Reviewing discussion on ICT convergence in the future of electricity industry

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Abstract

The smart energy, which is a convergence of energy and ICT, has been remarkable in the fields of electric power. This study has collected 58 reports on the future of the electric power industry for a total of 13 years from 2006 to 2018. We examined the association rules between ICTs and their functions and effects with the collected reports dealing with the future of the electricity industry. As a result, we identified that the debate on ICT convergence has continued to expand in the discussion of the future of the electricity industry from the late 2000s until recently. This study is differentiated in that the recognition of keyword 'ICT' were changed over time with association rules and discussions related to detailed technologies were examined.

Keywords: electricity industry, association rules, ICT convergence, text mining

1. Introduction

Information and Communications Technologies (ICTs) accelerate the creation of new products and services throughout convergence. As the boundary between ICT and non-ICT has disappeared, the capabilities of ICT convergence is considered as one of the core factors to secure competitiveness in the future. The ICT convergence can be understood as a trend of goods advancement, service innovation, and added value creation by embedding ICTs in goods and services belonging to other industries [1]. As the competitiveness of energy industries has been shifted from natural resources to technical capacities, it is expected that ICT convergence will be an increasingly common phenomenon in the energy industries [2].

The efficiency, safety, and environment-friendly features of energy systems can be improved throughout ICT convergence by energy sources (power, gas, oil, renewable energy, etc.) and life cycle (from production to delivery, and to consumption). Recently, the smart energy, which is a convergence of energy and ICT, has been remarkable in the fields of electric power. ICT convergence in the energy sector has led to considerable changes in policies related to energy industries [2].

In the power sector, smart grids are prime examples of ICT convergence. A smart grid can be defined as an electric power infrastructure that promotes energy conservation, renewable energy supplies, and electric vehicle (EV) operations by integrating ICT into existing power grids for real-time bidirectional power information exchange between the suppliers and the consumers. A smart grid is equipped with a distributed and intelligent power grid management platform that consists of smart devices, bidirectional communication, and advanced control systems. Applications such as the integration of renewable energy, intellectualization of charging methods for EVs, smart metering, power grid monitoring, and demand response can be run on this platform. The features of a smart grid can be broadly explained as consumer participation; expansion and reinforced storability of distributed energy; new electric power markets; high-quality power; asset optimization and operational efficiency; advanced grid monitoring, protection,

and self-healing; and infrastructure for operating EVs. The smart grid technology is dispersed throughout the entire power system, which encompasses the stages of power generation, transmission, distribution, and delivery to the consumers [3,4].

In recent years, as the fourth-generation industrial revolution technologies such as big data analytics, Internet of things (IoT), and artificial intelligence (AI) are becoming mature, the electric power industry is developing in a more intelligent direction. Therefore, reports on the future of the electric power industry deal with functions and effects of those intelligent technologies [5]. However, the reports on the future of electricity industry, including the convergence of the power industry and ICTs, are primarily focused on the characteristics and effects of the intelligent technologies rather than on the ICT convergence trends. That is, the discussions on the ICT convergence of the electricity industry has been not dynamic but static.

Recently, there has been a study of ICT convergence in the electric power industry by reviewing the contents of various reports. Park et al. [5] analyzed the trends of ICT convergence through text mining by collecting the reports published by specialized research institutes to see how ICT convergence is changing in the electric power industry. However, by focusing on the term frequency analysis, they could not show in detail how ICT convergence takes place in the electric power industry. Park et al. [5], which attempted to understand ICT convergence phenomena comprehensively in the rapidly changing electric power industry, made a meaningful approach but it needs to be supplemented more qualitatively. This study aims to update the related data at the recent time and to see how the experts' perceptions about the functions and effects of ICT technologies in the electricity industry are changing. This study will contribute to providing comprehensive information on how the ICT convergence discussion is proceeding in the electricity industry.

The structure of this study is as follows. We discuss the ICT convergence in the electricity industry on the whole in Chapter 2. We explain the methodology of this study in Chapter 3. In Chapter 4, we show research results. In Chapter 5, we review the discussion on ICT convergence in the electricity industry dynamically and draw conclusions.

