Technology forecasting from the perspective of integration of technologies: Drone technology

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Received February 22, 2022; revised September 13, 2022; revised November 8, 2022; accepted December 15, 2022; published January 31, 2023

Abstract

In the midst of dynamic industrial changes, companies need data analysis considering the effects of integration of various technologies in order to establish innovative R & D strategies.

However, the existing technology forecasting model evaluates individual technologies without considering relationship among them. To improve this problem, this study suggests a new methodology reflecting the integration of technologies. In the study, a technology forecasting indicator was developed using the technology integration index based on social network analysis. In order to verify the validity of the proposed methodology, 'drone task performance technology' based on patent data was applied to the research model.

This study aimed to establish a theoretical basis to design a research model that reflects the degree of integration of technologies when conducting technology forecasting research. In addition, this study is meaningful in that it quantitatively verified the proposed methodology using actual patent data.

Keywords: Technology forecasting, Integration of technologies, Social network analysis, Technology growth model, UAV

1. Introduction

In today's intense global competition, companies consistently invest in technological innovation. In order to efficiently use R&D costs for technological innovation, interest in and demand for technology forecasting based on objective data analysis are increasing [1]. In particular, in industries where technological environments are rapidly changing, studies that apply dynamic methodologies that reflect the characteristics of industries to the analysis and forecasting of technological competence have been carried out previously [2,3], and even studies at the stage of applying dynamic methodologies to the prediction of the diffusion of new products have been conducted [4].

However, studies that apply dynamic methods to technology forecasting currently remain at the level of forecasting of individual technologies, and technology forecasting considering the effect of technological integration and the relationships between various technologies cannot be found despite the importance of such technology forecasting. In reality, however, most technological innovations of companies occur thanks to technology integration and technology overlap [5]. When associations among technologies are stronger, technology integration (merger) occurs more frequently, and industries evolve thanks to the integration of related fields based on converged or integrated technologies and the rapid growth of the core elements that constitute products [5]. Therefore, for technology evaluation and technology forecasting, the relationships among technologies such as technology integration should be considered indispensable [6]. Although studies that analyze the characteristics of technology integration using patent data have been conducted recently [7,8,9,10,11,12,13,14,15], no studies that reflect the matter of technology integration in technology forecasting have been conducted to the best of this researcher's knowledge.

The main contributions of this study regarding technology forecasting, application of technology integration are as follows.

- For more effective technology forecasting, we design a new technology forecasting method that reflects the Social Network Analysis-based technology integration index.
- To verify the effectiveness of the proposed method, experiments were conducted to compare the predictive power of the proposed method and existing method. Compared with two methods, it was found that the proposed method is more suitable for technology forecasting.

As shown in **Fig. 1**, a technology forecasting indicator that measured the degree of technology integration using social network analysis (SNA) based on patent data was developed. In order to verify the validity of the study, actual patent data related to "drone technology" were used as the data for calculating the technology forecasting indicator.

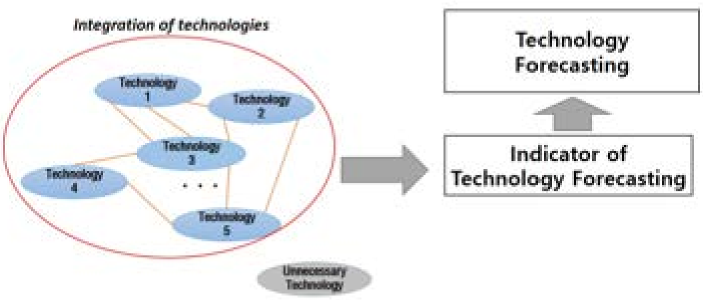


Fig. 1. Technology forecasting indicator that reflects the relationships among technologies

2. Theoretical background and related studies

2.1 Technology integration

The integration of technologies refers to the act of combining many technologies horizontally and vertically to perform a certain function [16]. That is, using technologies from multiple fields to solve a single technical problem in cases where the problem cannot be solved with technologies in one field is called the integration of technologies. Therefore, technology integration can be defined as a method of selecting and refining the technologies necessary to make new products, processes, or services [17].

Technology fusion is a concept similar to technology integration. Both concepts explain the phenomenon of technology overlap. Whereas the properties of individual element technologies are preserved in the outcomes of technology integration, the properties of individual element technologies may be changed in the outcomes of technology fusion. In addition, as for the functions of products, whereas expected new functions are created in the case of technology integration, unexpected new functions may be created in the case of technology fusion. **Fig. 2** briefly describes the outcomes of technology integration and technology fusion. Character of technical elements may be changed after technology fusion(the thick line in the picture on the left), whereas it remains the same after technology integration(the dashed line in the picture on the right) [18].

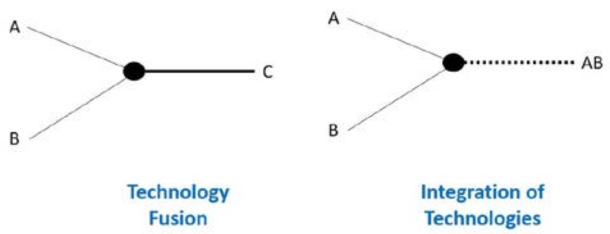


Fig. 2. Comparison of the processes of technology integration and technology fusion. Source:[18]

Kodama noted that new products or services are created through a combination of heterogeneous technologies. He came to have this recognition from numerous mechatronic products created by the combination of mechanical and electronic technologies [19]. Fleming et al. said that technological advancements are made through the process of technology integration between existing and new technologies, and conducted empirical analysis based on patent data [20].

2.2. Social network analysis (SNA)-based patent analysis

Social network analysis is a formal theory that defines and analyzes relationships between individuals or organizations. It is used to measure and visualize the directionality and intensity of existing associative relationships among components to identify the relationships among individual elements or the characteristics of the elements [21]. Kim, H. W., Kim, J. C., Lee, J. H., Park, S. S. and Jang, D. S published a study that applied social network analysis to the technology classification information and IPC codes, which are classification codes, currently contained in patent documents to explore the fields of R&D and technologies [10].

The fact that a patent simultaneously belongs to multiple classification codes means that relationships among the relevant technological domains occurred through the relevant patent. Patent co-classification analysis uses the patent information that has such relationships to identify the relationships among technological domains and analyzes knowledge flows within the technological domains using patent information with such relationships [11]. The International Patent Classification (IPC) is used for patent co-classification analysis. IPC codes are often used to study the technology portfolios of certain industries or companies because they can distinguish technologies and reveal the characteristics of technologies [22].

