empirical Study on the Technological Innovation Paths of Advanced Manufacturing Industry Clusters in the Chengdu–Chongqing Twin-City Economic Circle Based on High-Value Patents

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ABSTRACT

Collaborative innovation within advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle is an important measure for Western China to move toward high-quality development, promote coordinated regional progress, and improve the national strategic layout. However, existing research on the technological evolution paths of advanced manufacturing clusters in this region remains relatively scarce. To address this gap, this study constructs a high-value patent citation network using citation data of patents from advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle over the past decade, applies the SPC algorithm to identify technological paths, and conducts an empirical analysis of the technological evolution characteristics in key fields. The results show that the technological innovation paths of advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle tend to evolve from resource scheduling toward intelligent optimization, forming a collaborative innovation pattern centered on resource allocation and task scheduling. Under the background of cross-domain collaboration, technological evolution exhibits multi-path integration and stage-wise bifurcation. Accordingly, the paper proposes policy recommendations such as building intelligent manufacturing collaboration chains, improving technological integration mechanisms, and strengthening industry–academia–research collaboration systems, so as to promote the high-quality development of advanced manufacturing industry clusters in the region.

KEYWORDS

Chengdu–Chongqing Twin-City Economic Circle; Advanced manufacturing industry clusters; High-value patents; Technological path evolution; Patent citation network

1. INTRODUCTION

Industrial clusters are widely regarded as key spatial vehicles linking firms' competitive strategies with regional comparative advantages. Porter argues that geographical proximity, specialized division of labour, and networked collaboration make clusters a core organisational form for enhancing productivity, fostering innovation, and nurturing new industries [1]. Under the background of Industry 4.0 and intelligent manufacturing, digitalisation, networking and smart technologies are reshaping production processes and value-chain division of labour in manufacturing. Advanced manufacturing clusters have thus become crucial levers for upgrading manufacturing towards high-end, green and service-oriented development [2]. Recent studies further show that the deep integration of the digital economy and manufacturing helps accelerate the adoption of green technologies and the restructuring of production modes, thereby promoting high-quality development and green transition in the manufacturing sector [3]. Against this macro background, the Chengdu–Chongqing Twin-City

Economic Circle has been tasked with cultivating internationally competitive advanced manufacturing clusters and building a new growth pole in Western China, making its technological evolution paths and collaborative innovation mechanisms both representative and practically urgent.

Within clusters, collaborative innovation has become an important lens for explaining technological progress and capability restructuring. On the one hand, new generations of digital technologies—such as blockchain—are considered able to reconstruct the foundations of trust and collaboration in manufacturing, thereby improving the efficiency and traceability of cross-firm and cross-regional collaborative innovation [4]. On the other hand, the Triple Helix model and the open innovation paradigm emphasise that institutional arrangements and open organisational boundaries among universities, industry and government are key to building regional innovation ecosystems and fostering knowledge co-creation [5-6]. Building on this, prior research shows that structural characteristics of inter-organisational cooperation networks—such as the position in structural holes, tie strength and network embeddedness—have a significant impact on the quantity and quality of innovation outcomes and technological breakthroughs [7]. At the scale of urban agglomerations, the degree of collaborative innovation has been used to explain spatial disparities in high-quality regional economic development; empirical evidence suggests that cross-city flows of innovation factors, knowledge and technology are an important mechanism underpinning the high-quality development of city-regions [8]. At the same time, the use of points-of-interest (POI) data and machine learning methods to depict the evolving spatial patterns of manufacturing in major Chinese urban clusters further reveals the internal links between industrial agglomeration, innovation networks and spatial structure [9]. However, existing studies largely remain at the level of "collaboration intensity–economic performance" statistical correlations. They pay relatively little attention to how collaborative innovation shapes the internal technological evolution paths of clusters over time, and still lack dynamic identification based on fine-grained technological data.

From the perspective of innovation outcomes, simply counting patent numbers is insufficient to reveal the substantive process of technological upgrading in clusters. It is necessary to consider the position and role of high-quality technological outputs within knowledge networks. From the perspective of "intellectual capitalism", Granstrand systematically demonstrates the foundational role of patents in technological progress, industrial upgrading and welfare enhancement [10]. Patent-based studies indicate that disembodied knowledge flows diffuse across industrial clusters through citations, co-applications and other channels, and constitute a key driving force for regional technological upgrading and follow-on innovation [11]. On this basis, high-value patents have gradually emerged as a crucial bridge linking micro-level innovation activities with meso-level industrial evolution. International organisations and scholars have constructed patent quality indicator systems from multiple dimensions—such as citation frequency, patent family size, maintenance duration and technological breadth—to measure the technological and economic value of patents [12]. Meanwhile, machine learning and ensemble learning methods have been introduced into high-value patent identification, where multidimensional feature pre-screening and model training significantly improve the accuracy and interpretability of identifying high-value patents [13]. However, most existing work still focuses on "how valuable a patent is in itself", and less often situates patents in the context of regional clusters and collaborative innovation networks to answer "which high-value patents constitute the technological backbone of cluster evolution and exert amplified effects through collaboration networks".