2. Overview of ICT Convergence in the Electricity Industry

ICT convergence in the electric power industry can be seen on the whole from the perspective of power generation, delivery, and consumption [2]. In the production process for convertible energy, such as electric power, there is an increase in the use of technologies that enable real-time monitoring and control of electric power systems over a wide area, as well as big data, state-of-the-art control solutions, and GIS technology for enhanced productivity in distributed generation, including renewable energy. Mainly, production process simulation and modeling, optimization of the production system, and use of early warning sensors to respond to system anomalies are being emphasized. In particular, ICT plays an important role in the areas of productivity enhancement of renewables and intermittent output management. Regarding wind turbines, the 2.5 MW smart wind turbine that GE introduced in 2013 is one such example. This turbine is designed to produce high electrical output even in areas without strong winds. The hub has a maximum height of 139 m and the rotor has a length of 120 m, which allows 15% more annual energy production than existing models. At this height, the wind turbine has economic validity even in heavily wooded areas. Also, it can also withstand extreme weather conditions including harsh winter conditions [6]. This turbine is connected to the turbine monitoring and control center via sensors and software that are connected to the network. Cutting edge sensors check the vibrations of the turbine and assess thousands of data per second.

Considering electricity delivery, the use of ICT is increasing in the areas of energy loss reduction in the energy delivery network, improvements in network anomaly detection and recovery, and enhancements in the use of storage equipment to ensure the efficiency and delivery of high-quality energy. For smart grid projects, grid management includes transmission enhancement applications for increasing the efficacy of transmission, reductions in the number of power outages and recovery time through sensing and automation, and the maintenance of the voltage. Critical grid functions include autonomous adaptation to network and responses to sensed network anomalies. The establishment of sensor

monitoring and remote control, augmented reality (AR), and integrated databases are being emphasized in the management and assessment of gas pipeline grid integrity. For the delivery of distributed energy, the importance of battery storage systems is increasing. The operation of the storage system is essential as its capacity for which a solution on how to use the optimal energy at the ideal time is needed.

In energy consumption sector, there have been efforts on developing tools for managing and checking energy consumption in homes and businesses, as well as improving the control algorithm technology. Furthermore, user interfaces have been made to be more intuitive for easier energy management. Similarly to energy supply, the simulation and optimization of energy consumption technologies are valued, and interoperability between devices and systems is emphasized [7].

ICT automatizes meter inspections and payment systems and facilitates the expansion of consumer-oriented services. In the future, suppliers and consumers will be able to verify energy consumption related information using a method of their choice in real time through wired or wireless network technologies [8]. Moreover, the consumers will have access to transparent energy consumption information, and as they are given the authority to control energy-consuming devices directly, they will behave as the active subject in energy efficiency [7]. The sensor functions are significant in energy consumption as well. There are on-going technological developments for sensor data integration and analysis aimed at detection and more accurate interpretation of incidents.

3. Methodology

3.1. Data collection

Every year, reports covering the future development direction of the electric power industry are published by professional organizations. These reports reflect the issues and trends of the electricity industry quickly and provide a comprehensive picture of the effects those issues and trends will have. This study has collected reports on the future of the electric power industry for a total of 13 years from 2006 to 2018 and focused on how issues have changed over time.

First, we searched the report based on keywords of 'future', 'electricity' (including 'electric', 'power') and 'industry' through Google Search. The reports found from keywords 'energy' and 'utility' were also reviewed and added when the reports were mainly about the electricity industry. Additional reports were obtained from the academic database of the Korea Energy Economics Institute. Also, we collected reports that reflect the global trends in the electricity industry, not just in a certain region or country. Finally, we tried to exclude papers that were mainly based on particular individual's opinion. Instead, we selected 58 institute-level reports which have gone through several editors' review [9-66].

3.2. Data preprocessing

The collected report provides experts' prospects and grounds for the future predictions of the power industry in a logical way. The collected reports are logically well organized by experts' prospects and rationale for future forecasts of the power industry. From the introduction to the conclusion of the report, knowledge and insights of experts are well-presented and sufficient as an information source. In this study, we tried to systematically analyze reports using text mining as a methodology. With text mining, effective and customized analysis of large amounts of text is possible according to a purpose of study [67-69]. However, the terms that make up the text have a lot of parts of speech, and they are also represented in many different forms. Text with these terms is classified as unstructured data, and preprocessing needs to be performed for analysis.

In this study, we focused on understanding how the importance of the terms varies from period to period, assuming that the more repeated terms are important. It was also intended to identify the analysis of associations between the selected terms of importance. Reports were first grouped into three groups by the period. More specifically, the period consists of 2006-2009, 2010-2015 and recent three years. One 2015 report, three 2016 report, one 2017 report and five 2018 report were newly added compared to the

previous paper [5]. Sentences in the reports were considered as documents which are the main unit of the analysis, and all the reports were broken down into sentences.

