DECISION SCIENCES
A JOURNAL OF THE DECISION SCIENCES INSTITUTE

Decision Sciences
Volume 45 Number 1
February 2014

Exploiting Technological Indicators for Effective Technology Merger and Acquisition (M&A) Predictions*

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ABSTRACT

Mergers and acquisitions (M&A) play increasingly important roles for contemporary business, especially in high-tech industries that conduct M&As to pursue complementarity from other companies and thereby preserve or extend their competitive advantages. The appropriate selection (prediction) of M&A targets for a given bidder company constitutes a critical first step for an effective technology M&A activity. Yet existing studies only employ financial and managerial indicators when constructing M&A prediction models, and select candidate target companies without considering the profile of the bidder company or its technological compatibility with candidate target companies. Such limitations greatly restrict the applicability of existing studies to supporting technology M&A predictions. To address these limitations, we propose a technology M&A prediction technique that encompasses technological indicators as independent variables and accounts for the technological profiles of both bidder and candidate target companies. Forty-three technological indicators are derived from patent documents and an ensemble learning method is developed for our proposed technology M&A prediction technique. Our evaluation results, on the basis of the M&A cases between January 1997 and May 2008 that involve companies in Japan and Taiwan, confirm the viability and applicability

*This work was supported partially by the National Science Council of the Republic of China, under the grants NSC 98–2410-H-002–231-MY3, NSC 96–3114-P-007–002-Y, and NSC 97–2410-H-155–052. This article is an extended version of a paper presented at the *Workshop on e-Business* and included in its post-workshop proceedings (*Lecture Notes in Business Information Processing*, Vol. 22, Part 6, 2009, pp.187–200). We thank the anonymous reviewers of the workshop and the associate editor and anonymous reviewers of *Decision Sciences* for their comments and suggestions, from which this version has benefited greatly.

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of the proposed technology M&A prediction technique. In addition, our evaluation also suggests that the incorporation of the technological profiles and compatibility of both bidder and candidate target companies as predictors significantly improves the effectiveness of relevant predictions. [Submitted: February 14, 2012. Revised: March 3, 2013. Accepted: May 3, 2013.]

Subject Areas: Data Mining, Ensemble Learning, M&A Prediction, Mergers and Acquisitions (M&A), Patent Mining, Technological Indicators, and Technology M&A.

INTRODUCTION

The term mergers and acquisitions (M&A) refers to the process of combining or gaining parts or all of other companies' property rights under certain conditions in order to have the controlling rights. This critical business activity supports complementarity between companies, based on various dimensions such as resources, channels, brands, and technologies (Trautwein, 1990; James, Georghiou, & Metcalfe, 1998; Webber & Dholakia, 2000; An, He, Zhao, & Sun, 2006). M&A plays an increasingly important role in highly competitive business environments and is a major tool that companies adopt to sustain or even extend their market power and competitive advantages. According to Thomson Reuters' global M&A review (2013), the value of worldwide M&A activity in 2012 reached US$2.6 trillion and the number of announced M&A deals was over 37,000.

The motives for M&A deals vary (Falk & Gordon, 1979), but their goals are similar: to overcome the weaknesses and consolidate the strengths of companies. Effective deals can change market structures, increase market power, and generate economies of scale or other synergies (Gugler & Konrad, 2002). To conduct an effective M&A deal, a bidder company should first identify suitable target companies that own resources complementary to those of the bidder. This candidate selection process, also referred to as M&A prediction in this study, is a critical first step for any M&A activity, because an inappropriate M&A target selection likely leads to the failure of the M&A activity.

M&A prediction is also important for companies seeking opportunities to be acquired or merged. For example, M&A prediction might help startup companies assess their possibility of being acquired and identify possible bidders. Such assessment would facilitate startup companies to develop appropriate strategies that improve their possibility of being acquired and thereby increase the economic benefits to initial investors. In addition, M&A prediction can also benefit venture capitalists who hunt for investment targets. For venture capitalists, their first-rate investment targets are companies with the potential for near-future, rapid growth. In turn, an important indicator of the growth potential of a company is the possibility of being acquired, because M&A targets are generally those with unique resources or superior solutions for emerging technologies.

