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# Identifying convergence fields and technologies for industrial safety: LDA-based network analysis

Bomi Song[a], Yongyoon Suh[b,*]

[a] School of Air Transportation and Logistics, Korea Aerospace University, Goyang-si, Gyeonggi-do 10540, Republic of Korea
[b] Department of Safety Engineering, Pukyong National University, 45 Yongso-ro, Nam-Gu, Busan 48513, Republic of Korea

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ABSTRACT

As industrial systems expand and complex systems are developed, it is no longer effective to minimize hazards and risks for industrial safety using the technological solutions limited to a single industry. Thus, to resolve complicated problems, safety technology has been developed by promoting technology innovation and convergence. In this respect, this study aims at monitoring major safety fields and technologies through patent analysis to identify the trends in technology development that prevent the risks of various industrial systems. Patent information is effectively used for analyzing technology descriptions, which include the purpose and newness of technology. Using this patent information, we propose the major safety fields and related technology keywords using the following two techniques: (1) latent Dirichlet allocation (LDA), which aims to extract the latent topics and main keywords contained in documents, and (2) network analysis, which is useful for monitoring change patterns and relations. Further, the convergence trajectories of safety technology are identified to provide insights about the technology trends in safety fields. The results are expected to enable safety managers and engineers to effectively find relevant technology trends for reducing hazardous factors.

## 1. Introduction

In recent years, as the size of industrial systems has expanded and advanced technology has been introduced in complex industrial systems, hazardous factors that cause major accidents, such as unstable conditions and behavior, have become complicated (Strauch, 2015). It is no longer effective to minimize these complex industrial risks for industrial safety using conventional approaches that focus on specific problems in an individual industry (Wahlström, 1992). It becomes important to focus on the common safety issues shared across multiple industries (Swuste et al., 2010). In this respect, safety management has been highlighted to reduce the degree of critical risks by achieving "technology convergence" in various industries including machinery, chemistry, manufacturing, and construction (Kokangul et al., 2017; Patriarca et al., 2017). Recently, technological solutions for safety management have been developed by addressing complex factors (Wahlström and Rollenhagen, 2014). As the size of industrial sites is larger and the systems have multifunctional and interactive processes, the risk factors are entangled with the locations, facilities, hazard materials, workers, and environment (Leveson et al., 2009; Reason, 1990; Reiman et al., 2015). For example, in the complex safety systems of smart factory or building information systems, managers have attempted to reduce the faults and accidents through information technology such as Internet of Things (IoT) and cloud network which is capable of sensing physical signals in real time and controlling the movement of facilities in advance. The system innovation through technology convergence is recognized as useful ways for industrial safety (McCray et al., 2010).

During the past decade, the importance of technology innovation and convergence has been highlighted in various industries to achieve breakthroughs (Clauss, 2017; Dutta and Hora, 2017; Priem et al., 2017). In fact, many industries lead to emerging industry segments and offer opportunities through technology innovation and convergence (Geum et al., 2016; Song et al., 2017). On one hand, a few industries have focused on improving product development and removing loss due to inefficiency. On the other hand, rather than productivity, safety fields more focus on eliminating hazardous factors and preventing fatal accidents through technology innovation and convergence. By integrating various technological standards, risk management has been also improved simultaneously, such as the international standards of occupational health (OHSAS 18001), environment (ISO 14001), and quality (ISO 9001), in industrial systems (Lafuente and Abad, 2018; Li and Guldenmund, 2018; Oliveira et al., 2017). Recently, to provide a systematic framework for preventing death, work-related injury and ill

* Corresponding author.
*E-mail address:* ysuh@pknu.ac.kr (Y. Suh).

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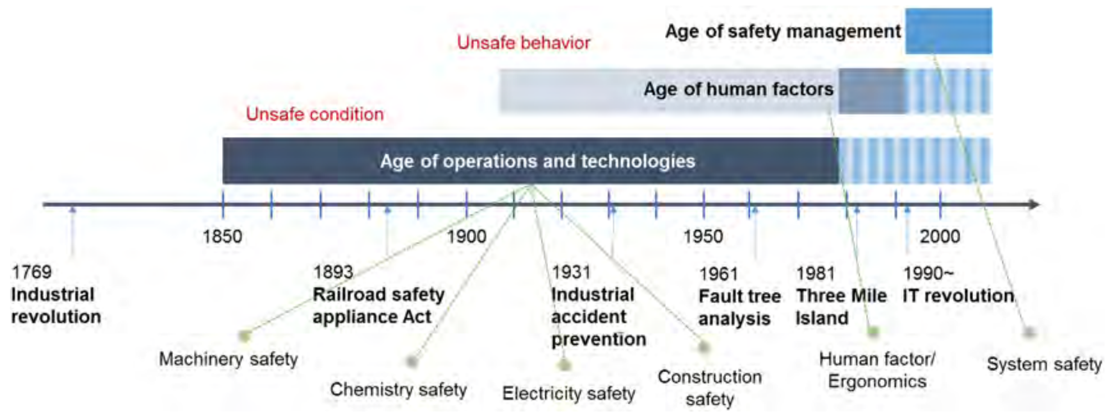


**Fig. 1.** History of industrial safety (modified from Hale and Hovden, 1998).

health, the ISO 45001 takes into account occupational health and safety management instead of OHSAS 18001. One of the purpose of these standards is to prevent the unintended risks and eliminate hazards based on technological and engineering solutions (ISO, 2018). Thus, understanding technology innovation and convergence enables safety engineers and managers to plan, develop, and maintain industrial safety systems according to the various standards.

Despite this importance of technological improvement in safety systems, most previous studies have been limited to the development of individual technological solutions by engineers (Lee et al., 2014; Silva, 2017) or the validation of determinants for safety management by managers (Cornelissen et al., 2017; Zaira and Hadikusumo, 2017). Several studies have tried to identify trends of safety research based on bibliometric analysis of academic papers (van Nunen et al., 2017). However, the perspective of policy and management in technology innovation for monitoring the trends in safety technology development and convergence has been less considered in academia and practice of safety fields. Research on understanding the important trends in safety technology is essential for forecasting the requirements of safety technology and designing safer industrial systems (Brocal et al., 2017). By identifying major safety fields and their convergence trajectories, policy makers can plan holistic roadmaps for industrial and societal safety (Zou et al., 2017). In addition, monitoring the technology trends in safety fields enables safety engineers and managers to introduce effective and useful technologies for developing reliable and robust industrial systems or processes.

Thus, this study aims at monitoring the major fields of safety technology and identifying the convergence trajectory for safety technology development. This is achieved primarily by applying patent analysis. Patent documents are more useful for analyzing more considerable bibliometric information including abstracts, assignees, inventors, classes, and citations than other documents sources such as academic papers (Leydesdorff et al., 2014; Park and Yoon, 2014). In this respect, patent analysis is a widely useful method that makes it possible to provide an overview of the newness and innovativeness of a large number of technologies in industries. Among the variables contained in the patent database, this study focuses on text analytics using the abstract of patent documents to extract the primary keywords of respective technologies. To this end, this study proposes latent Dirichlet allocation (LDA)-based network analysis as a systematic approach to applying two techniques. First, the text mining algorithm is used to extract the frequently commented keywords contained in patent documents. Then, the LDA algorithm is applied to determine the latent topics of each patent document by estimating the topic probability from given keyword distributions of patent documents. As a result, the topics determined through LDA indicate the major technology fields that are comprised of relevant technology keywords. Moreover, recent perilous areas and related safety technologies are understood by extracting the major safety fields. Second, the keywords related to the safety technology in the respective safety fields extracted from LDA are used to construct a convergence network of safety technologies. The primary keywords of the safety technologies that promote convergence are extracted according to the degree of strength of the linkage among keywords in the convergence network. Further, the types and processes of convergence trajectories are monitored to provide the evidence of technology planning in safety fields. The results provide a clear picture of the technology progress in the safety fields and help researchers and practitioners consider new safety technologies and convergence issues.

