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A Bibliometric Analysis of a Genetic Algorithm for Supply Chain Agility

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Abstract: As a famous population-based metaheuristic algorithm, a genetic algorithm can be used to overcome optimization complexities. A genetic algorithm adopts probabilistic transition rules and is suitable for parallelism, which makes this algorithm attractive in many areas, including the logistics and supply chain sector. To obtain a comprehensive understanding of the development in this area, this paper presents a bibliometric analysis on the application of a genetic algorithm in logistics and supply chains using data from 1991 to 2024 from the Web of Science database. The authors found a growing trend in the number of publications and citations over the years. This paper serves as an important reference to researchers by highlighting important research areas, such as multi-objective optimization, metaheuristics, sustainability issues in logistics, and machine learning integration. This bibliometric analysis also underlines the importance of Non-Dominated Sorting Genetic Algorithm II (NSGA-II), sustainability, machine learning, and variable neighborhood search in the application of a genetic algorithm in logistics and supply chains in the near future. The integration of a genetic algorithm with machine learning is also a potential research gap to be filled to overcome the limitations of genetic algorithms, such as the long computational time, difficulties in obtaining optimal solutions, and convergence issues for application in logistics and supply chains.

Keywords: genetic algorithm; metaheuristic; supply chain; logistics; bibliometric analysis

MSC: 00A06

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1. Introduction

Metaheuristics are capable of solving real-life problems [1,2]. These applied areas include power consumption prediction models [2], materials discovery [3], and feature selection [4]. A genetic algorithm is a famous population-based metaheuristic algorithm which adopts several candidate solutions [5,6]. Based on biological evolution and the concept proposed by Charles Darwin [7], a genetic algorithm was developed by J. H. Holland in 1975 to solve constrained and unconstrained optimization issues [8,9]. Genetic algorithms have been favored models since then because they have various strengths. Genetic algorithms can handle complex optimization issues for both stationary and non-stationary objective functions, linear and non-linear functions, continuous or discontinuous functions, and random noise [10]. Since a genetic algorithm is population-based, problems may occur in multiple directions simultaneously, and this makes it suitable for parallelism [10]. A genetic algorithm adopts probabilistic transition rules, crossover, recombination, mutation, and selection [11–13]. Genetic algorithms are also distinct from traditional algorithms, as genetic algorithms create a population of points in every iteration [14].

A standard genetic algorithm begins by identifying the initial population and then evaluating its fitness value, selection, crossover, and mutation. The entire genetic algorithm will end if the termination criteria are met [15]. There are a few popular variants of genetic algorithms, such as real-coded genetic algorithms, binary-coded genetic algorithms, and sawtooth genetic algorithms [16–18]. A real-coded genetic algorithm handles large domains with a continuous search space for precise numbers [19]. A binary-coded genetic algorithm commonly uses genes or chromosomes with strings of 0 or 1 [5]. Sawtooth genetic algorithms have been used to improve the efficiency of genetic algorithms. Variable population sizes and periodic initializations can be used in sawtooth genetic algorithms [20,21]. Genetic algorithms have been used in medicine for diagnoses and treatments [22–24]. Genetic algorithms have also been used in the field of electronics [25–27]. Genetic algorithms are also emerging in the field of computer systems [28–31]. At the same time, genetic algorithms are also popular in agriculture [32–34]. Researchers have also used genetic algorithms in materials science [35,36]. Genetic algorithms can also be used to solve sustainability issues and environmental engineering issues [37–39].

1.1. Applications of Genetic Algorithms in Logistics and Supply Chains

Researchers are also actively progressing with the application of genetic algorithms in the logistics and supply chain sector. A supply chain is defined as a network for the flow of goods, services, and information technology between the point of origin and the point of consumption [40,41]. Supply chain management is the planning and management of the flow of goods, services, and information technology [40]. Logistics is defined as the planning, implementation, and control of goods, services, and information technology for efficient and effective storage and two-way movement between the point of origin and point of consumption [42,43]. Logistics highlight the physical storage and movement of goods, services, and information technology between the point of origin and the point of consumption, while supply chains focus on the logistics flows from the upstream network to the downstream network [44–46].

According to Iris and Serdarasan [47], genetic algorithms are popular in solving supply chain problems. Babaeinesami et al. [48] applied a genetic algorithm in a closed-loop supply chain. Gen et al. [49] used a genetic algorithm for logistics and supply chain management network design. Roghanian et al. [50] and Zhou et al. [51] also presented an optimization model for a reverse logistics network with a genetic algorithm. At the same time, Gürler et al. [52] applied genetic algorithms for Logistics Performance Index rankings. However, Yeh [53] noted that a genetic algorithm has a lack of local search strategies in evolutionary aspects and cannot solve non-deterministic polynomial (NP-hard) problems in a supply chain. Nevertheless, Saif-Eddine et al. [54] formulated an improved genetic algorithm model to solve the inventory location routing problem, which is an NP-hard problem. For the usage of a genetic algorithm, only parts of the entire supply chain can be studied at a time [55]. To overcome this problem, Xin et al. [56] proposed an improved genetic algorithm to reduce the time required for local search. Meanwhile, the limitation of a genetic algorithm is that a genetic algorithm may decrease the quality and rate of convergence of the population and cause a loss of diversity in the population, which may result in premature convergence [5,57,58].

On the other hand, genetic algorithms have some significant advantages in the logistics and supply chain sector. Genetic algorithms have wide adaptability and flexibility as there is no unique mathematical requirement to optimize a problem. Genetic algorithms are also robust for global search to find optimal solutions and reduce computational efforts. Additionally, genetic algorithms are also suitable for parallelism for quicker computation [55]. An advantage of genetic algorithms is their ability to optimize transportation problems, such as vehicle routing issues. Having known that goods transportation is an important step in a supply chain, Rahman et al. [59] used a genetic algorithm to minimize the distance travelled for goods transportation to reduce operational costs and air and noise pollution. This paper also found that, with a genetic algorithm, the model has a greater convergence rate regardless of the population size and is more efficient in offering a lower travel distance. Okyere et al. [60] highlighted the benefits of genetic algorithms, such as their parallelism and probabilistic natures for global search, which allow them to be applied for multimodal transport issues. Genetic algorithms were also prioritized over other optimization models because genetic algorithms provide various solutions according to the population size with exploration and exploitation. Additionally, a genetic algorithm has been used to automate logistics and supply chain processes. For example, Jin [61] adopted a genetic algorithm as the core to develop an intelligent logistics supply chain management system. Furthermore, genetic algorithms are also suitable for both linear and non-linear problems [62,63]. Chen et al. [64] used a genetic algorithm to solve a multi-objective mixed-integer non-linear programming model for a sustainable reverse logistics network. Liu et al. [65] also formulated a mixed-integer non-linear programming model for integrated scheduling with a genetic algorithm.

Kannan et al. [66] built a multi-echelon, multi-period, multi-product closed-loop supply chain model to minimize the total supply chain cost comprising procurement, production, distribution, inventory, collection, disposal, disassembly, and recycling costs using a genetic algorithm. Lo and Shih [67] applied a quantum random number generator to provide true random numbers for a genetic algorithm to solve pollution-routing problems in sustainable logistics management. The objective of pollution-routing problems is to minimize carbon dioxide emissions. Wang et al. [68] addressed the two-echelon capacitated vehicle routing problem with stochastic demands in city logistics. A genetic-algorithm-based approach was proposed to solve this problem. A stochastic program with recourse was used to describe the problem. This program aims to minimize the sum of the travel cost and the expected cost of recourse actions resulting from potential route failures. Rasi and Sohanian [69] offered a solution to the problem by designing a multi-objective sustainable supply chain in a three-stage supply chain network using a genetic algorithm, particle swarm, and priority axis coding. An optimization approach was used to maximize profits and pricing products with definite and time-consuming demand and to minimize time. Nezamoddini et al. [70] proposed a model that deals with uncertainties associated with demands, facility interruptions, lead times, and failures in supply, production, and distribution channels. To solve the proposed model, a new genetic algorithm was designed, which was integrated with an artificial neural network that learns from previous plans and searches for better ones by minimizing any mismatches between supply and demand.

Saghaeeian and Ramezanian [71] studied supply chain vs. supply chain multi-product competition in duopolistic markets. Pricing, location, transportation, and production decisions are made in a Stackelberg game formulated as a bi-level model. The objective functions of the bi-level model maximize the annual profit of the leader's and follower's chain. An efficient hybrid genetic algorithm was proposed to solve large-sized problems. Kannan et al. [72] designed an integrated forward logistics multi-echelon distribution inventory supply chain model and a closed-loop multi-echelon distribution inventory supply chain model for a built-to-order environment using a genetic algorithm and particle swarm optimization. The objective function of the forward logistics multi-echelon distribution inventory model is to minimize the total costs of the forward logistics supply chain. The objective function of the closed-loop multi-echelon distribution inventory model is to minimize the total costs of a closed-loop supply chain. Han et al. [73] developed a cost model that considers different emission reduction policies and strategies. Furthermore, they proposed an improved quantum genetic algorithm based on a "fork gene" and elite strategy, which is specifically designed for shipping-related policies and strategies. The speed optimization model was established in this study. The optimization goal in the speed model is minimizing the total cost. Cui et al. [74] focused on the distribution route problem in township logistics and described the characteristics of customer distribution in townships. This study investigated the cost minimization routing problem. A new adaptive genetic algorithm was proposed to solve this problem.

1.2. Objectives of This Study

Since there is high application of genetic algorithms, there is a need to explore the research trends and hotspots regarding genetic algorithms to understand the development in this area. A bibliometric analysis, which involves the scientific evaluation of a research area, can be used to achieve this objective [75–77]. Based on our best understanding, there are no past studies that have conducted a bibliometric analysis of genetic algorithms in the logistics and supply chain sector. Bhoskar et al. [19] reviewed the applications of genetic algorithms in mechanical engineering. Lou and Hung [78] conducted a bibliometric analysis of genetic algorithms using the Social Science Citation Index (SSCI) with 878 publications from 2002 to 2021. Dao et al. [79] performed a bibliometric analysis of genetic algorithms from 1992 to 2014 using the Scopus database. Kaleybar et al. [80] reviewed the application of genetic algorithms in rail vehicle systems from 2008 to 2022. Ding et al. [81] reviewed the use of genetic algorithms in land use optimization. Yang et al. [82] studied the research on genetic algorithms in the library sector in China.

Therefore, this paper intends to conduct a bibliometric analysis on the application of genetic algorithms in the logistics and supply chain sector. This bibliometric analysis aims to answer the following questions:

1. What are the publication and citation trends in the application of genetic algorithms in the logistics and supply chain sector?
2. What are the types of documents and subject areas of the publications about the application of genetic algorithms in the logistics and supply chain sector?
3. What are the locations with the largest contributions of publications about the application of genetic algorithms in logistics and supply chains?
4. What are the top publication titles and most cited publications about the application of genetic algorithms in logistics and supply chains?
5. What are the important research keywords and research clusters regarding the application of genetic algorithms in logistics and supply chains?

This paper contributes to the existing literature by identifying the trends of scientific contributions in the application of genetic algorithms in logistics and supply chains. This paper also highlights the active research on the application of genetic algorithms in logistics and supply chains in the top contributing locations. Furthermore, this paper determines the most impactful publications in the application of genetic algorithms in logistics and supply chains. Additionally, this paper determines the prominent research areas and potential future areas in the application of genetic algorithms in logistics and supply chains. This paper intends to help researchers identify some research gaps to address with future studies.

Section 2 outlines the materials and methods used for a bibliometric analysis on the application of genetic algorithms in logistics and supply chains. Section 3 explores the results and discusses the outcomes of the bibliometric analysis. Section 4 concludes the paper with summaries, limitations, and future research objectives.

2. Materials and Methods

This bibliometric analysis focuses on the application of genetic algorithms in the field of logistics and supply chain management in the Web of Science database. The Web of Science database is selected for its enormous collection of peer-reviewed scientific papers with excellent indexing for research exploration [83]. The Web of Science database has also been widely used for bibliometric analyses [84–88]. A bibliometric analysis on the application of genetic algorithms in the logistics and supply chain sector has also not been conducted using the Web of Science database. This bibliometric analysis follows a 3-step approach, as shown in Figure 1 [89,90].