The theory of technology path evolution provides an important dynamic analytical framework for understanding these issues. Meyer and Schubert integrate path dependence and path creation into a unified framework, arguing that technological evolution manifests both as cumulative improvements along existing trajectories and as path-breaking at critical junctures, jointly constituting the generation and reshaping of technological paths [14]. Building on this, research on technological paths increasingly emphasises the shaping roles of institutional environments, market demand and industrial structure. In parallel with theoretical advances, main path analysis based on citation networks has gradually become a classic tool for depicting the main lines of technological development. Epicoco, for instance, uses main path analysis in the context of semiconductor miniaturisation to demonstrate how to identify the key chains of technological evolution and sources of leadership within a complex knowledge network [15]. Park and Magee propose a knowledge-persistence-based main path approach that traces technological development trajectories and patterns using patent citation data, providing a visual representation of the evolution of complex technological systems [16]. Overall, main path analysis offers an effective tool for extracting a "small number of decisive technological paths" from a "large number of dispersed patents". However, there is still limited research that systematically embeds this method into an integrated analytical framework encompassing "advanced manufacturing clusters–collaborative innovation networks–high-value patents".

Synthesising the above literature, three main gaps can be identified. First, studies on advanced manufacturing clusters have clearly revealed their crucial role in the intelligent, green and service-oriented transformation of manufacturing [1-3]. Yet they largely focus on industrial structure upgrading, spatial distribution and policy environment, and pay insufficient attention to how collaborative innovation within clusters shapes the main lines and branches of technological evolution over time. Second, methods for identifying high-value patents have become increasingly sophisticated in terms of indicator systems and modelling techniques [12-13], but are seldom embedded in the context of regional clusters and collaborative networks. It therefore remains difficult to identify "under what forms of collaboration, and which high-value patents become the key nodes driving cluster technology path upgrading". Third, although technology path evolution and main path analysis have been validated in several typical technological fields [14-16], systematic research on the technological evolution paths of advanced manufacturing clusters in newly emerging national-level urban agglomerations in Western China is still relatively scarce—especially empirical studies that integrate collaborative innovation networks, high-value patents and path evolution.

Against the dual backdrop of national strategies for coordinated regional development and the construction of the Chengdu–Chongqing Twin-City Economic Circle, this region is forming advanced manufacturing clusters represented by electronic information, intelligent equipment and automotive industries. Compared with mature urban clusters in Eastern China, the Chengdu–Chongqing region exhibits a dual characteristic of "rapid catching-up" and "path reconstruction" in terms of factor agglomeration, innovation capability and network structure, raising new practical questions about technology path evolution driven by collaborative innovation. Accordingly, this paper takes advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle as its research object. On the basis of identifying high-value patents, it constructs a patent citation network and applies main path analysis to identify collaborative innovation technology main paths and their stage-wise evolution characteristics. The study focuses on answering three questions: (1) Has a recognisable collaborative innovation technology main path already formed within advanced manufacturing clusters in the Chengdu–Chongqing region? (2) Which high-value patents act as "hub nodes" in the evolution of these paths, influencing subsequent technological diffusion through knowledge spillovers and collaboration networks? (3) Under the impetus of digital technologies and open collaboration, how do technologies within the cluster achieve coupling, divergence and recombination across different subfields?

Compared with existing research, the marginal contributions of this paper are as follows. First, from the perspective of "high-value patents–knowledge networks–technology main paths", it integrates three strands of literature—high-value patent research, collaborative innovation networks and technology path evolution—to provide a more explanatory analytical framework for understanding the upgrading mechanisms of advanced manufacturing clusters. Second, within the context of a newly emerging national-level urban agglomeration in Western China, it systematically depicts the collaborative innovation technology paths of advanced manufacturing clusters in the Chengdu–Chongqing region based on nearly ten years of patent data, offering empirical evidence on how latecomer regions can achieve technological path upgrading through collaborative innovation. Third, from a policy and practical perspective, the findings are expected to provide targeted implications for cultivating new quality productive forces, optimising the spatial layout of advanced manufacturing clusters, and building regional collaborative innovation platforms in the Chengdu–Chongqing Twin-City Economic Circle.

