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A Bottom-up Trend in Research of Management of Technology

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Abstract. *Management of Technology (MOT) is defined as an academic discipline of management that enables organizations to manage their technological fundamentals to create competitive advantage. MOT covers a wide range of contents including administrative strategy, R&D management, manufacturing management, technology transfer, production control, marketing, accounting, finance, business ethics, and others. For each topic, researchers have conducted their MOT research at various levels. However, a practical and pragmatic side of MOT surely affects its research trends. Finding changes of MOT research trends, or the chronological transitions of principal subjects, can help understand the key concepts of current MOT. This paper studied a bottom-up trend in research fields in MOT by applying a text-mining method to the conference proceedings of IAMOT (International Association for Management of Technology). First, focusing on only nouns found several keywords, which more frequently emerge over time in the IAMOT proceedings. Then, expanding the scope into other parts of speech viewed the keywords in a natural context. Finally, it was found that the use of an important keyword has qualitatively and quantitatively extended over time. In conclusion, a bottom-up trend in MOT research was detected and the effects of the social situation on the trend were discussed.*

Keywords: *Management of Technology; Text Mining; Research Trend; Bottom-up Trend; Patent*

1. Introduction

MOT (Management of Technology) is defined as the disciplines of management that enable organizations to manage their technological fundamentals to create competitive advantage. MOT should not only fulfill the management needs of a specific set of technologies within a domain and inter-domain relationship, but it should also develop the implementation strategies according to the available resources, current technologies, future markets, and socio-economic environment (Linn& Zhang, 2000). Therefore, how to manage technology has become an important issue in the past few decades, and the MOT community has developed a wide range of methodologies and applications for both academic research and practical applications (Drejer, 1997) (Liao, 2005). Nowadays, MOT covers a wide range of contents including administrative strategy, R&D management, manufacturing management, production control, marketing, accounting, finance, intellectual property strategy, business ethics, and others.

MOT research has been conducted at various levels for each kind of these contents. This made it difficult to understand an overall picture of the MOT research field. Finding research trends in MOT is useful for understanding the key concepts of current MOT. There are several approaches to find the research trends. One obvious method is to survey the trends in papers published in academic journals.

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However, since each academic journal has its own predetermined themes, it is difficult to grasp the overall trend of MOT by just reviewing a few journals. Moreover, since research that has already produced a result is presented in academic journals, there is a time lag between research running currently and research presented in journals.

Another method to investigate the research trends is to examine the topics presented in major international conferences on MOT. Such conferences are likely to reflect research trends without the time lag found in academic journals, and their proceedings would appear to be an appropriate research target. The problem is how to investigate them. In an international conference, not all presentations are assigned to appropriate sessions, since they are constrained by time and location. In other words, the number of presentations included in a session category does not give an accurate picture of research trends. In addition, the session categories themselves change every year, reflecting the opinions of the program committee.

In light of this situation, the very contents discussed at an international MOT conference are appropriate to this research purpose. This is why we have already studied the research trends in MOT by applying a text-mining method to the conference proceedings of IAMOT (International Association for Management of Technology) and found that the social situations have enormous impact on the research trends in MOT (Ishino, 2014). IAMOT is a non-profit, non-governmental professional association in the USA whose purpose is to encourage high quality research and education in the field of MOT. IAMOT's first international conference was held in 1988, and its 23rd conference will be held at Washington D.C. in USA in May 2014. The IAMOT conference is one of the most predominant international academic conferences concerning MOT *(http://www.iamot.com/)*.

Based on the achievements of our previous work, this paper studied the research trends in MOT, especially focusing on a bottom-up trend. By expanding the range of a text-mining method to several parts of speech including noun, verb, and adjective, we found that an important keyword representing a bottom-up research trend has become widely used over time, in the quantitative as well as the qualitative sense.

2. Materials and Methods

2.1. Data used for analysis

We selected proceedings of the IAMOT conferences held in 2003, 2008, and 2012, as the experimental materials. Although we obtained proceedings of both 2008 and 2012 conferences as digital PDF files, the proceedings of the 2003 conference were obtained as paper-based records. Therefore, we digitized the data of the 2003 conference using OCR software, and then manual check was conducted. Then, the abstract parts of research papers in those three proceedings were extracted. Although almost all papers had explicitly the abstract, some papers were free from boundaries between the abstract and the body text. In such cases, we determined by hand the text part corresponding to the abstract. In order to ensure a quality of materials, we eliminated any papers for which an abstract was clearly omitted during this process, although there were not many papers like that.