In step 1, the Web of Science database was queried based on the following terms on 17 January 2024: ("genetic algorithm*" OR "genetic algorithms" OR "genetic algorithm") AND ("logistics" OR "supply chain" OR "warehouse*" OR "port" OR "ports" OR "transport*" OR "transportation*"). A total of 11,064 documents were produced initially. Only articles, proceeding papers, review articles, book chapters, and books are analyzed in this study. After removing duplicate and unrelated documents, a total of 10,861 documents were found for this study with the document types displayed in Table 1. More than 97% of the documents are articles (8185 documents) and proceeding papers (2895 documents). Review articles make up 1.81% of the total documents (206 publications), while book chapters (117 documents) and books (4 documents) contribute 1.03% and 0.04%, respectively.

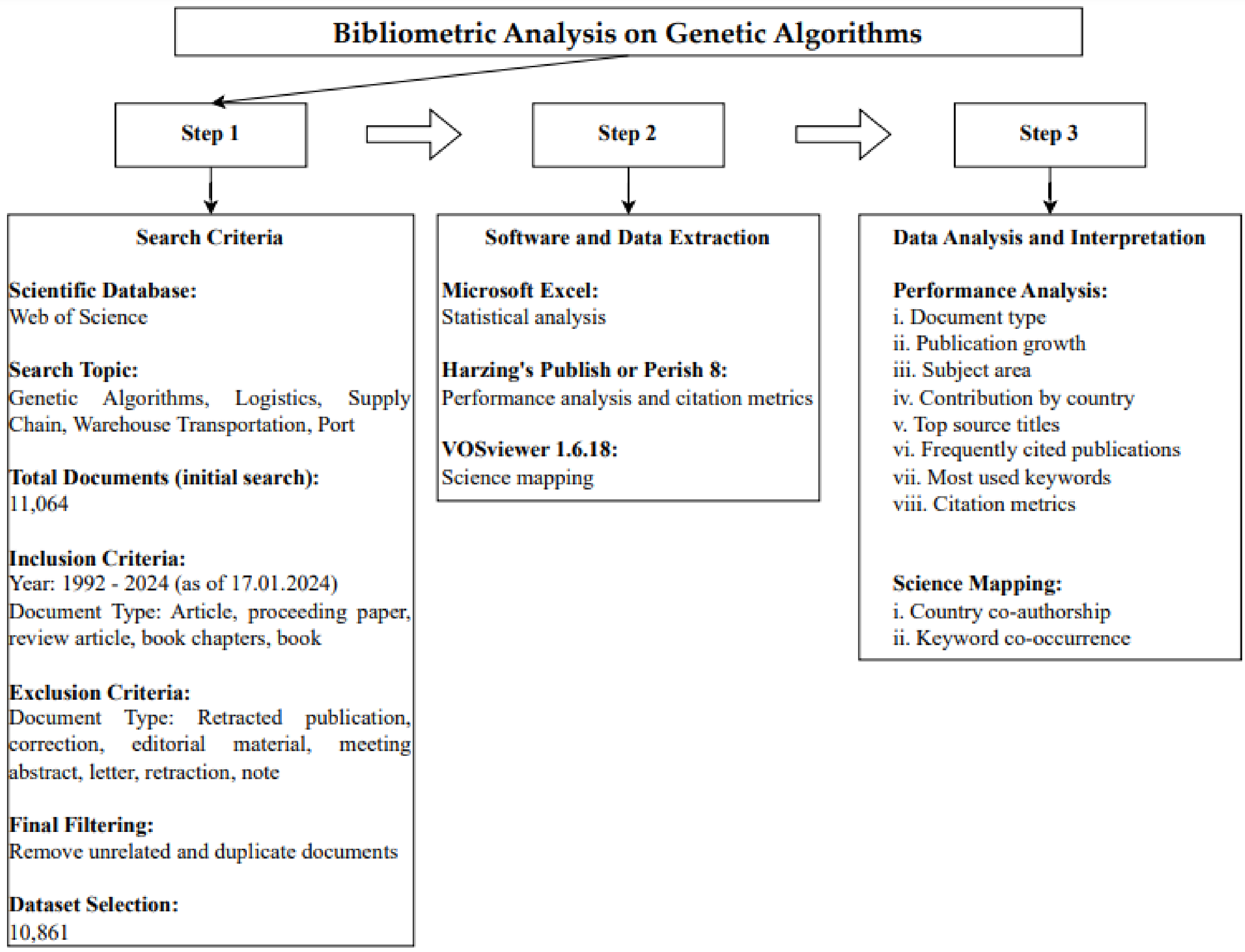

Figure 1. The 3-step approach for conducting a bibliometric analysis on genetic algorithms.

Table 1. Document types of publications on genetic algorithm.

Document Types	Total Publications (TPs)	Percentage (%)
Article	8185	71.75
Proceeding Paper	2895	25.38
Review Article	206	1.81
Book Chapter	117	1.03
Book	4	0.04

Step 3 begins after data extraction, where performance analyses and science mapping are used for data analysis. Performance analyses are performed using Harzing's Publish or Perish 8 [91,92]. A performance analysis is conducted to obtain the metrics for publication growths, subject areas, location contributions, source titles, and highly cited documents and to perform a keyword analysis [93,94]. The metrics used include total publications (TP), number of cited publications (NCP), total citations (TC), average citations per paper (C/P), average citations per cited paper (C/CP), *h*-index, and *g*-index [91,95]. The *h*-index and *g*-index are important for the forecast of future achievements [91]. Location co-authorship and keyword co-occurrence diagrams are science mappings for qualitative analyses [96,97].

They are performed using VOSviewer 1.6.18 (Centre for Science and Technology Studies, Leiden University, The Netherlands) [98–100].

3. Results and Discussion

This section presents the results of the bibliometric analysis of publications on genetic algorithms as of 17 January 2024. The results include publication growth, subject areas, location contributions, publication titles, highly cited publications, keyword analyses, and citation metrics.

3.1. Annual Publication Growth

The annual publication growth of genetic algorithm publications in the field of logistics and supply chain management is shown in Table 2. The first paper indexed in the Web of Science database is titled "A Genetic Algorithm for the Linear Transportation Problem" by Vignaux and Michalewicz [101], published in 1991. This paper, which investigated the application of genetic algorithms to solve non-linear and fixed-charge transportation problems, attained 125 total citations as of 17 January 2024. This paper became the foundation for the research in supplier management [102], vehicle routing optimization [103,104], fixed-charge transportation issues [105–107], and uncertainty estimation [108,109]. The second paper, published by Kopfer [110] in 1992, titled "Concepts of Genetic Algorithms and Their Application to the Freight Optimization Problem in Commercial Shipping", received eight total citations. This paper focused on minimizing freight rates in commercial road transport.

Even though fluctuations can be seen in the number of annual publications from 1991 to 2001, the total annual publication rate saw an increasing trend from 2001 to 2009. A slight drop in the total annual publication rate happened in 2010. However, the total annual publication rate continued to increase until it peaked in 2022 with 1021 publications. Since 2024 had just begun, there were only 40 documents as of 17 January 2024. The highest total citation (TC) was recorded in 2018 with 13,613 documents. The highest citations per paper (C/P) and citations per cited paper (C/CP) were in 1991 because there was only a single paper with 125 citations. The C/P is the total number of citations over the total number of published papers, while the C/CP is the total number of citations over the total number of papers which have only been cited [111]. The largest h-index (58) was found in 2016 and 2017, respectively. This can be implied as 58 documents obtained 58 or more citations for both years. The largest g-index (91) was found in 2015. In 2015, 91 documents obtained 91^2 (8281) total citations. The total citation (TC) trend experienced a fall since 2018 because there was only a short period of time between the time of publication and time of citation [112–116].

Table 2. Publication growth of research on genetic algorithms.

Year	TP [1]	P [2] (%)	CP [3]	NCP [4]	TC [5]	C/P [6]	C/CP [7]	h [8]	g [9]
1991	1	0.01	0.01	1	125	125.00	125.00	1	1
1992	1	0.01	0.02	1	8	8.00	8.00	1	1
1994	4	0.04	0.06	4	20	5.00	5.00	2	4
1995	7	0.06	0.12	7	390	55.71	55.71	7	7
1996	9	0.08	0.20	8	282	31.33	35.25	5	9
1997	26	0.24	0.44	17	505	19.42	29.71	9	22
1998	34	0.31	0.75	26	883	25.97	33.96	14	29
1999	30	0.28	1.03	21	463	15.43	22.05	11	21
2000	65	0.60	1.63	52	1810	27.85	34.81	24	42
2001	41	0.38	2.01	37	1581	38.56	42.73	17	39
2002	75	0.69	2.70	60	3267	43.56	54.45	31	57
2003	89	0.82	3.52	69	2372	26.65	34.38	27	48
2004	108	0.99	4.51	84	3441	31.86	40.96	31	58
2005	158	1.45	5.97	121	4890	30.95	40.41	37	67
2006	231	2.13	8.09	173	5189	22.46	29.99	42	67

Table 2. *Cont.*

Year	TP [1]	P [2] (%)	CP [3]	NCP [4]	TC [5]	C/P [6]	C/CP [7]	*h* [8]	*g* [9]
2007	246	2.26	10.36	172	4674	19.00	27.17	36	64
2008	284	2.61	12.97	189	4649	16.37	24.60	35	63
2009	349	3.21	16.19	169	6841	19.60	25.43	47	73
2010	306	2.82	19.00	233	7568	24.73	32.48	48	76
2011	327	3.01	22.01	272	7387	22.59	27.16	48	74
2012	423	3.89	25.91	341	7919	18.72	23.22	46	69
2013	437	4.02	29.93	359	9970	22.81	27.77	49	81
2014	507	4.67	34.60	423	10,574	20.86	25.00	48	87
2015	550	5.06	39.66	463	12,834	23.33	27.72	55	91
2016	630	5.80	45.47	524	11,469	18.20	21.89	58	80
2017	645	5.94	51.40	575	13,222	20.50	22.99	58	82
2018	762	7.02	58.42	672	13,613	17.86	20.26	55	81
2019	769	7.08	65.50	681	12,747	16.58	18.72	52	75
2020	808	7.44	72.94	714	11,977	14.82	16.77	47	70
2021	913	8.41	81.35	812	9527	10.43	11.73	40	57
2022	1021	9.40	90.75	786	5302	5.19	6.75	24	36
2023	965	8.89	99.63	454	1440	1.49	3.17	14	17
2024	40	0.37	100.00	7	7	0.18	1.00	1	1
Total	10,861	100.00			176,946				

[1] Total Publications (TP); [2] Percentage (P); [3] Cumulative Percentage (CP); [4] Number of Cited Publications (NCP); [5] Total Citations (TC); [6] Citations per Paper (C/P); [7] Citations per Cited Paper (C/CP); [8] *h*-index (*h*); [9] *g*-index (*g*).

3.2. Subject Areas

The 10,861 documents found on genetic algorithms can be sorted into more than 50 subject areas. Most of the papers are in engineering (5558 documents), computer science (3840 documents), and operations research/management science (2004 documents). A total of 1128 documents are in the field of transportation, while business economics has 805 documents. Other critical subject areas are environmental sciences ecology (692 documents), automation control systems (675 documents), mathematics (675 documents), science technology and other topics (639 documents), and telecommunications (464 documents). The top 20 subject areas are listed in Table 3.

Table 3. Top subject areas involving genetic algorithms.

Research Areas	Total Publications
Engineering	5558
Computer Science	3840
Operations Research/Management Science	2004
Transportation	1128
Business Economics	805
Environmental Sciences Ecology	692
Automation Control Systems	675
Mathematics	675
Science Technology Other Topics	639
Telecommunications	464
Energy Fuels	393
Materials Science	339
Physics	314
Water Resources	290
Chemistry	270
Mechanics	196
Construction Building Technology	167
Thermodynamics	166
Robotics	133
Geology	125

The Web of Science database also categorizes the documents into more than 100 areas. The top 20 categories are summarized in Table 4. The top five Web of Science categories are operations research/management science (2004 documents), computer science artificial intelligence (1809 documents), engineering electrical electronic (1617 documents), computer science interdisciplinary applications (1408 documents), and engineering industrial (1369 documents).

Table 4. Top Web of Science categories involving genetic algorithms.

