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Combining machine learning and main path analysis to identify research front: from the perspective of science-technology linkage

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Abstract
With the development of the era of big data, research data are accumulating, and various research directions emerge endlessly. It is difficult for researchers to grasp the hotspots and development trends of the discipline. Therefore, exploring methods to quickly and accurately identify research fronts is of great significance to scientific and technological innovation. This paper proposes a research front identification method integrating machine learning and main path analysis in conjunction with papers and patents based on the existing research. The innovation of this method is the combination of citation analysis and semantic analysis to identify research front from the perspective of science-technology linkage. This article takes the Internet of Things in supply chain as an example to verify the feasibility and effectiveness of the method. It is of great significance to identify important scientific and technological research fronts in a specific domain by intuitively revealing knowledge diffusion and text mining. The proposed method enriches the application of MPA and helps scholars grasp the latest information, mainstreams and future directions.

Keywords Main path analysis · Text classification · Machine learning · Science-technology linkage · Internet of Things

Introduction

The scientific and technological revolution and industrial transformation are on the ascendant. Accurately grasping the research front of scientific and technological development is crucial to the forward-looking deployment of innovation strategies, optimal allocation of innovation resources and improvement of global science and technology (S&T) competitiveness. "Research front" was proposed by Price (1965). The research front guides the direction of scientific development and the path of technological innovation (Wang et al.,

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2021a, 2021b). Marrone (2020) pointed out that detecting research fronts helps researchers track the evolution of knowledge structures. Therefore, how to quickly and accurately identify the research front in scientific and technological innovation has become the focus of academic world.

Scholars have carried out a great deal of research work on exploring and identifying research fronts. With the rapid development of data resources, more and more scholars use quantitative methods to identify research fronts. For example, Piñeiro-Chousa et al. (2020) mapped the research front in business science through bibliographic coupling and citation counts. Prabhaa et al. (2020) traced the research front and development prospect of organic electronics field by visualizing the development trajectory. However, these studies only take the citation relationship and citation counts into consideration, and ignore the semantic connection between documents. To overcome the limitations of citation analysis, some scholars have proposed methods combining semantic analysis. Such as Jung and Lee (2020) combined the co-word analysis with citation analysis to investigate research front based on scientific literature in text mining domains. Huang et al. (2017) took patents in 3D printing domain as an example to explore technical hotspots and research prospects by using co-word analysis and MPA (main path analysis). However, there are still several problems with the existing studies: (1) Most studies analyze the target field from a single perspective of science or technology, and fail to construct the linkage between S&T. Technological research is also essential for front detection. (2) MPA methods are widely used for front detection in science or technology. However, it is challenging to use them for citation networks consisting of papers and patents, as cross-citations between papers and patents are rare. (3) Existing research is based on the whole target field, but dividing subareas is necessary for a diversified development field.

Therefore, this paper proposes a research front identification method based on MPA and machine learning. This paper identifies scientific research front based on knowledge diffusion trajectories. Machine learning techniques classify the latest patent into corresponding subareas and extract technological research hotpots. Then, two indicators are used to identify technological research front further. Specifically, MPA is adopted to generate main paths that reveal scientific research font; machine learning techniques are used to associate patents with main paths, revealing technological research front. The fundamental techniques of the method are as follows: Firstly, edge-betweenness clustering and MPA are adopted to map development trajectories of subareas; Secondly, we use text classification model to classify recent patents into appropriate subareas. After then, we adopt topic model to extract the latest technical topics, thereby generating an extended main path. Finally, we use topic heat and novelty to evaluate the identified topics, so as to grasp the research front of a particular field. The main advantages of this method are as follows: (1) It solves the limitation of MPA method in dealing with citation relationships between different types of data, and integrates machine learning techniques to extend the scientific main path. (2) It comprehensively probes the research front of a particular field, not only from the scientific field but also from the technological field. (3) It uses a text classification model to build the linkage between S&T. Predict the class label of patents and classify them into multiple subareas.

The contribution of this paper is mainly reflected in the following aspects: (1) This paper adopts MPA and machine learning techniques, combines S&T, and effectively reveals the research front from the perspective of citation analysis and semantic analysis. (2) For the lack of existing research, this paper not only addresses the lack of recent important technologies on the main path, but also solves the problem of previous studies focusing on a single literature type of patents or papers. (3) This paper analyzes the research front of Internet of

Things (IoT) in the supply chain (SC) and provides inspiration for scholars in this field. In addition, the method in this paper is also applicable to research front identification in other fields.

This paper is organized as follows: "Methodology" section describes the techniques used in this paper, including edge-betweenness clustering algorithm, MPA, text classification model and topic model. "Dataset and experimental settings" section explains the dataset, data processing, and model settings. In "Results" section, IoT in SC is taken as an example for illustrative analysis. Discussion and conclusion are presented in "Discussion" section.

Related work

This section discusses the research front discovery, the concept of S&T linkage and related research, and the overview of IoT in SC.

Research front discovery

Research front can be divided into basic research front (scientific research front) and applied research front (technological research front). Generally, papers and patents are regarded as scientific and technological developments (Ba & Liang, 2021; Meyer, 2002; Wang et al., 2021a, 2021b). So far, there is no clear definition of research front, and scholars have given different definitions of research front. Price (1965) suggested that the research front is consist of highly cited papers published recently. Persson (1994) believed that co-citation papers constitute the knowledge base of the research front, and the citing paper represent the research front. Liu et al. (2016) regarded the research front as a set of publications dealing with coherent issues in recent years. The "research front" studied in this paper includes the scientific and technological front. This paper reveals the scientific research front by constructing a citation network of scientific publications and obtain the technological research front by analyzing the latest patent.

Existing methods for detecting research fronts fall into two main categories: qualitative and quantitative analysis. Qualitative analysis methods mainly extract the opinions of different experts through meetings and questionnaires, etc., to provide information support for the development of the target field. Quantitative analysis methods mainly include the citation-based, content-based and overlap analysis. For example, Huang and Chang (2014) explored research front of OLED by combining bibliographic coupling analysis with sliding time window. Wang et al. (2021a) tracked research front by integrating the topic evolution model. Dantu et al. (2021) combined a topic model with co-citation analysis to identify research front of IoT in healthcare.