2. RESEARCH METHODS AND DATA

2.1. Definition of High-Value Patents

In patent data analysis, accurately assessing the technological value of individual patents is a key step in identifying core technologies and innovation capabilities within clusters. The technological value of patents is reflected not only in the innovativeness of their technical solutions and market application potential, but also closely associated with their stability and advancement within the technological system.

On this basis, this paper constructs a multi-indicator comprehensive scoring system covering seven dimensions: citations made, citations received, technological advancement, technological stability, grant status, patent type, and degree of cooperation. Among them, citations made and citations received, as key indicators measuring the contribution and integration capacity of patent knowledge, have been widely used in high-value patent identification and demonstrate strong representativeness and explanatory power. Referring to patent value evaluation models and weight settings proposed by relevant technical standards alliances, this paper determines the weights of each indicator and proposes the scoring indicator system as shown in Table 1.

Table 1. Indicator System for Scoring High-Value Patents

Scoring Indicator	Description	Standardization Method	Weight
Citations received	Indicates the spillover impact and recognition of patent knowledge	$\frac{\log(1+x_i)-min}{max-min}$	0.25
Citations made	Indicates the depth of integration into existing technologies and technological complexity	$\frac{\log(1+x_i)-min}{max-min}$	0.20
Technological advancement	Indicates the novelty and frontier nature of the technology	Divided by 10 and standardized to 0–1	0.15
Technological stability	Indicates the maturity and implementability of the technology	Divided by 10 and standardized to 0–1	0.15
Grant status	Indicates whether the patent has legal validity and can be commercially transferred	Granted = 1, Not granted = 0	0.10
Patent type	Invention patents are superior to other types and represent higher innovation quality and entry barriers	Invention = 1, Others = 0	0.10
Degree of cooperation	Multiple applicants reflect collaborative innovation and higher likelihood of technological diffusion	Multiple applicants = 1, Single applicant = 0	0.05

After standardizing the raw data, we calculate the comprehensive technological value score of each patent using a weighted sum method, and then rank all patents by this score to identify patents with relatively high value. Given that patent value in practice typically exhibits a Pareto-like distribution or “80/20 rule,” that is, a small number of core patents carry the majority of technological and economic value, and that citations received also follow this pattern, this paper defines the top 20% of patents by comprehensive score as high-value patents.

2.2. Patent Citation Network and Main-Path Analysis

Network graphs are important tools for revealing the relational structure of complex systems. They can intuitively present multidimensional relationships among individuals or entities in a graphical way and have been widely used in social science, information science, technological innovation, and other fields. Their basic components are "nodes" and "edges," representing network elements and their relationships, respectively. Nodes are the basic units of a network, representing individuals, objects, or entities, whose specific meanings vary according to the research object. For example, in social networks, nodes can represent individuals, organizations, or groups; in scientific cooperation networks, they correspond to researchers or institutions.

Edges represent relationships between nodes and can be divided into directed and undirected edges, describing directional or symmetric relationships. In the patent citation network constructed in this paper, nodes represent patents and edges are directed, indicating citation relationships in which one patent cites another, thus revealing inheritance and evolution logic in technology transmission, knowledge diffusion, and innovation paths.

To further analyze technological innovation trends, this paper applies main-path analysis to the patent citation network to identify core patents and critical knowledge paths that lead technological development. Mainstream algorithms for main-path analysis include Search Path Count (SPC), Search Path Node Pair (SPNP), and Network of Evolving Technological Paths (NETP), among others. Among these, the SPC algorithm is one of the most commonly used classical algorithms in main-path analysis.

The SPC method, based on the patent citation network, systematically traverses all possible paths in the network, records how many times each edge is passed by different paths, and computes the SPC value of each edge. The SPC value essentially measures the importance of an edge as a channel for information or knowledge transmission in the entire network; the higher the value, the more central the edge is in the process of technological flow. By sorting all edges in the network in descending order by their SPC values, we can identify edges that serve as key hubs in knowledge transmission and construct main paths accordingly.

Subsequently, by extracting the nodes (i.e., key patents) connected by these critical edges, we reconstruct one or more paths that represent the main lines of technological evolution and thereby uncover the core direction and stage-wise breakthroughs in technological development.

2.3. Data Acquisition and Processing

The data used in this study are obtained from the IncoPat patent database. The retrieval period is from 31 October 2014 to 31 October 2024, and the geographic scope covers all granted patents in advanced manufacturing in the Chengdu–Chongqing Twin-City Economic Circle. A total of about 90,000 patents is finally collected.