Research Areas	Total Publications
Operations Research/Management Science	2004
Computer Science Artificial Intelligence	1809
Engineering Electrical Electronic	1617
Computer Science Interdisciplinary Applications	1408
Engineering Industrial	1369
Transportation Science Technology	1007
Engineering Civil	877
Computer Science Information Systems	854
Computer Science Theory Methods	844
Engineering Multidisciplinary	788
Engineering Manufacturing	764
Automation Control Systems	675
Environmental Sciences	635
Management	582
Transportation	480
Telecommunications	464
Green Sustainable Science Technology	405
Energy Fuels	393
Engineering Mechanical	366
Mathematics Interdisciplinary Applications	343

3.3. Location Contributions

Publications on genetic algorithms applied in the field of logistics and supply chain management received the attention of scholars from more than 120 locations. The top 10 locations with the most contributions of publications on genetic algorithms in logistics and supply chain management are China (4050 documents), the United States (1389 documents), Iran (1180 documents), India (751 documents), England (427 documents), France (410 documents), Taiwan (394 documents), South Korea (360 documents), Australia (343 documents), and Japan (336 documents). These top 10 locations contribute more than 88% of the total publications. There are 175,003 citations from the top 10 locations. China has the highest number of citations (50,602 citations) with 2940 cited papers. China also has the largest *g*-index, indicating that 125 documents received 125^2 (15,625) citations. England has the greatest citations per paper (C/P) (26.54) and citations per cited paper (C/CP) (30.54). The United States has the largest *h*-index (91), indicating that 91 documents have obtained 91 or more citations. The top 10 locations interested in the research on genetic algorithms are tabulated in Table 5.

Scholars from across the world are collaborating to expand and develop their research interests. This trend can be viewed using the location co-authorship analysis in VOSviewer. Figure 2 presents a location co-authorship diagram of studies on genetic algorithms in logistics and supply chain management. China has the largest international collaboration rate with a total link strength of 1221, followed by the United States, Iran, England, and India, with total link strengths of 965, 595, 431, and 369, respectively. The strongest international collaboration is between China and the United States with a link strength of 337, followed by China and England with a link strength of 101.

Table 5. Top locations interested in the research on genetic algorithms.

Location	TP [1]	NCP [2]	TC [3]	C/P [4]	C/CP [5]	*h* [6]	*g* [7]
China	4050	2940	50,602	12.49	17.21	88	125
United States	1389	1227	34,709	24.99	28.29	91	125
Iran	1180	1054	28,226	23.92	26.78	76	120
India	751	628	13,856	18.45	22.06	57	90
England	427	371	11,331	26.54	30.54	56	90
France	410	359	7948	19.39	22.14	44	71
Taiwan	394	345	7875	19.99	22.83	48	71
South Korea	360	299	5952	16.53	19.91	39	63
Australia	343	304	7635	22.26	25.12	47	71
Japan	336	256	6869	20.44	26.83	43	75

[1] Total Publications (TP); [2] Number of Cited Publications (NCP); [3] Total Citations (TC); [4] Citations per Paper (C/P); [5] Citations per Cited Paper (C/CP); [6] *h*-index (*h*); [7] *g*-index (*g*).

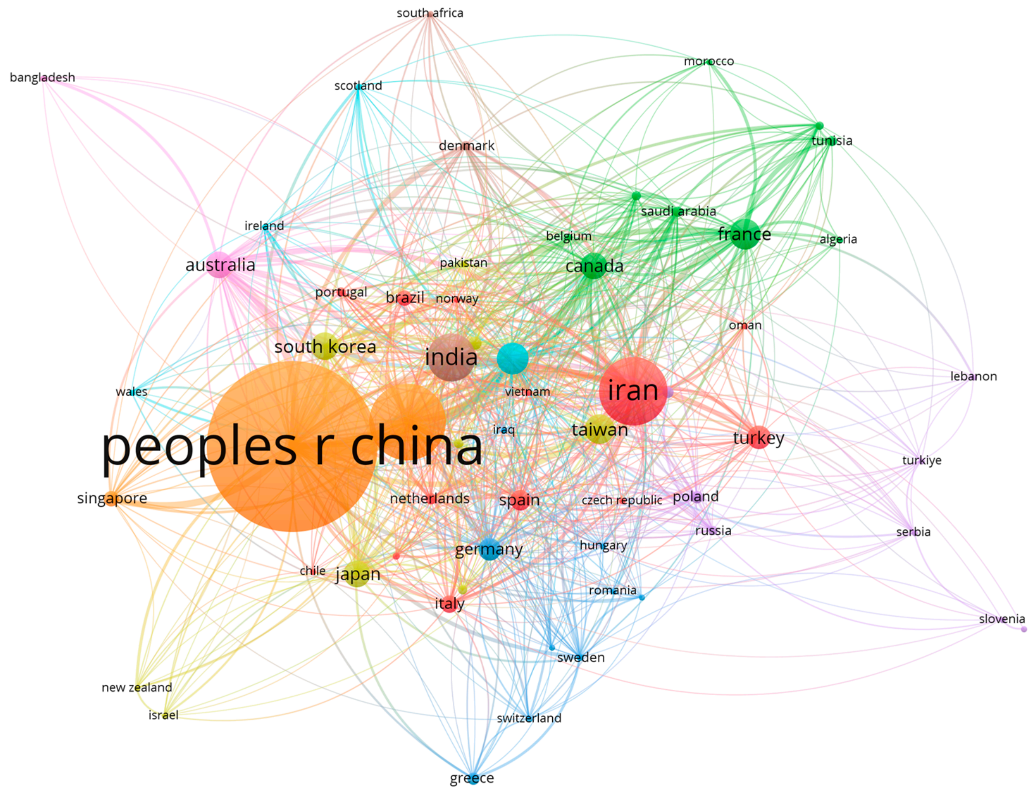

Figure 2. Location co-authorship diagram of genetic algorithm studies.

3.4. Publication Titles

There are more than 200 publication titles regarding the application of genetic algorithms in logistics and supply chain management. Table 6 shows the top 10 publication titles on genetic algorithms. *Computers and Industrial Engineering* (333 documents) published the most documents on genetic algorithms, followed by the *International Journal of Production Research* (210 documents), *Sustainability* (200 documents), *Expert Systems with Applications* (190 documents), *Applied Soft Computing* (157 documents), *IEEE Access* (151 documents), the *European Journal of Operational Research* (135 documents), *Lecture Notes in Computer Science* (118 documents), the *Journal of Cleaner Production* (111 documents), and *Mathematical Problems in Engineering* (110 documents).

Table 6. Publication titles regarding genetic algorithms.

Title	TP [1]	P [2] (%)	TC [3]	Publisher	JIF [4]	JCI [5]	CiteScore	SJR [6]	SNIP [7]	*h* [8]	*g* [9]
Computers and Industrial Engineering	333	3.07	11,038	Pergamon-Elsevier Science Ltd.	7.9	1.31	11.9	1.76	2.238	57	84
International Journal of Production Research	210	1.93	5909	Taylore & Francies Ltd.	9.2	1.46	18.1	2.976	2.875	42	61
Sustainability	200	1.84	1602	Multidisciplinary Digital Publishing Institute	3.9	0.67	5.8	0.664	1.198	18	31
Expert Systems with Applications	190	1.75	6125	Pergamon-Elsevier Science Ltd.	8.5	1.73	12.6	1.873	2.582	42	67
Applied Soft Computing	157	1.45	4155	Elsevier	8.7	1.57	14.3	1.882	2.314	38	53
IEEE Access	151	1.39	1427	IEEE-INST Electrical Electronics Engineers Inc.	3.9	0.89	9.0	0.926	1.422	20	29
European Journal of Operational Research	135	1.24	8879	Elsevier	6.4	1.44	11.2	2.371	2.706	53	91
Lecture Notes in Computer Science	118	1.09	625	Springer Nature	N/A	N/A	2.2	0.32	0.542	12	21
Journal of Cleaner Production	111	1.02	5092	Elsevier Sci Ltd.	11.1	1.53	18.5	1.981	2.379	42	68
Mathematical Problems in Engineering	110	1.01	762	Hindawi	N/A	N/A	2.6	0.355	0.709	13	21

[1] Total Publications (TP); [2] Percentage (P); [3] Total Citations (TC); [4] Journal Impact Factor 2022 (JIF); [5] Journal Citation Indicator 2022 (JCI); [6] SCImago Journal Rank 2022 (SJR); [7] Source-Normalized Impact per Paper 2022 (SNIP); [8] *h*-index (*h*); [9] *g*-index (*g*).

3.5. Top Cited Publications

Table 7 explains the top cited genetic algorithm publications. The document with the most citations is titled "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future" by Govindan et al. [117], which received 1162 citations. This paper reviewed reversed logistics and closed-loop supply chains between January 2007 and March 2013. The paper by Steenken et al. [118] titled "Container terminal operation and operations research—a classification and literature review" received 882 citations. This paper investigated the main logistics processes and operations in container terminals and presented a survey of methods for their optimization. The third most cited paper, written by Lin et al. [119], reviewed green vehicle routing problems in supply chain management. Govindan et al. [120] produced the article titled "Barrier analysis for green supply chain management implementation in Indian industries using analytic hierarchy process" and garnered 494 citations. This paper identified barriers to the implementation of green supply chain management based on procurement effectiveness. The next most cited paper, written by Guihaire and Hao [121], presented a review of crucial strategic steps in transit network design and scheduling.

The sixth most cited paper, written by Vlahogianni et al. [122], studied optimized and meta-optimized neural networks for short-term traffic flow prediction. Farahani et al. [123] presented a review of the definitions, classifications, objectives, constraints, network topology decision variables, and solution methods of the Urban Transportation Network Design Problem. The next most cited paper, written by Govindan et al. [124], presented a multi-objective optimization model by integrating sustainability in decision making and focusing on distribution in a perishable food supply chain network. Rojas et al. [125] reviewed transit network planning problems and real-time control strategies of bus transport systems. The tenth most cited paper, written by Jones et al. [126], investigated the types of multi-objective techniques and meta heuristics in solving multi-objective programming.

Table 7. Top cited genetic algorithm publications.

Title	Year	Citations	Source Title
Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future [117]	2015	1162	*European Journal of Operational Research*
Container terminal operation and operations research—a classification and literature review [118]	2004	882	*OR Spectrum*
Survey of Green Vehicle Routing Problem: Past and future trends [119]	2014	539	*Expert Systems with Applications*
Barriers analysis for green supply chain management implementation in Indian industries using analytic hierarchy process [120]	2014	494	*International Journal of Production Economics*
Transit network design and scheduling: A global review [121]	2008	445	*Transportation Research Part A—Policy and Practice*
Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach [122]	2005	439	*Transportation Research Part C—Emerging Technologies*
A review of urban transportation network design problems [123]	2013	419	*European Journal of Operational Research*
Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food [124]	2014	408	*International Journal of Production Economics*
Planning, operation, and control of bus transport systems: A literature review [125]	2015	398	*Transportation Research Part B—Methodological*
Multi-objective meta-heuristics: An overview of the current state-of-the-art [126]	2002	372	*European Journal of Operational Research*

3.6. Keyword Analyses

The keyword co-occurrence map and keyword overlay visualization map were generated using VOSviewer [127,128]. Research hotspots can be found using the keyword co-occurrence map by linking key research areas [129]. Table 8 lists the 20 keywords with the highest total link strengths. "Genetic algorithm" occurred 4964 times with a total link strength of 13,983, followed by "optimization" with 2285 occurrences and a total link strength of 8288 and "model" with 1596 occurrences and a total link strength of 6708. "Design" (4321), "management" (2851), "system" (2835), "algorithm" (2573), "supply chain" (2509), "transportation" (2286), and "logistics" (1803) also have high total link strengths. Figure 3 depicts a keyword co-occurrence map of genetic algorithm papers in the field of logistics and supply chain management.

Table 8. Keywords with the highest total link strengths in genetic algorithm publications.

