

Article

Logistics Technology Forecasting Framework Using Patent Analysis for Technology Roadmap

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Abstract: The rapid advancement of digital technologies has fundamentally changed the competitive dynamics of the logistics industry. For players in the logistics industry, digitization has become an unavoidable situation to achieve survival and sustainable competitiveness. A technology strategy is essential for digitization, and identifying opportunities and threats of technology development through technology trend exploration is important for technology strategy. In addition, to enable the implementation of the technology strategy, it is necessary to detect the change in technology and search for the technology that is expected to have a practical development effect. The purpose of this study is to identify opportunities and areas for technology development through patent data in establishing technology strategies. Previous research mainly relied on the expert interview method, and there was also a patent analysis study based on topic modeling, but only to grasp technology trends. This paper aims to propose a new framework for the extension to the stage for establishing a technology roadmap. By using the Word2Vec algorithm, we will investigate the patent search formula that reflects the trend, the prediction of changes in logistics technology through LDA (Latent Dirichlet Allocation) clustering of patent data, and the derivation of vacant technology by experimental methods. The proposed framework is expected to be utilized for predicting technological change and deriving promising technologies for establishing technology roadmaps in logistics companies.

Keywords: retail logistics; technology roadmap; patent analysis; time series; clustering; latent dirichlet allocation



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1. Introduction

In recent years, the logistics industry has been increasingly challenged by new disruptive business models and digital technologies [1,2]. For example, Uber Freight is a digital logistics startup acting as an intermediary [3,4]. These platforms enable cost-effective, real-time, on-demand transportation arrangements for logistics services [5]. IT-based players such as Amazon and Alibaba, which are e-retailers [6,7] that invest in robot-based automated warehouses and transportation, are providing their own logistics services. In addition, as the coronavirus crisis prolonged, logistics services became one of the most important core areas of the retail market due to the spread of “untact” [8] services and the growth of the e-commerce market [9]. Offline retailers such as Walmart are also trying to internalize logistics while investing in robot-based automated warehouses [10]. As such, digital technology is fundamentally changing the competitive dynamics of the retail and logistics industry [11].

The penetration of IT-based e-commerce companies into the logistics industry is changing the logistics industry from a labor-intensive industry to a technology-oriented industry. Robotics, AI (Artificial Intelligence), automation, and autonomous driving technologies will enable not only existing IT companies but also other players in the industrial value chain such as logistics real estate companies, automobile manufacturers, and robot manufacturers to enter the logistics industry with new technology-based business models [12]. It has become a situation that can change at any time to a competitive relationship between companies that were previously in a cooperative relationship. Existing traditional logistics service providers are facing such new challenges and competition situations [13]. To stay competitive and grow, logistics service providers must improve their value proposition for shippers and customers [11,14]. Technology is an important factor in differentiating the value of logistics and sparking and enabling innovation [15,16]. In particular, digital technologies such as Robots and AI are introduced into logistics, and this brings positive effects such as a new technology-based business models and the reduction of logistics costs [12,17,18]. In line with this trend, traditional logistics service providers need business innovation through technology [16].

DHL (Dalsey, Hillblom and Lynn), the world's largest logistics company, announced 'Strategy 2025' in 2019, selecting Globalization, E-Commerce, Digitalization, and Sustainability as future key trends in the logistics industry, and declared differentiation through positioning by trend. Among them, digitalization is the most important growth engine for improving customer/employee satisfaction and efficiency, and systematic digital transformation is being pursued throughout the business [19]. Alibaba, China's largest e-commerce company, is actively promoting the introduction of robots and autonomous driving technologies while presenting a new concept that combines distribution and logistics by announcing new retail [20]. CJ Logistics, a representative logistics company in Korea, defines TES-Technology, Engineering, and System/Solutions as its core competencies and is actively introducing digital technologies such as robot-based unmanned warehouses [21]. At the national level, logistics innovation is supported by developing policies to support the spread of digital technologies to strengthen the competitiveness of logistics companies and by establishing a roadmap for related technology development [22].

As such, with support from the government level and logistics companies, strategies and roadmaps for the digitalization of logistics are being established, and technology development is being pursued. With the strategic importance of identifying the opportunities and threats of technology development for logistics enterprises to achieve sustainable competitiveness, exploring the technological evolution trend is important for the successful technology development strategy of logistics [23–25]. To this end, predicting the direction of evolution and technology development in the rapidly changing [26] distribution and logistics industry is a very important prerequisite. Research on trends in future logistics technology and the discovery of vacant technologies [27,28] can provide implications for industry, government, and academia when developing new logistics-related businesses and R&D policies.

Until now, research on trends in logistics technology has been conducted using the Delphi and AHP methods, in which the contents of logistics technology forecasting institutions or literature are investigated, and related persons are interviewed [29,30]. As such, setting a technology strategy direction and creating a technology roadmap through interviews with experts and related persons requires a relatively large amount of time and money [31,32]. Additionally, since companies receive strategic services through the same expert group, similar technology development cases are found rather than differentiated technologies between companies. This can be said to be insufficient to secure differentiation through technology preemption and service superiority competitiveness.

The life cycle of technological innovation is getting very short [33]. In order to solve this challenge of technological innovation, short-term and periodic research on technology trends should be possible. In addition, in order to overcome the similarity in technology development due to the use of the same experts, quantitative research is needed to find

promising technologies that can be used by companies based on currently available data. Patents are data that are currently available and are constantly being updated. Patents also contain a large amount of technical information [34]. In other words, it can be seen as the best source for the analysis of technological change [35]. In addition, quantitative analysis is possible by providing information on a globally unified classification system such as the International Patent Classification (IPC). In relation to the analysis of technological change, in recent years, technology prediction research using patent information as a quantitative approach is being actively conducted [36]. However, most of the technology prediction research using patent information was conducted in a very detailed specific technology unit, and there were case studies such as the barriers to the digital innovation of logistics service providers and success factors in the digital technology-related research in the logistics industry. Although there have been studies on the impact and role of the digitization of logistics service providers, there has been insufficient research to derive differentiated technologies for predicting changes in the overall technology of the distribution and logistics industry and for establishing a technology development roadmap [37].

Against this background, the main purpose of this study is to propose a framework that can predict quantitative technological change and derive vacant technologies in the logistics field that can be implemented periodically in the short term to establish a technology roadmap necessary for the digitization of players in the logistics service industry. For this purpose, the following five research questions were derived.

First, is it possible to derive a patent search formula that reflects the latest trends, rather than a human-written patent search formula? Second, is it possible to classify detailed fields of the logistics industry through patent data and to predict quantitative technological change in the field? Third, can you discover technology areas with the potential for development in the logistics field through patent data? Fourth, is it possible to construct a technology roadmap by deriving a vacant technology with development value in a technology area with the potential for development? Fifth, if a technology roadmap is derived, will it have any meaningful value for players in the logistics industry?

To solve these research questions, first, the proposed research framework is reviewed by examining the status of technology development by major countries and companies through literature review on similar studies in the first stage. In the second stage, a structured research framework for this work is provided. The results of the application of the framework presented in Step 3 are deduced through the experimental research method. In four stages, the contribution of this study is explained, and the limitations and future research directions are explained.

2. Literature Review

2.1. Technology Innovations in Logistics Industry

2.1.1. Country Level Logistics Industry Technology Roadmap

Looking at the logistics technology policy trends of major countries, in the case of the United States, data-intensive computing including AI, big data, and CPS (Cyber Physical System), which are the core technologies of the 4th industrial revolution [38], IT and logistics systems, cyber-human systems, and high-performance computing are expanding investments in various areas. In addition, we have reduced traffic accidents, secured cargo transportation safety, established intermodal transportation infrastructure, and promoted eco-friendly technology development (Transportation for a New Generation ('14~'18)); PUDU(Pick-up/Drop-off) zone program is being promoted [39].

In the case of Germany, tasks necessary for logistics digitization were promoted through the High-Tech Strategy 2020 ('10) and the New High-Tech Strategy ('14). Intelligent zero-emission mobility strategy such as digitalization, new technology, and movement culture change were presented. The '2030 Logistics Innovation Plan' was announced in 10 areas including digital infrastructure expansion and platform development, new energy-using transportation development, and last-mile technology jointly planned with the industry [40].

Through 'Horizon 2020 ('14~'20)', the EU is promoting R&D investment plans for the development of science and technology with the goal of strengthening scientific competitiveness, strengthening industrial leadership, and solving social problems. EU is promoting the ALICE (Alliance for Logistics Innovation through Collaboration in Europe) project, which aims to improve efficiency by 30% in the entire logistics supply chain by 2030 by implementing the Physical Internet, a concept that interconnects all logistics and transportation activities based on IoT (Internet of Things) technology. ALICE presented a research and innovation roadmap that pursues 'Physical Ethernet' to build an interconnected logistics system as a European logistics technology platform. In this roadmap, it is suggested that future logistics technology will develop centering on 'information system for interconnected logistics', 'sustainable and safe supply chain', 'supply chain synchronization', 'supply chain coordination and cooperation', and 'urban logistics' [41].

Japan announced a plan to significantly improve logistics productivity and realize 'strong logistics' in order to respond to environmental changes such as the complexity of logistics needs and the 4th industrial revolution through the 'Comprehensive Logistics Policy Outline ('17~'20)'. In order to solve the problem of labor shortage in the logistics industry and improve productivity, a plan for collecting big data-based information and sharing real-time information ('18) was announced. In addition, we are trying to prepare solutions to problems such as the practical use of delivery using drones and the shortage of young truck drivers due to the low birth rate and aging population, and a logistics revolution strategy using new technologies such as IoT and AI to increase the efficiency and sustainability of inter-regional logistics transportation was presented [42].

China presented business innovations applying new technologies such as AI, big data, and cloud computing in the Chinese government work report (13th class in 2019) and announced the '13th Five-Year Plan ('16~'20) for logistics infrastructure. The key promotion directions in the logistics sector were presented, such as construction and "intelligentization", in addition to changes in the logistics industry fostering policy. The State Council of China has confirmed the logistics industry as a national base and strategic industry through the 'Mid and Long-Term Plan for Logistics Industry Development ('14~'20)' and is supporting innovation. Infrastructure construction, technological innovation, service level improvement, safety and efficiency improvement, and eco-friendly service system construction have been promoted since 2017 [43].