Finally, the numbers of extracted abstracts of conference year 2003, 2008, and 2012, were 369, 236, and 207, respectively — that is a total of 812 abstracts in all. There was some variation in the lengths of the abstracts, with the average being 246 words.

2.2. Analysis methods

First, we performed morphological analysis on the texts using Tree Tagger, software for annotating text with part-of-speech and lemma information (Schmid, 1994). Then, focusing on only the nouns (general nouns and proper nouns), we calculated numerical feature values of each noun including TF (term frequency), DF (document frequency), and TF-IDF (term frequency - inverse document frequency). Those are identified as follows:

$$TF(w_i) = \sum_j \left(\frac{n_{i,j}}{\sum_k n_{k,j}} \right) \quad (1)$$

, where represents the word i, and n_{ij} is the number of appearances of the word i in the document (abstract) j. Therefore, $TF(w_i)$ indicates the appearance frequency of the word i.

$$DF(w_i) = \left| \{ d : w_i \in d \} \right| \quad (2)$$

, where $DF(W_i)$ is the number of documents in which the word i appears.

$$TF \cdot IDF(w_i) = \sum_j \left(\frac{n_{i,j}}{\sum_k n_{k,j}} \right) \times \log \frac{|D|}{|\{d : w_i \in d\}|} \quad (3)$$

where $|D|$ is the total number of documents in the specified proceedings.

These features are commonly used as weighting factors in information retrieval and text mining. Subsequently, we investigated the relationships between words using network analysis, focusing on the co-occurrence of words. Based on the values of those features and the weight in the network of words, we selected keywords that represent an increasing research trend. Those words were discussed from the social aspect. Then a keyword selected as representing a bottom-up trend was more deeply investigated about how to use in the abstracts, by expanding the range of the text-mining to several parts of speech including noun, verb, and adjective.

In analyzing the data, we ignored the words "paper," "study," "research," and "result" since these are common to all academic paper abstracts, regardless of the research field.

3. Results and Discussion

3.1. Appearance frequency of words

First, we investigated the frequency distribution of the appearance of words. The results show that several dozen words from the top in the appearance frequency recorded very high frequency, while the overwhelming majority of words appeared only a few times. This was the result in line with expectations, because one of the statistical properties of natural languages is that the distribution of word frequencies is closely approximated by a power law. Then, we focused on statistics calculated for each word. Table 1 shows the top-10 ranking words of each conference year in terms of the TF value. The TF measures how frequently a word occurs in the proceedings of the specified conference year. From Table 1, the following words had the highest ranking: "technology","process", "development","innovation","management", and "product." Those words express characteristics of MOT, and the tendency remains much the same through the conference years. This result is adequate but insipid, since these words are clearly and directly related to MOT.

Table 1. Top 10 Nouns in Terms of the TF Value

TF Ranking	2003	2008	2012
1	technology	technology	technology
2	process	process	innovation
3	development	development	development
4	company	innovation	model
5	management	management	analysis
6	product	product	process
7	market	industry	firm
8	system	analysis	industry
9	model	knowledge	case
10	innovation	company	company

Table 2. Top 10 Nouns in Terms of the TF-IDF Value

TF-IDF Ranking	2003	2008	2012
1	technology	innovation	**patent**
2	R&D	technology	**service**
3	product	R&D	innovation
4	innovation	project	technology
5	firm	knowledge	firm
6	project	firm	industry
7	company	product	system
8	system	management	capability
9	model	model	country
10	process	service	company

In contrast, Table 2 shows the top-10 ranking words in terms of the TF-IDF value. The TF-IDF is introduced to reflect how important a word is to a document in a collection (Wu, Luk, Wong, &Kwok, 2008) (Salton& Buckley, 1988). The TF-IDF value increases proportionally to the number of times a word appears in the document (abstract), but is offset by the frequency of the word in the proceedings. This helps to control for the fact that some words are generally more common than others. What is interesting to note is that in 2012, the word “patent” and “service” appeared in first and second places. Based on the TF-IDF value, the rank order of the word "patent" was boosted up: 479 in 2003, 14 in 2008, and the first in 2012. The same thing was observed as to the word “service.” The rank order of the word “service” jumped: 40 in 2003, 10 in 2008, and the second in 2012.