Keywords	Appearance	Total Link Strength
Genetic algorithm	6134	17,046
Optimization	2285	8288
Model	1596	6708
Design	1060	4321
Management	602	2851
System	678	2835
Algorithm	778	2573
Supply chain	598	2509
Transportation	512	2286
Logistics	403	1803
Network design	336	1626

Table 8. *Cont.*

Keywords	Appearance	Total Link Strength
Demand	311	1561
Particle swarm optimization	383	1554
Network	350	1515
Multi-objective optimization	406	1497
Simulation	383	1434
Location	357	1357
Uncertainty	305	1340
Search	278	1318
Performance	310	1312

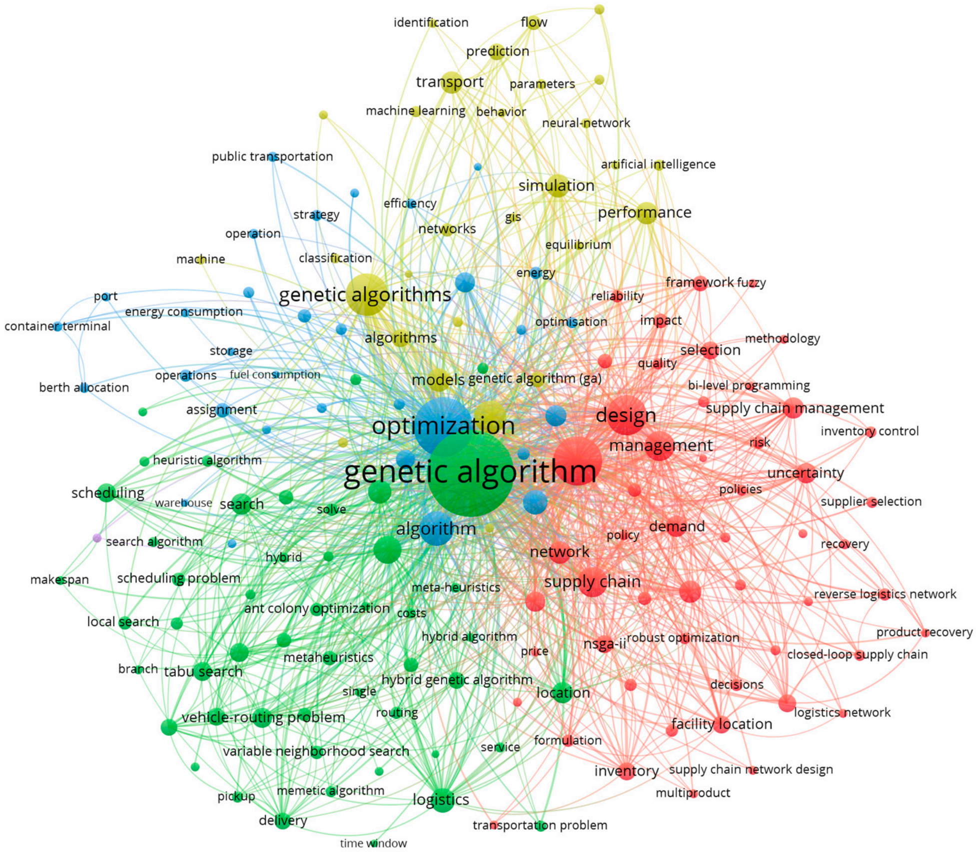

Figure 3. Keyword co-occurrence map of genetic algorithm papers in the field of logistics and supply chain management.

Based on Figure 3, the keyword genetic algorithm has the highest total link strength (17,046). Genetic algorithm has the highest link strength with optimization (1163), model (852), and design (535). There are four clusters in the keyword co-occurrence map, which was sorted based on their research areas. The first cluster is in red and contains keywords such as allocation, bi-level programming, carbon emission, closed-loop supply chain, coordination, cost, decision making, demand, design, environment, facility location, formulation, framework, fuzzy, impact, integrated production, inventory, inventory control, inventory management, logistics network, management, methodology, model, multiproduct, network, network design, Non-Dominated Sorting Genetic Algorithm II (NSGA-II), optimization model, policies, price, product recovery, programming approach, quality, recovery, reliability, reverse logistics, risk, robust optimization, selection, stochastic programming, supplier selection, supply chain, sustainability, and uncertainty. This first cluster revolves around the application of various types of multi-objective optimization algorithms to handle logistics and supply chain problems.

The second cluster is in green and contains the following keywords: ant colony optimization, branch, combinatorial optimization, delivery, differential evolution, formulations, heuristic algorithm, heuristics, hybrid algorithm, hybrid genetic algorithm, local search, location, logistics, machines, memetic algorithm, meta-heuristics, neighborhood search, optimization algorithm, particle swarm optimization, pickup, routing, scheduling, search algorithm, service, simulated annealing algorithm, tabu search, time window, transportation, traveling salesman problem, variable neighborhood search, and vehicle routing. Based on the keywords, this research area is related to metaheuristics.

The third cluster is in blue. It contains keywords such as algorithm, assignment, berth allocation, consumption, container terminal, electric vehicles, emissions, energy consumption, evolutionary algorithms, fuel consumption, improved genetic algorithm, integration, multi-objective optimization, operations, port, storage, strategy, system, time, and warehouse. This cluster highlights the use of optimization techniques to overcome sustainability issues in logistics.

The fourth cluster is in yellow and has keywords such as artificial intelligence, artificial neural network, behavior, capacity, classification, constraints, decomposition, equilibrium, flow, fuzzy logic, geographic information system (GIS), identification, intelligent transportation system, machine learning, neural network, parameters, performance, prediction, and simulation. This cluster stresses the importance of integrating genetic algorithms with other machine learning techniques in logistics and supply chain management.

The evolution of publications can also be visualized using the keyword overlay visualization map shown in Figure 4 [130–132]. Based on Figure 4, the nodes for pickup, delivery, routing problem, costs, optimization algorithm, heuristic algorithm, search algorithm, emissions, robust optimization, NSGA-II, energy consumption, electric vehicle, machine learning, and variable neighborhood search appear in yellow, signaling their importance in recent years [133]. As attention is paid to sustainability and environmental issues, genetic algorithms have been adopted to solve various challenges in developing efficient electric vehicles [134,135]. Bhakuni and Das [136] intended to handle uncertainty in the electric vehicle industry using generalized triangular neutrosophic numbers and modified neutrosophic compromise programming with validation using genetic algorithms. Qiang et al. [137] used a hybrid adaptive genetic algorithm to construct an electric vehicle path model with time windows for logistics distribution. To reduce logistics costs, Zahedi et al. [138] developed a metaheuristic algorithm with NSGA-II and teaching–learning-based optimization (TLBO) to solve the routing problem in electric vehicles with time window consideration.

NSGA-II has been in the spotlight in several research studies on genetic algorithms in recent years. The study by Jafarian et al. [139] integrated NSGA-II and multi-objective particle swarm optimization (MOPSO) to quantify the difference between the current and ideal states in supply chains with the use of the house of quality (HOQ), quality function deployment (QFD), and response surface methodology (RSM) to determine the characteristics and tune the parameters. Manupati et al. [140] developed a blockchain model with a Mixed-Integer Non-Linear Programming (MINLP) model to overcome sustainable issues in a multi-echelon supply chain and then validated the model with NSGA-II, signifying the recognition and practicability of NSGA-II. To reduce supply chain disruptions, Shekarian et al. [141] developed a Multi-Objective Mixed-Integer Programming (MOMIP) model with weighted goal programming, augmented ε-constraint (AUGMECON), and NSGA-II. Additionally, a closed-loop supply chain network with Multi-Objective Grey Wolf Optimization (MOGWO) and NSGA-II has been proposed for the COVID-19 pandemic [142]. In publications on genetic algorithms, NSGA-II has also been applied to solve pickup, delivery, and routing problems. Rabbani et al. [143] formulated an MINLP model with NSGA-II and Monte Carlo simulation in hazardous waste logistics management. Tirkolaee et al. [144] designed a Bi-Objective Mixed-Integer Linear Programming (BOMILP) model using Multi-Objective Simulated Annealing Algorithm (MOSA) and NSGA-II for efficient Pareto solutions to minimize pollution and routing costs and maximize supply reliability. In the past year, NSGA-II has been widely applied in maritime management [145,146].

NSGA-II has also been used in port management [147,148]. Moreover, NSGA-II is also commonly used to solve transportation and routing problems [149–151]. NSGA-II is also an important tool in overcoming sustainability problems in the supply chain [152–154]. Therefore, in the future, various optimization techniques and metaheuristics can be integrated into genetic algorithms in logistics and supply chain management.

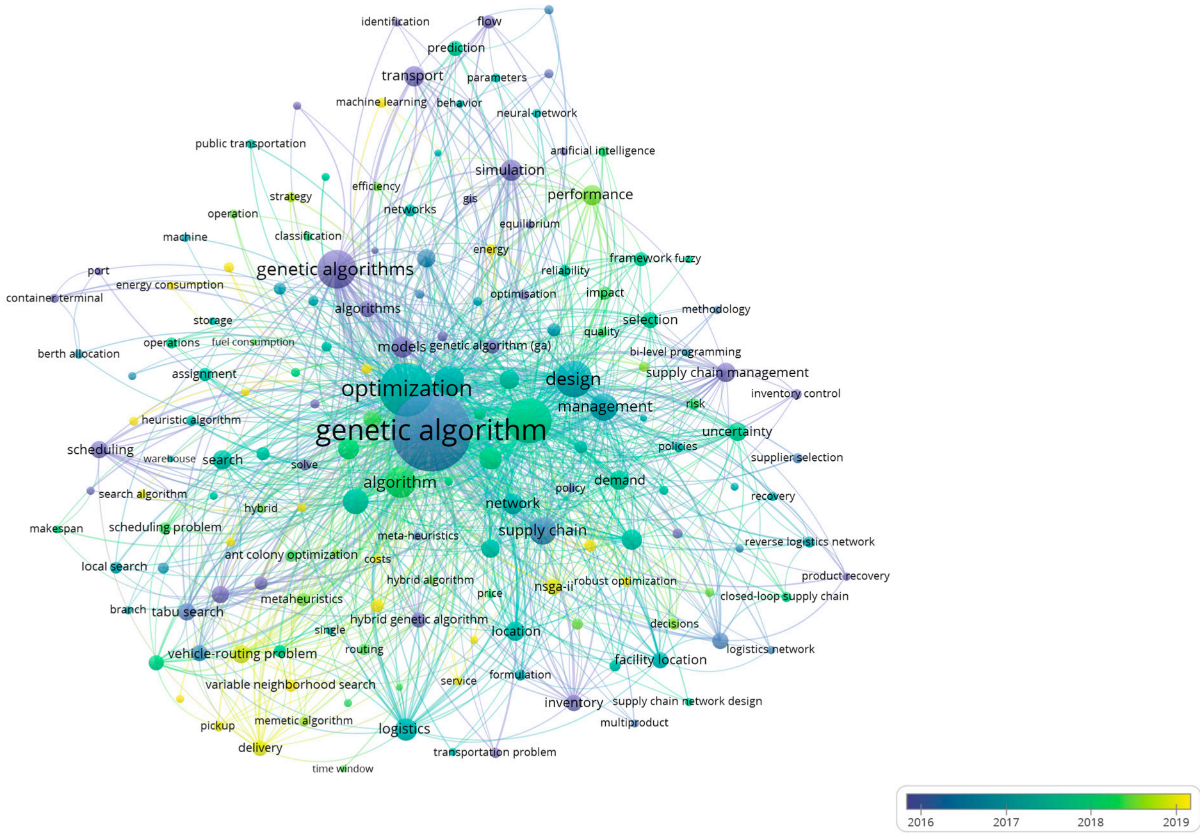

Figure 4. Keyword overlay highlighting recent hotspots in genetic algorithm research.

Variable neighborhood search is also popular in the research on genetic algorithms. Londoño et al. [155] used the variable neighborhood search algorithm within a Chu–Beasley Genetic Algorithm to overcome the multi-depot vehicle routing problem. Pan et al. [156] used hybrid metaheuristic algorithms involving a genetic algorithm and multiple population genetic algorithm (MPGA) with variable neighborhood search to optimize a perishable product supply chain network. When solving a routing problem with pickup and delivery, Wang et al. [157] compared the proposed model integrating the Clarke–Wright saving algorithm, variable neighborhood search, and MOPSO with multi-objective variable neighborhood search and NSGA-II. Zhu and Zhou [158] introduced a catastrophe adaptive genetic algorithm with variable neighborhood search to improve efficiency in fresh produce distribution. Multi-choice goal programming with a utility function with the integration of a genetic algorithm and variable neighborhood search is also used in supply chain management with new product development [159]. Variable neighborhood search and genetic algorithms have been used to solve various transportation problems [160]. From the keyword overlay analysis, it can also be found that future research can focus on the integration of metaheuristics with machine learning to overcome the limitations of genetic algorithms, such as their long computational time, difficulties in obtaining optimal solutions, and convergence issues [161–163]. Future studies can also find ways to overcome the challenges in the application of genetic algorithms in supply chains, such as the lack of local search strategies in evolutionary aspects, and to solve non-deterministic polynomial (NP-hard) problems in supply chains [53]. Kumar et al. [164] noted that a traditional genetic algorithm has a slower rate of convergence to create an agile supply chain in the warehouse scheduling problem. A traditional genetic algorithm is also easily affected by the degree of variations [165]. Wang and Huang [166] also noted the issue of convergence and stability in traditional genetic algorithms for agile supply chain scheduling optimization. Low rates of convergence and variability were also noticed when designing an agile medicine supply chain [167].

