Chapter 10
Identifying Targets for Technology Mergers and Acquisitions Using Patent Information and Semantic Analysis

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Abstract Technology plays an increasingly important role in today's enterprise competition. Technology mergers and acquisitions (Tech M&A), as an effective way to acquire the external technology resources rapidly, have attracted attention from researchers for their potential realization of value through synergy. A big challenge is how to identify appropriate targets to support the effective technology integration. In this study, we developed a model of target selection of Tech M&A from the perspective of technology relatedness and R&D capability. We present results for the Tech M&A case in China's cloud computing industry.

Keywords Technology merger and acquisition · Patent analysis · Semantic analysis · Cloud computing

10.1 Introduction

Rapid technological change and diverse customer needs make firms face increasing pressure of innovation. When enhancing the innovative capabilities, even the largest and most technologically self-sufficient firms do not always have the time to build their own new technologies from scratch. Getting external technology resources to enhance existing technology portfolios has been a preferred choice for firms.

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Technology mergers and acquisitions (Tech M&A), as an effective way to get external technology resources, have been a hot topic for innovation management (Sears and Hoetker 2014; Lodh and Battaggion 2014). Tech M&A enables firms to get quick access to the research frontier in the field of competence (Yoon et al. 2013) and facilitates firms to enter new technology areas with lower time cost and reduced R&D failure risk (Hussinger 2010). The main effect of Tech M&A was to achieve technological synergy to enhance acquirer's innovative capability (Di Guardo et al. 2015). The research on Tech M&A can be divided into three stages:

In the first stage, scholars found that in some cases, firms could develop fast after acquiring some small technology-based firms. Granstrand et al. (1982) strove to conclude what were key factors to Tech M&A success based on 13 M&A events in high-tech industries.

In the second stage, researchers began to explore motivations of Tech M&A and evaluate performance, especially from the perspective of finance. Scholars used multi-dimensional indexes and chose various time frames to evaluate acquisition performance (Loughran and Vijh 1997; Kohers and Kohers 2000).

Now, in the third stage, research on Tech M&A tends to be diversified, including Tech M&A integration, Tech M&A mode, and Tech M&A target selection. Paruchuri et al. (2006) analyzed the relationship between the research personnel and innovation output during Tech M&A integration. Wei and Tian (2011) identified attributes of target companies and proposed a theory to support the decision making of acquiring companies through four in-depth case studies conducted across three primary sectors in the medical technology industry. Lin (2012) tested an acquisition–learning–innovation framework and found that unrelated acquisitions also enhance exploration in an era of technology fermentation. Research at this stage mainly focuses on performance evaluation after Tech M&A. Few studies have been conducted on target selection pre-acquisition.

The volume of Tech M&A events has been steadily increasing in the recent years. However, it is not easy to realize Tech M&A successfully. The failure rate of Tech M&A is pretty high—between 70 and 90 % (Christensen et al. 2011). Taking account of the $2 trillion transactions of M&A every year, the failures are extremely costly. Tech M&A success or failure can be determined and influenced by many factors—e.g., strategic formulation, technology relatedness, and financial status. But the most fundamental step to increase the success of M&A is to select the right target companies, which are well matched to the strategic purpose of a given M&A action (Kengelbach and Roos 2011).

Existing studies on identifying M&A targets concentrate primarily on the development or application of financial and managerial variables (i.e., firm size, cash flow, and debt-to-equity ratio), neglecting consideration of the technological perspective (Ragothaman et al. 2003; Ali-Yrkkö et al. 2005).

Patents, as an important source for the management of technology in both industry and science, are useful sources for technology analysis. Traditional methods are mainly based on International Patent Classification (IPC) and citation analyses, without considering the text of patents, which constrain the analysis depth. Recently, the proliferation of patents worldwide has increased the demand

for the more advanced quantitative patents analyses to support expert evaluation processes for decision making (Yoon and Kim 2012; Yoon et al. 2013). In this paper, we introduce semantic analysis to devise a new framework to analyze technology relatedness, including technology similarity and technology complementarity of Tech M&A. We apply our method to Huawei Technologies Co. Ltd (Huawei), China's leading firm in the field of cloud computing, for Tech M&A needs.