Derek, J. conducted a study that became the beginning of knowledge network analysis using bibliographic information such as patents. He revealed the characteristics of citations for the first time using the reference information of papers published for one year, and thereafter, studies that collected certain patent data related to the technology field to combine patent citation information and social network analysis have been published. Kim, J. W., Jeong, B. K. and Yoon, J. H. analyzed the technology development levels using social network analysis and technology growth models for augmented reality technology-related patent data. Geum, Y., Kim, C., Lee, S. and Kim, M. collected patent data to measure the level of concentration and scope of technology fusion between biotechnology (BT) and information technology (IT) based on social network analysis [7]. Park et al. selected Building Information Modeling as a technology to be analyzed, and checked the speed of technology transfer and identified main technologies with patent citation network analysis [13]. In addition, there are cases where the intermediation of patents for 5G mobile communication technologies was studied using a social network analysis methodology in order to quantitatively measure the pattern of open innovation of the relevant technologies [14]. Hsu et al. investigated the evolution of biomass fermentation, an important part of hydrogen production, through patent exploration and citations and also investigated the driving force of the technology [15].

Meanwhile, studies intended to reveal the relationship between the development of patented technologies or relationships among technologies and industrial growth or companies based on patent data are also being conducted. Weng et al. constructed citation networks for individual pieces of literature using insurance business-related patent data to analyze the structural equivalence of technologies and argued that inventions are nodes and links are networks that are evolving, in which nodes are tied together to trigger mutual inventions [23]. Zhou et al. conducted a study that constructed a patent-based knowledge network structure with wind turbine engine manufacturing companies to analyze leading knowledge-based companies [24]. In addition, Sun, H., Geng. Y., Hu, L., Shi, L. and Xu, T. analyzed new energy vehicle-related patents in China using a social network analysis methodology. With this analysis, they investigated the growth stage of the new energy vehicle industry and the network density, and based on the results, they identified that relevant patents related to cooperation networks were gradually developing.

2.3 Technology growth model

Since the level of technology and the degree of diffusion change over time, time-series analysis is limited when only static evaluation methods are used. Therefore, studies that use the technology growth model to grasp the movement of technological changes over time are active [25,26].

The technology growth model is a sort of representative sigmoid function and is an analytical model developed from empirical studies that indicates that increases in the number of living organisms form S-shaped curves. Recently, studies that use changes in the number of patents over time to analyze the life cycles and growth stages of technologies have been conducted[11]. Ernst argued that as R&D is accumulated, patent applications, which are the results of R&D, will increase along an S-shaped curve [27]. By estimating trends, changes in the newest technologies such as mobile broadband, synthetic fiber, personal digital assistant technology, or CRISPR can be predicted [3, 28, 29].

Technology growth curves can be divided into four steps, as shown in **Fig. 3** [30]. Technologies develop at relatively high speed from the step of introduction to the step of growth. On the other hand, from the step of expansion after reaching the inflection point, the speed of technology development becomes slow and then the technologies ultimately reach their peak when they have reached the step of maturity. The peak is defined as the ultimate technology level [1].

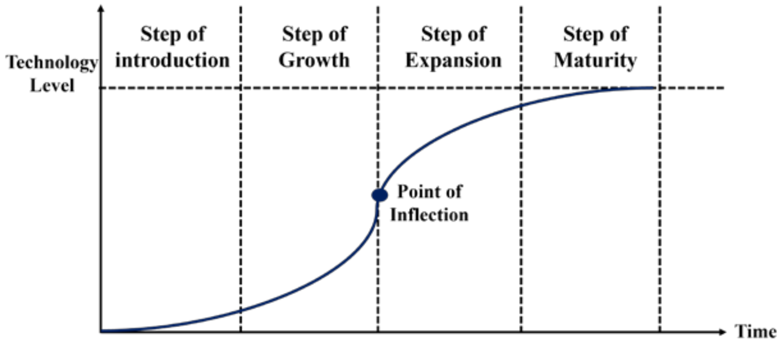


Fig. 3. Technology growth curve and life cycle

3. Proposed methodology

3.1 Proposal of indicator for technology forecasting

3.1.1 Introduction of variables that constitute the indicator

This study derives $T_{i,n}$ (the technology forecasting indicator), which is a new technology forecasting indicator that enables the understanding of the level of technology in year i, with the combination of $t_{i,n}$(technology), which means the sum of individual technology elements that constitute the nth technology cluster in year *i* and $IWT_{i,n}$, which is the degree of technology integration. Variables $IWT_{i,n}$ and $T_{i,n}$ are new variables that reflect the perspective of technology integration in technology forecasting. **Table 1** shows studies that have similar formulas and concepts connected to each variable.

Table 1. Definition of variables that constitute the indicator

Variable (name)	Definition of variable	Reference
$IWT_{i,n}$ (degree of technology integration)	Value obtained by measuring the degree of integration between technologies	[11, 31-34]
$t_{i,n}$ (sum of individual technology elements)	Sum of nth technology element in year i	[10, 15, 35]
$T_{i,n}$ (technology forecasting indicator)	New technology forecasting indicator that enables the understanding of technology trends and reflects the degree of technology integration	[1,2,30,35]

3.1.2 Sum of individual technology elements ($t_{i,n}$)

For technology forecasting, technologies should be classified considering their characteristics, and the classified sub-technologies can be called technology clusters [36]. If the trends of technologies by the classified technology cluster are grasped and comprehensively calculated, technology levels can be assessed [2]. **Table 2** shows an example of the classification of 3D printing technologies. Here, $t_{i,n}$, which is the sum of individual technology elements in year *i* that constitutes each technology cluster, becomes basic data for technology forecasting.

Table 2. Classification of 3D printing technologies

Target technology	Technology cluster(sub-technology)
3D printing technology	Process technology
	Materials and processing technology
	Application and service technology

Source: Institute for Information and Communications Technology Promotion(2018)

3.1.3 Degree of technical integration ($IWT_{i,n}$)

Patent co-classification analysis is possible because multiple IPC codes are assigned to each patent document in general so that the technologies can be classified by IPC code. In this study, taking note of the fact that links exist between IPC codes, each IPC code was considered a node of the network, and each integration between technologies was considered a link, which is a connection between nodes. That is, as shown in **Fig. 4**, the patented technologies classified by patent document numbers were reconstructed as network connections between IPC codes using the social network analysis methodology to determine the integrations between technologies [11,37,38,39]. Cyram Co.'s NetMiner 4 was used as a tool for social network analysis.