3.2. Co-occurrence of words

Words can be regarded as compositional units for expressing what an author would like to state. Since the words existing in the same abstract shape together the abstract according to author's aim, such relationships between words are very important. If any two nouns appear in the same abstract, we defined the relationship of them as the co-occurrence. The strength of the co-occurrence can be represented by the number of the abstract in which the co-occurrence is observed. By using a graphical network, we expressed the state of the co-occurrence of words in each conference year. In the network, each word is depicted as a node, and co-occurrent relationships are represented by edges. The edges are drawn when the strength of the co-occurrence exceeds a certain threshold value. We calculated the various feature values of each word network in each conference year, including the density, degree centrality, closeness centrality, betweenness centrality, and so on. We found that these feature values are very similar between the word networks of each conference year.

In investigating changes in research trends, we focused on the betweenness centrality of the network nodes. The betweenness centrality of a node indicates the ratio of the edges between all other pairs of nodes in which that node is included. This metric is proposed based upon the notion that the more routes that pass through a point, the higher its betweenness centrality will be. In this research, the betweenness centrality of a word becomes higher when the word is co-occurrent with more other kinds of words. With respect to the betweenness centrality, the rank orders of words "patent" and "service" jumped to 8 and 25, respectively, in 2012.

3.3. Bottom-up research trends

Words "patent" and "service" were candidates that represent an increasing research trend. Then, we investigated the social situation that influences MOT research.

Professor David Weber, Director of MOT program, MIT, gave a presentation that emphasized that the main theme of MOT has been changing every 10 years (Weber, 2003). They were "managing R&D," "Technology transfer," "Technology innovation," "Technology Strategy," and "Corporate Venturing" in every 10 years from 1960s to 2000s, respectively. The reason why the MOT main theme keeps changing would be that MOT has a practical aspect as an academic discipline closely related to the real world. Therefore, MOT research would be influenced largely by the social situation and industry's demand. Although the analysis of Professor D. Weber was finished at 2000s, what is the next major theme in 2010s? To answer this question, we investigated the session categories of the IAMOT conferences. Table 3 and 4 show a list of the session categories of the conferences held in 2003 and 2012, respectively.

Table 3. Session Categories of IAMOT 2003

1	Knowledge Management
2	Strategic Competencies for Sustainable Development
3	Social Impact of Technologies Development
4	MOT Education and Research/ Corporate Universities
5	Innovation and New Product Development
6	National Systems for Technology Development
7	Small Businesses and Entrepreneurship/ Technology Incubation
8	Emerging and Breakthrough Technologies
9	Technology Transfer/ Technology and Security
10	Technology Foresight and Forecasting
11	Information and Communication Technology Management
12	The Integration of Technology and Business Strategies
13	R&D Management
14	Project Management
15	Industrial and Manufacturing Systems Technologies/ Supply Chain Management
16	Virtual Organizations and Partnerships/ E-Commerce
17	MOT in Developing Countries
18	Managing R&D in China

Table 4. Session Categories of IAMOT 2012

1	Technology-Service Convergence
2	MOT in Services
3	R&D Management
4	Technology Strategy
5	Technology Transfer
6	Service Innovation
7	Logistics and SCM
8	Managing Energy Technology
9	ICT Management
10	Science and Technology Policies
11	Science and Technology Incubation and Entrepreneurship
12	Science, Technology and Society
13	Management of Technology in Developing Country
14	MOT Education and Research
15	Manufacturing Servitization
16	Measurement of Technology
17	User Innovation and Open Innovation in East Asia

There are many differences between the two session category lists. This is because the lists mirror the social demand for MOT. It is notable that the word “service” appeared in the 2012 list, not in the 2003 list. Moreover, there are three sessions related to "service" in the 2012 list: Session 1, 2, and 6.

The social situation related to "service" would be summarized as follows. The service sector has been becoming increasingly important throughout the developed countries. However, compared with the manufacturing industry, productivity in the service sector is low, and there are strong calls for its improvement. In response to this, a new concept has emerged, centered on IBM's "service science" (now abbreviated as SSME, for services sciences, management, and engineering). The goal of service science is to increase the productivity of the service industry, promote innovation, and create greater validity and transparency when assessing the value of investments in services. Eventually, "service" is a surely increasing research trend, but it is not a bottom-up trend. It can be regarded as a top-down trend.