10.2   Challenges and Methods

Tech M&A, by its very nature, is a method to get external technology resources. The primary factor in target selection of Tech M&A is technical relatedness. However, few methods have been proposed to analyze it. A big challenge that corporate managers and government policy makers are facing is how to confirm a methodological architecture to help them identify the appropriate targets to support effective technology integration.

Our research is based on the following driving questions:

1. How do we use a quantitative method to measure technology relatedness?
2. What factors should be considered for effective technology integration based on the analysis of technology relatedness?
3. How to devise a comprehensive method from the perspective of technology relatedness and technology integration on post-acquisition stage?

In this study, we try to provide a detailed guidance for identifying potential Tech M&A targets from a technological perspective based on patent information. Patents have long been considered to be up-to-date and valuable information sources in technology, and careful analysis of patents could provide information of not only technological competitiveness, but also overall technological opportunity in the specific technology areas. Therefore, the technological capabilities of a corporation can be represented by its set of patents.

In this study, we divide our method of Tech M&A target selection into three steps based on patent analysis. Figure 10.1 shows the process.

Step 1: Technology Similarity Analysis—The purpose of this step was to calculate the technology similarity between the acquirer and targets, and reduce the selection scope for Step 2. First, IPCs of each patent will be extracted, and the degree of overlap will be regarded as the preliminary evaluation of consistency of technology area. Second, we measure technology similarity through Subject—Action—Objective (SAO) analysis of the USE field in the abstract of patents after choosing the potential candidates that show commonality with the acquirer.

Step 2: Technology Complementarity Analysis—Technology morphology analysis is introduced to help the complementarity analysis. First, we extract keywords from patent texts and arrange them according to the related technology.
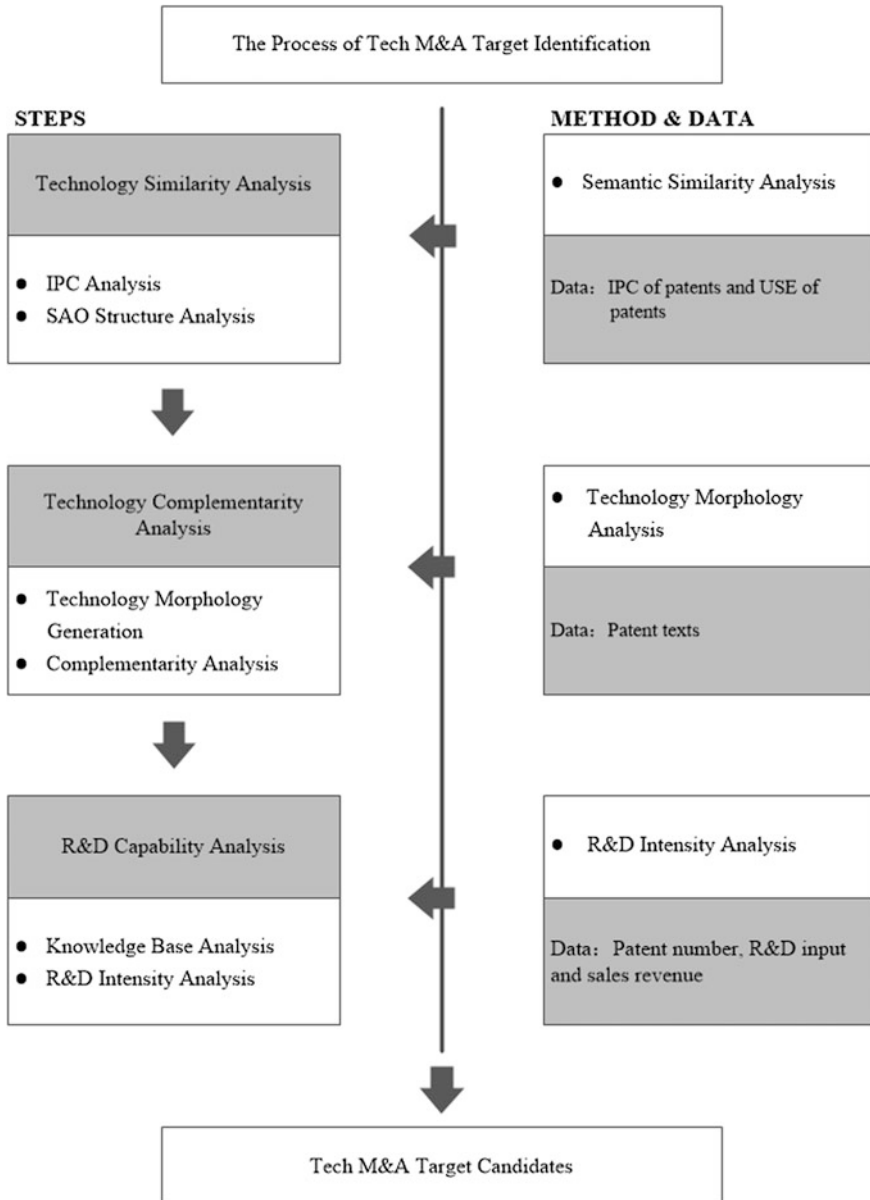
Fig. 10.1 Tech M&A target identification process

