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Text mining to gain technical intelligence for acquired target selection: A case study for China's computer numerical control machine tools industry

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Abstract

Technology strategy plays an increasingly important role in today's Mergers and Acquisitions (M&A) activities. Informing that strategy with empirical intelligence offers great potential value to R&D managers and technology policy makers, this paper proposes a methodology, based on patent analysis, to extract technical intelligence to identify technology M&A target technologies and evaluate relevant target companies to facilitate M&A target selection. We apply the term clumping process and a trend analysis together with policy and market information to profile present R&D status and capture future development signals and trends in order to grasp a range of significant domain-based technologies. Furthermore, a comparison between a selected acquirer and leading players is used to identify significant technologies and sub-technologies for specific strategy-oriented technology M&A activities. Finally, aiming to recommend appropriate M&A target companies, we set up an index-based system to evaluate the acquired target candidates from both firms-side perspective and target firm-side perspective and differentially weigh for specific M&A situations. We provide an empirical study in the field of computer numerical control machine tools (CNCMT) in China to identify technology M&A targets for an emerging Chinese CNCMT company – Estun Automation under different M&A strategies.

Keywords

Technical intelligence; Mergers and acquisitions; Patent analysis; Text mining.

Introduction

Mergers and Acquisitions (M&A) continues to be a hot topic for today's commercial activities (Baker and Kiymaz, 2011;Arora, 2013). M&A obtains valuable resources, immediate access to products, and/or distribution channels, and, thus, it is functioned as an external source of innovation (Heeley and King et al., 2006). Since more and more M&A deals are taking place in high-tech and science-based sectors, technology-driven mergers and acquisitions (Tech M&A) has received increasing attentions in recent years (Stahl, 2010; Lin, 2012; He and Wang, 2014). Tech M&A usually realizes values through a combination of technological assets (Jones and Lanctot et al., 2001), such as research and development (R&D) skills, experienced personnel, and specific technologies (Inkpen and Sundaram et al., 2002; Lehto and Lehtoranta, 2004). In this situation, technological variables start to occupy a larger proportion for considerations in M&A strategies, and would even be equal to financial and managerial variables, the leading factors of M&A in the past years (Wei and Jiang et al., 2009).

Although the volume of M&A deals is steadily increasing, its failure rate is also far high – normally between 70% and 90% (Christensen and Alton et al., 2011). The selection of appropriate target companies to well-match the strategic purpose of M&A has become a core phase of M&A (Kengelbach, 2011). In terms of the technological perspective, we summarize several issues that trouble M&A decision makers heavily as below: 1) which technology is our target, which aspects of technical potentials we are looking for, and which company could be the acquired candidates (Park and Yoon et al., 2013; Yurov and Greenstein et al., 2013); and 2) how to evaluate these candidates and select suitable target for a successful M&A on technical integration (Yu and Umashankar et al., 2015).

Technical intelligence has been always applied for strategic decision making in high technology environments (Daim and Kocaoglu et al., 2011) to assess the fit between a technology and a firm's strategy (Walsh and Linton, 2011). Such intelligence would hold great capability to aid Tech M&A-oriented strategic management and decision makings. Patent is considered as one of the most important science, technology, and innovation (ST&I) data for technical intelligence. New knowledge, technological capabilities, companies, and inventors reflect in patents as meaningful ST&I markers (Porter and Cunningham, 2004), and patent analysis is applied to help identify these markers for diverse ST&I needs, e.g. Tech M&A. For example, patent number, patent citation, inventor, and international patent classification (IPC) are employed as technological indicators to profile potential target candidates (Yang and Wei et al., 2014), and quite a few semantic approaches, e.g. co-word analysis and subject–action–object (SAO)-based analysis, are widely used to help investigate the concrete technological concepts of patents and the interactions among such concepts (Zhang and Zhou et al., 2014b). Those efforts make great sense to explore the technology relatedness between different companies (Park and Yoon et al., 2013).

In spite of a number of studies that have devoted efforts to engage patent analysis and text mining techniques to promote M&A target selection activities, real-world M&A needs are not as simple as what we imagine, where different acquiring companies have quite different situations, e.g., strategy, market position, and government policy (Brueller and Carmeli et al., 2014), and we could never use these quantitative approaches to take the place of expert knowledge and related decision-making actions. Therefore, how to further amplify the roles of patent analysis and text mining techniques and combine them with expert knowledge to explore meaningful technical intelligence to facilitate the M&A needs is still crucial. As an example, Tech M&A would hold interests on the target technologies, which are not only important from technological aspects but also promising for acquirers' long-term strategies. In the context, existing studies only pursued to set up comprehensive indexes to calculate technology relatedness and rank target technologies in a designed queue (Hussinger, 2010; Yang and Wei et al., 2014), but ignore to think about those numeric values with real-world M&A strategies, e.g. possibility and opportunities of post-M&A technological synergy, and combine them with necessary expert knowledge.

To address the above concerns, this paper attempts to propose a methodology, based on patent analysis and text mining techniques, to extract technical intelligence to identify Tech M&A target technologies and evaluate the possibility of technological synergy between relevant target companies to facilitate M&A target selection. We apply a term clumping process and a trend analysis together with policy and market information to profile present R&D status and capture future development signals and trends in order to grasp significant domain-based technologies. Furthermore, a comparison between an acquirer and leading players is used to identify significant technologies and sub-technologies for specific strategy-oriented Tech M&A activities. Finally, aiming to recommend appropriate M&A target companies, we set up an index-based system to evaluate target candidates from both firms-side perspective and target firm-side perspective and differentially weigh for specific M&A situations. A case study in China's computer numerical control machine tools (CNCMT) industry – a China's key technological field with high technical barriers and difficulties for new competitor to enter - is used to demonstrate the feasibility of our methodology. We specifically select an emerging Chinese CNCMT company – Estun Automation (ESTUN) as a given acquiring company to engage all the considerations that would happen in real M&A decision-making process into our empirical analysis, and the results would be utilized by the company for real Tech M&A activities.

The main contributions of this paper include: 1) An adaptive analytic method for Tech M&A target selection, which combines both quantitative and qualitative methodologies; 2) Focusing on specific M&A strategies, a text mining-based approach is applied to analyze both technical terms and IPCs to help identify significant technological components; and 3) An evaluation index is built up to investigate and measure the relationships between target firms and an acquirer, and target firms themselves, where both technical and strategic aspects are involved.

In next section, we review the literatures on Tech M&A and related patent analysis techniques. We detail the research design and methods in methodology section. Empirical study section offers a case study of the CNCMT field in China to demonstrate the feasibility of our method. Finally, we discuss insights gained from our method and the case study, and address concerns on limitations and future studies.

Literature review

Technology-driven merger and acquisition

Williamson (1975) defined Tech M&A as the efforts that acquired small firms to obtain technological knowledge. Follow-up studies first investigated the characteristics and preferences of Tech M&A activities (Granstrand and Jacobsson 1983; Granstrand and Sjölander, 1990), and, then, research concentrated on Tech M&A performance. Hitt and Hoskisson et al. (1991) summarized net negative effects on R&D and patent productivity via a 191-acquisition study. Then, research showed diversifying development, multiple processes, and mixed performance (Tsai and Wang, 2008; Lin, 2012; Ranft and King et al., 2012; Gomes and Angwin et al., 2013).

We categorized the literatures on Tech M&A into two parts: strategic decision-making (Elango and Lahiri et al., 2013) for pre-acquisitions, and performance evaluation (Le and Park et al., 2014) and integration processes (Wang and Cao et al., 2013) for post-acquisitions. By comparison, there are rare studies focusing on the pre-acquisition phase (Gomes and Angwin et al., 2013), however, Al-Laham and Schweizer et al. (2010) suggested that direct pre-acquisition alliances, as well as sector familiarity between the acquirer and the target, expedited post-acquisition integration.

The selection of the Tech M&A target should entail screening in search of potential candidates that will meet with the acquiring firm's strategic and organizational model and complement their technology portfolio (Chakrabarti and Mitchell, 2013). Park and Yoon (2013) classified the strategic purpose of M&A into three types when acquiring technological capabilities, e.g. enhancement of core technology, enhancement of sub or minor technology, and entry into the new technology areas. Kaul and Wu (2015), considering specific strategies, argued that acquirers pursued low capability targets in existing contexts to deploy existing capabilities and high capability targets in new contexts to acquire new capabilities. Some scholars also tried to look back the pre-acquisition stage, especially the selection of the Tech M&A target, to identify reasons for M&A failure (Kaul and Wu, 2015).

Previous studies provided sufficient analytic approaches and understandings to Tech M&A, and also highlighted the importance of the target selection for M&A. However, there is still a gap between technological variables, which hold capabilities to heavily influence M&A activities, and acquired target selections. In the context, this paper explores a tailor-made and systematic analyses framework addressing Tech M&A problems via tech mining and patent analysis techniques.

Patent analysis for Tech M&A

Patent analysis has been widely applied to many domains and its importance in strategic planning has become increasingly apparent (Lee and Yoon et al., 2009). However, related previous studies serving to Tech M&A are not as many as what we imagine. Most researchers introduced patent analysis for the innovation evaluation of post-M&As both on the target firms and acquiring firms via bibliographic information, e.g., whether Tech M&A affects target firms' innovation activities (Kaul and Wu, 2015); what happened with cross-border M&As or domestic M&As on innovation (Bauer and Matzler et al., 2016; Miozzo and DiVito et al., 2015; Zhu and Xia et al., 2015); what are the key technical determinants affecting post-acquisition invention performance (Makri and Hitt et al., 2010); and how key technical determinants affect post-acquisition R&D outputs (Miozzo and DiVito et al., 2015).

Unfortunately, there are few studies paying attention to employ textual content-based patent analysis to support Tech M&A target selection (Liu and Shih, 2011;Yang and Wei et al., 2014). Park and Yoon et al. (2013) applied subject–action–object (SAO)-based analysis to explore the technology relatedness between different companies, in which not only nouns but also nearby verbs are fully considered to identify in-depth relationships between textual elements, and the main objective of this paper is to measure the relationship between two firms and decide whether it makes sense for M&A or not. This attempt provides a novel direction for investigating Tech M&A by textual content-based patent analysis. One understanding here is: an SAO structure contains the full detail of a technological component, and sometimes the "verb" included in an SAO structure even greatly helps delve into the detailed interactions between two technological components. However, in some cases of Tech M&A, we might only need to stand at a more macro level to identify such relationships since technology similarity and complementarity is only one part of our framework. At this stage, our study blends statistical analysis and semantic analysis to retrieve significant technical intelligence to identify appropriate targets for Tech M&A, in which technical terms and IPCs are emphasized. The effectiveness of combining terms and IPCs in measuring the technological similarity between patent portfolios has been fully discussed and tested in the work of Zhang et al. (2016), in which IPC-based similarity measures were suggested as a pre-processing for raw data, term-based similarity measures could be efficient for deep-cleaned dataset, and the both worked complementarily in a combination.

In addition, since Tech M&A is one type of open innovation (Yoon and Song, 2014), many studies on R&D collaboration partner identification could be referred. For example, Ayerbe and Angué (2014) proposed an approach to take advantage of patent documents to identify basic and specific technological proximities between firms and potential R&D partner; and Yoon and Song (2014) applied hybrid approach that combines morphology analysis, generative topology map, and indices to help firms look for partners who could maximize the collaboration synergy.

Technology relativeness analysis for M&A

Previous empirical literatures found evidences that acquiring targets with related technological assets produces better performance than acquisitions with unrelated assets (Hussinger, 2010), and maximum performance can be realized when the two firms' technology portfolios are related (Cantwell and Gambardella et al., 2004), but not too similar, otherwise the potential for mutual learning is reduced (Cloodt and Hagedoorn et al., 2006). Ahuja and Katila (2001) stated that the relatedness of the acquired and the acquiring knowledge bases had a nonlinear impact on innovation output and aiming to calculate relatedness, they used common patent numbers appearing in both bases and divided them by the absolute size of the acquired knowledge base. Makri and Hitt (2010) treated technology similarity and technology complementarity according to the concepts of "economies of sameness" and "combination potential" (Larsson and Finkelstein, 1999), and analyzed the relationship between knowledge relatedness and invention outcomes of Tech M&A. Miozzo and DiVito (2011) interviewed 12 UK biopharmaceutical firms on 6 cross-border M&A cases and analyzed the effect of different knowledge base combinations on innovation. They followed Makri's calculation formula (Makri and Hitt et al., 2010) and found that companies with a technology similarity degree of 0.27 and technology complementarity of 0.49 would expand R&D in the host country; companies with a technology similarity degree of 0.73 and a technology complementarity degree of 0.13 would continue developing operations (D, but no R) in the host country.