Table 1. Text data for the analysis

category	2006~2009	2010~2015	2016~2018	Total
# of reports	15	23	20	58
# of sentences	17,198	18,075	17,613	52,886
# of terms	22,276	18,076	16,611	56,963

The stopwords were removed using the package 'tm' of R, and similar words with overlapping meanings were unified into one term [70]. In the process of selecting keywords for analyzing the frequency of terms, keywords are defined as terms associated with the research topic of the electricity industry's ICT convergence. We referred to existing studies including Park and Kim [71] that reviewed the impacts of the Internet of Things (IoT) on the energy industry and Park et al. [5] which comprehensively covered the convergence of energy and ICTs through text mining in order to select meaningful keywords. Those keywords include terms of ICT technologies, functions and effects. Keywords related to ICT technologies are 'data', 'mobile (network)', 'Internet of Things (IoT)', 'artificial intelligence (AI)' and 'cloud'. Keywords of ICT functions are 'monitoring', 'detection', 'tracking', 'analytics', 'optimization', 'control', 'predictive (maintenance)'. Lastly, keywords of ICT effects are 'efficiency', 'safety', 'environment', 'customization'.

3.3. Association rules analysis

In this study, association rules analysis was performed beyond the frequency analysis of the selected keywords. Association rules are used to find out the relationship between variables. Association rule mining was mainly used to find out consumers' purchasing pattern in the tremendous amount of transaction data. In this case, the buying pattern indicates how often certain items are purchased together. In business, insights from association rule mining were utilized for better display arrangement and promotion. There are three main indicators estimating how items correlate each other. First, *Support* is defined as the proportion of transactions in the data set which contain an itemset. Let 'T' indicates total transaction and 'T_I' indicates all transactions including 'I' which refers to a set of items we are interested in. It is defined as follows: *supp* (item 1) $= \frac{T_{\{item1\}}}{T}$ and *supp* (item 1 $\Rightarrow$ item 2) $= \frac{T_{\{item1,item2\}}}{T}$. That is, *support* is useful to understand how frequently certain items were purchased together in whole transactions. *Support* is closer to frequency than correlation, and itemset which has low *support* can also have a meaningful relationship. Second, *confidence* is a ratio of purchasing item 2 when item 1 has been purchased. In mathematical term, *conf* (item 1 $\Rightarrow$ item 2) $= \frac{supp(item1 \Rightarrow item2)}{supp(item1)} = \frac{T_{\{item1,item2\}}}{T_{\{item1\}}}$. *Confidence* is useful to understand how item 1 affected the purchase of item 2, but its weakness is not to consider item 2's *support*. For instance, when item 2 is so popular that it is purchased in every transaction, the rule *confidence* of any items with item 2 would be 1, and it has little useful information. Lastly, the following index can supplement this problem by considering both *support* and *confidence*. *Lift (Interest factor)* is comparing the probability that item 2 is purchased after purchasing item1 to the probability that item 2 is purchased without any conditions. That is, *Lift* is *confidence* divided by *support*. *Lift* (item 1 $\Rightarrow$ item 2) $= \frac{supp(item1 \Rightarrow item2)}{supp(item1)*supp(item2)} = \frac{conf(item1 \Rightarrow item2)}{supp(item2)}$. When ratio is equal to 1, that means item 1 doesn't have any influence on purchasing item 2. When the ratio is bigger than 1, that means item 1 and item 2 are positively correlated. Otherwise, it could be said that item 1 and item 2 are in substitution relationship [72-73]. Those three indices are called interestingness measure.

Other than market basket analysis, association analysis is applicable to various kinds of domains. Moreover, association analysis has been actively used as a methodology for text mining. In bioinformatics, alopecia treatment herbs were analysed with association rule mining. From prescription texts, lists of herbs were extracted and most frequent combination of herbs was found. Then, by network

analysis, each combination was classified by medical functionality, which could be developed into a customized prescription of alopecia [74]. In the hypothesis that most frequently used terms in documents can represent the documents well, association rule mining was used to find out frequently used terms in the collection of documents. One hundred fifteen papers from Computer Science, Electrical and Electronic Engineering and Mechanical Engineering were collected. After removing stop words, abstracts were analysed with association rule mining, and resulting words were trained as supervised learning. Unknown documents were classified with 89% of efficiency into the predefined 3 categories [75].

