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Production Logistics in Industry 3.X: Bibliometric Analysis, Frontier Case Study, and Future Directions

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Abstract: At present, the development of the global manufacturing industry is still in the transition stage from Industry 3.0 to Industry 4.0 (i.e., Industry 3.X), and the production logistics system is becoming more and more complex due to the individualization of customer demands and the high frequency of order changes. In order to systematically analyze the research status and dynamic evolution trend of production logistics in the Industry 3.X stage, this paper designed a Log-Likelihood ratio-based latent Dirichlet allocation (LLR-LDA) algorithm based on bibliometrics and knowledge graph technology, taking the literature of China National Knowledge Infrastructure and Web of Science database as the data source. In-depth bibliometric analysis of literature was carried out from research progress, hotspot evolution, and frontier trends. At the same time, taking the case of scientific research projects overcome by our research group as an example, it briefly introduced the synchronized decision-making framework of digital twin-enabled production logistics system. It is expected to broaden the research boundary of production logistics in the Industry 3.X stage, promote the development and progress of the industry, and provide valuable reference for steadily moving towards the Industry 4.0 stage.

Keywords: Industry 3.X; production logistics; LLR-LDA algorithm; scientific knowledge graph; synchronization

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1. Introduction

In order to realize the digitalization, networking, and intelligence of the manufacturing model, theories and methods related to the Industry 4.0 stage with Cyber-Physical Systems (CPS) as the core technology have been proposed one after another [1–6]. However, it is worth noting that, at present, the development stage of global manufacturing industry is still in the transition stage from Industry 3.0 to Industry 4.0 (i.e., Industry 3.X) [7–12]. In the stage of Industry 3.X, the production model is changing along with the change in customer demand, from the traditional high-volume, single-variety production to multi-variety, low-volume production based on a flexible production model [13]. It was revealed that it is the increasing demand for customized, small batch, short life cycle, and complex products that leads to the need for production logistics systems to be more flexible to respond to individualized demands. This results in a more dynamic production logistics process and a greater reliance on the perception of the real-time operational state of the system.

There are three periods before, during, and after the Industry 3.X stage: The beginning of Industry 3.X is the diversification stage of "corporate planning decisions". The company determines the production plan of diversified products according to its sales plan and carries out unitized production with its own resources. In the middle of Industry 3.X, the diversification stage is "customer demand-driven". Companies make production plans based on customer orders and rely on their own resources and supplemental cloud resources to complete the manufacturing of platform and differentiated components. The late stage of Industry 3.X is the advanced stage of the development of Industry 3.X to 4.0. It is a diversified stage of "random demand-led", where products are integrated with more personalized elements and the complexity of production unit type, quantity, distribution, and ownership increases. The production logistics system in the stage of Industry 3.X faces the following problems. In terms of production logistics resources, the advanced degree and intelligence of independent production logistics equipment is not high enough, and most of the resource allocation is still traditional purchase or rent. The maturity and popularity of cloud resource management platform is not high, which leads to low openness and high difficulty of flexible resource matching in the resource layer of production logistics system. In terms of data collection and transmission, due to the low degree of intelligence of the production logistics resources themselves and the lack of sufficient sensors, it is difficult for the operational status of production logistics resources to be collected in a real-time, accurate, and comprehensive manner. At the same time, the data between equipment, units, and systems are difficult to be fused and processed because of problems such as multiple sources and heterogeneity. In terms of management decision, on the one hand, the complexity of the production logistics system poses a challenge to accurate decision making; on the other hand, the lack of timely and accurate data acquisition at the executive level leads to inflexible decision making, making it difficult to adapt to the changing operational status of production logistics and order requirements at any time. Therefore, only by accurately grasping the theoretical research and engineering practice experience of the current Industry 3.X stage, and further exploring and exploring the integrated development path of "product demand–production logistics system–management and control method", can we truly enter the Industry 4.0 stage comprehensively and smoothly.

Production logistics generally refers to the physical flow of raw materials, work-in-process, semi-finished products, and finished products within the enterprise in the production process. Qu et al. [14], Agnetis et al. [15], and Zhang et al. [16] considered production logistics as the logistic activities in the production process, responsible for the transfer of materials between production stages. It is the key process that links multiple production activities back and forth and has a significant impact on the overall production efficiency. Logistics speed-up helps to shorten the production cycle, reduce the backlog of work-in-process, and accelerate the working capital turnover. In recent years, many scholars conducted research in the direction of production logistics process optimization, production logistics systems, and enabling technology applications. In production logistics process optimization, existing research focused on production logistics process optimization theories (e.g., lean logistics, green logistics), simulation modeling methods (e.g., Petri nets, heuristic algorithms) [17–27]. In terms of production logistics system research, existing studies focused on production equipment layout design, logistics scheduling, and process modeling (e.g., data flow diagram modeling, action diagram modeling) [14,28,29]. In terms of production logistics enabling technology applications, existing research mainly included equipment (e.g., Automated Guided Vehicle, AGV; Automatic Storage and Retrieval System, AS/RS), information systems (e.g., Enterprise Resource Planning, ERP; Warehouse Management System, WMS) and modern information technologies (e.g., Internet of Things, IoT; Digital Twin, DT) [30–37]. In general, the academic research results in the field of production logistics are fruitful and cover a wide range. However, there is still a lack of systematic sorting of the research progress, hot spots, and development trends of production logistics in Industry 3.X. It is difficult for scholars in related research fields to form a comprehensive and systematic knowledge of it. Therefore, it is necessary to adopt a scientific and reasonable way to scientifically measure and visually analyze the relevant literature. In this way, the limited research resources can be concentrated on the urgent research directions, so as to better promote the innovative and sustainable development of the research in the field of production logistics in the Industry 3.X stage, and then advance to Industry 4.0.

A common problem with traditional descriptive bibliometric analysis is that the analysis relies heavily on the industry context and research theory studied in the field, which is subjective and uncertain. At the same time, it is difficult to refine and summarize the internal logic among the literature, which inevitably leads to the blending of subjective experiences in the research conclusions. In contrast, bibliometric methods based on text mining can reveal a more three-dimensional overview of the development of a research field from macro, meso, and micro levels [38–40]. To a certain extent, it avoids these problems and then provides a comprehensive and scientific overview of the thematic structure and research hotspots of the research field. Based on this, this paper used the literature in the core databases of China National Knowledge Infrastructure (CNKI) and Web of Science (WoS) as data sources. The literature related to production logistics research in the Industry 3.X stage was collected from 1 January 2000 to 1 May 2023. A Log-Likelihood ratio-based latent Dirichlet allocation (LLR-LDA) algorithm was designed based on bibliometric principles and knowledge graph technology. It was used to conduct a bibliometric analysis of research in the field of production logistics in the Industry 3.X stage. At the same time, the unstructured abstract data were incorporated into the analysis dataset. Based on the macro-topic clustering analysis, the LLR-LDA algorithm was used to further extract the list of subject keywords of the abstracts included in each macro-topic for in-depth analysis. The previous paradigm of econometric analysis on production logistics research in the Industry 3.X stage was further deepened and extrapolated to make the interpretation more scientific and reasonable.

The Innovative points and research contributions of this paper are: First, the existing research paid less attention to the manufacturing paradigm of the Industry 3.X stage, and the current development stage of the global manufacturing industry is still in the transition stage from Industry 3.0 to Industry 4.0. After systematically combing the characteristics of the early, middle, and late stages of the Industry 3.X stage, this paper put forward the challenges faced by the production logistics in the Industry 3.X stage. It was further proposed to conduct bibliometrics to provide a valuable reference for the steady progress towards the stage of Industry 4.0. Second, an LLR-LDA algorithm for in-depth metrological analysis of production logistics literature in the Industry 3.X stage was proposed. Based on the clustering results, the production logistics corpus was custom-built and the typical clustering data were processed by NLP (natural language processing) technology, which made up for the deficiencies of traditional descriptive literature metrological analysis. It enhanced the depth and systematicity of scientific measurement of production logistics literature in the Industry 3.X stage. Third, using the bibliometric method proposed in this paper, the cluster nature and knowledge structure of research in the field of production logistics in the Industry 3.X stage were deeply explored. Six typical research issues surrounding production logistics research were explored and discovered. At the same time, the research gaps in the existing literature were analyzed. Fourth, a frontier case study was carried out on a new production logistics model in the Industry 3.X stage. The possible future research directions of production logistics in the Industry 3.X stage were further explored. It was also proposed that dynamic joint operation management of production logistics, multi-dimensional modeling optimization, and intelligent decision-making of complex production logistics systems will become research directions of great academic value and potential for future research. It provides the scientific reference basis and objective data support for future scholars to engage in related research work.

2. Data Sources and Research Methods

2.1. Data Sources

In this paper, the data sources were CNKI and WoS, and the keywords related to production logistics in the Industry 3.X stage were mainly extracted from the relevant research findings of Zhang et al. [41], Tao et al. [42], and Guo et al. [43] scholars by using subject term search. Two categories of keywords, production logistics, shop logistics, automated guided vehicle, RFID, internet of things, and digital twin were included. Through the free combination of these two types of keywords, they were used as the subject retrieval conditions in turn. At the same time, the time range was set from 1 January 2000 to 1 May 2023. In order to ensure the reliability and typicality of the research conclusions, the scope of journals in the CNKI database was limited to SCI source journals, EI source journals, and CSSCI journals, Peking University core journals and CSCD journals; in the WoS database, the scope was limited to Article and Review of the core collection. By manually reading the literature titles and abstracts, invalid records such as journal statements, call for papers, conference news, and literature that are not relevant or of low relevance to production logistics research in the Industry 3.X stage were removed. The literature was further processed for default values to remove duplicate literature records, and the final valid literature data in English and Chinese were 559 and 774, respectively.

2.2. Research Methods

Figure 1 shows the research idea and framework of this paper, which consisted of three parts: (1) Effective literature data acquisition. Based on CNKI and WoS core databases, the topic retrieval method was used to retrieve and screen effective literature data as the data input of bibliometrics. (2) Bibliometric analysis and frontier case study. Based on the principle of bibliometrics and knowledge graph technology, the LLR-LDA algorithm was designed to visualize the production logistics research in the Industry 3.X stage. Additionally, a frontier case study was carried out on a novel production logistics model in the Industry 3.X stage. (3) Research conclusions and prospects. This paper expounded the research status and frontier trends of production logistics in the Industry 3.X stage. Combined with the conclusion of bibliometric analysis and the current situation of engineering practice, the research prospect of production logistics was put forward.