## 2. History of safety technology and management

The safety issue in the modern industry first emerged from the industrial revolution of 1769. Efficient transportation and mass production have been made possible by the increasing development of mechanical and electrical power. Simultaneously, the level of technology and production has been rapidly improved. In contrast to this positive impact, this industrialization has had a negative effect on occupational safety and health in hazardous tasks (Swuste et al., 2010). In this respect, to reduce this negative impact, the history of safety management is divided into the following three ages: operations, human (worker), and system (Dezfuli et al., 2011; Hale and Hovden, 1998; Li and Guldenmund, 2018). The primary concerns of each age have been changed according to the perspective of innovation (Hollnagel, 2014). The history of industrial safety is summarized as shown in Fig. 1.

First, as the evolution of operations and technology includes all industries such as mechanical, chemical, and electrical plants, numerous accidents continue to occur because of the risks related to plants, facilities, and materials (Hale et al., 1997; Swuste et al., 2018). The hazardous side effects of operations have been recognized as the unsafe conditions of a working environment through industrialization in developed countries (Perrow, 1999; Swuste et al., 2010). Moreover, the risk of danger in the use of machinery or equipment, such as a milling machine and lathe, is rapidly rising. Because of these problems, employers have focused on learning the safe use of machines and maintaining a safe working environment (Reason, 1995). Thus, for the next industrialization, the operational and technological methods for industrial safety, such as shields, safe processes, and harmless materials, have been continuously improved.

Even though the safety technologies in each industry protect employees from risks, accidents are no longer limited to only technology or operation. In the second age, which started from the 1970s, the risks of human errors, rather than the risks related to technology, are highlighted as unsafe behavior; e.g., the misuse of machines by workers and the poor skills of workers (James and Dickinson, 1950; Kjellén, 1984; Reason, 1990). Thus, the management of human factors and ergonomics has been attempted in academia and practice (Miall et al., 1985;

Nimbarte et al., 2010). Musculoskeletal and vital reaction issues have been considered for improving, maintaining, and protecting the health of workers (Valero et al., 2016).

However, as technology is continuously improved and the scope of industries is extended because of enhancement in technology level and increase in production scale, accidents occur because of complex manufacturing processes and multiple risk factors (Perrow, 1999). Thus, since the 1990s, a holistic approach to safety management systems has been introduced, focusing on the control of system safety primarily through information technology (Stewart et al., 2009). All safety requirements related to technology, operation, and humans are administrated in social-technical system that aim to diagnose the risks factors in physical environment and to forecast the emergency conditions in industrial practice (Hollnagel, 2014; Leveson, 2011).

## 3. Research methodology

### 3.1. Research structure

This study consists of two analysis sections: identification of major safety fields (Section 4.1) and convergence trajectory (Section 4.2) as shown in Fig. 2. The first section includes analysis results of identifying major safety fields using all patents granted from 2007 to 2015. Text-mining algorithm is used to structure document-term matrix for the title and the abstract contained in patent documents. In specific, the pre-processing is conducted with stemming keywords and removing stop-word using the "tm" package and the "textstem" package of *R* application, respectively. Representative safety fields and their technology keywords are then extracted using the "lda" and "topicmodels" packages of *R* for LDA algorithm. There has been no consensus on how to decide the parameters (Blei, 2012). Thus, we set that the number of keywords that structure latent topics is 10 because it is difficult to characterize the latent topics based on the small number of keywords. Also, 10 of latent topics are selected to provide enough information on safety fields. As a result, the result of this section presents the dominant trends of safety technology with respect to the safety fields.

The second section aims at illustrating convergence trajectory using co-word (co-occurrence) network analysis based on results of the LDA. From 2007 to 2015, safety fields and their technology keywords in each year are driven from results of LDA algorithm, respectively. Next, the co-word matrix is made up by integrating technology keywords assigned into same safety fields. As a result, we trace the convergence trajectory in terms of the number of co-occurrence of technology keywords that are assigned into same safety fields. Lastly, we can monitor the change of convergence trajectory, adjusting the number of co-occurrence.

**Table 1**
Document-keyword matrix extracted from text mining algorithm.

| | Keyword 1 | Keyword 2 | … | Keyword n |
|---|---|---|---|---|
| Document #1 | $tf_{1,1}$ | $tf_{1,2}$ | … | $tf_{1,n}$ |
| Document #2 | $tf_{2,1}$ | $tf_{2,2}$ | … | $tf_{2,n}$ |
| … | … | … | … | … |
| Document #m | $tf_{m,1}$ | $tf_{m,2}$ | … | $tf_{m,n}$ |

### 3.2. Methods

#### 3.2.1. Textmining algorithm

Text mining is the algorithm of extracting meaningful information from unstructured text data (Hashimi et al., 2015). The main task of text mining is to extract patterns or relationships of keywords contained in multiple text documents in terms of their frequency or weight. Many statistical and computerized algorithms are associated for information retrieval, pattern recognition, and natural language processing (Cambria et al., 2013; Spasić et al., 2014). The basic process is to transform keywords (or terms) contained in text documents into document-keyword matrix as described Table 1. This keyword structure is especially called as a keyword vector. Based on the document-keyword matrix, various datamining methods have been applied such as clustering, latent semantic analysis, and sentimental analysis (Mostafa, 2013; Suh et al., 2017).

In this study, the term frequency-inverse document frequency (TF-IDF) index is used to represent importance of keywords in the corpus. The TF-IDF index is one of the widely used measures for calculating the important weight of terms (keywords) in all documents (Kuang and Xiaoming, 2010; Zhang et al., 2011). First, for term frequency (TF), $tf_{i,j}$ indicates the number of term (keyword) $j$ in each document $i$. Second, inverse document frequency (IDF) is obtained by dividing the total number of documents $N$ by $df_j$, which denotes the number of documents containing the term $j$. In general, the IDF is obtained from the logarithm function. Consequently, the weighted term frequency of TF-IDF ($w_{i,\,j}$) is calculated based on the TF multiplied by the IDF as the following equation.

$$w_{i,j} = TF \times IDF = tf_{i,j} \times \log\left(\frac{N}{df_{\cdot,j}}\right)$$

#### 3.2.2. LDA (latent Dirichlet allocation) algorithm

The LDA algorithm is a generative probabilistic model for topic modeling based on collections of discrete data such as frequency and text corpora (Blei, 2012; Blei et al., 2003). The LDA is considered the