Measure the linkages between science and technology

"Science-technology linkage" refers to the combined relationship between scientific and technological knowledge systems (Xu et al., 2020). Existing studies construct citations between patents and papers to detect the associations between S&T. Carpenter and Narin (1983) first analyzed patent citations and identified scientifically dependent fields. Liaw et al. (2014) used nonpatent references to assess the technological impact of academic journals. There are relatively few studies on patents cited by papers. Glänzel and Meyer (2003) explored connections between S&T fields by analyzing "reverse" citations. Due to the shortcomings of one-way analysis, some scholars study the two-way citation between S&T. Huang et al. (2015) studied the cross-citation of papers and patents in the fuel cell domain and found that the relationship between S&T is getting more and more closer. However, the method based on citation analysis cannot reveal the textual associations between S&T.

Some researchers explore S&T linkage through author-inventor links. Noyons et al. (1994) first proposed to study the S&T interface by constructing author-inventor relationship. They took the application of lasers in medicine as an example to analyze the collaboration between universities and enterprises. Wang and Guan (2011) constructed author-inventor links based on Chinese Nanotechnology patents data. They analyzed the roles and functions of researchers in the network and found that the research performance of academic inventors was significantly higher than academic researchers. Balconi et al. (2004) found that academic inventors are more centrally located in social network than non-academic inventors and play a greater role in knowledge dissemination. However, the lack of relevant data limits the application of this method. In addition, the problem of author homonymy can affect the accuracy of the results.

In addition, some studies mine the topics of publications and patents and calculate the similarity to measure topic linkages between S&T (Ba & Liang, 2021; Xu et al., 2019). Xu et al. (2020) constructed a topic-linked innovation path in S&T by measuring the co-word linkage degree, co-author linkage degree and co-citation linkage degree among knowledge units. Some scholars combine citation and content analysis to conduct an S&T association analysis. Ba and Liang (2021) integrated knowledge association and structural association to measure the network connection between S&T. In this paper, the linkage between S&T is captured through text analysis, and the latest patents are assigned to collections of scientific literature on similar topics.

Internet of Things in supply chain

With the further development of the information age, the application of the IoT is further optimized and improved on the traditional SC model. The IoT is continuously evolving, but it has no uniform definition. The International Telecommunication Union defines the IoT as the global infrastructure of the information society, enabling advanced services through interconnections based on existing and evolving interoperable information and communication technologies. The IoT has been widely used in many fields, among which the key technologies are RFID technology, wireless sensor network technology and cloud computing technology. The application of the IoT in SC makes the overall logistics circulation link more intelligent and improves the problems in the process of traditional logistics transportation, and provide the circulation efficiency of products. Since IoT has been applied in SC, many scholars have paid attention to it and achieved many achievements. For example, Rejeb et al. (2021) systematically analyzed the Internet of Things in the Halal food supply chain, identifying its advantages and future challenges. In addition, some research focuses on the simulation and optimization of SC model. Sun et al. (2020) analyzed the impact of the application of the IoT on upstream and downstream wholesale prices, costs and revenues, providing a basis for enterprises to invest in the IoT. Leng et al. (2019) applied RFID technology to agricultural SC detection to promote the development of logistics SC management.

Methodology

This paper aims to capture the research front from the extended main paths. The theoretical framework of this article is shown in Fig. 1. The composition of the article is mainly divided into three parts: (1) Extracting relevant documents and patents from Web of Science (WOS) and Derwent Innovations Index (DII), respectively. Then, Perform data preprocessing operations on the downloaded data. (2) Applying the edge-betweenness clustering to group the nodes in the citation network and then extract the main paths from them. (3) In this paper, we classify patents into corresponding main paths through text classification model. Then, LDA model is used to extract topics of the classified patents as an extension of the main paths. Finally, the identified topics are evaluated by indicators to obtain the technological research front.

Stage 1: data collection and data processing

Step 1: data retrieval

The retrieval strategy needs to be predetermined before data collection. This paper selects the WOS and DII databases as the retrieval systems. WOS contains more than 13,000 authoritative and high-impact academic journals worldwide, including multiple subject areas, and it is one of the important databases for obtaining global academic information

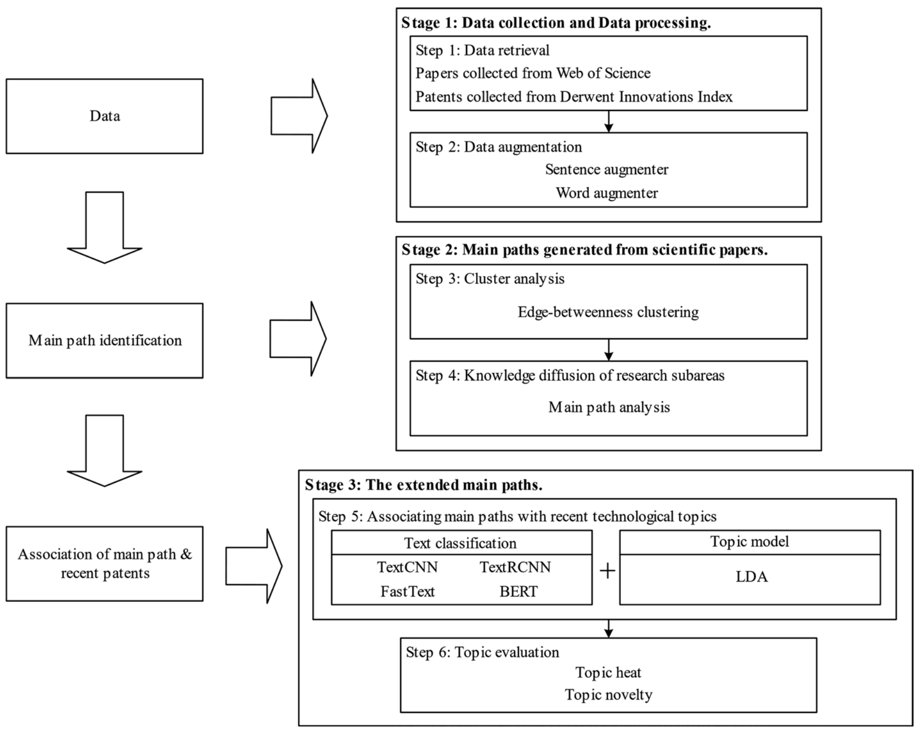


Fig. 1 Theoretical framework of this paper

(Liu & Lu, 2012). DII is composed of the Derwent World Patents Index (DWPI) and Patents Citation Index (PCI), which is one of the most comprehensive databases of international patent information (Ji et al., 2019; Jiang et al., 2021). Candidate search terms are extracted from literature review in the target field, and a period of testing is conducted to optimize the search terms and finalize the search strategy.

