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The evolution of the cold chain logistics vehicle routing problem: a bibliometric and visualization revie

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Abstract

This paper uses the bibliometric analysis software CiteSpace to examine the current status and evolution of cold-chain logistics vehicle routing problems (CCVRP). 7381 relevant articles published in the Web of Science core collection from 2008 to 2024 were analyzed, an in-depth understanding of the publication trends and category distribution were gained. Subsequently, CiteSpace was used to create a scientific knowledge graph and perform visualization analysis. The analysis includes collaboration among authors, countries, and institutions; co-citation analysis of authors, journals, and references; citation burst detection of keywords; and co-citation cluster analysis of references. Based on a deep understanding of current research hotspots, an in-depth discussion of existing research was conducted from three perspectives: optimization objectives, distribution scenarios, and solution algorithms. The results show that CCVRP involves complex factors such as temperature requirements, time window constraints, and multi-objective optimization. These intricate constraints are causing research to become increasingly interdisciplinary and comprehensive. The evolution of hot topics shows that the research directions span multiple fields, from algorithm design to logistics management. This review helps researchers better understand the history, current status, and future development directions of CCVRP research, and provides valuable references and inspiration for academia and practice.

Keywords: Cold chain logistics; Vehicle routing; Carbon emissions; Optimization objective; Solution algorithm

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Introduction

In today's growing logistics industry, cold chain logistics has become an important link in ensuring the quality and safety of perishable goods such as food and medicine. However, the efficiency and cost management of cold chain logistics are often challenged by logistics vehicle route planning. The cold chain logistics vehicle routing problem has thus emerged, and its evolution and research history demonstrate the continuous attention and exploration of logistics efficiency and resource utilization. As a key supply chain management field, cold chain logistics aims to keep the goods at a low temperature throughout the distribution process to ensure the freshness and quality of the products. In this field, the cold chain logistics vehicle routing problem has always been the focus of attention because it is directly related to transportation efficiency, cost control, and the safety of goods. With the development of the logistics industry and the continuous advancement of technology, the cold chain logistics vehicle routing problem has also been evolving and escalating. To better understand this evolution process, this paper conducts a comprehensive bibliometric and visualization review to trace the development trajectory of the cold chain logistics vehicle routing problem research.

The research on cold chain logistics vehicle routing problems has a long history. The initial focus was mainly on optimizing static route planning, with the goal of reducing transportation costs and time. As shown in Fig. 1, cold chain logistics has expanded to many aspects of social production and transportation. With the continuous expansion of logistics networks and the diversification of customer needs, the research focus has gradually shifted to dynamic route planning, considering real-time traffic conditions, climate change and other factors to ensure the safety and timely delivery of goods. However, the cold chain logistics vehicle routing problem also faces many challenges and evolutions. Traditional route planning methods often fail to effectively cope with complex environmental changes and uncertainties, resulting in inefficiency and waste of resources. In addition, with the acceleration of urbanization and the improvement of environmental protection awareness, the demand for reducing traffic congestion and reducing carbon emissions is becoming increasingly urgent, which poses new challenges to the research on cold chain logistics vehicle routing problems.

In the past few decades, scholars have conducted extensive and in-depth research on the cold chain logistics vehicle routing problem. This research explores the challenges of multi-objective optimization, time window constraints, temperature control, etc., and solves these problems by introducing intelligent algorithms and optimization models. At present, the research on the cold chain logistics vehicle routing problem shows a trend of diversification and integration. Traditional methods are mainly based on mathematical optimization models, such as vehicle routing problem (VRP) and dynamic path planning (DVRP), and the optimal route is obtained through algorithmic solution. Desrochers & Verhoog[1] discovered a hybrid vehicle routing model; Solomon & Desrosiers introduced the concept of service time window in VRP

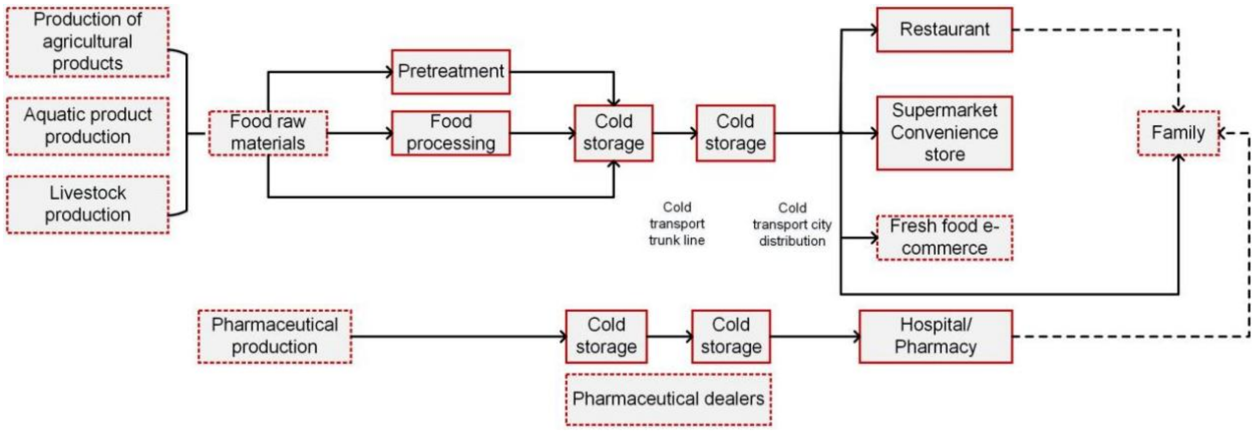

Fig. 1 Cold chain logistics production and transportation route map.

research[2] ; Jabali et al.[3] considered the penalty cost based on the restriction of service time window, and proposed a soft time window VRP model; Moghaddam et al.[4] considered the demand uncertainty factor in the VRP model; Cattaruzza et al.[5] discussed the vehicle routing problem of multiple trips. There are also many research results on VRP model algorithms: for example, precise algorithms include the branch and bound method proposed by Laporte et al.[6] the dynamic programming algorithm studied by Righini & Salani[7], and the cutting plane method proposed by Kallehauge[8] and others. Heuristic algorithms include the saving algorithm[9], the two-stage algorithm[10] , and the taboo search algorithm[11]. However, these methods often ignore the impact of real-time information and environmental changes on route planning, resulting in unsatisfactory results in actual applications.

In contrast to traditional methods, modern methods have emerged, including intelligent route planning systems based on artificial intelligence (AI) and big data technologies. These systems can monitor factors such as traffic conditions and climate change in real-time, and combine historical data for prediction and optimization, thereby improving the accuracy and flexibility of route planning. Traditional methods focus on the precise solution of mathematical models and algorithms, and their advantages lie in their solid theoretical foundation and strong interpretability. However, when faced with complex actual situations, it is often difficult to fully consider various uncertainties, resulting in unstable results and difficulty in real-time adjustment. In contrast, modern methods are based on big data and AI technology and are more adaptable and real-time. They can adapt to environmental changes and changes in demand through continuous learning and optimization, improving the flexibility and adaptability of route planning.

Considering these broad objectives leads to more complex optimization problems and inspires more variants applicable to various real-world application scenarios. To fully understand the current state of research in this particular area and to determine the significance of the present work, a summary of previous review papers on the vehicle routing problem in cold chain logistics was compiled and ranked by their relevance as retrieved by WOS. This summary is listed in Table 1, which provides the publication year, information on the research, WOS category, research method, time-span, and the number of articles it reviewed.

Through the review of the above review papers, it can be found that most of the existing research adopts content analysis and system analysis methods. Therefore, this paper systematically combs the research literature in related fields through bibliometric methods to reveal the main trends and hotspots of the research. The visual review section will show the key nodes, development paths, and academic cooperation relationships in the research field through charts and graphics. In this way, we will be able to see the overall pattern of research on cold chain logistics vehicle route issues more clearly and provide guidance for future research.

The contributions of this paper are: first, compared with other studies that only focus on certain aspects of the cost problem, the scope of the study of cold chain logistics routes is broader. Second, the article uses bibliometric methods and visualization software to conduct in-depth analysis, including exploring the development stage of the field, analyzing the countries, authors, and journals that have made significant contributions, analyzing the evolution of topics based on keywords, and exploring research hotspots based on the co-citation network of literature. Finally, the article discusses future trends in a quantitative way, which is a valuable supplement to the subjective conclusions limited by the author's knowledge.

The following sections of this paper will introduce the data source collection and processing process in turn, and present the results of the bibliometric analysis. Next, the differences in cost quantification methods and constraint settings in cold chain logistics vehicle routing optimization will be analyzed from the perspectives of objectives, problem scenarios, and solution algorithms. In addition, the solution algorithms of different models will be classified, and the applicability of various algorithms under different optimization objectives and problem scenarios will be compared. Finally, the full article will be summarized and future research directions will be prospected.

Data collection and research methods

To systematically and comprehensively review and analyze the literature related to the cold chain logistics vehicle routing problem, the original literature database of this paper comes from the Web of Science Core Collection. The reasons for choosing the Web of Science Core Collection for bibliometric analysis are as follows: (1) The Web of Science Core Collection has covered 18,000 high-quality leading journals in different

Table 1. Summary of review articles on cold chain logistics vehicle routing issues.

Publication	Year	Scope (WOS)	Methodology	Time span	Count
Li et al.[12]	2023	GVRP	Bibliometric analysis	2000–2021	166
Pillac et al.[13]	2013	DVRP	Content analysis	1995–2013	154
Qin et al.[14]	2019	VRP-CSC	Systematic analysis	1983–2018	53
Ostermeier et al.[15]	2020	MCVRP	Content analysis	1981–2020	89
Koç et al.[16]	2016	HVRP	Content analysis	1981–2015	137
Kucukoglu et al.[17]	2021	EVRP	Systematic analysis	2001–2021	165
Sar & Ghadimi[18]	2023	RLVRP	Bibliometric analysis	1959–2022	109
Erdelic & Carić[19]	2019	EVRP	Content analysis	1959–2018	175
Braekers et al.[20]	2016	VRP	Systematic analysis	2009–2015	309
Zhang & Van Woensel[21]	2022	DVRPRR	Systematic analysis	1980–2022	185
Asghari & Mirzapour Al-e-hashem[22]	2021	GVRP	Systematic analysis	2000–2020	313
Li et al.[23]	2022	VRP-LBO	Content analysis	1959–2020	212
Ni & Tang[24]	2023	VRP	Bibliometric analysis	1955–2022	209
Demir et al.[25]	2014	GVRP	Content analysis	1996–2013	118
Mardešić et al.[26]	2023	SDVRP	Content analysis	1957–2022	180

fields since 1900, with a total citation count of 1.3 billion[27] . (2) The present research focuses on visual analysis of authors, journals, countries, institutions, keywords, references, etc. The Web of Science Core Collection not only covers a series of metadata related to this information, but also outputs it in a recognizable format for direct reading through CiteSpace. (3) Due to duplication of literature, using other databases such as Google Scholar and Scopus would also produce fairly similar results[28] . Therefore, it may not be necessary to consider various databases at the same time in this paper. The data was first generated by performing a basic search in the Web of Science (WOS) Core Collection, setting the time span from January 2000 to January 2024 and obtaining 55,298 articles containing the keywords 'vehicle routing problem', 'cold chain logistics', 'vehicle routing optimization', 'electric vehicle routing', 'transportation cost', 'carbon emission', and 'models and algorithms'. Thus, a preliminary database was formed for subsequent analysis based on these 55,298 records.

Data processing and results

The existence of duplicate documents in the database is inevitable. To improve the credibility of the analysis results, the 55,298 documents were imported into the software CiteSpace 6.3.R1 (64-bit) and duplicate documents removed. At the same time, the time interval in CiteSpace was set to 2008 to 2024 (this is because the publication year of the documents included in the WOS core started in 2008), the year of each slice was set to 1, and the top 10 high-frequency nodes were selected from each slice. That is, Top N = 10. In order to reduce waiting time and simplify the network structure, the Pathfinder pruning method in CiteSpace was used when generating different visualization graphs. According to the above data processing procedures, a total of 7,381 unique documents were obtained, including 4,606 articles, 137 reviews, 2,528 conference papers, and 110 online publications. Figure 2 shows the detailed information of each type. From the results of Fig. 2, it can be seen that 4,606 articles account for 62% of the entire sample size and other types of documents account for 38% of the total. Of course, these filtered 7381 documents published between 2008 and 2024 were considered for the subsequent bibliometric analysis.

Basic statistical results of the Web of Science

Temporal evolution of publications and citations

An article and other studies that cite it can provide information about the influence and importance of the article in the academic community. Information such as the author, affiliation, and research field reflects the author's background and professional field. Through this information, we can understand the topic of the article, the author's identity, the research region, the reputation and academic level of the publishing journal, etc. In addition, through keyword and citation analysis, we can also understand the research hotspots and trends in the field, as well as the connection and impact of related research results.