Contrarily, there are no words like “patent” or “intellectual property” in the session category lists. In other words, the existing session categories did not have any categories that specialized patent analysis. However, the ratio of documents (abstracts) containing the word “patent” increased over time as shown in Table 5. There were 30 papers that included the word “patent” in their abstracts in 2012. The majority of these did not include “patent” in the title, and they were spread across the session categories. Therefore, research related to "patent" can be viewed as an increasing bottom-up research trend.

Table 5. Quantitative Changes of Abstracts Containing the Word “patent”

conference year	2003	2008	2012
total abstracts	369	236	207
abstracts containing the word "patent"	10	17	30
ratio	2.7%	7.2%	14.5%

3.4. Extended Text Mining for a Bottom-up Trend

The word "patent" was selected as a keyword that represents an increasing bottom-up trend of MOT research. In order to investigate more deeply about what other words are related to the word "patent," we extracted abstracts in which the word "patent" was contained. In addition, expanding the range of the text mining to several parts of speech including noun, verb, and adjective, we performed the text mining against the abstracts extracted. Figure 1 and Figure 2 indicate co-occurrent relationships between words in abstracts of the conferences held in 2003 and 2012, respectively. The definition of co-occurrent relationships and the manner of drawing are the same as mentioned before in Subsection 3.2. In Figure 1 and Figure 2, larger nodes represent higher frequency words. In the similar way, thicker lines roughly represent stronger edges. In the 2003 proceedings, technology transfer, R&D evaluation, and management of intellectual properties were main purposes to use the patent data. The 2012 proceedings, however, described much more various use of patents, including investigation of knowledge flow, measurement of differences between two patent databases, and evaluation of patents as intangible assets.