Patent application number	Main IPC	IPC	IPC	IPC
15/019551	B64	G07	G08	H04
15/186215	G05	B64	H04	G08
14/866719	G01	B64	G05	-

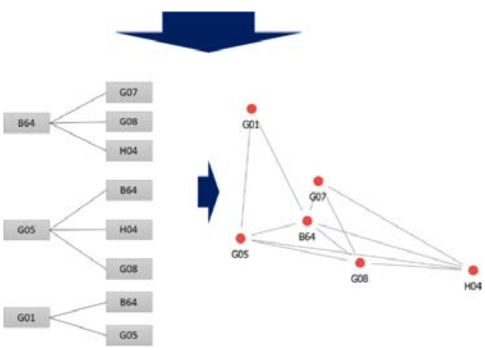


Fig. 4. Process of construction of patent co-classification analysis network

$IWT_{i,n}$ (Integration Within a Technology cluster) refers to the degree of technology integration within the n^th^ technology cluster in year *i* and is calculated using inclusiveness, one of the indicators of social network analysis. Inclusiveness is defined as the ratio of the total number of nodes included in the network to the total number of nodes, minus the number of nodes not connected (isolated nodes). When the structure of network technology networks such as patents cohere, mutual exchanges between technologies become active, leading to the development of technologies [11,31]. Inclusiveness is an indicator that can show the coherence of networks, and higher inclusiveness means more interrelations between nodes [31]. That is, since higher inclusiveness can be judged to be associated with higher levels of information sharing or mutual exchanges among nodes, inclusiveness is used as an indicator to grasp connection structures or the degree of integration of the networks [40,41].

In this study, IPC codes that are not connected, such as nodes H01 and B29 in **Fig. 5**, were judged to have no effect on connected IPC codes. Therefore, such IPC codes were assumed to not be relevant to the calculation of the degree of technology integration for the development of technologies. A formula for the degree of technology integration using inclusiveness is written as shown in Equation (1), where $I_{i,n}$ refers to the degree of technology integration of the n^{th} technology in *i*, N_{total} refers to the total number of all IPC codes, which corresponds to the entire nodes, and $N_{isolated}$ refers to the number of IPC codes that are not connected.

$$I_{i,n} = \frac{N_{total} - N_{isolated}}{N_{total}} \quad (1)$$

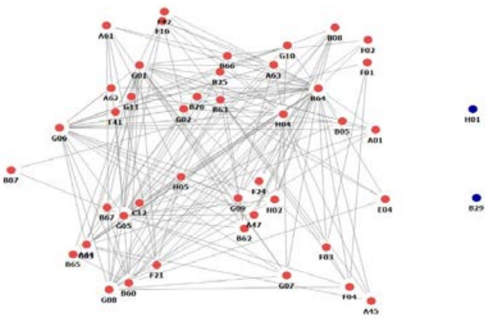


Fig. 5. Example of patent co-classification networks

3.1.4 Formula for calculating technology forecast indicator ($T_{i,n}$)

This study goes through an intermediate process for calculation of the technology forecasting indicator as shown in Equation (2). $P_{i,n}$ refers to the cumulative number of patents up to year i of the n^{th} technology cluster. The numbers of patents are often used as an indicator for technology analysis or technology forecasting because of the ease of collection of relevant data [42,43]. However, there have been arguments that new indexes should be developed in addition to the existing patent indices, such as the number of patents, to conduct patent analysis from various perspectives [44,45,46,47,48].

Therefore, this study devises a technology forecasting indicator using $\acute{P}_{i,n}$, which is the cumulative number of patents modified by calculating the degree of integration of patent technologies in the technology cluster. $T_{i,n}$, which is the technology forecasting indicator considering the degree of technology integration, is calculated by Equation (3), which has undergone logarithmic scaling considering rapid increases in numerical values after calculating Equation (2) [35,48]. $T_{i,n}$ has the effect of correcting the existing number of patents with the value of the degree of technology integration.

$$\acute{P}_{i,n} = IWT_{i,n} \times P_{i,n} \quad (2)$$

$$T_{i,n} = \ln\left(\frac{\acute{P}_{i,n}}{P_{i,n}}\right) \quad (3)$$

3.2 Validity verification

3.2.1 Model estimation

In order to determine whether the proposed forecasting indicator can actually be used, patent data related to "drone technology" were entered into the indicator to estimate technology growth models. The Logistic model and Gompertz model were used as the technology growth models, and the proposed technology forecast indicator was substituted into the models as a dependent variable to estimate the models [26,30]. In addition, the cumulative number of patents by year ($P_{i,n}$), which is an existing forecasting indicator, was substituted into the models to estimate the models, and comparative analysis was conducted.

Nonlinear least squares methods were used for model estimation [49], and STATA 16 was used as a tool for analysis [50]. Equation (4) is for logistic models, and Equation (5) is for Gompertz models. Independent variable $\acute{\imath}$ is the modified values of the years of application of patents by adjusting the year of start of patent application (1980) to 1. The models use the technology forecasting indicator as a dependent variable. L_n in Equation (4) and (5) are the values of the ultimate technology levels obtained through model estimation. When calculating the value of the technology level at a certain time point, the value of the technology forecasting indicator is divided by L_n and the result is indicated as $\acute{T}_{i,n}$.

Thereafter, the parameters(L_n, α_n, β_n) of equations for the logistic model and the Gompertz model are estimated by the nonlinear least squares method. The p values of the parameters used to estimate each model are identified at a significance level of 5%. Whether the technology forecasting indicator proposed in this study is suitable as a dependent variable of the technology growth models is judged based on the results of the identification.

$$T_{i,n} = L_n \,/\, \left(1 + exp\left(-\alpha_n \times (\acute{\imath} - \beta_n)\right)\right) \quad (4)$$

$$T_{i,n} = L_n \times exp\,\left(-exp\left(-\alpha_n \times (\acute{\imath} - \beta_n)\right)\right) \quad (5)$$

3.2.2 Verification of the model fit of the proposed indicators by comparing predictive power

Mean absolute percentage error (MAPE) [51,52,53], mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE) were used to verify the goodness of fit of the models [51]. The excellence of the predictive power of the proposed technology forecasting indicator is identified by comparing the sizes of the values obtained when the existing numbers of patents and the proposed technology forecasting indicator are substituted into individual indicators. When estimating the models, the differences between the calculated predicted values and the actual observed values were used to calculate the values of predictive power. The calculation formulas for individual indicators are as shown in **Table 3**.