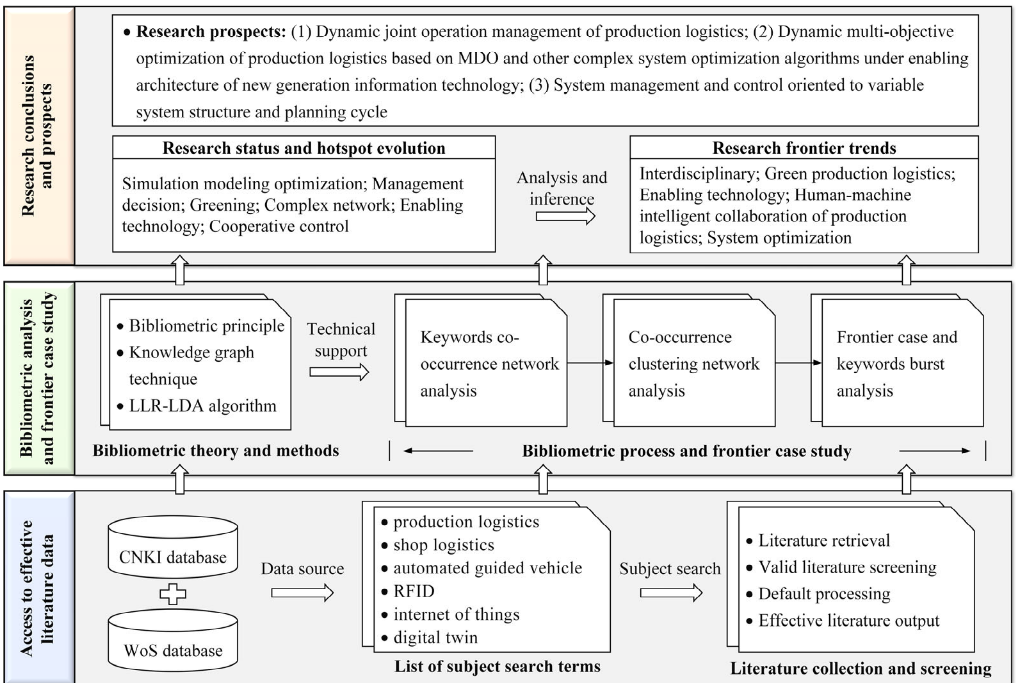


Figure 1. Research idea and frame diagram.

(1) Literature clustering mining method

Cluster analysis can screen the closely related keywords, reveal the knowledge structure of the production logistics research field in the Industry 3.X stage, and characterize the research themes that have been formed. At the same time, in order to fully tap the literature clustering results and analyze the research context of the production logistics field in the 3.X stage of industry in a more comprehensive and three-dimensional way, it is hoped that the topic keyword list contained in the abstract of each macro topic after clustering can be extracted to make the typical cluster analysis more scientific and reasonable. Considering that literature abstracts belong to long text data, with unstructured and sparse data characteristics, this paper proposed a bibliometric method based on LLR-LDA algorithm. Cluster analysis was performed on the cleaned and valid dataset in the field of production logistics research in the Industry 3.X stage. The algorithm flow is shown in Figure 2.

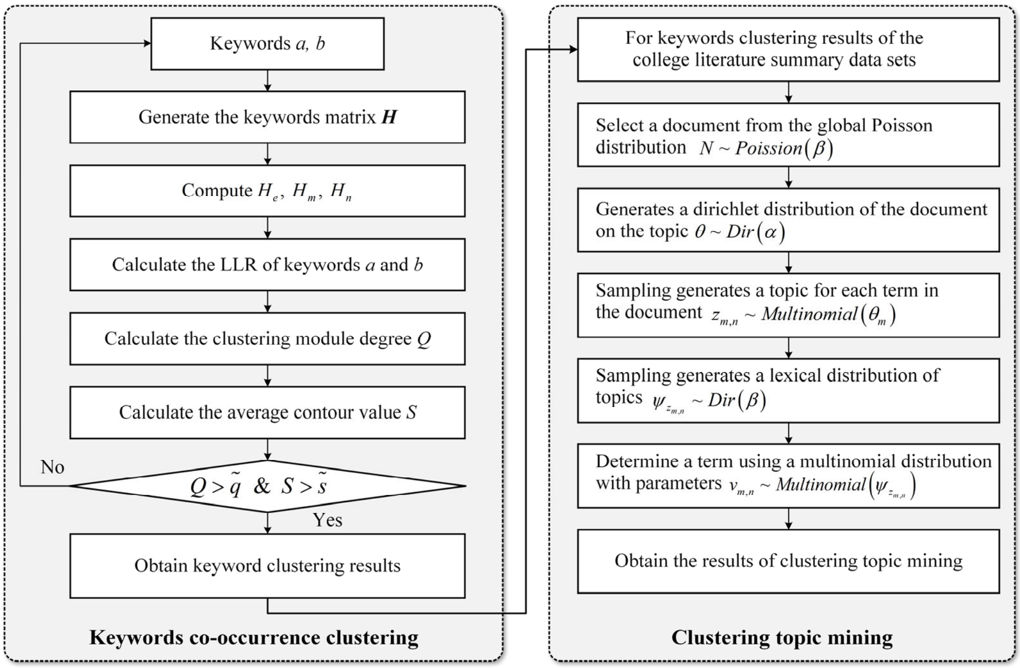


Figure 2. The algorithm flow of cluster analysis based on LLR-LDA algorithm.

In the first stage, macro-topic cluster analysis was performed. Assuming that N is the number of all literature on production logistics in the Industry 3.X stage, there are four scenarios as follows: If a literature contains both keywords a and b marked as x_{ab}; if it contains keyword a but not keyword b marked as $x_{a\bar{b}}$; if it contains keyword b but not keyword a marked as $x_{\bar{a}b}$; if it contains neither keyword a nor keyword b marked as $x_{\bar{a}\bar{b}}$, the following relationships exist:

$$N = x_{ab} + x_{a\bar{b}} + x_{\bar{a}b} + x_{\bar{a}\bar{b}} \tag{1}$$

Denote the keyword matrix $\boldsymbol{H} = \begin{bmatrix} x_{ab} & x_{a\bar{b}} \\ x_{\bar{a}b} & x_{\bar{a}\bar{b}} \end{bmatrix}$. Then, the *Similarity* of keywords a and b is calculated as:

$$Similarity = 2 \cdot (\boldsymbol{H}_c - \boldsymbol{H}_m - \boldsymbol{H}_n) \tag{2}$$

$$\boldsymbol{H}_c = -\left(\frac{x_{ab}}{N}\log\left(\frac{x_{ab}}{N}\right) + \frac{x_{a\bar{b}}}{N}\log\left(\frac{x_{a\bar{b}}}{N}\right) + \frac{x_{\bar{a}b}}{N}\log\left(\frac{x_{\bar{a}b}}{N}\right) + \frac{x_{\bar{a}\bar{b}}}{N}\log\left(\frac{x_{\bar{a}\bar{b}}}{N}\right)\right) \tag{3}$$

$$\boldsymbol{H}_m = -\left(\frac{x_{ab} + x_{a\bar{b}}}{N}\log\left(\frac{x_{ab} + x_{a\bar{b}}}{N}\right) + \frac{x_{\bar{a}b} + x_{\bar{a}\bar{b}}}{N}\log\left(\frac{x_{\bar{a}b} + x_{\bar{a}\bar{b}}}{N}\right)\right) \tag{4}$$

$$\boldsymbol{H}_n = -\left(\frac{x_{ab} + x_{\bar{a}b}}{N}\log\left(\frac{x_{ab} + x_{\bar{a}b}}{N}\right) + \frac{x_{a\bar{b}} + x_{\bar{a}\bar{b}}}{N}\log\left(\frac{x_{a\bar{b}} + x_{\bar{a}\bar{b}}}{N}\right)\right) \tag{5}$$

In the formula, $\boldsymbol{H}_c$ represents the matrix entropy of the keyword matrix $\boldsymbol{H}$; $\boldsymbol{H}_m$ and $\boldsymbol{H}_n$ represent the information entropy obtained by adding each row and column of the matrix, respectively.

In order to evaluate the clustering effect of LLR-LDA algorithm, two indexes of clustering modularity Q and average contour value S are used to measure. The modularity Q is calculated as follows:

$$Q = \frac{\sum_{ab}(u_{ab} - e_{ab})\phi(G_a, G_b)}{2k} \tag{6}$$

In the formula, u_{ab} represents the number of lines between keywords a and b; e_{ab} represents the expected number of lines between keywords a and b in the random case; G_a and G_b represent the clustering of keywords a and b, respectively; ϕ is a Boolean variable, if $\phi = 1$ means that keywords a and b belong to the same cluster, otherwise $\phi = 0$; k represents the number of connections in the literature network. The average contour value S is calculated as follows:

$$S_a = \begin{cases} 1 - \frac{i_a}{o_a},\ i_a < o_a \\ 0,\ i_a = o_a \\ \frac{o_a}{i_a} - 1,\ i_a > o_a \end{cases} \tag{7}$$

In the formula, i_a represents the average distance between keyword a and other keywords in the cluster; o_a represents the average distance between keyword a and all keywords in other cluster G_b.

In the second stage, the topic keyword list of abstracts contained in each macro topic is extracted. Assume that a document consists of a number of topics. Each document is generated as follows. First, a document of length $N \sim Poission(\beta)$ is selected from the global Poisson distribution. Secondly, the Dirichlet distribution $\theta \sim Dir(\alpha)$ on the topic of the document is generated. From the second, sample to generate a topic $z_{m,n} \sim Multinomial(\theta_m)$ for each term of the document (length N), and sample to generate a topic distribution $\psi_{z_{m,n}} \sim Dir(\beta)$ in terms of vocabulary; Finally, a term $v_{m,n} \sim Multinomial(\psi_{z_{m,n}})$ is determined by the polynomial distribution of parameters z and ψ. The formulaic expression of the joint distribution in the cluster mining stage is:

$$P(v, z, \theta_m, \psi_k | \alpha, \beta) = \prod_{n=1}^{N} P(\theta_m|\alpha)P(z_{m,n}|\theta_m)P(\psi_k|\beta)P(v_{m,n}|\theta_{z_{m,n}}) \tag{8}$$

In this paper, Gibbs algorithm is used to estimate the Dirichlet prior distribution parameters θ_m and ψ_k, and the topic confusion degree is used to determine the topic extraction number of the abstract text by referring to Blei [44]. The formulaic expression of the confusion degree calculation of document set D is:

$$Perplexity(D) = \exp\left\{-\frac{\sum_{d=1}^{M} \log P(v_d)}{\sum_{d=1}^{M} N_d}\right\} \tag{9}$$

$$\log P(v_d) = \sum_{v_i \in d} \log\left\{\sum_{z \in d}[P(z|d) \cdot P(v_i|z)]\right\} \tag{10}$$

In the formula, the $Perplexity(D)$ of the document set D represents the uncertainty of the document belonging to the topic. The lower the degree of confusion, the better the performance.