One of the problems with association rules is that there are too many associations. Moreover, some portion of associations is not useful to people who know the field well. To overcome this problem, there was an attempt to estimate the novelty of association rules as a user-oriented measure. Keywords extracted from the documents which have been read by individuals are regarded as their backgrounds. Semantic distance between background keywords and keywords from the new document was used as interestingness indicators [76].

In text association analysis, it was suggested that association rules could be applied to keywords or concept-based phrases rather than tokenized words. Medical papers were used, and keywords from the abstract were selected. Also, concept-based phrases were extracted with domain knowledge. At the perspective of usefulness and plausibility, which are evaluated by physicians, the result of text association analysis showed better results when keywords and concept-based word phrases were used. Moreover, this new approach made it possible to reduce dimensionality by discarding irrelevant words [77]. In the healthcare sector, comments in online health social networks discussing Adverse Drug Reactions (ADRs) were utilized. Whether the comments are talking about ADRs was classified by experts. Documents consist of each sentence, and association rules were utilized to find out what combinations of terms are mainly used in ADRs. By supervised learning method, those terms were trained, and resulting algorithm recorded 70.01% of accuracy [78].

In the energy industry, there are few cases where association rules are applied to text mining. At the perspective of energy and ICT convergence, there was an attempt to use association rules to keywords from 48 reports of the future of the electricity industry. However, term frequency analysis was mainly covered to figure out a change in the convergence of energy and ICT. Also, association analysis was limited to the relationship between two keywords, 'ICT' and 'convergence', and the rest of the keywords [5]. In this study, reports are updated, and term frequency change is analysed. However, the main focus is association rules analysis between keywords which has been classified as three categories: ICTs in convergence, ICT functions, and ICT effects. Associations between technologies, functions, and effects are expected to give insights to better understand trends in electricity industry. We have utilized 'arules' package [79] of R as analysis tools.

4. Results

4.1. Term frequency analysis

Table 2 shows the frequency percentage for each keyword compared to the total number of terms which was presented at Table1. The frequency of the terms 'ICT' and 'convergence' which are the keywords of the research topic was increasing continuously for three consecutive periods. More specifically, the terms representing technologies that makeup ICT convergence and the terms describing ICT functions and effects were also presented in the Table 2. First, in ICTs in convergence, the term 'big data' and 'cloud' did not appear in the period of 2006-2009 but started to be seen from the period of 2010-2015. The most prominent technology among ICTs is IoT. The term IoT showed almost 300% of increasing rate for three consecutive periods.

Second, the frequency of keywords related to ICT functions showed explosive growth rate between the first period (a) and the second period (b). Especially, the keyword 'analytics' was mentioned 69 times more in the second period than the first period. In addition, the keyword of 'detection' was mentioned 22 times more in the same periods. On the other hand, between the second and third period (c), the frequency

of keywords including 'monitoring', 'detection' and 'tracking' decreased in percentage. However, remaining keywords still showed an increasing rate over 100%.

Third, the frequency of keywords related to ICT effects showed a similar trend with that of keywords linked to ICT functions. In case of keyword 'customization', usage of the term peaked in the second period of 2010-2015. Most of the keywords' frequency ratio showed a decreasing trend in the third period. However, when it comes to the keywords of ICT effects, the terms contain a wide range of meanings. Considering it, it is necessary to confirm the context of the keywords whether the keywords were used to describe the effects of ICTs. For further examination, associations between keywords related to ICTs are checked.