In the '5th National Logistics Basic Plan', Korea presented six strategies under the vision of 'Leap as a global logistics leader through smart logistics industry, digital innovative growth and creation of a sustainable ecosystem'. The main contents are to promote the digitalization of the logistics system through the advancement of delivery equipment, such as robots, the innovation of the urban logistics system such as the digital underground logistics system, and the preparation of the foundation for autonomous cargo transportation, and to build an integrated platform for the accumulation, management, processing, and provision of logistics information; they are promoting a logistics information platform to disseminate 'National Logistics Map' through the establishment of national logistics big data [22].

As a result of reviewing the logistics policies of major countries, we recognize the importance of logistics innovation in the digital age and support policy support for the development of digital logistics and R&D for technology development at the national level. It can also be said that it plays a very important role.

2.1.2. Company Level Logistics Technology Development Status

Technology is becoming the basic condition for logistics innovation [44]. Through digitization, even hardware solutions are being "technologicalized" and gradually becoming high-tech products. Hardware and software solutions, whether standardized or customized, do not have to be new to the market to be considered a technological innovation [45].

Looking at the status of the technology development of logistics service providers, DHL, a global logistics company, uses the AI-based 'Resilience 360' system to reproduce

the supply chain flow at each logistics stage in a virtual space to diagnose and evaluate the possibility of supply chain disruption [46]. UPS, a large American courier company, has improved and improved WES (Warehouse Execution System) jointly with the technology company Softeon to build an automatic system for prompt order reception and fulfillment so that customers can receive orders in a timely manner, even if they change orders, and AMR (Autonomous Investment in Mobile Robot) is increasing. In addition, it is trying to commercialize drone delivery by signing a contract to deliver commercial drugs from the drugstore chain CVS by drone.

Looking at the technology development status of the retailer, Wakefern Food, a grocery distributor, partnered with the technology company Takeoff Technology to establish a Hyperlocal Fulfillment Center that fully automates the picking and delivery of orders using robots. Walmart, a large American offline company, is implementing warehouse automation by introducing a GTP (Goods to Person)-type platform 'Alapabot' according to its Micro Fulfillment strategy. JD Logistics of China is working on building a supply chain in which AI technology is applied to the fulfillment solution of Blue Yonder [47].

Toyota Motor Corporation of Japan established 'MONET Technology', a self-driving car service provider, jointly with SoftBank to develop MaaS (Mobility as a Service) with commercial vehicles and logistics companies, and Yamato Holdings launched an unmanned courier service with autonomous driving technology, the Robo NeKo Yamato' project. Uber, a US company, developed the freight brokerage app 'Uber Freight', and the trucking company C.H. Robinson is using it [48].

Examining the status of technology in the logistics industry shows that technology is an essential condition for innovation in retail and logistics. The field of retail and logistics is in the stage of changing from a labor-intensive industry in the past to a technology-based industry [49]. Logistics operators must improve their value propositions for shippers and customers in order to face these future challenges and create opportunities by new technologies, maintain competitiveness, and grow [11]. Smarter, faster, and more sustainable logistics should provide a better customer experience [14]. Therefore, if you look at the current status of players in the logistics industry for improving customer value propositions, you can see that the logistics technology roadmap is a key issue that plays a very important role at the national and industrial levels.

2.2. Patent-Based Logistics Technology Prediction

One of the key components of the technology roadmap is technology that aligns with the strategic goals of the company and it plays a critical role in logistics value differentiation [11,14,50]. In order to select the technology to be developed, the prediction of the technology must be preceded. The forecasting of technology plays an important role in the decision-making of the technology strategy of countries and companies. Previously, morphological analysis, logistic growth model, Delphi, bibliometrics, and scenario approaches were widely used to predict technology [51]. However, this method is subjective and unstable [52]. To overcome this limitation, patents were analyzed along with detailed information on patented technologies in numerous studies on forecasting future promising technologies. This is because patents provide sufficient data to draw reliable conclusions from studies investigating technological change and innovation [53].

For example, research is underway to predict future technologies using a growth curve based on the number of patent applications filed. The logistic growth curve was applied to the nano-sized ceramic powder technology patent [54] and the integrated solar technology patent establishment [55], respectively. The logistic growth curve and Bass model were then applied to patents for information and communication technology (ICT) applications [56,57]. In addition, the growth curve of future citations for TFT and LCD, the flash memory system, and personal digital assistants (PDA) were applied as criteria for predicting future technologies [57].

There was a study in which technology forecasting was made by applying data mining techniques to patents. Promising techniques were identified using association

rule mining of the International Patent Classification for Patent Documents (IPC) [58]. In addition, we determined promising aspects of the technology by applying association rule mining to changes in patent index values over time for each IPC [59]. In addition, (Park et al., 2015) network analysis was applied to IPC to visually express the relationship between technologies and to judge whether the technology was promising based on the centrality between IPCs and the distance between nodes [60].

Research was also conducted to forecast future promising technologies by applying text mining techniques to patents. Apple Inc. Text mining for patents was applied to identify promising vacant technologies [61]. In addition, a study was conducted to forecast the vacant technology by applying the generation probability model of the Dirichlet potential allocation to the renewable energy technology patent [62]. In another study, after obtaining patented keywords, generative topographic mapping was applied as a probabilistic reconstruction of self-organizing maps to investigate vacant technological areas and promising aspects [63]. For the prediction of blockchain technology, there have been studies through text mining, clustering, and life cycle prediction of technology [64]. Patent matrix map and k-medoids clustering were used for technical prediction [52]. Unlike previous algorithms that clustered by measuring simple distances, the ensemble method and Bayesian learning were combined. A new clustering method was proposed, and research was conducted to derive the future technology of humanoid robot system technology through this method [65].

To understand trends in logistics technology, patent data was identified through LDA, and the subject was identified through patent share and growth rate [66]. In order to develop an IoT roadmap for the provision of logistics services and to understand the IoT patent trends in the logistics field [67], text mining technique was used for patent abstracts to understand IoT patent trends in the logistics field [68]. There was also a study of technological opportunity and evolutionary exploration [69].

These studies are meaningful in objectively deriving promising data-based technologies. However, it still requires the qualitative judgment of the researcher [70]. In addition, there have been studies in the existing literature that predict promising technologies of specific technical units or grasp technology trends in the logistics field, but research on the overall framework that minimizes the derivation of vacant technologies for the technology roadmap and the qualitative judgment of researchers was lacking. Therefore, in this study, we try to predict future technologies for future technology roadmaps through a new approach to patent analysis so that players in the real logistics field can strengthen their technological competitiveness and overcome the shortcomings of existing promising technology forecasting.

2.3. Patent Analysis

2.3.1. Patent Map

Patent maps describe the relationships between patents through visual elements such as charts, graphs, bars, and tables [71,72]. Since the patent map provides practical and intuitive information, it is an effective technique for establishing a technology development strategy [73]. Although various types of patent maps have been developed, most of them analyzed the technical fields through author, technical field, citation, etc., which are information of patent documents, in order to provide simple statistical results. While this method is simple and intuitive to develop, it is limited to specific technical fields because it does not use the description of the patent document that contains the definition of the technology [74]. As keyword extraction became possible with the development of text mining techniques, patent maps using unstructured data developed [75]. PCA (Primary Component Analysis), SOM (Self-Organizing Map), and GTM (Generative Topographic Mapping) are representative technologies for finding patents in the patent map.

PCA is a dimensionality reduction and feature extraction technique and is performed by converting multiple variables into several linear combinations [76]. PCA can extract latent dimensions by extracting primary variables and define latent dimensions as primary dimensions. However, there is a limitation in that it is difficult to interpret the meaning

because too much dimensional data is included in one variable. SOM is an artificial neural network that maps multidimensional data to a two-dimensional topological grid [77]. The SOM-based patent map can cluster similar patents on individual nodes and visualize the similarities and differences of nodes with color contrast [78,79]. However, since patents are not included in blank nodes, there is a limitation in that the characteristics of blank nodes cannot be identified. These limitations make it difficult to interpret the potential and implications of technological opportunities. To overcome the limitations of PCA and SOM, GTM was applied to the patent map. GTM is a mathematical model for density modeling and visualization [80]. Unlike PCA and SOM, which must be interpreted based on experience and knowledge, GTM can reduce and re-project multidimensional data to lower dimensions. GTM can identify empty nodes and resolve them through an inverse mapping algorithm. As a result of comparing the characteristics of the PCA, SOM, and GTM-based patent maps, the GTM-based patent map was easy to interpret, unlike PCA and SOM, which require manual analysis of the patent map results [81].

In this study, we aim to identify vacant technologies by applying a GTM-based patent map that can interpret the results with an inverse mapping algorithm. In previous studies, the map size was qualitatively designed through various sensitivity analysis in deriving the patent map, but this study derives a vacant technology in a huge industry called the logistics industry. The identified vacant technology will help develop a technology roadmap for logistics services providers.

2.3.2. Patent Network

Network analysis is a method of measuring and visualizing the relationships and interactions of actors, such as people, groups, and organizations [82]. The visual representation of the network provides an overall understanding of the structure of relationships between actors and the location of individual nodes in the network [83,84]. In addition, in-depth analysis of the network is possible through various analysis indices such as the centrality and density of the role of nodes in the network [85,86]. Network analysis can be applied to various fields. In particular, the patent network is a network analysis based on patent data, and the relationship between patents is visualized and analyzed [87]. In-depth analysis of the patent network allows you to explore technology trends and technical cooperation in specific technical fields. Patent network analysis provides important information to the person in charge of technology development by dividing it into a citation network based on patent citation information and a keyword-based network extracted from patent documents [88].

Citation network analysis treats patent documents as nodes and visualizes the network as links between patent documents. Citation networks can contribute to the generation/dissemination of ideas for the R&D of new technologies because they intuitively show the links between patent diffusion and patents [89,90]. However, since the citation network only considers the frequency of citations, there is a limitation in that the relational analysis of details is not performed [91]. To overcome the limitations, an IPC-based network analysis was developed using the international patent classification (IPC) developed by the World Intellectual Property Organization (WIPO) [92]. Since all patents are given IPC codes classified into specific technical fields, technical contents can be analyzed through the IPC-based network. As the analysis of unstructured data has recently become more sophisticated, network analysis is possible through keywords, which can be applied to a detailed roadmap. Keyword-based network analysis aims to understand the core technical information of the document content included in the patent [93]. Patent documents contain unstructured text information, and the network is analyzed by extracting key keywords through text mining techniques. Since the keywords extracted through the text mining technique mean the main technical elements of the patent, the technology can be analyzed effectively [94].