(2) Frontier mining method of literature

In order to further explore the dynamic development trend of research frontiers in the field of production logistics research in the Industry 3.X stage over time, this paper used the Kleinberg burst detection method to extract the burst keywords of effective literature data [45]. Suppose that the start time and end time are t_{start} and t_{end} respectively, the total number of keywords at each time node is d, the number of target keywords is r, and the goodness of fit between the observed proportion and the expected probability of each state is δ. Keywords Kleinberg burst detection method formulaic expression:

$$Strength = \sum_{t=t_{start}}^{t_{end}} (\delta(0, r_t, d_t) - \delta(1, r_t, d_t)) \tag{11}$$

$$\delta(i, r_t, d_t) = -\ln\left(\binom{d_t}{r_t} p_i^{r_t} (1 - p_i)^{d_t - r_t}\right) \tag{12}$$

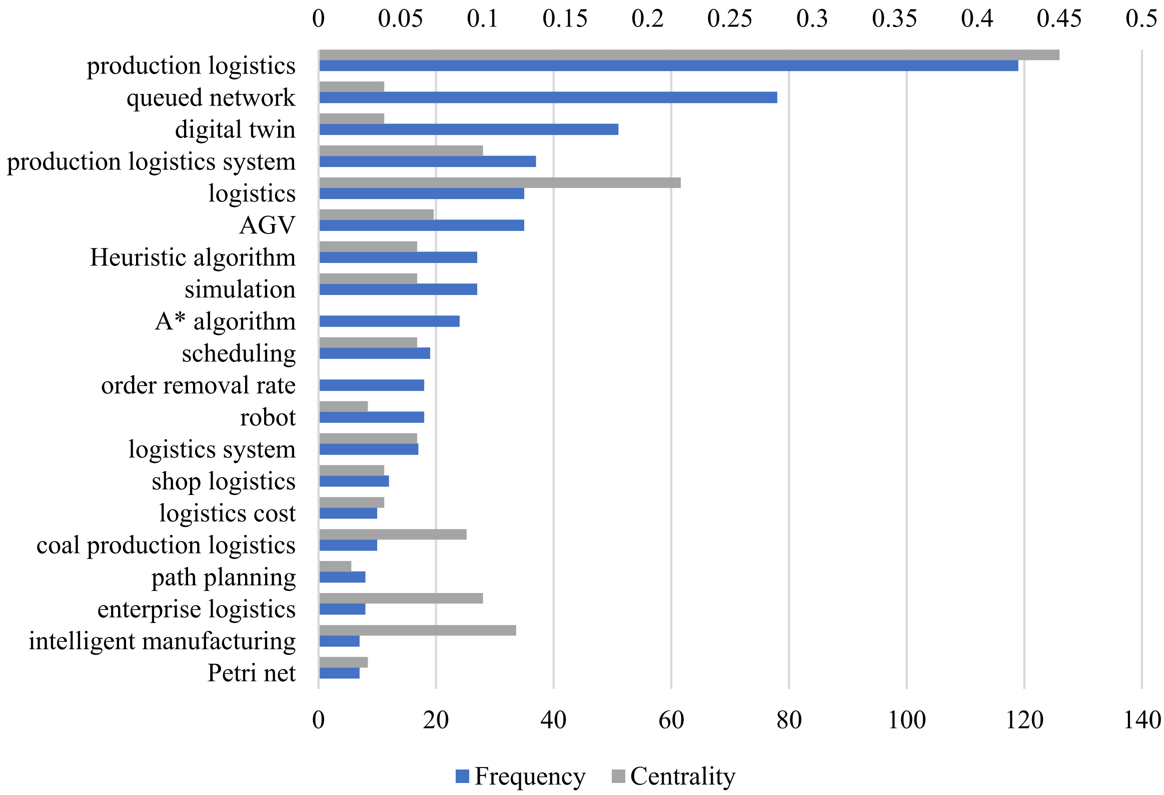
In the formula, i represents the corresponding different states, when $i = 0$ represents the corresponding baseline state, $i = 1$ represents the corresponding burst state, p_0 represents the baseline probability, p_1 represents the burst probability, $p_0 = r/d$ and $p_1 = s \cdot p_0$.

3. Research Progress and Gaps of Production Logistics in Industry 3.X

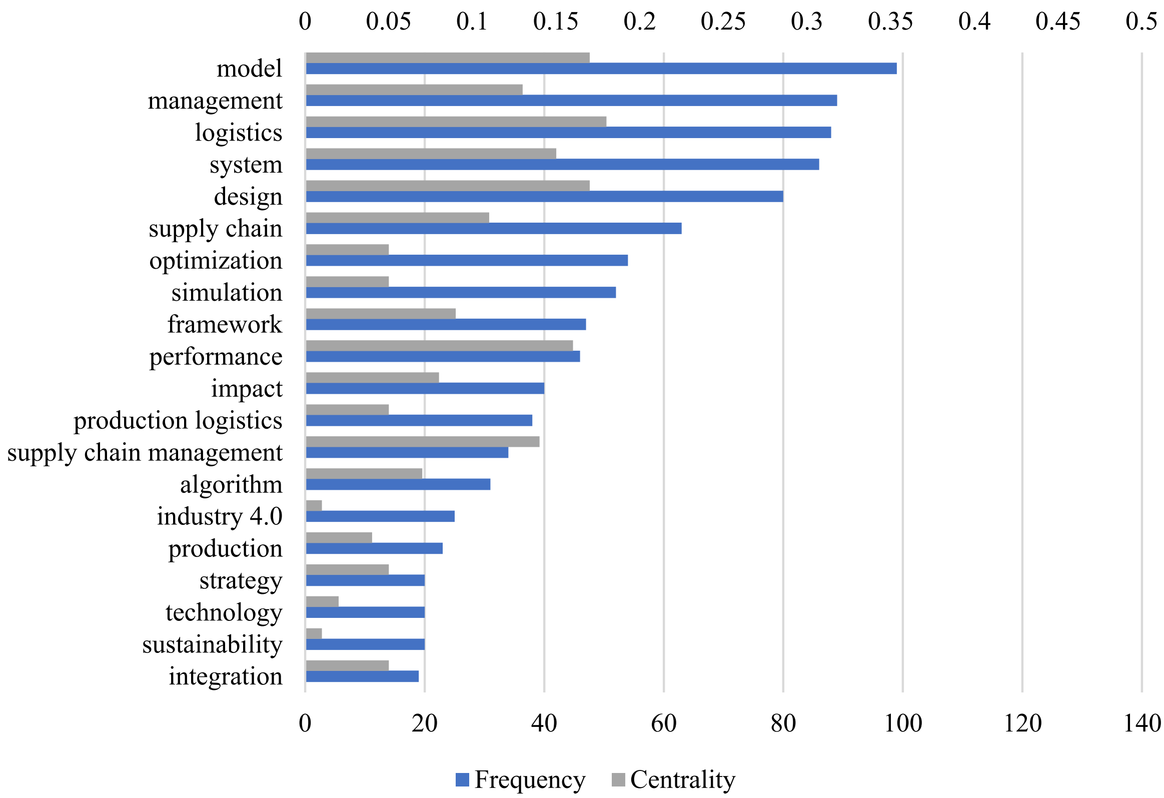
3.1. Bibliometrics of Production Logistics in the Industry 3.X stage Based on LLR-LDA Algorithm

Based on the LLR-LDA algorithm proposed in this paper, on the basis of keyword co-occurrence clustering, the topic keyword list of abstracts contained in each macro topic was further extracted for in-depth analysis. First, the co-occurrence analysis of keywords on effective literature data can preliminarily explore the links, threads, and hot spots among the research contents under the research theme of production logistics in the Industry 3.X stage. Figure 3 shows the top 20 most frequent Chinese and English keywords. From the perspective of keyword co-occurrence frequency, in CNKI literature, "production logistics", "queuing network", "digital twin", "production logistics system" and "AGV", in WoS literature, "model", "management", "logistics", "system" and "design" are the keywords in the research field of production logistics in the Industry 3.X stage. From the perspective of the type of keywords, around the research theme of production logistics, including simulation modeling, optimization algorithm design, green sustainability, intelligent manufacturing, and other research directions of keywords. The Betweenness Centrality in the table quantifies the extent to which a node falls on the shortest path between any other two nodes in the co-occurrence network. That is, if a node has a high betweenness centrality, it indicates that the node plays a more significant role as a bridge in the whole co-occurrence network. If the betweenness centrality of a node exceeds 0.1, it is regarded as an important "bridge" [46]. From the perspective of Betweenness Centrality, the keywords with the highest centrality in CNKI and WoS literature were "production logistics (0.45)", "model (0.17)", "design (0.17)", respectively. In addition, keywords with centrality over 0.1 also included "production logistics system (0.10)", "intelligent manufacturing (0.12)", "logistics (0.18)", "system (0.15)", etc. The above nodes connected different research directions and played an important intermediary role in the research of production logistics in the Industry 3.X stage.

Second, the effective literature data collected by CNKI and WoS database were analyzed by keyword clustering (see Figure 4), and clustering map modules $Q_{CNKI} = 0.862$ and $S_{CNKI} = 0.950$ were obtained. $Q_{WoS} = 0.659$, $S_{WoS} = 0.847$, referring to clustering standard [47,48]: $Q > 0.5$, indicating significant clustering structure; $S > 0.5$ indicates that the clustering is reasonable; $S > 0.7$ indicates that the clustering is convincing. The clustering map was divided into several coupled network clusters, and the homogeneity of components in each network cluster also met the parameter requirements, indicating that the clustering structure was significant and credible. Finally, calculate the size, contour value, and median year of each cluster, write a Python program, use the Jieba library to perform word segmentation, and perform word segmentation processing on the cleaned literature abstract text to construct a production logistics research in the Industry 3.X stage. The academic text corpus in the field, based on the LLR-LDA algorithm, used Gensim and pyLDAvis libraries for topic extraction and visualization, and mined the semantic structure of each cluster, and then extracted top terms of hot topics. The results are shown in Tables 1 and 2.