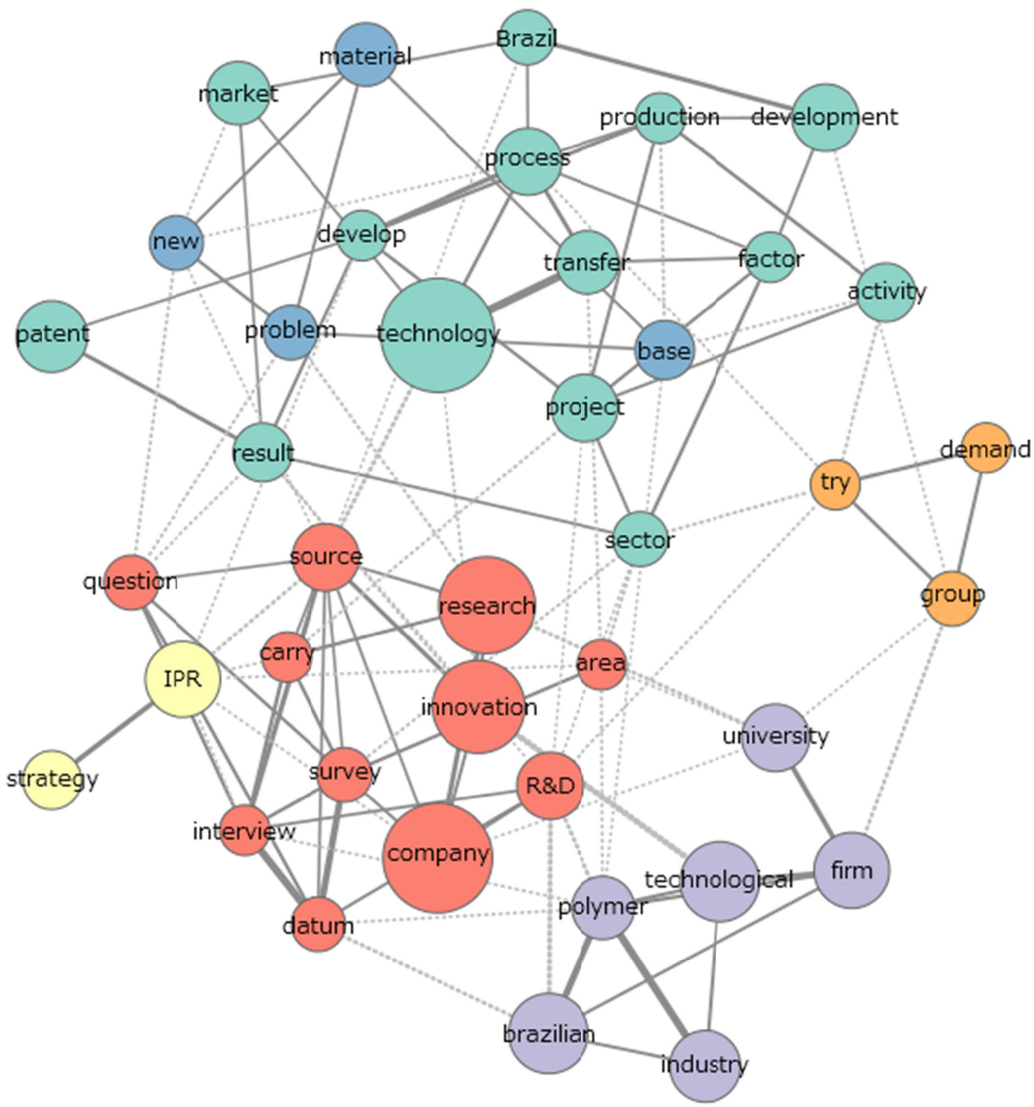

Figure 1. Co-occurrence Network of Words in the Proceedings of IAMOT 2003

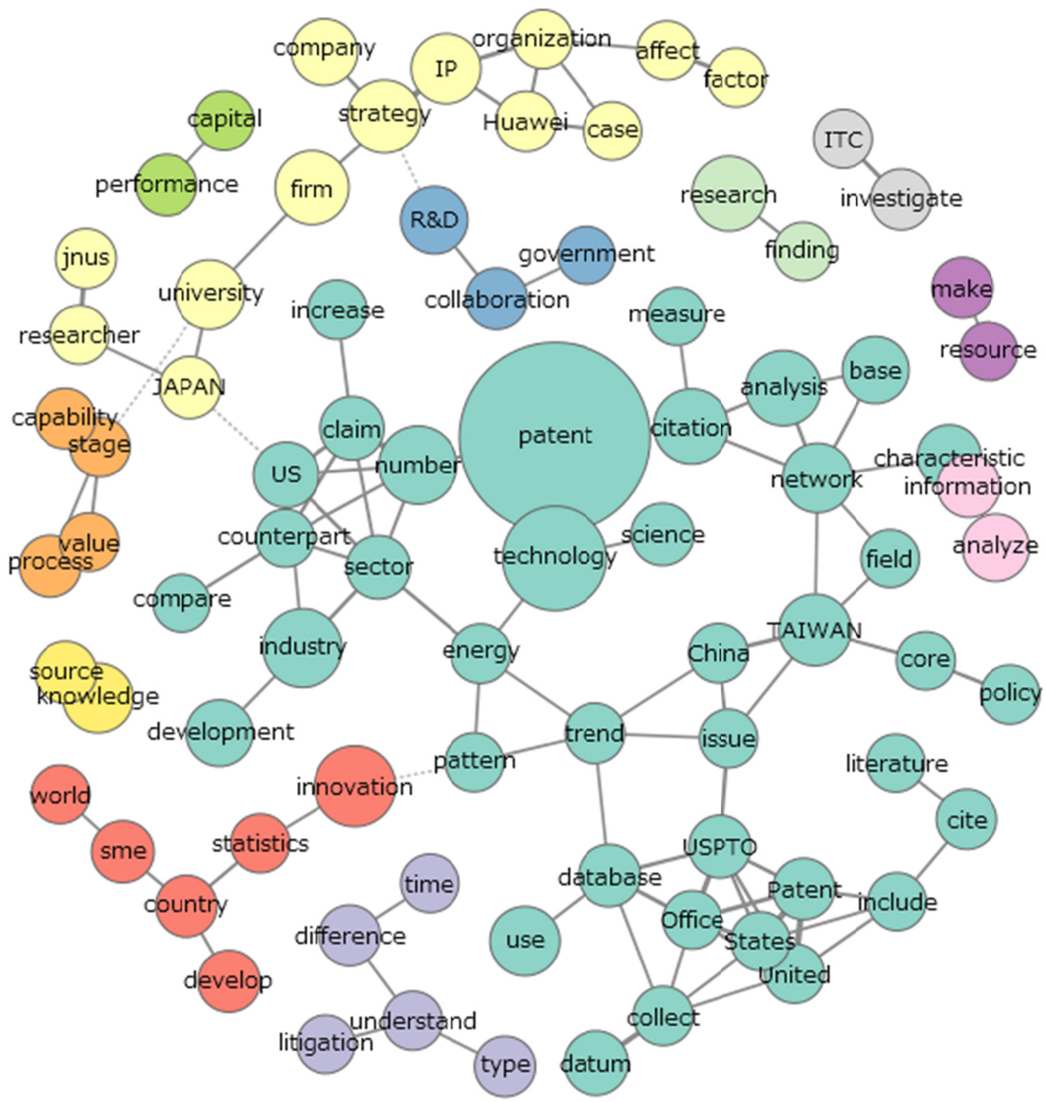

Figure 2. Co-occurrence Network of Words in the Proceedings of IAMOT 2012

The increase of patent-related MOT research would be due primarily to the progress of the ICT technology that permitted enhancement of the data processing ability and development of the patent analysis tools. This might indicate a new bottom-up trend where people come to use more of the patent analyses in making business strategy.

We have shown that patent-related MOT research has been qualitatively and quantitatively increasing at the IAMOT conference. It would have been impossible to discover this phenomenon by investigating only the conference session titles. This demonstrates the effectiveness of the proposed method, where the text mining is first conducted against the abstracts and then the network analysis of the co-occurrence of words is performed.

4. Related Research

4.1. Topic Extraction Using Text Mining

Research and development in the field of text mining has increased and spread since the rapid digitalization of text began in the late 1990s (Nasukawa, 2006). One field of application for text mining involves topic extraction (Fukui, Saito, Kimura, &Numao, 2007). This is the automatic extraction of the appropriate main topics from a group of texts after natural language processing, in order to assist with text sorting. Currently, mechanical topic extraction methods are generally based on a vector space model, in which significant clusters of words that appear in a text are conceived as the base of a feature space, and each text document is treated as a word frequency vector. This study employs concepts that are similar to topic extraction, in which a text is characterized using a vector that represents the appearance or non-appearance of words. However, this study does not select beforehand a set of words that characterizes the topic. A typical research of the topic extraction uses a training dataset where documents for training are already classified into topics before learning (Wayne, 2000). That is called the supervised learning, whereas this study, by contrast, does not aim to learn the classification of a training set.

4.2. Co-Occurrence Network of Words