Step 2: data argumentation

Data augmentation techniques are widely used in text classification tasks and can effectively improve classification performance (Jiang, 2021). On the one hand, it can prevent the neural network from learning irrelevant features and fundamentally improve the overall performance. On the other hand, data augmentation is equivalent to increasing the amount of training set, so it is of great help to improve the model performance in a scenario with a small amount of data. The data augmentation techniques adopted in this paper can be roughly divided into two categories: (1) Sentence augmenter: back translation and abstractive summarization under the condition of maintaining the same semantics. (2) Word augmenter: substitute word by similarity to adjust parts of the text. Through data augmentation techniques, the sample size is expanded and the class imbalance is solved.

Stage 2: main paths generated from scientific papers

Step 3: cluster analysis

Grouping articles on similar issues is important in exploring the research front (Liu et al., 2016). The citation relationship between papers forms a complex social network structure, and the mutual citation relationship indicates certain similarities between them. Otherwise, they may focus on entirely different issues. Therefore, articles dealing with the same issues form a tightly distributed "community" in the citation network. This study adopts edge-betweenness clustering for large-scale grouping networks, originating from Girvan and Newman (2002) and Newman (2006). The calculation process of the network is shown as below: (1) Calculate the betweenness of all edges in the network. (2) Remove the edge with the highest betweenness, and when a new community is created, calculate modularity and record network structure. (3) After removing the edges, recalculate the betweenness of the rest of edges in the network. (4) Repeat the process until there are no edges in the network. Finally, the maximum modularity is found and its corresponding network structure is recorded.

Step 4: knowledge diffusion of research subareas

After obtaining the grouped citation networks, this article uses the MPA to extract important documents from citation networks. The main paths of scientific development and technological evolution identified from the citation network reflect the main development of a specific field and reveal the process of domain knowledge diffusion. MPA was first proposed by Hummon and Dereain (1989). They proposed three traversal algorithms, SPLC (search path link count), NPPC (node pair projection count) and SPNP (search path node pair), to generate main paths and applied them to DNA network analysis to verify the validity of MPA. Batagelj (2003) proposed SPC algorithm based on three traversal algorithms and pointed out that it has additional "nice" properties. MPA method has been adopted by many scholars (Hwang & Shin, 2019; Jiang & Zhuge, 2019; Liu & Lu, 2012; Yu & Yan, 2021; Yu & Pan, 2021).

The generation of the main path is divided into three parts. First, obtain the network topological sequence, that is, the directions and paths from the starting point to the end point of the citation network. Second, assign weight to the network. This paper selects the SPC algorithm to calculate the weights because it effectively analyzes large networks (Hwang & Shin, 2019; Yu & Sheng, 2020). SPC represents the number of times the path from the starting point to the end point in the network passes through a certain edge. The number of traversals is automatically increased by 1 for each link passed once, and finally, the network transforms from an unweighted network to a weighted network. Third, the principle of link selection. This article selects the global search strategy to obtain the main paths. That is, the path with the max SPC value is extracted. In this method, the starting point of the main path search is the starting node in the network, which is also called the source. This node is the first node to select the next node, and the above steps are repeated until the end of the network.

Stage 3: the extended main paths

Step 5: associating main paths with recent technological topics

This section contains three critical components: (1) model pre-training and fine-tuning; (2) patent class label prediction; (3) identification of patent topics.

After cluster analysis and MPA, the target domain was divided into many subareas, focusing on similar issues. Therefore, we treat scientific publications in the same groups as one category and give them the corresponding class labels, similar to [“Food SC”, “RFID”, “Sensor Network”, …]. Each class label represents a set of publications in a specific category. We use the abstracts and keywords of scientific publications as the corpus to input text classification models for pre-training and fine-tuning. Four models are used for testing and the model with the best performance was selected for subsequent analysis. Details of models are as follows: TextCNN (Kim, 2014): TextCNN is a text classification algorithm based on CNN (convolutional neural network), which is transformed on the basis of CNN. Multiple convolutions of different sizes are used to convolve several words to extract the key information in the sentence. The obvious advantages of this algorithm are simple network structure, fast training speed and superior performance. TextRCNN (Lai et al., 2015): TextRCNN first uses Bi-LSTM to process the input vector, and then splices the output of Bi-LSTM with the corresponding word vector at each time step, and then uses the pooling layer to select features. Therefore, TextRCNN can obtain contextual semantic features of text. FastText (Joulin et al., 2016): FastText is a fast and accurate text classification algorithm mainly used to solve supervised text classification problems. BERT (Devlin et al., 2018): BERT is a pre-trained language representation model that trains the bidirectional transformers to generate deep bidirectional language representations and builds multi-task models through fine-tuning.

Next, the text encoder trained in the pre-training and fine-tuning period is used to perform the single sentence classification task. The purpose of this step is to allocate patents to different subareas. We take each patent title as input and eventually predict a class label for them. For example, if we identify a patent as “Food SC”, then it is classified in the scientific publications group with “Food SC” label. In this way, we match all patents to different subareas. After obtaining classified patents, this paper uses the Latent Dirichlet allocation (LDA) model to extract topics. This model is an unsupervised text mining technique based on the word bag model proposed by Blei et al. (2003). In this paper, the Gibbs sampling method is used to solve the topic distribution of each document and the word distribution in each topic. In order to obtain the most appropriate number of topics, this paper adopts the confusion degree to determine the optimal number of topics.

Step 6: topic evaluation

This paper introduces two metrics to evaluate the identified topics: topic heat and topic novelty. These two indicators are extended from the study of Kim and Shin (2018). These two metrics evaluate the development trends of technological topics.

Topic heat Topic heat is the proportion of patents for each topic to the total patents on the path. The metric can directly reflect the impact of the research topic in each subarea, which is helpful to grasp the development process and direction of the subarea. The calculation formula of topic heat is as follows:

$$TH = \frac{P_i}{\sum_{j=1}^{n} P_j}, \tag{1}$$

where TH represents the topic heat; P_i represents the number of patents on a topic; $\sum_{j=1}^{n} P_j$ is the sum of patents under all topics in a subarea.