(**a**)



(**b**)

Figure 3. Industry 3.X stage production logistics research keywords with high co-occurrence frequency: (**a**) CNKI database; (**b**) WoS database.

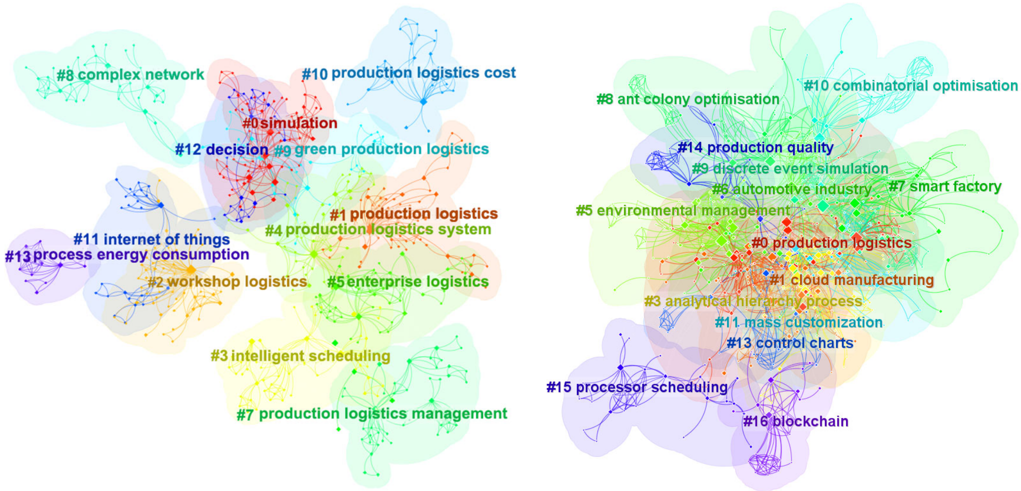


Figure 4. Industry 3.X stage production logistics research keyword co-occurrence clustering map: (**a**) CNKI database; (**b**) WoS database.

Table 1. CNKI—Industry 3.X stage production logistics literature keywords co-occurrence clustering.

Cluster	Size	Contour Value	Median Year	Hot Topic Words
simulation	70	0.931	2010	lean logistics, genetic algorithm, production scheduling, combinatorial optimization logistics analysis, production capacity, system layout design
production logistics	63	0.962	2010	production logistics, industry engineering, bottleneck constraint, simulation model, radio frequency identification, optimization
workshop logistics	62	0.917	2010	logistics, produce, system layout design, storage, material distribution, process layout reform, seamless interface
intelligent scheduling	55	0.964	2016	genetic algorithm, automatic guidance vehicle (AGV), digital twin, cigarette production, transportation, stacker, production scheduling
production logistics system	48	0.868	2010	logistics system, flexible manufacturing system, parts supplier, delay in production, logistics tracking, cost control, intelligent decision making
enterprise logistics	45	0.928	2010	enterprise logistics, logistics cost of enterprises, leather production, logistics cost control, e-commerce enterprise
production logistics management	44	0.977	2008	logistics management, value stream map, lean production, work-in-process inventory, functional layout, greedy algorithm, WMS, RFID
complex network	38	0.984	2012	complex network, production workshop, Petri nets, robot, DEA, distribution scale, degree distribution, shortest path, discrete manufacturing, MRPII
green production logistics	37	0.94	2013	coal logistics, resource allocation, safety evaluation, security, green logistics, environmental protection, chemical enterprises, performance evaluation

Table 1. *Cont.*

Cluster	Size	Contour Value	Median Year	Hot Topic Words
production logistics cost	29	0.972	2008	logistics cost, logistics cost accounting, waste logistics, secondary subjects, discussion of problems
internet of things	29	0.964	2016	internet of things, intelligent, smart factory, autonomous production control, human–machine-material integration, overall framework
decision	21	0.988	2009	decision making, industrial park, collaborative decision making, synchronized control, information, dynamic, system integration, digital twin
process energy consumption	15	0.991	2001	process energy consumption, actual logistics diagram, comprehensive energy consumption, reference logistics diagram

Table 2. WoS—Industry 3.X stage production logistics literature keywords co-occurrence clustering.

Cluster	Size	Contour Value	Median Year	Hot Topic Words
production logistics	80	0.769	2015	lean thinking, prediction model, simulation modelling, bottleneck index, knowledge graph, big data analytics, digital twin
cloud manufacturing	69	0.666	2019	production mode, product customization, industry 4.0, internet of things, automated guided vehicles, distributed genetic algorithm
analytical hierarchy process	58	0.85	2011	analytical hierarchy process, complex networks, dynamics, planning, uncertain demand, recurrence plots, coordination, optimal program control
environmental management	55	0.817	2013	environmental management, operation management, agile production, lean production, sustainable business, delay factors
automotive industry	54	0.809	2012	automotive industry, energy efficiency, energy management system, green supply chain management, modular assembly, cardinal and ordinal data
smart factory	48	0.882	2013	smart factory, information visualization, holonic manufacturing systems, social network analysis, functional layout, inventory pooling
ant colony optimisation	46	0.872	2009	ant colony optimization, linear programming, mixed integer, scheduling, vehicle routing, dynamic programming, disassembly line balancing, Lagrangian heuristic
discrete event simulation	45	0.919	2007	discrete event simulation, virtual reality, cloud manufacturing system, augmented reality, model coupling, integer programming
combinatorial optimisation	43	0.803	2018	machine learning, in-plant logistics, multi-objective optimization, bus scheduling, network design problems, metaheuristics, colored Petri nets

Table 2. *Cont.*

Cluster	Size	Contour Value	Median Year	Hot Topic Words
mass customization	39	0.909	2010	mass customization, flexibility, product development, self-adaptive collaborative control, operations management
control charts	30	0.848	2010	control charts, regression analysis, nonlinear optimization, manufacturing systems engineering, demand curve
production quality	28	0.921	2010	production quality, local branching, agent-based systems, interaction protocols, holonic systems, garment manufacturing
processor scheduling	26	0.924	2012	processor scheduling, smart manufacturing, job shop scheduling, social computing, deep reinforcement learning, reverse logistics, cloud-edge collaboration
blockchain	25	0.951	2013	blockchain, uncertainty analysis, technical feasibility, steel products, life cycle assessment

3.2. Analysis of Bibliometric Results of Production Logistics in the Industry 3.X Stage

Combined with Figure 4, Tables 1 and 2, it can be seen that, on the whole, the research on production logistics in the Industry 3.X stage can be divided into the following six topics:

Topic I. Simulation Modeling Optimization for Intelligent Scheduling of Workshop production Logistics: Hot words in this topic include "lean logistics", "genetic algorithm", "combinatorial optimization logistics analysis", "ant colony optimization", "machine learning", "multi-objective optimization", etc. Yang et al. [17] set up a combinatorial optimization model with production capacity, process timing, and other factors as constraints, designed "SM&PR&GA" (simulation & priority rule & genetic algorithm) for simulation tests, and improved the scheduling efficiency of discrete production operations. In the field of production logistics research, the accurate prediction of production and assembly efficiency is highly complicated. Dobra et al. [18] designed a supervised machine learning prediction algorithm based on beat time, and verified its efficiency prediction effectiveness and robustness in single machine and automatic assembly line through examples. Furthermore, aiming at the intelligent scheduling problem of shop-level logistics facilities, Zhou et al. [19] studied AGV intelligent scheduling of mixed load based on JIT based sustainable material handling scheduling for mixed-flow assembly lines with time window and capacity constraints, effectively reducing the inventory level of the production line. Yao et al. [49] proposed a new mixed integer linear programming (MILP) model based on the improved disjunctive graph model, and verified its effectiveness in solving the job-shop scheduling problem of mobile robots through examples. Zhang et al. [20] proposed a DRTS method based on deep reinforcement learning, which effectively solved the distributed real-time scheduling problem of job shop AGVs in cloud manufacturing mode. In general, this topic category revealed that under the guidance of lean logistics, production capacity and other constraints, Heuristic algorithm, machine learning, system dynamics, Witness, and other simulation modeling optimization methods are used to solve the problems of workshop production job scheduling, efficiency prediction, logistics AGV intelligent scheduling, combinatorial optimization logistics analysis, system layout design, and so on [50–60].

Topic II. Management Mode and Decision-making Method for Efficient Operation of Production Logistics: Hot words in this topic include "logistics system", "cost control", "logistics tracking", "uncertain demand", "manufacturing systems engineering", and "holonic manufacturing systems", etc. Liu et al. [61] built a parallel management and control platform framework for workshop logistics system in view of key issues such as logistics blockage and route selection in workshop logistics. Li et al. [62], guided by CPFR

(Collaborative Planning Forecasting and Replenishment), established a production logistics push–pull management mode, which effectively reduced the inventory of products in process and improved the collaborative efficiency of production logistics. Tanasic et al. [63] proposed a new lean method and tool, and verified its effectiveness in improving internal logistics efficiency, reducing pipeline waste and changing workplace layout through dynamic simulation cases. Cherchata et al. [64] proposed a design method of enterprise production logistics system based on the principle of process matrix (unified function and process management method), which effectively coordinated the flow of materials, information, and funds within the enterprise and ensured the efficient operation of enterprise production logistics system. Furthermore, Neumann et al. [65] considered the influence of human factors, and based on the content analysis method, proposed to incorporate "human" as the core resource into the construction of complex production logistics system platform framework. Baroroh et al. [66] put forward a new idea of mixed-reality (MR) production logistics system simulation in consideration of the changes in system performance caused by individual differences in human behavior, which significantly improved the quality and flexibility of production logistics facility planning. In general, from the perspective of operation, the production logistics system contains many production operation problems, such as the allocation of production logistics equipment and the balance of production line beats. The integration and optimization of the operation of the production logistics system, and then the improvement of production efficiency and the reduction in logistics costs in the operation process, have become the key issues urgently to be solved by manufacturing enterprises [16,67,68]. At present, the research on the management model and decision-making method of production logistics mainly focuses on the following aspects [65,66,69–73]: First, the research on the influencing factors and mechanism of resource allocation of production logistics system; the second is the design and research of production logistics system platform, and focuses on improving the intelligent service level of operation system; the third is the optimization research of production logistics system, including the optimization of production process flow and production logistics system. At the same time, it was gradually noticed that the production logistics system is essentially a social technology system, and human factors play an important role in improving the system operation performance [74–77].