Table 2. ICT convergence-related term frequency and increasing rate

Terms	Term frequency / Total frequency (%)			Increasing rate (%)		
	2006-2009(a)	2010-2015(b)	2016-2018(c)	b/a*100	c/b*100	(c/a)^(1/2)*100
Main terms						
ICT	1.131	2.119	3.444	187.3	162.5	174.5
convergence	0.076	0.094	0.217	123.2	230.4	168.5
median	0.604	1.106	1.830	155.3	196.5	171.5
ICTs in convergence						
big data	0.000	0.194	0.151	-	77.7	-
mobile	0.117	0.171	0.151	146.9	87.8	113.6
IoT	0.022	0.066	0.367	295.8	553.2	404.5
AI	0.099	0.277	0.506	280.1	182.8	226.3
cloud	0.000	0.138	0.247	-	178.5	-
median	0.081	0.171	0.247	280.1	178.5	226.3
ICT functions						
monitoring	0.090	0.271	0.211	301.9	77.7	153.2
detection	0.004	0.100	0.078	2,218.2	78.6	417.5
tracking	0.081	0.111	0.090	136.9	81.6	105.7
analytics	0.004	0.310	0.470	6,901.2	151.6	1022.7
optimization	0.117	0.398	0.728	341.3	182.9	249.8
control	0.669	1.892	2.035	282.9	107.5	174.4
predictive	0.031	0.138	0.409	440.1	296.0	360.9
median	0.081	0.271	0.409	341.3	107.5	249.8
ICT effects						
efficiency	4.341	3.292	4.316	75.8	131.1	99.7
environment	2.478	3.364	2.161	135.7	64.3	93.4
safety	0.889	1.178	0.873	132.6	74.1	99.1
customization	0.009	0.055	0.054	616.2	97.9	245.7
median	1.683	2.235	1.517	134.2	86.0	99.4

4.2. Association rules analysis

In 2006-2009, there were not any significant associations between the groups of keywords. One noticeable association was between keyword 'ICT' and the keyword 'efficiency' from ICT effects. Confidence is 0.176, which is the proportion of the keyword 'ICT' and 'efficiency' appear together in a sentence given the keyword 'ICT' exist in a sentence. When we interpret this confidence index as a percentage, it is 17.6%. On the other hand, Lift is 3.339, which means the percentage of the keyword 'efficiency' appears given the word 'ICT' exist was about 3.3 times higher than the percentage of the keyword 'cloud' appears randomly in the sentences.

Table 3. Association rules in the period of 2006-2009

	Lhs		Rhs	support	confidence	lift
keyword ICT vs. ICT effects	ICT	=>	efficiency	1.70E-04	0.176	3.339

Note 1) Lhs: Left hand side, Rhs: Right hand side

In 2010-2015, when the keyword 'ICT' is at left-hand side (Lhs) and the keyword 'big data' is at right-hand side (Rhs), confidence is 0.019 and lift is 9.931. Also, when the keyword 'ICT' appears, the terms including 'control', 'monitoring' and 'analytics' representing the function of ICT appear in descending order of confidence. In the relationship between the term 'ICT' and the terms of ICT effects, the terms including 'environment', 'efficiency', 'safe', and 'customization' appear in descending order of confidence. Specially, the lift of the keyword between 'ICT' and 'customization' is 38.622, which means the word 'customization' is covered together with the word 'ICT' in high probability.

For the further investigation to figure out the relationship between ICTs and ICT functions, what functions were mentioned together by technology was searched with association rules. In the case of the 'big data', terms related to ICT functions including 'analytics', 'optimization', 'monitoring' and 'control' were discussed together. In specific, the probability that 'analytics' is discussed given 'big data' is mentioned was 57 times higher than the probability that 'analytics' was mentioned randomly. Mobile technology was in relations with 'control'. AI was mainly mentioned at the perspective of analytics and optimization.

Lastly, the relationship between ICTs and their effects were examined with association rules. The effects of big data were considered in the perspective of efficiency, safety, and environment. Mobile technology was related to the keyword of 'safety', and 'efficiency'. Furthermore, AI was more connected with environment, efficiency, and safety. Cloud system was mainly dealt with efficiency and safety

Table 4. Association rules in the period of 2010-2015

	Lhs		Rhs	support	confiden	lift
keyword ICT vs. ICTs	ICT	=	big data	5.53E-	0.019	9.931
keyword ICT vs. ICT functions	ICT	= >	control	2.21E-	0.077	4.514
			monitoring	1.11E-	0.038	12.87
			analytics	5.53E-	0.019	6.437
keyword ICT vs. ICT effects	ICT	= >	environment	2.77E-	0.096	3.255
			efficiency	2.77E-	0.096	2.863
			safety	1.11E-	0.038	3.799
			customizatio	5.53E-	0.019	38.62
ICTs vs. ICT functions	big data	= >	analytics	3.32E-	0.171	57.38
			optimization	1.11E-	0.057	14.34
			monitoring	5.53E-	0.029	9.563
			control	5.53E-	0.029	1.677
	mobil	=	control	1.11E-	0.071	4.192
	AI	= >	analytics	1.11E-	0.095	31.87
			optimization	1.11E-	0.095	23.90
ICTs vs. ICT effects	big data	= >	efficiency	1.11E-	0.057	1.702
			safety	5.53E-	0.029	2.822
			environment	5.53E-	0.029	0.967
	mobil e	= >	safety	1.11E-	0.071	7.055
			efficiency	5.53E-	0.036	1.063
	AI	= >	environment	1.11E-	0.095	3.224
			efficiency	1.11E-	0.095	2.836
			safety	5.53E-	0.048	4.703
	cloud	= >	efficiency	1.11E-	0.111	3.309
			safety	5.53E-	0.056	5.487

Note 1) Rhs was arranged based on the index confidence.