Topic novelty The topic novelty represents the emerging dynamic research in this field, revealing the research innovation ability in this field. The topic novelty can help researchers grasp the latest front dynamic information of the discipline development as soon as possible. The calculation formula of topic novelty is:

$$TH = \frac{\sum_{i}^{n} year_i}{n}, \tag{2}$$

where TN represents the topic novelty; n represents the sum of the number of patents under the topic; $\sum_{i}^{n} year_i$ is the year of all patents published under the topic.

Dataset and experimental settings

Datasets

Data collection

As the mainstream research on the IoT in SC has clearly differentiated, this research mainly focuses on various fields such as Radio Frequency Identification (RFID) technology, intelligent manufacturing, reverse logistics, and food SC. Therefore, this article takes the IoT in SC as a case for further analysis. The datasets in this article are collected from two databases, namely WOS and DII. WOS and DII are world-renowned academic resource systems and patent information databases, respectively. This paper selects two major citation indexes in WOS core collection, Science Citation Index Expanded (SCIE) and Social Science Citation Index (SSCI). We have investigated the literature in this field and evaluated existing retrieval strategies. Then, the retrieval strategy is determined as: TS = ((“internet of

Things" OR IoT OR RFID OR WSN OR "wireless sensor network*" OR GPS OR actuator* OR sensor*) AND ("supply chain*" OR logistic*)). The end of the time limit is 2020. Document types include article and review. Finally, 5709 articles are obtained. The same search strategy was used in DII to obtain patents. The year for obtaining the latest patents was customized from 2018 to 2020, and 3300 patents are finally selected.

Data preprocessing

This paper constructs a citation network with 5407 nodes and 7440 links based on the literature. Next, divide groups based on citation relationships and extract main paths of each group. Abstracts and keywords are selected as the input of the model. The dataset is divided into training set, test set and validation set in a 6:2:2 ratio, and use 6 folds as the training data.

Experimental setting

In order to obtain the model with the highest accuracy, this paper selects four models to perform the text classification task and test their performance. For TextCNN, TextRCNN, FastText and BERT model settings, the same batch size and maximum sentence length of 8 and 160. The learning rate is set to 2e−5. According to the comprehensive evaluation, the number of iterations (epochs) is set to 20. The optimizer used in the model is Adam. We adjust the parameters of the models to achieve optimal results, and the parameters are set as follows: TextCNN: The convolution kernel size is (2, 3, 4), and the number of convolution kernels is 128. The dropout is 0.3. TextRCNN: The number of hidden layers of LSTM is 2 and the number of neurons in the hidden layer is 128, and the dropout is 0.5. FastText and BERT: The dropout is 0.3.

After the long-term practice of training model, a unique set of evaluation metrics has been formed. In the field of NLP, commonly used evaluation indicators include *Precision*, *Recall* and *F1*. *F1* takes into account the *Precision* and *Recall* of the model. *F1* and accuracy (ACC) are calculated in Fig. 2, and we can see that BERT is significantly better than other models. On the one hand, due to the small sample size adopted in this paper, some models fail to show their advantages. BERT model can be adapted to small sample training through fine-tuning (Zhang et al., 2020). On the other hand, since BERT is a bi-directional

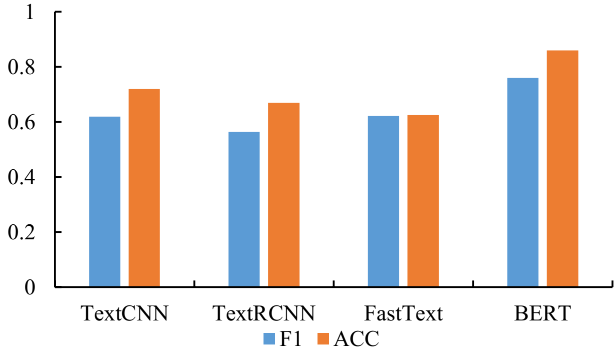


Fig. 2 Performance of different models. (Color figure online)

language model, bi-directional Transformer can better extract context information for feature extraction. Finally, BERT model is selected to perform the text classification task.

Results

This section takes IoT in SC as an example. MPA and machine learning techniques are applied to explore research front of the field.

Major research groups

The edge-betweenness clustering algorithm is used to identify influential communities. As shown in Fig. 3, nodes with different colors represent different groups. The modularity of network community is roughly equivalent to 0.6, which indicates that community detection is effective. The results show that hundreds of groups are obtained, and the number of papers contained in the groups ranges from 1 to 600. The detailed information of the community division is shown in Fig. 4. It can be seen that more than 90% of the clusters contain papers between 1 and 10, among which more than half of the clusters contain papers less than 2. There are three groups with more than 100 documents. In order to better explore the development prospect of IoT in the SC, this paper selects the top three largest groups for further main path analysis.

Knowledge diffusion of three subareas

In order to clarify the development history and research trends of each group. Based on three largest groups, the global main path is used to identify important papers and scientific trajectories.

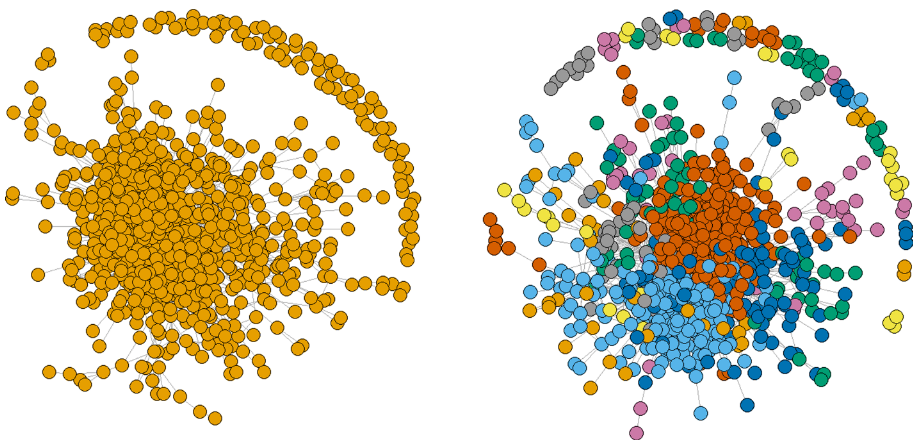


Fig. 3 Groups classified by edge-betweenness clustering. (Color figure online)