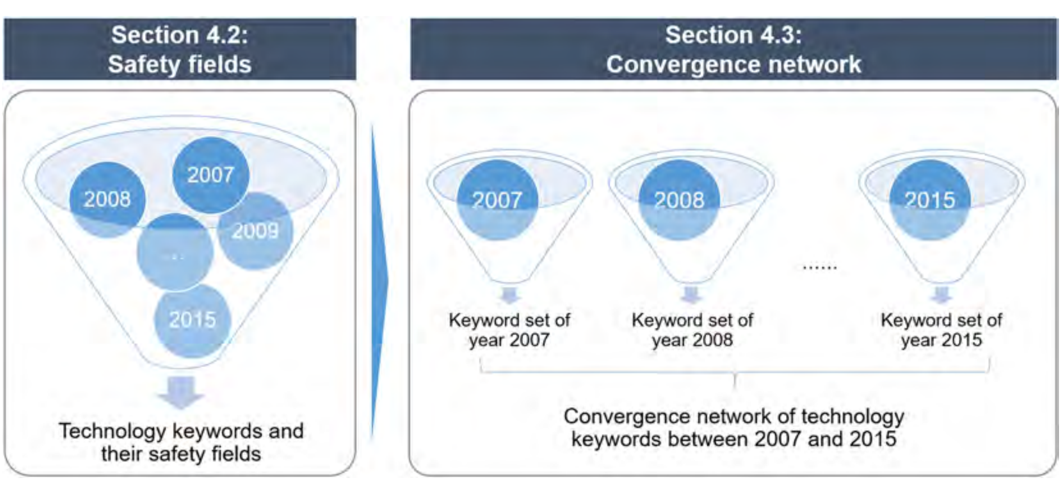


**Fig. 2.** Research structure.

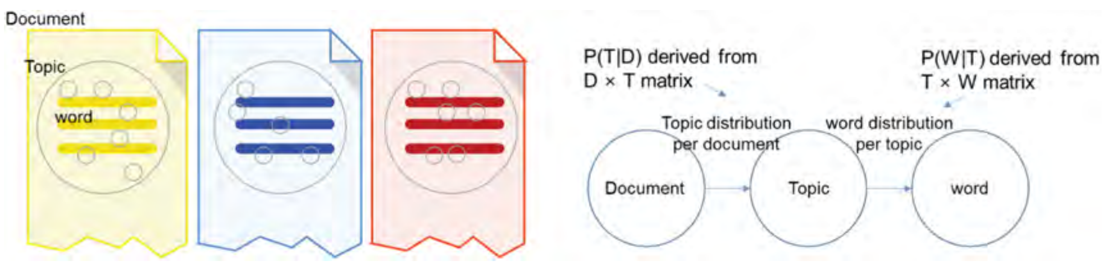


**Fig. 3.** Concept of LDA (Kim et al., 2018).

useful method for basic tasks of the natural language processes such as classification, novelty detection, summarization, and similarity and relevance judgments (Blei et al., 2003). The main tenet of this algorithm lies in the basic idea that documents are represented as random mixtures over latent topics, where each topic is determined by a distribution over words (terms). Put simply, latent topics are derived from topic probability conditioned on the document distributions and word probability conditioned on the topic distribution. As shown in Fig. 3, when we have text information contained in documents, distribution of words in given documents can be known. Using these information, topic probability is inferred based on Gibbs sampling algorithm for empirical Bayes parameter estimation. Consequently, several topics based on words contained in a set of documents are classified. Since providing possible probabilities that documents are included in each of topics based on the word distribution, in the context of text modeling, the LDA is useful in the case that the topic probabilities indicate an explicit representation of words contained in documents (Lee et al., 2015).

### 3.2.3. Co-word network

Through the LDA algorithm for patents in each year from 2007 to 2015, safety fields and their technology keywords of each year are extracted and the co-occurrence matrix of technology keywords is constructed as shown in Table 2. For example, when a keyword 1 and a keyword 2 are classified into a same topic in both 2007 and 2008, the number of co-occurrence between keyword 1 and keyword 2 (i.e. both Co-occurrence$_{12}$ and Co-occurrence$_{21}$) becomes two. In this respect, it should be noted that the maximum number of co-occurrence can be nine because the LDA is applied during nine years from 2007 to 2015. This co-occurrence matrix is then used to develop the keyword network that represents the degree of convergence of safety fields.

## 4. Results

### 4.1. Data collection

The patent documents are collected from the USPTO database, by searching keywords: safety, technology, accident, risk, hazard, and danger. The query of search keywords is structured with AND gate of *safety* and *technology* and OR gate of *accident*, *risk*, *hazard*, and *danger*. The patents may be differently gathered through the different queries of search. However, because safety technologies and fields have been unclearly defined thus far, we searched for the patents using general words to collect a large size of the patent sample as possible. The data is collected from 2007 to 2015 because this is the first year that the number of patents is larger than 500. As a result, 6360 documents of granted patents are gathered as the analysis target. The increasing pattern is shown in Fig. 4, and the number of patents are continuously increasing except year of 2009. It implies that the safety technology started to be concentrated in practice from 2010.

**Table 2**
Co-word matrix of technology keywords.

| | Keyword 1 | Keyword 2 | … | Keyword n |
|---|---|---|---|---|
| Keyword 1 | Co-occurrence$_{11}$ | Co-occurrence$_{12}$ | … | Co-occurrence$_{1n}$ |
| Keyword 2 | Co-occurrence$_{21}$ | Co-occurrence$_{22}$ | … | Co-occurrence$_{2n}$ |
| … | … | … | … | … |
| Keyword m | Co-occurrence$_{m1}$ | Co-occurrence$_{m2}$ | … | Co-occurrence$_{mn}$ |

### 4.2. Identification of major safety fields

Above all, the topics of patents extracted by the textmining and LDA algorithm are summarized as described in Table 3. The textmining algorithm is used to extract keywords of patent and these keywords represent the technology description contained in the abstract of patents. Then, the LDA algorithm is applied to derive topics of patent documents that are comprised of technology keywords extracted from the textmining. Lastly, the major safety fields are defined in terms of the likelihood of related technology keywords which are assigned into each of topics. In fact, most of the safety fields have been considered interest topics in practice. Although unnecessary keywords are eliminated automatically by stemming with the technology dictionary, the title of topics is determined with the help of experts. However, during this process, it is difficult to classify some of technology keywords into the specific field because general keywords that describe safety technologies are included. For example, the topic 8 consists of common words for worker safety such as member, body, or arm. In this case, we made a title of the topic, manually investigating patents classified in this topic with experts. Since this is the almost first study for defining safety technology, we targeted numerous and various keywords as possible, and then, with the help of experts, the safety fields are lastly specified.

The safety management means ‘a systematic control of worker performance, machine performance, and physical environment’ (Heinrich et al., 1980). Consequently, according to this definition of safety management, these safety fields are divided into threefold: operations safety, worker safety, and system safety.

First, the operations safety is defined as the safety technology for facility and process management in plant or construction sites. From Topic 1 to Topic 6, most of technology keywords are involved in the activities for machine, facility, and process management. To be specific, the operations safety through R&D of machinery, chemistry, and manufacturing engineering include equipment (field 1), electricity (field 2), vehicle (field 3), pipe/plumbing (field 4), material surface (field 5), and pressure/joint (field 6).

Second, several technology keywords are extracted to define the worker safety based on prevention of workers' activities and behaviors. The worker safety through management of working practice and organization consists of barrier (field 7) and work/musculoskeletal (field 8). The barriers have been considered defence of workers in physical environment (Reason, 1995). Thus, compared operations safety, the barrier for worker safety more focuses on how to safely operate machines and avoid dangers from the machines in workplace (Valero et al., 2016), with respect to several technology keywords: prevent, block, handle, stop, and actuate. Also, work/musculoskeletal has distinctive features such as body, seat, support, secure, belt, and arm to protect the workers' health.

Third, the system safety is defined by the technology keywords related to sensor, data, network, and information technologies. The