The time series distribution of research papers and their citations can reflect the research status and trends of a certain research topic in a specific period. Figure 3 shows the number of publications related to cold chain logistics vehicle routing issues and their citations between 2008 and 2024. In the past 16 years, the number of publications and citations have increased significantly, indicating that research on this issue is receiving increasing attention. It can be observed from Fig. 3 that from 2008 to 2014, the number of publications was in a slow growth stage, always staying below 400, and even showed a downward trend in 2010, which indicates that the research attention at this stage was relatively limited. From 2015 to 2022, the number of publications gradually increased, reaching a peak of 836 articles in 2022, ranking second in history in terms of citation frequency. From 2008 to 2023, the number of citations has been on an upward trend. Although the number

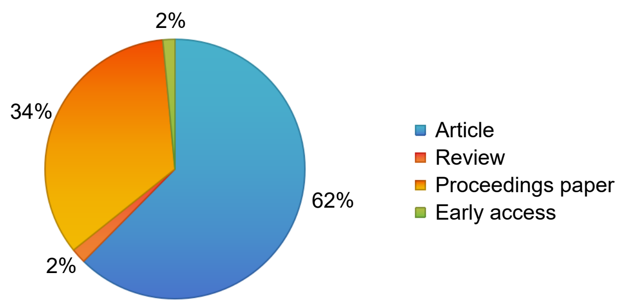

Fig. 2 Literature types in CCVRP research.

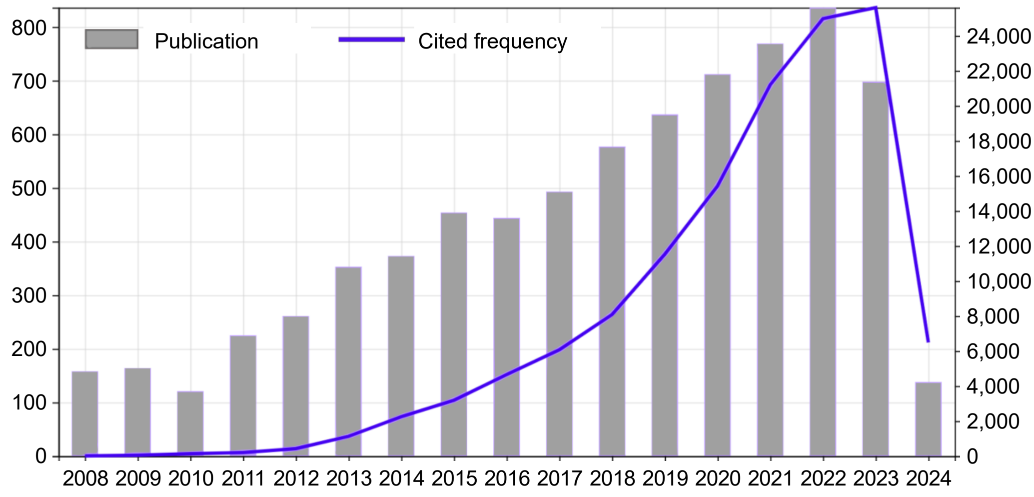

Fig. 3 Distribution of publications and citation records from 2008 to 2024.

of publications has declined in 2023, the number of citations has reached a historical high of 25,606 times. Therefore, a decrease in the number of publications does not necessarily lead to a decrease in citation frequency. Comparing the data in 2017 and 2024, although the number of publications in 2017 was about three times that in 2024, the number of citations was almost the same at about 6,600 times, which shows that people still maintain interest in this field.

Category distribution

Table 2 lists the top 10 subject categories in the PDP field from 2008 to 2024. It should be stated in advance that in the records exported by Web of Science, a publication may belong to multiple different subject categories, which results in the number of papers in Table 2 exceeding the sample size and the sum of the percentages exceeding 100%.

As shown in Table 2, the first and second most relevant categories are 'Operations Research and Management Science' and 'Computer Science and Artificial Intelligence'. Among them, 'Operations Research and Management Science' ranked first with 2749 papers, accounting for 37.07% of the total number of publications; 'Computer Science and Artificial Intelligence' ranked second with 1487 papers, accounting for 20.05% of the sample size. The third place is 'Engineering Electrical and Electronics', which shows that the main purpose of this research is to solve complex management and engineering problems in the real world. Moreover, in recent years, with the advent of the big data era and the development of artificial intelligence, the scope of this research has expanded to 'Transportation Science and Technology' and 'Interdisciplinary Applications of Computer Science', which also indicates that the research analysis framework is highly adaptable and widely applicable. Based on the remaining five categories shown in Table 2, we can further conclude that this research has gradually become interdisciplinary and highly comprehensive.

Table 2. Distribution of the top 10 categories in CCVRP research.

No.	Web of Science category	Count
1	Operations Research Management Science	2749
2	Computer Science Artificial Intelligence	1487
3	Engineering Electrical Electronic	1214
4	Computer Science Interdisciplinary Applications	1123
5	Engineering Industrial	1084
6	Computer Science Theory Methods	956
7	Transportation Science Technology	918
8	Computer Science Information Systems	707
9	Management	637
10	Transportation	531

Visualization results and bibliometric analysis based on CiteSpace

Analysis of authors and cited authors

In this section, bibliometric and visual analysis of authors and cited authors was conducated by setting the node types to 'author' and 'cited author' in CiteSpace respectively. The purpose of author analysis is to find the scholars who publish the most papers and show the collaborative relationship between different scholars in research. Generally speaking, the more papers he or she publishes, the stronger the ability to accelerate the development of this research. The results of the cited author analysis can not only help us identify scholars with the highest academic level and academic influence, but also sort out the complex co-citation relationships between authors. After running the software, the main results obtained are the author's collaboration network diagram and co-citation network diagram, as shown in Figs 4 & 5, respectively. Table 3 lists and compares the distribution of the top 10 highly published authors and highly cited authors.

Figure 4 consists of 239 nodes and 203 links, where each node represents an author and each link represents a collaboration between two authors. The density value of the entire network is 0.0069, which indicates that the research directions of these authors are relatively scattered and there are few connections and collaborations between them. Combined with the results in Table 3, it is obvious that Juan is the most prolific author, having published 83 papers, mainly focusing on the application of business analytics, optimization, simulation, and artificial intelligence in computational transportation and logistics, production and manufacturing, computational finance and insurance, and smart cities. Wang is the second most prolific author, and is also the only Chinese author who has published more than 60 papers. His research areas are

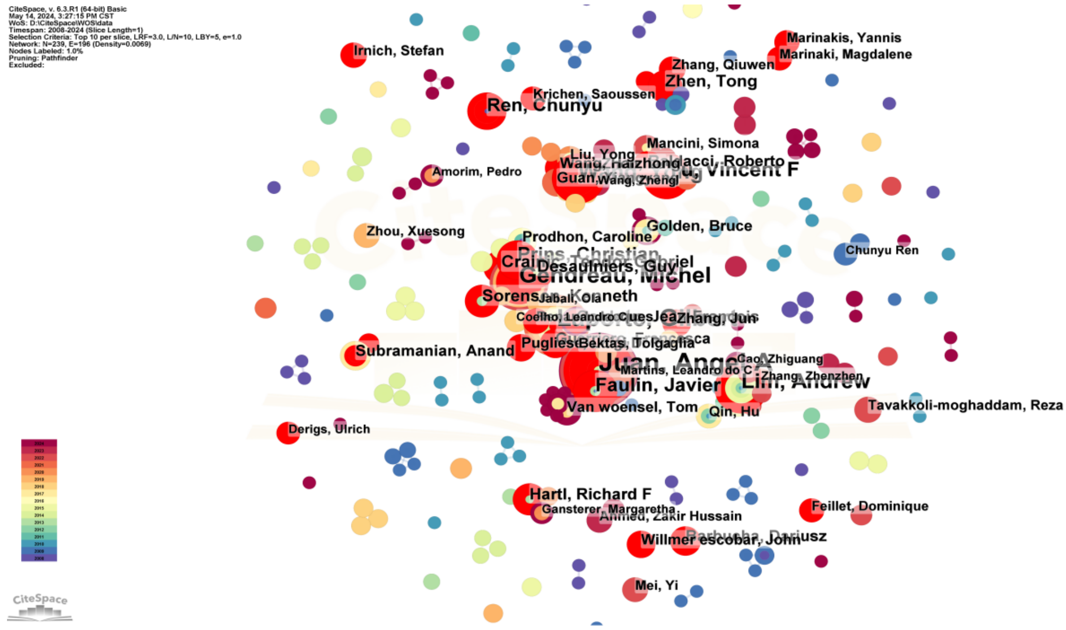

Fig. 4 Collaboration network diagram of CCVRP research authors.

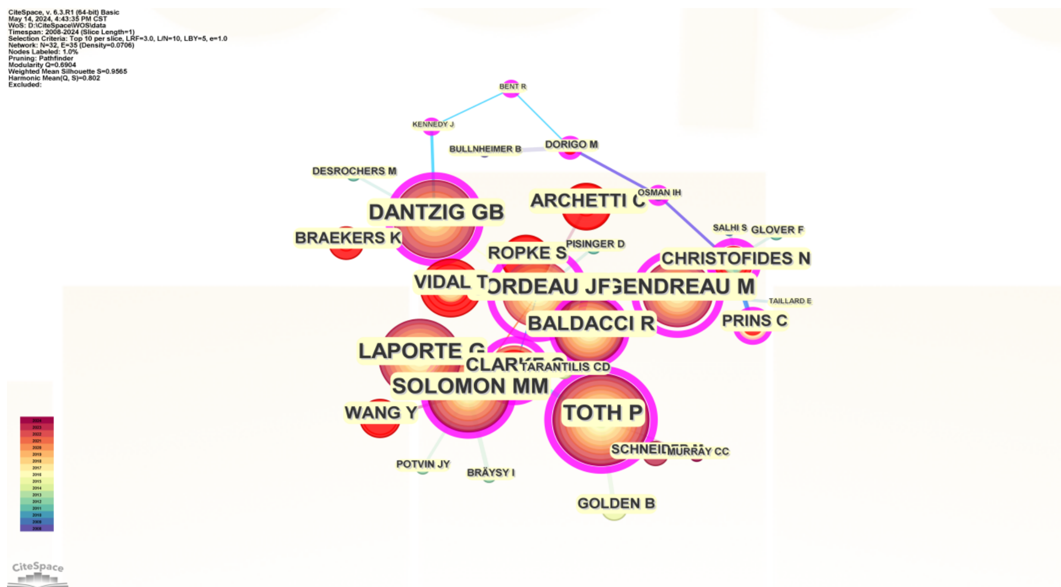

Fig. 5 Co-citation network of CCVRP research authors.

Table 3. Top 10 most published and most cited authors in the study.

No.	Highly published authors			Highly cited authors		
	Author	Count	7,416 percentile	Author	Count	Half-life
1	Juan AA	83	1.119	Dantzig GB	1443	10.5
2	Wang Y	69	0.93	Solomon MM	1282	10.5
3	Laporte G	63	0.85	Door G	1457	9.5
4	Gendreau M	50	0.674	T oth P	1628	9.5
5	Lim A	45	0.607	C oreau JF	1097	8.5
6	Zhang J	42	0.566	Gendreau M	1197	8.5
7	Li J	39	0.526	Clarke G	564	7.5
8	Zhang ZZ	39	0.526	B aldacca R	848	6.5
9	Van Woensel T	38	0.512	C hristofides N	261	4.5
10	Yu VF	38	0.512	Prins C	156	4.5

mainly focused on logistics and transportation, vehicle routing problems, and intelligent transportation systems. His outstanding work[29] formulated the PDP with split loads and time windows as a mixed integer programming problem (MILP) and proposed a mixed integer programming problem (MILP). Laporte[6] is the first author and is a famous Canadian operations researcher and logistics expert. He is well-known for his research in combinatorial optimization, vehicle routing problems (VRP), and logistics and transportation problems. He first proposed the concept of DARP and designed a taboo search heuristic algorithm to solve it. An interesting phenomenon is that among the top 10 prolific authors, Chinese authors account for as much as 50%, and the top 10 prolific authors have published more than 30 papers.