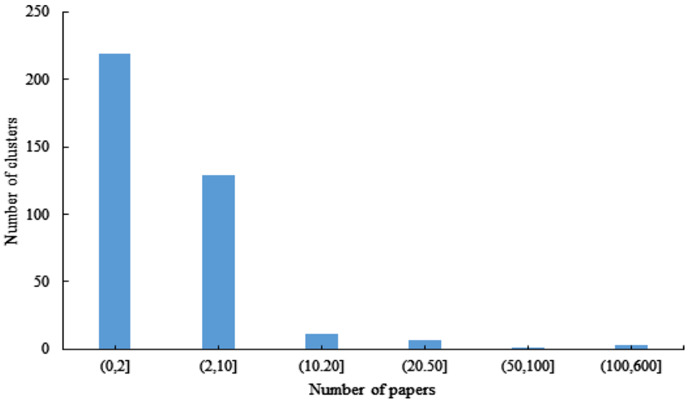


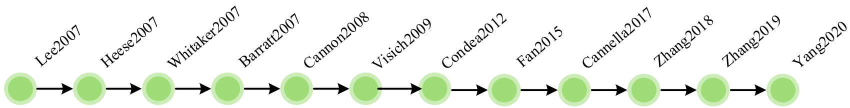
Fig. 4 The distribution of groups

Subarea 1: the application of RFID

Papers in this group focus on RFID technology in the SC, including inventory management, inventory records accuracy and RFID cost. Figure 5a shows the papers on the path of group "The application of RFID" (MP-a).

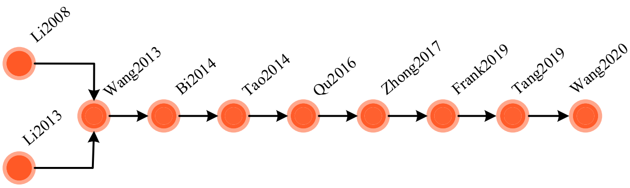
Lee and Özer (2007) revealed the value of RFID technology and explained the application of this technology in existing researches. Through the evaluation of RFID technology, it is found that it is beneficial to inventory optimization and shrinkage reduction, so it is an effective means of SC management. Heese (2007) investigated the reasons for the inventory records inaccuracy and used RFID technology to ensure full transparency of inventory information and eliminate the inventory records inaccuracy. Barratt and Choi (2007) used four decentralized business units as examples to discuss the pressure of using RFID technology and related measures to cope with the pressure. Based on previous information systems and SC management studies, Whitaker et al. (2007) showed that having extensive IT deployments and RFID applications is more likely to obtain early return expectations. Cannon et al. (2008) and Visich et al. (2009) discussed the impact of RFID technology on the SC from different perspectives. Cannon et al. (2008) pointed out the benefits and risks of RFID technology in operation management from many aspects. Visich et al. (2009) investigated the impact of RFID technology on SC performance through empirical analysis.

Condea et al. (2012) considered the flow of products between the backroom and the sales area, and used RFID technology to adopt heuristic methods to improve the accuracy of automated shelf replenishment. Fan et al. (2015) indicated that the application of RFID technology can reduce or eliminate the inventory storage in the SC, but the cost of RFID has a serious impact on SC decision-making. Cannella et al. (2017) introduced different SC structures and evaluated key operational factors. They found that the complexity of the SC structure aggravates the inventory records inaccuracy. Zhang et al. (2018) investigated RFID adoption strategy in the SC and showed that competition is a key factor driving retail companies to adopt RFID. Yang and Chen (2020) and Zhang and Yang (2019) pointed out that RFID technology effectively solves the misplacement of products. Zhang and Yang (2019) analyzed two strategies for manufacturers to compensate for the additional costs incurred by adopting RFID. Yang and Chen (2020) used



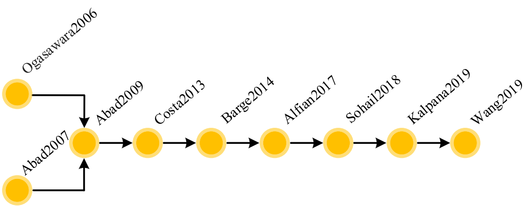
(a) MP-a: The application of RFID.

• Subarea 2: Intelligence manufacturing and industry 4.0



(b) MP-b: Intelligence manufacturing and industry 4.0.

• Subarea 3: food SC



(c) MP-c: IOT in food SC.

Fig. 5 Global main paths of different groups: (**a**) MP-a: The application of RFID; (**b**) MP-b: Intelligence manufacturing and industry 4.0; (**c**) MP-c: IOT in food SC

a modeling framework to understand the game model adopted by RFID in the retail SC and the starting point of investment costs.

By analyzing the scientific literature on the main path, the application of RFID technology in inventory management mainly focuses on three aspects. Firstly, evaluate the cost and benefit of applying RFID in inventory management qualitatively or quantitatively. Secondly, provide guidance for the application of RFID in enterprise inventory management. Thirdly, how RFID improves the efficiency of inventory management. The early researches focus on discussing the availability, effectiveness and impact factors of RFID technology. The latest researches focus on discussing the adoption strategies and cost issues of RFID technology.

Subarea 2: intelligence manufacturing and industry 4.0

Figure 5b shows the development trajectory of the second group (MP-b). These papers discuss cloud manufacturing, tracking and orientation technology in SC and logistics, and strategies in the industry 4.0 era.

Li et al. (2008) proposed a method for accurately positioning wireless sensor network (WSN) nodes, which can be applied to monitor logistics and transportation systems. Li (2013) aimed to combat phony products against the background of trade globalization, and discussed the technology of tracing and tracking products in the SC. Wang et al. (2013) proposed an architecture that integrates WSN and RFID, and constructed a new cleaning algorithm for data redundancy. Bi et al. (2014) studied the application, opportunities and future challenges of the IoT on enterprise systems in modern manufacturing. Tao et al. (2014) established a cloud manufacturing service system based on cloud computing and IoT. Qu et al. (2016) Integrated cloud manufacturing and IoT to achieve dynamic logistics synchronization. Under the background of industry 4.0, Zhong et al. (2017) provided a comprehensive review of topics related to cloud manufacturing and IoT manufacturing. Frank et al. (2019) surveyed a number of manufacturing enterprises to understand the technology implementation and integration in the industry 4.0 era. Tang and Veelenturf (2019) discussed the strategies and future directions of logistics and transportation services in a new technological environment. Wang et al. (2020) proposed an intelligent logistics scheduling system based on IoT.