Current calculation approaches could quantitatively express the technology relativeness, but they have some limitations. For example, these approaches mainly focus on the patent distribution of the intersectional parts of acquirer and potential targets, and ignore the general patent distributions of acquired targets. There's still space and practical demands for the improvement of current technology similarity and complementary measures approaches. In our study, we endeavor to bring the technology relatedness analysis forward to the target selection stage, and improve algorithm to better adapt the complex and changing Tech M&A practices. We also try to bring in some other indicators for compensate to associate with technology similarity and complementarity for a more comprehensive study.

Comparing with previous studies, this paper attempts to blend text mining and bibliometric techniques with expert knowledge, and helps related decision making processes in Tech M&A. We take both IPC and terms into consideration to overcome possible limitation while only involving one of them, and statistical analysis and sematic analysis are cooperated to retrieve significant technical intelligence to identify appropriate target technologies and firms for Tech M&A. We also address concerns on the great influence that diverse strategic purposes and commercial situations would take into the actual process of Tech M&A, and specifically discuss several types of

Tech M&A in real world and the manners that how to involve our method with these real-world needs.

Methodology

Our research proposes a framework that aims to guide selection of M&A targets for acquirers, especially from technological perspective. Patent data is appropriate to present technology portfolios and research collaborations of a company; therefore, patent analytic methods are implemented in the framework as the part of the quantitative analysis. Expert knowledge also plays an important role in our research, and interviews and workshops are introduced to investigate experts' opinion, which acts as the part of the qualitative analysis to supplement and explain our patent analytic results. The framework contains two steps, shown in Figure 1.

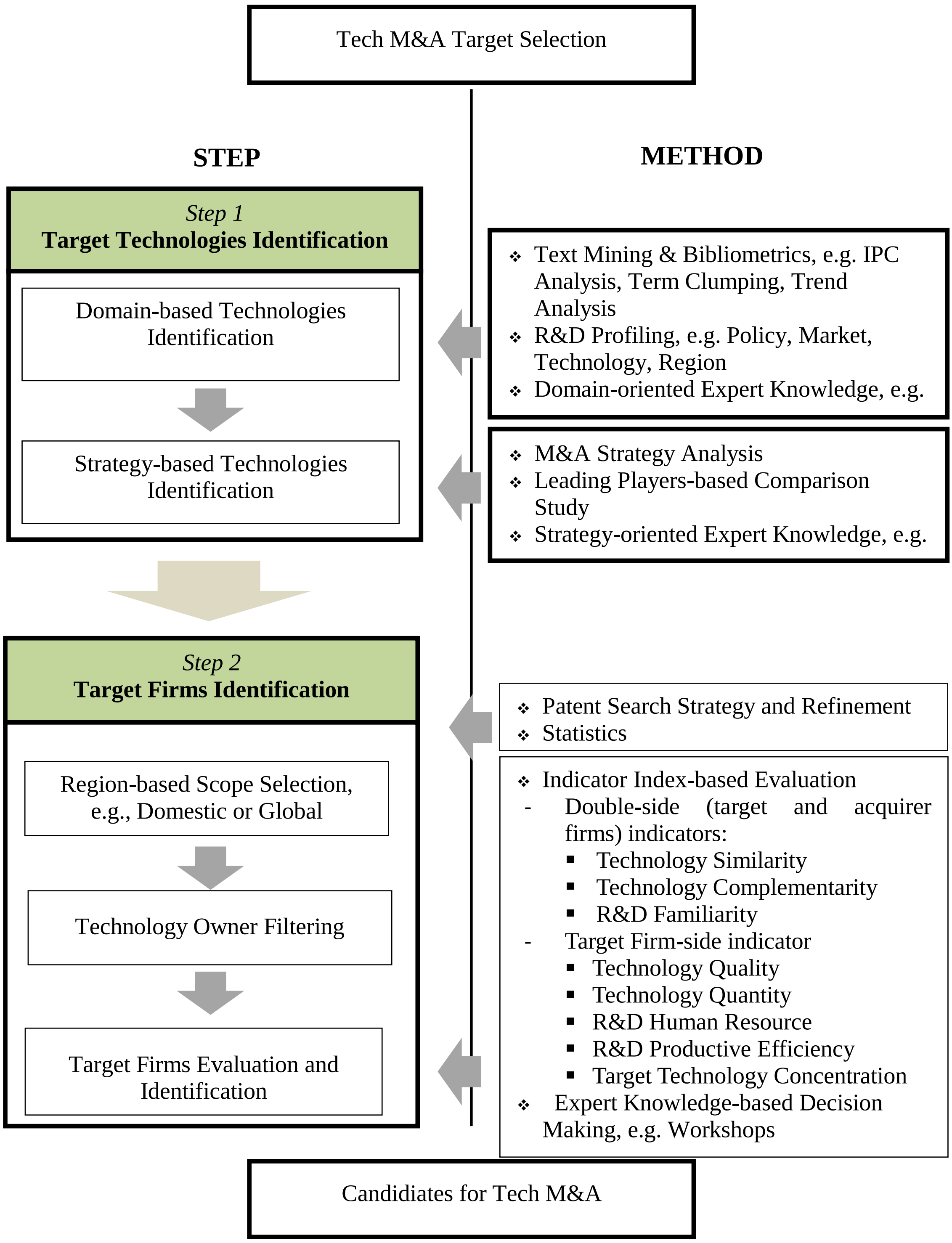

Fig.1.Tech M&A Target Selection Framework

Target technologies identification

The purpose of this step is to identify target technologies for the acquirer in order to fulfill the strategic purpose of M&A.

We address this step in two parts:

(1) Domain-based Technologies Identification

This part refers to the importance of target technologies for a given acquirer, where patent analysis and expert-based assessment are combined to profile present R&D status and capture future development signals and trend.

First, we compose a global patent database in an acquirer's technology domain, and identify key technologies through analyzing the top IPCs and top technical terms. The term clumping process (Zhang and Porter et al., 2014a) is used to capture major technology topics for the acquirer via term cleaning, consolidating, and clustering. Here, term clumping process is served as a relatively automatic extraction method for identifying core terms and technological topics, which can help us effectively reduce the scale of terms and remove noisy terms. It is based on statistical models of language use, such as term condensation, distribution over textual units, etc., which offers an important tool set to approach real improvements in identifying, tracking, and forecasting emerging technologies and their potential applications (Zhang and Porter et al., 2014a). A trend analysis follows (Huang and Zhang et al., 2014; Ma and Porter et al., 2014), which will be implied to grasp high-growth trend technologies that represent hot and promising key technologies. It can make up the deficiencies of term clumping in profiling technology development trend. Later, the list of key and promising domain-based technologies will be submitted to the experts, and be assessed with qualitative factors, such as policy environment, market prospects, and technical values.

(2) Strategy-based Technologies Identification

In this part, we need to further identify the technologies, which are not only important and promising but also fit for acquirers' Tech M&A strategies. These technologies also can meet the specific requirements of the acquirer for its sustainable development.

Consequently, Tech M&A strategies need to be determined in the first. For example, if M&A is designed to achieve or maintain its leading position in current sector, it needs to pay attention to the fields of its own core technologies. If M&A does not limit to its own subsector and wants to enter new subsectors to achieve product extension, it would better focus on the technologies that acquirer lacks. The determined Tech M&A strategies provide directions for further technologies selection.

Second, to identify leading players within a target domain and analyze their foci, where constructing a comparison study between the acquirer and leading players would be an effective way to help us further understand the acquirer's strengths and weaknesses and better identify strategy-based target technologies.

As well as domain-based target technologies identification, this part will also engage strategy-oriented expert knowledge to support the final decision in term of interviews and questionnaires.

Target firms identification

In this step, based on selected technologies in Step 1, we further compose patent datasets for these target technologies to support subsequent firms search.

This step includes three parts: First, we need to decide the region scope for the M&A, e.g., an acquirer wants to consider domestic or global activities. If it just wants to acquire firms in a domestic or special region, we need to narrow our global patent datasets according to its special region, in order to lock the search range of target firms.

Second, we set up a patent search strategy, and statistical analysis is used to detect abnormal values and help refine the search strategy. We also apply text mining methods to filter patent applicants from these target technology-based patent datasets. The filtered patent applicants are the candidates of target firms.

Last, we construct an index-based system to evaluate the patent applicants to identify target firms in principle of facilitating follow-up M&A integrations and decreasing its failure risk. In order to recommend appropriate M&A target companies, the candidate firms are evaluated from double firms-side perspective and target firm-side perspective (Table 1).

Table 1. Target Firms Evaluation Indicator

	Index	Description
Double-side (target and acquirer firms) indicator	Technology Similarity (Makri and Hitt et al., 2010; Miozzo and DiVito et al., 2015)	The degree to which the target and acquirer firms' technological problem-solving focuses on the same narrowly-defined areas of knowledge
	Technology Complementarity (Makri and Hitt et al., 2010; Miozzo and DiVito et al., 2015)	The degree to which the target and acquirer firms' technological problem-solving focuses on different narrowly defined areas of knowledge within a broadly defined area of knowledge that they share
	R&D Familiarity (Al-Laham and Schweizer et al., 2010)	The degree to which target and acquirer firms are familiar with each other, especially on R&D format, R&D procedure & flow, and R&D personnel
Target Firm-side indicator	Technology Quality (Hitt and Hoskisson et al., 1996)	Average citation frequency of patents
	Technology Quantity (Hitt and Hoskisson et al., 1996)	Number of granted patents
	R&D Human Resource (Park and Yoon et al, 2013)	Number of inventors of all patents
	R&D Productive Efficiency (Cook, 2011)	Average patent records per inventor
	Target Technology Concentration (Wong and Singh, 2005)	Percentage of target-technology-related patents out of all patents

Double-side (target and acquirer firms) indicator

For double-side (target and acquirer firms) indicators, we mainly investigate the questions whether acquirer and candidate target firms have potentials for post-M&A integration or not, in which technology similarity, technology complementarity (Makri and Hitt et al., 2010) and R&D familiarity (Al-Laham and Schweizer et al., 2010) are major factors.

(1) Technology similarity

Technology similarity and technology complementarity between targets and acquirer could be used to evaluate if the technologies of candidate firms relate to the acquirer's technologies, and they are described as the degree to which the target and acquirer firms' technological problem-solving focuses on the same or different narrowly defined areas of knowledge within a broadly defined area of knowledge that they share (Miozzo and DiVito et al., 2015).

We introduce a hybrid model to calculate technology similarity between two patent portfolios (Zhang and Shang et al., 2016).

We denote "Tech M&A firms" as the universe $X = \{x_1, x_2, \dots, x_i, \dots, x_{n-1}, x_n\}$, where n is the total number of the firms, and denote "each IPC code" as a fuzzy set A_j defined on the X where $j \in [1, m]$ and m is the total number of IPC codes. The membership function $A_j(x_i)$ is considered as the degree with which firm x_i engages IPC A_j.

The membership function $A_j(x_i)$ was set as below, where $PN(x_i)$ means the patent number of firm x_i, and $PN(j|x_i)$ was used for the number of the patents belonging to IPC j in x_i.

$$A_j(x_i) = \sqrt{\frac{PN(j|x_i)}{PN(x_i)}}$$

Once the membership function is figured out, each firm will have a m-dimensional vector $V(x_i) = \{\vartheta_{1,i}, \vartheta_{2,i}, \dots, \vartheta_{j,i}, \dots, \vartheta_{m-1,i}, \vartheta_{m,i}\}$, and $\vartheta_{j,i}$ is the membership grade that the firm x_i belongs to the fuzzy set A_j. We then use Cosine function to measure the categorical similarity between two patent portfolios x_i and x_k as below:

$$CS(x_i, x_k) = \frac{V(x_i) \cdot V(x_k)}{|V(x_i)||V(x_k)|}$$

(2) Technology complementarity

The technology complementarity would be considered in specific technical scope. Shown as Fig. 2, we denote U and U' as two different technical scopes, where $U \subset U'$, and A, B, and C as the patent portfolios of three firms, where $A \subset U, B \subset U, C \subset U', C \cap U = 0, A \cap B \neq 0$, and $A \cap C = 0$. In the context, it is promising to understand that within the scope U, A and C have no complementarity while the complementarity exists in the scope U'.