Second, we calculate the complementarity of each technology combination with the help of expert experience.

Step 3: R&D capability analysis—We use knowledge base and R&D intensity as indicators to make further selection of potential targets after the first two steps.

For technology similarity analysis, we extract the IPCs of every patent and measure the consistency of technology area with the method of Makri (2010). After that, NLP tools are used to extract the SAO structures from the patents collected with the help of an open API. In order to identify the semantic similarity of SAO structures, a semantic knowledge base, WordNet, is introduced to calculate the similarity between two words or phrases in the SAO structures.

For technology complementarity analysis, first, we extract the keywords from patents and map them into their associated morphology. Second, we evaluate the technology complementarity level with the help of experts and then calculate technology complementarity.

For R&D capability analysis, we emphasize the view of knowledge base and R&D intensity of potential targets. Knowledge base of a firm is measured by the related number of patents, and R&D intensity is measured by a firm's ratio of expenditures on R&D to the firm's sales.

10.3   Case Study

10.3.1   Patent Collection

Rapid technology renewal keeps emerging technology a hotspot in Tech M&A for years, and we chose a representative one—cloud computing technology, focusing on opportunities within China. Patents for cloud computing were collected from Derwent Innovations Index (DII), employing the search strategy devised by Owens and Logue (2012), from 2000 to 2012.

We got 621 patents on cloud computing in China after data cleaning.

Table 10.1 lists the top 10 assignees. According to technology development strategy and the layout of the cloud computing technology area, we chose Huawei Corp (Huawei) as an acquirer to search for Tech M&A targets. Huawei is a leading global provider of Information Communication Technology solutions and is also the most professional one-stop cloud service provider in China. Huawei has been expanding the layout of cloud computing since 2010, and in the year 2011, Huawei acquired Huasy Firm for 5300 million dollars to enhance the security of cloud platforms. Tech M&A is regarded as an important way to achieve the rapid development of related technologies on cloud computing for Huawei.

Table 10.1 Top 10 assignees in cloud computing

Assignee names	Patent number	Percentage (%)
ZTE Corp	52	8.4
Microsoft Corp	41	6.6
Inspur Electronic Information Co. Ltd.	33	5.3
LI Z (Individual)	24	3.9
Huawei Crop	**23**	**3.7**
IBM Corp	21	2.7
Univ Qinghua	19	2.1
Hon Hai Precision Ind Co. Ltd.	19	1.9
Guangdong Electronics Ind Inst Co. Ltd.	17	1.4
Univ Beijing Aeronautics & Astronautics	15	1.4