Topic III Green Control for Intensive Operation of Production Logistics: Hot words in this topic include "process energy consumption", "chemical enterprises", "coal logistics", "energy management system", "sustainable business", "carbon emission", etc. From the perspective of its conceptual attributes, the greening of production logistics aims to reduce environmental pollution and reduce resource consumption, and uses advanced logistics technology to plan, optimize, and implement logistics activities in the production process to ensure the greening of the entire production operation process [78,79]. From the perspective of green management and control of production logistics in manufacturing enterprises, Li et al. [80] studied how to design and build a green logistics system for coal, providing a beneficial reference for coal enterprises to implement green logistics. From the perspective of enterprise green performance, Sarkar et al. [81] proposed the optimal management decision-making framework of intelligent production logistics system based on carbon footprint and carbon emissions. From the perspective of green control of shop-level production logistics, Dai et al. [82] constructed a multi-objective optimization model aiming at minimizing energy consumption and production time, and proposed an enhanced genetic algorithm (EGA) to solve the flexible job-shop scheduling problem considering logistics transport constraints between processes. Furthermore, in order to minimize energy consumption and carbon emissions in the process of production logistics without sacrificing production efficiency, Wang et al. [83] studied the multi-objective optimization and carbon efficiency evaluation of flexible production logistics under low carbon constraints. By establishing a mathematical model of carbon efficiency optimization, both carbon emissions and production logistics indexes were optimized. In general, from the perspective of their fields, the existing research on the greening of production logistics was mainly concentrated in energy, chemical, and automobile manufacturing enterprises. From the perspective of research problems, existing studies mainly focus on enterprise-level performance evaluation, information traceability, shop-level production logistics and transportation energy consumption, etc., and there is still room to expand the perspective of research problems [84–86].

Topic IV Complex Network Structure Optimization for Discrete Manufacturing Production Logistics: Hot words in this topic include "discrete manufacturing", "shortest path", "degree distribution", "complex networks", "colored Petri nets", "discrete event simulation", and "knowledge graph", etc. A complex network is an abstract network that describes individuals through "points" and relationships among individuals through "lines". Complex network theory is widely used in technical networks and social networks. Zhao et al. [87] calculated the average path length, agglomeration coefficient, and other important characteristic parameters of the network model of logistics system by using complex network statistics method. Considering the spatial disorder and time asynchronism of production logistics resources, Zhao et al. [88] proposed a production logistics resource allocation method based on dynamic spatio-temporal knowledge graph (DSTKG), and discussed the feasibility and practicability of large-scale deployment of the proposed method. In order to verify the effectiveness and accessibility of flexible manufacturing system modeling, Li et al. [89] proposed an object-oriented time-colored Petri net (OOCTPN) and conducted dynamic simulation with Flexsim. Yin et al. [90] proposed a workshop production logistics network modeling method based on complex network theory to solve the problem that production logistics in discrete manufacturing workshops could not support the optimal operation of production lines. Guo et al. [91] proposed an adaptive collaboration method for production logistics based on timed-color Petri nets, and verified through examples that the proposed method was superior to the event-driven method in terms of reducing waiting time, manufacturing time, and power consumption. In general, the production logistics network belongs to the category of technical network. The application of complex network theory in the field of production logistics is an important research direction, and the discrete manufacturing research is one of the subdivisions. The complex network modeling theory can provide theoretical support for the optimization and stable operation of production logistics business in discrete manufacturing workshops by constructing the network topology of production logistics system, and has practical guidance and reference significance for enterprises to effectively implement the optimization of production logistics system [92–95].

Topic V. Development and Application of Enabling Technology for Intelligent Operation of Production Logistics: Hot words in this topic include "internet of things", "digital twin", "blockchain", "smart manufacturing", etc. Yuan et al. [96] developed a real-time management system of production logistics based on RFID, aiming at the difficulty in realizing accurate management of production logistics. The system is capable of material and product label identification, dynamic acquisition of work in process information, electronic Kanban management of warehouse and station, real-time monitoring of distribution process, etc. Cao et al. [97] proposed a production logistics information processing method based on RFID, which divides a large number of RFID data into different clusters with high closeness to detect anomalies. Chen et al. [30] shifted their research focus to discrete workshop data management and constructed a manufacturing Internet of Things system oriented to shop-floor production process. Considering the complexity and flexibility of production logistics operation, Andronie et al. [31] proposed that real-time sensor networks should be further developed in the future, so as to configure AI-driven big data analysis through the use of network physical production logistics networks. Furthermore, Flores et al. [32] proposed a data model for multi-channel communication for material handling inside manufacturing enterprises, and realized the digital servification based on the industrial Internet of Things in intelligent production logistics. In general, the Internet of Things and digital twin rely on sensing devices to collect data, information, and status of devices in real time, so as to realize the integration of logistics resources, equipment tracking, positioning, regulation, and management [14,41,98,99]. Internet of Things, digital twin and blockchain technologies are important enabling technologies of production logistics system. Especially in the context of Germany's "Industry 4.0" and "Made in China 2025" development strategies, Internet of Things, digital twin, and blockchain technologies are used to promote the interconnection, intellectualization, and resource utilization of production logistics. It is of great significance to the efficiency improvement and steady-state operation of production logistics system [31,100–105], and so, this direction has great research potential.

Topic VI Intelligent Collaborative Decision-making and Control for Optimal Operation of Production Logistics: Hot words in this topic include "industrial park", "synchronized control", "dynamic", "human–machine-material integration", "self-adaptive collaborative control", "cloud-edge collaboration", and "optimal program control", etc. Oriented to collaborative decision-making and control of production logistics system, Li et al. [106] established an agent-based collaborative production scheduling system for the collaborative production scheduling problem of container terminal logistics system. Monostori et al. [107] systematically sorted out various distributed methods and technologies from control theory to cooperative game theory, distributed machine learning to holographic systems, collaborative enterprise modeling, and system integration. Guo et al. [108] proposed a self-adaptive collaborative control (SCC) mode of intelligent production logistics system to enhance intelligence, flexibility, and elasticity. Zhang et al. [109] took "production–transport–storage" three units of intermittent manufacturing enterprises as synchronized decision objects, and adopted the analytical target cascading (ATC) method to realize synchronized control and dynamic optimization of production logistics system at unit level. Furthermore, aiming at shop-level production logistics collaborative decision-making, Cai et al. [110] constructed a physical system framework of fully reactive scheduling information to solve the problem of personalized customized production logistics collaborative dynamic scheduling, and based on this, designed a "two-step" scheduling algorithm considering two-step operations of production logistics. Guo et al. [111] introduced the graduation ceremony mode into the collaborative decision-making of the production logistics system and proposed an overall framework of the graduation intelligent manufacturing system (GiMS). Based on this, a collaborative decision-making mechanism of production logistics based on mixed integer programming was designed, and the effectiveness of the proposed scheme was verified by an example. In general, the optimal operation of the entire production logistics system was promoted by the horizontal collaboration within and between production logistics units and the vertical collaboration through the interconnected manufacturing system of production logistics facilities and human resources [107,112–117]. From the perspective of technical means supported by intelligent collaborative decision-making and control, It mainly included DT, CPS, Multidisciplinary Design Optimization (MDO) et al. [118,119]; this research direction is still relatively new and at the initial stage of research.

3.3. Research Gaps Analysis Based on Bibliometric Results

On the basis of previous studies, facing the new needs and new challenges in the current internal and external environment, in order to make the research of production logistics in the Industry 3.X stage achieve sustainable development of innovation, it is still necessary to break through the following research gaps:

First, from the perspective of dynamic disturbance, the existing literature often only studied production logistics operations under static or specific types of disturbances, and the disturbance probability was often assumed to be known or predictable. For example, AGV path planning in the workshop, WIP transfer between processes, etc. However, the real production logistics system is affected by a variety of predictable and unpredictable uncertainties. At present, the propagation path and influence mechanism of disturbances in the system are not clear. There is still a lack of a systematic and universal technology to analyze the propagation and influence characteristics of different types and degrees of disturbances, so as to provide a basis for achieving accurate dynamic response.

Second, from the perspective of system optimization objectives, the existing literature mostly considered the production logistics portfolio optimization problem with fixed target dimensions. For example, job shop scheduling usually minimizes the production logistics operation cycle, minimizes the machine processing cost, minimizes the AGV logistics transportation time or energy consumption between processes, etc. However, the real production logistics system faces many dynamic disturbances. In the process of interference, the original target may not adapt to the current state of the system. At this time, it is necessary to change the original target, which may include the change of the absolute number of the same target, the change of the number of target dimensions, and even with the occurrence of interference, the number of dimensions of the original target and the absolute number completely change. Therefore, in the dynamic environment, the dynamic multi-dimensional variable target optimization research will be more in line with the current high-frequency changes in the internal and external environment, with strong theoretical and practical significance. However, there is a big research gap in this direction.

Third, from the perspective of system collaborative management and control, facing random demand, relying on open resources, and maintaining the optimal adaptability of the system through continuous self-organization are the new requirements and challenges of the current production logistics system. Most of the research on production logistics system focuses on the dynamic coordination of distributed operation units oriented to dynamic requirements under the determined system structure configuration. For example, the dynamic coordination of production logistics machinery and equipment, materials and personnel in the workshop, and the dynamic coordination of multiple production logistics units such as production workshops, forklifts, and warehouses in the enterprise. However, for the dynamic system structure and resource allocation (e.g., the introduction of cloud resources) in the random order environment, the research on how to make open Opti-state decision-making through the evolution of system and environment is still limited.

Fourth, from the perspective of enabling technology, most researchers and practitioners still follow the traditional operation and management mode, rather than exploring how to reconstruct the underlying interactive logic and operation mode of various production logistics resource elements and tasks in the intelligent production logistics system with wide connection of resource elements and deep integration of information-physical space, so as to give full play to the potential of new technologies. To this end, based on enabling technologies such as big data, cloud computing, Internet of Things, and digital twin, the construction of a production logistics system information architecture that can fully consider the real-time perception of multi-resource factor status in the new environment, visible traceability of the operation process, and accurate identification and positioning of disturbances contributed less.

4. SPLS: A Novel Production Logistics Mode in the Industry 3.X Stage

Based on the bibliometric results and research gaps in Sections 3.2 and 3.3, it is not difficult to find that the research on collaborative decision making of production logistics system enabled by digital twin is the current hot spot and frontier direction of production logistics research in the Industry 3.X stage. It has important research significance and will emerge as a great research value in future research [14,28,109]. The author's group also conducted some research work in this area and made some breakthroughs. In this section, this paper will take the research project that was tackled by the group—the research on synchronized decision-making framework of digital twin-enabled production logistics system—as an example, and hope to elaborate the application research of the production logistics system collaborative decision-making driven by digital twin through specific case studies. This section further concretizes and deepens Section 3, proposing a novel production logistics management mode and decision-making method, including digital twin enabled information architecture, synchronized decision-making mechanism, and system optimization method. We aimed to provide certain reference and inspiration for the research on production logistics in the Industry 3.X stage.