M&A activities are especially critical for high-tech industries, such as information and communications technology (ICT), electronics, biotechnology, or pharmacy, because in these industries, M&A activity is common as a means to improve technology market power and strengthen innovative performance (Ahuja

& Katila, 2001; Hagedoorn & Duysters, 2002; Cloodt, Hagedoorn, & van Kranenburg, 2006; Grimpe & Hussinger, 2008). For instance, between 2005 and 2009, Oracle spent US$30 billion to buy 56 companies, including its ambitious merger with Sun Microsystems. This series of M&A activities doubled Oracle's revenues to an estimated US$24 billion in 2009 (Hamm & Ricadela, 2009). Moreover, prior studies show that technology M&As have positive impacts on the post-M&A invention performance of bidder companies in high-tech industries (Ahuja & Katila, 2001; Cloodt et al., 2006; Makri, Hitt, & Lane, 2010), leading to the increasing popularity of such activities in recent years. According to a recent global technology M&A report (Ernst & Young, 2011), the total number of global technology M&A deals has been trending upward for five consecutive quarters. Due to the importance and popularity of technology M&A, this study will concentrate on technology M&A prediction.

M&A prediction has received much research attention (Meador, Church, & Rayburn, 1996; Barnes, 2000; Ragothaman, Naik, & Ramakrishnan, 2003; Ali-Yrkkö, Hyytinen, & Pajarinen, 2005; Song & Chu, 2006; Pasiouras & Gaganis, 2007; Tsagkanos, Georgopoulos, & Siriopoulos, 2007). However, most existing studies consider only financial and/or managerial variables to support M&A predictions. The empirical results are encouraging, yet such prior studies suffer several limitations. First, most of them fail to take technological indicators into consideration. The growing importance of technology and innovation for strategic competitiveness makes it essential for bidder companies to pay attention to technological factors in their M&A decision making (James et al., 1998). In the few M&A prediction studies that consider technological aspects (e.g., Ali-Yrkkö et al., 2005), the technological indicators employed are limited. Second, most existing studies develop M&A prediction models depending solely on information about candidate target companies, without considering the profile of the bidder company under discussion. Such M&A prediction might reveal the likelihood of a company being acquired or merged, but it cannot effectively identify potential bidder companies for the target company.

In response to these limitations, we propose a technology M&A prediction technique that not only incorporates a more comprehensive set of technological indicators as predictors but also takes into account the technological profiles of both the bidder company and a candidate target company, along with their technological compatibility. Specifically, we employ patent data analyses to derive technological indicators for M&A prediction, then incorporate an ensemble learning method to deal with data skewness problem associated with M&A prediction. To detail this approach, we organize the remainder of this article as follows: The following section reviews literature relevant to our study. Next, we depict the detailed design of our proposed technology M&A prediction technique. Then we describe our data collection and experimental design and discuss important evaluation results. Finally, we conclude with a summary and some future research directions.