These patents cover multiple key sub-fields such as automobile manufacturing, electronic information, equipment manufacturing, and new materials. Their technological classifications span major IPC categories such as B, H, and G, which are high-frequency categories in manufacturing, indicating that the data have good industrial coverage and professional representativeness. At the same time, there exist numerous citation relationships among patents, reflecting vibrant technological inheritance and frequent knowledge flows in the region and providing a solid foundation for analyzing technological evolution and main innovation paths.

Furthermore, the data contain a large number of patents co-applied by multiple inventors, and enterprises, universities, and research institutes all occupy significant shares, indicating an emerging trend of industry–academia–research integration. This further enhances the representativeness of the sample in reflecting actual technological innovation activities in advanced manufacturing within the region. Therefore, in terms of technological field coverage, knowledge association structure, and composition of innovation actors, the data are highly aligned with the needs of this study for technological evolution analysis of advanced manufacturing in the Chengdu–Chongqing Twin-City Economic Circle.

To ensure the integrity of the patent network structure and the scientific validity of the analysis results, we perform cleaning and screening of noise information in the raw data during preprocessing. Noise data mainly include invalid patents, outdated data, and patents for which effective citation relationships cannot be established. In particular, patents in the examination stage are excluded because they have not yet been formally granted, and their technical solutions, innovation level, and legal status remain unstable, making it difficult to accurately reflect their real technological value. Thus, we remove patents under examination to improve the accuracy and reliability of the analysis.

In addition, patents with both zero citations made and zero citations received are excluded, as they do not participate in any effective citation relationships and cannot be incorporated into the construction and analysis of the patent citation network.

3. RESULTS

3.1. Identification of Main Technological Paths

After screening high-value patents, this paper constructs a high-value patent citation network based on their citation relationships and applies the SPC (Search Path Count) algorithm for main-path analysis. By calculating SPC values of network edges, we identify a number of key patents with relatively high SPC values and reconstruct the main technological paths.

The results show that advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle have formed two major technological evolution paths, each reflecting the evolutionary trajectory of a core technological direction within the cluster. Based on the citation relationships within sub-paths, we visualize these paths and generate main-path network graphs that reflect the technological evolution of the cluster, as shown in Fig.1 and 2. In these figures, nodes represent main-path patents, and node size and color depth correspond to degree; the higher the degree, the larger and darker the node, indicating its centrality in technological evolution.

As shown in Fig. 1, the main technological path includes 13 patents such as “Task offloading and resource allocation method for vehicular networks based on 5G mobile edge computing,” “Joint optimization method for task offloading and resource allocation based on 5G mobile edge computing,” “Joint optimization method for task offloading and resource allocation based on mobility awareness,” “Task offloading method for mobile edge computing based on independent learning,” and “Task offloading and resource allocation scheme based on MEC.” These patents mainly focus on MEC environments and use various intelligent optimization strategies to improve task offloading efficiency and resource allocation performance in vehicular networks and smart terminals, emphasizing coordinated solutions in energy consumption control, delay optimization, and overall system performance. This technological direction is named “Task Offloading and Resource Optimization Technologies in Mobile Edge Computing (MEC) Environments.”

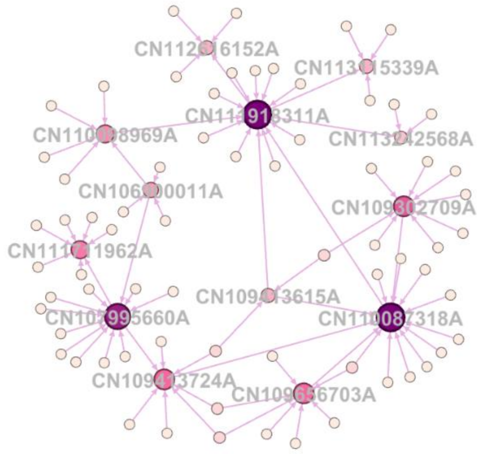

Figure 1. Task Offloading and Resource Optimization Technologies in MEC Environments

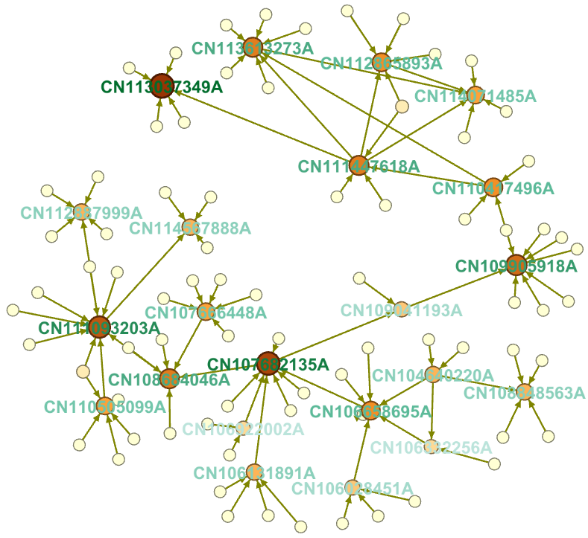

Figure 2. Energy-Efficiency-Oriented Intelligent Resource Allocation Technologies for 6G