Figure 5 shows the co-citation relationship between two authors, which means that their articles are cited together by another article written by a third author. Figure 5 contains a total of 32 nodes and 87 links. Table 3 lists the top 10 highly cited authors according to their citation half-life. Authors who publish a large number of articles are not necessarily the authors with a large number of citations. Highly cited authors are usually regarded as the most advanced and influential scholars in a certain field, and their papers and works are necessary references and studies for beginners interested in this research. The first one is Dantzig[30] , who was one of the pioneers in the field of linear programming and operations research. His most famous contribution is the invention of the simplex method, which has led to a wide range of scientific and technological applications in important problems such as logistics, scheduling, and network optimization, as well as the effective use of mathematical theories using computers. Solomon[2] was the second most cited author, he was a well-known scholar in the field of optimization, scheduling, and supply chain management, famous for his research on vehicle routing problems and logistics management. Solomon designed a set of famous benchmark problems (Solomon's benchmark problems) for evaluating and comparing different VRP algorithms. These benchmark problems have become the standard reference in the VRP research field.

Another noteworthy phenomenon is that Laporte is the only scholar who is both a high-publishing and highly cited author, which also means that his academic contributions have been widely recognized by his peers in PDP research. Gendreau's[31] paper publication ranks fourth, but his citation half-life ranks sixth. Specifically, from 1996 to 2024, Gendreau's papers in this field were cited 1,197 times, and many scholars from different institutions have worked closely with him, such as Coreau, Taillard, and Christofides, Coreau, and Christofides ranked 5th and 9th respectively.

Analysis of cited journals

To have a clearer understanding of the research directions involved, CiteSpace was used to draw a co-citation network diagram of the journals in the CCVRP research, as shown in Fig. 6, which consists of 21 nodes and 49 links. Table 4 lists the top 10 highly cited journals and their basic information. Among them, the European Journal of Operations Research ranks first among the highly cited journals, with 5,787 citations, a centrality of 0.86, and an impact factor of 6.4. That is, the European Journal of Operations Research is an important journal that must be paid attention to in the field of cold chain logistics vehicle routing problems. 'Optimization for dynamic ride-sharing: 'A review'[32], 'Dynamic pickup and delivery problems'[33], and 'Heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries'[34] are the most cited papers published in the *European Journal of Operations Research*. The second is *Computers & Operations Research*, with 5,338 citations and an impact factor of 4.7. The journal has published 1,204 articles in the past four years, with an average citation rate of 8.355 (OOIR) per article. One of the most cited papers is 'Vehicle Routing Problem: An Overview of Exact and Approximate Algorithms' by Laporte[35], published in 1992. This paper has a high citation rate in the field, reflecting its importance in the study of vehicle routing problems. The third is Transportation Science, with 4,157 citations and an impact factor of 5.1. It is mainly based on theory, supplemented by observation and experimental research on traffic phenomena. The article entitled 'An Adaptive Large Neighborhood Search Heuristic for Pickup and Delivery Problem with Time

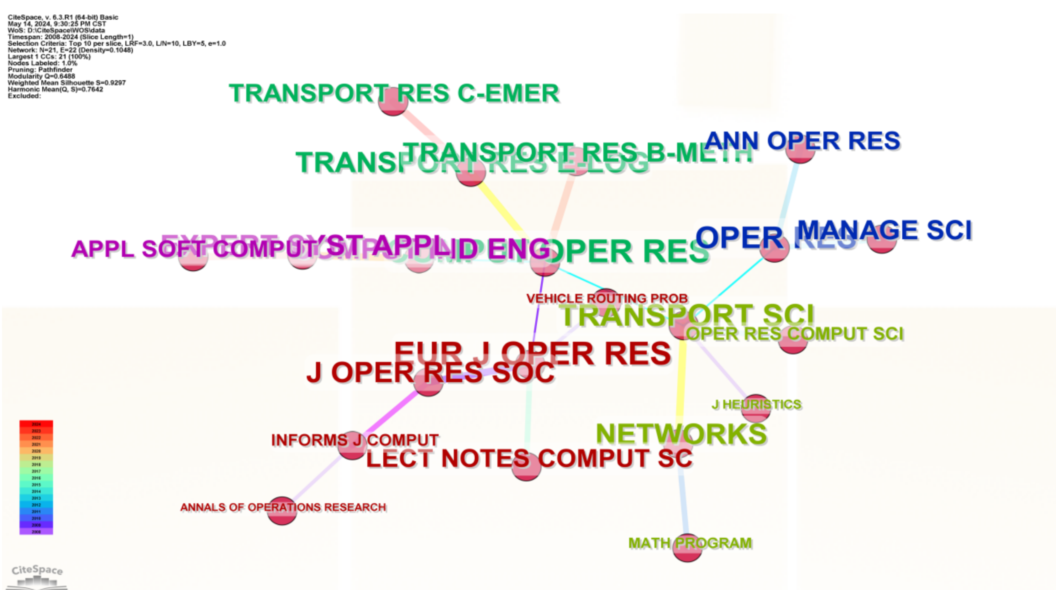

Fig. 6 Network diagram of co-citations of CCVRP research journals.

Table 4. Top 10 CCVRP research journals with the highest citations.

No.	Citation	Centrality	SSCI/SCIE	Journal title	Count	7,416 percentile	Five-Year Impact Factor
1	5787	0.86	SCIE, Q1	*European Journal of Operational Research*	330	4.45%	6.4
2	5338	1.51	SCIE, Q1	*Computers & Operations Research*	321	4.33%	4.7
3	4154	1.14	SCIE, Q1	*Transportation Science*	149	2.01%	5.1
4	3947	0.39	SCIE, Q1	*Operations Research*	27	0.36%	4.6
5	2892	0.38	SCIE, Q1	*Computers & Industrial Engineering*	220	2.97%	4.3
6	2387	0.2	SCIE, Q1	*Expert Systems with Applications*	195	2.63%	6.9
7	2273	0.38	SCIE, Q2	*Journal of the Operational Research Society*	52	0.70%	2.6
8	2184	0.2	SCIE, Q2	*Networks*	85	1.15%	2.8
9	2053	0.2	SCIE, Q1	*Transportation Research Part E: Logistics and Transportation Review*	160	2.16%	4.0
10	1424	0	SCIE, Q1	*Transportation Research Part B: Methodological*	74	1.00%	5.6

Windows'[36] has the highest citation rate among the papers published in Transportation Science.

Considering the distribution of highly cited journals, CCVRP research results mainly focus on using optimization theory and combining methodologies from other professional fields to analyze managers' path selection behavior in real logistics situations. Moreover, the main scope of these journals coincides with the above categories, further proving that it is the intersection and combination of knowledge in diversified fields that has promoted the progress of research on cold chain logistics vehicle routing issues.

Country and institution analysis

To confirm the contribution and influence of each country/institution and better examine the mutual cooperation relationship between different countries/institutions, CiteSpace was used to perform country and institution analysis, setting the node type to 'country' and 'institution' respectively. First, the country collaboration network diagram is shown in Fig. 7, where each circle represents a country and each link represents the cooperation relationship between countries. Next, the institution collaboration network diagram is shown in Fig. 8, where each node represents a research institution and each link represents the cooperation relationship between two institutions. Tables 5 & 6 show the top 10 countries and the top 10 institutions in terms of publication volume from 2008 to 2024, respectively.

According to Fig. 7 & Table 5, China is the most productive country in the world, publishing 2,280 papers from 2008 to 2024, accounting for about 30.80% of the total number of published documents. Although China's CCVRP-related research work started later than in other countries, it has achieved rich results so far. Among them, Singapore and France have close academic cooperation with China. The United States is one of the countries that analyzed CCVRP earlier, ranking second with 796 publications. From the country composition in Table 5, except for China, Turkey, and Iran, other output countries are from Europe and North America, and the academic cooperation between countries is still weak and loose.

As shown in Table 6, three Chinese institutions (Beijing Jiaotong University, Huazhong University of Science and Technology, and Tsinghua University) are among the top 10 institutions with the highest number of publications, which is consistent with the conclusion that China ranks first among all countries . In terms of the number of publications, the University of Montreal in Canada ranks first in the world, with 252 publications, which is roughly equivalent to the total of 246 publications from the United Kingdom. However, the most influential institution is HEC Montreal in Canada. According to

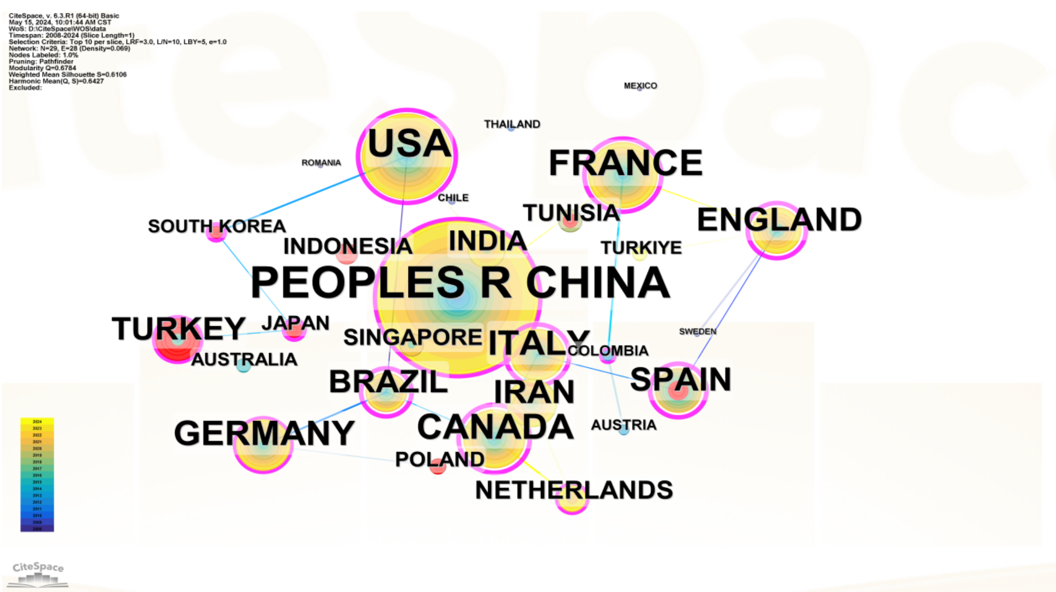

Fig. 7 CCVRP research cooperation network of various countries.

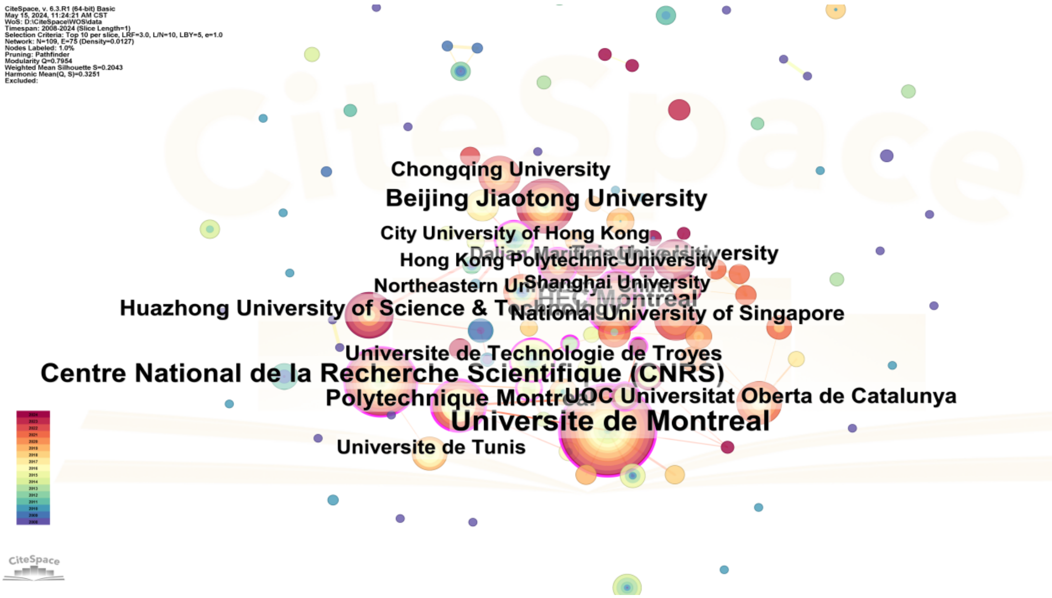

Fig. 8 CCVRP research institution cooperation network.

Table 5. The top 10 countries with the highest publication rates between 2008 and 2024.

No.	Count	Centrality	Year	Country
1	2280	0.36	2008	China
2	796	0.65	2008	USA
3	504	0.74	2008	France
4	428	0.93	2011	Canada
5	401	0.83	2008	Italy
6	344	0.13	2008	Germany
7	265	0	2009	Iran
8	262	0.81	2008	Spain
9	246	0.88	2009	England
10	215	0.13	2011	Turkey

Table 6. Top 10 institutions in terms of publication volume from 2008 to 2024.