Aiming to convey the technology complementarity to defined numeric value, we introduce the volume of patent portfolio to calculate the complementarity – e.g. in Fig. 2, the volume of A is bigger than B, thus, within scope U, patent portfolio A contributes more to the complementarity than B, and we can calculate the complementary that A contributes to B as:

$$Complementarity(B|A) = \frac{A - A \cap B}{U}$$

We define two basic elements for the technology complementarity: 1) the scope – in which technical area you are considering such complementarity, and 2) the volume – depending on specific targets, we could use different indicators to quantify the volume, e.g. IPC, patent number, technical terms. Note that the technology complementarity varies with diverse scopes, the calculation would be on the promise that we have already figured out the scope.

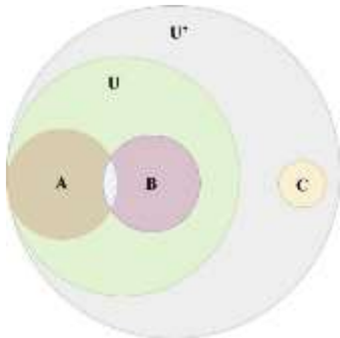

Fig. 2. The Sample of the Technology Complementarity Definition

(3) R&D familiarity

Considering general technological synergies between two firms, we define R&D familiarity as the degree to which target and acquirer firms are familiar with each other, and particularly R&D format, R&D procedure & flow, and R&D personnel are involved. Previous research shows that sector familiarity between the acquirer and the target expedited post-acquisition integration (Al-Laham and Schweizer et al., 2010). The more familiar they are, the easier and lower the failure risk for post-M&A integration will be.

We combine text mining and some investigation ways to help evaluate the R&D Familiarity. The stepwise process of identifying the R&D Familiarity is given as follows:

First, text mining techniques are used to retrieve co-invented patents (Lei and Zhao et al., 2013) between target and acquirer firms. Co-invented patents include patents that have been issued or applied resulting from the co-operation between the target and acquirer firms, which could be considered as the remarkable R&D outcome of cooperation (Kerr and Kerr, 2015). A list of those co-invented patents will be generated.

Second, we define the level of the R&D Familiarity in Table 2. Referring to the list of co-invented patents, we automatically set the score of the R&D Familiarity of those firms with co-invented patents as 1. When there are no remarkable R&D outcomes, we need to take advantage of some ways (i.e., questionnaire, workshop, interview) to investigate other R&D collaboration situations, such as, the personal collaboration or communication networks between the R&D technicians of the acquirer firm and other target firms.

Third, the potential target firm list with related background information (e.g., R&D programs, product system) and above investigation results would be gathered together and sent to experts for evaluation. Experts need to give a score according to Table 2. The means of the scores given by the experts will be used as the score of the R&D Familiarity of the firms without co-invented patents, and the degree of R&D familiarity between two firms is in the interval [0,1], where 0 means the two firms have no interaction experiences while 1 is for a strong on-going collaborative relationship.

Table 2. R&D Familiarity 5-level grade

Score	Definition
1	Target and Acquirer firms have remarkable R&D outcomes. e.g., co-invented patents.
0.75	Target and Acquirer firms had/have R&D collaborations but haven't remarkable R&D outcomes yet.
0.5	Target and Acquirer firms had/have a number of R&D contacts but haven't achieved collaboration yet.
0.25	Target and Acquirer firms had/have a few R&D contacts.
0	Target and Acquirer firms had no contacts before.

Target firm-side indicator

Aiming to lead related Tech M&A analysis in a broader scope, we also need to consider more about the target firm to select higher R&D value and more target technology-focused candidates.

(1) Technology quality and technology quantity

Since Technology Quality and Technology Quantity are both traditional indicators and have been broadly used to represent firms' technology level (Hitt and Hoskisson et al., 1996), we keep employing these two indicators to help us identify technologically rich firms. In the study, Technology Quality and Technology Quantity are represented respectively by the average citation frequency of patents and the number of granted patents.

(2) R&D human resource

Griliches (1998) stated that key researchers that hold the capability of patenting an invention can be the most important human resource of a firm, and Park and Yoon et al. (2013) used the number of patent inventors to be an indicator to measure the strength of a company's R&D human resource. In this paper, we follow this design.

(3) R&D productive efficiency

Our study also pays attention to the quality of these patent inventors. R&D Productive Efficiency is employed to represent it and could be measured as the average patent records of per inventor (Cook, 2011).

(4) Target technology concentration

In addition, as there are some studies show that innovation performance (invention quantity) was lowest for M&As in which the firms operated in largely unrelated technology areas (Ahuja and Katila, 2001;Cloodt et al., 2006), which implies that acquirer prefers to acquire a firm which focuses on its target technologies closely to achieve more M&A values. In our index-based system, Target Technology Concentration (Wong and Singh, 2005) is proposed to express whether the target technologies are the major parts for the candidate firms, and is measured by the percentage of target technology-related patents out of all patents.

For the weights of the 8 indicators in Table 1, Analytic Hierarchical Process (AHP) method would be a favorable option here. We emphasize the weights would be considered based on actual requirements and situations, and especially the preference of the two indicators: Technology Similarity and Technology Complementarity, which would vary with different M&A situations.

On the basis of lines of a business activity, there are five kinds of M&A (Angwin, 2012): 1) Horizontal M&A takes place when two or more companies are dealing with similar lines of activity, i.e. direct competitors; 2) Vertical M&A would bring together the companies that are in the same industry but at different stages of production, process or operation, taking the form of forward or backward integration; 3) Product Extension M&A could combine firms with non-competing products but functionally relating in production and distribution; 4) Market Extension M&A would lead the firms with the same products but in different geographical markets; 5) Conglomerate M&A is the integration of firms that are involved in totally unrelated business activities.

We illustrate these types in the medical device industry (Fig. 3). A and B represent Home Care Device and Medical Instrument, the two subsectors of medical device. If the firm in the A subsector acquires the one in A, it's a Horizontal M&A; if it acquires the firm in B, it's a Product extension M&A; if it acquires the firm in C (Precision Machining Sector) or C' (Large-scale Diagnostic Equipment Manufacturing Sector), it's an extension of industry chain of medical device, and it belongs to Vertical M&A; if it acquires a firm in D (Internet or Consumer Electronics Sectors), it's a pure Conglomerate M&A; if it acquires the firm in A' (Home Care Device Sector in other geographical areas), it's a Market extension M&A.

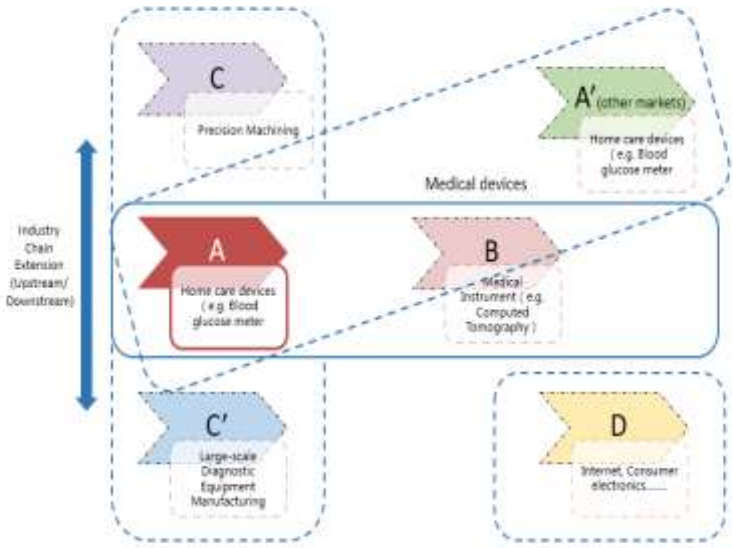

Fig. 3. The Sample of Four Tech M&A Types in Medical Device Industry

Based on our understanding and research experience, we clarify that different Tech M&A types have different preference on technology similarity & complementarity, and concerning actual situations, we summarize such preference in Table 3, where √ means that Technology Similarity or Technology Complementarity is important while × represents that the indicator is not essential in the given situation. The Horizontal M&A and Product extension M&A both represent that the product of the acquired firm is in the same sector with the acquirer firm, thus, technology similarity is important for both of them. Since Product Extension M&A aims to acquire the firms not only in the same sector but also different subsector, technology complementarity is another important indicator for consideration. Vertical M&A emphasizes the product of the upstream or downstream chain, and technology complementarity is definitely the major factor comparing with the similarity. However, Conglomerate M&A is aiming to acquire the firms that are involved in completely unrelated business activities, and Market M&A pays attention to the different geography, therefore, technology relatedness is not important and we could neglect technology similarity & complementarity for both of them.

Table 3. Different Preference of technology similarity & complementarity for different Tech M&A types

	Horizontal M&A	Product Extension M&A	Vertical M&A	Conglomerate M&A	Market extension M&A
Technology Similarity	√	√	×	×	×
Technology Complementarity	×	√	√	×	×

Empirical study

We selected China's computer numerical control machine tools (CNCMT) industry for our empirical study. We began by searching several Chinese commercial databases (e.g. Chinaventure, Wind, and CSMAR) to find listed companies in China's CNCMT industry. Eventually, we identified 45 companies here, where 42 companies were listed in China, one was listed in Singapore and two were listed in "China's new third board" – an emerging section of China's new over-the-counter market. After searching the companies' M&A deals, we found that 32 companies were involved in M&A, in which 26 companies had made acquisitions as acquirers from 2000 to 2015 while the other 6 companies had been acquired as targets. Studies for these selected companies addressed a good shot for the reasons why we chose CNCMT as a case.

Shown as Fig. 4, the M&A activities in China's CNCMT industry started from 2000, but only kept in a small amount before 2006. Since 2004, the state council of China had published a series of policies and programs to support the scientific research and technological development for the machine tool industry, e.g. "National Medium and Long-Term Educational Reform and Development Program (2010-2020)" and "Certain Suggestions of State Council on Supporting Promotion and Development of the Equipment Manufacturing Industry (2006)." After that, the M&A deals jumped into a much higher level, and maintained the total amount around 20 per year. An important national program "Key Project Guide for High-End Computer Numerical Control (CNC) Machine Tools and Basic Manufacturing Equipment" (2009) claimed that an increasing development of CNC machine tools was required for the key industries, and since 2010, tax benefits and financial supports had also been involved in such national R&Ds. In addition, in 2015, "Made in China 2025" plan, one of the most technological policy published by the leading government that aimed to promote China's transition from a manufacturing giant to a global manufacturing powerhouse, clearly put forward high-end CNC machine tools as one of the ten key areas. At this stage, we believed that the insights on the M&A deals of China's CNCMT industry would be promising for being a demonstration to understand China's national technological policy and commercial re-actions.

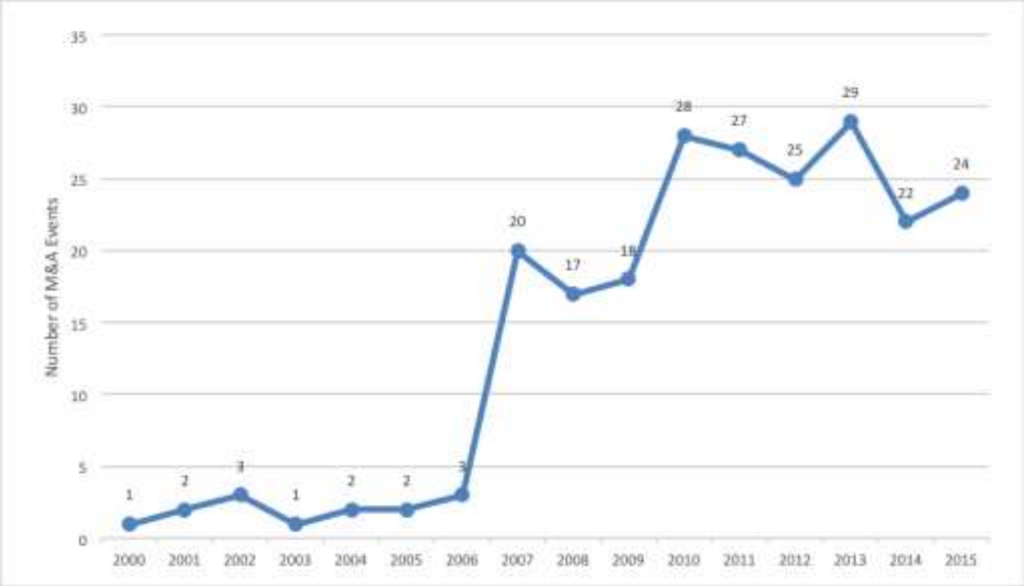

Fig. 4. Trend of M&A Transactions in Numerical Control Machine Tool Industry

Since one of our foci is to support the M&A strategy for one company, in the context, we further chose Estun Automation (ESTUN) as the acquirer. Three perspectives are: 1) focusing on technological advancement, ESTUN is a leading manufacturer in china's domestic high-end CNCMT industry, the major products of which include metal forming CNC control system, electro-hydraulic servo system, alternate current servo system (AC servo system), and motion control system. These are the high-value parts and advanced & core technologies for CNCMT, and ESTUN greatly values these technical assets in its R&D plans; 2) ESTUN holds strong strengths for sustainable development. ESTUN's sales of CNC metal forming control system and electro-hydraulic servo have been on the top of China's domestic market, and ESTUN has become listed company since 2015; 3) ESTUN pursues impressive R&D strategies. ESTUN clarified two-parallel strategies in 2014, one of which focused on the basic research of CNCMT industries while the other was to extend its existing technological advantages to be a leading company in China's industrial robots industry. In addition, ESTUN is a private undertaking without any governmental background, and its success pathway would make great sense to be an example for similar companies.