4.1. Case Background and SPLS Operation Mode

In Industry 3.X, the market is changing from the traditional mass production mode to a production mode that caters to diversified customer needs, and the ability to provide customized products or small lots and multiple varieties with fast response has become the core competitiveness of enterprises. Based on this, the author's group hopes to use systemic thinking to maximize the combination of open resources from different standard modules to form a customized synchronized production logistics system (SPLS). The proposed synchronized production logistics system operation mode and control mechanism are shown in Figure 5.

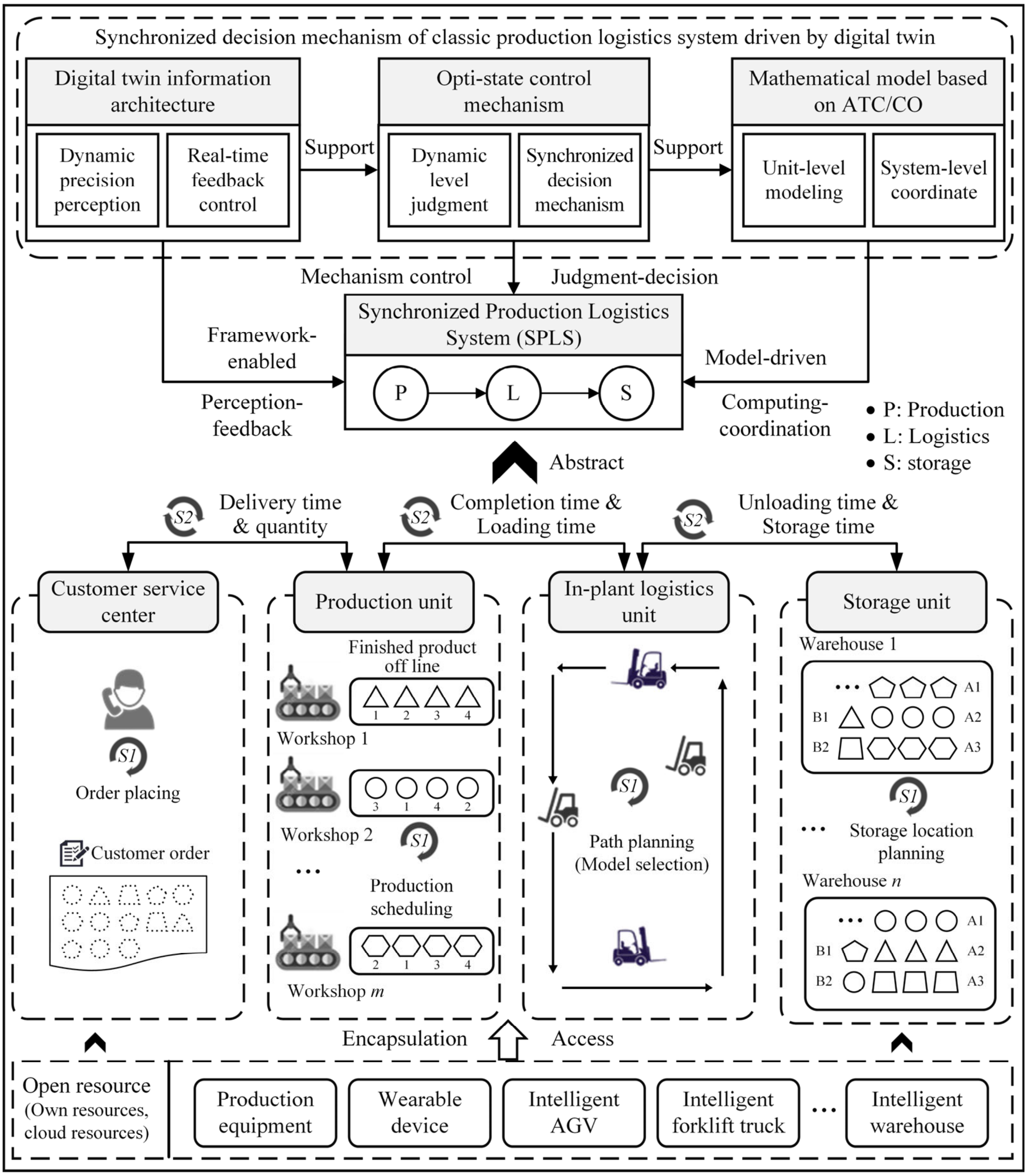


Figure 5. Synchronized production logistics system operation mode and control mechanism.

From the production logistics operation level, the production logistics system includes four important components: Customer service center, production unit, in-plant logistics unit, and warehouse unit. Its operation process can be outlined as follows: The customer service center receives customized orders and assigns enterprise-level tasks to production execution units. Each execution unit plans with the relevant units according to the current overall resource occupancy, resource rental demand, and order demand, including resource planning, production planning, transportation planning, and warehousing planning. When the plan is executed, the production unit organizes the production of products according to the production plan and stores the finished products in the buffer zone for transportation by the in-plant logistics fleet (e.g., smart forklift). Based on the product attributes, completion time, and transportation plan, the transportation fleet transports the finished products to the storage unit, which allocates the finished products inventory according to the predefined space allocation plan, and then completes the order delivery task before the due date. It should be noted that the units of the production logistics system are controlled by digital twin technology for dynamic and accurate sensing and real-time feedback.

From the perspective of the principle of synchronized decision-making mechanism, the synchronized decision-making architecture of digital twin-enabled production logistics system consists of three parts: Digital twin information architecture, Opti-state control mechanism, and ATC/CO-based "production-In-plant logistics-storage" mathematical model. The synchronized decision-making mechanism can be summarized as follows: First, the information architecture based on digital twin is used to realize dynamic accurate perception and real-time feedback control among production logistics units. Second, the optimal control mechanism of "Theoretical Optimal State–Actual State–Adaptive Optimal State" is proposed. When the production logistics system is disturbed by uncertain factors, the decision-making layer can judge the dynamic level according to the real-time data and state of the production logistics operation environment, and then, make agile and accurate management decisions. At the same time, MDO methods such as ATC and CO (collaborative optimization) are used to globally model multiple "production–In-plant logistics–storage" decision-making units with independent decision-making and synchronized operation [109,112].

4.2. Synchronized Decision-Making Methods of SPLS

Here, one of the core methods in the synchronized decision-making mechanism, ATC, is taken as an example. ATC is a model-based, multi-level distributed decision-making method for large-scale systems proposed by Kim and Michelean in the MDO method cluster [120,121]. Because of its superiority in solving problems in the field of complex large-scale system optimization design, it is widely used in engineering theory and practice problems, such as automobile optimization design [122–124] and supply chain configuration [125,126]. As shown in the first part of Figure 6, the core idea of ATC optimization is to decompose the complex system layer by layer to form a hierarchical element combination of optimization problems. The optimization goal is to minimize the deviation of target transfer between different levels of elements. Through parallel optimization between layers with independent decision-making power and collaborative optimization between layers, the final optimization design results of complex large-scale systems are obtained. The second part of Figure 6 is the original ATC model and data flow diagram. Based on this, we modeled the ATC of the production logistics system in Figure 5, as shown in Part 3 of Figure 6. Interested readers can refer to Qu et al. [126] to understand these ATC modeling design and implementation details.

For the local optimization problem of production unit, in-plant logistics unit and storage unit, heuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) and adaptive large neighborhood search algorithm (ALNS) can be used to solve it. Finally, the systematic coordination and control are carried out in the mode of global optimization and distributed control, so that each unit of the production logistics system can be agile, self-organizing and self-adaptive to cope with customer customized orders. Thus, the dynamic synchronized decision-making of customized synchronized production operation system is realized.

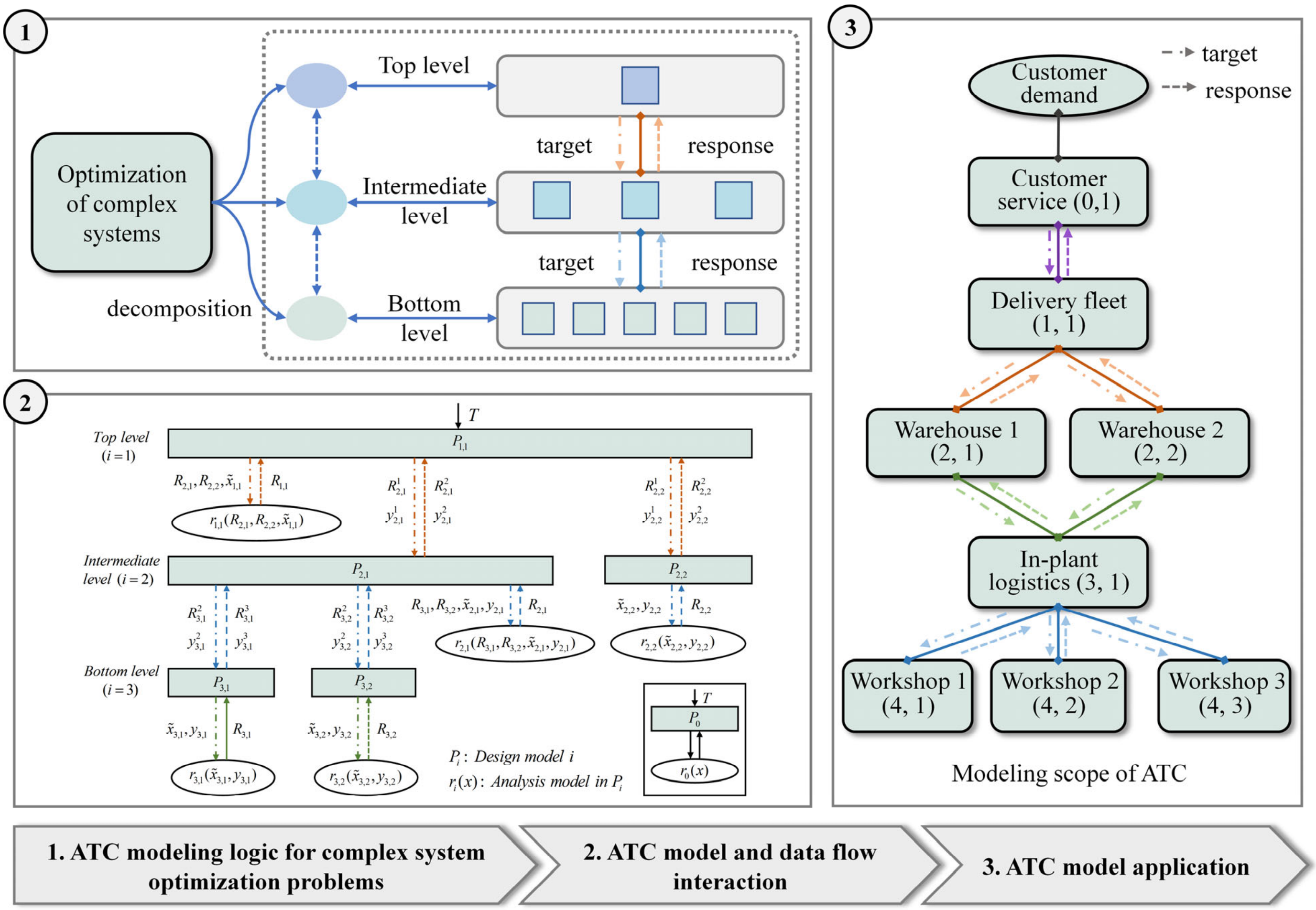


Figure 6. Synchronized decision-making method: Principle and application diagram of ATC.