No.	Count	Centrality	Year	Country	Institution
1	252	0.31	2008	Canada	Montreal University
2	153	0.19	2008	France	National Center for Scientific Research (CNRS)
3	94	0.02	2008	China	Beijing Jiaotong University
4	83	0.35	2011	Canada	HEC Montreal
5	74	0.25	2011	Canada	Polytechnique Montreal
6	64	0.04	2009	China	Huazhong University of Science & Technology
7	53	0.04	2009	Spain	UOC Open University of Catalonia
8	49	0.13	2008	France	University of Technology of Troyes
9	48	0.04	2008	China	Tsinghua University
10	47	0.08	2019	Singapore	National University of Singapore

the analysis of authors and cited authors above, we know that Cordeau's[37] research team is from the Montreal Institute of Technology and Laporte's[35] research team is from HEC Montreal. These two institutions are ranked 4th and 5th in terms of the number of publications, respectively. In fact, each top institution maintains cooperative relationships with other institutions. For example, in China, Huazhong University of Science and Technology's close partners include City University of Hong Kong, Shanghai Jiaotong University, and Henan University of Science and Technology. In addition, the University of Montreal has established extensive cooperative relations with more than 30 academic institutions, including Polytechnic University of Milan, Universidad de la Laguna, Laval University, Technical University of Munich, Mines Saint-Etienne, and University of Vienna. In addition, given that the overall density of the institutional cooperation network is only 0.0127, the breadth and depth of international cooperation in the academic community needs to be further strengthened.

From the perspective of collaborative networks, centrality is a crucial indicator that represents the central position of a node in the entire network. The larger the value of a node's centrality, the more nodes other nodes in the network must pass through when they connect. Specifically, the outermost color of the nodes in Figs 7 & 8 is used to measure their centrality. The closer to purple, the higher the centrality of the node, and the more critical the position of the country or institution in this study. As shown in Tables 5 & 6, countries or institutions with many publications do not necessarily have strong centrality. For example, although the United States is lower than China in the number of publications, its centrality is about 1.8 times that of China. Moreover, the sum of the centralities of all three Chinese universities in Table 6 (Huazhong University of Science and Technology, Beijing Jiaotong University, and City University of Hong Kong) is still smaller than the centrality value of the 8th-ranked Polytechnic Institute of Troyes, France. These all indicate to some extent that China and its institutions play a limited mediating role in the CCVRP study.

Another noteworthy example is Canada. Among the top 10 countries in Table 5, Canada ranks 4th in quantity but first in centrality. Among the top 10 institutions in Table 6, three are from Canada and all are in the top 5. The University of Montreal dominates in the number of publications, and the HEC Montreal dominates in global centrality. In other words, Canada and its institutions not only make great contributions to the number of publications, but also play an important 'hub' role in the cooperation network, connecting two different nodes, which is particularly worthy of attention.

Table 7 lists and compares the top 10 most productive countries and institutions over the past decade, which can better identify the emerging forces of CCVRP research. Obviously, even if we shorten the time interval to nearly ten years, China and the United States are still the top two countries in terms of the number of publications, and the HEC Montreal has maintained its central position in the network of institutional collaborations. Among the top 10 institutions in Table 7, universities from China (Huazhong University of Science and Technology, Beijing Jiaotong University, Chongqing University, and Tsinghua University) have published a total of 221 documents since 2011, which exceeds the number of publications published by the United Kingdom, Brazil, and Turkey. Combining the visualization results of Figs 7 & 8 with Tables 5 & 6, we can see that China, Canada, and the United States not only have a deep accumulation of professional knowledge, but also have strong academic innovation capabilities necessary to promote scientific and technological progress.

Keyword analysis

Keywords are considered as a high-level summary and refinement of the document content. In keyword analysis, the frequency of occurrence is an indicator of the core strength of keywords, and burst detection can be used to review the explosive research hotspots in various periods. In this section, keywords were collected from two streams: keywords given by authors and keywords plus. In particular, keyword analysis uses co-occurrence analysis and citation burst detection.

Keyword co-occurrence analysis

Co-occurrence analysis attempts to explore the relationship between research topics by calculating the frequency of two keywords appearing in the same document. Figure 9 shows the keyword co-occurrence network related to CCVRP research, where a total of 268 keywords were selected from 7,381 publications. In Fig. 9, each node represents a keyword, and each link between nodes represents their co-occurrence relationship. The larger the size of the node, the higher the frequency of the word.

Table 8 lists the top 20 keywords with the highest co-occurrence frequency. Among them, 'VRP' is the most important keyword, appearing 3,617 times with other related terms. Keywords related to 'VRP' include 'traveling salesman problem', 'system', 'time window', 'transportation', 'tabu search', 'vehicle routing', 'distribution' and 'cold chain logistics'. The second is 'algorithm', with a co-occurrence frequency of 1,573 times ,

Table 7. The top 10 most productive countries and institutions in the past decade.

No.	High-published countries			High-published institutions		
	Count	Centrality	Country	Count	Centrality	Institution
1	1847	0.55	China	209	0.64	University of Montreal
2	683	1.3	USA	126	0.42	Centre National de la Recherche Scientifique (CNRS)
3	424	0.97	France	77	0.05	Beijing Jiaotong University
4	374	0.85	Canada	64	0.51	Polytechnique Montreal
5	341	0.2	Italy	64	0.77	HEC Montreal
6	299	0	Germany	57	0	Huazhong University of Science & Technology
7	257	0	Iran	49	0.11	UOC Universitat Oberta de Catalunya
8	217	0.2	United Kingdom (UK, England)	47	0.2	National University of Singapore
9	196	0.37	Spain	44	0.05	Chongqing University
10	181	0	Turkey	43	0.11	Tsinghua University

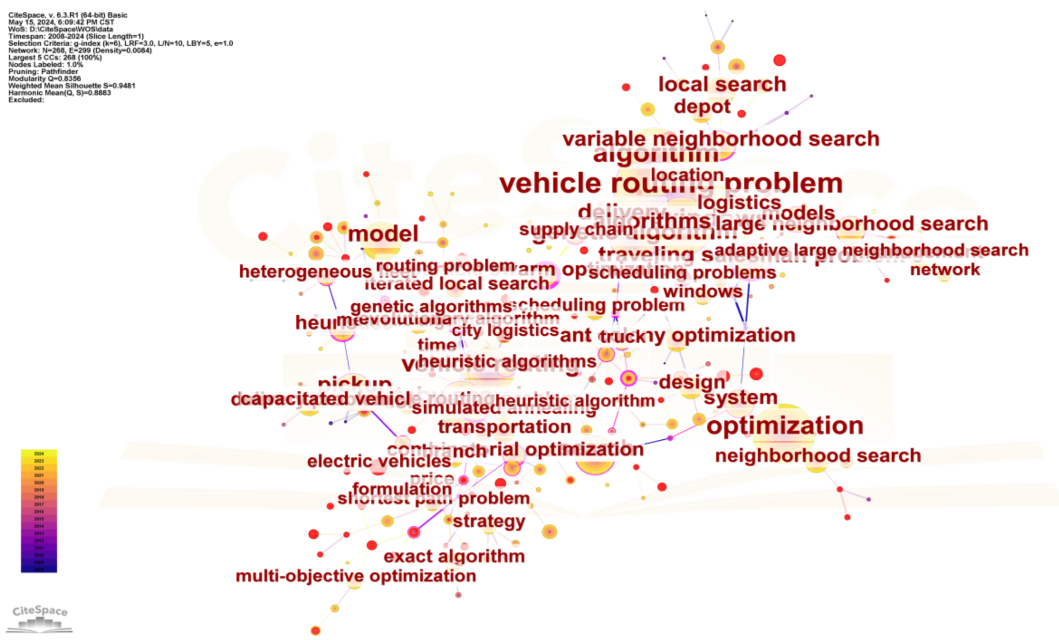

Fig. 9 Keyword co-occurrence network diagram in CCVRP research.

which is closely related to 'model', 'optimization', 'meta-heuristic', 'scheduling', 'tabu search', 'genetic algorithm', and 'particle swarm optimization'. In addition, based on the distribution of keywords in Table 8, we can further draw the following conclusions: (1) Scholars attach great importance to establishing mathematical models under realistic backgrounds and assumptions to study the relationship between routing selection and optimization. (2) Most of the research results of CCVRP involves designing algorithms and methods with high computational efficiency to ensure the computability of the formulated models and further obtain the optimal strategy for reference by logistics managers. (3) The most commonly used algorithms include genetic algorithms, taboo search, ant colony algorithms and other heuristic algorithms, which are also an important basis for proposing more innovative and better-performing methodologies.

Keyword citation burst detection

To reflect the historical development of research hotspots and highlight current research hotspots to inspire scholars to conduct follow-up research, we list the top 28 keywords with the strongest citation bursts in Table 9. Generally speaking, for a specific keyword, the longer the burst duration and the higher the burst intensity, the more people will pay attention to it within a certain period of time.

As shown in Table 9, 'tabu search' ranks first with a citation burst intensity of 33.9, starting in 2008 and ending in 2015. The second is the keyword 'vehicle routing', with a citation burst intensity of 23.95, starting in 2009 and ending in 2013. It is worth noting that reinforcement learning, deep reinforcement learning, and machine learning appeared in the keywords with a surge in citation bursts, starting in 2021 and ending in 2024. This also shows that new directions may have emerged in the research of CCVRP in recent years.

Emerging keywords such as 'last mile delivery', 'electric vehicle routing problem', 'reinforcement learning', 'deep reinforcement learning', 'carbon emissions', and 'machine learning' have become hot topics in recent years. Judging from the distribution of emerging keywords, the current hot topics are focused on solving more complex business needs involved in CCVRP. For example, Phiboonbanakit et al.[38] proposed a novel approach to a new vehicle route optimization model, using reinforcement learning interconnected with a tree-based regression model to create a reinforcement learning traffic environment. The reinforcement learning agent uses the previous environment state as experience to select appropriate actions to determine the current vehicle route by selecting the optimal strategy.

Table 8. Top 20 keywords with the highest co -occurrence frequency.

No.	Freq.	Centrality	Year	Keyword
1	3617	0.16	2008	Vehicle routing problem
2	1573	0	2008	Algorithm
3	1178	0.09	2008	Optimization
4	1137	0.12	2008	Time windows
5	815	0.04	2008	Vehicle routing
6	698	0.19	2008	Genetic algorithm
7	653	0.1	2008	Tabu search
8	594	0.08	2009	Model
9	562	0.13	2008	Search
10	506	0.03	2008	Delivery
11	485	0.46	2008	Traveling salesman problem
12	460	0.15	2009	Pickup
13	440	0.04	2008	Algorithms
14	365	0.23	2010	Variable neighborhood search
15	345	0.09	2009	Local search
16	305	0.19	2008	System
17	276	0.1	2013	Large neighborhood search
18	258	0.05	2008	Ant colony optimization
19	250	0.12	2011	Models
20	244	0.62	2008	Particle swarm optimization

Reference analysis

Reference co-citation is measured by the frequency with which two documents are cited together by other documents[39,40] . Generally speaking, the more times two documents are cited together by a third document, the more likely they are to be related in content and the more likely they are to be classified into the same cluster, which is also the principle of the co-citation cluster analysis below. Understanding the co-citation relationship between references helps us to master the knowledge base and review previous research frontiers in our research. References with high co-citation frequencies usually represent the most influential and prominent literature resources. Therefore, in the CCVRP research, the node type was set to 'reference' and CiteSpace was used to visualize the co-citation relationship between references to grasp the composition and historical development of the knowledge base.

Co-citation network analysis of references

As shown in Fig. 10, each node in the reference co-citation network represents a reference, and each line connecting two nodes represents the co-citation relationship between the two

Table 9. Top 28 keywords with a surge in citations between 2008 and 2024.

No.	Keywords	Year	Burst	BurstBegin	BurstEnd
1	Tabu search	2008	33.9	2008	2015
2	Vehicle routing	2008	23.95	2009	2013
3	Constraints	2008	22.83	2012	2018
4	Scheduling problems	2008	20.22	2008	2017
5	Genetic algorithm	2008	19.7	2008	2010
6	Reinforcement learning	2021	13.37	2021	2024
7	Last-mile delivery	2020	12	2021	2024
8	Vehicle routing problem	2008	11.58	2008	2010
9	Deep reinforcement learning	2022	11.39	2022	2024
10	Stochastic demands	2011	11.24	2016	2019
11	Bee colony algorithm	2019	10.33	2019	2021
12	Mathematical model	2019	10.29	2020	2021
13	Electric vehicle routing problem	2022	10.21	2022	2024
14	Shortest path problem	2011	10.16	2013	2015
15	Vehicle routing problems	2011	10.07	2011	2015
16	Multi-depot vehicle routing problem	2011	9.87	2011	2018
17	Approximation algorithms	2011	9.84	2011	2016
18	Resource constraints	2013	9.62	2013	2015
19	Hybrid	2019	9.53	2021	2024
20	Search problems	2020	9.49	2020	2022
21	Carbon emission	2022	9.44	2022	2024
22	Machine learning	2021	9.3	2021	2024
23	Energy consumption	2019	9.27	2022	2024
24	Column generation	2009	9.23	2013	2014
25	Fleet	2019	9.16	2021	2024
26	Task analysis	2022	9.01	2022	2024
27	Optimization model	2020	8.82	2020	2022
28	Tabu search algorithm	2011	8.72	2013	2016

references. The larger the radius of the circle, the more frequently the reference is cited. In addition, considering that the overall density of the co-citation network is only 0.0084, since the references contained in some academic papers may be from different disciplines, there may be few opportunities for co-citation between core references.