As shown in Fig. 2, the other main technological path covers 22 patents such as “Energy-efficiency-based robust resource allocation method for cognitive NOMA networks,” “Energy-efficiency-maximizing resource allocation method for intelligent reflecting surfaces in secure communication,” “Energy-efficiency optimization method for intelligent reflecting surfaces in secure communication with imperfect channels,” “Environment-aware low-cost intelligent deployment method for service function chains,” “Random-learning-based deployment method for access network service function chains,” “Adaptive virtual resource allocation method for network slicing based on NOMA,” and “Internal-auction-based virtual resource allocation method for network slicing.”

These patents mainly target key 6G scenarios and focus on energy-efficiency-aware and robust optimization issues under new architectures such as NOMA, intelligent reflecting surfaces (IRS), service function chains (SFC), and network slicing. By constructing physical-layer security mechanisms, jointly modeling imperfect channels, and introducing game theory and reinforcement learning methods, they design low-latency, high-energy-efficiency, and high-reliability intelligent resource scheduling strategies for complex dynamic environments. This technological direction is named “Energy-Efficiency-Oriented Intelligent Resource Allocation Technologies for 6G.”

In summary, the technological evolution of advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle mainly shows two path characteristics: (1) a MEC-based vehicular network task offloading and resource optimization path that highlights efficiency collaboration and intelligent optimization in MEC environments; and (2) an energy-efficiency optimization technological system oriented toward 6G network architectures that emphasizes intelligent resource allocation and robust control across multiple scenarios and objectives. Together, these two paths constitute the core technological evolution routes of advanced manufacturing clusters in the region.

3.2. Keyword Frequency Analysis

Based on the two main paths obtained from the patent main-path analysis above, patent topic keywords were extracted from the corresponding patent abstracts and their term frequencies were counted, yielding the keyword frequency table shown in Table 2.

Table 2. Keyword Frequency Table

T1 Keyword	T1 Frequency	T2 Keyword	T2 Frequency
Task offloading	22	Resource (power) allocation	34
Latency	19	Channel (subchannel)	27
Minimization	17	Latency	18
Resource allocation	14	Data rate	17
Computing resources	12	NOMA	16
Joint	10	Service function chain deployment	14
Energy consumption	10	Dynamic adjustment	13
Total overhead	9	Network slicing	11
Power	9	Phase-shift matrix	9
Scheduling	8	Virtualization	9
Mobile edge computing	8	Communication system	8
Optimization	8	Intelligent reflecting surface	8
Subtask	8	Access network	8
Algorithm	5	Mobile communication technology	7
Mobile device	5	UAV	7

Based on the analysis of Table 2, “task offloading and resource optimization technologies in Mobile Edge Computing (MEC) environments” push computing and storage resources to the network edge, effectively reducing data-transmission latency and significantly enhancing the processing capability of mobile devices. In this context, task offloading has become a key technology for improving mobile computing performance. An analysis of patent abstracts shows that “task offloading” and “latency” are the most frequently occurring keywords, appearing 22 and 19 times, respectively, indicating that how to offload computation tasks effectively and optimize latency in MEC environments is at the core of technical research. In addition, “resource allocation” (14 occurrences) and “computing resources” (12 occurrences) highlight how to allocate limited computing resources appropriately within MEC systems. When mobile devices face heavy computational loads, task offloading can transfer computation tasks to edge nodes or the cloud, which not only prevents device overload but also helps minimize energy consumption and total overhead. Therefore, how to use intelligent algorithms for dynamic resource scheduling and task assignment to improve offloading efficiency and reduce latency is a key challenge for this technological theme.

An analysis of the keyword frequencies for the technological theme “energy-efficiency-optimized intelligent resource allocation for 6G” indicates that 6G networks will place higher demands on bandwidth and latency, particularly in intelligent manufacturing, the Internet of Things, and autonomous driving, making efficient utilization of network resources especially important. In the frequency table, “resource (power) allocation” (34 occurrences) and “channel (subchannel)” (27 occurrences) are the two most frequent keywords, suggesting that in 6G multi-user, multi-channel environments, optimizing resource allocation—especially power allocation—will be a core issue. Meanwhile, the occurrence frequencies of keywords such as "virtualization" and "network slicing" show that 6G resource management will no longer be confined to traditional physical infrastructures; instead, it needs to leverage virtualization and network slicing technologies to enable flexible resource scheduling and energy-efficiency optimization. Intelligent Reflecting Surface (IRS) technology thus becomes an important tool for achieving efficient resource allocation.