In the process of deriving a technology roadmap for the logistics industry, a keyword-based network is applied to the identified vacant technology field to identify major technol-

ogy elements, surrounding technology elements, and related technology elements and to build a technology roadmap clearly from a detailed technical point of view.

3. Methodology

3.1. Research Framework

The research framework consists of a total of three steps as shown in Figure 1 and aims to finally develop a technology roadmap for the logistics industry through patent analysis.

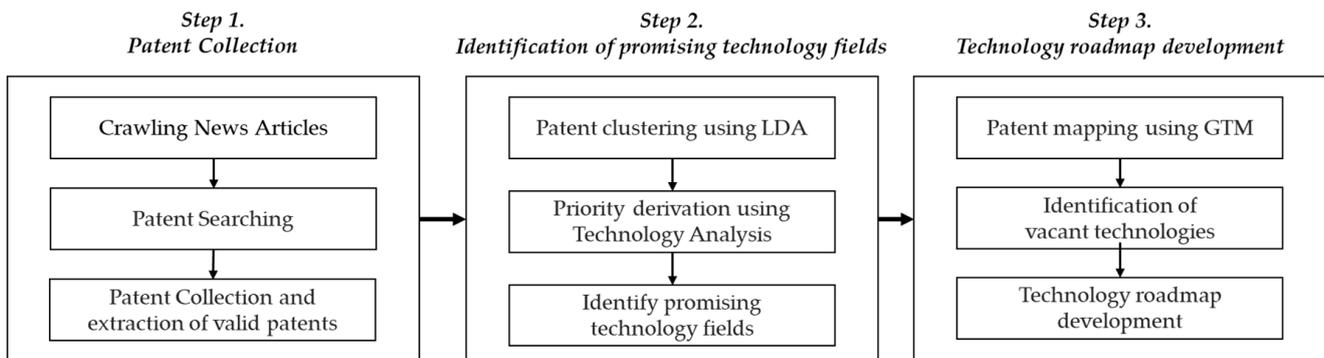


Figure 1. Research framework.

Step 1: In the first step, keywords for writing a patent search formula are derived. It can be done with human insight, but for a more systematic method, we use news data to derive key keywords for the logistics industry and generate a patent search formula to derive input data for analysis.

Step 2: In the second step, it is necessary to classify and determine what kind of technology area the logistics technologies existing in the collected patent data are in. Technology clusters are derived through patent analysis, and promising technology clusters are identified. Technology clustering proceeds based on the keywords of the patent text. Then, three analyses are applied to derive a cluster of promising technologies. The three analyses are divided into qualitative evaluation and quantitative evaluation to derive promising technologies. Qualitative assessment analyzes network analysis and technology level maps, which analyze the associations between technology and current technology positions. Quantitative evaluation is a trend analysis that evaluates future prospects through future trends by technology cluster.

Step 3: The final step is to draw a technology roadmap for promising technology fields, identify vacant technologies in the field of technology through the GTM algorithm, and establish a technology development roadmap through network analysis and patent analysis.

3.2. Detailed Methodology

3.2.1. Unstructured Data

Unstructured data require a preprocessing step to structure the unstructured data by cleaning and filtering the text data. In particular, patent documents aim to create a Patent-IPC matrix through a pre-processing step. Text data cleanup should remove punctuation marks, abbreviations, and unnecessary words [95]. This process can be converted to the appropriate analysis format [96]. Additional cleanup can be performed through data tokenization and the deletion of stopwords [97]. There are stemming techniques and Lemmatization techniques as methods of processing stopwords. Although the two techniques have different characteristics, the stemming technique that can identify synonyms in terms of the interpretation of terms was applied to this study. It includes only the words essential to describe the patent document through text cleanup, which is unstructured data [98]. In this study, keywords were derived by applying the TF-IDF algorithm for detailed technical explanation. The TF-IDF algorithm can select essential words by considering the frequency of words and the frequency of specific words for each docu-

ment by weighting the importance of each word [99]. The TF-IDF algorithm develops the Patent-Keyword matrix based on high-order words.

3.2.2. Technology Clustering

To subdivide the technical field, the topic modeling technique, LDA (Latent Dirichlet Allocation) algorithm, is applied. The LDA algorithm is the process of finding a topic in a set of documents [100]. Patent documents consist of documents on various topics. The LDA algorithm assumes that topics generate words based on a probability distribution and traces back the way documents were created [101]. The LDA algorithm needs to determine the number of topic clusters K . The number of clusters is determined through K -cross validation. K -cross validation evaluates the complexity of the language model. Therefore, it is possible to derive the optimal K [102]. In general, lower complexity values mean that the topic model better reflects the results of the actual literature. However, since overfitting problems can arise, we vary K and make decisions based on qualitative evaluations.

3.2.3. Technology Level Assessment

For technology level evaluation, qualitative evaluation and quantitative evaluation are applied. Qualitative evaluation is a method of evaluating the level of technology based on the information in the patent document, and it identifies the location and current status of the technology field by applying network analysis and a technology level map. Quantitative evaluation confirms future prospects by applying trend analysis based on the quantitative criterion of the number of patents.

Applying network analysis takes into account the linkages between technology disciplines. Patent network analysis analyzes the interactions between technologies by measuring and visualizing them. The Patent-Keyword matrix is a co-occurrence matrix, and it has information on whether words appear in each patent document. Network analysis is performed based on the Patent-Keyword matrix. Network analysis quantitatively analyzes the location and role of actors in the network through various indicators [103,104]. To analyze the role of nodes, various indicators exist such as degree centrality, closeness centrality, and betweenness centrality [105]. Degree centrality is an indicator that quantifies the number of connections between a node and other nodes connected to it. Closeness Centrality is an index that considers indirect connections within the network by developing Degree Centrality, which can only be interpreted locally. In order to consider the indirect connection, it is defined as the distance between nodes. In other words, it is expressed as the sum of the shortest path lengths between one node and all other nodes.

Betweenness Centrality is an indicator of the degree of controlling or mediating the relationship between nodes that are not directly connected. A node with a large Betweenness Centrality can be interpreted as a threatening node that has the potential to disrupt network activity because it can distort or filter information when transmitting information within the network.

Through the above various indicators, the relationship between the detailed technologies of vacant technologies and detailed technologies linking vacant technologies can be identified, which can be used for R&D and the development of a technology roadmap for companies and research institutes to establish business plans.

For practical technology development, technology trends and characteristics were identified, and areas with potential for technology development were derived [28,34,106]. Therefore, in this study, an importance analysis was performed through a technology level map that evaluates the current technology level in order to derive technology development priorities by topic, and trend analysis was performed through time series analysis to predict future prospects. The importance analysis aims to evaluate the current technology level, and in this analysis, the technology level map was used to evaluate the relative level of the technology. As shown in Figure 2, the technology level map uses the number of patent applications as a quantitative evaluation criterion and applies the number of IPCs which is patent citations as a qualitative evaluation criterion. Define the X-axis as the Technological

Activity Index (TAI) for the quantitative assessment of a technique. As more patents are filed, it is indicated that the technology is growing rapidly. The Y-axis implies the Technology Impact Index (TII) for the qualitative evaluation of a technology. It is suitable as an evaluation index because it cites previous patents in developing new technologies [107]. Therefore, in order to evaluate the current level of the blank technology field, we conduct a materiality analysis through the technology level map. Through the technology level map, technology fields can be located in the 1st, 2nd, 3rd, and 4th quadrants. ① In the first quadrant, both TAI and TII indicators are high, which is defined as high level, and ② in the second and ③ third quadrants, one of the TAI and TII indicators is high and is defined as medium level. Finally, ④ the fourth quadrant is defined as the low level where all indicators are low [108,109].

The technology level map

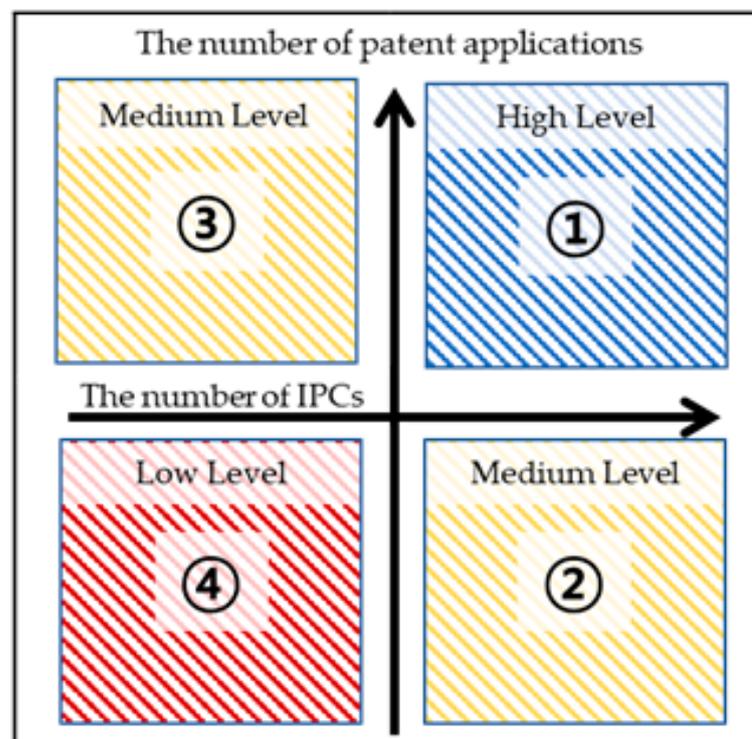


Figure 2. Technology level map.

Trend analysis aims to predict the future of technology. We apply the Time series method for predicting future trends, which are historical data. Time series data consist of time point and frequency, and time point becomes an independent variable and frequency becomes a dependent variable to predict the future through statistical methods [110]. Although various predictive analysis models exist in time series analysis. In this study, we apply the ARIMA model, which reflects the autocorrelation of previous values. As shown in the figure example in Figure 3, based on the derived trend results of the technological field, the fields of increasing interest are defined as hot fields, the fields of decreasing interest are defined as cold fields, and if there is a certain trend, it is analyzed as an active field [111].