Table 10 lists the top 10 most cited papers in CCVRP research, sorted by citation frequency. For example, the top-ranked paper, 'The vehicle routing problem: State of the art classification and review'[20], provides a taxonomic review of VRP literature published between 2009 and June 2015. Based on an adapted version of an existing comprehensive taxonomy, 277 papers were classified and trends in VRP literature were analyzed. This classification is the first to classify papers to such a detailed level. Lin et al.[41] conducted an extensive literature review on the Green Vehicle Routing Problem (GVRP). They provided a taxonomy of GVRP, dividing GVRP into Green-VRP, polluted routing problem, and VRP in reverse logistics, and proposed research gaps between its state and richer models that describe the complexity of real-world cases.

The goal is to review the state of the art in GVRP, discuss how traditional VRP variants interact with GVRP, and provide insights into the next wave of GVRP research. Another study that extended the VRP was conducted by Sacramento et al.[43] . Although they were not the pioneers in studying the truck-drone problem, they proposed a new mathematical formulation for the problem, which is an extension of FSTP for multiple trucks, including capacity and time completion constraints, while minimizing cost as the objective function. They proposed an adaptive large neighborhood search (ALNS) metaheuristic method to solve the multiple truck problem. This algorithm represents a new method for two vehicles to cooperate in planning routes.

Although the optimal solution is difficult to obtain, some researchers have reformulated CCVRP as a special optimization model and adopted an exact algorithm that matches the model structure to cope with the computational difficulties. In contrast, Hiermann et al.[44] combined exact algorithms with heuristic algorithms and introduced the electric fleet size and mixed vehicle routing problem with time windows and charging stations (E-FSMFTW) to model the decisions on fleet composition and actual vehicle routes (including the choice of charging time and location). To accurately define the problem, they provided a mathematical formulation of a MIP model and used a state-of-the-art branch and price algorithm designed specifically for VRPTW to solve a set of smaller instances to provide a benchmark for heuristic methods. Based on this, they proposed a metaheuristic method based on adaptive large neighborhood search (ALNS) with embedded local search and labeling procedures. There is an interesting phenomenon that Table 10 lists two highly cited papers related to the topic of 'electric vehicles'[44,45] and three highly cited papers related to the topic of 'unmanned aerial vehicles'[41,47,48] . 'Electric vehicles' and 'drone vehicles' are both hot topics in the current VRP field. It can be seen that in the co-cited literature, the research on vehicle routing problems related to cold chain logistics does not occupy an advantage.

Co-citation cluster analysis of references

Co-citation cluster analysis is an indispensable component of bibliometric research. First, the distribution of co-citation clusters usually represents the composition of a domain knowledge base, and the top terms contained in each cluster can be regarded as the research frontier of each knowledge field. In addition, analyzing the co-citation cluster results over the entire time range can help us correctly conduct time series analysis of the historical development of the knowledge system.

Based on the above reference co-citation network, the log-likelihood ratio (LLR) weighted algorithm was used in CiteSpace to generate and label co-citation clusters, and the characteristics of the top 15 largest clusters are listed in Table 11. As shown in Table 11, cluster labels are selected from keywords by running the LLR algorithm to ensure that the

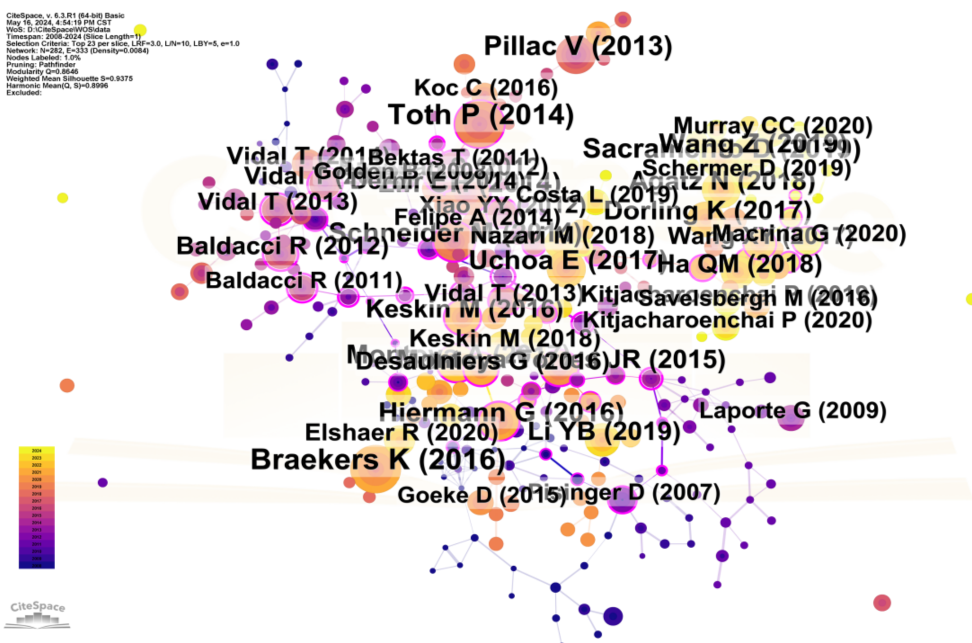

Fig. 10 Co-citation network of references in CCVRP research.

Table 10. The top 10 most cited references in CCVRP research.

No.	Article title	Author	Freq.	Journal title
1	The vehicle routing problem: State of the art classification and review	Braekers K (2016)[20]	181	*Computers & Industrial Engineering*
2	Vehicle Routing: Problems, Methods, and Applications	Toth P (2014)[42]	168	*Society for Industrial and Applied Mathematics*
3	Survey of green vehicle routing problem: past and future trends	Lin CH (2014)[41]	141	*Expert Systems with Applications*
4	An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones	Sacramento D (2019)[43]	124	*Transportation Research Part C: Emerging Technologies*
5	A review of dynamic vehicle routing problems	Pillac V (2013)[13]	122	*European Journal of Operational Research*
6	The electric fleet size and mix vehicle routing problem with time windows and recharging stations	Hiermann G (2016)[44]	116	*European Journal of Operational Research*
7	The electric vehicle-routing problem with time windows and recharging stations	Schneider M (2014)[45]	112	*Transportation Science*
8	New benchmark instances for the capacitated vehicle routing problem	Uchoa E (2017)[46]	112	*European Journal of Operational Research*
9	Vehicle routing problem with drones	Wang Z (2019)[47]	112	*Transportation Research Part B: Methodological*
10	Optimization approaches for the traveling salesman problem with drone	Agatz N (2018)[48]	107	*Transportation Science*

labels of each cluster have high uniqueness and coverage. Size refers to the number of documents grouped into the same cluster. Silhouette is used as a measure of the homogeneity or consistency level of clustering. When the silhouette score is higher than 0.7, the clustering results are reliable and convincing. The average value indicates the average citation year of the references included in a cluster. In Table 11, the silhouette scores of the top 15 largest clusters are all higher than 0.7, which indicates that the relevant results of the clustering analysis are of high quality and reasonable.

Different from the descriptive co-citation analysis in traditional bibliometric research, the timeline/time zone visualization of reference co-citation clusters in CiteSpace can more intuitively show the temporal distribution and historical evolution of knowledge fields. As shown in Fig. 11, the top of the timeline visualization shows the time when the reference was first cited, from 2008 to 2024. The right side of the timeline visualization shows the top 15 largest co-citation clusters. The references contained in a cluster are represented by nodes, which are distributed on the horizontal timeline according to the year of the first citation. The curve connecting two nodes represents the citation evolution path of the reference.

As shown in Table 11 & Fig. 11, the largest Cluster #0 (column generation) has 28 members and a silhouette score of 0.986. It mainly focuses on processing TSP. Traditionally, the Christofides algorithm plays an important role in TSP approximate solutions, ensuring that the solution is within 50% of the optimal solution. Recent research attempts to make breakthroughs on this basis. For example, the algorithm proposed by Karlin et al.[49] improves the solution for specific types of TSP instances (such as graph TSP) by using a random tree selection method. Quantum computing has shown great potential in solving TSP. Pirnay's[50] research team explored the application of quantum algorithms (especially Shor's algorithm) in solving TSP and found that quantum computing can reduce the computational complexity from exponential time to polynomial time.

Cluster #1 (delivery request) ranks second with 25 members. In the Cold Chain Logistics Vehicle Routing Problem (CCVRP), it is crucial to analyze the role and principle of delivery requests. This problem not only involves the complexity of the traditional vehicle routing problem but also needs to consider the special temperature requirements and time sensitivity in cold chain logistics. Based on the data of delivery requests,

Table 11. The top 15 largest reference co-citation clusters in CCVRP studies.

Cluster ID	Size	Silhouette	Label (LLR)	Average year
0	28	0.986	Traveling salesman problem	2019
1	25	0.98	Delivery request	2007
2	25	0.923	Split delivery vehicle	2007
3	22	1	Green vehicle	2013
4	21	0.948	Electric vehicle	2017
5	20	0.982	Path flexibility	2014
6	20	1	Electric vehicle	2016
7	20	0.9	Multi-depot vehicle	2005
8	19	0.965	Electric vehicle	2010
9	16	0.878	Electric vehicle	2013
10	15	1	Multiple stack	2008
11	13	1	Grain logistics vehicle	2005
12	13	0.892	Periodic location-routing problem	2004
13	11	0.879	Different traffic condition	2006
14	5	1	Neighborhood-based search heuristic	2010

optimization algorithms (such as genetic algorithms, ant colony algorithms, etc.) are used to plan the optimal path. These algorithms consider factors such as time windows, temperature requirements, delivery locations, and cargo priorities to generate efficient distribution plans. For example, Liu & Zhang[51] proposed a time window constraint for trapezoidal fuzzy membership functions based on the analysis of the characteristics of urban cold chain transportation. Based on whether the distribution center is out of stock and customer priority, the cold chain distribution path optimization was analyzed. A cold chain distribution path optimization model considering customer priority was constructed, and the improved genetic algorithm was used to solve the two scenarios of no out-of-stock and out-of-stock. Xu et al.[52] proposed a two-stage segmentation strategy based on multiple distribution centers and demand splitting based on the consideration of the impact of manufacturers joining the overall logistics distribution. This strategy comprehensively considers vehicle load capacity, mixed cargo restrictions and service time window constraints, provides services in multiple rounds, and fully considers factors such as vehicle driving distance, waiting time, and vehicle occupancy rate.

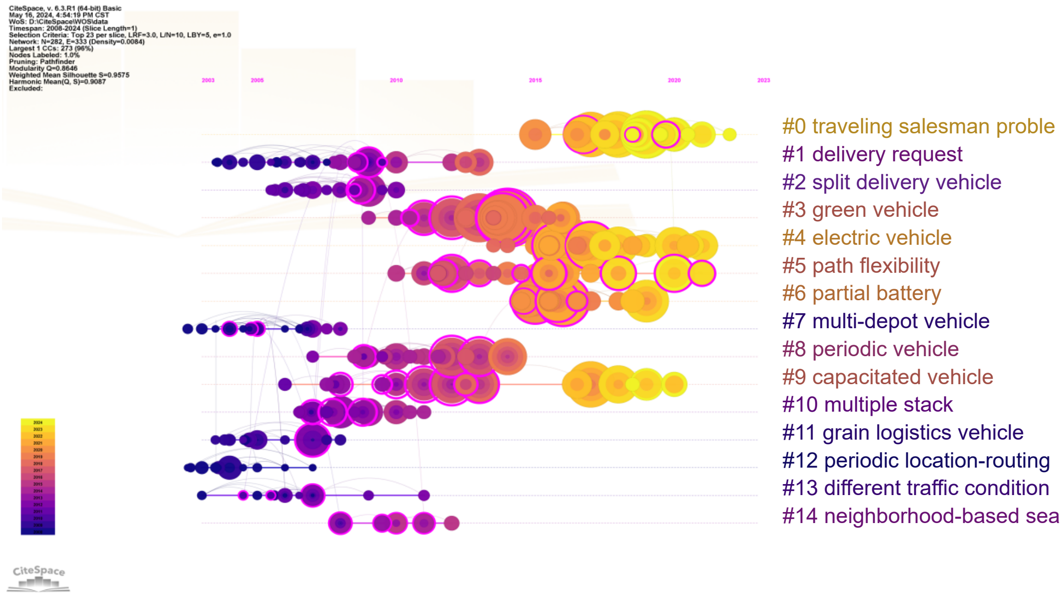

Fig. 11 Timeline view of the top 15 largest reference co-citation clusters.