Table 3. Model fit measuring indicators

Indicator	Formula
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{i}{v}\sum_{k=1}^{v}\left\lvert\frac{y_k - \hat{y}_k}{y_k}\right\rvert \times 100$
Mean Absolute Error (MAE)	$MAE = \frac{i}{v}\sum_{k=1}^{v}\lvert y_k - \hat{y}_k\rvert$
Mean Squared Error (MSE)	$MSE = \frac{i}{v}\sum_{k=1}^{v}(y_k - \hat{y}_k)^2$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{k=1}^{v}(y_k - \hat{y}_k)^2}{v}}$
y_k= predicted value, $\hat{y}_k$= actually observed value, v= number of variables	

4. Experiment results and analysis

4.1 Experimental data

4.1.1 Technology classification and descriptive statistics

This study utilized drone technology-related patent data to verify technology forecasting methodologies including the proposed technology forecasting indicator. Technologies were classified as shown in **Table 4** referring to the drone technology classification of the South Korean civil-military technology cooperation project [54], and patent data for each technology were collected. Under the patent search conditions, 1,799 registered patent documents in the United States for 38 years (1980 to 2017) were downloaded from the Wipson database. Thereafter, a total of 1,494 cases were selected as experimental data through a data preprocessing process.

Patents belonging to technology cluster 1 include patents for parts of motors, etc. that affect flight capability, and patents related to component parts such as manipulating arms for fine work. Patents constituting technology cluster 2 include patents related to controllers, sensors, and transmission systems that belong to the base system that supports drone takeoff and landing, and patents for component parts for stable takeoff and landing, such as landing gears. Finally, technology cluster 3 includes technologies related to charging such as technologies that support charging of power necessary for drone flying or systems that analyze a drone's remaining power for flight and designate charging bases.

Table 4. Details of experiment data

Technology	Technology cluster (sub-technology)	Number of patents (cases)
Drone task performance technology	**Technology cluster 1** High-precision manipulation technology for drone task performance	817
	Technology cluster 2 Precise drone takeoff and landing technology	484

	Technology cluster 3 Drone charging technology	193
	Total	1,494

4.2 Result of technology forecasting

$\acute{P}_{i,n}$, which reflects the degree of technology integration, is calculated using the cumulative numbers of patents by year and the calculated $IWT_{i,n}$ as shown in Equation (2) and a logarithmic scaled [36,48] technology forecasting indicator ($T_{i,n}$) is calculated considering rapid changes in the numerical value of $\acute{P}_{i,n}$. Thereafter, the values of $T_{i,n}$ by year are substituted into the Logistic model and Gompertz model, which are technology growth models, by technology cluster as shown in Equation (4) and (5), and the parameters (L_n, α_n, β_n) of the models are estimated. If the results of estimation of parameters are statistically significant, technology forecasting is possible. It can be seen that, over time, individual technologies reach the ultimate levels of technologies to show S-curves and reach saturated conditions.

Table 5 shows the results of logistic model estimation of technology cluster 1, and **Table 6** shows the results of Gompertz model estimation of technology cluster 1. It can be confirmed that the parameters(L_1, α_1, β_1) are statistically significant at the 5% level in both technology growth models. Therefore, the proposed technology forecasting indicator can be used for technology forecasting because it is suitable for the technology growth models. For your reference, on reviewing changes in technologies in 2017 based on the Logistic model, it can be seen that 2017 belongs to the growth step because the level of technologies is 73% compared to the ultimate level of technologies.

Table 7 shows the results of logistic model estimation of technology cluster 2. It is found that all parameters(L_2, α_2, β_2) are statistically significant at the 5% level. However, the results of the Gompertz model estimation in **Table 8** show that the parameter L_2 is not statistically significant at the 5% level. Therefore, based on the results of the proposed technology forecasting of technology cluster 2, only the results obtained from the logistic model are valid. For your reference, on reviewing changes in technologies in 2017 based on the Logistic model, it can be seen that 2017 belongs to the growth step because the level of technologies is 57% compared to the ultimate level of technologies.

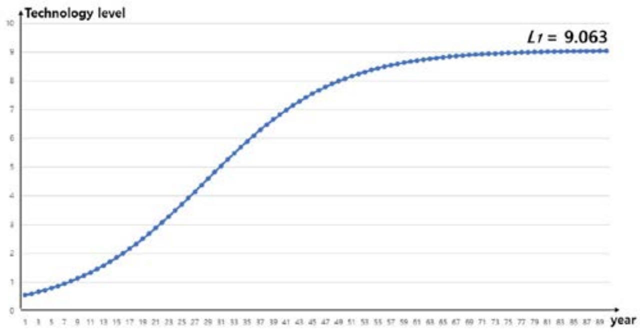
Table 9 and **Table 10** are the results of model estimation of technology cluster 3. It is found that all the parameters(L_3, α_3, β_3) are statistically significant at the 5% level in the case of both technology growth models. For your reference, on reviewing changes in technologies in 2017 based on the Logistic model, it can be seen that 2017 belongs to the growth step because the level of technologies is 66% compared to the ultimate level of technologies.

By substituting $\acute{T}_{i,n}$, which is each calculated technology forecasting indicator, into Equation (6), the resultant general level of technologies for a certain year can be calculated. After scaling each $\acute{T}_{i,n}$ to (0, 1), the average is calculated for the results of assessment of the general level of technologies, as shown in Equation (6). According to the results of calculation, the level of "drone task performance technology" in 2017 is 0.657, which means the relative technology level when the final ultimate technology was set to 1. That is, the current level of drone task performance-related technologies is about 65.7% of the ultimate level, indicating that the technologies are at the growth stage.

$$TI_{2017} = \frac{1}{3}\begin{bmatrix}0.735\\0.570\\0.667\end{bmatrix} = 0.657 \qquad (6)$$

Table 5. Results of technology growth model estimation of technology cluster 1 (Logistic model)

Number of observations	R^2	Parameter	Estimated value	Standard deviation	P-value
38	0.996	L_1	9.0633	0.784	0.000**
		α_1	0.098	0.007	0.000**
		β_1	28.701	1.931	0.000**

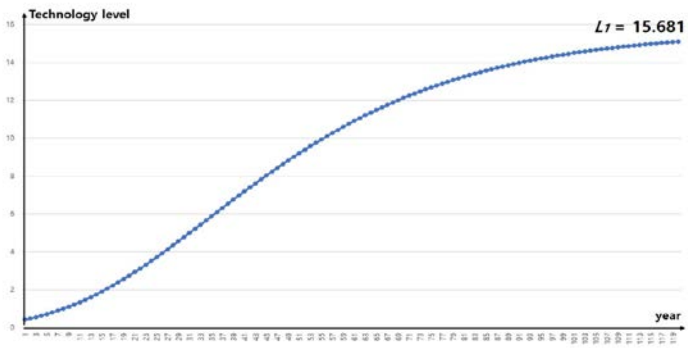


Results of technology forecasting (2017)	$\acute{T}_{2017,1}= T_{2017,1}/L_1$= 73.490%(6.661/9.063)