3.3. Keyword Evolution Analysis

For the core patents identified above, keywords were extracted and analyzed to examine their evolution. Through a systematic analysis of the overall technology main path, this study further clarifies the core technological development directions of the advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle. Based on the key patents covered by the main path, a keyword evolution analysis was conducted, as shown in Fig. 3.

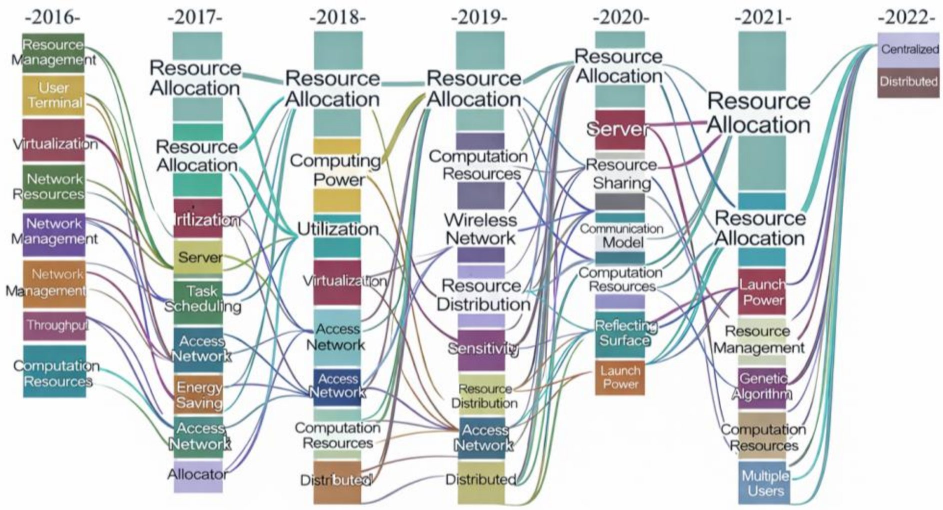

Figure 3. Keyword evolution along the technology main path

From Fig. 3, we can see that the main technological paths of advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle were relatively simple prior to 2016, focusing mainly on basic resource management. With the introduction of technologies such as edge computing and artificial intelligence, paths began to bifurcate around 2018, expanding into multiple directions including task scheduling, network scheduling, and data fusion.

The period from 2019 to 2020 marks an acceleration of integration, during which technologies related to device interconnection and control coordination were intertwined, promoting the transformation of clusters toward "intelligent manufacturing + digital interconnection." After 2021, evolution gradually converged into an intelligent optimization system centered on resource and task allocation, and by 2022, it had developed into a closed-loop system with intelligent control as the core. Resource allocation runs through the entire process—from basic research to technological applications and system integration—and plays a crucial supporting role at every stage.

4. DISCUSSION

4.1. Analysis of Conclusions

Existing research on technological path evolution of industrial clusters focuses mainly on mechanism analysis, innovation network construction, and the evolution of technological knowledge systems. Scholars have explored path dependence versus path creation, co-evolution, and networked innovation to reveal the complex mechanisms by which technological path evolution is jointly influenced by organizational collaboration, regional environments, and institutional factors.

However, most studies concentrate on specific industries such as new energy vehicles and low-carbon technologies, and regional studies often emphasize industrial clusters in coastal developed regions, such as empirical analyses of innovation network evolution paths in Guangdong's industrial clusters. Special studies focusing on technological path evolution of advanced manufacturing industry clusters are still relatively scarce. Existing work often nests advanced manufacturing within broader industrial cluster frameworks and lacks in-depth analysis of features particular to advanced manufacturing, such as accelerated technological iteration and cross-chain collaborative innovation.

Notably, in the Chengdu–Chongqing Twin-City Economic Circle—a national strategic region—although advanced manufacturing industry clusters have taken shape, relevant research remains largely at the level of macro policy analysis. Systematic research on the internal evolution of technological paths, stage characteristics, and technological integration and bifurcation within clusters is still weak.