Through the above analysis, monitoring and tracking technology, cloud manufacturing and industry 4.0 are the main development topics. Monitoring and tracking technology is the basis for realizing intelligent SC, and it can locate the location of goods in real time to facilitate logistics management. Cloud manufacturing SC has the characteristics of flexibility and interaction and can coordinate and optimize the allocation of resources. In the era of industry 4.0, SC management is developing in the direction of digitalization and intelligence. From the development trajectory we can find the industry 4.0 is a watershed. After then researchers turn to the researches of intelligent manufacturing and cloud services.

Subarea 3: food SC

Figure 5c shows the main path of group "food SC" (MP-c). The major topics such as smart tags and smart packaging technology exists in food SC.

In order to ensure the safety and quality of food, Ogasawara and Yamasaki (2006) proposed an RFID tag with a temperature sensor to reduce risks in the food SC. Abad et al. (2007) introduced a flexible tag for food monitoring that incorporates a gas sensor. Abad et al. (2009) used RFID smart tags for real-time monitoring cold chain. Costa et al. (2013) reviewed the application of RFID technology in agricultural products. Barge et al. (2014) aimed to investigate the technology of fixing tags on different cheeses to ensure their reading performance and reliability. Alfian et al. (2017) proposed a food traceability system, which uses RFID to track product location and uses WSN to collect temperature and humidity data. Kalpana et al. (2019) and Sohail et al. (2018) emphasized the important role of smart packaging in the food industry. Wang et al. (2019) focused on smart packaging technology for perishable products.

There is no doubt that food preservation is most important in the food SC. From the development history of scientific researches, early researches focus on temperature monitoring and intelligent tags, and recent researches focus on intelligent packaging. Smart tags can convey information in products or product packaging. There are various types of smart tags, including temperature smart tags, gas smart tags and RFID tags. With the rapid development of IoT technology, commodity packaging is gradually high-end and intelligent. Therefore, intelligent packaging is bound to become the mainstream trend of food SC.

Associations of recent patents with main paths

It is undeniable that MPA helps scholars have a general understanding of scientific field. However, the lack of the latest technological researches is difficult to accurately grasp the technological research hotpots of this field. This paper uses the BERT to classify latest patents and assign them to corresponding main paths. Then, LDA model is adopted to extract topics. Each topic reveals the latest technological hotpots of three subareas.

MP-a focuses on managing inventory, ensuring inventory records accuracy and controlling RFID cost. As shown in Fig. 6 and Table 1, the subareas focus on warehousing management systems, logistic management systems, RFID and logistics monitoring systems. It can be observed from the number of patents that the warehousing management system is a hot topic under MP-a path. Driven by IoT technology, the warehousing management system includes an automated control module based on RFID technology, intelligent storage shelves, and cargo information collection. The application of IoT technology in warehousing management can record and transmit information about

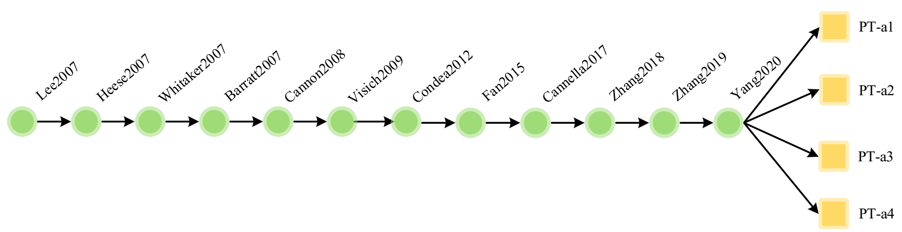


Fig. 6 The extension of MP-a

Table 1 Themes associate with MP-a

Path	Number	Theme	Count	Keywords
MP-a	PT-a1	Warehousing management system	180	Warehousing Management System Storage Automatic
	PT-a1	Logistics monitoring system	59	Monitoring System Track Device Location
	PT-a3	Logistic management system	48	Logistic Management System Distribution Method
	PT-a4	RFID tag	44	RFID Label Electronic Intelligent Chip

items in time, thereby effectively improving the efficiency and quality of warehousing management. In the logistic management system, IoT technology has changed the traditional way of in–out stock. RFID technology is used to implement data collection and inventory goods area. In addition, with the help of RFID technology, the inventory of goods can be monitored and tracked at all times, and intelligent replenishment can be performed. There is no doubt that RFID technology plays a vital role in warehousing management, and these technical topics are centered on optimizing warehousing operation processes.

As shown in Fig. 7 and Table 2, it is found that intelligent manufacturing is currently developing in the direction of intelligent manufacturing equipment, replacing workers with machines and optimizing resource allocation. For example, the handling, distribution and sorting work can be realized by robots. Researchers have designed multifunctional trolleys for logistics transportation and logistics sorting. The logistics monitoring device includes cargo transportation monitoring and vehicle monitoring, which helps better to realize the unification of logistics and information flow. High-precision weighing devices are an important prerequisite for automatic sorting. It can be seen that the existing technology focuses on combing load cells and other parts to facilitate SC and logistics management.

The third main path, MP-c, mainly studies content related to the food SC. The latest technological research in this field is related to cold chain products, perishable products and agricultural products. As shown in Fig. 8 and Table 3, the latest technology uses RFID to read product information into electronic tags, tracing product quality through RFID tags to achieve effective market management. Researchers use electronic tags and temperature and humidity sensors to monitor temperature and collect data. In addition, multifunctional packaging boxes are also one of the latest research technologies. These logistics boxes include monitoring systems, temperature control systems, and freshness detection functions. The food traceability system uses database management technology and communication technology to record information on each link of the entire product processing chain, so as to quickly trace the problematic link and the whereabouts of the food.

In summary, the technological fronts of the three subareas have been clarified by linking recent patents with the main paths. Compared with the research findings drawn by MPA, this section splits more leading edge of technological development. This article provides future scholars with research directions from the perspective of science-technology linkage.