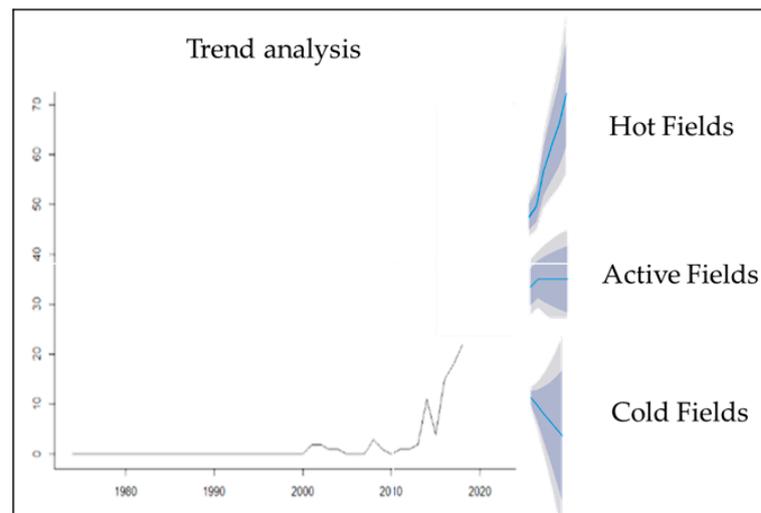


Figure 3. Trend analysis example.

3.2.4. Identification of Vacant Technology

We develop a GTM-based patent map by using the Patent-Keyword matrix to identify vacant technologies. In the GTM-based patent map, patents are mapped in two dimensions according to the distribution of words for each patent document. The GTM-based patent map consists of a grid of map size $N \times N$. There are no rules for determining map size. If the map size is too small, vacant nodes cannot be identified, and if the map size is too large, there are too many blank nodes to analyze. Therefore, this study determines the map size at which the initial blanking technique is identified by starting with a small size and gradually increasing the map size to derive a developable blanking technique. The GTM-based patent map developed in this way is divided into two nodes as shown in Figure 4; a node where a patent exists and a blank node where a patent does not exist. Vacant technology identifies by connecting blank nodes for which no patents exist. Patents belonging to the surrounding nodes must be analyzed to define the corresponding Vacant technology. Since various patents exist in the nodes around, we define a space technique based on the distribution of words belonging to those patents.

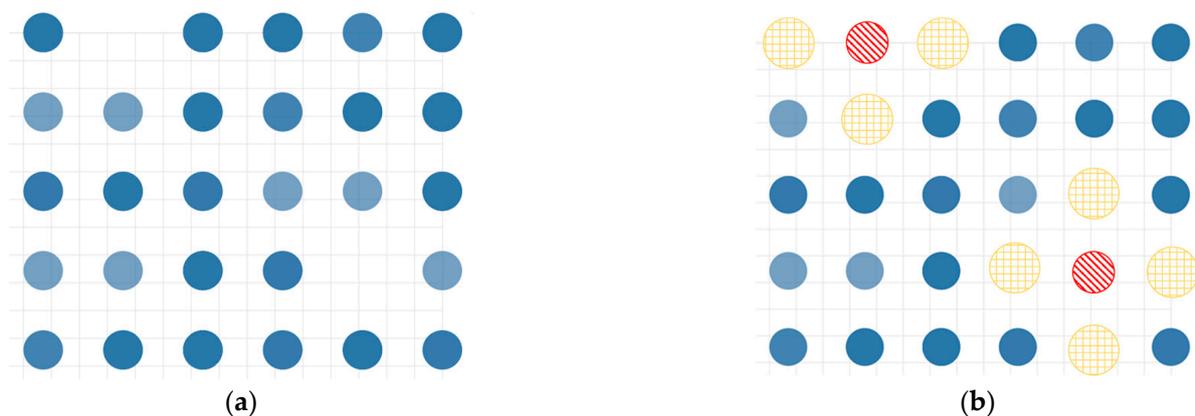


Figure 4. GTM-based patent map: (a) Schematic of GTM-based patent map: The dark blue and light blue area is where the patent exists in the node, which can be interpreted as a situation where technology development has taken place.; (b) Description of GTM-based patent map: Red area for vacant technologies, yellow area for analysis area.

4. Result

4.1. Step 1: Patent Search Using News Data

4.1.1. News Data Crawling and Patent Search Formula Derivation

In order to collect issues in the distribution and logistics industry, using the R'rstvst package, as shown in Table 1, 18 websites of representative economic newspapers and logistics magazines with industry-related news searched for logistics and retail as keywords in Google were searched. From January 2016 to August 2021, 1132 documents were searched and collected.

Table 1. Crawling Sites.

News Sites
Supply Chain Digital, Business Standard, Yahoo Finance, Freightwaves, Logistics Management, Bloomberg, The Business Times, Supply Chain Quarterly, The Business Journals, China.org, Hellenic Shipping News Worldwide, Business Wire, The Wall Street Journal, Financial Express, Air Cargo News, Forbes, Supply Chain Management Review, The Economic Times, Inbound Logistics

First, data preprocessing was performed to remove unnecessary words from the collected data. In data preprocessing, stopwords and special characters were removed. Before the frequency calculation and topic modeling of the extracted morpheme words, words that are not of high semantic value were removed.

The frequency of the occurrence of words was calculated for the data to which preprocessing was applied, and a topic modeling algorithm was applied. After vectorizing the words extracted from the crawled data into a word-document matrix, the top 20 high-frequency words were output as graphs using Python's matplotlib visualization library module as Figure 5.

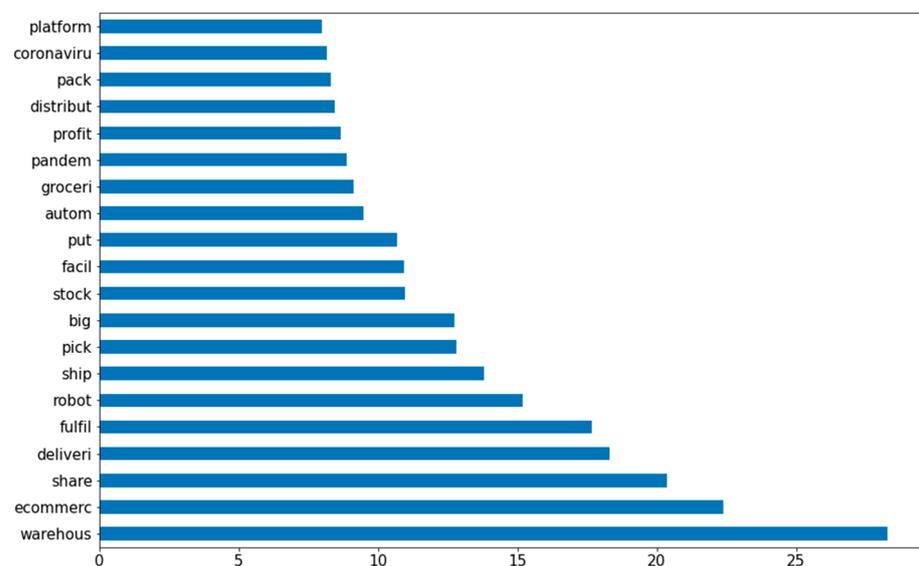


Figure 5. Top 20 high-frequency words.

The Word Embedding model, which is a Skip-gram model based on Word2Vec, was applied to classify the significant similarity between the vectors of each occurrence word. This model is an unsupervised learning-based model that learns by inferring contexts that appear from words.

The K-means algorithm was used to obtain an appropriate number of clusters from the data. A state with a small value of cohesion while classifying into not too many cluster can be said to be an appropriate number of clusters. The degree of aggregation is confirmed by the inertia value. To determine the K value, we drew a 'Cohesion according to the number

of cluster' graph as shown in Figure 6 using Python's matplotlib. From the graph, it can be seen that the inertia value decreases at the K value of 4. In general, the larger the number of clusters, properly reflect the contents of the document, whereas the meaning of cluster extraction becomes blurred. So 5 to 10 clusters might be appropriate.

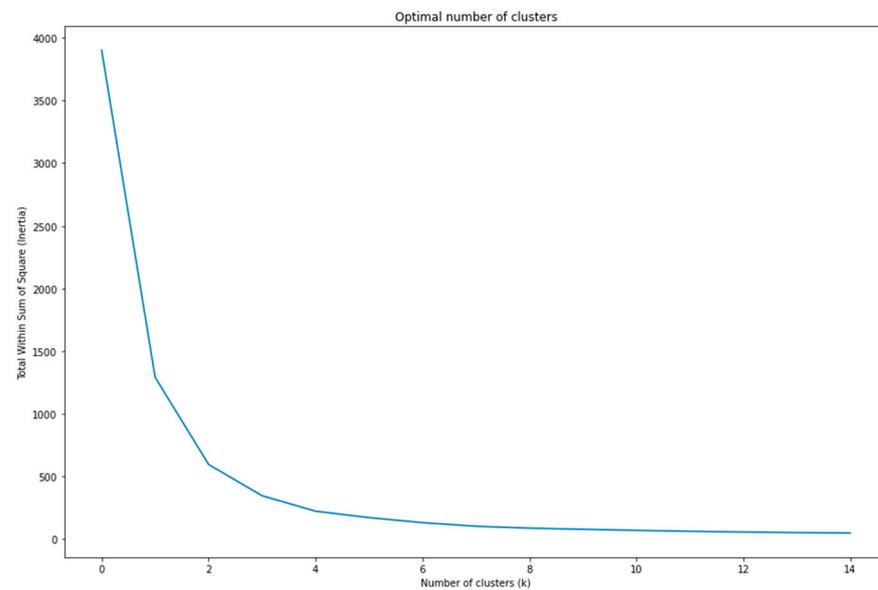


Figure 6. Cohesion according to the number of clusters.

Table 2 shows the results of extracting 10 topics and the top 20 words for each topic as a result of topic modeling. Looking at the 10 topics, Topic 1 is identified as Micro fulfillment, which is emerging recently, Topic 2 is considered warehouse automation, Topic 3 is robotics technology, Topic 4 is Robot-based loading and unloading technology, Topic 5 is classification facility optimization technology, Topic 6 is AI-related technology, Topic 7 is logistics and packaging technology, Topic 8 is inventory management technology, Topic 9 is same-day delivery, mobility, etc., so it is judged to be a last-mile technology, and Topic 10 can be interpreted in the areas of warehouse and logistics delivery.

Table 2. Topic modeling results and technical discrimination words by topic.