Data

We collected patents from the Derwent Innovation Index (DII) patent database to help identify the target technologies. For this paper, we chose the Derwent Innovation Index (DII) as the target patent database since the DII contains patent families from 47 patent authorities, it is a quite comprehensive and global patent dataset (Ma and Porter et al., 2014). Furthermore, DII provides ''second order'' patent data, meaning that Thomson Reuters' indexers rewrote the abstract of every patent record and provided abstracting indexing services to facilitate the users better understanding patents (Zhou and Zhang et al., 2014). We devised a Boolean term search modular (Porter and Youtie et al., 2008) retrieve patents, which covered the period from 2000 to May 1, 2015. Table 4 shows the patent search query. After removing duplicates, 20,452 granted patents were obtained. Note that this corpus contained the patents from all the countries in the CNCMT industry.

Table 4. Patent Query of CNCMT

Search Field	Query
TS	"Compute* Numeric* Control* Machine" or "Numeric* Control* Machine" or "CNC Machine" or "NC Machine"

Domain-based technologies identification

Following the designed framework, we first applied the term clumping process (Zhang and Porter et al. 2014a) to identify core terms and phrases. The term clumping process has been fully integrated in VantagePoint (VantagePoint 2015) and well-adapted to the pre-processing task for DII database.

The stepwise results of the term clumping process are shown as Table 5.

Table 5. Stepwise Results of the Term Clumping Process

No.	Step	# Terms
1	Natural Language Processing (Retrieve terms and phrases from the combined fields of titles and abstracts of the 20,452 patents)	254,246
2	Basic Cleaning with thesaurus (Remove meaningless terms and common terms in patents)	23,2617
3	Fuzzy Matching (Consolidate terms based on the stem)	21,5127
4	Pruning (Remove terms appearing only in less than 3 records)	101,169
5	Association Rules-based Consolidation (Combine low-frequency terms to high-frequency terms that appear in the same records)	78,139
6	Association Rules-based Consolidation (Combine terms with more than 3 sharing words)	51,997
7	Pruning (Remove terms appearing only in less than 5 records)	9,547
8	Term frequency inverse document frequency (TFIDF) Weighting (Rank terms via TFIDF weights)	9,547
9	Expert Knowledge-based Selection (Select core terms from a list of top 2500 TFIDF weighted terms)	1,470

* VantagePoint is a text-mining tool for discovering knowledge in search results from patent and literature databases. It can help extract technical intelligence from massive data repositories to support patent analysis, technology planning, investment decisions, and more (see the website: https://www.thevantagepoint.com/). Currently, it has been widely used into a range of ST&I studies (Zhou and Porter et al., 2014; Guo and Ma et al., 2012; Zhang and Guo et al., 2013), which provides effective means to retrieve core technological terms and visualization for further studies.

Specifically, the Fuzzy Matching was a step designed to consolidate terms based on the stem, e.g., technological and technology. It also made good sense to address the concerns on the singular and plural and the tense issues. The Association Rule-based Consolidation was based on certain rules and here we applied two of them: 1) to consolidate low-frequency terms to the high-frequency terms that always appear together with them, and 2) to consolidate terms with certain sharing words.

We set certain thresholds here, e.g., removing terms appearing only in less than 3 records and combing terms with more than 3 sharing words. Actually, there was no strict rule to follow, and we made such decision by our experiences and certain experiments. For example, if terms only appear in one record, they would make no contribution to the latter part of similarity measure. However, if apply the term clumping process to a large-scale data set, it could be promising to understand that the influence of those low-frequency terms might be ignorable. In addition, the threshold of the 3-sharing-word could be identified from the observation that 85% technological terms in a solar cell sector were constituted by 2, 3 or 4 words (Zhang and Porter et al., 2014a), and we extended such observation to an assumption that terms sharing with 3 words or more could be synonyms and could be consolidated.

Based on the results derived by the term clumping process, we invited five technical experts from the Information Research Institute of Machinery Industry of China to help us select core terms and phrases from a top-2500-term list and collected 1,470 core terms finally. Then, the five experts were involved again to help further modify the Term Correlation Map and identify core topics.

We first used VantagePoint (VantagePoint 2015) to generate a core-term-based factor map (Fig. 5) via Principal Component Analysis (PCA). As an initial setting, we obtained 8 factors, and then, the factor map was sent to the experts via emails. We highlighted certain questions such as, "whether the 8 factors in Fig. 5 can represent the sub-technologies of CNCMT?" "Whether duplicate factors exist?" "Whether we missed certain important sub-technologies?" and "Which sub-techniques do you think hold strong potential over the next three to five years?" Based on the feedback of the first three questions, the three factors (shown in the red cycle in Fig. 5) were grouped together as Machine Body technology of CNCMT, and the remaining factors were approved. We also got some valuable views on the final question, which were considered as important references for subsequent analysis. In parallel, we imported the core terms and their co-occurrence statistics to Gephi (Bastian and Heymann et al., 2009), which is an open-source and free interactive visualization and exploration platform for all kinds of networks and complex systems, dynamic and hierarchical graphs, and its developed modules can import, visualize, spatialize, filter, manipulate and export all types of networks1. A raw Term Correlation Map was generated (shown as Fig. 6), in which similar clusters also can be identified. Finally, we summarized six clusters for CNCMT as follows: Numerical Control Device, Servo

[1] More detail can be seen at the website: https://gephi.org/

system, Machine Body, Processing Program, Accessory and Robot (marked in Fig. 6). Top terms and IPCs are shown in Table 6.

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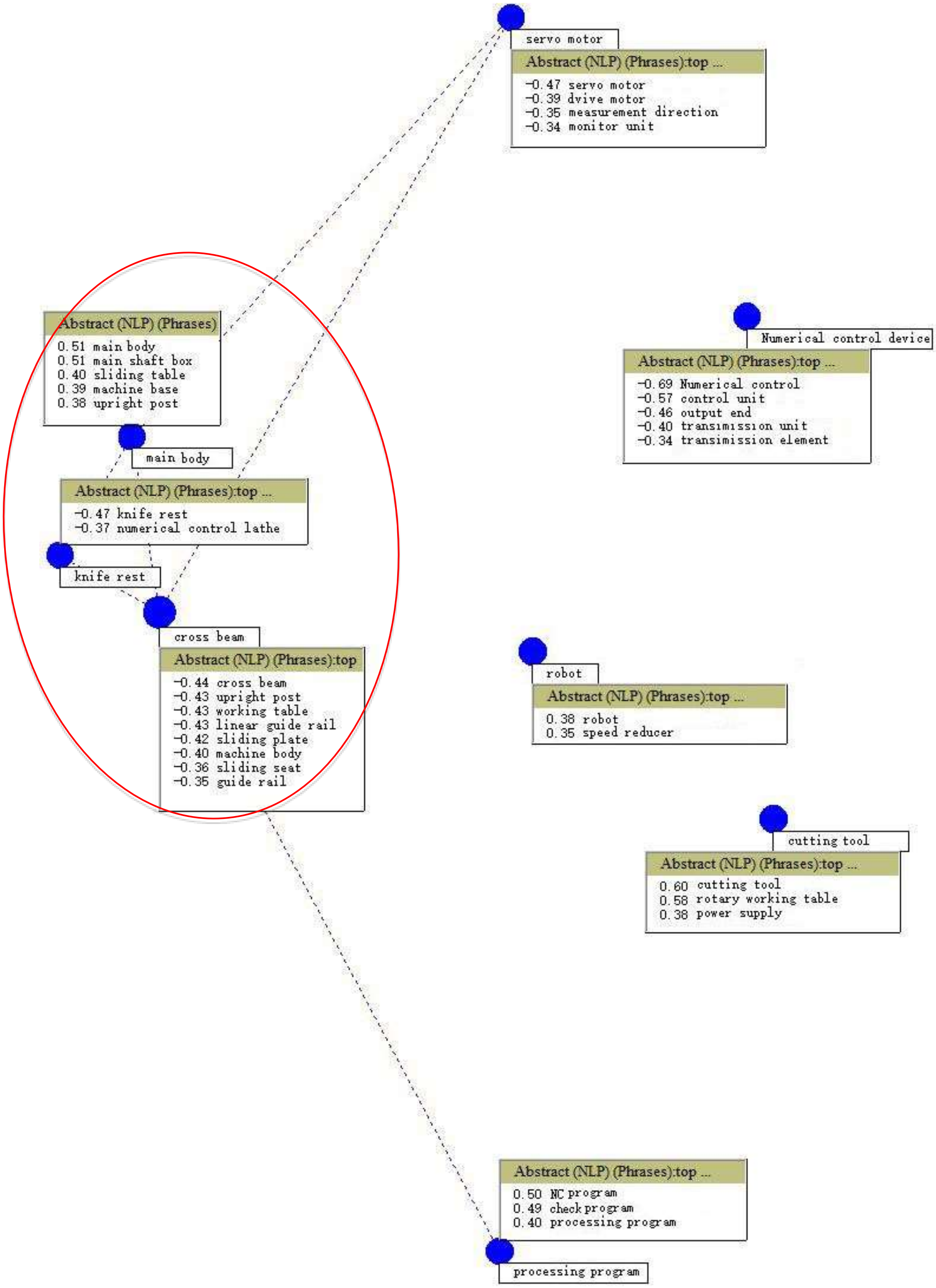