**means that it is significant within the significance level of 5%

Table 6. Results of technology growth model estimation of technology cluster 1 (Gompertz model)

Number of observations	R^2	Parameter	Estimated value	Standard deviation	P-value
38	0.997	L_1	15.681	2.839	0.000**
		α_1	0.038	0.005	0.000**
		β_1	34.488	4.638	0.000**

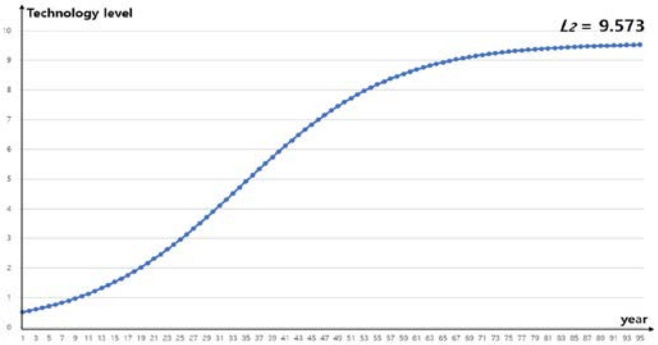


Results of technology forecasting (2017)	$\acute{T}_{2017,1}= T_{2017,1}/L_1$= 42.476%(6.661/15.681)

**means that it is significant within the significance level of 5%

Table 7. Results of technology growth model estimation of technology cluster 2 (Logistic model)

Number of observations	R^2	Parameter	Estimated value	Standard deviation	P-value
38	0.995	L_2	9.573	1.502	0.000**
		α_2	0.086	0.007	0.000**
		β_2	34.347	3.599	0.000**

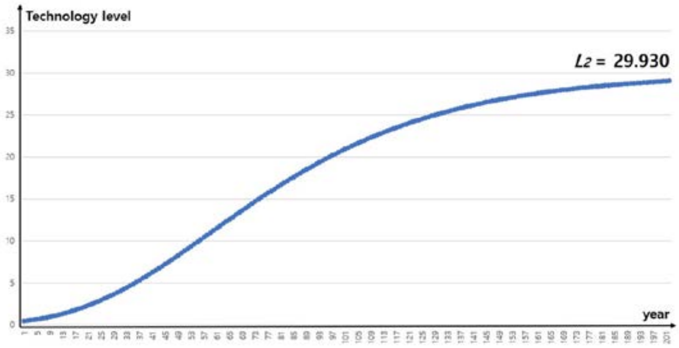


Results of technology forecasting (2017)	$\acute{T}_{2017,2}= T_{2017,2}/L_2$=57.046%(5.461/9.573)

**means that it is significant within the significance level of 5%

Table 8. Results of technology growth model estimation of technology cluster 2 (Gompertz model)

Number of observations	R^2	Parameter	Estimated value	Standard deviation	P-value
38	0.995	L_2	29.930	15.883	0.068
		α_2	0.025	0.006	0.000**
		β_2	59.107	17.307	0.002**

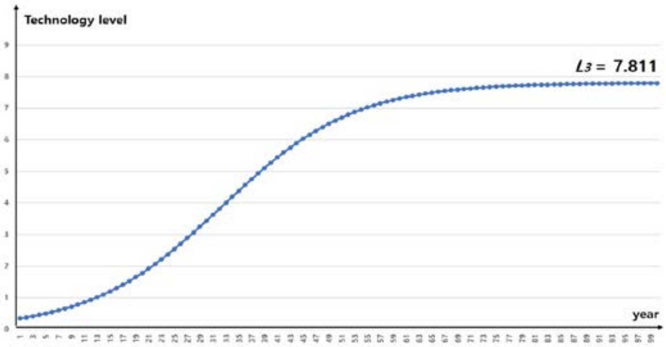


Results of technology forecasting (2017)	Not calculated ($L_2$is not statistically significant)

**means that it is significant within the significance level of 5%

Table 9. Results of technology growth model estimation of technology cluster 3 (Logistic model)

Number of observations	R^2	Parameter	Estimated value	Standard deviation	P-value
38	0.993	L_3	7.811	1.180	0.000**
		α_3	0.098	0.009	0.000**
		β_3	32.476	3.181	0.000**

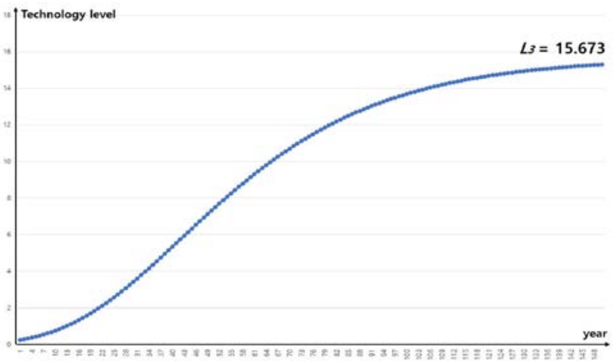


Results of technology forecasting (2017)	$\acute{T}_{2017,3}= T_{2017,3}/L_3$= 66.661%(5.207/7.811)

**means that it is significant within the significance level of 5%

Table 10. Results of technology growth model estimation of technology cluster 3 (Gompertz model)

Number of observations	R^2	Parameter	Estimated value	Standard deviation	P-value
38	0.993	L_3	15.673	5.041	0.004**
		α_3	0.035	0.006	0.000**
		β_3	42.121	8.431	0.000**



Results of technology forecasting (2017)	$\acute{T}_{2017,3}= T_{2017,3}/L_3$=66.225%(5.207/15.673)

**means that it is significant within the significance level of 5%

4.3 Validity verification

4.3.1 Verification of the goodness of fit of the models

The model estimation results of the technology growth models using the technology forecasting indicator proposed in this study and the technology growth model using the existing indicators were compared. As shown in **Table 11**, it was confirmed that the parameters of both the existing and proposed indicators were statistically significant except for L_2, which is the parameter of the Gompertz model when the proposed technology forecasting indicator was input to the model. Therefore, it can be judged that the proposed technology forecasting indicator can be used for technology forecasting based on the technology growth model.