Topic	Keyword	Technical Discrimination Words
Topic 1	'microfulfillment', 'trolley', 'mega', 'bot', 'scanned', 'autonomous', 'integrating', 'subscribing', 'farflung', 'diversify', 'cathy', 'locally', 'vacuum', 'smarter', 'oversees', 'omnichannel', 'reception', 'qualify', 'sank', 'litter'	Microfulfillment, Autonomous, omnichannel
Topic 2	automation', 'robotics', 'deliver', 'app', 'shelf', 'mobile', 'packing', 'equipment', 'transportation', 'safe', 'protection', 'shared', 'express', 'freight', 'urban', 'transport', 'container', 'listing', 'seek', 'simple'	Automation, robotics, Packing, transportation Shared, express, freight Urban, container, transport
Topic 3	robotic', 'hub', 'warehousing', 'instore', 'conveyor', 'cargo', 'fulfill', 'expressed', 'cyber', 'recognize', 'apps', 'frequent', 'virtual', 'scan', 'emerging', 'rail', 'predicted', 'loaded', 'engaged', 'operated'	Conveyor, cargo, fulfill, expressed, cyber, virtual, scan, predicted,
Topic 4	'robot', 'shipping', 'grocery', 'distribution', 'package', 'machine', 'safety', 'storage', 'coronavirus', 'profit', 'shift', 'port', 'piece', 'pack', 'physical', 'created', 'covid', 'station', 'vehicle'	Robot, shipping, distribution, package, machine, storage, pack, physical, vehicle

Table 2. Cont.

Topic	Keyword	Technical Discrimination Words
Topic 5	'automate', 'disruption', 'algorithm', 'profitability', 'receiving', 'fulfilled', 'robust', 'parcel', 'repair', 'map', 'capability', 'distributor', 'corridor', 'outdoor', 'packaging', 'intelligent', 'scanner', 'monitored', 'crowded', 'offline'	Receiving, fulfilled, robust, parcel, repair, distributor, packaging, intelligent, scanner, crowd
Topic 6	'automated', 'electronics', 'convenience', 'maintain', 'productivity', 'protect', 'artificial', 'emerged', 'unloading', 'drone', 'secure', 'route', 'responsible', 'supplier', 'cloud', 'quick', 'pickup', 'broker', 'dealing', 'cool'	Automated, electronics, artificial, unloading, drone, secure, route, cloud, pickup, cool
Topic 7	'packer', 'sorting', 'loading', 'courier', 'transformation', 'shelving', 'bigbox', 'maritime', 'pricing', 'consolidation', 'brokerage', 'forwarding', 'trunk', 'uber', 'supplement', 'lifting', 'panic', 'crossborder', 'visible', 'unload'	Packer, sorting, loading, transformation, shelving, maritime, consolidation, forwarding, trunk, crossborder, visible
Topic 8	'inventory', 'ship', 'article', 'search', 'energy', 'particularly', 'fresh', 'approach', 'measure', 'picked', 'factory', 'considered', 'leading', 'investigation', 'complex', 'forecast', 'intelligence', 'traffic', 'picker', 'arm'	Inventory, ship, fresh, picked, forecast, intelligence, traffic, picker, arm
Topic 9	'sameday', 'forklift', 'automating', 'shipper', 'emission', 'subscription', 'lastmile', 'mobility', 'optimize', 'indoor', 'sustainable', 'recycling', 'arbitrator', 'fireplace', 'secretly', 'varied', 'reliable', 'iconic', 'subscriber', 'flex'	Automating, forklift, emission, lastmile, mobility, recycling,
Topic 10	'warehouse', 'ecommerce', 'share', 'big', 'put', 'delivery', 'fulfillment', 'facility', 'sort', 'stock', 'international', 'pick', 'sense', 'picking', 'labor', 'security', 'pandemic', 'decision', 'platform', 'location'	Warehouse, share, big, put, delivery, fulfillment, facility, sort, stock, pick, sense, picking, labor, security, platform

The redundancy was removed from the 200 words, and 30 terms related to logistics technology were extracted. The results are shown in Table 3. The extracted keywords were mainly composed of words frequently seen in news or on the Internet and terms used in the domain of the logistics industry.

Table 3. Logistics technology related term keywords for patent search.

Keyword
Warehouse, fulfillment, ecommerce, lastmile, omnichannel, autonomous, automation, share, robot, platform, express, cyber, physical, virtual, pick, pack, storage, artificial, intelligent, loading, drone, secure, cool, sort, visible, mobility, recycling, big, crowd, predict, cloud, delivery, shipping, freight, vehicle, electric

4.1.2. Valid Patent Collection

In this analysis, Korean, Chinese, American, and European published/registered patents were extracted from January 2000 to June 2021 through the WIPSON database. The patent search formula was prepared based on the issue keywords obtained through the keyword extraction of news data related to the distribution and logistics industry, and patents in related fields were searched. In addition, for the convenience of searching, we searched and collected data by combining issue keywords based on the industry standard process of distribution and logistics. When preparing the patent search formula, sample data were checked by dictionary keyword search, and when the amount of valid data were insufficient and there were a lot of unnecessary data, the IPC code was partially used for the convenience of the classification of validity. A total of 13,382 patent data were extracted through the patent search formula for each process in Table 4, and 6985 patent data were finally analyzed through the valid patent selection process.

Table 4. Patent search formula by process.

Logistics High Level Process	Search Expression	Number of Data	Number of Valid Data
Customs	(logistics or customs) and (Freight or transport* or warehouse or fulfillment or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or big)) AND (G06*) IPC.	362	99
International transport	(logistics or international or overseas) and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	1256	181
Transport	(logistics or transportation or "line-haul") and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	702	475
Distribution	(logistics or distribution) and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	1885	1382
sorting	(logistics or sorting or sort*) and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	2318	2187
order	(logistics or order) and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or big)	1324	473
Warehouse	(logistics or fulfillment or warehouse) and (Freight or transport* or marketplace or retail or ecommerce or last or delivery or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	1396	1330
delivery	(logistics or delivery or deliver*) and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	533	487
Return	(logistics or return or reverse) and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or shipping or robot or automate* or tech* or order or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or green or big)	544	39
Customer service	(logistics or customer or "customer service" or "help desk" or "call center" or "after service") and (Freight or transport* or marketplace or warehouse or fulfillment or retail or ecommerce or last or shipping or robot or automate* or online or mobile or truck or port or marine or vehicle or "supply chain" or SCM or pick* or pack* or electric or big)	561	332
Total		10,901	6985

*: The * mark is a search operator, and all documents with a word of any length after * are searched.

4.2. Step 2: Technology Clustering through Patent Analysis

4.2.1. Clustering of Technical Fields

Cluster analysis is necessary to classify the collected patent data into technical fields. For cluster analysis, the number of clusters (K) must be determined in advance. The number of clusters (K) is possible through the complexity algorithm and silhouette analysis of the language model. The complexity algorithm of the language model indicates that the lower the complexity value, the better the result of the data is reflected. Silhouette analysis is evaluated numerically based on clustering between data. When the complexity value is the lowest, an overfitting problem occurs in which the model over-learns the data. Therefore, in this study, the number of clusters (K) is at the point when the complexity value sharply decreases and the time when the silhouette number is minimized. The optimal number of clusters was determined. The figure below shows the complexity graph of the data according to the number of different clusters (K) and the graph of the silhouette analysis result. In the complexity graph, the final number of clusters (K) was determined by deriving 15 points at which the number of silhouettes was the minimum and the point at which the number of silhouettes was the minimum as shown in Figure 7.

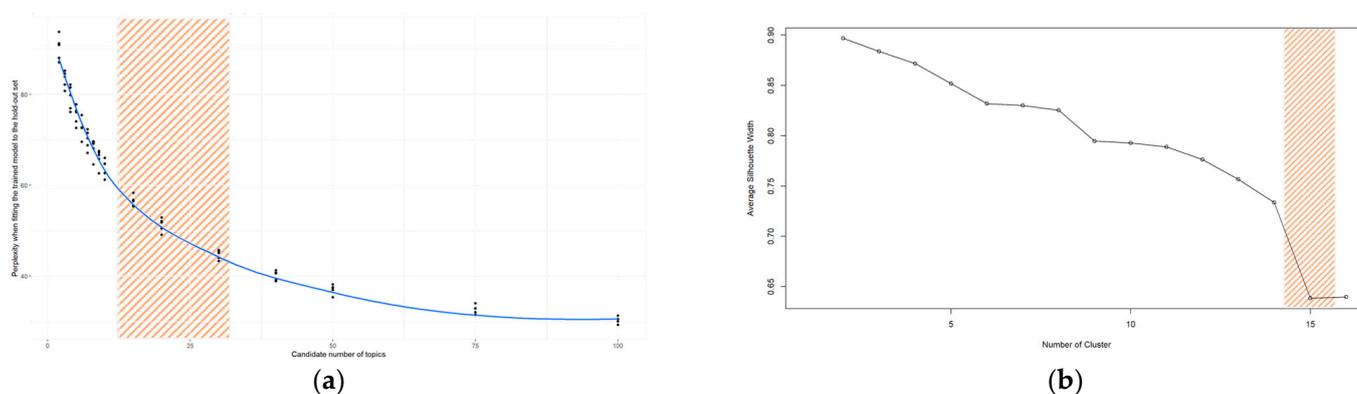


Figure 7. Optimal number of clusters (K): (a) Complexity results graph; (b) silhouette result graph.

Table 5 shows the results of extracting major patents included in 15 clusters and identifying topics through patent content analysis. Five major patents were selected for the topic in the cluster, and the topic name was defined. Topic 1, Topic 3, and Topic 8 were classified into clustering, but similarity exists in the content of the patent and was identified as a sorting-related technology. In addition, Topic 2 and Topic 9 were identified as distribution areas, but Topic 2 was closer to the SW area, and Topic 9 tended to be closer to HW or tool, but the overall patent content had a common tendency. Topic 4 and topic 13 were related to the logistics information management area, and Topic 5 was related to packaging equipment and sorting equipment. Topic 6 has patents for simulation and evaluation methods, so it was judged as an intelligent logistics management area. Topic 7 was identified as the Delivery area because there were patents for delivery and related systems and delivery methods. In the case of Topics 10 and 11, there are similar patents in terms of warehouse management. Topic 10 had warehouse control system related patents for facility or AGV operation. Topic 12 had equipment-oriented patents for material handling. Topic 13 had patents related to the display and acquisition devices of logistics information. Topic 14 had sensor and cold chain related patents. Finally, Topic 15 was occupied by Robot in Warehouse Relevant patents, so it was identified as the Robot area.

Table 5. 15 Major Patents by Topic.