From 2016 to 2018, we found that the ICTs, ICT functions, and ICT effects have relevance to the keyword ICT. In addition, the relationship between ICTs and ICT functions and the relationship between ICTs and ICT effects also showed more several association rules than those of 2010-2015.

The keyword 'ICT' was highly correlated with the keyword 'cloud' and 'IoT' of ICTs, followed by

'big data' and 'AI'. At the relationship between the keyword 'ICT' and the keywords representing ICT functions, 'analytics', 'optimization', and 'control' were mentioned more frequently together with the keyword 'ICT', followed by 'monitoring' and 'predictive'. In particular, 'predictive' emerged as a newly related term in 2016-2018, and we can interpret that the predictive maintenance through ICTs has attracted attention. As it has been, 'efficiency' was emphasized most between the keyword 'ICT' and keywords of ICT effects, followed by 'environment', 'safety' and 'customization.

Table 5. Association rules in the period of 2016-2018

	Lhs		Rhs	support	confiden	lift
keyword ICT vs. ICTs	ICT	=	cloud	1.70E-	0.013	6.264
		=	IoT	1.70E-	0.013	4.373
		=	big data	1.14E-	0.009	6.438
		=	AI	1.14E-	0.009	4.414
		=	mobile	5.68E-	0.004	3.359
keyword ICT vs. ICT functions	ICT	=	analytics	5.68E-	0.044	8.306
		=	optimization	5.68E-	0.044	7.288
		=	control	5.68E-	0.044	2.566
		=	monitoring	3.41E-	0.026	11.885
		=	predictive	2.84E-	0.022	5.598
		=	detection	5.68E-	0.004	5.942
keyword ICT vs. ICT effects	ICT	=	efficiency	7.95E-	0.061	1.595
		=	environment	5.68E-	0.044	2.601
		=	safety	3.41E-	0.026	4.176
		=	customizatio	5.68E-	0.004	8.583
ICTs vs. ICT functions	big data	=	analytics	7.38E-	0.542	102.58
		=	predictive	2.27E-	0.167	42.543
		=	optimization	1.14E-	0.083	13.847
	mobil	=	analytics	5.68E-	0.043	8.234
	IoT	=	control	2.27E-	0.075	4.416
		=	optimization	1.14E-	0.038	6.270
		=	monitoring	5.68E-	0.019	8.521
	AI	=	analytics	2.84E-	0.143	27.055
		=	predictive	1.14E-	0.057	14.586
		=	control	1.14E-	0.057	3.344
	cloud	=	analytics	1.70E-	0.081	15.356
		=	monitoring	1.14E-	0.054	24.412
		=	optimization	1.14E-	0.054	8.982
		=	control	1.14E-	0.054	3.163
		=	predictive	5.68E-	0.027	6.899
ICTs vs. ICT effects	big	=	efficiency	1.70E-	0.125	3.247
	mobil	=	environment	5.68E-	0.043	2.578
	IoT	=	efficiency	1.70E-	0.057	1.470
		=	environment	5.68E-	0.019	1.119
		=	safety	5.68E-	0.019	2.994
	AI	=	safety	1.70E-	0.086	13.601
		=	efficiency	5.68E-	0.029	0.742
	cloud	=	safety	1.14E-	0.054	8.577
		=	customizatio	5.68E-	0.027	52.892

In ICTs and ICT functions, various kinds of functions were interrelated with ICTs. 'Predictive', which was newly emerged in 2016-2018, has a high correlation with 'big data' and 'AI'. Between ICTs and ICT effects, 'big data' and 'IoT' were mainly emphasized with the keyword 'efficiency', while 'mobile' was emphasized with the keyword 'environment'. On the other hand, 'AI' and 'cloud' were usually discussed with the safety issue.