In this study, therefore, we use high-value patent citation information from advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle to analyze technological path evolution in depth, focusing specifically on technological integration and bifurcation within advanced manufacturing clusters in the region. Based on the research questions posed in the introduction, we derive the following conclusions:

(1) Advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle exhibit collaborative innovation technological evolution paths. These paths are mainly reflected in two core fields: "Task Offloading and Resource Optimization Technologies in MEC Environments" and "Energy-Efficiency-Oriented Intelligent Resource Allocation Technologies for 6G." During technological evolution, these fields show a gradual progression from basic theories to complex applications, with trends such as intelligentization, multi-objective optimization, and dynamic adaptation, and their technological development trajectories are stable and clear. Among them, "resource allocation" acts as a key node throughout the entire evolution process, forming a core mechanism driving innovation collaboration and fully reflecting the clustering advantages and clarity of paths in the intelligent transformation of advanced manufacturing in the Chengdu–Chongqing region.

(2) The technological paths of advanced manufacturing industry clusters in the Chengdu–Chongqing region demonstrate significant integration and bifurcation trends. Since 2018, with the implementation of national policies such as "Made in China 2025" and "Industrial Internet," multiple key technologies within clusters—such as edge computing, artificial intelligence, and network collaboration—have been continuously integrated, driving a shift from automation to intelligentization. In particular, between 2019 and 2020, under local policy guidance, deep integration between manufacturing resources and digital technologies accelerated the evolution of branch technologies such as task scheduling and device interconnection.

Starting in 2021, technological paths further converged toward energy saving, efficiency, and autonomous collaboration, gradually building an intelligent manufacturing system centered on "task allocation–resource optimization." By 2022, overall technological paths tended to converge, reflecting a maturing pattern of technological evolution under policy support and regional collaboration. This maturity endows clusters with the capability to guide coordinated regional development and participate in global industrial restructuring.

Compared with existing research on advanced manufacturing in the Chengdu–Chongqing Twin-City Economic Circle, this study differs in the following aspects. First, with respect to research objects, this study focuses on technological path evolution from the perspective of high-value patents in advanced manufacturing, while existing studies mostly focus on the firm level and lack systematic portrayals at the regional cluster level. Second, with respect to research methods, this study introduces patent citation network analysis and main-path identification to systematically reconstruct technological evolution processes. In contrast, existing research mainly uses factor analysis, regression modeling, and spatial econometric methods. Third, this study not only focuses on the main trunks of paths but also identifies key technological nodes and bifurcation paths, revealing internal mechanisms of technological integration and bifurcation in advanced manufacturing clusters in Chengdu–Chongqing.

4.2. Policy Recommendations

As global industrial competition intensifies and technological paradigms continue to evolve, the high-quality development of advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle requires a more systemic, differentiated, and forward-looking policy system. Based on the collaborative evolution characteristics identified in this study, we propose the following three policy recommendations.

(1) Focus on Resource Optimization as the Main Line and Build an Intelligent Manufacturing Collaborative Innovation Chain

In light of the collaborative evolution paths found in task allocation and resource optimization, we recommend taking “precise configuration of resource factors” as the core policy line and promoting efficient linkage along intelligent manufacturing innovation chains. First, according to differences in industrial bases and functional positioning between Chengdu and Chongqing, a “differentiated collaboration” mechanism should be established: Chengdu focuses on algorithm optimization and technological sourcing, while Chongqing focuses on equipment manufacturing and industrial hosting. This can promote spatial coupling and collaborative division of labor along the industrial chain. Second, relying on major scientific and technological infrastructures and national-level development zones, manufacturing scenario innovation pilot zones should be built, focusing on key technologies such as MEC-based edge intelligence, resource scheduling, and network slicing, and establishing factory-level platforms for testing, iteration, and diffusion.

(2) Guide Multi-Technology Fusion Paths and Build Cross-Chain Collaborative Innovation Systems

This study reveals that technological paths in advanced manufacturing clusters in the Chengdu–Chongqing region have shown multi-directional integration and stage-wise bifurcation under policy incentives, particularly with significant technological integration after 2018. In line with these evolution characteristics, we recommend building organizational and resource systems for cross-chain technological collaboration. Specifically, a multilateral collaboration mechanism centered on “chain-leading enterprises + multi-chain alliances” should be established. Leading enterprises should be encouraged to form innovation consortia with universities, research institutes, and SMEs around technological integration nodes to promote multi-technology coupling in key fields. Governments can establish “technology integration guidance programs” focusing on bottleneck segments, common platforms, and cross-scenario collaboration problems, and support integrated research on heterogeneous technologies such as artificial intelligence, industrial software, and edge intelligence. Meanwhile, multi-chain collaboration technological roadmaps and phased evaluation mechanisms should be developed to strengthen visualization, dynamic management, and strategic intervention of evolution paths, gradually building a regional “technology integration ecosystem.” This approach can improve the organizational efficiency and resource allocation capability of multi-chain collaboration within clusters and accelerate the transition from dispersed exploration to convergent integration, thereby strengthening the adaptive capacity and systemic innovation capabilities of advanced manufacturing clusters in the Chengdu–Chongqing region in relation to future manufacturing systems.