Cluster	5 Major Patents in Cluster
Topic 1 (sorting)	<ul style="list-style-type: none"> - Express sorting and conveying device - Express delivery letter sorting loading and unloading conveyer - Automatic sorting system for logistics - Express parcel sorting machine for logistics transportation - Logistics piece sorting equipment
Topic 2 (distribution)	<ul style="list-style-type: none"> - Warehouse logistics distribution automatic control management system - User-based logistics distribution information feedback system and method - Unmanned logistics storage goods shelf general assembly and warehouse automatic sorting, taking and distributing system - Logistics warehouse management system based on mobile internet of things - Logistics distribution terminal device
Topic 3 (sorting)	<ul style="list-style-type: none"> - Logistics automatic sorting equipment - Rapid sorting device for express packages - Transportation device for logistics centralized sorting - Intelligent carrying robot with convenient and fast use function for logistics distribution - Conveying device special for automatic logistics sorting system
Topic 4 (logistics information management)	<ul style="list-style-type: none"> - Collecting -distributing logistics management platform based on app - Intelligent logistics management system - Remote communication cabinet opening driving device for e-commerce logistics delivery box - Dynamic scheduling method for processing newly added express pickup demands during express distribution process - Delivery logistics management method and device based on block chain, terminal, and storage medium
Topic 5 (packaging)	<ul style="list-style-type: none"> - Vacuum packaging machine for logistics warehouse - Intelligent robot is patrolled and examined in commodity circulation express delivery warehouse - Sorting and packaging table for logistics - Feeding and sorting integrated logistics packaging platform - Packaging robot facilitating logistics distribution
Topic 6 (intelligent logistics management)	<ul style="list-style-type: none"> - Intelligent logistics window and delivery method and collection method thereof - Cloud computing-based logistics express commodity distribution evaluation database establishment analysis method - Simulation method for sorting line of logistics distribution center - Logistics warehouse device and unmanned logistics distribution equipment comprising same - Stock calculation method of distributed type integrated-project storage logistics system
Topic 7 (Delivery)	<ul style="list-style-type: none"> - Intelligent express cabinet system and distribution method thereof - Unmanned logistics vehicle distribution method and system based on motion analysis - Automatic logistics goods allocation truck - Unmanned express vehicle, unmanned express distribution system, and automatic distribution method of unmanned express distribution system - Logistics management method capable of monitoring cargo operation state and judging driving route
Topic 8 (sorting)	<ul style="list-style-type: none"> - Logistics sorting device with horizontal pushing device - Sorting device for logistics storage - Sorting structure of narrow-band type logistics sorting machine - Intelligent sorting logistics robot - Express item sorting belt conveying line

Table 5. Cont.

Cluster	5 Major Patents in Cluster
Topic 9 (distribution)	<ul style="list-style-type: none"> - Buffer apparatus for stereo logistics warehouse shelf - Logistics distribution point addressing method and device, electronic equipment, and storage medium - Logistics order optimal distribution system and method with privacy protection function - Logistics mobile electronic delivery system - Logistics distribution service system, logistics distribution terminal device, and logistics distribution method
Topic 10 (warehouse control)	<ul style="list-style-type: none"> - Novel automobile logistics rotation goods shelf that delivers - Novel AGV logistics distribution dolly - Integrated logistics warehousing control system - Automated guide vehicle (AGV) for express delivery logistics warehouse and control system of AGV - Cloud-warehouse order processing system used for omni-channel retailing
Topic 11 (warehouse management)	<ul style="list-style-type: none"> - System of warehouse and logistic services - Logistics intelligent sorting evaluation system - Warehousing logistics door system based on UHF RFID technology - Movable goods shelf for warehouse logistics management - Order management system based on third-party logistical business
Topic 12 (material handling)	<ul style="list-style-type: none"> - Warehouse logistics transporting tray - Carrying robot and warehouse logistics system - Warehouse logistics pallet stack arrangement device - Shuttle vehicle assembly of logistics sorting carriage based on urban public transportation type freight transport - Warehouse logistics goods loading and unloading automatic carrying and conveying intelligent equipment
Topic 13 (Logistics information)	<ul style="list-style-type: none"> - Code spraying device for logistics management warehouse - Method for purchasing new retail warehouse logistics delivery internet commodities via two-dimensional codes - Rapid information acquisition device for logistics sorting - Control scheduling method of multi-Agent regional logistics distribution system - Image acquisition device and express item sorting device
Topic 14 (cold chain)	<ul style="list-style-type: none"> - Cold-chain logistics real-time environment monitoring and positioning system - Total asset visibility management system based on Internet of Things technology - Cold-chain logistics transportation truck temperature control system - Cold-chain logistics profit distribution system based on block chain - Cold-chain logistics express delivery distribution device
Topic 15 (Robot)	<ul style="list-style-type: none"> - Inspection robot for logistics warehouse - Warehouse logistics robot and article identification method and chip thereof - Walking robot lamplight indication system, method and device, terminal, and storage medium - Warehousing logistics robot control system based on MSP430 - Loading robot for logistics distribution

4.2.2. Technical Field Assessment

Logistics technology was divided into 15 detailed technical fields through the LDA algorithm. In order to derive a technology development roadmap for the logistics industry, it is necessary to identify promising fields of technology. In order to confirm the potential of the technology field, we conducted qualitative evaluation of network analysis, technology level map analysis, and quantitative evaluation of trend analysis.

Network analysis, one of the qualitative evaluations analyses, converts the patent-keyword matrix into a topic-keyword matrix and confirms the linkage between topics. The network analysis result is shown in Table 6. We analyzed mediation centrality, proximal

centrality, and connection centrality indicators, which are indicators that can be confirmed through network analysis, and the main indicators confirmed mediation centrality as the most important in order to consider the linkage between topics. As a result, it was confirmed that the mediation centrality index of Topic 1 and Topic 7 recorded the highest value, and other indices recorded high values and were identified as a major topic.

Table 6. Network analysis results.

Topic	Betweenness	Closeness	Connected	Priority
Topic 1	7.139755	0.029412	7	2
Topic 2	9.067965	0.030303	8	14
Topic 3	5.955988	0.028571	6	10
Topic 4	2.376623	0.027027	4	6
Topic 5	1.639394	0.027778	6	3
Topic 6	1.888889	0.027027	5	5
Topic 7	0	0.004762	0	1
Topic 8	1.5	0.026316	5	10
Topic 9	1.142857	0.025641	3	8
Topic 10	1.843362	0.029412	7	4
Topic 11	3.452381	0.027778	5	7
Topic 12	6.71912	0.030303	8	12
Topic 13	5.208081	0.030303	8	9
Topic 14	1.843362	0.029412	7	15
Topic 15	2.222222	0.027027	5	13

Each of the 15 technical areas of logistics technology has a different current skill level. This creates uncertainty in developing the technology. Therefore, in the importance analysis, the technology level for each topic is checked through the technology level map using the number of claims, which means the scope of technology and the number of IPC fields. The Technology level map shows the relative level of each technology field and shows the results, as shown in the Figure 8. Logistics technology is classified into three levels.

TECHNOLOGY MAPPING

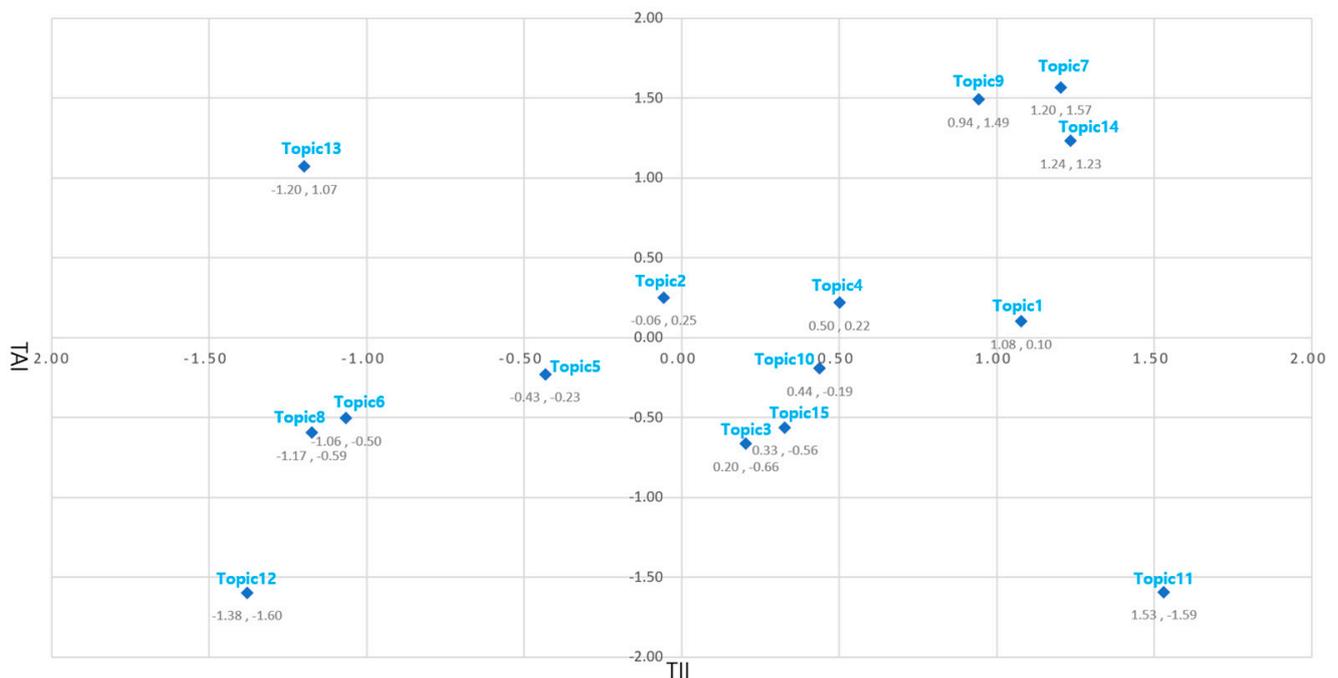


Figure 8. Result of Technology level map.

Looking at the results, Topics 1, 4, 7, 9, and 14 were identified as high level because all indicators had positive values, and Topics 5, 6, 8, and 12 were identified as low level because all indicators had negative values.