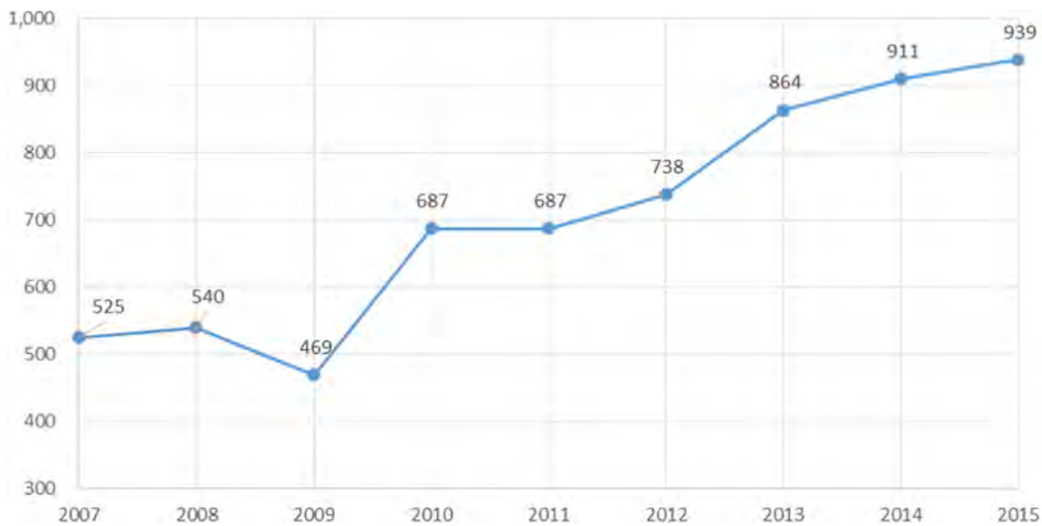


**Fig. 4.** Change of the number of patents related to safety technology.

**Table 3**
Safety fields and their technology keywords.

| Safety fields (topics) | | Technology keywords |
|---|---|---|
| Operations safety | 1. Equipment/facilities | Needle, assembly, house, mount, extend, spring, force, dispose, outer, inner |
| | 2. Electricity | Control, signal, unit, switch, power, circuit, light, electrical, state, supply |
| | 3. Vehicle | Vehicle, drive, present, operation, load, conjurer, relate, area, comprise, motor |
| | 4. Pipe/plumbing | Position, lock, open, valve, mechanism, move, close, release, latch, flow |
| | 5. Material surface | Side, surface, form, cover, plate, contact, structure, low, material, wall |
| | 6. Pressure/joint | Less, connect, couple, configure, pressure, plurality, compromise, battery, module, gas |
| Worker safety | 7. Barrier | Safety, prevent, part, door, block, handle, slide, trigger, stop, actuate |
| | 8. Work/musculoskeletal | Member, portion, body, seat, support, secure, belt, frame, arm, direction |
| System safety | 9. Sensor systems | System, sensor, communication, component, operate, detect, condition, embodiment, monitor, andor |
| | 10. Information systems | Datum, safe, receive, user, process, information, determine, time, predetermine, value |

patents of sensor (field 9) and information (field 10) systems have increased with respect to system safety. Such systems play a role in gathering data and monitoring task information for maintaining safe and sound industrial systems. The automated plant and the management information system (MIS) are powerful to supervise the overall situation of work sites such as the manufacturing factory and the construction site. In fact, many studies on application of information technology to made systems safer have been conducted in practice such as detecting workers and information sharing (Fang et al., 2018; Grabowski et al., 2018; Nath et al., 2017). For example, according to IEC 61508, the building information management is focused on automating and controlling the particular objects in safety systems (Li and Guldenmund, 2018; Novak et al., 2007).

To figure out the static status of the technological trend, Table 4 indicates that the safety field that has recently granted most patents is information systems (122), followed by work/musculoskeletal (108), pipe/plumbing, and material surface (104). With respect to safety filed 10, data information systems for designing safety systems are recently interested in academia and practice. In fact, various industries have substantially accelerated the application of smart and connected processes such advanced information systems as internet of things, cloud, and real-time processing. For increasing productivity and safety, the information infrastructure is essentially improved as well.

A change of the average number and the average proportion of patents in each safety field over time as displayed in Figs. 5 and 6, respectively, is then useful for understanding a trend of safety fields. The safety field that continuously published many patents from 2007 to 2015 is revealed as electricity (90.67), followed by pipe/plumbing (81.44), equipment/facilities (79.89), and material surface (78.33). Naturally, the average proportion has a similar pattern with the average number as well; the safety field of electricity has comprised a large proportion at 12.92%, and followed by equipment/facilities (11.67%),

**Table 4**
Patent statistics in safety fields.

| Safety fields | Number of patent in last year (2015) | Average number of patents | CAGR (number) | Average proportion of patents | CAGR (proportion) |
|---|---|---|---|---|---|
| 1. Equipment/facilities | 90 | 79.89 | 4.56% | 11.67% | −2.77% |
| 2. Electricity | 99 | 90.67 | 6.24% | 12.92% | −1.21% |
| 3. Vehicle | 94 | 68.33 | 7.43% | 9.63% | −0.11% |
| 4. Pipe/plumbing | 104 | 81.44 | 6.26% | 11.64% | −1.19% |
| 5. Material surface | 104 | 78.33 | 6.47% | 11.24% | −1.00% |
| 6. Pressure/joint | 84 | 56.22 | 13.27% | 7.70% | 5.33% |
| 7. Barrier | 47 | 38.67 | 3.04% | 5.53% | −4.19% |
| 8. Work/musculoskeletal | 108 | 71.44 | 11.88% | 10.10% | 4.04% |
| 9. Sensor systems | 87 | 67.22 | 6.14% | 9.38% | −1.30% |
| 10. Information systems | 122 | 74.44 | 10.47% | 10.19% | 2.73% |

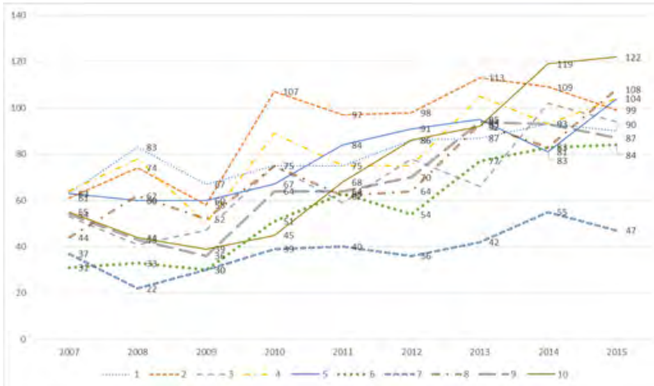


**Fig. 5.** Change of the number of patents with respect to safety fields.

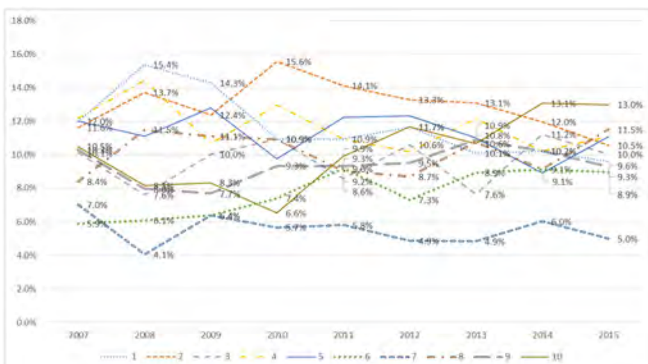


**Fig. 6.** Change of the proportion of patents with respect to safety fields.

pipe/plumbing (11.64%), and material surface (11.24%). This result presents that operations safety has continuously focused during a decade, and most of interest in safety has arisen from the attempts to solve problems and prevent hazards with advanced technology.

Furthermore, the increasing rate of the number of patents and their proportions in each safety field is an effective indicator to measure a trend of safety technology. Among others, the measure of compound annual growth rate (CAGR) is useful for monitoring a trend of safety technology. The CAGR is calculated for identifying the generic exponential growth rate when the exponential growth interval is one year. For example, if CAGR is equivalent to 5% for three years, the value of final year, $T_3$, is get through the value of first year, $T_1$, multiplied by $(1 + CAGR)^3$ (i.e. $T_3 = T_1 * (1 + CAGR)^3$). The result shows that increase rate of several safety fields is remarkable. The steep growth in the number of patent is represented in pressure/joint (13.27%) for operations safety, work/musculoskeletal (11.88%) for worker safety, and information systems (10.47%) for system safety. Also, only these three safety fields show a positive CAGR of the proportion: pressure/joint at 5.33%, work/musculoskeletal at 4.04%, and information systems at 2.73%. The others record a negative CAGR of the proportion and especially the safety field of the barrier for worker safety presents a remarkable decline rate (−4.19%).