4.3. Application and Effect of Industrial Enterprises

The dynamic and synchronized decision-making framework was recently applied in a leading paint manufacturer in China, with which the group is working. It was mainly used in the production and warehousing logistics phases of the enterprise operation. We defined this production logistics control framework as a digital twin-enabled synchronized decision-making framework of production logistics system (DTSDF-PLS), as shown in Figure 7.

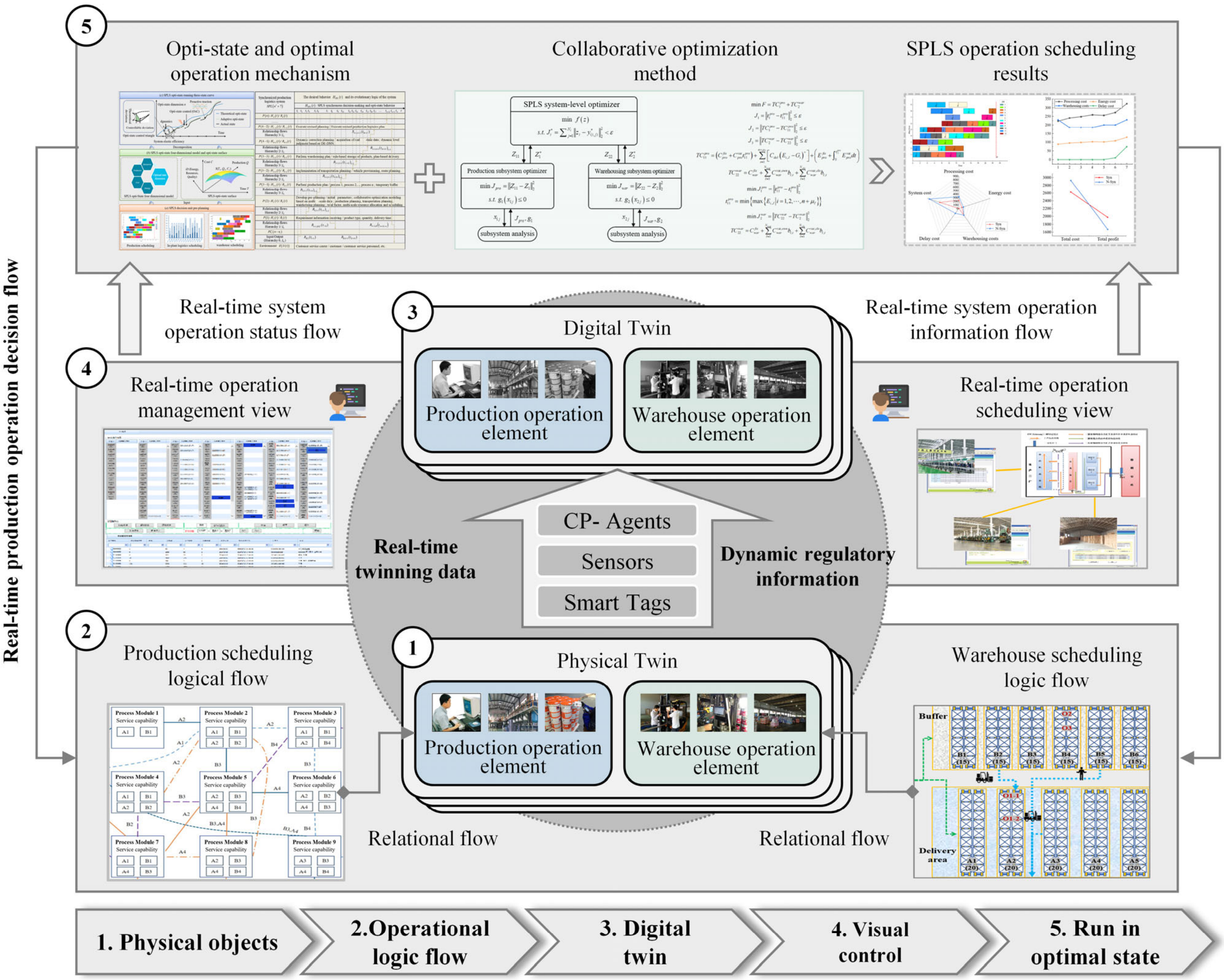


Figure 7. Diagram of digital twin-enabled synchronized decision-making framework of production logistics system (DTSDF-PLS) for the paint manufacturing company.

4.3.1. Physical Objects and Operational Logic Flow

Physical objects are a collection of entities objectively existing in SPLS, including multiple elements such as operators, machine equipment, materials, forklifts, etc. At the same time, the internal and inter unit interactions between the production workshop and warehouse form the logical flow of production logistics operations. For the production workshop, intermittent production was adopted, with batch processing as the production strategy. Multiple scattered and small batch customer orders were combined in an aggregated manner, and processed and produced in sequence through independent processes. Among them, the production logistics decision-making issues involved include batch selection, machine selection, transfer of work-in-process products between processes, etc. For warehouses, the storage space was divided into temporary storage and shipping areas according to their functions. It was necessary to plan the storage area and location of customer order products according to certain storage rules. This involves complex production logistics decision-making issues such as the selection of storage areas within the warehouse, allocation of storage locations, optimization of forklift paths, and transportation between temporary storage areas and shipping intervals. By analyzing and constructing the production logistics operation logic flow of the production workshop and warehouse units, physical entities and their dependency relationship data were provided for the "virtual-real" mapping driven by digital twin.

4.3.2. Digital Twin: Smart Digitization

Smart digitization is an important part of dynamic synchronized decision-making of production logistics. A series of intelligent sensing devices and technologies such as RFID tags, handheld RFID readers, wireless sensor networks (WSN), SOA (Service-Oriented Architecture), and EAI (Enterprise Application Integration) were used to collect, perceive, and process all-factor multi-source heterogeneous information generated during the operation of SPLS, including personnel, machines, raw materials, processes, environments, and detection. Through CPS transmission to the twin image layer, the total factor data of multi-dimensional real-time production logistics from multiple sources were mapped to the corresponding digital twin. It provides multi-source, multi-dimensional, and real-time twin data support for the dynamic control instructions issued by the twin image layer, and provides basic data support for the precise control and synchronized decision-making of each link in the dynamic operation environment.

4.3.3. Visual Control: Visibility and Traceability Analytics

Driven by virtual simulation data, the execution process of production logistics and the behavior of resources were analyzed and judged independently, and the intelligent production logistics decision-making service was provided to realize the distributed optimization and adaptive control of the whole process. The terminal equipment provided a multi-dimensional view of historical and real-time, global and local conditions as the basis for synchronized decision-making of real-time production logistics. On-site operators can access the information, space-time, and status of local terminal equipment, including the space-time trajectory of production logistics resources, resource availability, error status, planned motion, etc.

4.3.4. Run in Optimal State

As described in Sections 4.1 and 4.2, based on the synchronized decision-making mechanism and ATC method proposed by the author's group, the optimal operation scheduling results of SPLS were obtained. By using the synchronized production logistics system developed by the group, the simulation modeling was carried out based on the real-time production logistics information obtained by digital twin technology, and the optimization instructions were issued to the physical entity for execution. In particular, under dynamic disturbances such as random insertion of orders, the preplanning was rescheduled based on the Opti-state and optimal operation mechanism after the dynamicity level judgment. This cycle continued until the end of the production operation task. Ultimately, it helped the enterprise to effectively realize the multi-unit self-organization and self-adaptive collaborative operation of production logistics, and to reduce the cost of production logistics and the time of orders in the warehouse.

The data show that after applying DTSDF-PLS, the company's average order delivery cycle time dropped from 84 h to 65 h, which decreased by 29.2%. Paint production efficiency improved from 243 kg per capita to 298 kg per capita, which increased by 22.6%. Product inbound timeliness improved from 78% to 93%. Average storage time decreased from 45 h to 36 h, which decreased by 25%.

5. Discussion and Future Directions

5.1. Future Directions and Suggestions

Based on Kleinberg burst detection method, Tables 3 and 4 list the burst intensity, emergence, and end time of key words in production logistics research of Industry 3.X stage, in which the blue part represents the overall time span of keyword emergence, and the red part represents the stage of keyword emergence. Combined with the clustering results in Figure 4, by analyzing the distribution and emergence of keywords in different years of each topic clustering, it was found that the evolution trend of production logistics research field in the Industry 3.X stage presented the following characteristics:

Table 3. CNKI—Industry 3.X stage production logistics literature emergent keywords.

Keywords	Strength	Start Year	End Year	From 2000 to 2023
reference logistics diagram	3.22	2000	2005	
logistics cost management	2.09	2004	2007	
simulation	2.02	2007	2011	
information system	1.65	2008	2010	
lean production	1.72	2012	2018	
genetic algorithm	1.65	2012	2013	
production logistics system	2.3	2013	2014	
coal mine production logistics	4.7	2014	2017	
production efficiency	2.28	2014	2016	
safety level	1.63	2014	2016	
resource allocation	2.53	2015	2018	
intelligent manufacturing	2.87	2016	2023	
multi-objective optimization	2.26	2017	2023	
digital twin	1.73	2018	2020	
internet of things	2.11	2019	2020	

Table 4. WoS—Industry 3.X stage production logistics literature emergent keywords.