LITERATURE REVIEW

Several prior studies have concentrated on M&A prediction, but most of them consider only financial and managerial variables for M&A prediction. Common financial variables include firm size (Meador et al., 1996; Barnes, 2000; Ali-Yrkkö et al., 2005; Song & Chu, 2006; Pasiouras & Gaganis, 2007; Tsagkanos et al., 2007), market-to-book-value ratio (or Tobin's Q) (Meador et al., 1996; Barnes, 2000; Ragothaman et al., 2003; Song & Chu, 2006), cash flow (Ragothaman et al., 2003; Ali-Yrkkö et al., 2005; Song & Chu, 2006), return on assets (Meador et al., 1996; Pasiouras & Gaganis, 2007), sales to total assets (asset turnover) (Meador et al., 1996; Barnes, 2000; Tsagkanos et al., 2007), debt-to-equity ratio (Meador et al., 1996; Ragothaman et al., 2003; Song & Chu, 2006), price-to-earnings ratio (Meador et al., 1996; Barnes, 2000; Ragothaman et al., 2003; Song & Chu, 2006), current ratio (Meador et al., 1996; Barnes, 2000; Ragothaman et al., 2003; Tsagkanos et al., 2007), return on equity (Barnes, 2000; Meador et al., 1996; Tsagkanos et al., 2007), debt-to-assets ratio (Barnes, 2000; Pasiouras & Gaganis, 2007), capital-expenditures-to-total-asset ratio (Barnes, 2000; Ragothaman et al., 2003), and growth (Meador et al., 1996; Barnes, 2000; Pasiouras & Gaganis, 2007; Tsagkanos et al., 2007). Other financial variables—such as cost-to-income ratio (Pasiouras & Gaganis, 2007), cost of goods sold divided by inventory (Meador et al., 1996), outperformance (Gugler & Konrad, 2002), tax shield effects (Song & Chu, 2006), ratio of tangible (fixed) assets to total assets (Ali-Yrkkö et al., 2005), return on investment (Ali-Yrkkö et al., 2005), profit margin (Tsagkanos et al., 2007), average dividend for last three years/shareholders' equity (Barnes, 2000), earnings before interest and taxes or operating income after depreciation (Meador et al., 1996), and common shares traded divided by common shares outstanding (Meador et al., 1996)—appear somewhat less frequently in prior studies. Managerial variables, such as management inefficiency (Meador et al., 1996; Ali-Yrkkö et al., 2005), resource richness (Meador et al., 1996), industry variations (Meador et al., 1996), relevance degree of business boundaries (Song & Chu, 2006), export orientation (Tsagkanos et al., 2007), and age of the firm (Tsagkanos et al., 2007), represent another category of indicators adopted by existing M&A prediction studies.

Regarding the analysis methods applied to developing M&A prediction models, logistic regression (Meador et al., 1996; Barnes, 2000; Ragothaman et al., 2003; Ali-Yrkkö et al., 2005; Pasiouras & Gaganis, 2007) is the most common, though discriminant analysis (Barnes, 2000; Ragothaman et al., 2003), rule induction (Ragothaman et al., 2003), and decision tree (Tsagkanos et al., 2007) models also appear in some prior studies.

The results of these prior M&A prediction studies are encouraging and beneficial for M&A research and practice. However, some of their limitations may restrict their applicability to technology M&A prediction. First, as the preceding list of variables reveals, most of existing M&A prediction studies ignore technological issues, despite the growing importance of technology and innovation for strategic competitiveness (James et al., 1998). Appropriate assessments of the technological capabilities of the bidder and target companies in an M&A not only enable them to avoid costly errors and reduce failure rates but also help the bidder company realize the value of the technological assets it has acquired (James et al., 1998). Moreover, in the few studies that include technological information, the technological indicators tend to be limited. For example, Ali-Yrkkö et al. (2005) employ such indicators as whether a candidate target company has any granted or applied patents (and if so, the number of patents), to help select M&A candidates for a bidder company. The exclusion or limited use of technological indicators for M&A prediction limits the application scenarios for M&A prediction, especially in the critical context of high-tech industries (e.g., ICT, electronics, biotechnology, pharmaceutical) that often use M&As to acquire state-of-the-art technologies or rapidly expand their R&D capabilities. That is, most existing M&A prediction studies may not be applied effectively to high-tech industries dominated by technology-oriented competitive strategies. As a result, there is a pressing need to develop an alternative approach that employs comprehensive technological indicators for technology M&A predictions.