10.3.2 Technology Similarity Analysis

Literature on Tech M&A suggests that the maximum benefits from an acquisition can be realized when technology portfolios of both firms are related (Hussinger 2010; Gupta 2013; Ahn et al. 2014). We applied Makri's theory (Makri et al. 2010) to make a preliminary assessment of technology similarity between the Acquirer and the Target (A&T) with the help of IPC analysis. IPC of patents shows the distribution of technology areas. Technology similarity of firms with high consistency of technology distribution will probably be higher than the others'. The measure of technology similarity is described below. The Total Patent A&T in the formula means the total number of patents of both the A&T.

$$
\text{Technology Similarity} = \frac{\text{Overlap All Patent Class}}{\text{Total Patent A\&T}} \\
\times \frac{\text{Total Acquirer Patent In Common Classes}}{\text{Total Acquirer Patent}} \quad (10.1)
$$

We extracted IPC information from the patents collected to illustrate technology similarity. We refined the data first. Individual assignees and firms whose total number of cloud patents was fewer than 6 were excluded. Second, we defined the degree of "common classes." For example, there are three patents P_1, P_2, P_3 with IPCs: H04L29/08, H04L29/06, H04H60/72. P_1 and P_2 represent similarity because they are under the same subcategory H04L29, and the combination with P_3 does not. In this way, we calculated the technology similarity between the acquirer and the potential target for each of the leading Chinese firms in the domain. The results are shown in Table 10.2. The left part of the table is the potential target list, and the right part is the evaluation of technology area. We found that GCI SCI & Technology Co. Ltd. (GCI), Shanghai Hechen Information Technology (Hechen), ZTE Corp (ZTE), and Shuguang Cloud Computing Technology Co. (Shuguang)

Table 10.2   Preliminary technology similarity analysis

Potential targets	Preliminary technology similarity analysis
GCI SCI & Technology Co. Ltd.	0.064
Shanghai Hechen Information Technology	0.061
ZTE Corp	0.058
Shuguang Cloud Computing Technology Co.	0.053
Inspur Electronic Information Co. Ltd.	0.048
Hon Hai Precision Ind Co. Ltd.	0.036
Microsoft Corp	0.024
IBM Corp	0.014
Beijing Z & W Technology Consulting Co. Ltd.	0.011
Yulong Computer Telecom Technology	0.009
Shenzhen Zidong Technology Co. Ltd.	0.008

offer high consistency in the technology area. The IPC distribution is densely located in H40L29 and G06F09.

We further analyzed technology similarity from the perspective of the SAO structure of patent text. The SAO structure can express the precise meaning and can thus represent technological key concepts and key findings in the patent. Moehrle et al. (2005) proposed a method of using patent-based inventor profiles to guide human resource decisions. Park et al. (2013) used semantic patent maps to identify technological competition trends for R&D planning. We extracted the USE field from the patent abstracts and then transformed the content to SAO structures (Table 10.3). After filtering out some duplicated SAO structures using a set of Stop Words (2015), we got the data ready for semantic analysis.

WordNet-based semantic similarity between two SAO structures is computed by using the C# library (Simpson and Dao 2015). We set a threshold value as 0.7 to determine whether the two SAO structures are the same according to semantic similarity calculation results and the advice of experts. If the result is more than s, the two structures can be considered the same. For any two SAO structures (SAO_i and SAO_j), we determined the Similarity (SIM) between them as follows:

$$\text{SIM}(\text{SAO}_i, \text{SAO}_j) = \begin{cases} 1, & \text{if}(\text{Measure}(\text{SAO}_i, \text{SAO}_j)) \geq s \\ 0 & \text{otherwise} \end{cases} \quad (10.2)$$

The USE of a patent includes more than one SAO structure. We defined the semantic similarity between the patents as the basis of how many SAO structures the two patents share. Suppose that there are two patents P_1 and P_2, and we denote that $\text{Num}_{\text{SAO}}(P_1)$ is the number of SAO structures in patent P_1, $\text{Num}_{\text{SAO}}(P_2)$ is the number of SAO structures in patent P_2, and $\text{Num}_{\text{SAO}}(P_1, P_2)$ is the number of the semantically identical SAO structures shared by patents P_1 and P_2. The Patent Similarity (PSIM) can be described as follows:

Table 10.3 Sample of extracted SAO structure from patents

S (Subject)	A (Action)	O (Object)
Method	Execute	Software application, e.g., batch application and user-interactive application, on a computer system, according to a SLA
System for creating a composite public cloud	Delivery	Hosted services
Method	Schedule	Cloud computing open platform
Virtualized desktop application display platform	Used	Cooperative computing of an electric power system
System	Control	Quantum microscopy instrument
Issuing network invoice	Based	Cloud computing and data asynchronous transmission technology
Method	Protect	Data and privacy of user in cloud environment
Multi-tenant service providers	Request	Dynamic platform reconfiguration
Distributed systems on a set of computer processors	Perform	Coordinated upgrades
Experiment cloud platform system	Manage	Computer calculation and software resources

$$\text{PISM}(P_1, P_2) = \frac{2 \times \text{Num}_{\text{SAO}}(P_1, P_2)}{\text{Num}_{\text{SAO}}(P_1) + \text{Num}_{\text{SAO}}(P_2)} \tag{10.3}$$

After measuring the similarity between patents, we took the pairwise average similarity of patents owned by two different firms as the technology similarity. For any two firms (F_1, F_2), Firm Technology Similarity (FSIM) could be measured as follows:

$$\text{FSIM}(F_1, F_2) = \frac{\sum_{i=1}^{i=\text{PN}(F_1)} \left(\sum_{j=1}^{j=\text{PN}(F_2)} \text{PSIM}(P_i, P_j) \right)}{\text{PN}(F_1) \times \text{PN}(F_2)} \tag{10.4}$$

Here, $\text{PN}(F_1)$ and $\text{PN}(F_2)$ are the patents of the two firms $(F_1$ and $F_2)$, respectively, and the $\text{PSIM}(P_i, P_j)$ means the PSIM of the two firms. Figure 10.2 illustrates the degree of technology similarity between each other, and the first column is the technology similarity with Huawei.

We found that the three firms with highest technology similarity with Huawei were GCI, ZTE, and Hechen. The result matched with the IPC analysis that technology similarity of firms with high consistency of technology distribution is higher. We chose the firms whose technology similarity with Huawei was not less than 0.7 for technology complementarity (Table 10.4).
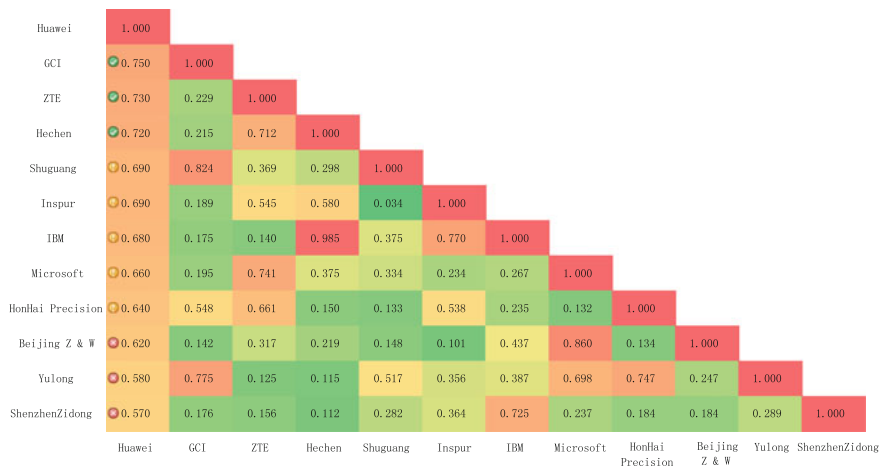
Fig. 10.2 Degree of technology similarity between each other of the selected firms