Table 11. The goodness of fit of the models

Technology cluster	Technology forecasting indicator	Parameter	P-value	
			Logistics model	Gompertz model
1	Proposed technology forecasting indicators ($T_{i,1}$)	L_1	0.000**	0.000**
		α_1	0.000**	0.000**
		β_1	0.000**	0.000**
	Existing Cumulative number of patents ($P_{i,1}$)	L_1	0.000**	0.017**
		α_1	0.000**	0.000**
		β_1	0.000**	0.007**
2	Proposed technology forecasting indicators ($T_{i,2}$)	L_2	0.000**	0.068
		α_2	0.000**	0.000**
		β_2	0.000**	0.000**
	Existing Cumulative number of patents ($P_{i,2}$)	L_2	0.000**	0.002**
		α_2	0.000**	0.000**
		β_2	0.000**	0.000**
3	Proposed technology forecasting indicators ($T_{i,3}$)	L_3	0.000**	0.000**
		α_3	0.000**	0.000**
		β_3	0.000**	0.000**
	Existing Cumulative number of patents ($P_{i,3}$)	L_3	0.004**	0.002**
		α_3	0.000**	0.000**
		β_3	0.000**	0.000**

**means that it is significant within the significance level of 5%

4.3.2 Comparison of predictive power

The excellence of predictive power was compared between the existing cumulative numbers of patents($P_{i,n}$) and the proposed technology forecasting indicator to verify the validity of the proposed indicator. Four predictive power comparison indicators were used to compare predictive power, and the predictive power of the indicators with smaller values was judged to be more excellent. As shown in **Table 12**, The proposed technology forecasting indicator($\boldsymbol{T_{i,n}}$) had better predictive power than the existing indicator($\boldsymbol{P_{i,n}}$) in 22 out of 24 cases.

Table 12. Comparison of predictive power

Technology cluster	Technology growth model	Comparison of predictive power	Existing Cumulative number of patents ($P_{i,n}$)	Proposed technology forecasting indicators ($T_{i,n}$)	Results of comparison
1	Logistic	MAPE	0.078	0.054	$T_{i,n}$ Excellent
		MAE	0.220	0.160	$T_{i,n}$ Excellent
		MSE	0.106	0.049	$T_{i,n}$ Excellent
		RMSE	0.325	0.222	$T_{i,n}$ Excellent
	Gompertz	MAPE	0.078	0.057	$T_{i,n}$ Excellent
		MAE	0.215	0.145	$T_{i,n}$ Excellent
		MSE	0.095	0.038	$T_{i,n}$ Excellent
		RMSE	0.309	0.195	$T_{i,n}$ Excellent
2	Logistic	MAPE	0.074	0.068	$T_{i,n}$ Excellent
		MAE	0.208	0.150	$T_{i,n}$ Excellent
		MSE	0.085	0.040	$T_{i,n}$ Excellent
		RMSE	0.292	0.201	$T_{i,n}$ Excellent
	Gompertz	MAPE	0.071	0.071	-
		MAE	0.194	0.151	$T_{i,n}$ Excellent
		MSE	0.070	0.040	$T_{i,n}$ Excellent
		RMSE	0.264	0.199	$P_{i,n}$ Excellent
3	Logistic	MAPE	0.087	0.130	$T_{i,n}$ Excellent
		MAE	0.214	0.176	$T_{i,n}$ Excellent
		MSE	0.074	0.045	$T_{i,n}$ Excellent
		RMSE	0.271	0.213	$T_{i,n}$ Excellent
	Gompertz	MAPE	0.079	0.112	$P_{i,n}$ Excellent
		MAE	0.199	0.160	$T_{i,n}$ Excellent
		MSE	0.062	0.035	$T_{i,n}$ Excellent
		RMSE	0.249	0.188	$T_{i,n}$ Excellent

4.4 Results of analysis

In this chapter, an empirical analyses was conducted using actual “drone task performance technology” patent data to understand the trend of drone technologies. In order to verify the validity of the technology forecasting indicator proposed in this study, two verification were carried out.

① Existing technology forecasting indicator and the indicator proposed in this study were respectively applied into the technology growth model. After that, the model estimation results were compared. We found that the proposed indicator was identified to be suitable for model estimation except one parameter in Gompertz model.

② The predictive power of the previously used indicator and the indicator proposed in this study ware compared. It was identified that the predictive power of the proposed method was more excellent in many results of comparison of predictive power(22 cases out of 24 cases).

Summarizing the analysis results, it can be concluded that the proposed method in this study, which reflects the degree of technology integration, is more suitable for technology forecasting than the existing method using only the cumulative number of patents.

5. Conclusion

With a view to improving the limitations of existing technology forecasting, this study proposed a technology forecasting methodology that can reflect the degree of technology integration considering the relationship between technologies based on patent data. Social network analysis, which enables easy understanding of the relationships between technologies, was used to measure the degree of technology integration. The significances of this study are as follows. First, this study established a theoretical basis for research models that reflect the degree of technology integration based on Social Network Analysis. Second, this study quantitatively verified the proposed methodology using actual patent data. Since this study utilized quantitative data, the technology forecasting indicator or formulas, which belong to the research models, were verified from various angles with model estimation and comparison of predictive power.

On the other hand, there are some limitations in the study. First, for more sophisticated technology forecasting, verification using datasets from other technology fields besides drone technology is required. Second, from the point of view of policy implementation, it is necessary to analyze its cost-effectiveness in future research.

References

[1] J. Ryu, S. C. Byeon, “Technology level evaluation methodology based on the technology growth curve,” *Technological Forecasting and Social Change*, Vol. 78, no. 6, pp. 1049-1059, 2011. Article (CrossRef Link)

[2] S. C. Byeon, J. Ryu, S. Son, K. H. Choi, K. Hwang, B. S. Kim and Y. G. Kim, “Research on the Technology Level Evaluation Methodology using a Technology Growth Model,” in *Proc. of PICMET 2009, conference*, Portland, USA, 2009.