3.7. Citation Metrics

The citation metrics of the publications on genetic algorithms in logistics and supply chain management are shown in Table 9.

Table 9. Citation metrics of genetic algorithm publications.

Items	Descriptions
Date	17 January 2024
Total Number of Papers	10,861
Total Citations	17,6946
Total Number of Years	32
Citations per Year	5529.56
Citations per Paper	16.29
Citations per Author	61,887.17
Papers per Author	3899.46
Authors per Paper	3.4
h-index	135
g-index	192

4. Conclusions

This paper has successfully achieved the objective of presenting a bibliometric analysis of genetic algorithm research in the field of logistics and supply chain management. In general, the publication trend in this field has been increasing in recent years. Most of the documents are articles (71.75%) and proceeding papers (25.38%). Engineering (5558 documents), computer science (3840 documents), and operations research management science (2004 documents) make up the top three subject areas in the research on the application of genetic algorithms in logistics and supply chain management. China has the most total publications (4050 documents), while England has the most citations per paper (26.54 citations per paper) and citations per cited paper (30.54 citations per cited paper). *Computers and Industrial Engineering* (333 documents), the *International Journal of Production Research* (210 documents), and *Sustainability* (200 documents) are the top three publication journals. The document by Govindan et al. [117] titled "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future" received 1162 citations and is the most important and influential paper in the research on the application of genetic algorithms in logistics and supply chain.

This paper has captured the prominent themes shaping the current and future research involving (1) the application of various types of multi-objective optimization algorithms to handle logistics and supply chain problems, (2) metaheuristics, (3) the use of optimization techniques to overcome sustainability issues in logistics, and (4) the integration of genetic algorithms with other machine learning techniques in logistics and supply chain management. In the future, genetic algorithms can be integrated with other optimization and metaheuristic strategies for logistics and supply chain management. Sustainability issues will also encourage researchers to continue their explorations in this area. Machine learning, which is also able to overcome the limitations of genetic algorithms, such as their long computational time, difficulties in obtaining optimal solutions, and convergence issues, is also one of the future trends in genetic algorithm research.

This paper is focused on the publications listed in the Web of Science database. Future studies can consider other notable databases, such as Scopus, for bibliometric analyses of genetic algorithms in logistics and supply chain management. The Web of Science database provides excellent references and experiences to scholars with continuous updates. In the future, this bibliometric analysis can be revisited to capture the constant changes in industry and academy.

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References

1. Yang, D.; Yu, Z.; Yuan, H.; Cui, Y. An Improved Genetic Algorithm and Its Application in Neural Network Adversarial Attack. *PLoS ONE* **2022**, *17*, e0267970. [CrossRef] [PubMed]
2. Oh, S.; Yoon, J.; Choi, Y.; Jung, Y.-A.; Kim, J. Genetic Algorithm for the Optimization of a Building Power Consumption Prediction Model. *Electronics* **2022**, *11*, 3591. [CrossRef]
3. Jennings, P.C.; Lysgaard, S.; Hummelshøj, J.S.; Vegge, T.; Bligaard, T. Genetic Algorithms for Computational Materials Discovery Accelerated by Machine Learning. *npj Comput. Mater.* **2019**, *5*, 46. [CrossRef]
4. Rostami, M.; Berahmand, K.; Forouzandeh, S. A Novel Community Detection Based Genetic Algorithm for Feature Selection. *J. Big Data* **2021**, *8*, 2. [CrossRef]
5. Katoch, S.; Chauhan, S.S.; Kumar, V. A Review on Genetic Algorithm: Past, Present, and Future. *Multimed. Tools Appl.* **2021**, *80*, 8091–8126. [CrossRef] [PubMed]
6. Goldberg, D.E. *Genetic Algorithms*; Pearson Education India: Delhi, India, 2013; ISBN 978-81-7758-829-3.
7. Darwin, C.R. *On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life*, 1st ed.; John Murray: London, UK, 1859.
8. Simoncini, D.; Zhang, K.Y.J. Population-Based Sampling and Fragment-Based De Novo Protein Structure Prediction. In *Encyclopedia of Bioinformatics and Computational Biology*; Ranganathan, S., Gribskov, M., Nakai, K., Schönbach, C., Eds.; Academic Press: Oxford, UK, 2019; pp. 774–784, ISBN 978-0-12-811432-2.
9. Papanicolaou, C.G.; Papantoniou, I.C. 11—Optimum Design of Textile-Reinforced Concrete as Integrated Formwork in Slabs. In *Textile Fibre Composites in Civil Engineering*; Triantafillou, T., Ed.; Woodhead Publishing: Cambridge, UK, 2016; pp. 245–274, ISBN 978-1-78242-446-8.
10. Yang, X.-S. Chapter 6—Genetic Algorithms. In *Nature-Inspired Optimization Algorithms*, 2nd ed.; Yang, X.-S., Ed.; Academic Press: Oxford, UK, 2021; pp. 91–100, ISBN 978-0-12-821986-7.
11. Roetzel, W.; Luo, X.; Chen, D. Chapter 6—Optimal Design of Heat Exchanger Networks. In *Design and Operation of Heat Exchangers and their Networks*; Roetzel, W., Luo, X., Chen, D., Eds.; Academic Press: Oxford, UK, 2020; pp. 231–317, ISBN 978-0-12-817894-2.
12. Yang, X.-S. Chapter 5—Genetic Algorithms. In *Nature-Inspired Optimization Algorithms*; Yang, X.-S., Ed.; Elsevier: Oxford, UK, 2014; pp. 77–87, ISBN 978-0-12-416743-8.
13. Tsai, C.-W.; Chiang, M.-C. Chapter Seven—Genetic Algorithm. In *Handbook of Metaheuristic Algorithms*; Tsai, C.-W., Chiang, M.-C., Eds.; Uncertainty, Computational Techniques, and Decision Intelligence; Academic Press: Oxford, UK, 2023; pp. 111–138, ISBN 978-0-443-19108-4.
14. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*; The MIT Press: Cambridge, MA, USA, 1992; ISBN 978-0-262-58111-0.
15. Albadr, M.A.; Tiun, S.; Ayob, M.; AL-Dhief, F. Genetic Algorithm Based on Natural Selection Theory for Optimization Problems. *Symmetry* **2020**, *12*, 1758. [CrossRef]
16. Narques, T.V.N.; Carvalho, R.C.; Christoforo, A.L.; Mascarenhas, F.J.R.; Arroyo, F.N.; Bomfim Junior, F.C.; dos Santos, H.F. Use of Real Coded Genetic Algorithm as a Pre-Dimensioning Tool for Prestressed Concrete Beams. *Buildings* **2023**, *13*, 819. [CrossRef]
17. Hassanat, A.; Almohammadi, K.; Alkafaween, E.; Abunawas, E.; Hammouri, A.; Prasath, V.B.S. Choosing Mutation and Crossover Ratios for Genetic Algorithms—A Review with a New Dynamic Approach. *Information* **2019**, *10*, 390. [CrossRef]
18. Koumousis, V.K.; Katsaras, C.P. A Saw-Tooth Genetic Algorithm Combining the Effects of Variable Population Size and Reinitialization to Enhance Performance. *IEEE Trans. Evol. Comput.* **2006**, *10*, 19–28. [CrossRef]
19. Bhoskar, M.T.; Kulkarni, M.O.K.; Kulkarni, M.N.K.; Patekar, M.S.L.; Kakandikar, G.M.; Nandedkar, V.M. Genetic Algorithm and Its Applications to Mechanical Engineering: A Review. *Mater. Today Proc.* **2015**, *2*, 2624–2630. [CrossRef]

20. Gen, M.; Cheng, R.; Lin, L. (Eds.) Multiobjective Genetic Algorithms. In *Network Models and Optimization: Multiobjective Genetic Algorithm Approach*; Decision Engineering; Springer: London, UK, 2008; pp. 1–47, ISBN 978-1-84800-181-7.
21. García-Martínez, C.; Rodriguez, F.J.; Lozano, M. Genetic Algorithms. In *Handbook of Heuristics*; Martí, R., Pardalos, P.M., Resende, M.G.C., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 431–464, ISBN 978-3-319-07124-4.
22. Suhail, K.; Brindha, D. Microscopic Urinary Particle Detection by Different YOLOv5 Models with Evolutionary Genetic Algorithm Based Hyperparameter Optimization. *Comput. Biol. Med.* **2024**, *169*, 107895. [CrossRef] [PubMed]
23. Zhang, Z.; Xie, D.; Lv, F.; Liu, R.; Yang, Y.; Wang, L.; Wu, G.; Wang, C.; Shen, L.; Tian, Z. Intelligent Geometry Compensation for Additive Manufactured Oral Maxillary Stent by Genetic Algorithm and Backpropagation Network. *Comput. Biol. Med.* **2023**, *157*, 106716. [CrossRef] [PubMed]
24. Ustabaş Kaya, G.; Onur, T.Ö. Genetic Algorithm Based Image Reconstruction Applying the Digital Holography Process with the Discrete Orthonormal Stockwell Transform Technique for Diagnosis of COVID-19. *Comput. Biol. Med.* **2022**, *148*, 105934. [CrossRef] [PubMed]
25. Li, T.; Duan, X.; Liu, K.; Huang, Y. Parameter Extraction for Photodiode Equivalent Circuit Model Based on Hybrid Genetic Algorithm. *Microelectron. J.* **2024**, *143*, 106017. [CrossRef]
26. Hassan, A.; Bass, O.; Masoum, M.A.S. An Improved Genetic Algorithm Based Fractional Open Circuit Voltage MPPT for Solar PV Systems. *Energy Rep.* **2023**, *9*, 1535–1548. [CrossRef]
27. Jin, F.; Chen, D.; Hu, L.; Huang, Y.; Bu, S. Optimization of Zigzag Parameters in Printed Circuit Heat Exchanger for Supercritical CO_2 Brayton Cycle Based on Multi-Objective Genetic Algorithm. *Energy Convers. Manag.* **2022**, *270*, 116243. [CrossRef]
28. Çavdar, M.C.; Korpeoglu, I.; Ulusoy, Ö. A Utilization Based Genetic Algorithm for Virtual Machine Placement in Cloud Systems. *Comput. Commun.* **2024**, *214*, 136–148. [CrossRef]
29. Mishra, R.; Bajpai, M.K. A Novel Multi-Agent Genetic Algorithm for Limited-View Computed Tomography. *Expert Syst. Appl.* **2024**, *238*, 122195. [CrossRef]
30. Arufe, L.; Rasconi, R.; Oddi, A.; Varela, R.; González, M.A. New Coding Scheme to Compile Circuits for Quantum Approximate Optimization Algorithm by Genetic Evolution. *Appl. Soft Comput.* **2023**, *144*, 110456. [CrossRef]
31. Ding, Z.; Tian, Y.-C.; Wang, Y.-G.; Zhang, W.; Yu, Z.-G. Progressive-Fidelity Computation of the Genetic Algorithm for Energy-Efficient Virtual Machine Placement in Cloud Data Centers. *Appl. Soft Comput.* **2023**, *146*, 110681. [CrossRef]
32. Sakthipriya, S.; Naresh, R. Precision Agriculture Based on Convolutional Neural Network in Rice Production Nutrient Management Using Machine Learning Genetic Algorithm. *Eng. Appl. Artif. Intell.* **2024**, *130*, 107682. [CrossRef]
33. Wei, Q.; Lv, M.; Wang, B.; Sun, J.; Wang, D. A Comparative Study of Optimized Conditions of QuEChERS to Determine the Pesticide Multiresidues in Lycium Barbarum Using Response Surface Methodology and Genetic Algorithm-Artificial Neural Network. *J. Food Compos. Anal.* **2023**, *120*, 105356. [CrossRef]
34. Wang, Y.; Jiang, K.; Shen, H.; Wang, N.; Liu, R.; Wu, J.; Ma, X. Decision-Making Method for Maize Irrigation in Supplementary Irrigation Areas Based on the DSSAT Model and a Genetic Algorithm. *Agric. Water Manag.* **2023**, *280*, 108231. [CrossRef]
35. Fujii, S.; Kuwabara, A. Interatomic Potentials for Cubic Zirconia and Yttria-Stabilized Zirconia Optimized by Genetic Algorithm. *Comput. Mater. Sci.* **2024**, *233*, 112722. [CrossRef]
36. Lu, H.; Dong, Q.; Yan, S.; Chen, X.; Wang, X. Development of Flexible Grouting Material for Cement-Stabilized Macadam Base Using Response Surface and Genetic Algorithm Optimization Methodologies. *Constr. Build. Mater.* **2023**, *409*, 133823. [CrossRef]
37. Ning, Y.; Zhang, F.; Jin, B.; Wang, M. Three-Dimensional Path Planning for a Novel Sediment Sampler in Ocean Environment Based on an Improved Mutation Operator Genetic Algorithm. *Ocean Eng.* **2023**, *289*, 116142. [CrossRef]
38. Kumi, L.; Jeong, J. Optimization Model for Selecting Optimal Prefabricated Column Design Considering Environmental Impacts and Costs Using Genetic Algorithm. *J. Clean. Prod.* **2023**, *417*, 137995. [CrossRef]
39. Tang, D.; Zhang, Z.; Hua, L.; Pan, J.; Xiao, Y. Prediction of Cold Start Emissions for Hybrid Electric Vehicles Based on Genetic Algorithms and Neural Networks. *J. Clean. Prod.* **2023**, *420*, 138403. [CrossRef]
40. Zhang, Z.; Li, J. Chapter 10—Big-Data-Driven Low-Carbon Management. In *Big Data Mining for Climate Change*; Zhang, Z., Li, J., Eds.; Elsevier: Oxford, UK, 2020; pp. 287–299, ISBN 978-0-12-818703-6.
41. Norrman, A.; Olhager, J. Global Supply Chain Management. In *The Palgrave Handbook of Supply Chain Management*; Sarkis, J., Ed.; Springer International Publishing: Cham, Switzerland, 2024; pp. 53–88, ISBN 978-3-031-19884-7.
42. Makris, S.; Alexopoulos, K.; Chryssolouris, G. Logistics. In *CIRP Encyclopedia of Production Engineering*; Laperrière, L., Reinhart, G., Eds.; Springer: Berlin/Heidelberg, Germany, 2014; pp. 762–768, ISBN 978-3-642-20616-0.
43. Antonyová, A.; Antony, P.; Soewito, B. Logistics Management: New Trends in the Reverse Logistics. *J. Phys. Conf. Ser.* **2016**, *710*, 012018. [CrossRef]
44. Chen, I.J.; Paulraj, A. Understanding Supply Chain Management: Critical Research and a Theoretical Framework. *Int. J. Prod. Res.* **2004**, *42*, 131–163. [CrossRef]
45. Zijm, H.; Klumpp, M.; Heragu, S.; Regattieri, A. Operations, Logistics and Supply Chain Management: Definitions and Objectives. In *Operations, Logistics and Supply Chain Management*; Zijm, H., Klumpp, M., Regattieri, A., Heragu, S., Eds.; Lecture Notes in Logistics; Springer International Publishing: Cham, Switzerland, 2019; pp. 27–42, ISBN 978-3-319-92446-5.
46. Globerson, S.; Wolbrum, G. Logistics Management and Supply Chain Management: A Critical Evaluation. *Int. J. Bus. Econ. Res.* **2014**, *3*, 82–88. [CrossRef]