Fig. 5. PCA map of CNCMT

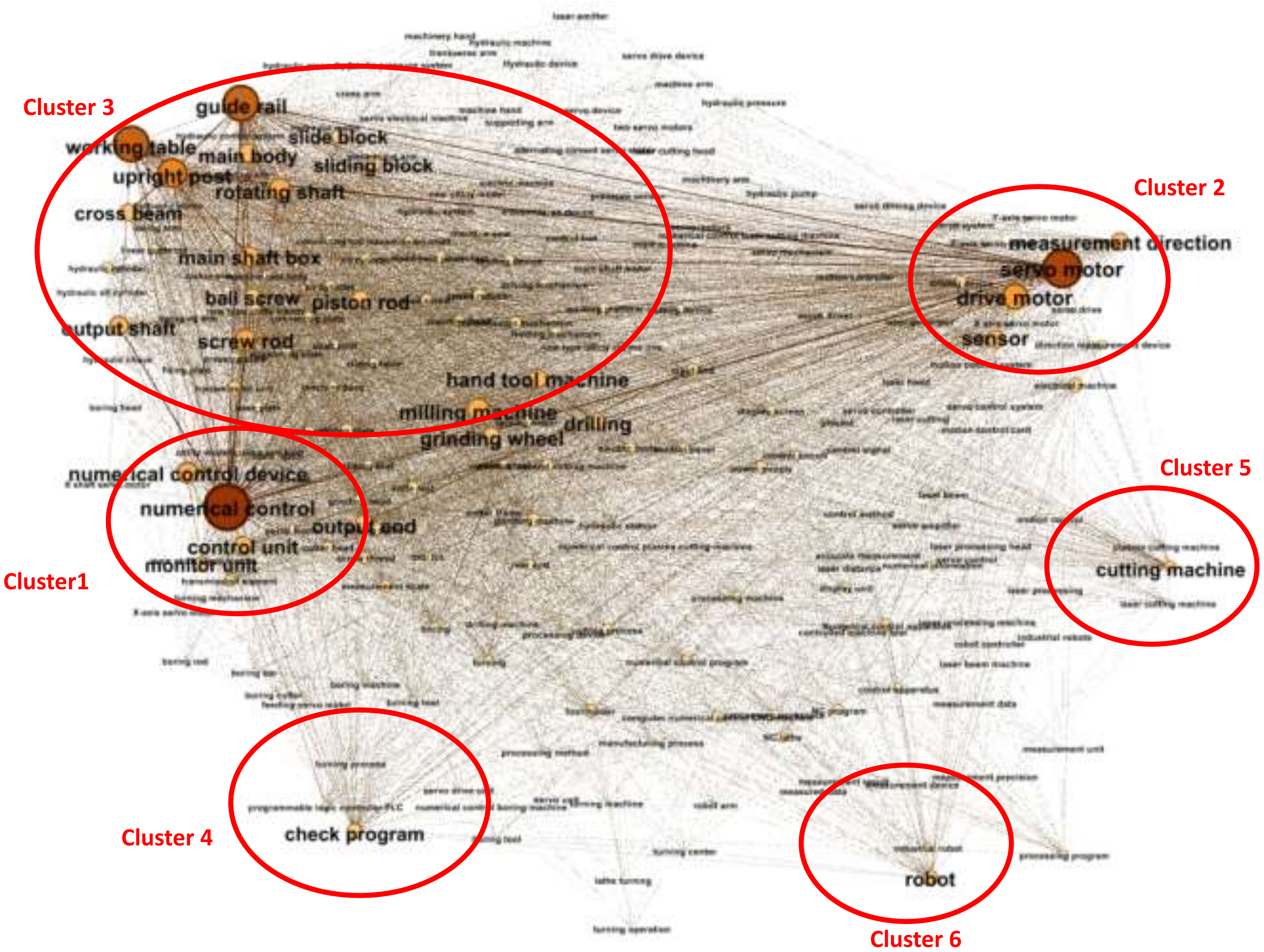

Fig. 6. Term Co-occurrence Map of China's CNCMT Industry

Table 6. Six CNCMT Technology Clusters and their top terms & IPCs

No.	CNCMT Technology Clusters	Top Technology Terms	Top IPCs
1	Numerical Control Device	numerical control; control unit; output end; transmission unit; transmission element; Numerical control apparatus; input end	G05B-019/18 B23Q-015/00 G05B-019/414 G05B-019/404 G05B-019/19
2	Servo system	servo motor; drive motor; sensor; measurement direction; monitor unit; electrical machine; driving device; measurement scale; transmission mechanism; feeding mechanism; hydraulic pressure system; servo electrical machine; servo driver; direction measurement device	G05B-019/18 B23Q-005/40 B23Q-001/25 B23P-023/02 B23Q-005/36
3	Machine Body	working table; guide rail; upright post; rotating shaft; main shaft box; output shaft; main body; cross beam; slide block; knife rest	B23Q-001/01 B23Q-001/25 B23Q-005/40 B23P-023/02 B23Q-011/00
4	Processing Program	NC program; check program; processing program; programmable logic controller PLC	B23Q-015/00 G05B-019/18 G05B-019/4093 G06F-019/00 G05B-019/4097
5	Accessory	cutting tool; power supply; rotary working table; air cylinder; oil cylinder[;hydraulic cylinder; cooling device; switching unit; chip machine	B23Q-011/00 G05B-019/18 B23Q-015/00 B23Q-011/10 B23P-023/02
6	Others (Robot)	robot; hand tool machine; Hand-held power tool; speed reducer	G05B-019/18 B23Q-007/04 G05B-019/416 G05B-019/4103 G05B-019/414

Following the framework designed in Fig. 1, in addition to text mining and bibliometrics analysis, some qualitative factors, such as policy environment, market prospects, and technical values, should also be considered to help further refine more promising technologies from above six clusters. In this part, we carefully studied the documents of “Made in China 2025” program and the “13th Five-Year Plan”, which is another important long-term national R&D program in China. Both programs clearly pay great attention to CNCMT, where high-end CNS, servo motor, shaft bearing, and raster, are highly emphasized. Meanwhile, we invited 3 staff working in the National Development and Reform Commission of China, who are familiar with the high-technology industry policy and market environment in China, to help sort out the major parts of the six CNCMT clusters, and then refine more promising clusters which would be strongly supported by the government in the future.

We addressed key concerns to the six clusters as below:

- Cluster 1 - Numerical Control Device: This is the core part of CNCMT, which coordinates the whole system of CNCMT through computer system program and acts as the brain of human beings. The innovation of Numerical Control Device could benefit CNC in higher accuracy in manufacturing, shorter production time, greater manufacturing flexibility, simpler fixturing, and etc.
- Cluster 2 - Servo system: This is another important part of CNCMT, which accepts command signals from Numerical Control Device and then converts them into the movement of machine tool. The accuracy and speed of CNC machine tools are often determined by the servo system, which takes on the same priority place with Numerical Control Device for highly intelligent CNCMT.
- Cluster 3 - Machine Body: This is a traditional mechanical part of CNCMT, which supports the completion of cutting & machining processes.
- Cluster 4 - Processing Program: It includes all kinds of programs that are employed to control the movement of CNCMT.
- Cluster 5 – Accessory: It refers other necessary supporting or accessory devices for fully exerting functions of CNCMT.
- Cluster 6 - Robot: This part contains several new & emerging techniques that belong to ESTUN, but here we concentrate on the robotic techniques. The robotic techniques of CNCMT compose of the key technological components of robot industry, and it is a normal phenomenon that CNCMT players enter into robot-related business. Especially, the "Made in China 2025" indicates special interests to the development of industrial robots.

Apparently, Cluster 1 (numerical control device), Cluster 2 (servo system), and Cluster 6 (industrial robot) are at the high end of the value chain of CNCMT, and are in accordance with China’s national industrial policy and development planning. The former two clusters are the core technological components that determined the advancement and accuracy of CNCMT, while the latter one was considered as the significant emerging commercial branch for traditional CNCMT industry, and would become the main battlefield for the whole high-tech manufacturing industries. Therefore, with the help of expert knowledge, these three clusters are determined as promising technology sectors for further analysis.

We then applied trend analysis to identify core technologies or sub-technologies for these three selected clusters with bubble charts. We generally divided the term frequency of core technological components by year, and the frequency was represented by the size of the ball. As an example, Fig. 7 shows the trend analysis results of the top 10 technology terms of servo system. It is noteworthy that the terms we used here have been pre-processed in the term clumping process, in which we consolidate terms based on the same stem. Thus, terms representing the same technology have already been consolidated.. In our study, we focus more on the terms increasing rapidly in recent years (especially after 2010), e.g. servo motor, electro-hydraulic servo system, alternate current servo system (AC servo system), drive motor, and motion control, and consider them as the core technologies for each cluster. These terms are becoming or have already been hot issues, which indicate that the R&D foci have turned to the most intelligent parts and advanced technologies of CNCMT. By contrast, there are some terms developing steadily but not changing significantly in the past 15 years, e.g. hydraulic pressure servo system, feeding system, position control, servo control and transmission unit - these terms represent that they are necessary ingredients of the servo system, however, it dose not mean that they are core technologies with greatest potentiality. Note that the total number of terms decreased from 2014 while the peaks appeared in 2013. We confirmed our data and the instruction documents of the DII database, and a reasonable explanation is that DII database is not updated in time because it collects data from different nation's patent administration offices and then assigns these patents for translations and re-writings – an 18-month delay usually exists (Fabry and Ernst et al., 2006). In the same way, we identified key and hot technologies in the sub-technology field of numerical control device and robot, which are not demonstrated in the paper because of space limitation.

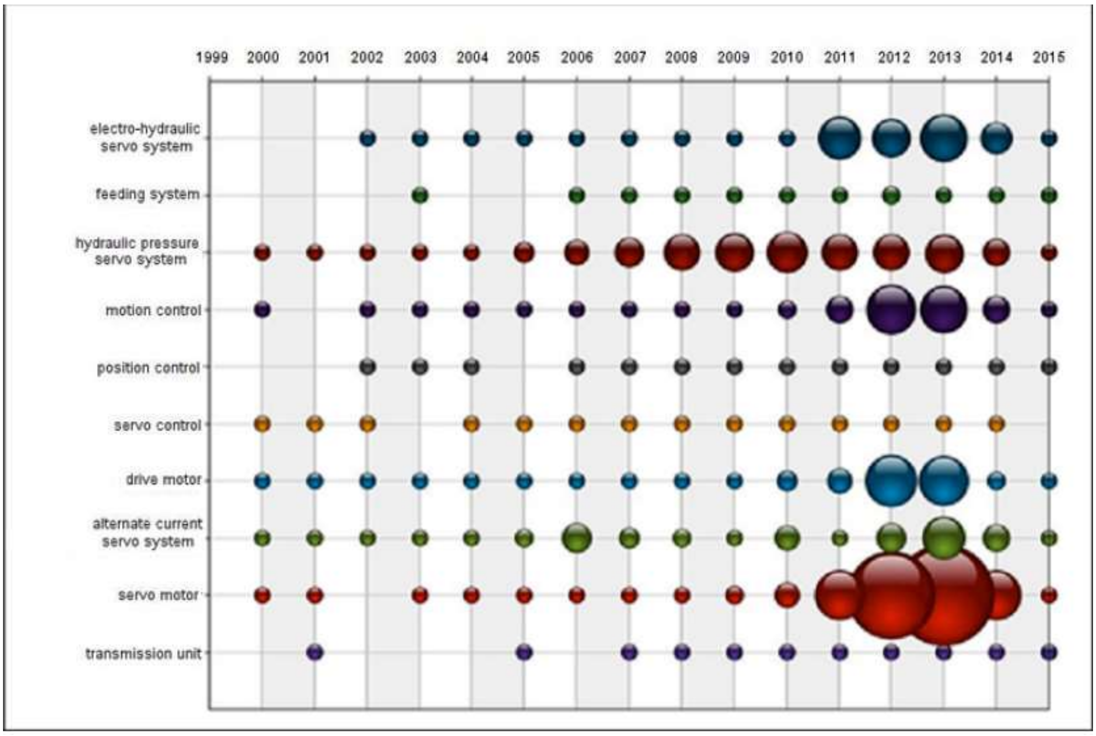

Fig. 7. Sample: Trend Analysis of top 10 terms in Servo System

We highly value the efficiency of the trend analysis in identifying core technologies or sub-technologies. Traditional bibliometric analysis might only consider term frequency and use certain high-frequency technological terms to describe a given technological area, however, the trend analysis takes the time into consideration, which helps us obtain more detail to answer the questions such as, which technology is becoming more and more important and which technology does not change too much in the recent years, and which technology is not important any more. Based on the trend analysis, a series of increasingly important terms were identified, and the insight obtained from these terms can be definitely more promising than the terms derived from traditional bibliometric analysis. Therefore, the trend analysis effectively helps us reduce the candidates of core terms, and we are able to provide a smaller set of core terms to experts for screening manually.

As an output of this step, we blended our quantitative results and expert knowledge to refine the core technologies of the three clusters, and identified the relationships between the traditional CNCMT technologies and robotic technologies (shown as Fig. 8). Servo system (Cluster 2) and numerical control device (Cluster 1) are located on the left side while the robotic technologies (Cluster 6) are on the top of this graph. The high-growth core technologies identified by the trend analysis are listed under the label of each cluster, as given in Fig. 8. Furthermore, we marked the similar techniques among different technology clusters, for example, we highlighted a triple-side relationship – the motion control was assigned as the core technique of all the three clusters, which would be considered as one of the most important sub-technologies of ESTUN.