[3] A. Jha, D. Saha, “Forecasting and analyzing the characteristics of 3G and 4G mobile broadband diffusion in India: A comparative evaluation of Bass, Norton-Bass, Gompertz and logistic growth models,” *Technological Forecasting & Social Change*, Vol. 152, 2020. Article (CrossRef Link)

[4] M. Lee, K. Kim and Y. Cho, “A study on the relationship between technology diffusion and new product diffusion,” *Technological Forecasting and Social Change*, Vol. 77, pp. 796-802, 2010. Article (CrossRef Link)
[5] M. S. Kim, C. Kim, “On A Patent Analysis Method for Technological Convergence,” *Procedia – Social and Behavioral Sciences*, Vol. 40, pp. 657-663, 2012. Article (CrossRef Link)
[6] D. Thorleuchter, D. Van den Poel and A. Prinzie, “A compared R&D-based and patent-based cross impact analysis for identifying relationships between technologies,” *Technological Forecasting and Social Change*, Vol. 77, no. 7, pp. 1037-1050, 2010. Article (CrossRef Link)
[7] Y. Geum, C. Kim, S. Lee, M. Kim, “Technological convergence of IT and BT: Evidence from patent analysis,” *ETRI Journal*, Vol. 34, no. 3, pp.439-449, 2012. Article (CrossRef Link)
[8] J. H. Han, J. G. Na and C. B. Kim, “ A Study of ICT Technology Convergence Analysis and Development Direction by Using the Patent Information : focusing on Kyongbuk area company,” *The Journal of Intellectual Property*, Vol. 10, no. 3, pp.203-238, 2015. Article (CrossRef Link)
[9] C. W. Hsu, C. Y. Lin, “Using social network analysis to examine the technological evolution of fermentative hydrogen production from biomass,” *International Journal of Hydrogen Energy*, Vol. 41, no. 46, pp. 21573-21582, 2016. Article (CrossRef Link)
[10] H. W. Kim, J. C. Kim, J. H. Lee, S. S. Park and D. S. Jang, “A Novel Methodology for Extracting Core Technology and Patents by IP Mining,” *Journal of Korean Institute of Intelligent Systems*, Vol. 25, no. 4, pp. 392-397, 2015. Article (CrossRef Link)
[11] J. W. Kim, B. K. Jeong and J. H. Yoon, “A Technology Planning Approach Based on Network and Growth Curve Analyses : the Case of Augmented Reality Patents,” *Journal of the Korean Institute of Industrial Engineers*, Vol. 42, no. 5, pp.337-351, 2016. Article (CrossRef Link)
[12] Moussa, B., Varsakelis, N. C., “International patenting: An application of network analysis,” *The Journal of Economic Asymmetries*, vol. 15, pp. 48-55, 2017. Article (CrossRef Link)
[13] Y. N. Park, Y. Lee, J. Kim and T. Lee, “The structure and knowledge flow of building information modeling based on patent citation network analysis,” *Automation in Construction*, Vol. 87, pp. 215-224, 2018. Article (CrossRef Link)
[14] Y. Suh, J. Jeon, ”Monitoring patterns of open innovation using the patent-based brokerage analysis,” *Technological Forecasting and Social Change*, Vol. 146, pp. 595-605, 2019. Article (CrossRef Link)
[15] H. Sun, Y. Geng, L. Hu, L. Shi and T. Xu, “Measuring China’s new energy vehicle patents: A social network analysis approach,” *Energy*, Vol. 153, pp. 685-693, 2018.
[16] K. R. Lee, J. T. Hwang, “A Study on Innovation System with Multi-technology Fusion,” *Science & Technology Policy Institute*, 2005.
[17] M. Iansiti, J. West, “Technology Integration: Turning Great Research into Great Products,” *Harvard Business Review*, 1997.
[18] K. R. Lee, “Patterns and processes of contemporary technology fusion: The case of intelligent Robots,” *Asian Journal of Technology Innovation*, Vol. 15, no. 2, pp. 45-65, 2007. Article (CrossRef Link)
[19] F. Kodama, “Analyzing Japanese High Technologies: The Techno Paradigm Shift,” *London: Pinter Publishers*, 1991.
[20] L. Fleming, O. Sorenson, “Technology as a complex adaptive system: evidence from patent data,” *Research Policy*, Vol. 30, no. 7, pp. 1019-1039, 2001. Article (CrossRef Link)
[21] S. Wasserman, K. Faust, *Social network analysis*, Cambridge, UK: CambridgeUniversity Press, 1994.
[22] S. Jun, S. S. Park, “Examining technological innovation of Apple using patent analysis,” *Industrial Management & Data Systems*, Vol. 113, no. 6, pp. 890-907, 2013. Article (CrossRef Link)
[23] C. S. Weng, W. Y. Chen, H. Y. Hsu and S. H. Chien, “To study the technological network by structural equivalence,” *The Journal of High Technology Management Research*, Vol. 21, no. 1, pp. 52-63, 2010. Article (CrossRef Link)
[24] Y. Zhou, X. Li, R. Lema and F. Urban, “Comparing the knowledge bases of wind turbine firms in Asia and Europe: Patent trajectories, networks, and globalization,” *Science and Public Policy*, Vol. 43, no. 4, pp. 476-491, 2016. Article (CrossRef Link)
[25] T. U. Daim, G. Rueda, H. Martin and P. Gerdsi, “Forecasting emerging technologies: Use of bibliometrics and patent analysis,” *Technological Forecasting and Social Change*, Vol. 73, no. 8, pp. 981-1012, 2006. Article (CrossRef Link)

[26] M. K. Han, B. S. Kim, J. Y. Ryu and S. C. Byeon, “Technology Level Evaluation Based On Technology Growth Model and Its Implication - In Case of Biochip and Biosensor Technology,” *Journal of Korea Technology Innovation Society*, Vol. 13, no. 2, pp. 252-281, 2010.

[27] H. Ernst, “The use of patent data for technological forecasting: The diffusion of CNC-technology in the machine tool industry,” *Small Business Economics*, Vo. 9, pp.361-381, 1997. Article (CrossRef Link)

[28] M. Gupta, M. Gerard, S. S. Padmaja and R. K. Sastry, “Trends of CRISPR technology development and deployment into Agricultural Production-Consumption Systems,” *World Patent Information*, Vol. 60, 2020. Article (CrossRef Link)

[29] A. Lotfi, W. E. Hala, “Forecasting technology diffusion: a new generalization of the logistic model,” *Technology Analysis & Strategic Management*, Vol. 16, no. 8, pp. 943-957, 2014. Article (CrossRef Link)

[30] W. M. Kim, J. C. Park and P. M. Bark, “Comparative Study on Science and Technology Level Assessment – Case Study of Fishery and Construction Engineering Technology areas between Korea and Other Countries including Japan,” *JOURNAL OF NORTH-EAST ASIAN CULTURES*, Vol. 50, pp. 225-239, 2017. Article (CrossRef Link)

[31] S. Li, E. Graces and T. Daim, “Technology forecasting by analogy-based on social network analysis: The case of autonomous vehicles,” *Technological Forecasting and Social Change*, Vol. 148, 2019. Article (CrossRef Link)

[32] B. J. Sauser, “System Maturity Metrics for Decision Support in Defense Acquisition,” U.S. Army Armament Research Development Engineering Center, 2007.