47. Iris, Ç.; Serdarasan, S. A Review of Genetic Algorithm Applications in Supply Chain Network Design. In *Computational Intelligence Systems in Industrial Engineering*; Atlantis Press: Paris, France, 2012; pp. 203–230, ISBN 978-94-91216-76-3.
48. babaeinesami, A.; Ghasemi, P.; Abolghasemian, M.; chobar, A.P. A Stackelberg Game for Closed-Loop Supply Chains under Uncertainty with Genetic Algorithm and Gray Wolf Optimization. *Supply Chain. Anal.* **2023**, *4*, 100040. [CrossRef]
49. Gen, M.; Lin, L.; Yun, Y.; Inoue, H. Recent Advances in Hybrid Priority-Based Genetic Algorithms for Logistics and SCM Network Design. *Comput. Ind. Eng.* **2018**, *125*, 394–412. [CrossRef]
50. Roghanian, E.; Pazhoheshfar, P. An Optimization Model for Reverse Logistics Network under Stochastic Environment by Using Genetic Algorithm. *J. Manuf. Syst.* **2014**, *33*, 348–356. [CrossRef]
51. Zhou, J.; Yang, S.; Feng, H.; An, Z. Multi-Echelon Sustainable Reverse Logistics Network Design with Incentive Mechanism for Eco-Packages. *J. Clean. Prod.* **2023**, *430*, 139500. [CrossRef]
52. Gürler, H.E.; Özçalıcı, M.; Pamucar, D. Determining Criteria Weights with Genetic Algorithms for Multi-Criteria Decision Making Methods: The Case of Logistics Performance Index Rankings of European Union Countries. *Socio-Econ. Plan. Sci.* **2024**, *91*, 101758. [CrossRef]
53. Yeh, W.-C. An Efficient Memetic Algorithm for the Multi-Stage Supply Chain Network Problem. *Int. J. Adv. Manuf. Technol.* **2006**, *29*, 803–813. [CrossRef]
54. Saif-Eddine, A.S.; El-Beheiry, M.M.; El-Kharbotly, A.K. An Improved Genetic Algorithm for Optimizing Total Supply Chain Cost in Inventory Location Routing Problem. *Ain Shams Eng. J.* **2019**, *10*, 63–76. [CrossRef]
55. Kallina, D.; Siegfried, P. Optimization of Supply Chain Network Using Genetic Algorithms Based on Bill of Materials. *Munich Pers. RePEc Arch.* **2021**, *10*, 37–47.
56. Xin, L.; Xu, P.; Manyi, G. Logistics Distribution Route Optimization Based on Genetic Algorithm. *Comput. Intell. Neurosci.* **2022**, *2022*, 8468438. [CrossRef]
57. Sun, J.; Chen, Z.; Chen, Z.; Li, X. Robust Optimization of a Closed-Loop Supply Chain Network Based on an Improved Genetic Algorithm in an Uncertain Environment. *Comput. Ind. Eng.* **2024**, *189*, 109997. [CrossRef]
58. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Trans. Evol. Computat.* **2002**, *6*, 182–197. [CrossRef]
59. Rahman, A.; Shahruddin, N.S.; Ishak, I. Solving the Goods Transportation Problem Using Genetic Algorithm with Nearest-Node Pairing Crossover Operator. *J. Phys. Conf. Ser.* **2019**, *1366*, 012073. [CrossRef]
60. Okyere, S.; Yang, J.; Adams, C.A. Optimizing the Sustainable Multimodal Freight Transport and Logistics System Based on the Genetic Algorithm. *Sustainability* **2022**, *14*, 11577. [CrossRef]
61. Jin, X. Intelligent Logistics Supply Chain Management System Based on Genetic Algorithm. In Proceedings of the International Conference on Mathematics, Modeling, and Computer Science (MMCS2022), Wuhan, China, 16–18 December 2022; SPIE: Philadelphia, PA, USA, 2023; Volume 12625, pp. 687–691.
62. Liang, X.; Cheng, L.; Liu, T.; Du, J. Nonlinear Dynamic Analysis of the Bridge Bearing and Genetic Algorithm–Based Optimization for Seismic Mitigation. *Adv. Struct. Eng.* **2020**, *23*, 2539–2556. [CrossRef]
63. Schmitt, L.M.; Nehaniv, C.L.; Fujii, R.H. Linear Analysis of Genetic Algorithms. *Theor. Comput. Sci.* **1998**, *200*, 101–134. [CrossRef]
64. Chen, W.; Liu, Y.; Han, M. Designing a Sustainable Reverse Logistics Network for Used Cell Phones Based on Offline and Online Trading Systems. *J. Environ. Manag.* **2024**, *354*, 120417. [CrossRef]
65. Liu, S.; Deng, Q.; Liu, X.; Luo, Q.; Li, F.; Jiang, C. Dual-Service Integrated Scheduling of Manufacturing and Logistics for Multiple Tasks in Cloud Manufacturing. *Expert Syst. Appl.* **2024**, *235*, 121129. [CrossRef]
66. Kannan, G.; Sasikumar, P.; Devika, K. A Genetic Algorithm Approach for Solving a Closed Loop Supply Chain Model: A Case of Battery Recycling. *Appl. Math. Model.* **2010**, *34*, 655–670. [CrossRef]
67. Lo, S.-C.; Shih, Y.-C. A Genetic Algorithm with Quantum Random Number Generator for Solving the Pollution-Routing Problem in Sustainable Logistics Management. *Sustainability* **2021**, *13*, 8381. [CrossRef]
68. Wang, K.; Lan, S.; Zhao, Y. A Genetic-Algorithm-Based Approach to the Two-Echelon Capacitated Vehicle Routing Problem with Stochastic Demands in Logistics Service. *J. Oper. Res. Soc.* **2017**, *68*, 1409–1421. [CrossRef]
69. Ehtesham Rasi, R.; Sohanian, M. A Multi-Objective Optimization Model for Sustainable Supply Chain Network with Using Genetic Algorithm. *J. Model. Manag.* **2020**, *16*, 714–727. [CrossRef]
70. Nezamoddini, N.; Gholami, A.; Aqlan, F. A Risk-Based Optimization Framework for Integrated Supply Chains Using Genetic Algorithm and Artificial Neural Networks. *Int. J. Prod. Econ.* **2020**, *225*, 107569. [CrossRef]
71. Saghaeeian, A.; Ramezanian, R. An Efficient Hybrid Genetic Algorithm for Multi-Product Competitive Supply Chain Network Design with Price-Dependent Demand. *Appl. Soft Comput.* **2018**, *71*, 872–893. [CrossRef]
72. Kannan, G.; Noorul Haq, A.; Devika, M. Analysis of Closed Loop Supply Chain Using Genetic Algorithm and Particle Swarm Optimisation. *Int. J. Prod. Res.* **2009**, *47*, 1175–1200. [CrossRef]
73. Han, Y.; Ma, W.; Ma, D. Green Maritime: An Improved Quantum Genetic Algorithm-Based Ship Speed Optimization Method Considering Various Emission Reduction Regulations and Strategies. *J. Clean. Prod.* **2023**, *385*, 135814. [CrossRef]
74. Cui, H.; Qiu, J.; Cao, J.; Guo, M.; Chen, X.; Gorbachev, S. Route Optimization in Township Logistics Distribution Considering Customer Satisfaction Based on Adaptive Genetic Algorithm. *Math. Comput. Simul.* **2023**, *204*, 28–42. [CrossRef]