Trend analysis, which is a quantitative analysis, is an analysis to check not only the skill level but also the future promise. Trend analysis is performed through time series analysis to confirm the potential of future technology fields. This study applies the ARIMA method to 15 logistics industry technology fields during time series analysis to identify trends. The ARIMA algorithm requires the definition of p , d , and q parameters, which are variables related to the order, difference, and moving average of the auto regression model. For this variable, the “auto.arima” function of the R programming package is applied. In addition, since patents are published 18 months after filing, we analyzed based on the number of patent applications up to 2020. The trends in logistics technology are categorized into hot, active, and cold. As a result of the trend analysis of 15 technology fields, Topic 11 was identified as an active field continuously developed by technology, and all other topics were identified as a steadily increasing hot field. Looking at Figure 9, (a) is an ARIMA graph output for topic 11, showing an upward trend, and (b) is an AIRMA graph output for the remaining topics, which is confirmed as an active field.

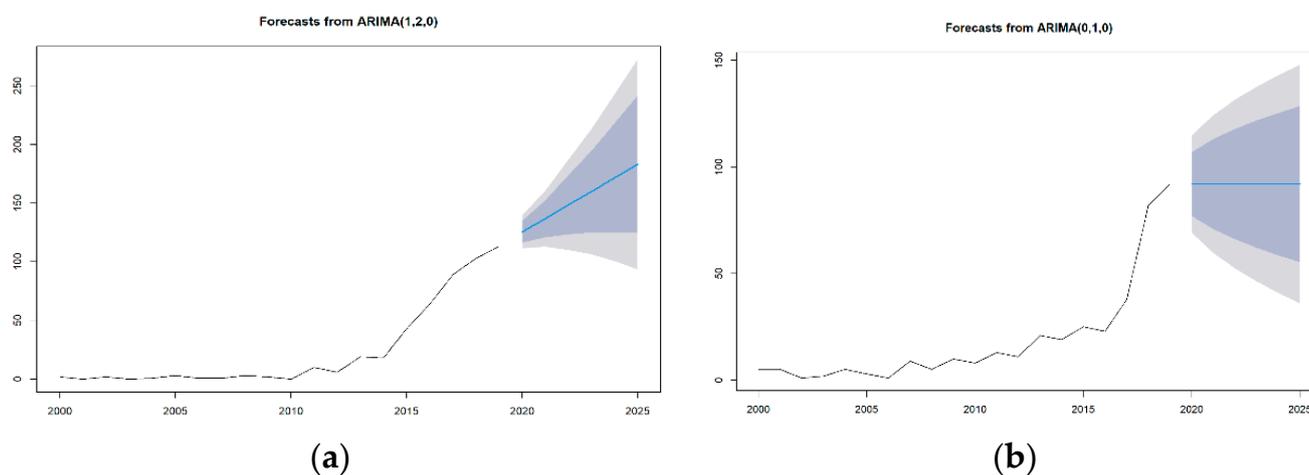


Figure 9. Trend Analysis Results: (a) Hot Field; (b) Active Field.

4.2.3. Identify Promising Technology Areas

The results of the above integrated analysis are summarized in Table 7 below. As can be seen from the table, the results of all analyses are absolutely inconsistent. This means that it is very important to derive promising technology fields through various analysis applications, as each analysis has a different meaning. The network analysis focused on identifying the linkages between topics, and the technology level map analyzed the technology level based on the number of patent claims and the number of IPCs. Finally, trend analysis is because future trends are analyzed based on data over time. Of course, if all three of these analyses are satisfied, it is necessary to preempt the market by developing technology in the vacant technology field. Therefore, Topic 1 and Topic 7 are technology fields with technological promise, and countries and companies need to take the lead. Additionally, technology development has a high priority. The topic is very important, and it is judged that steady technology development will be made. Therefore, it is necessary to intensively analyze the relevant technology field in establishing the technology development roadmap.

Table 7. Integrated network analysis results.

Topic	Qualitative Evaluation		Quantitative Evaluation	Priority
	Network Analysis	Technology Level Map	Trend Analysis	
Topic 1	2	High	High	High
Topic 2	14	Medium	High	Low
Topic 3	10	Medium	High	Low
Topic 4	6	High	High	Medium
Topic 5	3	Low	High	Medium
Topic 6	5	Low	High	Medium
Topic 7	1	High	High	High
Topic 8	10	Low	High	Medium
Topic 9	8	Medium	High	Medium
Topic 10	4	Medium	High	Medium
Topic 11	7	Medium	Active	Medium
Topic 12	12	Low	High	Low
Topic 13	9	Medium	High	Medium
Topic 14	15	High	High	Low
Topic 15	13	Medium	High	Low

4.3. Step 3: Promising Technology Development and Technology Roadmap Development

4.3.1. Identification of Vacant Technologies by Topic: GTM-Based Patent Map

To detect vacant patents in promising technology fields, a GTM-based patent map was designed using the patent-keyword matrix. Before developing a GTM based patent map, we need to define a parameter called map size. There is no rule to determine the map size parameter, but since there is a need to develop skills for the initially identified Vacant technology, we started with a small map size and gradually removed the size to establish the map size at which the vacant technology was identified. We applied a 9×9 sized map for Topic 1 and a 7×7 sized map for Topic 7. The Figure 10 is a visualization of the GTM results. As can be seen in the figure below, patent vacuums can be discovered more clearly and automatically because all patent documents are mapped to each latent grid point on the map.

Looking at the GTM-based patent map, in Topic 1, two vacant technology fields were identified, and in Topic 7, three vacant technology fields were identified.

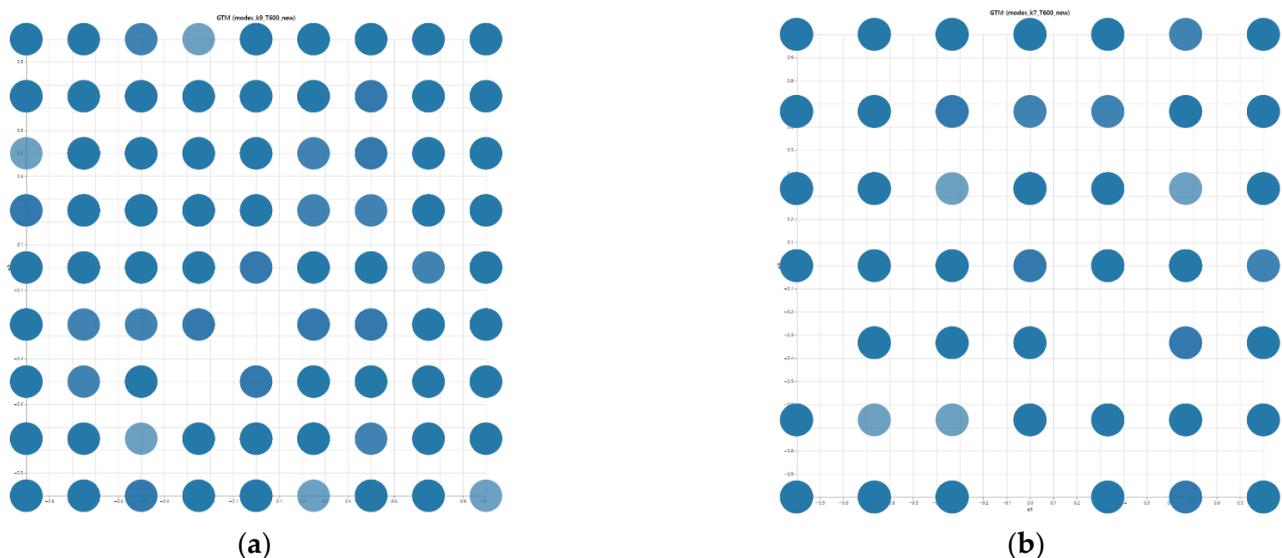


Figure 10. Results of GTM-based patent map: (a) Topic 1's patent map; (b) Topic 7's patent map.

4.3.2. Vacant Technical Analysis by Topic

By examining the patents included in the vacant technology field identified through the GTM-based patent map, the technology names that can be represented were identified as shown in Table 8. Two vacant technologies were identified.

Table 8. Patent of vacant technology identified through GTM-based patent map.

Topic	1 Group	5 Major Patents
Topic 1	1 Distribution device technology for the delivery and transport of goods	<ul style="list-style-type: none"> - Unmanned aerial vehicle system applied to warehouse logistics of containers - Goods moving device for logistics warehousing - Logistics automatic goods distribution vehicle - Sorting-free system and method for warehouse logistics - Foldable warehouse logistics vehicle
	2 Unmanned delivery technology	<ul style="list-style-type: none"> - Unmanned logistics vehicle distribution method and system based on motion analysis - Adaptive network-centric online autonomic supply chain management system - Unmanned aerial vehicle with logistics flight-throw system - Unmanned aerial vehicle intelligent logistics distribution terminal - Unmanned aerial vehicle for logistics transportation
	3 Distribution route optimization and monitoring technology	<ul style="list-style-type: none"> - A logistics distribution route planning method with a time window based on a cuckoo algorithm - Logistics distribution vehicle route optimization method - Logistics crowdsourcing distribution order screening method and device - Express delivery intelligent distribution system based on urban public transportation system - Real-time reporting system for logistic dist.
Topic 7	1 Intelligent sorting device technology	<ul style="list-style-type: none"> - Logistics sorting device and warehouse logistics sorting system - Intelligent logistics sorting device - Express delivery distribution and receiving system and method based on classification algorithm - Double-RFID logistics combined transportation flat tray - Automatic auxiliary sorting equipment for logistics storage
	2 Mobile based classification device technology	<ul style="list-style-type: none"> - Convenient and quick express package delivery and distribution vehicle - Coordinate platform of logistics flying delivery system - Vehicle-mounted portable intelligent express sorting and filling system - Automatic feeding and discharging robot for logistics warehouse - Position distribution method for express cabinet

Topic 1 was identified as a classification technology, and as a result of searching for vacant patent documents for classification technology, two vacant technologies were identified as an intelligent classification device technology and a moving object-based classification device technology. This means that classification technology is an area that still requires a lot of labor, it is necessary to increase productivity and work efficiency, and the identification of patents for mobility response is also meaningful as a future technology area.

Topic 7 was identified as a delivery system technology, and as a vacant technology in this field, distribution device technology for product delivery and transfer, un-

manned delivery technology, and distribution route optimization and monitoring technology were identified.

It is meaningful as a technology in the last mile area, and unmanned delivery, distribution device technology for delivery suitable for product characteristics, and route optimization technology to monitor and control unmanned delivery are extracted as vacant technologies.