5. Discussion and Conclusion

This study examined the association rules between ICTs and their functions and effects with 58 reports dealing with the future of the electricity industry. What's distinctive is that the debate on ICT convergence has continued to expand in the discussion of the future of the electricity industry from the late 2000s until recently. Between 2006 and 2009 the keyword 'ICT' was associated with the keyword 'efficiency,' but the association between other selected keywords was not noticeable. In the 2010-2015 period, the functions and effects of the ICTs were mentioned along with ICTs except for IoT. In 2016-2018 the relationship between keyword 'ICT' and each of ICTs, ICT functions, and ICT effects became relatively clear, and the relationship between ICTs and related functions and effects was also well presented. This indicates that ICT became more significant in the discussion of the future of the electricity industry.

In 2006-2009, keyword 'ICT' and 'efficiency' were often mentioned together, and it can be understood that ICT was mainly emphasized to enhance the efficiency of the electricity industry. As seen above, the proportion of sentences containing the keyword 'efficiency' in all sentences containing the keyword 'ICT' is about 17.6%, which means ICT was frequently referred in the sense of efficiency of the electricity industry.

A variety of related keywords were derived between 2010 and 2015 compared to the period 2006-2009. In the technical dimension, the correlation between the keyword 'ICT' and the 'big data' was shown. In the functional dimension, the keywords 'analytics' and 'optimization' were noted. In the effects dimension, the keyword 'efficiency' was relatively more discussed than other keywords. In other words, perception that it is possible to enhance operational efficiency by analyzing big data is widespread. When we look at the relationship between ICTs and ICT effects, 'efficiency' appears to be a relevant keyword in all combinations. As a result, it was confirmed that expectation toward efficiency was the highest when utilizing ICTs in the electricity industry from 2010 to 2015 along with the period of 2006-2009.

Between 2016 and 2018, the more several association rules were derived compared to other periods. As a major means and driver of digitalization, ICTs are perceived as significant technologies in terms of efficiency, environment, safety, and customization of the electricity industry. Keyword 'ICT' was mentioned together in the order of 'cloud', 'IoT', 'big data', 'AI' and 'mobile'. It was emphasized that data are collected through sensors and stored in the cloud system to build big data and to attempt various analyses through AI. Between the keyword 'ICT' and ICT functions, 'analytics', 'optimization', 'control', 'monitoring', and 'predictive' were highly relevant at similar levels. Keyword 'predictive' was not mentioned in 2010-2015, but it is noteworthy that it was derived as an interrelated keyword during 2016-2018. This means that the importance of predictive maintenance is increasing. Repairing devices that operate in the industry and predicting when their performance may deteriorate are important in terms of managing productivity, efficient staffing, and long-term capital investment. Corporate managers can identify return on investment (ROI) when investing in sensors and networks to maintain optimal performance or to prevent machine damage [80]. One of the biggest challenges for energy companies is to maintain the performance of their equipment. Expensive assets must not only cope with ever-increasing weather changes but also with deterioration. Data generated through the IoT can be analysed and it could be used to predict proactively the possible problems of the equipment and avoid unexpected failures or accidents. The software will automatically and consistently find out where the problem may occur and what the cause of the problem is, which helps to build a more productive system [81]. The benefits of predictive maintenance include avoiding a major failure, longer time to prepare before a major failure, and reducing unnecessary inspections [82].

Although a previous study [5], similar to this study, has reviewed the trends of ICT convergence by gathering reports on the future of the electricity industry, the study did not deeply examine the relationship between ICTs and related functions and effects by focusing on just analyzing the frequency variation of keywords. This study is differentiated in that the recognition of keyword 'ICT' were changed over time with association rules and discussions related to detailed technologies were examined.

However, energy sector technologies such as storage devices and renewable energy technologies are also important topics for discussion, and there are complex debates such as regulation, policy, economics,

and business regarding social science. Additional issues such as subjects utilizing ICTs in the electricity industry, application scopes of ICTs, and potential challenges need to be examined. This study is meaningful in term of helping to understand how the main ICTs, functions, and effects have changed over time. Further studies need to investigate the benefits, limitations, and challenges of ICT convergence in a comprehensive way by considering more relevant issues. Besides, the related research needs to be extended by using advanced methods such as topic analysis and word embedding that help to derive insights from text data effectively.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

A designed the research; B analyzed the data; A,B wrote the paper; all authors had approved the final version.

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