75. Dino, M.J.; Vital, J.C.; Patricio, C.; Catajan, M.W.; Ong, I.; Gallardo, A.; Macaspac, R.; de Vera, O.; Santos, F.; Agustin, P.D.; et al. Charting the Uncharted: Mapping Scientific Publications on Online Disinhibition Effect in the Digital Space via Bibliometrics and Network Analyses. *Comput. Hum. Behav. Rep.* **2023**, *12*, 100336. [CrossRef]
76. Liu, A.; Yuan, C.; Xu, L.; Zhao, L. Scientific Mapping of Hotspots and Trends of Post and Core Research Based on the Web of Science: A Bibliometric Analysis. *Heliyon* **2024**, *10*, e23786. [CrossRef]
77. Verano-Tacoronte, D.; Flores-Ureba, S.; Mesa-Mendoza, M.; Llorente-Muñoz, V. Evolution of Scientific Production on Urban Passenger Transport: A Bibliometric Analysis. *Eur. Res. Manag. Bus. Econ.* **2024**, *30*, 100239. [CrossRef]
78. Lou, T.-F.; Hung, W.-H. Revival of Classical Algorithms: A Bibliometric Study on the Trends of Neural Networks and Genetic Algorithms. *Symmetry* **2023**, *15*, 325. [CrossRef]
79. Dao, S.D.; Abhary, K.; Marian, R. A Bibliometric Analysis of Genetic Algorithms throughout the History. *Comput. Ind. Eng.* **2017**, *110*, 395–403. [CrossRef]
80. Kaleybar, H.J.; Davoodi, M.; Brenna, M.; Zaninelli, D. Applications of Genetic Algorithm and Its Variants in Rail Vehicle Systems: A Bibliometric Analysis and Comprehensive Review. *IEEE Access* **2023**, *11*, 68972–68993. [CrossRef]
81. Ding, X.; Zheng, M.; Zheng, X. The Application of Genetic Algorithm in Land Use Optimization Research: A Review. *Land* **2021**, *10*, 526. [CrossRef]
82. Yang, G.; Chen, L.; Yu, Z.; Yihei, A. Current Research Status of Genetic Algorithm Research in China's Library Sector. *SHS Web Conf.* **2023**, *179*, 05013. [CrossRef]
83. Butt, N.S.; Malik, A.A.; Shahbaz, M.Q. Bibliometric Analysis of Statistics Journals Indexed in Web of Science Under Emerging Source Citation Index. *SAGE Open* **2021**, *11*, 2158244020988870. [CrossRef]
84. Azañedo, D.; Visconti-Lopez, F.J.; Hernández-Vásquez, A. A Web of Science-Based Bibliometric Analysis of Global Noma Publications. *Trop. Med. Infect. Dis.* **2022**, *7*, 198. [CrossRef] [PubMed]
85. Patra, R.K.; Pandey, N.; Sudarsan, D. Bibliometric Analysis of Fake News Indexed in Web of Science and Scopus (2001–2020). *Glob. Knowl. Mem. Commun.* **2022**, *72*, 628–647. [CrossRef]
86. Liu, M.; He, J.; Liu, D.; Hou, M.; Ma, Y. Bibliometric and Visualized Analysis of Dynamic Balance and Brain Function Using Web of Science and CiteSpace from 1995 to 2022. *Heliyon* **2024**, *10*, e24300. [CrossRef]
87. Su, M.; Peng, H.; Li, S. A Visualized Bibliometric Analysis of Mapping Research Trends of Machine Learning in Engineering (MLE). *Expert Syst. Appl.* **2021**, *186*, 115728. [CrossRef]
88. Patra, A.K.; Praharaj, A.; Sudarshan, D.; Chhatoi, B.P. AI and Business Management: Tracking Future Research Agenda through Bibliometric Network Analysis. *Heliyon* **2024**, *10*, e23902. [CrossRef]
89. Herrera-Franco, G.; Montalván-Burbano, N.; Carrión-Mero, P.; Jaya-Montalvo, M.; Gurumendi-Noriega, M. Worldwide Research on Geoparks through Bibliometric Analysis. *Sustainability* **2021**, *13*, 1175. [CrossRef]
90. Mejia, C.; Wu, M.; Zhang, Y.; Kajikawa, Y. Exploring Topics in Bibliometric Research through Citation Networks and Semantic Analysis. *Front. Res. Metr. Anal.* **2021**, *6*, 742311. [CrossRef] [PubMed]
91. Anugerah, A.R.; Muttaqin, P.S.; Trinarningsih, W. Social Network Analysis in Business and Management Research: A Bibliometric Analysis of the Research Trend and Performance from 2001 to 2020. *Heliyon* **2022**, *8*, e09270. [CrossRef]
92. Gogoi, B.; Acharjee, S.A.; Bharali, P.; Sorhie, V.; Walling, B. Alemtoshi; A Critical Review on the Ecotoxicity of Heavy Metal on Multispecies in Global Context: A Bibliometric Analysis. *Environ. Res.* **2024**, *248*, 118280. [CrossRef]
93. Azman, A.A.; Leow, A.T.C.; Noor, N.D.M.; Noor, S.A.M.; Latip, W.; Ali, M.S.M. Worldwide Trend Discovery of Structural and Functional Relationship of Metallo-β-Lactamase for Structure-Based Drug Design: A Bibliometric Evaluation and Patent Analysis. *Int. J. Biol. Macromol.* **2024**, *256*, 128230. [CrossRef] [PubMed]
94. Zheng, B.; Masrabaye, F. Sustainable Brownfield Redevelopment and Planning: Bibliometric and Visual Analysis. *Heliyon* **2023**, *9*, e13280. [CrossRef]
95. Hassan, S.A.; Amlan, H.A.; Alias, N.E.; Ab-Kadir, M.A.; Sukor, N.S.A. Vulnerability of Road Transportation Networks under Natural Hazards: A Bibliometric Analysis and Review. *Int. J. Disaster Risk Reduct.* **2022**, *83*, 103393. [CrossRef]
96. Ghorbel, F.; Hachicha, W.; Boujelbene, Y.; Aljuaid, A.M. Linking Entrepreneurial Innovation to Effectual Logic. *Sustainability* **2021**, *13*, 2626. [CrossRef]
97. Karakose, T.; Papadakis, S.; Tülübaş, T.; Polat, H. Understanding the Intellectual Structure and Evolution of Distributed Leadership in Schools: A Science Mapping-Based Bibliometric Analysis. *Sustainability* **2022**, *14*, 16779. [CrossRef]
98. Yalcinkaya, T.; Cinar Yucel, S. Mobile Learning in Nursing Education: A Bibliometric Analysis and Visualization. *Nurse Educ. Pract.* **2023**, *71*, 103714. [CrossRef] [PubMed]
99. Fosso Wamba, S.; Queiroz, M.M.; Hamzi, L. A Bibliometric and Multi-Disciplinary Quasi-Systematic Analysis of Social Robots: Past, Future, and Insights of Human-Robot Interaction. *Technol. Forecast. Soc. Chang.* **2023**, *197*, 122912. [CrossRef]
100. Xu, J.; Liu, Q.; Wider, W.; Zhang, S.; Fauzi, M.A.; Jiang, L.; Udang, L.N.; An, Z. Research Landscape of Energy Transition and Green Finance: A Bibliometric Analysis. *Heliyon* **2024**, *10*, e24783. [CrossRef]
101. Vignaux, G.A.; Michalewicz, Z. A Genetic Algorithm for the Linear Transportation Problem. *IEEE Trans. Syst. Man Cybern.* **1991**, *21*, 445–452. [CrossRef]
102. Kumar, A.; Gupta, A.; Mehra, A. A Bilevel Game Model for Ascertaining Competitive Target Prices for a Buyer in Negotiation with Multiple Suppliers. *RAIRO Oper. Res.* **2022**, *56*, 293–330. [CrossRef]

103. Zarouk, Y.; Mahdavi, I.; Rezaeian, J.; Santos-Arteaga, F.J. A Novel Multi-Objective Green Vehicle Routing and Scheduling Model with Stochastic Demand, Supply, and Variable Travel Times. *Comput. Oper. Res.* **2022**, *141*, 105698. [CrossRef]
104. Zhang, Q.; Deng, N.; Zhu, Y.; Huang, Z. Multidepot Two-Echelon Vehicle Routing Problem for Earthwork Allocation Optimization. *Math. Probl. Eng.* **2022**, *2022*, e8373138. [CrossRef]
105. Zhu, K.; Ji, K.; Shen, J. A Fixed Charge Transportation Problem with Damageable Items under Uncertain Environment. *Phys. A Stat. Mech. Its Appl.* **2021**, *581*, 126234. [CrossRef]
106. Biswas, A.; Pal, T. A Comparison between Metaheuristics for Solving a Capacitated Fixed Charge Transportation Problem with Multiple Objectives. *Expert Syst. Appl.* **2021**, *170*, 114491. [CrossRef]
107. Shen, J.; Zhu, K. An Uncertain Two-Echelon Fixed Charge Transportation Problem. *Soft Comput* **2020**, *24*, 3529–3541. [CrossRef]
108. Sarma, D.; Das, A.; Bera, U.K. Uncertain Demand Estimation with Optimization of Time and Cost Using Facebook Disaster Map in Emergency Relief Operation. *Appl. Soft Comput.* **2020**, *87*, 105992. [CrossRef]
109. Zhao, G.; Pan, D. A Transportation Planning Problem with Transfer Costs in Uncertain Environment. *Soft Comput.* **2020**, *24*, 2647–2653. [CrossRef]
110. Kopfer, H. Konzepte genetischer Algorithmen und ihre Anwendung auf das Frachtoptimierungsproblem im gewerblichen Güterfernverkehr. *OR Spektrum* **1992**, *14*, 137–147. [CrossRef]
111. Zakaria, R.; Ahmi, A.; Ahmad, A.H.; Othman, Z. Worldwide Melatonin Research: A Bibliometric Analysis of the Published Literature between 2015 and 2019. *Chronobiol. Int.* **2021**, *38*, 27–37. [CrossRef] [PubMed]
112. Abdul Ghaffar, A.R.; Melethil, A.; Yusuf Adhami, A. A Bibliometric Analysis of Inverse Optimization. *J. King Saud Univ. Sci.* **2023**, *35*, 102825. [CrossRef]
113. Bagdi, T.; Ghosh, S.; Sarkar, A.; Hazra, A.K.; Balachandran, S.; Chaudhury, S. Evaluation of Research Progress and Trends on Gender and Renewable Energy: A Bibliometric Analysis. *J. Clean. Prod.* **2023**, *423*, 138654. [CrossRef]
114. Cheng, Q.; Zhang, S. Research Status and Evolution Trends of Emergency Information Resource Management: Based on Bibliometric Analysis from 2003 to 2022. *Int. J. Disaster Risk Reduct.* **2023**, *97*, 104053. [CrossRef]
115. Demir, G.; Chatterjee, P.; Pamucar, D. Sensitivity Analysis in Multi-Criteria Decision Making: A State-of-the-Art Research Perspective Using Bibliometric Analysis. *Expert Syst. Appl.* **2024**, *237*, 121660. [CrossRef]
116. Lin, Q.; Cai, B.; Shan, X.; Ni, X.; Chen, X.; Ke, R.; Wang, B. Global Research Trends of Infantile Hemangioma: A Bibliometric and Visualization Analysis from 2000 to 2022. *Heliyon* **2023**, *9*, e21300. [CrossRef]
117. Govindan, K.; Soleimani, H.; Kannan, D. Reverse Logistics and Closed-Loop Supply Chain: A Comprehensive Review to Explore the Future. *Eur. J. Oper. Res.* **2015**, *240*, 603–626. [CrossRef]
118. Steenken, D.; Voß, S.; Stahlbock, R. Container Terminal Operation and Operations Research—A Classification and Literature Review. *OR Spectrum* **2004**, *26*, 3–49. [CrossRef]
119. Lin, C.; Choy, K.L.; Ho, G.T.S.; Chung, S.H.; Lam, H.Y. Survey of Green Vehicle Routing Problem: Past and Future Trends. *Expert Syst. Appl.* **2014**, *41*, 1118–1138. [CrossRef]
120. Govindan, K.; Kaliyan, M.; Kannan, D.; Haq, A.N. Barriers Analysis for Green Supply Chain Management Implementation in Indian Industries Using Analytic Hierarchy Process. *Int. J. Prod. Econ.* **2014**, *147*, 555–568. [CrossRef]
121. Guihaire, V.; Hao, J.-K. Transit Network Design and Scheduling: A Global Review. *Transp. Res. Part A Policy Pract.* **2008**, *42*, 1251–1273. [CrossRef]
122. Vlahogianni, E.I.; Karlaftis, M.G.; Golias, J.C. Optimized and Meta-Optimized Neural Networks for Short-Term Traffic Flow Prediction: A Genetic Approach. *Transp. Res. Part C Emerg. Technol.* **2005**, *13*, 211–234. [CrossRef]
123. Farahani, R.Z.; Miandoabchi, E.; Szeto, W.Y.; Rashidi, H. A Review of Urban Transportation Network Design Problems. *Eur. J. Oper. Res.* **2013**, *229*, 281–302. [CrossRef]
124. Govindan, K.; Jafarian, A.; Khodaverdi, R.; Devika, K. Two-Echelon Multiple-Vehicle Location–Routing Problem with Time Windows for Optimization of Sustainable Supply Chain Network of Perishable Food. *Int. J. Prod. Econ.* **2014**, *152*, 9–28. [CrossRef]
125. Ibarra-Rojas, O.J.; Delgado, F.; Giesen, R.; Muñoz, J.C. Planning, Operation, and Control of Bus Transport Systems: A Literature Review. *Transp. Res. Part B Methodol.* **2015**, *77*, 38–75. [CrossRef]
126. Jones, D.F.; Mirrazavi, S.K.; Tamiz, M. Multi-Objective Meta-Heuristics: An Overview of the Current State-of-the-Art. *Eur. J. Oper. Res.* **2002**, *137*, 1–9. [CrossRef]
127. Bornmann, L.; Haunschild, R.; Hug, S.E. Visualizing the Context of Citations Referencing Papers Published by Eugene Garfield: A New Type of Keyword Co-Occurrence Analysis. *Scientometrics* **2018**, *114*, 427–437. [CrossRef]
128. Bukar, U.A.; Sayeed, M.S.; Razak, S.F.A.; Yogarayan, S.; Amodu, O.A.; Mahmood, R.A.R. A Method for Analyzing Text Using VOSviewer. *MethodsX* **2023**, *11*, 102339. [CrossRef] [PubMed]
129. Jiang, J.; Lyu, W.; Chen, N. A Bibliometric Analysis of Diffuse Large B-Cell Lymphoma Research from 2001 to 2020. *Comput. Biol. Med.* **2022**, *146*, 105565. [CrossRef] [PubMed]
130. Guo, Y.-M.; Huang, Z.-L.; Guo, J.; Li, H.; Guo, X.-R.; Nkeli, M.J. Bibliometric Analysis on Smart Cities Research. *Sustainability* **2019**, *11*, 3606. [CrossRef]
131. Guo, X. A Bibliometric Analysis of Child Language during 1900–2021. *Front. Psychol.* **2022**, *13*, 862042. [CrossRef] [PubMed]
132. Weng, R.; Lin, D.-X.; Song, Y.-K.; Guo, H.-W.; Zhang, W.-S.; He, X.-M.; Li, W.-C.; Lin, H.-H.; He, M.-C.; Wei, Q.-S. Bibliometric and Visualized Analysis of Research Relating to Minimally Invasive Spine Surgery Reported over the Period 2000–2022. *Digit. Health* **2023**, *9*, 20552076231173562. [CrossRef] [PubMed]