5. Conclusions

5.1. Conclusions

5.1.1. Deriving a Patent Search Formula Reflecting the Latest SNS Trends for Logistics Technology Research

This study used a keyword approach to find the data to be analyzed rather than a classification code and company-based approach [112]. This was not to be a patent search formula written by humans but a derived patent search that reflected the latest trends in SNS for future systemization.

Since logistics includes both intangible and tangible elements according to the definition and scope of logistics, logistics-related technologies are likely to include both software technology and hardware technology [23]. Therefore, for comprehensive analysis, keywords, not business method patents, were used for all utility patents in the 'WIPSON' database. However, although this method can reduce the probability of missing logistics-related patents, on the other hand, there is a disadvantage in that patents whose search keyword is not related to logistics, such as those in the medical field, are also searched. When there is a lot of irrelevant data, it takes a lot of time to manually validate the data. In order to improve this and, at the same time, for the convenience of search, the result of using SNS keywords as a unit of high level process of logistics as showed in Table 9 6985 valid selected patents out of 10,901 cases of total collected data, which was 64% effective.

Table 9. Patent effective ratio.

High Level Process	Collected	Selected	Effective Ratio
Customs	362	99	27%
Overseas	1256	181	14%
Transport	702	475	68%
Distribution	1885	1382	73%
Sorting	2318	2187	94%
Order	1324	473	36%
Fulfillment/Warehouse	1396	1330	95%
Delivery	553	487	88%
Return	544	332	59%
Customer Service	561	332	59%
Total	10,901	6985	64%

In order to reduce the time and effort of the valid selection process, which is currently being handled manually, additional research is needed on a patent search formula that can increase the effectiveness hit rate. We were able to draw conclusions, and we were able to confirm the possibility of systematization.

5.1.2. Usefulness as a Tool for Predicting Changes in Logistics Technology and Exploring Vacant Technologies

Logistics service providers were generally application-oriented as technology consumers rather than technology developers [113]. In an industry where the competitive dynamics due to digitalization have changed, logistics service providers no longer simply apply technology but must create a convergence business model while developing it themselves. The entry of logistics startups that invest in digital technology as a core competency and the investment in logistics technology by e-commerce companies such as Amazon and

Alibaba mean that logistics technology should no longer be applied as a core competency but should be viewed as a development investment.

In this situation, logistics service providers must preemptively search for development opportunities as well as trends in logistics technology. In addition, according to the rapidly changing technology, the work on this needs to be thoroughly and regularly performed by the technology-related department, which requires more resources and time. In this study, by classifying patent data in this regard, an overall framework for quantitative technological change prediction and the exploration of potential technological areas was proposed. Through the proposed framework, representative keywords of the logistics industry were extracted from SNS, and patent data were collected using them. Technology topics were identified through pre-processing and topic modeling of the collected patent data. Based on the qualitative evaluation of the network analysis, the number of claims, and the number of IPCs, the technology level analysis was conducted through the Technology Level Map. In addition, future trend analysis according to time series analysis, which is a quantitative evaluation, was combined to confirm the promise of the technology field. Even vacant technologies of detailed technologies in the technological field with confirmed promise were derived. Through this, it was confirmed that detailed fields of the logistics industry were classified as patent data, and quantitative technological change prediction in the relevant field was possible. This method can effectively support a wide range of tasks such as exploring the technology trends of players in the logistics industry and exploring technology development opportunities for establishing logistics technology roadmaps. This will soon help not only players in the logistics industry but also the government's work to support industrial development.

5.1.3. Patent-Based Approach to Exploring Potential Technology Areas in Logistics

Technological output can appear in various forms, but most of it is expressed as a patent, and a patent can be an indicator representing technology [114]. In addition, because patent data meets explicit criteria for originality, technical feasibility, and commercial value, it includes both technical and market attributes, which can be used to identify new opportunities and plan future R&D activities. Therefore, it can be said that it is possible to discover logistics technology opportunities by utilizing the technical information of patent data [115].

Several approaches can be taken to explore the technological areas with potential for development, and the number of patents included in a Cluster over time can be separated into phases of introduction, growth, maturity, and decline according to an S-curve. Accordingly, it is possible to determine which stage of the technology life cycle the patent group is in. Another method is to measure the market share by dividing the number of patent applications for a clustered subject by the total number of patent applications collected, and it can be judged based on two criteria that quantify the change in the subject share by CAGR (compound annual growth rate). Subjects with a low patent share and negative GAGR may be in the introduction stage [23]. Another view measures the radicality of innovation at the patent level using a citation-based index and invention content, assuming that individual patents should have different levels of novelty and impact even if they are applied at a similar time.

Logistics patents discovered through LDA may vary depending on the time zone selection of the target patent. By limiting the period to only recent patents, only those patents related to the latest technology in logistics can be considered. However, the amount of information collected is small in the recent period. In order to see the change in technology, we need data over a wider range of time. However, the disadvantage of data collected over too wide a timeframe may be to consider outdated topics and risk judging their importance. Therefore, this study used the entire patent data set to explore technology subject identification and change. The derived technology is a classification technology domain, and by confirming the correlation with the keywords positioned high in SNS, it was possible to conclude that the results were acceptable to some extent.

5.2. Contribution

This study contributes to closing the gap in technological innovation research through the use of patent data. In addition, it demonstrates the use of the Word2Vec algorithm to derive a patent search formula for patent search, a topic modeling approach to patent data using LDA of patent data, network analysis, technology level map, and Arima-time series analysis to predict technological change and derive promising technologies. By proposing a framework, it is contributing to logistics innovation research from a research methodological point of view. In addition, it provides a basis for systematizing the proposed methodology by applying a clustering algorithm based on the black box mechanism.

As a result of the proposed framework, which technology areas are emerging and important in the logistics industry and the derivation of detailed vacant technologies can help to enhance the understanding of technological change and make a technology roadmap. As a result of this study, the distribution and sorting areas for product distribution in the existing logistics field were classified as consistently promising. In the distribution area, especially, distribution device and inventory management technology for delivery and goods transfer, intelligent delivery method and unmanned delivery equipment technology, and route optimization and distribution monitoring technology were analyzed as still worth challenging. In the classification area, intelligent classification algorithms and classification device technology and mobile-mounted classification devices and distribution technology were derived as vacant technologies. It can be confirmed that this coincides with the trend of delivery, distribution, and mobility diffusion in the last mile, which is currently widely mentioned in the logistics field. Additionally, by predicting the importance and opportunity fields of the logistics technology field, it suggests the need for a patent strategy and technology strategy tailored to this.

Although this study explored technological change trends and technology development opportunities for the logistics industry, it can be applied to other industries as well. If we crawl the news on SNS using key keywords for each industry to derive key keywords for the industry and apply the proposed framework by grafting the high level process with industry characteristics, we will find technological change trends and technology development opportunities in the industry.

5.3. Discussion

Major implications of this study are to be found in the methodological aspect and the management aspect of logistics service providers.

In this study, a more diverse and systematic analysis process was applied in comparison with previous studies for the purpose of improving the accuracy of the research results and increasing the usability of the research results. There have been previous studies to predict the innovative trends in logistics technologies and to identify promising future technologies using topic modeling, but they only searched for the gaps in specific technologies or looked at the overall technology trends. There was no framework study premised on the systematization of the entire process from predicting the technological changes in the logistics industry to discovering promising technologies. To bridge this gap, we combined various analytical techniques on this subject.

The methodological differentiation of this study is that, first, the patent search keyword extraction process through news data crawling is added so that expert intervention is not required. Second, patent search of classification-based and company-based approaches may be limited with a limited data range, and if a keyword-based approach is used to compensate for this, there is no missing data, but patent data in an area too far from the subject is also extracted. As a result, a lot of time and effort is required in the process of selecting valid data. To improve that case, in this study, the quality of patent search was improved by combining the keywords extracted from SNS with the mega-process words of the logistics industry. Third, in identifying promising areas through LDA-based clustering, a multidimensional analysis technique was applied by combining not only time series analysis, which is the existing quantitative trend evaluation technique, but also network

analysis and technology level map analysis, which are qualitative evaluations. This allowed for clearer targeting of promising technology areas. In addition, it is meaningful that the process from the beginning of the search for promising technology to the selection of technology for the final roadmap is consistent by combining GTM analysis to search for the reality of specific promising technology rather than just exploring the promising technology area. It forms the basis for our contribution to the research of future logistics technologies.

Finally, the management implications of this study for logistics service providers can be helpful in providing a reference point for roadmap development and guiding technology management tasks to actual logistics company practitioners in the implementation of digitalization. Because it provides a standardized process of technical research for the digitalization of logistics companies, it can be carried out with less time and cost. In addition, by making learning data in areas such as the processing of unstructured data, a procedure that was carried out through the intervention of researchers in the research process, it created a basis for development as an automated tool for predicting future technological changes and deriving blank technologies. For the development of this study, it is necessary to further subdivide the overall process in the future and pay attention and effort for standardization.

5.4. Limits

This study has limitations that require future research. First, there is a disadvantage that the quality and quantity of data can be affected by keywords and search terms when searching for a patent. For this study, two keywords, logistics and distribution, were used in combination with the process terms of logistics and keywords representative of SNS. Nevertheless, it would not have included all patents involving logistics and state-of-the-art technology, and many patents not related to logistics were also included. Therefore, it is necessary to improve the patent collection policy through a more refined patent search formula for collecting patents in the relevant industry field. In other words, in this study, the search was conducted by a logistics process unit, but it can be used in the patent search formula by replacing it with a logistics business model component or a value chain component.

Second, if the integrated analysis that combines the network analysis, technology level map, and time series analysis used in this study and the methods used in the previous studies, such as technology life cycle, patent share, and CAGR method, are additionally combined, it will be possible to analyze in more various dimensions. It will be possible to suggest a more rational and useful form analysis method, and it will be possible to make it easier to understand technology in real companies and to lay a practical foundation.

Third, patent data is the best source of data including technical information, but there may be limitations in predicting future logistics technology. This is because, in the patent registration process, it takes a considerable amount of time for an actual patent to be registered, so even data collected with the latest time can be an opportunity for technology development two years ago. In other words, it can be said that patent data contains past and present technologies. As a way to supplement this, it is proposed to apply the framework proposed in this study to the thesis data. The thesis data have many characteristics that are closer to the future than patents, so it will be possible to increase the probability of predicting future technologies. Through this, a more practical technology roadmap can be developed if an empty technology with development potential and valuable development is derived.

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