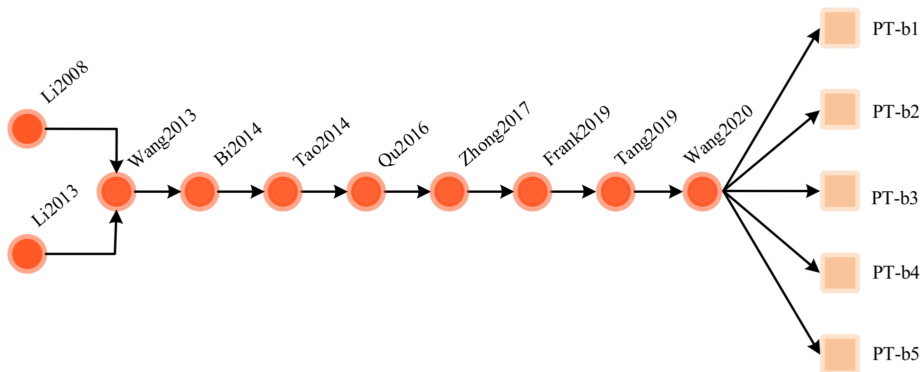


Fig. 7 The extension of MP-b

Table 2 Themes associate with MP-b

Path	Number	Theme	Count	Keywords
MP-b	PT-b1	Intelligent robot	143	Robot Position Controller Unmanned Conveying
	PT-b2	Intelligent logistics vehicle	120	Vehicle Body Logistics Plate Sensor
	PT-b3	Logistics sorting device	129	Sorting Device Fix Shaft Material
	PT-b4	Logistics monitoring system	82	Server Monitoring System Communication Data
	PT-b5	Logistics weighing device	80	Weight Item Pressure Vehicle Device

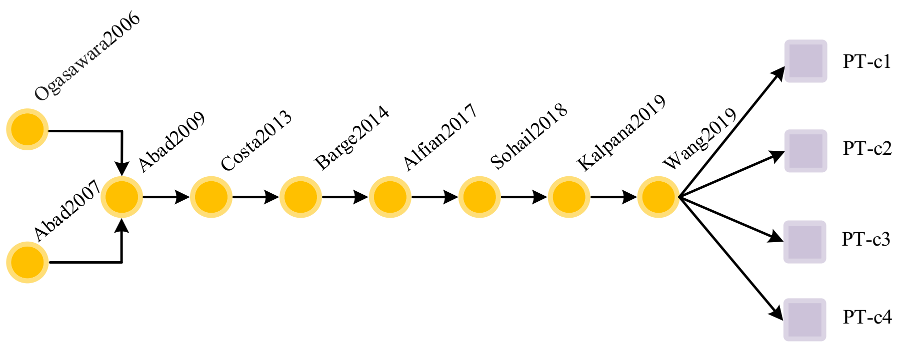


Fig. 8 The extension of MP-c

Topic evaluation

This paper uses *TH* and *TN* to evaluate the technological research front of IoT in SC. We combine these indicators into two-dimensional images. Figure 9 shows the topic details. The size of sphere indicates the number of publications. The abscissa represents the *TH*, and the ordinate is the *TN*. Different topics are distinguished by various colors.

Table 3 Themes associate with MP-c

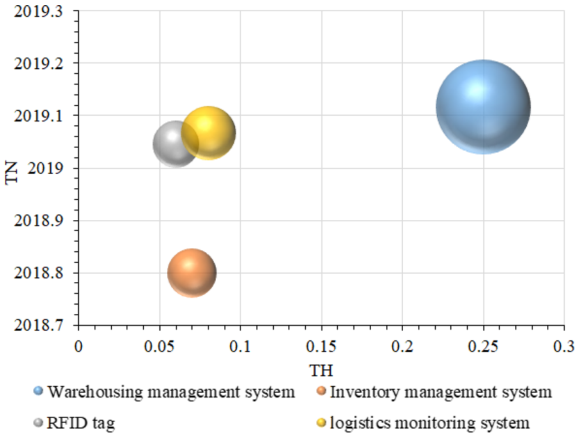
Path	Number	Theme	Count	Keywords
MP-c	PT-c1	Temperature monitoring system	98	Temperature Monitoring Control Cold Chain
	PT-c2	Logistics packaging box	85	Box Plate Packages Body layer
	PT-c3	RFID tag	69	RFID Chip Device Signal Electronic
	PT-c4	Food traceability system	29	Food Traceability System Tag IoT

It can be seen from Fig. 9a that the warehousing management system has the highest TH, TN and the number of patents. This shows that the warehousing management system is developing towards automation and intelligence, and IoT points out the direction for the its development. In addition, RFID tags and logistics monitoring systems also have high TN. The development of these two topics has a close association with the warehousing management system. RFID technology can track and identify the goods, and the logistics monitoring system is used to obtain the real-time location of the goods. These two technical topics are both important parts of an intelligent warehouse management system. Through the above analysis, it is found that intelligent warehousing management system has outstanding performance, and this topic will continue to show its advantages in the future development.

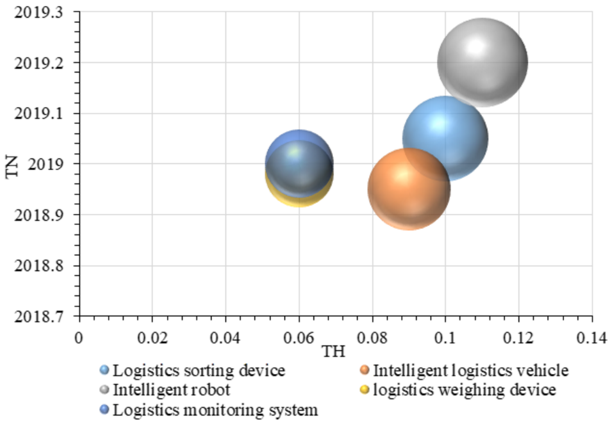
The intelligent robot is the topic with the highest TH and TN in Fig. 9b, which indicates that with the advent of Industry 4.0, industrial robots have become the main force of intelligent manufacturing, which not only saves labor force, but also improves work efficiency. Sorting devices and smart vehicle have a high number of patents as the focus of researchers' attention. The purpose of the intelligent sorting device is to replace manual sorting with intelligent automatic sorting equipment. Researchers design and integrate multiple technologies to build smart cars for sorting and transporting goods. It can be seen that the latest technology in MP-b focuses on the automation and intelligence of the equipment.

In the field of food SC, RFID tags, temperature control systems and logistics packaging boxes are the most concerning issues in this field. These three themes have good performance. The researchers aim to develop a cold chain temperature control system based on a smart incubator, and combine RFID technology and monitoring technology to achieve real-time data collection, ensuring the insurance of the products in the box and reducing logistics loss. There is no doubt that these three themes will remain the top priority in the future. Relatively little research has been done on food traceability systems, and there is more room for development in this research direction.