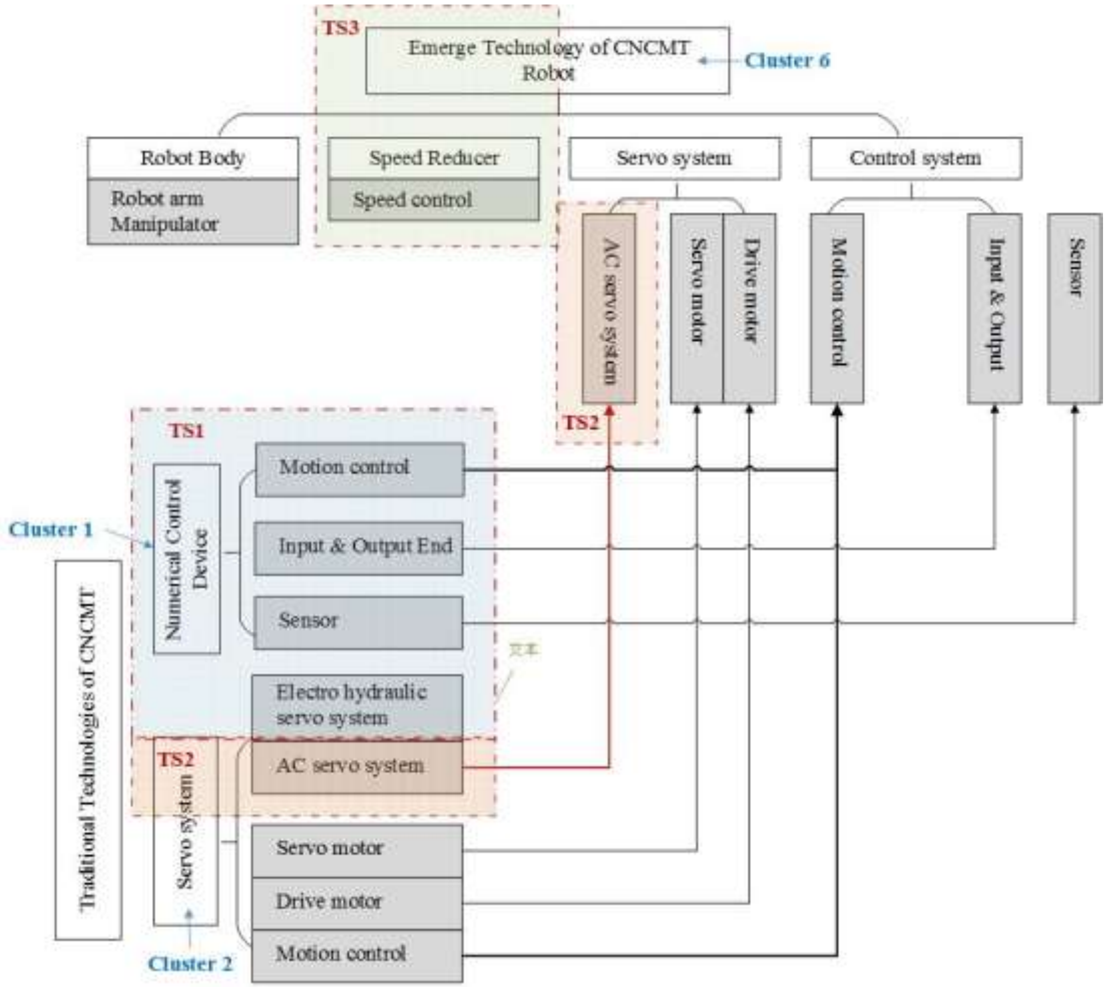

Fig. 8. CNCMET Domain-based Technologies

Strategy-based technologies identification

A list of core and promising technologies for CNCMT was derived in the above sections, in this part, we further identified the ones that are also fit for acquirers' Tech M&A strategies and able to meet the specific requirements of the acquirer for its sustainable development.

Tech M&A strategies of ESTUN are determined in the first. ESTUN was implementing its two-parallel strategies: to consolidate its technically-advanced status in CNCMT industry, and be a leading company in China's industrial robot industry. Engaging several staff in the technology department of ESTUN, we decomposed the firm strategies into three Tech M&A strategies (shown in Table 7): 1) TS1 – to maintain the leading position in sub-sectors of domain CNC metal forming machine tools; 2) TS2 – to extend technological advantages to other sub-sectors of CNC machine tools; 3) TS3 – to acquire core technologies of Robot beyond existing technology system of ESTUN.

Then, we explored the bridge between ESTUN's Tech M&A strategies and the technology sectors that we need to focus on. We conducted a simple investigation, providing the detailed descriptions of ESTUN's Tech M&A strategies and the list of core technologies in Fig. 8 to ten technicians, which were composed of five technical experts from China's Information Research Institute of Machinery Industry, three staff working in the technology department of ESTUN, and two technical experts from China's Robot Association. Ten investigators ticked related technologies from the list for each Tech M&A strategies, and their feedback had been comprehensively considered. The final results are shown in Table 7, which include: 1) numerical control device and electro-hydraulic servo system (the blue block in Fig. 8), which specifically served CNC metal forming machine tools, and ESTUN was on the top of the domestic market share in this sub-sector; 2) AC servo system (the orange block in Fig. 8), which is an advanced category of servo system, has characteristics of over load and low inertia which the traditional servo systems (e.g. hydraulic pressure servo system, direct current servo system) don't have, thus, it could be widely used in multiple kinds of mechanical equipments. If ESTUN needs to extend its technology advantage outside metal forming machine tools and radiate to other CNCMET subsectors, AC servo system would be a given priority to pursue; 3) Robot– especially servo system and control system, but ESTUN lacked another high-end but core technology section for Robot-speed reducer (the green block in Fig. 8).

Table 7. ESTUN's two-parallel strategies and specific Tech M&A strategies

No.	Firm Development Strategy	Tech M&A Strategy	Related technologies
1	**Basic business:** Consolidate its technically-advanced status in CNCMT industry	**TS1:** Maintain technology leading position in domain CNC metal forming machine tools sub-sector	Numerical Control Device Electro-hydraulic servo system
		TS2: Extend technology advantages to other CNC machine tools sub-sectors	AC servo system
2	**Emerging business:** Pursuing as the leading company in China's industrial robot industry	**TS3:** Acquire Robot core technologies beyond ESTUN existing technology system	Speed Reducer

The strategies in Table 7 pointed out the direction of ESTUN's technology development, in order to explore the detailed demands, we, following our framework, conducted a leading-players-based comparison to understand the weakness and strengthen of ESTUN so as to further select technologies in different strategic technology sections. We continued to take servo system as an example here. For TS2, AC servo system was highlighted as the strategic technology section. A term-based correlation map (shown as Fig. 9) was generated to illustrate the characteristics of AC servo system and the relationships among the top ten companies in the world.

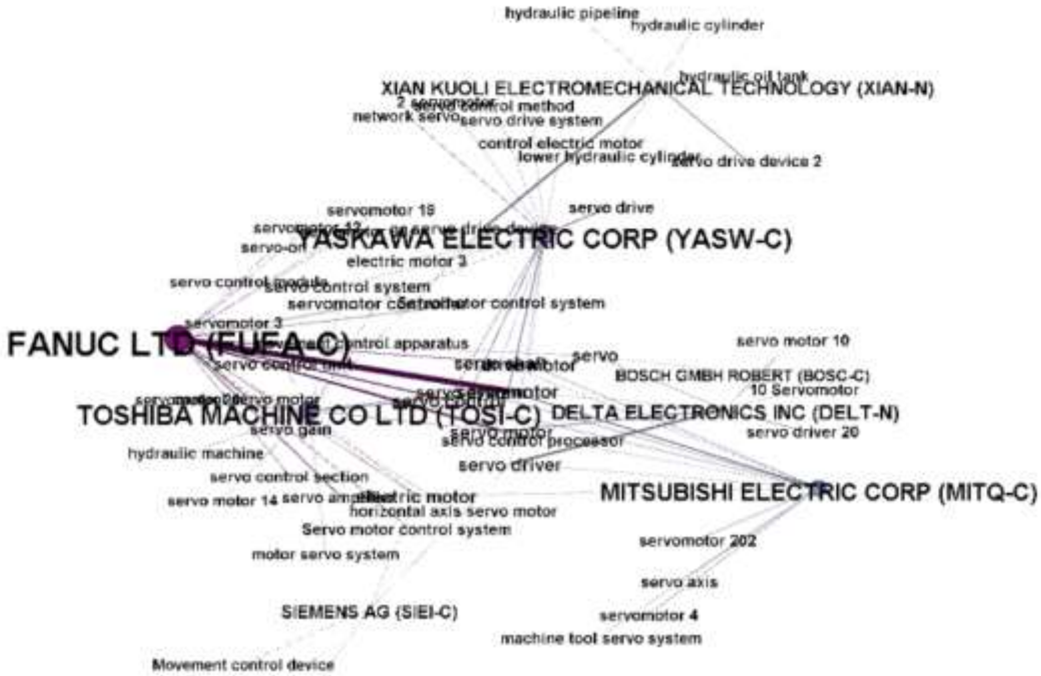

Fig. 9. Correlation Map of top 10 players for AC servo system

Shown as Fig. 9, Japan dominated AC servo system since the first top 4 companies - FANUC, YASKAWA, TOSHIBA, and MITSUBISHI -were Japanese companies, which accounted for more than 80% patents in our selected dataset. Another 4 companies- SIEMENS, HEIDENHAN, BOSCH and LUST – were from Germany. It was clear that Japanese companies focused more on the control technologies of both drive motor and servo control, while German companies paid more attention on motion control and position control technologies. Another two of the ten companies were from China mainland and Taiwan, but they only hold limited proportions on the patents.

ESTUN technicians helped us pick MITSUBISHI, YASKAWA, and SIEMENS as our comparative models, and the top 5 IPC codes of these three corporations and ESTUN are all shown in Fig. 10. The number in bracket close to the IPC represents the order of this IPC code ranking in top 5 IPCs of each company. There are some IPCs co-existing in several companies but with different ranking, and we marked the initial letter of each company's name in front of the number to label specific circumstances.

The top 1 IPC code of these four companies is G05B-019, which represents program control system. The patents with this IPC mainly refers to control method or apparatus for servo system or servo motor, including position control, motion control, speed control, welding control, actuator control etc. The leading companies paid attention to it since it was a core technology that determined accuracy and advancement of servo system for CNCMT. We also highlighted 4 IPCs as below:

- H02P-005 and H02P-029 (MITSUBISHI & YASKAWA):The parent IPC class H02P represents control or adjustment of an electric motor, a generator or an electromechanical converter, where H02P-005 represents device for regulating or controlling the speed or torque of two or more motors, while H02P-029 represents device for regulating or controlling a electric motor. The two sub-technologies both relate with the control technologies of servo electric motor.
- G05D-003 (YASKAWA & SIEMENS) and H02P-007 (MITSUBISHI & SIEMENS): The both represent position or direction control, and they are important sub-technologies of motion control in servo system.

Above four IPCS did not appear in ESTUN's top 5 list, and H02K-001 was the only IPC that appeared in both ESTUN and MITSUBISHI. The other top IPCs of ESTUN showed that ESTUN concentrated on the servo motor, especially permanent magnet motor, and feeding, positioning or storing device. Therefore, the top IPCs between ESTUN and other three leading companies shared little similarities, and ESTUN was not as good as other leading companies in the control technologies of servo motor, and position & direction control technologies of motion control for the AC servo system.

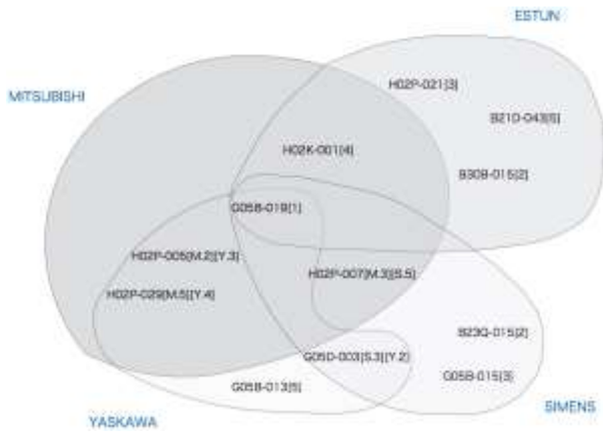

Fig. 10. Top 5 IPCs Distribution of three companies and ESTUN in AC Servo System

We conducted the same analyses on TS1 (focusing on Numerical Control Device and Electro-hydraulic servo system) and TS3 (focusing on Speed Reducer) as strategic technology sections respectively, and we list the core IPCs and technology terms of the three Tech M&A strategies in Table 8.