[33] B. Sauser, J. E. Ramirez-Marquez, D. Henry and D. DiMarzio, “A system maturity index for the systems engineering life cycle,” *International Journal of Industrial and Systems Engineering*, Vol. 3, no. 6, pp. 673-691, 2008. Article (CrossRef Link)

[34] B. Sauser, R. Gove, E. Forbes and J. E. Ramirez- Marquez, “Integration maturity metrics: Development of an integration readiness level,” *Information Knowledge Systems Management*, vol. 9, no. 1, pp. 17-46, 2010. Article (CrossRef Link)

[35] J. Han, “2018 Technology Level Assessment,” *Korea Institute of Science & Technology Evaluation and Planning*, 2019.

[36] B. R. Lim, W. Jutidamrongphan, K. Y. Park, ”Comparison of Models to Describe Growth of Green Algae Chlorella vulgaris for Nutrient Removal from Piggery Wastewater,” *Journal of the Korean Society of Agricultural Engineers*, Vol. 52, no. 6, pp. 19-26, 2010. Article (CrossRef Link)

[37] H. M. Baek, M. S. Kim, “Technological Convergence Trend through Patent Network Analysis: Focusing on Patent Data in Korea, U.S., Europe, and Japan,” *Asia-Pacific Journal of Business Venturing and Entrepreneurship*, Vol. 8, no. 2, pp.11-19, 2013. Article (CrossRef Link)

[38] B. C. Choi, H. M. Baek, M. S. Kim, “Patent Citation Network Analysis as a Measure of Technical Knowledge Diffusion in Korea: Focusing on ICT,” *Asia-Pacific Journal of Business Venturing and Entrepreneurship*, Vol. 10, no. 1, pp.143-151, 2015. Article (CrossRef Link)

[39] C. S. Curran, J. Leker, “Patent indicators for monitoring convergence – examples from NFF and ICT,” *Technological Forecasting and Social Change*, Vol. 78, no. 2, pp.256-273, 2011. Article (CrossRef Link)

[40] S. S. Kim, S. Y. Lee and A. Shishkov, “Service Networks between Trunk and Feeder Liners in the intra-Asia Container Shipping Market: A Comparison Study,” *The Journal of shipping and logistics*, Vol. 32, no. 4, pp. 579-598, 2016. Article (CrossRef Link)

[41] M. P. Vittoria, G. L. Lavadera, “Knowledge networks and dynamic capabilities as the new regional policy milieu,” *A social network analysis of the Campania biotechnology community in southern Italy. Entrepreneurship and Regional Development*, Vol. 26, no. 7, pp. 594-618, 2014. Article (CrossRef Link)

[42] C. V. Trappey, H. Y. Wu, F. Taghaboni-Dutta and A. J. C. Trappey, “Using patent data for technology forecasting: China RFIP patent analysis,” *Advanced Engineering Informatics*, Vol. 25, Issue 1, pp. 53-64, 2011. Article (CrossRef Link)

[43] R. J. Watts, A. L. Porter, “Innovation Forecasting,” *Technological Forecasting and Social Change*, Vol. 56, no. 1, pp. 25-47, 1997. Article (CrossRef Link)

[44] M. Bengisu, R. Nekhili, “Forecasting emerging technologies with the aid of science and technology databases,” *Technological Forecasting and Social Change*, Vol. 73, no. 7, pp. 835-844, 2006. Article (CrossRef Link)

[45] S. D. Cho, "Assessment of Technological Level using the Quantitative Method. Doctoral dissertation," *University of Science and Technology*, Daejeon, S.Korea, 2017. Article (CrossRef Link)

[46] G. Kim, J. Bae, "A novel approach to forecast promising technology through patent analysis," *Technological Forecasting and Social Change*, Vol. 117, pp.228-237, 2017. Article (CrossRef Link)

[47] J. C. Kim, J. H. Lee, S. S. Park and D. S. Jang, "Technology Strategy based on Patent analysis," *Korean Institute of Intelligent Systems*, Vol. 26, no. 2, pp. 141-146, 2016. Article (CrossRef Link)

[48] G. W. Seo, "Development and application of technology level evaluation research methodology using patent indicators," *Korea Institute of Science &Technology Evaluation and Planning*, 2011.

[49] S. K. Yeom, S. P. Hong, H. I. Kang, J. S. Kim and C. H. Jun, "Determination of starting values in estimating growth curves by using non-linear least squares," *IE Interfaces*, Vol. 14, no. 2, pp. 190-197, 2001. Article (CrossRef Link)

[50] D. W. Lee, "Exploratory research on the analysis of national R&D programs using growth model," *Korea Institute of Science and Technology Evaluation and Planning*, 2013.

[51] D. H. Kim, S. S. Park, Y. G. Shin and D. S. Jang, "Forecasting the Diffusion of Technology using Patent Information : Focused on Information Security Technology for Network-Centric Warfare," *JOURNAL OF THE KOREA CONTENTS ASSOCIATION*, Vol. 9, no. 2, pp.125-132, 2009. Article (CrossRef Link)

[52] Y. J. Min, K. S. Lim, "Comparative Evaluation of Diffusion Models using Global Wireline Subscribers," *Journal of Information Technology Applications & Management*, Vol. 21, no. 4, pp. 403-414, 2014. Article (CrossRef Link)

[53] K. Y. Noh, S. B. Sim, S. M. Hong and B. J. Jeong, "A study on hybrid demand forecasting for mobile phone," *Korean Institute Of Industrial Engineers*, pp. 1222-1228, 2011. Article (CrossRef Link)

[54] *National Science and Technology Council*, 2nd Master Plan for the Civil-Military Technology Cooperation Project, 2018.

[55] P. Sharma, R. C. Tripathi, "Patent citation: A technique for measuring the knowledge flow of information and innovation," *World Patent Information*, Vol. 51, pp. 31-42, 2017. Article (CrossRef Link)

[56] C. Sternitzke, A. Bartkowski and R. Schramm, "Visualizing patent statistics by means of social network analysis tools," *World Patent Information*, Vol. 30, no. 2, pp. 115-131, 2008. Article (CrossRef Link)

[57] B. S. Kim, S. H. Bae and S. I. Baek, "Exploring the Network Structure of Online Communities by Using Social Network Analysis," *Entrue Journal of Information Technology*, Vol. 11, no. 1, pp. 59-72, 2012.

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