Table 10.4 Technology similarity evaluation of potential targets

Potential targets	Technology similarity
GCI SCI & Technology Co. Ltd.	**0.75**
ZTE Corp	**0.73**
Shanghai Hechen Information Technology	**0.72**
Shuguang Cloud Computing Technology Co.	0.69
Inspur Electronic Information Co. Ltd.	0.69
IBM Corp	0.68
Microsoft Corp	0.66
Hon Hai Precision Ind Co. Ltd.	0.64
Beijing Z & W Technology Consulting Co. Ltd.	0.62
Yulong Computer Telecom Technology	0.58
Shenzhen Zidong Technology Co. Ltd.	0.57

10.3.3 Technology Complementarity Analysis

Analysis of technology complementarity is based on the results of the technology similarity analysis. Technology complementarity is considered as an important driver of invention (Golombek and Hoel 2004). Acquiring complementary technologies can promote exploratory learning within the organization, which may accelerate the process of innovation (Cassiman and Veugelers 2006). Different from technology similarity, complementary technology contributes to post-merger invention performance by stimulating higher quality and more novel inventions (Miozzo et al. 2011). Sparse research has been conducted on the measurement of technology complementarity at the pre-acquisition stage. In this paper, we apply

morphology analysis for this. Technology Morphology Analysis was introduced to patent assessment by Yoon and Park (2005) and now is widely used for technology opportunities analysis. Technology complementarity before Tech M&A can be evaluated by analyzing different technology morphological combinations with the help of expert experience.

First, we converted the patents into structured data using keyword vectors according to their frequency of occurrence and with reference to technology dictionaries. Second, we set words associated with a specific technology and appearing frequently as keywords. Then, we mapped the patent keywords into their associated morphology and got Table 10.5, which shows the main technologies, subdivision technologies, and the corresponding keywords of cloud computing from the patents.

After that, we generated a table of subdivision technology complementarity according to the experts' assessment for complementarity between Huawei and the potential targets. If the firms had related patents, we added a group of lines to indicate that they had related technologies. The groups of vertical lines and horizontal lines reflected the technology distribution of Huawei and the target, respectively. The depth of background color of each cell showed the complementarity level, which was divided into 3 layers, and the white background meant the two technologies had no complementarity. The crossing lines with red background meant the two firms had complementary technologies. The table was symmetrical, so we took the lower triangular region for analysis. We set the degree

Table 10.5 Technology morphology of cloud computing

Main technology composition		Sample keywords
Display technology	Based on plug-in	Flash, Silverlight, JavaFX
	Based on browser	HTML5, Ajax, CSS3
Multi-tenancy	Shared nothing	Separate database, separate schema
	Shared hardware	Shared database, separated data storage, additional storage subsystems
	Shared everything	Shared schema, network monitoring, shared schema
Virtualization	Platform virtualization	Virtual machine monitor, hypervisor, host OS
	Resource virtualization	Load balancing, monitoring resources
	Application virtualization	Virtual terminal, remote access, application access
Security	Application security	Anti-virus services, network security monitoring, DDoS attack warning
	Platform security	Access control management, security API, network security
	Infrastructure security	Secure hypervisor, full disk encryption, secure virtual machine
Distributed Storage		Horizontal scalability, area network storage, secret sharing

of complementarity to three levels marked by the depth of color, and the three levels were set as 1, 2, and 3 for calculation. To measure the technology complementarity, we just needed to take the cells with crossing lines and background into consideration. Again, we supposed there were two firms F_1 and F_2. We denoted the related patent number of F_1 and F_2 in the ith cell with crossing lines and red background as $F_1PN(i)$ and $F_2PN(i)$. The complementarity formula between the two firms is below:

$$\text{Complementarity} = \sum_{i \in D} (F_1PN(i) \times F_2PN(i) \times \text{complementarity level}) \quad (10.5)$$

where D means the technology areas in which the technologies of the two firms are complementary.

After calculating the complementarity of all the potential targets with the acquirer, we normalize the result by calculating the percentage of each complementarity result in the sum of all the complementarity results.