Table 8. Strategic-technologies for three Tech M&A strategies

No.	Tech M&A Strategy & Related Technologies		Core IPCs	Core technology terms
1	**TS1:** Maintain technology leading position in domain CNC metal forming machine tools sub-sector	Numerical Control Device	G06F-009 G06F-015 G05B-013	Numerical controller Numerical control unit Numerical control device Position control
		Electro-hydraulic servo system	F15B-015	Hydraulic actuator Hydraulic system
2	**TS2:** Extend technology advantages to other CNC machine tools sub-sectors	AC servo system	H02P-005 H02P-029 G05D-003 H02P-007	Servo motor control Drive motor control Direction control Position control
3	**TS3:** Acquire Robot core technologies beyond ESTUN existing technology system	Speed Reducer	B25J-009 F16H-001 F16H-057	Speed control Speed reducer

Region-based scope selection

ESTUN did not conduct any M&A practices before, and in the past years, ESTUN preferred independent innovation to overcome technical difficulties. However, aiming to reduce the pressure of competition environment and capture possible opportunities in CNCMT industry, ESTUN realized the importance of snatching market share, and increased the priority to M&A. However, ESTUN lacked the experiences on M&A, and it made the decision to pursue the M&A strategy in China's domestic regions to avoid high risk in international markets.

Technology owner filtering

Since ESTUN planned to implement the M&A strategy in China's domestic regions, in the study, we narrowed the scope of our selection to Chinese firms. We constructed a search strategy to narrow our global CNCMT patent dataset by selecting the patents whose patent number starts from "CN", e.g., CN100562822. These patents are from the State Intellectual Property Office of the P. R. China (SIPO). Based on the selected SIPO dataset, we further retrieved the patents that were applied by companies, since it is impossible to acquire institutions and universities in China. In the context, we strictly selected the patents that were applied in the SIPO by commercial companies and blended with the Tech M&A strategies and the target technologies presented in Table 8.

We continued to take AC servo system as an example in this section. The core IPCs and core technology terms for TS2 were combined together as the search strategy in the selected patent dataset. We proposed a process to refine technology owners from a corpus of patents, and the stepwise results of which is given in Table 9.

Technology owners holding with few patents would have limited competitive capability, when considering indicators such as technology complementary, R&D capability, R&D human resource, etc. However, a large number of technology owners only have one patent, which greatly increases the workload of related analyses. Therefore, we decided to select patent assignees holding with more than 2 patents （not less than 3 patents）, which reduced 96% workload and greatly improved the work efficiency.

Table 9. Technology owner refining process for AC servo system

No.	Step	Number of the technology owner
1	Retrieve the patent assignees of the 7343 patent records	4596
2	Select patent assignees, the patent records of which are not less than 3	168
3	Remove oversea patent assignees	126
4	Remove individual patent assignees	119
5	Remove companies whose main business were not in CNCMT – external information was engaged, e.g. web, and expert knowledge	16
6	Remove companies whose total assets were more than the one of ESTUN	9
7	Remove companies that have been announced to be merged recently*	8

*We just got the news that one of the 9 selected companies would be merged by another one, thus, we removed that firm from our list, and such news also could be considered as the evidence to support the feasible of our refining process – we retrieved similar firms in technical aspect for Tech M&A.

Target firms evaluation and identification

Each potential target company (in Table 10) was evaluated from double firms-side perspective and target firm-side perspective in Table 1. In our case, for TS2, the target technology was AC servo system and it was a product extension M&A which aiming to extend existing product priority from CNC metal forming machine tools to other CNCMT subsectors, therefore, we need to take both technology similarity and technology complementarity into consideration.

Table 10. Eight potential target companies for AC servo system

No.	Abbreviation	Name
1	A1	CHANGZHOU LIANLI AUTOMATION TECH CO LTD(LIANLI)
2	A2	GUILIN STARS SERVO & LASER SCI & TECHNOL(STARS)
3	A3	JIAXING RUIHAI MECHANICAL HIGH-TECH CO (RUIHAI)
4	A4	SHENZHEN DAZU PRECISION MECHATRONICS CO(DAZU)
5	A5	SHANDONG LUNENG INTELLIGENT TECHNOLOGY(LUNENG)
6	A6	SHENZHEN IDEAL TECHNOLOGY CO LTD (IDEAL)
7	A7	SHENZHEN INVT ELECTRIC CO LTD (INVT)
8	A8	SUZHOU BOZHONG SEIKO TECHNOLOGY CO LTD (BOZHONG)

The whole corpus contained 56 4-digit IPCs and 406 7-digit IPCs. We set the universe as $X = \{x_1, x_2, \ldots, x_8, x_9\}$, where x_i was for the patent portfolio of firm i, and denoted each 7-digit IPC j as a fuzzy set A_j where $j \in [1,406]$. The membership function $A_j(x_i)$ was set as below, where $PN(x_i)$ means the patent number of portfolio x_i, and $PN(j|x_i)$ was used for the number of patents belonging to IPC j in x_i.

$$A_j(x_i) = \sqrt{\frac{PN(j|x_i)}{PN(x_i)}}$$

We, then, obtained the membership grade matrix between 8 portfolios with the one of ESTUN using 406 7-digit IPCs. We calculated the similarity via the cosine function, the similarity results between eight companies and ESTUN is shown as Table 11.

Table 11. Results of Similarity Measures

	A1	A2	A3	A4	A5	A6	A7	A8
ESTUN	0.2390	0.2199	0.2396	0.4084	0.1171	0.0944	0.2856	0.0080

We denote the 7-digit IPCs of AC Servo system-related techniques as U, where 179 IPCs were included, and the set for the 41 IPCs of ESTUN as B, and A = {A1:11, A2:12, …, A7:12, A8:43} was used to represent the IPCs of the selected companies respectively. Following the designed formula in the Methodology section, the complementarity measure was calculated and given in Table 12.

Table 12. Results of Complementarity Measures

	A1	A2	A3	A4	A5	A6	A7	A8
ESTUN	0.011	0.015	0.005	0.008	0.386	0.040	0.017	0.151

In order to test the validation of our method, we sent the collected auxiliary information (i.e., firm introduction, patent data, etc.) of both ESTUN and the eight candidates to nine technical experts, and asked them to grade the eight candidates into three ranks (A, B and C) according to their understanding to the degree of technology complementarity between the candidates and ESTUN. Rank A represents relatively high degree of technology complementarity, while C represents relatively low and B is the middle. Base on expert knowledge, we extended the rank to five groups (e.g., A, A-B, B, B-C, and C). For instance, if there are five experts giving A for one candidate, this firm would be graded to group A; if no more than four experts assigned the candidate to A, it will belong to group A-B. Finally, we got the results of the expert-based analysis in Table 13, which were consistent with the results of the IPC-based analysis. In addition, the inter-rater agreement between the nine experts was calculated, and all of the correlations were within the interval [0.74, 0.89], which indicates a high correlation between the experts and can be the evidence to endorse the reliability of the expert knowledge-based validation.

Table 13. Comparison Results of Complementarity Measures

	A1	A2	A3	A4	A5	A6	A7	A8
IPC-based score	0.011	0.015	0.005	0.008	0.386	0.040	0.017	0.151
Expert-based rating group	B	B	C	C	A	C	B	A-B

In R&D familiarity part, we found that ESTUN had not applied co-invented patents with these eight companies. In this context, we need to introduce other ways to investigate the network and relationships among them so as to support further expert evaluation. Thus, we designed a questionnaire and sent to a number of employees of ESTUN to capture the information whether their employees have close cooperation or communication with the ones in the other eight companies. The questionnaire mainly included three parts: 1) the investigator needs to pick out the companies with whose employees he/she has personal connections; 2) the investigator needs to provide detailed information of their cooperation and communication experience, e.g., discussing some technique issues frequently online, attending the same workshop or conference session often; and 3) the investigator needs to provide a ranking list of these 8 firms based on his/her personal understanding of R&D familiarity. The feedback of this questionnaire was only used as the results derived from quantitative analysis and printed as handout to support the discussion in the subsequent evaluation. Based on the feedback and their own knowledge, the ten technicians contributed to Table 7 were invited again to evaluate scores of R&D familiarity between ESTUN and other eight candidates, and then, we calculated the final scores of R&D familiarity respectively (shown in Table 14) through weight-average way. Interestingly, A8 and A1 were in the same province with ESTUN, which made ESTUN more familiar with them.

Table 14. Results of R&D Familiarity Measures

	A1	A2	A3	A4	A5	A6	A7	A8
ESTUN	0.63	0.45	0.26	0.58	0.19	0.23	0.36	0.82

We introduced AHP to set the weights of the three compared pairs. Following the basic steps and the fundamental scale of AHP proposed by Saaty (1990), we, based on our understanding to the three compared pairs, constructed the pairwise comparison matrix in Table 15. Since the Consistency Ratio (CR) was less than 0.1, the estimate of the pairwise comparison matrix was acceptable. Therefore, we set the priority vector as the vector of the weights, where $\mathrm{W} = \{\mathrm{w}_1, \ldots, \mathrm{w}_3\} = \{0.27, 0.55, 0.18\}$.

Table 15. The Pairwise Comparison Matrix

	Technology Similarity	Technology Complementarity	R&D Familiarity	Priority Vector
Technology Similarity	1.00	0.50	1.50	0.27
Technology Complementarity	2.00	1.00	3.00	0.55
R&D Familiarity	0.67	0.33	1.00	0.18
			$\lambda_{\max}$ =3.0017, C.R.=0.0014	

Finally, we normalized the technology similarity, technology complementarity, and R&D familiarity indicators then calculated the comprehensive score of double firms-side indicators by the method of weighted sum rules for each of the eight companies. The calculated results are showed in Table 16.

Table 16. The comprehensive score in double firms-side perspective

	A1	A2	A3	A4	A5	A6	A7	A8
Comprehensive score in double firms-side perspective	0.29	0.23	0.18	0.39	0.62	0.12	0.26	0.39

We next followed the same way to calculate the target firm-side indicators and got the results in Table 17. The index weights and comprehensive scores are showed in the last row and column. For technology quality indicator, in our framework, we intended to rely on the patent citation, however, SIPO did not provide citation information before 2013, and we applied the percentage of invention patents as measurement indicator of Technology Quality here.

Table 17. The target firms-side measurement results of the eight potential target companies

Corp.	Technology Quantity		R&D Human Resource		R&D Productive Efficiency		Target Technology Concentration		Technology Quality		Comprehensive Score
	Raw	Normalized	Raw	Normalized	Raw	Normalized	Raw	Normalized	Raw	Normalized	
A1	209	0.20	135	0.27	154.81%	0.04	1.44%	0.05	27.08%	0.48	0.27
A2	38	0.02	6	0.00	633.33%	1.00	13.16%	0.62	49.99%	0.99	0.58
A3	19	0.00	5	0.00	380.00%	0.49	21.05%	1.00	5.26%	0.00	0.20
A4	59	0.04	32	0.06	184.38%	0.09	6.78%	0.31	39.29%	0.75	0.33
A5	663	0.67	483	1.00	137.27%	0.00	0.90%	0.03	38.30%	0.73	0.59
A6	478	0.48	264	0.54	181.06%	0.09	0.63%	0.02	50.36%	1.00	0.55
A7	501	0.50	209	0.43	239.71%	0.21	0.60%	0.01	42.19%	0.82	0.48
A8	977	1.00	186	0.38	525.27%	0.78	0.31%	0.00	48.89%	0.97	0.67
Index Weight	0.1182		0.2530		0.1655		0.1215		0.3418		

We generated a scatter diagram (shown as Fig.11) to represent these eight companies based on the results from Table 16 and Table 17. The vertical axis is the double-firm side comprehensive score while the horizontal axis represents the target-firm side comprehensive score, dividing the whole area into four sub sections, and the eight spots represent the candidate target firms respectively. The firms in Section I have high scores of both double-firm side and target-firm side indicators, which represents that they have a better chance of realizing synergy with ESTUN as well as providing high technical values for ESTUN. To the contrary, the firms in Section III with low scores of both double-firm side and target-firm side represent a not bright prospect. Therefore, we focused on the two firms in Section I—A5 and A8—for further investigation.

We organized certain small-range workshops with local government officers, staff of local machinery industry association, and senior managers and customers of A5 and A8 respectively to explore other advantages of the two firms. In the process of communication, A5's local government - Shandong Province - showed its sincerity of pushing forward this potential M&A transaction and encouraging setting up an advanced manufacturing base in the future. In contrast, the reactions of A8's customers were relatively negative. On one hand, they were not familiar with the brand of ESTUN and the geographical factor would also influence their judgment; on the other hand, they were very concerned about whether A8 would continue to develop its own products after the M&A. Furthermore, the discussions indicated that A5 held more advantages on the servo drive system, motion control system, position system, and especially the application in both CNCMT and robot; while A8 was more powerful in the servo motor control system, and synchronized servo-driven machines. Therefore, A5 was a better candidate to help ESTUN enhance its technical capability in the whole AC servo system and could also benefit ESTUN in Robot's key motion control sub-section.