Keywords	Strength	Start Year	End Year	From 2000 to 2023
inventory control	1.62	2000	2008	
mass customization	2.62	2003	2010	
optimisation	2.1	2003	2010	
expert system	1.77	2008	2011	
information technology	1.48	2009	2012	
decision making	1.3	2010	2020	
energy efficiency	1.47	2011	2016	
internet of things	4.16	2016	2020	
sustainability	3.43	2018	2023	
genetic algorithm	2.33	2018	2020	
industry 4.0	7.41	2020	2023	
blockchain	2.81	2020	2023	
smart factory	1.51	2020	2023	
digital twin	6.69	2021	2023	
artificial intelligence	1.48	2021	2023	

(1) Interdisciplinary research is more frequent, and the research of production logistics in the Industry 3.X stage involves many categories such as simulation modeling of production logistics, optimization of production operation system, change and innovation of management mode, etc. The interdisciplinary characteristics are significant and the evolutionary journey is closely intertwined. The specific suggestions are as follows: In the future, we can further consider strengthening the degree of communication and cooperation among scholars in different disciplines, and systematically and deeply promote the interdisciplinary integration of production logistics research in the Industry 3.X stage.

(2) The research results of green production logistics are scarce, and the research is relatively weak. However, the current low-carbon economy has become the trend of the world, and will lead the global production mode, life style, values and national rights and interests to undergo profound changes. Under the implementation of a series of low-carbon and green environmental protection policies, it is necessary to accelerate the pace of clean and low-carbon transformation. In the future, certain scientific research resources should be invested to study how to achieve carbon reduction and decarbonization in the production logistics operation process through technological innovation and management innovation, so as to steadily promote the realization pro-

cess of green environmental protection goals. The specific suggestions are as follows: On the one hand, when studying the production logistics combination optimization problem, the resource and energy consumption indicators are reasonably included in the decision-making objectives and constraints of the optimization model; on the other hand, encourage the government and enterprises to jointly formulate the green manufacturing environmental protection index system, design a reasonable incentive mechanism and punishment mechanism, and strengthen the research efforts of scholars in the field of production logistics in the mechanism design.

(3) Enabling technologies such as big data, cloud computing, Internet of Things, and digital twin continue to promote intelligent and lean production logistics operation, especially against the background of Germany's "Industry 4.0" and "Made in China 2025" development strategies. In the future, the academic community should conform to the development trend of the current new generation of information technology era and make good use of enabling technologies in the era of big data, and the practice of enabling production logistics [119,127–131]. The specific suggestions are as follows: Formulate the system and standard of enabling technology, actively explore how to reconstruct the underlying interactive logic and operation mode of various production logistics resource elements and tasks in the intelligent production logistics system with extensive connection of resource elements and deep integration of information-physical space, and design a set of information architecture to support real-time and efficient management and control of production logistics system, so as to give full play to the potential of new technology.

(4) The production logistics system is no longer satisfied with process optimization and efficiency improvement, scholars paid attention to the fact that the production logistics system is essentially a complex socio-technical system, in which "human" is an important subject, and human–computer intelligent collaboration is the key to the future human-centered intelligent manufacturing. Therefore, the future of production logistics system will be gradually changed from technology-driven to value-driven, and the key technology of human-centered manufacturing needs to be studied [132,133]. The specific suggestions are as follows: The human factor engineering theory is introduced and applied to the combination optimization of production logistics, and the optimal configuration and optimal scheduling problem in the human–machine cooperation environment are further studied. It is worth noting that the human–machine collaboration here includes not only the collaboration between people and production logistics robots but also the collaboration between people and machine tools/information systems/production logistics systems.

(5) From the perspective of system optimization, the production logistics system changed from the traditional system local optimization mode to the multi-unit collaborative optimization mode. Current studies started to apply systematic thinking and focus on collaborative decision-making of production logistics operation to maximize the combination of open resources of each unit. The whole production logistics system can respond quickly and effectively to dynamic intervention when facing uncertain demand environment, and dynamic synchronized optimization will be the frontier trend of future research [43,109,134,135]. The specific suggestions are as follows: From the perspective of the research object, the optimization problem of local problems such as workshop, forklift, and AGV can be extended to the system-level collaborative optimization problem of multi-units such as workshop, vehicle, and warehouse. From the perspective of the research methods of production logistics combination optimization, there are few collaborative optimization methods for production logistics systems in a dynamic operating environment. A small number of research work on multi-subsystem collaborative optimization also uses the quasi-separable model based on parameter association, and there are few multi-level tightly coupled decision-making models that support objectives, constraints, and parameters. In the future, local optimization methods such as heuristic algorithms (e.g., GA, ALNS) and machine learning algorithms

(e.g., Reinforcement Learning) can be extended to system-level distributed coordination optimization algorithms such as CO, ATC, and ALC (Augmented Lagrangian Coordination).

(6) The potential areas of improvement of SPLS proposed in this paper are further discussed. From the perspective of the research object, only the synchronized decision-making problem of production logistics within the enterprise is considered at present. In the current high dynamic environment, it is sometimes difficult for enterprises to effectively cope with the interference of dynamic environment by virtue of their existing production logistics resources. Therefore, future research can consider the synchronized decision-making problem of SPLS variable structure multi-unit considering cloud resources in the digital twin control system when external resources can be expanded. From the perspective of research methods, due to the high dynamics of the external environment and the introduction of external cloud resources, the original ATC/CO and other MDO methods may be difficult to obtain the optimal solution space of SPLS. Considering that the hyper probability-based ATC (H-PATC) has the advantages of facing a large number of different structures, coupling relationships, uncertain parameters, etc., in the future, the H-PATC method will be considered to solve the SPLS variable structure multi-unit synchronized decision-making problem.

5.2. Comparative Analysis of the Methods

At present, there are literature management software such as Mendeley and Endnote, with which researchers can easily manage literature. They have the advantages of easy and fast operation. For this kind of literature management tools, researchers mainly use them to organize and summarize existing literature manually, focusing on literature management, but the flexibility, automation, and visualization are not good. Based on the principle of bibliometrics and knowledge graph technology, this paper designed a set of bibliometrics and visualization scheme for the literatures of production logistics in the Industry 3.X stage. Compared with literature management software such as Mendeley and Endnote, the proposed scheme has the following advantages:

First, from the perspective of flexibility and system of data mining, NLP technology has good flexibility and can carry out more in-depth and systematic data mining. By writing programs, researchers can flexibly and efficiently identify the internal logic of the same document of production logistics in the Industry 3.X stage, identify the correlation and interweaving relationship of different documents, and then, identify the knowledge network in this field. This reflects the processing logic and analysis framework of "point-line-surface". Second, from the perspective of visualization of data mining, based on knowledge graph technology, researchers can intuitively present the research progress of production logistics in the Industry 3.X stage, the evolution of hot spots and other external development characteristics and the changes of internal knowledge structure by constructing keyword collinear networks and clustering graphs. Furthermore, it can effectively help researchers identify the knowledge structure and frontier trend of production logistics in the Industry 3.X stage.

6. Conclusions

This paper systematically analyzed the research progress, hotspot evolution, and frontier trends of Industry 3.X stage production logistics. Combining the findings of the above bibliometric analysis and the current situation of engineering practice, the research on production logistics in the Industry 3.X stage was prospected from the following aspects:

First, the dynamic joint operation and management of production logistics will become a research field of great academic value in the future. It is currently in the transition stage from Industry 3.0 to Industry 4.0 (i.e., Industry 3.X). Under the support of wide open cloud resources, the production logistics system takes multi-level production unit as the basic organizational unit, and achieves small lot size through repetitive operation within the unit and multiple varieties through dynamic combination between units to meet individualized order requirements. Dynamic joint operation management of production logistics is an emerging field with strong research value in the era of Industry 3.X. Therefore, how to realize the wide dynamic configuration of production units and the collaborative dynamic control of production logistics execution through the global, long-cycle, and real-time dynamic joint operation management of production logistics has become the key to Industry 4.0.

Second, with the new generation of information technology such as cloud computing, Internet of Things, digital twin, and artificial intelligence as the enabling framework and complex system optimization algorithms such as MDO as the means to achieve, the dynamic pursuit of production logistics system time, cost, energy consumption, customer satisfaction, and other multi-dimensional decision-making objectives will become the key research direction for future theoretical research and engineering practice. The reason for this is that with the introduction of smart manufacturing strategies and concepts such as "Made in China 2025", "German Industry 4.0", and "Industrial Metaverse", cloud computing, Internet of Things, the new generation of information technology such as cloud computing, Internet of Things, digital twin, artificial intelligence, and production logistics will be deeply intertwined. It will become a key enabling technology to solve production logistics problems, and can effectively empower intelligent decision-making in production logistics management. At the same time, in view of the increasing complexity of production logistics systems due to individualized customer demand and high frequency of order changes, complex system optimization algorithms such as MDO will have wider applicability than traditional single optimization methods. The optimal configuration of production logistics usually takes time and cost as the optimization objectives. With the manufacturing industry's focus on green manufacturing and customer demand, energy consumption and customer satisfaction gradually become common decision goals for production logistics optimization. Furthermore, in the face of dynamic disturbances such as random insertion or cancellation of customer orders, fluctuation of production resource capacity, and random failure of manufacturing equipment, the production logistics system puts forward higher requirements for its online dynamic anti-disturbance and adaptive control decisions in order to dynamically pursue the optimal multi-dimensional decision objectives.

Third, the optimization of system for random target and the evolution of system for random environment will become the new difficulty in the control of production logistics system in the post-Industry 3.X period. Specifically, the later stage of Industry 3.X is the advanced stage of the development of Industry 3.X to 4.0, where products are integrated with more personalized elements, and it is a diversified stage of "random demand guidance". Customer orders are highly random, and enterprises rely on social resource platforms to organize production. Unlike the second point of this section, the production logistics system has no stable system structure and planning cycle. It is an evolutionary system that "faces random demand, relies on open resources, and maintains optimal adaptability through continuous self-organization". For this kind of large and complex production logistics system with variable plan, variable strategy and variable structure, we can consider the introduction of system hypercyclic theory. The hyper probability-based ATC (H-PATC) can be used to solve the synchronized optimization problem of "goal-plan-structure" for production logistics systems with multi-layer and dynamic operation structures in stochastic environments. This will be a very interesting and meaningful research direction, which deserves further in-depth study by scholars in related fields.

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