(3) Deepen Industry–Academia–Research Integration Mechanisms and Consolidate the Regional Innovation Base

To support continuous evolution and high-quality upgrading of cluster technological paths, efforts should focus on building deeply integrated industry–academia–research systems grounded in real-world scenarios and problem orientation.

We recommend using regional leading enterprises and high-level universities as dual cores to establish collaborative innovation platforms integrating technological R&D, talent cultivation, and technology transfer, so as to overcome disconnections between university research and enterprise needs. Governments can promote the establishment of "application-oriented" joint laboratories, engineering research centers, and demonstration platforms. These should focus on fields such as edge computing, resource scheduling, and intelligent sensing, and provide intermediate support from original innovation to pilot testing.

In terms of mechanisms, multiple industry–academia–research collaboration models, such as dual-supervisor systems, enterprise-defined research topics in universities, and joint problem-solving teams, should be explored to enhance talent cultivation and research organization. At the same time, a "technology transfer incentive fund" can be set up to reward teams that successfully commercialize key technologies, thus mobilizing the enthusiasm of all actors. By optimizing policy incentives, organizational structures, and resource allocation, a collaborative innovation ecosystem covering the whole process and full chain can be built, providing strong talent and knowledge support for technological path evolution in advanced manufacturing clusters in Chengdu–Chongqing.

In sum, advancing the high-quality development of advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle requires coordinated efforts along three dimensions: collaborative innovation paths, technological integration mechanisms, and industry–academia–research ecosystems. First, resource optimization should be taken as the main line to construct an intelligent manufacturing innovation chain with clear division of labor and efficient collaboration between Chengdu and Chongqing, consolidating the internal logic of cluster technological evolution. Second, in response to trends of multi-technology integration and path bifurcation, cross-chain collaborative research systems should be built to improve organizational capacity for complex technological integration and systemic innovation. Third, deep integration of industry, universities, and research institutes should be strengthened, and whole-process support systems from original innovation to pilot testing should be improved, smoothing key links in innovation chains and stimulating regional indigenous innovation vitality.

These three recommendations are mutually reinforcing and jointly constitute a policy pathway that supports sustainable technological evolution and enhanced global competitiveness of advanced manufacturing clusters in the Chengdu–Chongqing region.

5. CONCLUSION

As an important engine of modern economic development, advanced manufacturing industry clusters are of unquestionable importance. Although advanced manufacturing clusters in China have grown substantially in scale, they still face the challenge of "low-end lock-in." Meanwhile, the Chengdu–Chongqing region, as a key growth pole for high-quality development in Western China, has been largely overlooked in academic research on this topic.

In this context, this study constructs a patent citation network based on nearly ten years of patent data from advanced manufacturing in the Chengdu–Chongqing Twin-City Economic Circle, and excavates the technological path evolution mechanisms of collaborative innovation in advanced manufacturing clusters in the region, exploring technological integration and bifurcation under cross-domain collaborative innovation. The main findings are as follows:

(1) Advanced manufacturing industry clusters in the Chengdu–Chongqing Twin-City Economic Circle exhibit collaborative innovation technological evolution paths. These paths evolve from basic theories toward complex application scenarios and show characteristics such as intelligentization,

multi-objective optimization, and dynamic adaptation. Resource allocation runs through the entire process of technological evolution and plays a critical role at every stage.

(2) Under the background of cross-domain collaborative innovation, the technologies of advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle undergo both integration and bifurcation, and this process is highly consistent with regional policies.

Based on the above analysis, this study proposes three policy recommendations: (1) focus on resource optimization as the main line and construct intelligent manufacturing collaborative innovation chains; (2) guide multi-technology fusion paths and build cross-chain collaborative innovation systems; and (3) deepen industry–academia–research integration mechanisms and consolidate the regional innovation base.

By using patent citation analysis, this study conducts an empirical examination of the technological evolution paths of advanced manufacturing clusters in the Chengdu–Chongqing Twin-City Economic Circle. The findings provide theoretical support for improving the regional technological innovation system and promoting industrial transformation and upgrading, and offer practical policy suggestions.

However, there are also limitations. First, the study relies primarily on patent citation data, which may overlook technological innovation activities in non-patent forms and thus introduce some bias into the analysis. Second, the selected patent data cover only the past decade. Although they include all patents in advanced manufacturing in the region during this period, they can only reflect short-term technological evolution. For longer-term technological path evolution, this time span is still insufficient to fully reveal trends and patterns of technological development. Future research will further broaden data sources, extend the time horizon, and strive to provide more comprehensive and in-depth analyses.

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