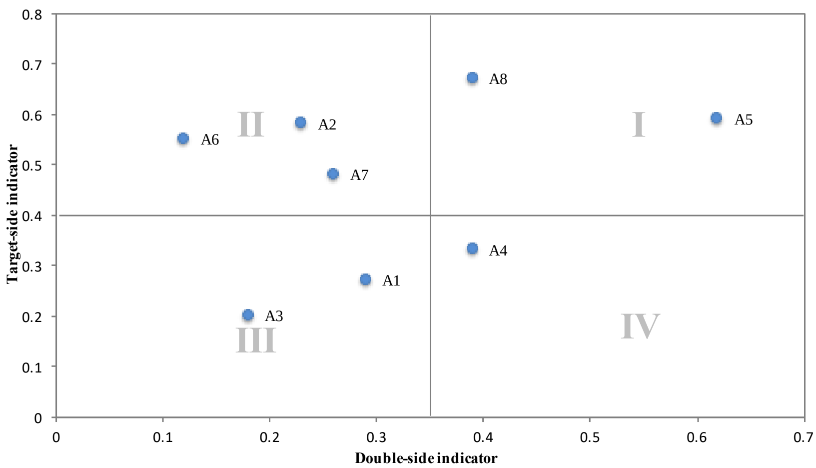

Fig. 11. Scatter Diagram of eight companies

Following the same procedures, we also identified the Tech M&A candidates for other two M&A strategies (in Table 18).

Table 18. Tech M&A strategies and their acquired target company

No.	Tech M&A Strategy & Related Technologies		Target Company	Advantages
1	**TS1:** Maintain technology leading position in domain CNC metal forming machine tools sub-sector	Numerical Control Device	PADAUK TECHNOLOGY CO LTD	It was good at developing multiple microcontrol system. It mainly engaged in CNC machine tool and industrial robot industry.
		Electro-hydraulic servo system	SHANGHAI NORMA HYDRAULIC SYSTEM CO LTD	It was good at research and large scale manufacturing electro-hydraulic servo valves with precise transmission control and the proportion of high-end hydraulic components.
2	**TS2:** Extend technology advantages to other CNC machine tools sub-sectors	AC servo system	SHANDONG LUNENG INTELLIGENT TECHNOLOGY	It was good at research on servo drive system, motion control system, and position system. It mainly engages in CNC machine tool and industrial robot industry.
3	**TS3:** Acquire Robot core technologies beyond ESTUN existing technology system	Speed Reducer	BEIJING PEITIAN DAFU PRECISION MACHINERY	It was good at research and development of cyclonical pin wheel reducer and harmonic reducer.

Discussion

We apply our method to deal with real-world data and discuss related strategic management topics, closely engaging expert knowledge to some extent to validate the reliability of our methodology. The significance of our study can be summarized from the following two aspects.

Technical significance of the hybrid methodology

There are rare studies using patent analysis to address concerns on the pre-acquisition phase of Tech M&A (Gomes and Angwin et al., 2013), our study applied technical intelligence to aid Tech M&A-oriented strategic management and decision-makings, which enriched pre-acquisition research of promoting M&A target selection activities.

(1) An adaptable analytic method for Tech M&A target selection

An adaptable analytic method for Tech M&A target selection, which combines both quantitative and qualitative methodologies, is proposed in this study.

Patent-based term clumping, trend analysis, co-patent analysis and some other bibliometric methods are involved to ensure the objectivity of the analysis, and expert knowledge is engaged to adjust and validate the results to help identify acquisition targets for a given acquirer. However, the development of M&A strategy is a complicated process, and subjective factors further add issues (Zollo and Meier, 2008; Gupta, 2012). Thus, relying on pure quantitative method is certainly not enough. How to make the process more effective drives us to pursue our study.

First, text mining is applied to deal with massive information processing, which can overcome limitations of human intelligence and provide more comprehensive technical information. Nowadays, it is impossible to manually capture the information of all firms in a given industry, in particular high-technology industries, since in these industries many firms are new and small-size companies but hold some advanced technologies (Rainnie, 2016). In this situation, text mining technique-based patent analysis is a useful way to help us identify these candidates from a large number of firms. For example, Fig. 9 profiles the top ten companies of AC servo system in the world and also illustrates the characteristics and the relationships among them. Then, aiming to answer the questions of "how to evaluate these candidates" and "which candidate would be fit for the acquirer," we employed some advanced text mining techniques to obtain technology intelligence for target technology identification. For example, Fig. 5 and Fig. 6 are the outcomes of the term clumping process, which quickly helped identify the sub-technologies.

Second, expert knowledge is engaged to adjust and validate the results. We are fully aware of the fact that scientific research could not be managed in a black box and we need to take both internal and external factors into consideration (Ravelomanana and Yan et al., 2015), and feedback from various stakeholders can be one of the most important inputs. As an example, in this paper we consulted technical experts to identify the core technologies, we communicated with the senior managers of related firms to understand Tech M&A strategies, we invited governmental officers and policy makers to help consider strategic technologies, and we involved the voices of the customers to evaluate the M&A candidates. Concretely, our empirical study engaged expert knowledge in different ways, including formal workshops, face-to-face interviews, telephone and email contacts, and questionnaires. From the perspective of the function of expert knowledge, some processes were very simple, which only take advantage of expert knowledge to "check" the results, while several other processes need to arrange experts together to discuss and finalize the results formally. For example, Figure 8 is the outcome generated by the cooperation between the technical experts from the Information Research Institute of Machinery Industry of China and us.

Third，we combined quantitative and qualitative methodologies in a systemic step-by-step process.

(2) A method to combine terms and IPCs to help identify target technologies from patents

We combine terms and IPCs to help identify target technologies from patents, which improve the accuracy of traditional patent analysis. It is also interesting to compare the strengths and weaknesses of terms with Subject-Action-Object (SAO) analysis, in which SAO structures can transmit more information and to some extent make up for the deficiency of terms (Park and Yoon et al., 2013). Focusing on the case in this paper, it is too specific on semantic analysis which focuses on a small granularity and the SAO analysis is not mature enough which lacks of mature analytical tools. As our study is mainly for the practical applications of Tech M&A, we combined terms and IPCs, which are both relatively mature patent analytic approaches, and this combination can overcome the limitation of term-based analysis. For instance, if the abstract or title of a patent contains the term of "AC servo system", we cannot make sure that the patent really relates to AC servo system-related core technology, since we do not know the reason why the term was mentioned by authors. However, if a patent contains terms of "AC servo system" and belongs to IPC "H02P" or "G05D" (see Table 8), the possibility extremely increases. Therefore, compared with individual term-based or IPC-based analysis, our method has significant advantages on patent content identification.

(3) An evaluation index to investigate the technological level of all potential target firms and measure the relationships between target firms and an acquirer

The evaluation index built up in this study can not only investigate the technological level of all potential target firms, but also measure the relationships between target firms and an acquirer. Different from previous studies, when we evaluate potential target firms, the indicators are weighted differently under diverse strategic purposes and commercial situations. For instance, in our case study, as ESTUN's TS2 is to extend technology advantages to other CNC machine tools sub-sectors, when we evaluate the candidate target firms, the technology complementary is weighted heavier than other double-side indicators (see Table 14) since acquiring complementary technologies is the main consideration. In contrast, as ESTUN's TS1 is to maintain technology leading position in its traditional advantage sub-sector - CNC metal forming machine tools, the technology similarity is weighted heavier since strengthening its existing technologies by M&A is more important. In addition, we proposed a way to measure technology complementarity, in which we not only consider the scope – in which technical area we are considering the complementarity, but also the volume – depending on specific targets. Compared with Makri's calculation formula (Makri and Hitt et al., 2010), our method is more adaptable to various M&A strategies since the scope and the volume of specific M&A cases are usually different.

Practical significance for China's Tech M&A

China has become one of the most import commercial markets in the world, and not only international companies but also small and medium enterprises (SMEs) need to take Tech M&A into their R&D plan and long-term strategies (Gassmann and Zedtwitz, 1998). However, China's companies, especially SMEs, have rare theoretical and practical experiences in such field, and the high failure rate of Tech M&A has become one of the most negative factors that influence the sustainable development of the companies – failed Tech M&As would result in terrible disasters, e.g. resource wasting, and technology integration misleading. Unfortunately, China's companies are lack of both theoretical knowledge and practical experience, and the pluralism of the targets of the Tech M&A and the booming of high-technology-oriented Tech M&A activities further increase such difficulties and uncertainty (Farrell and Grant, 2005).

It has been a long time that subjective decision makings, which heavily depend on the personal knowledge of managers and decision makers, lead to Tech M&As (Pablo, 1994). Traditional Tech M&A strategy in China usually take both internal and external impact factors into consideration, e.g. technologies, regions, and previous collaborative experiences, and decision makers, depending on their personal background and experiences, decided the direction and detailed process of Tech M&A (Tang and Metwalli, 2003; Reuer and Ragozzino, 2008). In past decades Tech M&As were not as popular and frequent as what we see these years, and the limitations of such old-fashioned strategies had been easily overcome by the supports of China's powerful governments and were not obvious in China's immature economic environment.

Obviously, individual expertise or even expert panel would not be always fit for the changing environment of high-technology industries. In our empirical study, more than 20,000 patents were applied from 2000 to 2015 in global CNCMT industry, and such amount has been already out of the control of expert knowledge. At this stage, we attempt to introduce advanced text mining techniques to analyze a massive number of patents, and apply quantitative results to support expert-based qualitative approaches. We take both technical and R&D strategic factors into consideration, and appropriate quantitative methods are engaged with expert knowledge to construct an evaluation process to help company select best acquirers. Such combination, we believe, would hold great capability to enrich the structure of traditional strategic management, and explore potentials and insights from massive data to support expert-based decision makings.

On the one hand, the target technologies identification step sought approaches to explore technologies that were not only important and promising for technological domains but also fit for acquirers' Tech M&A strategies and long-term sustainability.

On the other hand, the target firms identification step was to select suitable targets from the list of potential acquired candidates. We summarized a series of factors that would play active roles in diverse technical synergies with different Tech M&A situations and requirements, and proposed an evaluation process to measure technology relatedness between acquirers and acquired firms. These efforts investigated both technical and strategic perspectives and provided referring results to help reduce the risk of post-M&A technological integration failures.

We fully understood the complex internal and external environment of Tech M&A, thus, we specifically chose China's CNCMT as the empirical technological domain. In China, the development of CNCMT has been listed onto a prior level for several years, and the "Made in China 2025 Plan" pointed CNCMT industry as one of the key technology fields of China from 2015 to 2025. Meanwhile, CNCMT industry in China is entering a development peak of M&A, and the number of M&A transactions has kept a high level-more than 20 per year since 2007. We had sufficient reasons to believe that the Tech M&A activities would be active in China's CNCMT industry, and a case study to address insights for such activities would lead to really meaningful understandings for real-world needs. We specifically chose the ESTUN - a leading company in China's CNCMT industry – for the acquirer of the case, where we integrated ESTUN's R&D strategies and Tech M&A needs with our analytic methodologies. The results not only demonstrated the feasibility and adaptability of the method, but also provided interesting results for similar firms that aimed to follow ESTUN's developmental pathways of success.

Conclusion

We used patent data to map the development trends of CNCMT-related technologies, and then, referring to ESTUN's real strategic needs, identified the Tech M&A candidates for ESTUN. We also constructed an evaluation index to measure technology relatedness and judge the degree to which candidates match ESTUN's technology portfolio. In addition, our study may prove informative to industry R&D management and product development planning.

This study also has some limitations. First, by using the methodology proposed in this study, it could be possible to narrow down M&A targets with more accuracy. However, it is not confirmed how much the accuracy improved. It would be the future work. Second, we concentrated more on how to reduce the risk of post-M&A technological integration phrase, which relied on exploring the possibility of technology synergies between acquirer and potential, however, we also need consider how to maximize the profit of technology synergies in the future, which may involve more technology forecasting and technology value estimation methods. Finally, how to bridge Tech M&A- oriented results and other factors, e.g., operation, market, organization, geography, and culture considerations, is a big challenge for future work.

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