Cluster #4 (electric vehicles) plays an increasingly important role in CCVRP. They not only help reduce transportation costs and environmental impact but also improve operational efficiency and service quality. Electric vehicles reduce costs in the cold chain logistics process. Modern electric cold chain vehicles are also equipped with efficient electric refrigeration systems that can continuously supply power while the vehicle is in motion to maintain the temperature conditions required for cold chain goods. Electric vehicle batteries can also continue to power refrigeration equipment when parked, avoiding temperature fluctuations caused by engine shutdown. However, the current range of electric vehicles is limited, and vehicle routing planning in cold chain logistics needs to take into account the location and charging time of charging stations. Combined with advanced routing optimization algorithms, it is possible to optimize charging arrangements while meeting cold chain transportation needs and maximize distribution efficiency. For example, Chen et al.[53] studied the cold chain green multi-station vehicle routing problem with time windows and mixed fleets (CC-GMD-VRPTW-MF) in urban logistics distribution, using electric vehicles (EVs) and gasoline and diesel vehicles (GDVs). To accurately evaluate energy consumption, a realistic energy consumption model was used. An improved Variable Neighborhood Search (VNS0) algorithm is proposed, which introduces a new equilibrium perturbation mechanism and a new memory-based local search mechanism to enhance the computational performance. Numerical studies are conducted on the newly designed CC-GMD-VRPTW-MF instance to investigate the effects of incorporating electric vehicles into joint delivery, considering different carbon prices, and adjusting the time window.

Cluster #13 (different traffic conditions) focuses on evaluating the negative impact of traffic congestion, road closures, accidents, and other uncertainties on the cold chain logistics cargo delivery process, such as time delays, increased fuel consumption and costs, increased routing complexity, and decreased service levels. The latest research is mainly reflected in two aspects: dynamic routing planning and the use of hybrid and electric vehicles. For example, the transportation route is adjusted based on real-time traffic conditions, and artificial intelligence and machine learning algorithms are used to predict traffic congestion and adjust the distribution plan. Zhao et al.[54] designed an electric vehicle routing problem (EVRP) model under time-varying traffic conditions to plan the itinerary of fresh products in the urban cold chain. The goal of the EVRP model is to minimize the total cost of logistics distribution, including economic costs and fresh value loss costs. To reflect the real situation, the EVRP model considers multiple influencing factors, including time-varying road network traffic, road type, customer time window requirements, freshness of fresh products, and queuing during charging. To solve the EVRP problem, an improved adaptive ant colony algorithm is designed. The algorithm also takes into account the charging station layout strategy based on the principle of minimum power consumption to solve the key problem of when and where to charge quickly during the layout process.

As the research content deepens, mathematical models with complex structures and multiple constraints put forward higher requirements for solution algorithms, and the scenarios in which precise algorithms can be applied are subject to certain restrictions. Therefore, scholars often use more powerful and efficient heuristic algorithms and meta-heuristic algorithms in CCVRP research. As can be seen from Fig. 12, Cluster #14 (neighborhood-based search heuristics) has undergone roughly 4 years of development, and references related to heuristics have been frequently cited in recent years. Neighborhood-based search heuristics are widely used in CCVRP, mainly used to optimize paths to meet the special needs of cold chain logistics. Neighborhood-based search methods find the optimal solution by continuously searching for adjacent solutions in the solution space. Specific methods include local search, simulated annealing, taboo search, and particle swarm optimization. These methods can effectively reduce transportation time and cost in CCVRP and ensure that goods are delivered within the specified time window. For example, considering multiple paths between two nodes and real-time traffic

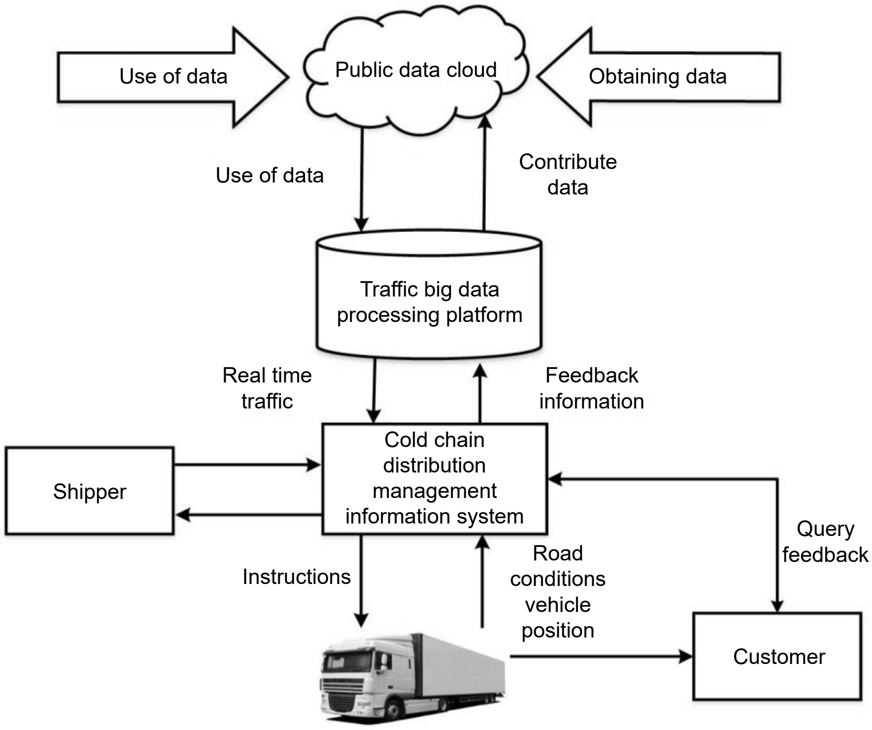

Fig. 12 Application of traffic big data in cold chain logistics distribution.

information on different paths, as well as cargo damage costs and refrigeration costs during the distribution process, Hou et al.[55] established a two-stage mixed integer programming model based on the idea of pre-optimization to minimize the total cost through real-time adjustment. A hybrid variable neighborhood chaotic genetic algorithm was designed to solve the model. The pseudo-randomness of the chaotic system was introduced into the algorithm to ensure the diversity of the initial solution and an adaptive neighborhood search number strategy was introduced to take into account the breadth and depth required for population evolution.

Through the visualization analysis previous, we have a full understanding of the development and evolution of CCVRP research, the strength of different countries and institutions, the collaborative relationship between authors, the transformation of research hotspots, and future development trends. Next, the progress of CCVRP research from three aspects: CCVRP optimization objectives, problem scenarios, and solution algorithms will be elaborated on.

Cold chain logistics vehicle routing optimization objectives

Like the traditional vehicle routing problem, the vehicle routing of cold chain logistics also needs to solve a specific objective function to achieve the routing layout. From the perspective of cost priority, the goal of cold chain logistics vehicle routing is to minimize the distribution cost. Ming & Zhou[56] constructed a cold chain vehicle routing model with the goal of minimizing the total cost. The total distribution cost is mainly composed of fixed costs, transportation costs, refrigeration costs, cargo damage costs, and overload penalty costs. From the cost perspective, agricultural product cold chain logistics has problems such as a high turnover rate, insufficient hardware facilities, insufficient number of cold chain logistics centers, and imperfect construction of agricultural product logistics information platforms[57] . When analyzing to minimize cost, the constraint of picking up and delivering goods at the same time can also be added to improve the distribution efficiency[58]. Zeng et al.[59] added a time window penalty factor to the model of various cost factors affecting the cold chain logistics vehicle routing. A mixed time window mode is adopted, and a multi-segment function is used to represent the penalty cost of violating the time window.

From the perspective of customer priority, the goal of cold chain logistics vehicle routes is to maximize customer satisfaction. Cold chain logistics has strict time requirements, but due to the influence of subjective and objective conditions such as scheduling strategies and transportation, there may be situations where delivery cannot be made within the specified time range. Most studies on traditional vehicle routing problems use single-objective models and consider traditional time windows, ignoring the diversity of objectives and the effectiveness of algorithm calculation time. Due to the particularity of cold chain transportation goods, the setting of time windows often needs to be more flexible, and the connection with customers must also be closer. Not only costs need to be considered, but also time and customer satisfaction. Considering that the goods carried by cold chain logistics have certain particularities and have high-temperature requirements, Liang et al.[60] proposed setting a fuzzy time window in cold chain logistics distribution to reflect customer satisfaction, and added the goal of maximizing customer satisfaction by quantifying the fuzzy time window in the target optimization. The freshness of fresh products directly determines customer satisfaction. Based on the cost-effectiveness idea, Wu et al.[61] proposed a comprehensive cold chain vehicle routing optimization model to minimize the unit cost of product freshness. The establishment of a fuzzy time window means that the vehicle should try its best to provide services within the time window required by the customer. However, unlike the rigid requirements of fixed time windows, it mostly faces non-rigid requirements. When necessary, services can be provided outside the service hours, but part of the fee will be charged as a penalty. Improving the timeliness of delivery will also improve customer satisfaction. Lu & Zhang[62] considered the proximity of customer geographical locations and the similarity of delivery time windows, and proposed a cold chain logistics partition vehicle routing model based on spatiotemporal similarity measurement to solve the problem of cold chain logistics. The problem of low timeliness of chain logistics distribution, customer time window, and product quality are important factors affecting customer satisfaction. Ren et al.[63] added the weights of the time window and product quality, and used a VRP model with soft time window constraints and penalty functions to describe customer satisfaction. The satisfaction level of cold chain logistics distribution quality transforms the maximum goal of customer satisfaction into the minimum goal of penalty cost. In addition, based on the cost-benefit idea, a comprehensive cold chain vehicle routing optimization model with minimization of unit customer satisfaction cost as the objective function can also be established[14] . For customer satisfaction, on-time delivery is used as the evaluation criterion.

From the perspective of energy conservation and emission reduction, the goal of cold chain logistics vehicle routes is to minimize carbon emissions. Cold chain logistics vehicles consume fuel and generate carbon emissions during transportation and refrigeration. Since cold chain logistics uses cooling equipment such as air conditioners during transportation, cold chain logistics has the disadvantages of high energy consumption, and high emissions. Tao et al.[64] analyzed the carbon tax cost caused by the fuel consumption of vehicle transportation and its refrigeration equipment in the establishment of a target model for minimizing total cost. Low-carbon routing will increase the total distance of distribution, but can significantly reduce carbon emissions and energy consumption. Unlike other models with cost as the optimization goal, Wang & Lu[65] established a vehicle routing model to minimize carbon emissions while considering factors such as vehicle speed, distance, and load capacity. Yang et al.[66] also aimed to minimize carbon emissions, but subdivided the carbon emissions of refrigerated truck transportation and emptying. Cold chain logistics can also be linked to joint distribution and carbon trading mechanisms. Ning et al.[67] established a joint distribution-green vehicle routing problem (JD-GVRP) model for cold chain logistics companies to coordinate the distribution of cold chain goods under the premise of considering carbon tax policies. Under the influence of carbon neutrality, green logistics concepts, and economic background, cold chain logistics of agricultural products is a relatively energy-consuming project in the logistics industry. On this basis, the optimization objective of the cold chain distribution model of fresh agricultural products established by Jia[68] takes into account the pollution cost, including the cost of atmospheric pollutant emissions, the cost of solid and liquid pollutant emissions, and the cost of noise pollution. In the cold chain logistics vehicle routing model, the optimization objective of most models is to minimize the total distribution cost. To consider carbon emissions, the method of converting carbon emissions into economic benefits in the target optimization and introducing carbon emission costs[69–74] is widely used.