### 4.3. Construction of convergence network of safety technology

The second approach is to identify the convergence trajectory using the keyword co-occurrence (co-word) network. Through the LDA algorithm for patents in each year from 2007 to 2015, safety fields and their technology keywords of each year are extracted and the co-word matrix of technology keywords is constructed. It should be noted that the maximum number of keyword co-occurrence can be nine because the LDA is applied during nine years from 2007 to 2015. This co-word matrix is then used to develop the keyword network that represents the degree of convergence of safety fields. When the frequency of co-occurrence is higher, it is indicated that the matching keywords are highly correlated in convergence clusters. Thus, we can trace the trajectory of technology change in a decade because the co-occurrence indicates the degree of linkage during technology convergence (for more detail, the overall keyword network is also shown in Appendix A).

After construction of technology keyword network, the initial basic clusters of converging safety fields are grouped with respect to the number of co-occurrence. As a result, the number of co-occurrence of basic cluster is initially determined with six since the largest number of co-occurrence has six. In other words, the keywords involved in the initial basic cluster co-occurred in six years during nine years. Thus, these basic clusters are indicated as the strongly connected safety fields because there are the largest number of co-occurred technology keywords. Table 5 summarizes basic clusters of safety technology and their representative keywords that could define the types of safety technology clusters among 107 keywords.

The technology keywords organize six clusters and the basic convergence clusters which include several safety fields are structured as depicted in Fig. 7. The network is visualized using UCINET software and structured through the distance-based clustering based on co-word vectors. In general, the keywords that have similar keywords are closely positioned.

The first convergence cluster is defined as the barriers for locking, integrating safety fields of pipe/plumbing and barrier that include technology keywords such as *block*, *force*, *latch*, *movement*, *lock*, *position*, *release*, and *engage*. The second convergence cluster is process safety that includes safety fields of pipe/plumbing and pressure/joint. This convergence cluster is represented with such technology keywords: *gas*, *valve*, *flow*, *pressure*, *open*, *trigger*, *close*, and *fluid*. This cluster includes the safety technology for pipe management using pressure and joint technology. Third, general engineering and managerial safety of work environment is extracted as one of technology convergence among the safety fields of equipment, material surface, pressure/joint, and work/musculoskeletal. The main keywords structuring Cluster 3 are related to machinery and human such as *needle*, *assembly*, *mount*, *frame*, *surface*, *seat*, and *material*. This cluster mainly presents general safety technology for management of overall safety. Fourth, the convergence Cluster 4 for electrical management safety is structured based on safety fields of electricity and pressure/joint. This convergence cluster

**Table 5**
Basic convergence clusters of safety technology.

| Basic convergence cluster | Converging fields | Main co-occurring technology keywords |
|---|---|---|
| 1. Barriers for locking | Pipe/plumbing & Barrier | Block, force, latch, movement, lock, position, release, engage |
| 2. Process safety | Pipe/plumbing & Pressure/joint | Gas, valve, flow, pressure, open, trigger, close, fluid |
| 3. Working safety | Equipment, Material surface, Pressure/joint, Work/musculoskeletal | Needle, assembly, extend, mount, frame, surface, form, portion, secure, attach, seat, dispose, material |
| 4. Electrical management safety | Electricity & Pressure/joint | Switch, electrical, circuit, power, connect, supply, load, voltage, connection, control |
| 5. Safety monitoring systems | Sensor & Information | Signal, sensor, detect, process, datum, system, communication, determine |
| 6. Vehicle systems (but no convergence) | Vehicle | Drive, vehicle, condition, state, brake, motor, location |

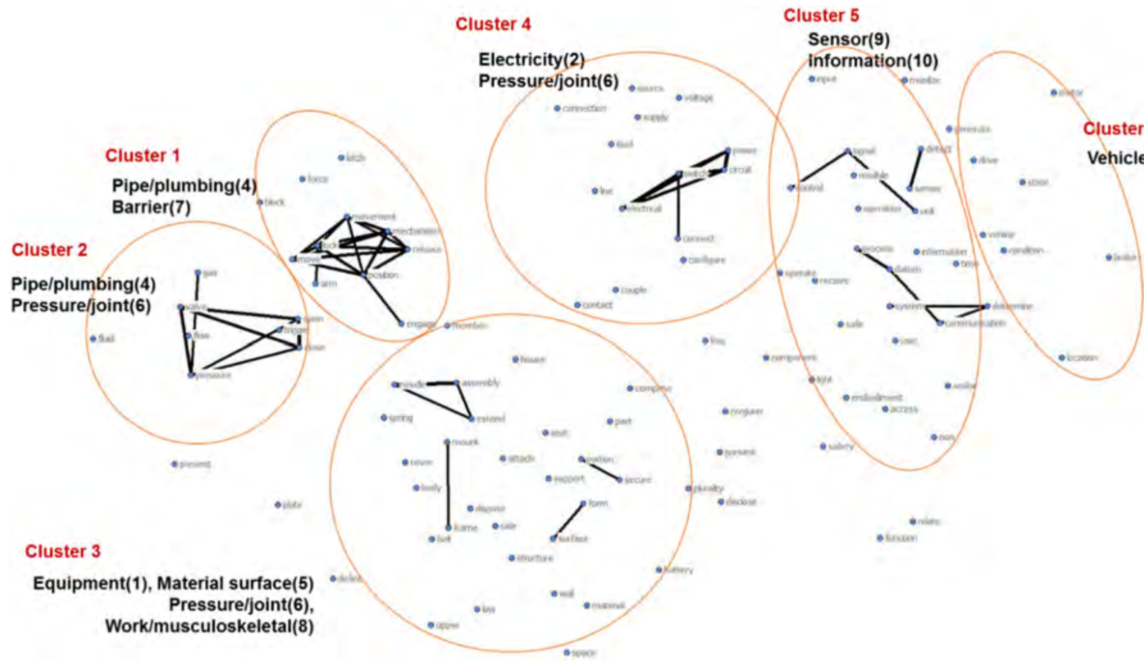


**Fig. 7.** Initially basic convergence clusters of safety technology.

includes safety technology related to *switch*, *circuit*, *power*, *supply*, *voltage*, and *connection*. Fifth, safety monitoring system related to information systems is classified as a basic Cluster 5. For the system safety, safety fields of sensor and information systems strongly interact with other technologies including keywords of *signal*, *sensor*, *detect*, *process*, *datum*, *communication*, and *determine*. These keywords propose the technology convergence for decision making in safety management using sensor-based information systems. The sensor collects the data such as human health and working environment, and the information processing is then conducted to derive the valuable information and knowledge for decision making of safety managers. Lastly, Cluster 6 that indicates vehicle systems is shown in keyword network. Cluster 6 plays a critical role in presenting strong connection among other keywords in convergence network of lower degree of linkage in next analysis procedure although having a single safety field of vehicle in this initial network, not a convergence.

Based on basic clusters, trajectory of technology convergence can be traced in terms of linkage strength. As shown before, basic convergence clusters have no connection between clusters of technology convergence. When the number of co-occurrence decreases by 1 (from six to five), several clusters start to interact with related clusters.

As shown in Fig. 8, the convergence network, which is made with the number of co-occurrence of above five, shows two trajectories: convergence between Cluster 1 and Cluster 3 and between Cluster 5 and Cluster 6. The other clusters have still no distinctive linkages. This first convergence network is defined as the particular barriers for locking machinery in manufacturing in terms of technology keywords of *engage*, *extend*, *needle*, and *assembly* in Cluster 1 and Cluster 3. The second convergence network focuses on the sensor and information safety systems for vehicle by liking between *sensor* of technology keywords in Cluster 5 and *drive-vehicle-condition* of technology keywords in Cluster 6. The vehicle is first connected with another cluster in this stage. Among sensor network technologies, the technology of sensor and information has been strongly converged for vehicle safety.