133. Murdayanti, Y.; Khan, M.N.A.A. The Development of Internet Financial Reporting Publications: A Concise of Bibliometric Analysis. *Heliyon* **2021**, *7*, e08551. [CrossRef] [PubMed]
134. Lagrandeur, J.; Uzundurukan, A.; Mansour, A.; Poncet, S.; Bénard, P. On the Benefit of Integrating Vortex Tubes in PEMFC System for Preheating Hydrogen in FCEV Technologies. *Int. J. Hydrogen Energy* **2024**, *52*, 1141–1152. [CrossRef]
135. Li, Y.; Lim, M.K.; Xiong, W.; Huang, X.; Shi, Y.; Wang, S. An Electric Vehicle Routing Model with Charging Stations Consideration for Sustainable Logistics. *Ind. Manag. Data Syst.* **2023**, *ahead-of-print*. [CrossRef]
136. Bhakuni, P.; Das, A. Profit Maximizing Business Model for Electric Vehicle Industry Incorporating Fuzziness in the Environment: Encompassing a Case Study from Silicon Valley of India. *Expert Syst. Appl.* **2024**, *242*, 122828. [CrossRef]
137. Qiang, H.; Ou, R.; Hu, Y.; Wu, Z.; Zhang, X. Path Planning of an Electric Vehicle for Logistics Distribution Considering Carbon Emissions and Green Power Trading. *Sustainability* **2023**, *15*, 16045. [CrossRef]
138. Zahedi, F.; Kia, H.; Khalilzadeh, M. A Hybrid Metaheuristic Approach for Solving a Bi-Objective Capacitated Electric Vehicle Routing Problem with Time Windows and Partial Recharging. *J. Adv. Manag. Res.* **2023**, *20*, 695–729. [CrossRef]
139. Jafarian, A.; Rabiee, M.; Tavana, M. A Novel Multi-Objective Co-Evolutionary Approach for Supply Chain Gap Analysis with Consideration of Uncertainties. *Int. J. Prod. Econ.* **2020**, *228*, 107852. [CrossRef]
140. Manupati, V.K.; Schoenherr, T.; Ramkumar, M.; Wagner, S.M.; Pabba, S.K.; Inder Raj Singh, R. A Blockchain-Based Approach for a Multi-Echelon Sustainable Supply Chain. *Int. J. Prod. Res.* **2020**, *58*, 2222–2241. [CrossRef]
141. Shekarian, M.; Reza Nooraie, S.V.; Parast, M.M. An Examination of the Impact of Flexibility and Agility on Mitigating Supply Chain Disruptions. *Int. J. Prod. Econ.* **2020**, *220*, 107438. [CrossRef]
142. Tirkolaee, E.B.; Goli, A.; Ghasemi, P.; Goodarzian, F. Designing a Sustainable Closed-Loop Supply Chain Network of Face Masks during the COVID-19 Pandemic: Pareto-Based Algorithms. *J. Clean. Prod.* **2022**, *333*, 130056. [CrossRef] [PubMed]
143. Rabbani, M.; Heidari, R.; Yazdanparast, R. A Stochastic Multi-Period Industrial Hazardous Waste Location-Routing Problem: Integrating NSGA-II and Monte Carlo Simulation. *Eur. J. Oper. Res.* **2019**, *272*, 945–961. [CrossRef]
144. Tirkolaee, E.B.; Goli, A.; Faridnia, A.; Soltani, M.; Weber, G.-W. Multi-Objective Optimization for the Reliable Pollution-Routing Problem with Cross-Dock Selection Using Pareto-Based Algorithms. *J. Clean. Prod.* **2020**, *276*, 122927. [CrossRef]
145. Zhao, K.; Zhang, D.; Jin, J.G.; Dong, G.; Lee, D.-H. Vessel Voyage Schedule Planning for Maritime Ore Transportation. *Ocean Eng.* **2024**, *291*, 116503. [CrossRef]
146. Yu, J.; Tang, G.; Voß, S.; Song, X. Berth Allocation and Quay Crane Assignment Considering the Adoption of Different Green Technologies. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *176*, 103185. [CrossRef]
147. Wang, W.; Huo, Q.; Liu, Q.; Ni, J.; Zhu, J.; Wei, T. Energy Optimal Dispatching of Ports Multi-Energy Integrated System Considering Optimal Carbon Flow. *IEEE Trans. Intell. Transp. Syst.* **2023**, 1–11. [CrossRef]
148. Shi, J.; Li, H. Operational Planning of International Freight Trains Considering the Dynamic Demands and Capacities of Border Ports. *Comput. Ind. Eng.* **2023**, *185*, 109658. [CrossRef]
149. Yaghoubi, A.; Fazli, S. Designing a New Multi-Objective Model for the Vehicle Routing Scheduling at a Cross-Docking Center in Mitigating CO_2 Emissions at Green Supply Chain under Uncertainty. *Ann. Oper. Res.* **2023**. [CrossRef]
150. Peng, S.; Liu, Q.; Hu, J. Green Distribution Route Optimization of Medical Relief Supplies Based on Improved NSGA-II Algorithm under Dual-Uncertainty. *Sustainability* **2023**, *15*, 11939. [CrossRef]
151. Peng, Y.; Gao, S.H.; Yu, D.; Xiao, Y.P.; Luo, Y.J. Multi-Objective Optimization for Multimodal Transportation Routing Problem with Stochastic Transportation Time Based on Data-Driven Approaches. *RAIRO Oper. Res.* **2023**, *57*, 1745–1765. [CrossRef]
152. Ala, A.; Goli, A.; Mirjalili, S.; Simic, V. A Fuzzy Multi-Objective Optimization Model for Sustainable Healthcare Supply Chain Network Design. *Appl. Soft Comput.* **2024**, *150*, 111012. [CrossRef]
153. Gholian-Jouybari, F.; Hajiaghaei-Keshteli, M.; Smith, N.R.; Calvo, E.Z.R.; Mejía-Argueta, C.; Mosallanezhad, B. An In-Depth Metaheuristic Approach to Design a Sustainable Closed-Loop Agri-Food Supply Chain Network. *Appl. Soft Comput.* **2024**, *150*, 111017. [CrossRef]
154. Tian, Y.; Song, S.; Zhou, D.; Yang, R.; Wei, C. Toward Sustainable Joint Optimisation for Product Family and Supply Chain Configuration with Smart Contracting Consideration. *J. Eng. Des.* **2023**, *34*, 1013–1045. [CrossRef]
155. Londoño, A.; Gil González, W.; Montoya Giraldo, O.; Escobar, J. A Hybrid Heuristic Approach for the Multi-Objective Multi Depot Vehicle Routing Problem. *Int. J. Ind. Eng. Comput.* **2024**, *15*, 337–354. [CrossRef]
156. Pan, L.; Shan, M.; Li, L. Optimizing Perishable Product Supply Chain Network Using Hybrid Metaheuristic Algorithms. *Sustainability* **2023**, *15*, 10711. [CrossRef]
157. Wang, Y.; Wang, X.; Wei, Y.; Sun, Y.; Fan, J.; Wang, H. Two-Echelon Multi-Depot Multi-Period Location-Routing Problem with Pickup and Delivery. *Comput. Ind. Eng.* **2023**, *182*, 109385. [CrossRef]
158. Zhu, M.; Zhou, X. Research on Data-Driven Fresh Produce Joint Distribution Network Optimization Under Distribution Center Sharing. *IEEE Access* **2023**, *11*, 111154–111168. [CrossRef]
159. Rostami, A.; Paydar, M.M.; Asadi-Gangraj, E. A Hybrid Genetic Algorithm for Integrating Virtual Cellular Manufacturing with Supply Chain Management Considering New Product Development. *Comput. Ind. Eng.* **2020**, *145*, 106565. [CrossRef]
160. Nanthasamroeng, N.; Khonjun, S.; Srichok, T.; Pitakaso, R.; Akkararungroeungkul, R.; Jirasirilerd, G.; Sirisan, S. Transborder Logistics Network Design for Agricultural Product Transportation in the Greater Mekong Subregion. *Asian J. Shipp. Logist.* **2022**, *38*, 245–262. [CrossRef]

161. Raj, A.; Kumar, A.; Sharma, V.; Rani, S.; Shanu, A.K.; Singh, T. Applications of Genetic Algorithm with Integrated Machine Learning. In Proceedings of the 2023 3rd International Conference on Innovative Practices in Technology and Management (ICIPTM), Uttar Pradesh, India, 22–24 February 2023; pp. 1–6.
162. Cavallaro, C.; Cutello, V.; Pavone, M.; Zito, F. Machine Learning and Genetic Algorithms: A Case Study on Image Reconstruction. *Knowl.-Based Syst.* **2024**, *284*, 111194. [CrossRef]
163. Hamdia, K.M.; Zhuang, X.; Rabczuk, T. An Efficient Optimization Approach for Designing Machine Learning Models Based on Genetic Algorithm. *Neural Comput. Appl.* **2021**, *33*, 1923–1933. [CrossRef]
164. Kumar, V.; Mishra, N.; Chan, F.T.S.; Verma, A. Managing Warehousing in an Agile Supply Chain Environment: An F-AIS Algorithm Based Approach. *Int. J. Prod. Res.* **2011**, *49*, 6407–6426. [CrossRef]
165. Chibani, A.; Delorme, X.; Dolgui, A.; Pierreval, H. Dynamic Optimisation for Highly Agile Supply Chains in E-Procurement Context. *Int. J. Prod. Res.* **2018**, *56*, 5904–5929. [CrossRef]
166. Wang, J.; Huang, X. A Hybrid Genetic Algorithm for Agile Supply Chain Scheduling Optimization. In Proceedings of the 2010 2nd International Conference on Future Computer and Communication, Wuhan, China, 21–24 May 2010; IEEE: Wuhan, China, 2010; pp. V1-396–V1-400.
167. Shayannia, S.A. Presenting an Agile Supply Chain Mathematical Model for COVID-19 (Corona) Drugs Using Metaheuristic Algorithms (Case Study: Pharmaceutical Industry). *Environ. Sci. Pollut. Res.* **2023**, *30*, 6559–6572. [CrossRef]