We took GCI (GCI SCI & Technology Co. Ltd.) as an example. The technology complementarity of the two firms is shown in Table 10.6. The two firms had complementary technologies in the area of display technology area and security technology area, of which the cells appear with crossing lines and red background. For GCI, 1 patent was on display technology based on plug-in; 2 patents were based on browsers, and 2 patents on application virtualization. For Huawei, 3 patents were on platform security. Using (5), we calculated the technology complementarity as 39. We could compute the technology complementarity for the remaining firms in the same way. We then carried out a normalization process. Technology complementarity of other potential targets is listed in Table 10.7. ZTE had the highest complementarity with Huawei, the second being GCI, and the third being Hechen.

Table 10.6 Technology complementarity of Huawei and GCI

Table 10.7 Technology complementarity evaluation of potential targets

Potential Targets	Technology complementarity
ZTE Corp	0.56
GCI SCI & Technology Co. Ltd.	0.23
Shanghai Hechen Information Technology	0.21

Table 10.8 Appropriate target candidates of Tech M&A for Huawei

Potential targets	Knowledge base	R&D intensity
ZTE Corp	52	0.12
Shanghai Hechen Information Technology	13	0.06
GCI SCI & Technology Co. Ltd.	10	0.05

10.3.4 R&D Capability Analysis

Wu and Reuer (2014) indicated that R&D capability is an important factor of technology integration and innovation after Tech M&A. Acquiring firms with high R&D capability will promote technology integration and technology synergy creation after Tech M&A (Benitez and Ray 2012). In this study, we used the absolute size of the knowledge base measured by the number of related patents and R&D intensity to evaluate the R&D capability of candidate acquisitions. R&D intensity was defined as the ratio of expenditures by a firm on R&D to the firm's sales. We used the average of three years' ratio. All of the three firms could be target candidates for Huawei from the perspective of Tech M&A, and ZTE was the most appropriate target. Considering the scales of the three firms, if Huawei hoped to become the leading firm through Tech M&A, ZTE Corp could be the preferred target; if Huawei hoped to enhance subdivision technologies in cloud computing, Shanghai Hechen and GCI would be the better choices (Table 10.8).

10.4 Conclusions

This paper presented a framework to identify and evaluate companies from the technological perspective to support M&A target selection decision making. The paper took technology similarity, technology complementarity, and R&D intensity as main indicators to evaluate potential targets. We introduced patent text analysis to generate a more comprehensive method for technology relatedness evaluation.

First, technology similarity was preliminarily evaluated according to patent IPCs. Further analysis was conducted using SAO-based semantic similarity analysis based on patent text. The approach enables one to extract the technological key concepts and key findings in patents and can complement the IPC-based analysis. Firms with high technology similarity with the acquirer can be selected.

Second, technology morphology analysis was introduced to analyze the technology complementarity between the targets and the acquirer. Keywords from patent text were mapped into their associated morphology. Technology complementarity level was set by the experts to all the possible technology combinations. The technology complementarity could be computed according to the patent distribution and the corresponding technology complementarity level. Thus, firms were further selected.

Third, this paper used R&D capability, including the absolute size of knowledge base and R&D intensity, to help choose the targets for an acquirer. We verified the usability and practicality of the method by applying it to patents related to cloud computing technologies and selected Huawei Technologies Co. Ltd. as an example to assess Tech M&A in the cloud computing technology area.

During the whole analysis process, we kept in contact with department of cloud computing of Huawei. Huawei showed interest in our research results, especially the measurement of the technology similarity and technology complementarity. Huawei extended requests for our research, including further technology similarity and complementarity analyses and the analysis of technology development trends of cloud computing, to support the firm's present work.

However, there are a few limitations in the study. Some doubts remain regarding the reliability of patent data. Sometimes, patent data cannot reflect the core technology of a firm because an emerging technology is not patented. The analysis based on patents does not take tacit knowledge into account per se. Another limitation is to what extent the framework can be applicable to other industries. Firms in some kinds of industries may not have many patents, though they have complex knowledge. Other indicators, such as the stage of technology development and the range of multiple sector interests of the players, should be considered in further studies.

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