In the framework of a co-occurrence network, words that appear in a document are treated as nodes, and words that appear in proximity to each other are linked by edges. In such a network, words that have a significant degree of relatedness form solid mutual connections called cluster structures. On the other hand, the connections between words with a low degree of relatedness are sparse. Several methods have been proposed for grasping the meanings of words and for eliminating polysemy, by focusing on this characteristic of density of connections in network structure (Ferret, 2004).

Recently, a complex network approach has been used to express the relationships between factors, in an attempt to investigate not only the static characteristics, but also the dynamics of factors. Previous research demonstrated how well the core words of a language (the kernel lexicon) could be extracted based on the difference in the exponential distribution of the co-occurrence network of words (Dorogovtsev& Mendes, 2001). Another research investigated the difference in the formation of the cluster structure appeared in the co-occurrence network of words in newspaper articles (Sato, Fukuda, Sugawara, &Kurihara, 2007).

5. Conclusions

In this study, we studied the research trends in MOT by applying a text-mining method to the conference proceedings of IAMOT. By performing the network analysis of the co-occurrence of words, we detected a change in the research stream and finally found the influence of the social situation on the research trends. We have shown that both patent-related research and service-related research have increased in MOT research. However, the increase of service-related research was caused under the initiative of the business industry, and it can be regarded as a top-down trend. On the other hand, the increase of patent-related research is a spontaneously arising phenomenon. It can be viewed as a bottom-up trend. This phenomenon could not be discovered by analyzing only the conference session titles.

In the future, we will study the word co-occurrence networks in more detail by using new indices representing word features, so that we may find other signs of the research trends. The insights obtained will then be used to create effective educational materials of MOT as the graduate school level.

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