With the number of co-occurrence of above four, the convergence trajectory is presented as shown in Fig. 9. Many convergence linkages among technology keywords have started from the number of co-occurrence of above four. The technology keywords in each cluster have been mostly interconnected and several clusters begin to be connected. Three major types of convergence network are presented: linkage between Cluster 3 and Cluster 4, between Cluster 3 and Cluster 5, and between Cluster 4 and Cluster 5.

The Cluster 3 and 4 are connected through the keywords of *house* and *contact* contained in Cluster 3 and Cluster 4, respectively. This result implies that a part of technologies related to electric shock caused by a short circuit of contact in the house are developed; further, buildings such as plant, and any buildings can be concerned as a house. The electricity safety is improved and converged focusing on the house for the life of human beings and workers.

Furthermore, it is interestingly found that the convergence focusing on Cluster 5 for system safety suggests distinctive significance for information systems in electricity and in vehicle. First, the hub keywords which link Cluster 4 with Cluster 5 are identified as *control*, *signal*, and *sensor* in terms of the number of linkage. These keywords take the control factors for electric wiring systems using sensor systems into account. The direct link of keywords between *control* and *signal* presents the automated management systems in electric power of safety fields such as plant and construction sites: *power-circuit-control-signal-sensor-process-detect-datum*. Thus, it is noted that this convergence trajectory focuses on control problems for safety fields. Second, the hub keywords which connect between Cluster 5 and Cluster 6 are extracted as *sensor*, *vehicle*, *drive*, and *condition* in terms of the number of linkage. These keywords are referred as to the safety technology for vehicle is in particular being highlighted for managing drive conditions based on sensor technology. In general, the traffic accident is considered one of the most important safety fields and thus, this convergence network indicates that safety technology related to the road safety for driving vehicle has been developed. To be specific, during the decade, the direct linkage among *detect-time-determine-sensor-drive-vehicle-condition* is progressing incrementally. Compared with other products, the vehicle industry has been improved as an independent safety field by promoting convergence in technology and system safety fields.

In the end, at the number of co-occurrence of above three, the keywords are completely connected as the whole convergence network as shown in Fig. 10. Two paths of convergence trajectory are monitored: Cluster 1 and Cluster 2, and Cluster 1 and Cluster 3. These two paths are simply summarized as technology convergence for operations safety in general safety fields.

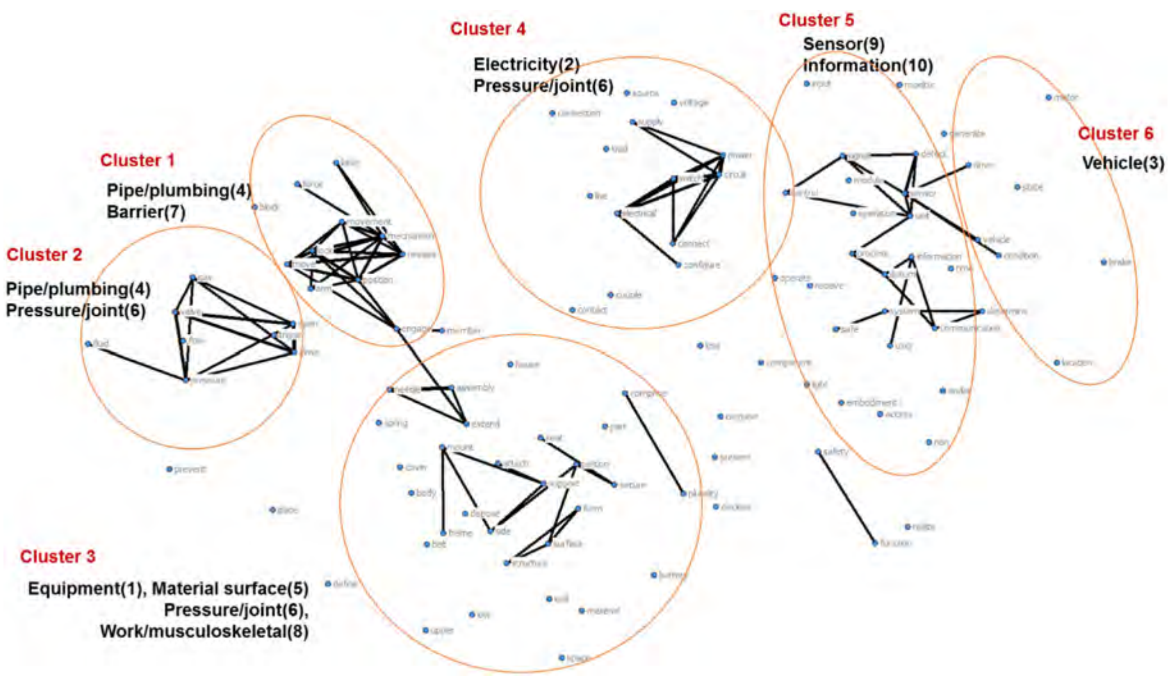


**Fig. 8.** Convergence network: the number of co-occurrence of above five.

## 5. Discussion

### 5.1. Types of safety technology convergence

According to the change of connection among technology keywords in clusters, significant trajectories are detected to explain the types of safety technology convergence. We summarize distinctive convergence network as described in Table 6.

With regard to the degree of strength, different perspectives can be discussed. First, the strong convergence as shown in Fig. 8 presents the dominant trends of all safety technologies. The results of patent analysis represent two convergence trajectories are progressed for machinery safety and vehicle safety. In practice, the machinery safety is essential for workers' life, and thus, many barriers are developed and perilous tasks tend to be automated for preventing accidents in plant. Also, a vehicle is most important transportation in modern industry, but it is one of the most perilous factors that cause accidents as well. Conventionally, the vehicle safety is considered in traffic and driver safety. Thus, many technologies have been infused into the vehicle, including the sensor-based information technologies for checking conditions of parts such as engine, tire, and dashboard and them of drivers such as stress, health, and mental of drivers.

However, the context of strong convergence network is somewhat broad to understand which safety technologies have been made in more