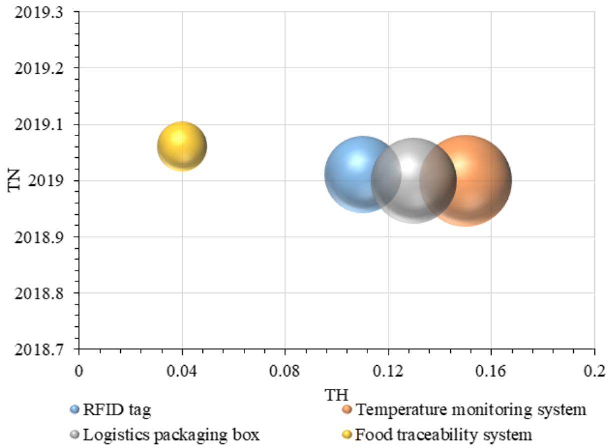
Fig. 9 Topic evaluation of different paths: (**a**) Topics associate with MP-a; (**b**) Topics associate with MP-b; (**c**) Topics associate with MP-c. (Color figure online)



(a) Topics associate with MP-a.



(b) Topics associate with MP-b.



(c) Topics associate with MP-c.

The above analysis shows warehousing management system, logistics monitoring system, intelligent robots and temperature control management are the technological research front, and other topics have the potential for further development.

Discussion

Research front is the seed of scientific and technological innovation in S&T, which is of great significance to scientific researches and economic development. Under this background, this article proposes a research front identification method from science-technology linkage. To grasp the research front and development history of scientific researches, MPA is used to explore the development trajectories. Besides, machine learning techniques are integrated to associate recent technological topics with the main paths. A research front identification method integrating MPA and machine learning are adopted to explore the research fronts of IoT in SC. The main paths reveal the research trends in scientific field from the macro perspective of citation relationship. Machine learning techniques reveal the research front in technological field from the microscopic perspective of semantic relations.

In our case, we explore the research front of IoT in SC. Through above analysis, MP-a focuses on RFID adoption strategies and inventory management. Technological researches focus on warehouse management system, and inventory management is a part of warehouse management. In addition, the technological topics reveal the application of RFID technology in logistics management system. In MP-b, intelligent manufacturing and cloud services are at the core of scientific researches. The technology field reveals the development of intelligent robots, intelligent vehicles and other equipment. The scientific researches of food SC are consistent with the research front of technology field. Researchers and managers should grasp the development front from multiple angles, so as to promote the prosperity and development of this field.

As mentioned above, the method in this paper not only helps researchers to grasp the research fronts in this field, but also helps production managers to obtain the development front of latest technologies. Through the latest scientific and technological research fronts, the R&D managers can clearly and quickly grasp the development history and future directions of the field. In addition, the science-technology linkage allows managers to predict future developments in the field.

Compared with the existing literature on research front, some researches only obtain research front based on citation relationship. For example, Ma and Liu (2016) adopted MPA to explore the knowledge evolution and research fronts of shareholder activism. Liu et al. (2016) divide data envelopment analysis domain into four subareas and apply key-route main path to explore research front. Compared with the traditional MPA-related researches, most studies of MPA focus only on papers and ignore patents. This paper extends the scientific main path by integrating MPA and machine learning techniques. Besides, this paper uses the text classification model to classify the latest patents into corresponding subareas. Some researchers combine machine learning and citation analysis to identify research front. For example, Li and Chu (2017) explored the research front of nanomedicine through keyword mining and co-word analysis. However, they failed to integrate basic research and applied research to identify research front. Some of the literature with similar methods or ideas to this study such as Li et al. (2020) and Xu et al. (2022). Li et al. (2020) integrated citation analysis and text mining to mine and forecast the development trends of nanogenerator technology. They compared the difference between the time of technical topics' appearances in papers and patents. However, this paper identifies the research front based on the complementary perspective of S&T and not only predicts technological development of target field. In addition, Li et al. (2020) identified knowledge trajectory based on citations, and nodes on the path are highly cited. They ignore the importance of the most recent documents and the fact that the citations of these documents are often low, whereas this paper traverses the network from source to sink. Xu et al. (2022) proposed the S&T semantic linkage integration model. They predicted future networks by term co-occurrence networks, which means that a keyword must appear in both science and technology to construct links. In contrast, this paper constructs linkages between S&T by training a text classification model and then assigns patents to the corresponding categories and extracts topics. This paper integrates citation analysis with semantic analysis to identify research front in S&T, and Xu et al. (2022) only adopted semantic analysis to identify and predict linked topics in S&T.

Conclusion

This paper takes the IoT in SC as an example, and downloads 5709 papers and 3300 patents from WOS core collection and DII databases. We propose a novel method that integrates MPA, text classification technique and topic models to identify research front from science-technology linkage. The method uses edge-betweenness clustering to obtain three important groups. MPA is adopted to identify the main paths of the three groups, and then the latest technological topics are extracted as a derivation of the main path. Finally, technological research front is identified by topic evaluation. After data verification, the method achieves good performance and captures many findings of IoT in SC.

This article has the following contributions: (1) This article combines MPA and machine learning techniques to identify research front in S&T. This method has good performance and can be used in other fields in the future. (2) Based on the MPA, it is found that this field is concentrated in RFID technology, RFID cost intelligent manufacturing, cloud services and intelligent packaging. The latest technologies focus on RFID technology, warehousing management systems, Intelligent robots and temperature control systems. These findings provide directions for future researches and production. (3) Existing studies show that RFID cost and intelligent manufacturing are future research directions (Ben-Daya et al., 2019). In addition, China's latest public documents show that temperature control system or equipment and intelligent packaging are important conditions to accelerate the development of high-quality food SC. This indicates that our findings are credible and can support expert decision-making to some extent.

Although it has made some contributions, our research still has some limitations. First of all, the dataset of this article is selected from the WOS database and the DII database. Although it already contains most important documents and patents, some data may be missing. In addition, conference papers, news and funding information, etc., are not taken into account in this paper. Second, expert engagement plays an important role in corpus processing, decision-making and other issues, so the importance of expert judgement should be emphasized in future experiments. Third, link prediction algorithm is widely used in the existing researches, and we can expand on the existing research and predict cutting-edge trends by link prediction in the future.

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