Generally speaking, the focus of cold chain logistics vehicle route objectives can be summarized as distribution costs, customer satisfaction, carbon emissions, etc. When setting goals, the above points can also be considered at the same time. For example, through multi-temperature collaborative configuration, customer satisfaction can be improved and distribution costs can be reduced. For traditional cold chain logistics distribution, multi-temperature co-configuration can achieve complex temperature requirements during the distribution process and meet the different storage temperatures required by various products. Ding[75] constructed a multi-temperature co-location cold chain logistics vehicle route model based on the total cost, time, and risk of multi-temperature co-location cold chain logistics distribution. When optimizing the target, temperature is taken as an important influencing factor, and the deterioration rate that changes exponentially with temperature is applied to the model[76] . The temperature is adjusted in real-time to find a route that can meet the customer's freshness requirements and reduce the supplier's costs. In addition, the actual road conditions during the delivery process should also be considered when optimizing the target. The actual road conditions of cold chain logistics during the distribution process indirectly affect the delivery timeliness. Therefore, optimizing the distribution model target based on real-time road traffic conditions[77−80] can greatly reduce distribution costs, improve customer satisfaction, and better meet the actual situation of cold chain logistics distribution of fresh products. Yao & He[81] obtained urban road congestion information from big data based on cost optimization and used it to optimize the vehicle routes for cold chain distribution of agricultural products. To reduce the number of times cold chain distribution vehicles travel to and from the distribution center, reasonable docking points are set in cold chain distribution, and a mathematical model of the route of agricultural product cold chain logistics vehicles based on real-time road conditions are established. Chen[82] uses cloud computing technology as the basis for the constituent elements of the cold chain distribution problem, obtains real-time traffic information in the transportation system through a unified access interface, and analyzes the delivery time and cost of refrigerated trucks to establish a cold chain distribution vehicle route optimization model. Compared with the single-objective model that only provides a single distribution route to minimize costs, multi-objective optimization can provide logistics companies with a variety of distribution route options in practice[83] . The focus types of optimization objectives and corresponding literature are shown in Table 12.

Problem scenarios for cold chain logistics vehicle routes

According to the different objective function settings and constraints of the cold chain logistics vehicle route model, the problem scenarios of cold chain logistics vehicle routes can be roughly divided into three categories: distribution cost scenarios, time window penalty cost and customer satisfaction scenarios, and real-time traffic conditions scenarios.

Distribution cost scenario

The total cost of cold chain logistics distribution is mainly composed of fixed costs, transportation costs, refrigeration costs, cargo damage costs, and carbon emission costs. It is

Table 12. Objective function types and characteristics of cold chain logistics vehicle routes.

Objective function type	Priorities of optimization objectives	Ref.
Multiple targets	Based on minimizing the total cost of distribution	[56, 57]
	Based on maximizing customer satisfaction and minimizing total distribution cost	[14, 58−63]
	Based on carbon emission minimization, total distribution cost minimization	[14, 64], etc.
	Based on the minimization of total distribution cost and multi temperature co distribution	[75, 76]
	Based on real-time road conditions and minimize total distribution cost	[77−82]
	Based on minimizing total distribution cost, minimizing carbon emissions, and maximizing customer satisfaction	[14]
Single target	Based on minimizing carbon emissions	[65]

generally believed that fixed costs will not change with transportation conditions and are fixed values[57]. But there is overlap in scenario building for fixed costs and transportation costs. Fixed costs include vehicle repairs, maintenance, depreciation, and personnel wages[56]. There are also views that transportation costs should be composed of fixed costs and variable costs[84]. The variable costs are vehicle fuel costs, and maintenance costs. Some models are relatively rough in quantifying transportation costs, directly giving the transportation cost per unit mile during calculation[62]; the quantification of transportation costs can be subdivided into fuel consumption and fuel costs are calculated based on volume[64], Wu et al.[61] quantified through fixed costs, vehicle maintenance costs during transportation and loading and unloading stages; taking into account the freight price per unit weight, the distance between customers, and customer demand, Zhao et al.[83] used customer demand to calculate refrigerated truck transportation costs. The construction of refrigeration cost and cargo damage cost scenarios is more complex than fixed costs and transportation costs. The quantification of refrigeration costs is related to the consumption of refrigerant during vehicle transportation and loading and unloading[57], and the fuel consumed by refrigeration equipment[85]. When measuring refrigerant consumption, it is necessary to consider the heat load caused by the temperature difference between the inside and outside of the refrigerated truck during transportation and the heat load caused by air convection during loading and unloading at the customer point[76] . The heat load is related to the volume of the carriage, the area inside and outside the carriage, and the degree of depreciation. Among them, Li et al.[86] considered the transportation and loading and unloading process when calculating the refrigeration cost, and considered factors such as heat load, compartment damage, and compartment heat transfer area. Although Lü & Sun[87] also considered the heat load, the unit cooling cost was used in the calculation. Refrigeration equipment is powered by generators powered by fuel consumed by delivery vehicles, which increases fuel consumption in the process[64]. Given the differences in energy consumption parameters during cooling of different vehicles, the energy consumption assessment adjustment coefficient can be introduced into the energy cost calculation[59]. The most direct manifestation of refrigeration cost is fuel consumption. Shen et al.[69] quantified the amount of fuel consumed to reduce unit heat load during transportation and loading, and then calculated the fuel cost.

Part of the cargo damage cost is the damage caused by the increase in delivery time and temperature fluctuations during the delivery process; the other part is caused by the temperature inside the refrigerated box rising due to the hot air from the outside entering the car body due to opening and closing the door when serving customers. In fact, the deterioration rate will change with the transportation distance and temperature. Liang & Zhou[76] added the temperature constraints during transportation and the temperature-related deterioration rate into the cargo damage cost, where the deterioration rate is determined by the AllenNieus equation, the cost of cargo damage can be measured more effectively through temperature. Warm co-balancing is a new way to reduce the cost of cargo damage. Given the risk of cargo damage during transportation and reloading, the probability of product damage and transportation accidents is introduced during the transportation process, and the value is [0,1]. During the transfer process, the probability of cost and accident probability are introduced. Each type of product has a corresponding vulnerability value, and risk offset factors can also be added during the calculation process[75], including traffic risk offset factors corresponding to driver skills, traffic vehicle performance, road conditions, replacement technicians, tool performance, and replacement factors. Risk offsetting factors generated by installation management. The longer the delivery time, the greater the chance that the goods will be lost. Accordingly, Huang et al.[88] constructed a cargo damage coefficient formula based on the sensitivity of cargo to time to express the exponential change pattern of the cargo damage coefficient with time. Kang et al.[73] established a variable function for the quality of refrigerated goods, and based on this, calculated the cost of cargo damage during the transportation and loading and unloading stages. With the improvement of scientific and technological levels, the logistics industry is paying more and more attention to sustainable development. Optimizing the carbon emission structure of the cold chain logistics industry is the top priority to ensure the sustainable development of the logistics industry[89] .

Carbon emission cost is the cost for enterprises to purchase corresponding carbon emission indicators through carbon exchanges. In the quantification of carbon emission costs, CCD releases more carbon dioxide than ordinary commodities. The load estimation method can be used for calculation and the fuel consumption is calculated based on the fuel consumption rate and distance under different loads[61,90,91]. There is a certain linear relationship between carbon emissions and fuel consumption[92], so that the carbon specific values for emissions. Given the double calculation of fuel consumption costs in transportation and refrigeration and the fact that most scholars only consider the fuel consumption in transportation and ignore the impact of refrigeration fuel consumption on carbon emissions, Fang et al.[93] unified the measurement of fuel consumption and carbon emissions, and unified the measurement of fuel consumption and carbon emissions. The cost of fuel consumption during distribution and the environmental cost of carbon pollution are considered as green costs and entered into the model. Moncer et al. proposed an activity-based cost minimization model and a carbon footprint minimization model[94]. The introduction of a carbon tax mechanism[64] can also quickly obtain the cost of carbon emissions, provided that the carbon emissions are calculated based on fuel consumption and carbon dioxide emission coefficients[71,88]. Some scholars collected relevant statistical data for regression analysis and found that fuel consumption per unit distance can be expressed as a linear function that depends on the truck's cargo capacity[95]. The total vehicle weight is divided into vehicle weight and cargo weight, then the fuel consumption per unit distance can be expressed linearly by the two[73] .

Time window penalty cost and customer satisfaction scenario

In cold chain logistics vehicle routes, the establishment of time window penalty costs has become increasingly important. Cold chain goods are shipped from distribution centers to various customer points. The temperature in the container needs to be constantly adjusted to ensure the quality of cold chain goods. At the same time, the shorter the delivery time and service time, the more conducive it is to maintaining the quality of the goods. Customer satisfaction is converted from the vehicle service time and is determined by the specific time when the vehicle arrives at the customer point. Specifically, given a time period, it is determined by the lower or upper limit of the fuzzy time window and the lower or upper limit of the optimal service time. According to the actual arrival time, it is determined which time period it is, and the difference between the upper or lower limit of the optimal service time and the arrival time and the difference between the time segments are calculated. The ratio of the difference is used to measure customer satisfaction[60]. Similar to the traditional VRPTW problem, cold chain distribution logistics also has corresponding early and late arrival penalty costs. Ren et al.[63] studied the maximum customer satisfaction by converting it into penalty cost minimization.

Real-time traffic scene

Big data can be used to easily obtain real-time traffic information in the traffic system. Therefore, using big data and cloud computing analysis to build a cold chain logistics distribution model based on real-time road conditions is one of the current hot topics. Traffic big data plays an important role in cold chain logistics. Its application in distribution is shown in Fig. 12.

Chen[82] obtained real-time traffic information during the model construction process. Through the unified interface of the established service architecture, real-time traffic information of urban road sections where vehicles are distributed is obtained in the traffic information cloud. Using the real-time road conditions of the vehicles, the driving speed of the distribution vehicles on the relevant sections is obtained, and the driving time of the distribution vehicles is calculated, so that the vehicles can choose the shortest route during driving. Obtaining urban road congestion information from big data can also be used for vehicle route optimization in cold chain distribution of agricultural products. To reduce the number of cold chain distribution vehicles traveling to and from the distribution center, it is recommended to introduce docking points and equipment connections in the cold chain distribution of fresh agricultural products. The shuttle solution[81] (cold chain distribution shuttles are mainly small and micro electric vans with low investment and operating costs. They generally use phase change cold storage materials for refrigeration or foam boxes for insulation to ensure the temperature and freshness of agricultural products) further studied the docking point selection and cold chain logistics vehicle routes based on the docking point situation, and established an agricultural product cold chain vehicle route model based on traffic big data including docking points.

Regarding the construction of real-time traffic scenarios, Zhu & Wang[77] directly considered the time window penalty cost caused by the failure of medicines to be delivered within the specified time due to weather and other reasons in their model. In addition, by introducing the corruption function of fresh products, under the premise of time-varying road network theory, the time variable in the corruption function that is closely related to food quality can be solved[80], and the cargo damage cost of multi-temperature distribution under the time-varying road network traffic environment can also be solved. Lan et al.[78] divided the actual road conditions into five categories based on the theory of road accessibility and fuzzy comprehensive evaluation method of road accessibility. The real-time traffic scenario constructed by Bai et al.[79] is divided into two stages. The first stage is to obtain the travel time based on the real-time traffic conditions of each connected path of the initial customer point, and the second stage is the dynamic allocation process. After each refrigerated truck delivers to a customer point, it is eliminated, and then the delivery order is planned based on the real-time traffic conditions between the remaining customer points, the demand conditions of each customer point, and the time window. Wu[96] plan logistics vehicle routes based on real-time traffic information, and consider the impact of road congestion, intersection congestion, and one-way road restrictions on the path planning.

In general, the distribution cost scenario, time window penalty cost, and customer satisfaction scenario are both different and related to the real-time traffic scenario. The difference is that the constraints and variables are set differently when constructing the three scenarios. When constructing the distribution cost scenario, if the variables involved in each type of cost are different or the quantification method of the same variable is different, the corresponding constraint settings will also be different. In the process of setting such scenarios, it is necessary to pay attention to the repeated accounting of cost variables. Repeated accounting does not mean that they appear repeatedly in the target, but when setting the cost variables, different quantification methods are used to repeatedly quantify the same variables. In the time window penalty cost and customer satisfaction scenarios, it is necessary to consider adding time window constraints and customer satisfaction functions and quantify customer satisfaction by setting delivery time variables and cargo damage cost variables. When constructing the real-time traffic scenario, it is necessary to consider the quantification of variables such as traffic flow, customer demand, road congestion, road infrastructure, and weather. By introducing the traffic congestion coefficient, constraints such as delivery speed, delivery volume, and delivery priority can be set to measure the impact of road traffic conditions on the route selection of cold chain logistics vehicles. Different distribution scenario types and corresponding literature are shown in Table 13.