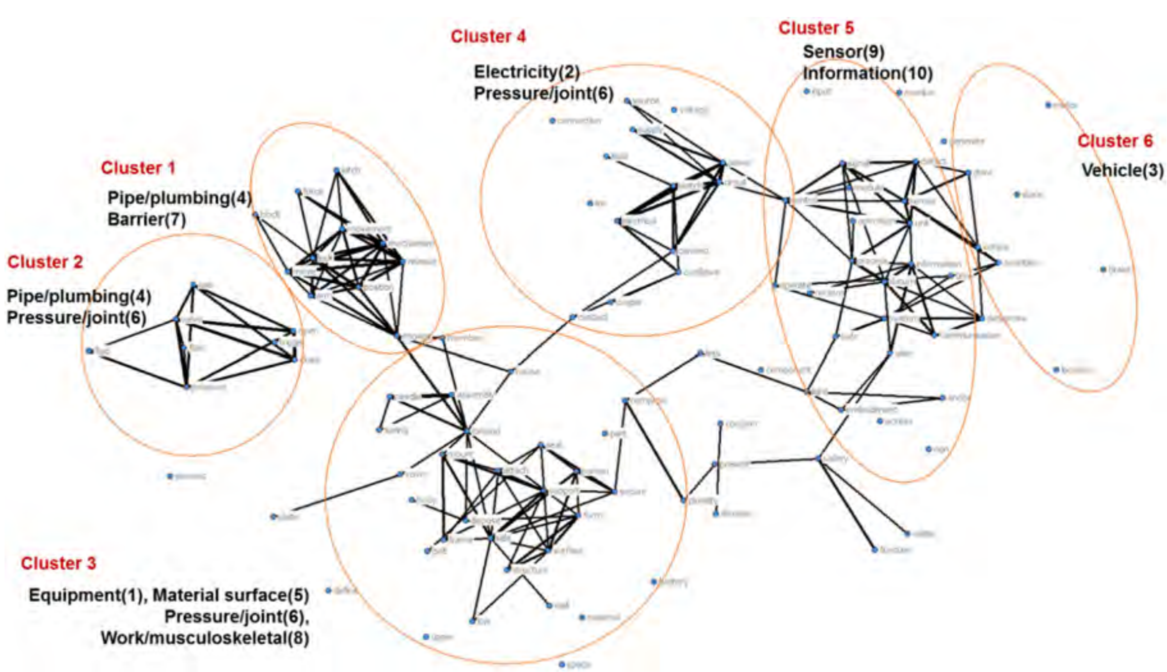


**Fig. 9.** Convergence network: the number of co-occurrence of above four.

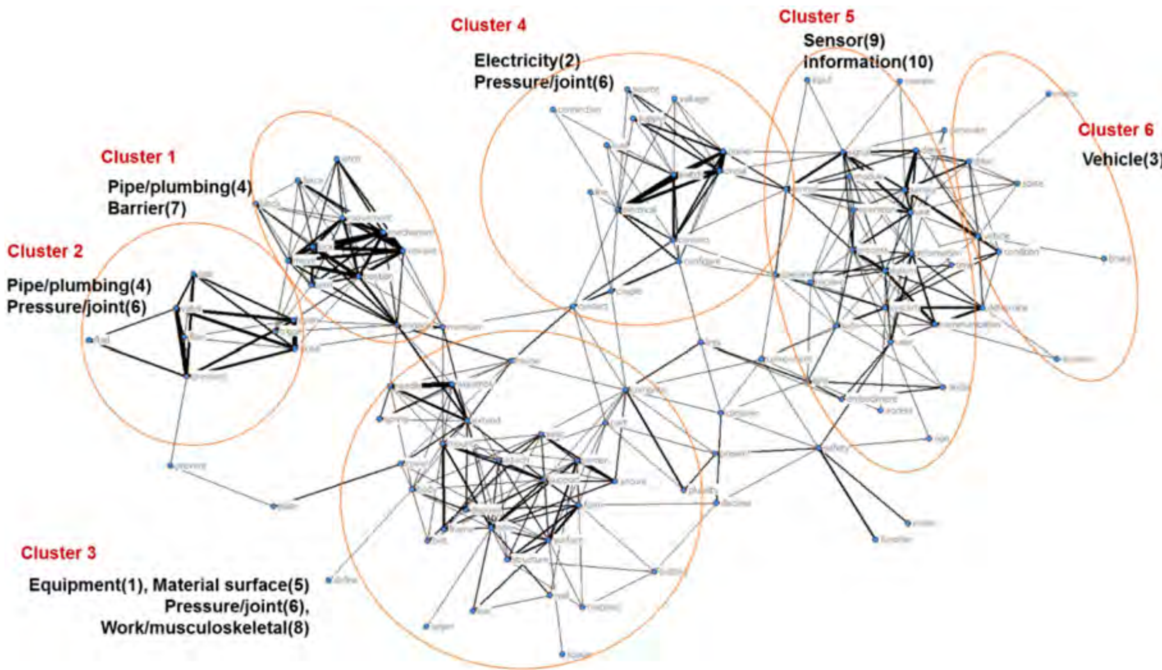


**Fig. 10.** Convergence network: the number of co-occurrence of above three.

detail. The weak convergence network as shown in Fig. 10 is useful for identifying specific technologies for safety. For example, the vehicle safety presented in weak convergence network shows explicit technology functions according the combination of a few keywords. The main technology of vehicle safety is revealed as the support functions during driving vehicles. For example, the patents included in this cluster are mostly related to advanced driver assistant systems (ADAS). In addition, some patents related to electronic control units (ECU) are identified and this pattern shows the connection among Cluster 4, 5, and 6. Thus, the weak convergence network is meaningful for extracting particular safety technologies.

### 5.2. Convergence trajectories of safety technologies

According to the strength of linkage as shown in Fig. 11, convergence networks are structured through distinctive development paths; based on the main Cluster 3, 4, and 5, the convergence trajectories are divided into threefold. The left side of Fig. 11 shows strong convergence fields based on Cluster 1–3 and Cluster 5–6, while the right side of Fig. 11 represents weak convergence fields based on multiple clusters related to Table 6. Through the change of paths from weak linkage to strong linkage, several types of the convergence trajectory can be defined.

The first trajectory is dominantly changed through the convergence across Cluster 1, 2 and 3. This trajectory has been improved for the general machinery safety in the production process of plants. The pipe/plumbing contained in Cluster 1 and 2 is revealed as a main safety field, but it is identified that a wide range of safety fields for general machinery safety, not limited to pipe/plumbing, are included by monitoring technology keywords in Cluster 3 such as needle, assembly, attach, structure, cover, surface, and mount. Also, several human factors such as body, seat, and belt are shown in this trajectory.

The second trajectory is focusing on Cluster 5 connected with Cluster 3 and 4. As the automated machinery and electricity systems were developed for productivity and health management, the sensor and information systems (Cluster 5) have been introduced in plants of manifold industries. In fact, recently, the smart factory for the efficient production based on application of Internet of Things (IoT) has been highlighted in academy and practice as well. Thus, the support system based on information technology has been continuously converged and improved for maintaining safety of various industries.

The third trajectory presents the development path of vehicle safety which interact between Cluster 5 and 6. The target of safety is focused

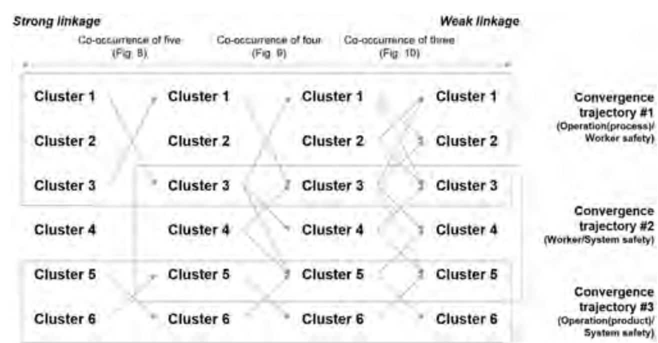


**Fig. 11.** Types of convergence trajectory.

**Table 6**
Types of safety technology convergence.

| Type | Purpose | Safety technology convergence | Related clusters |
|---|---|---|---|
| Strong convergence network | Identifying dominant trends | Barriers for locking machinery in plants | 1, 3 |
| | | Sensor and information safety systems for vehicle | 5, 6 |
| Weak convergence network | Identifying particular technologies | Prevention from electric shock in the buildings | 3, 4 |
| | | Control factors for electric wireless systems using sensor systems | 4, 5 |
| | | Sensor-based vehicle control systems for managing drive conditions | 5, 6 |

on the product level in operations safety. Many sensor and information technologies have been applied into improving vehicle itself and driving conditions. During a century, technology innovation in vehicle shows a remarkable achievement along with technology convergence among machine, chemistry, production, fabrication, design, and information. In future, the unmanned vehicle is being developed with numerous electronic and information technologies, and thus, the convergence network in vehicle safety will be concretely structured by improving support technology which prevents accidents in advance and maintains safe driving.

### *5.3. Implications of future safety management*

Furthermore, we suggest the direction of technology convergence in safety fields. The convergence trajectory #1 (CT #1) includes technology in safety of facilities in the plant, focusing on operations and worker safety. This trajectory has been developed for technology in practical sites such as chemistry, manufacturing, and construction sites. Next, the convergence trajectory #2 (CT #2) is defined as information system for supporting industrial sites and workers by designing safety management systems. This trajectory has been improved through overall innovation in operations, worker, and system safety. Lastly, convergence trajectory #3 (CT #3) includes safety technology for vehicle products. This trajectory has emerged through operations and system safety because workers are not involved in product safety. It is indicated that each of convergence trajectories is related to the target of safety for site, support, and product, respectively. Among others, the information technology (CT #2) as complementary for the system safety has been dominantly developed to mediate the safety management for industrial sites (CT #1) and vehicle (CT #3).