Cold chain logistics vehicle route solving algorithm

Generally, algorithms for solving vehicle path optimization problems can be roughly divided into two categories, one is the exact algorithm and the other is the heuristic algorithm. The exact algorithms mainly include the branch and bound method[98−101], the dynamic programming algorithm[102] , the branch and cut method[103,104] , etc. When conducting case analysis on a few cases at the customer site, the exact solution algorithm is often used. For example, Wang et al.[105] focused on dynamic path planning for unmanned environment monitoring vehicles under complex road conditions. Based on the idea of two-level planning, they proposed a hybrid algorithm that combines global and local path planning. It can effectively solve the local optimization problem of the path, but the optimization of path cost and carbon emission problems still needs to be further studied. In practical applications, since most problems do not have a benign structure, it is impossible to establish a strict mathematical expression; some problems do not have a strict optimal solution, or some problems are large in scale and it takes too much cost to obtain the optimal solution. Therefore, heuristic algorithms are generally used to solve them. Among them, the ant colony algorithm[71] is the most common. Other intelligent algorithms mainly include genetic algorithm[82], simulated annealing algorithm[80,91], particle swarm algorithm[56,106], A* algorithm[93], artificial fish swarm algorithm[66], hybrid algorithm[72], etc.

Table 13. Cold chain logistics vehicle routing problem scenario types and characteristics.

Scene type	Content of scenario construction	Ref.
Distribution cost scenario	Transportation cost	[60, 62, 97]
	Fixed cost, transportation cost	[56]
	Cargo damage cost	[75]
	Carbon emission cost	[66, 70], etc.
	Fixed cost, refrigeration cost	[57]
	Refrigeration cost	[69, 85]
	Refrigeration cost, transportation cost	[59, 64], etc.
	Cargo damage cost, transportation cost	[76]
	Transportation cost, carbon emission cost	[61, 64], etc.
	Refrigeration cost, cargo damage cost	[76]
	Refrigeration cost, carbon emission cost	[64]
	Cost of cargo damage, carbon emission	[73, 88]
	Transportation cost, refrigeration cost, cargo damage cost	[76]
	Transportation cost, refrigeration cost, carbon emission cost	[64]
Time window penalty cost and customer satisfaction scenario	Time window penalty cost	[60]
	Maximize customer satisfaction	[63]
Real time traffic scene	Get real-time road conditions based on big data	[81, 82]
	Fuzzy comprehensive evaluation method based on road smoothness	[78]
	Real time traffic scene construction	[77, 79]
	Based on time-varying road network theory	[80]

Ming & Zhu[56] improved the particle swarm algorithm by using Levy flight and reverse learning optimization. The step size of reverse learning was obtained through Levy flight. When the search was stuck in the local optimal state, the particle individual was learned from the worst position. The optimization was performed through reverse learning, which prevented the particle swarm algorithm from falling into the local optimal state and causing the algorithm search to stagnate. At the same time, the algorithm's search ability was also improved. When using genetic algorithms to solve problems, Liang & Zhou[76] used the double-point cut crossover method, took the objective function value as the individual fitness value, and used natural number coding to encode the data, while considering the vehicle configuration and vehicle temperature. Ding[75] first used the linear weighted method to transform and simplify the multi-objective optimization problem into a single-objective optimization problem to solve, thereby improving the efficiency of path optimization. Secondly, they used quantum bits to describe the relevant information of the path and gave the individual probability radiation of the quantum bits in the corresponding two-state system. The corresponding quantum individuals can be represented as the pheromones contained in each cold chain logistics distribution path. Finally, the ant colony algorithm was combined to obtain the pheromone coding of ants on each cold chain logistics transportation path. Based on the solution idea of a non-dominated sorting genetic algorithm, the adaptive adjustment of crossover rate and mutation rate can be improved to improve the convergence speed. After the improvement, the potential optimal solution population is formed through optimization between different generations to avoid local optimality and search for Pareto optimal solution. Compared with the traditional algorithm, Liang et al.[60] selected the genes after crossover for repair, which effectively prevented the situation that the chromosome did not meet the constraint conditions. The non-dominated sorting and crowding calculation after merging the new population improved the accuracy of selecting the optimal solution. Xie[106] combined the advantages of the particle swarm algorithm in multidimensional search space with the improved ant colony algorithm, used the insertion-based heuristic method to construct weak feasible solutions, and used crossover and inversion to optimize individual ant colonies. After operations such as crossover and inversion, the optimal path planning is found under constraints such as time window, avoiding the ant colony algorithm from being unable to obtain the local optimal solution due to the fast convergence speed. Fang et al.[93] used the global convergence and rapidity of the A* algorithm to perform initial pheromone distribution on the path corresponding to the optimal solution, and then made full use of the positive feedback and high solution efficiency of the ant colony algorithm to find the optimal solution. Ding[75] proposed an optimization method for the delivery routes of multi-temperature and low-temperature cold chain logistics vehicles. Considering the interference factors at each stage, controlling the delivery time, delivery cost, and delivery risk of multi-temperature cold chain logistics, optimizing the vehicle routes of multi-temperature cold chain logistics, and realizing the route optimization by using the ant colony algorithm. This method can effectively plan the route, but since the ant colony algorithm requires a large number of iterations to obtain the optimal value, the data results are redundant, which can easily extend the route optimization time. By improving the traditional pheromone update mode, limiting the maximum and minimum concentrations of pheromones on the road, and changing the path selection transfer probability, a cold logistics vehicle route plan based on the improved ant colony optimization algorithm (IACO) is formed. Xiong[107] conducted simulation experiments and results and showed that the IACO algorithm is lower than the hybrid simulated annealing ant colony algorithm (CSAACO) and the traditional ACO algorithm in terms of convergence speed, logistics transportation distance and logistics delivery time. Ren et al.[108] integrated the taboo search operator and the knowledge model of dynamic probability selection under the knowledge-based elite strategy into the ant colony algorithm and designed a new knowledge-based ant colony algorithm. The effectiveness of the proposed model and knowledge-based ant colony algorithm was verified by comparing the traditional ant colony algorithm, the improved ant colony algorithm based on taboo search, and the proposed knowledge-based ant colony algorithm. Liu et al.[72] combined the genetic algorithm with strong global search ability and the taboo search algorithm with good local optimization ability. They used the genetic algorithm for the entire vehicle route in the global space and the taboo search algorithm for a single vehicle route in the local space, thereby improving the efficiency of the algorithm. Considering that the traditional genetic algorithm is prone to premature convergence, local convergence, difficulty in obtaining the optimal solution, and insufficient global search characteristics of the simulated annealing algorithm when solving the VRP problem, Bai et al.[79] combined the two to solve the cold chain logistics distribution path optimization problem.

To avoid the premature convergence and local optimality of the genetic algorithm, Fu et al.[109] introduced the Tent chaos perturbation method to optimize the genetic algorithm. This method uses a perturbation mechanism to initialize the population perturbs it again after the selection operation to increase the diversity of the population, and designs the rules of selection, crossover, and mutation operators to speed up the solution. Chen & Shen[110] proposed a cold chain logistics path decision optimization method for fresh products considering transportation risk factors and constructed a cold chain transportation risk factor index system using risk quantification methods. At the same time, the K nearest neighbor algorithm was used to predict traffic congestion risks and extract cold chain logistics transportation risk factors, thereby shortening transportation time. To reduce the error of path planning, the hierarchical analysis method was used to establish a calculation model, and the risk factor matrix was used to calculate the indicator weights of risk factors. To maximize the robustness of the solution, Yang et al.[111] proposed a multidimensional robust optimization model and solved the problem through a hybrid algorithm combining the Pareto genetic algorithm and the improved grey relational analysis (IGRA). The research results show that this method can slightly reduce costs and improve robustness, and can effectively avoid the blindness of allocation while considering the urgency of demand.

Generally speaking, the path optimization problem is an NP-Hard problem. When choosing a solution algorithm, we should first determine whether to choose an exact algorithm or a heuristic algorithm based on the size of the solution case. Secondly, we should choose the algorithm that best suits the model based on the differences in the objective function and the scenario. Through the application of actual cases, we can compare the differences in the optimal solution, solution speed, and solution process under different algorithms to determine whether the algorithm needs to be improved, other algorithms should be used, or a hybrid algorithm should be used to solve the problem. Finally, when designing an algorithm, we should fully combine the characteristics of the model, fully embed the elements in the model into the algorithm, and establish an effective connection between the algorithm and the model. In response to the existing literature, a series of summaries on the improvements of the algorithms used have been made, where the null value means that the algorithm has not been improved. The types, characteristics, and effects of the improved algorithms are shown in Table 14.

Table 14. Solving algorithm types and characteristics.

Type	Refs	Improved advantage
Ant colony algorithm	[61, 63, 73, 75, 83] [62, 86, 107, 108, 112]	[63] Good optimization effect, high solution stability, and stronger search ability, suitable for medium and large-scale data sets; [73, 85]: Overall cost reduction; [75]: High timeliness and low cost greatly improve the distribution and transfer efficiency of multi-temperature co-distribution cold chain logistics; [107, 112]: fast convergence speed and high solving efficiency; [108]: Reduction in convergence time, total distance and total cost of carbon emissions satisfaction.
Genetic algorithm	[60, 70, 72, 74] [76, 84, 86, 109]	[60]: Double optimization that effectively takes into account cost and customer satisfaction, the total distribution cost is better than the standard genetic algorithm; [70]: Significant cost reduction; [72]: Has better convergence efficiency and optimization capabilities; [74, 76, 109]: Total cost reduction, closer to reality; [86]: More suitable for solving distribution problems with narrow time windows and random geographical locations of customers or partial clustering and partial randomization.
Simulated annealing algorithm		
Particle swarm optimization	[56]	[56]: Lower total cost and 100% on-time rate.
A* algorithm		
Artificial fish swarm algorithm	[66]	[66]: Fast convergence speed, strong global search capability, and can further balance costs such as fuel consumption, refrigeration, and carbon emissions during the distribution process.
Hybrid algorithm	[62, 111]	[62]: The time penalty cost is significantly reduced, and the total distribution cost is lower; [111]: Reduce costs, improve robustness, and effectively avoid blindness in distribution.

Conclusions and outlook

Through bibliometrics and visualization techniques, this paper systematically traces the research evolution of the cold chain logistics vehicle routing issues. The early focus on basic route optimization has gradually shifted to research on the optimization of complex cold chain logistics networks, reflecting the increasing emphasis by academia and industry on the efficiency and sustainable development of cold chain logistics. Bibliometric analysis shows that the current research hot spots on cold chain logistics vehicle routing issues mainly focus on dynamic route optimization, multi-modal transportation, electric vehicles, and intelligent algorithms. These research hotspots reflect the urgent need to improve cold chain logistics transportation efficiency, reduce costs, and cope with complex environmental challenges. With the continuous development of fields such as computer science, operations research, and logistics management, research methods and technologies for cold chain logistics vehicle routing problems have been significantly improved and expanded. The application of traditional mathematical programming methods to heuristic algorithms, meta-heuristic algorithms, and hybrid optimization algorithms provides more options and possibilities for solving complex problems in actual cold chain logistics transportation. The study also found that the research on cold chain logistics vehicle routing is not only limited to a single field but also involves the intersection of multiple disciplines and fields, such as operations research, computer science, logistics management, etc., which provides more information for the further development of this field.

Based on the research conclusions of this study, the following prospects for future research directions are proposed.

(1) Interdisciplinary integration: Future research can further cross disciplinary boundaries and combine knowledge from computer science, logistics management, operations research, etc. to conduct more in-depth research. For example, cutting-edge technologies such as artificial intelligence and big data analysis can be introduced into the solution of cold chain logistics vehicle routing problems to improve the intelligence and real-time nature of the solution.

(2) Customization of application scenarios: As the application of cold chain logistics in various industries continues to deepen, future research will focus more on personalized solutions for different industries and specific scenarios. For example, in the pharmaceutical field, special transportation requirements for drugs may need to be considered, while in the food field, logistics path optimization under different temperature requirements may need to be considered.

(3) Sustainable development considerations: As the world pays more attention to sustainable development, future research will pay more attention to the potential contribution of cold chain logistics vehicle route optimization in energy conservation, emission reduction, resource utilization, etc. Therefore, future research may incorporate more sustainable development concepts such as environmental protection and carbon neutrality to achieve the sustainable development goals of the cold chain logistics industry.

In summary, with the continuous development and innovation of the cold chain logistics industry, the research on cold chain logistics vehicle routing problems will continue to face new challenges and opportunities. Through interdisciplinary integration, customized solutions, and sustainable development considerations, the research on cold chain logistics vehicle routing problems will provide more effective support and guidance for the development of the cold chain logistics industry.

Author contributions

The authors confirm contribution to the paper as follows: research concept and manuscript draft preparation: Qi B; data collection and chart analysis: Li G. Both authors reviewed the results and approved the final version of the manuscript.

Data availability

The data that support the findings of this study are available in the Web of Science (WoS) repository.

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Conflict of interest

The authors declare that they have no conflict of interest.

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