Thus, in future, sensor-based information technology along with CT #2 can be considered a very opportune issue in constructing safer systems for workers and be strongly applied into various industry sites. Recently, many studies have already been tried to develop the smart factory and construction using new information technology such as Internet of Things (IoT), Cyber-Physical System (CPS), and digital twin architecture (Albino et al., 2015; Fang et al., 2018; Nath et al., 2017). The IoT has been introduced in preventing accidents by automating processes of factory layout and CPS has designed with IoT systems and digital twin applications (Sung, 2018). For example, the Siemens, which is one the global corporates of manufacturing technology, has concentrated on intelligent manufacturing systems for high quality and safe manufacturing processes using IoT and CPS (Li, 2017). Constructing intelligent systems, many manufacturing and process companies have struggle to increase productivity with reducing perilous risks.

Consequently, along with the dynamic change of safety issues during history of industrial safety, safety technology convergence has a positive impact on the human health and society. During the history of industrial safety, this study notes that technology and social convergence plays a critical role in safe and secure working environment and society. Many fields of technology have been related to each other for preventing risks of industry practice. Ultimately, identifying convergence trends of safety fields and technologies should be required in the recent age. Through integration among many safety fields and technologies, effective strategy of safety technology management can be formulated by safety engineers and managers. Thus, we also attempt first to identify which technology fields are mostly related to safety technology and to investigate the potential technology that is applied to future industrial fields.

## 6. Conclusion

This study presents change and evolution of technology development for investigating various industrial safety issues. The safety technology has continuously been improved for protecting perilous and hazardous factors, covering all aspects of the safety fields, but previously, the studies of identifying major safety fields and technologies have rarely been conducted. Thus, the contribution of this study lies on monitoring major safety fields and improvement trajectories for providing the safety managers and engineers with practical insights. This is almost first approach to identifying the types of safety technology fields and the change of safety technology development. By visualizing convergence clusters and trajectories, we also monitor which technologies are mostly developed for safety. According to path of convergence trajectories, it is indicated that safety technologies are developed for safety in industrial sites, information systems, and vehicles. Each of safety technologies is directly or indirectly related to operations, worker, and system safety as well. The highlight of this study is that information technology is a dominant trend and plays a critical role in mediating between safety managers in the control tower and workers in the industrial site. Also, needs of product innovation in safety such as vehicles are addressed.

Despite these contributions, several research issues have arisen for constructing better safety systems. First, although this study shows the dominant safety technologies based on the keywords, the detailed technology specifications for safety innovation are not commented. For providing more implications for managers and researchers of safety technology, we should take a look at individual patent descriptions. By defining the scope of industry and industrial safety more precisely in future study, the specific outcomes of technology description can be derived as well. Second, the patent networks can be used to solve problems of industrial systems, matching with risk and hazard factors. By using risk keywords extracted from accident reports, new insights are obtained to find and forecast new technology that solve risky problems in practice. Providing detailed technology specifications and applicable technology for dealing with risky problems, we propose practical guidelines based on patent analysis. Further, when we can gather the text-based accident data, the new technologies are usefully predicted by matching risk keywords contained in accident report documents published by Occupational Safety and Health Administration (OSHA) or International Labor Organization (ILO) and technology keywords contained in patent documents, based on data analytics such as novelty detection methods or machine learning algorithms.

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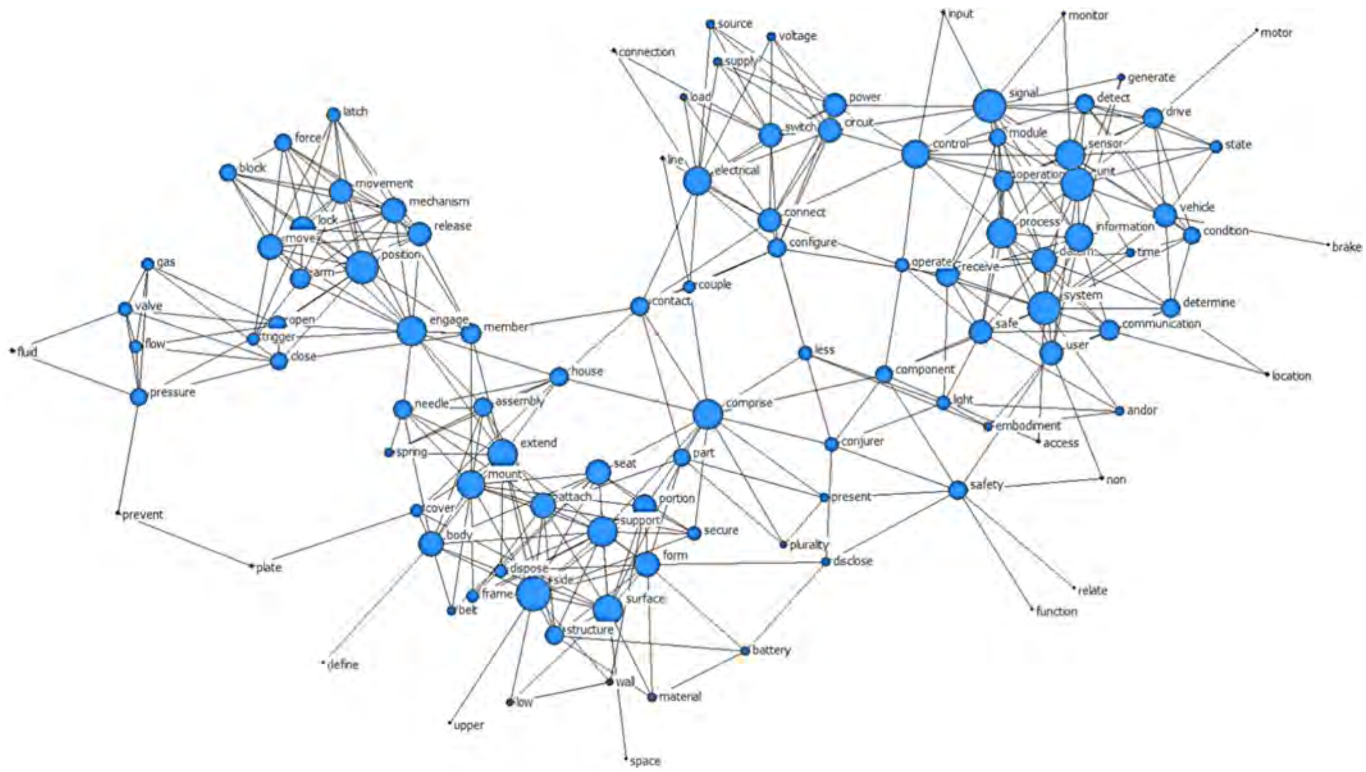
### Appendix A. Detailed convergence network




* Node size represents the number of keyword occurrence

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**Bomi Song** is an assistant professor of the School of Air Transport, Transportation and Logistics at Korea Aerospace University (KAU). She holds a BS, MS, and Ph.D. in Industrial Engineering from Seoul National University (SNU). Her research interests include the areas of technology innovation, technology intelligence, technology forecasting, service engineering, service innovation, and information visualization.

**Yongyoon Suh** is an assistant professor of the Department of Safety Engineering at Pukyong National University (PKNU). He holds BS, MS, and Ph.D in Industrial Engineering, from Seoul National University (SNU). He was involved in many projects related to the ICT policy of South Korea at the Electronics and Telecommunications Research Institute (ETRI). His research currently focuses on safety and risk analysis in operations systems and technology management in ICT systems.