Second, most existing studies develop M&A prediction models depending solely on the information about candidate target companies, not about the bidder company under discussion. Such M&A prediction can support the assessment of the likelihood of a company being acquired or merged, but the identification of potential bidder companies is not a concern in this assessment. Cassiman, Colombo, Garrone, and Veugelers (2005) show that technological relatedness between the bidder and target companies has an important impact on the new merged entity's R&D and innovation processes. Accordingly, most prior studies are not practicable for some important application scenarios. For example, for venture capitalists, existing M&A prediction studies provide insufficient information for hunting investment targets, because the growth potential of a company that is likely to be acquired depends on its potential bidder company (e.g., whether the bidder is an industry leader). In addition, prior studies may not produce effective M&A prediction models because they fail to take the profile of the respective bidder company and its compatibility with a candidate target company into consideration.

PATENT MINING FOR TECHNOLOGY M&A PREDICTION

In this study, we formulate the technology M&A prediction problem as follows: Given a bidder company and a candidate target company, the technology M&A prediction problem is to determine whether the candidate target company is likely to be acquired or merged by the bidder company. We thus consider technology M&A prediction a classification problem with two possible decision categories: M&A (i.e., the candidate target company is likely to be acquired or merged by the bidder company) or non-M&A (i.e., the candidate target company is unlikely to be acquired or merged by the bidder company). In this section, we first define and describe technological indicators that we derive from patent analysis to employ in our proposed technology M&A prediction technique; we then detail the design of our proposed technique.

Variables for Technology M&A Prediction

A patent constitutes a collection of exclusive rights that protect an inventor's new machine, process, article, or improvement theory for a fixed period of time. Because of their novelty and exclusion properties, patents represent an excellent source for evaluating the technological or innovative capability of a company. Patent analysis has been widely applied to many domains, including estimations of stock performance (Deng, Lev, & Narin, 1999), M&A analysis (Breitzman & Thomas, 2002; Breitzman, Thomas, & Cheney, 2002; Ali-Yrkkö et al., 2005), collaboration partner selection (Mowery, Oxley, & Silverman, 1998; Teichert & Ernst, 1999), analyses of technological progress (Kayal & Waters, 1999), assessments of technological capability (Hagedoorn & Duysters, 2002; Schoenecker & Swanson, 2002), identification of technologically similar organizations (Breitzman, 2005), and analyses of corporate strategy (Narin, 1993).

According to our review of existing patent analysis studies, we summarize and develop five categories of variables for technology M&A prediction: *technological quantity*, *technological quality*, *technological innovation*, *technological diversity*, and *technological compatibility*. The first four categories comprise 13 variables, estimated to measure the individual technological capabilities of the given bidder company (f_b) and the given candidate target company (f_c), respectively. In addition, we include 17 variables to measure the technological compatibility between f_b and f_c. As a result, we employ a total of 43 variables for technology M&A prediction.

For each company involved in the focal M&A prediction (i.e., f_b or f_c), we measure the company's *technological quantity* as follows:

- *Number of Patents (NP): NP* measures the number of patents granted to a company, which provides an indicator of its technological capability (Pegels & Thirumuthy, 1996; Deng et al., 1999; Breitzman et al., 2002; Breitzman & Thomas, 2002; Schoenecker & Swanson, 2002; Ali-Yrkkö et al., 2005). A company with more patents is likely to have better technological capabilities. For each company i (f_b or f_c), $NP_i = |P_i|$, where P_i is the set of patents granted to company i.
- *Number of Recent Patents (NRP):* Although *NP* measures the overall technological capability of a company from its establishment, for a company with a long history, *NP* may be a less effective measure of recent technological capability because some patents may have been granted years ago. Thus, we consider the number of recent patents (*NRP*) to estimate the recent technological capability of the company (Breitzman & Thomas, 2002). Specifically, *NRP* considers the number of patents granted within the preceding three years. For each company i (f_b or f_c), $NRP_i = |\{j|\ j \in P_i \text{ and } age(j) \leq 3\}|$, where $age(j)$ refers to the number of years between the year the patent j was granted and the current year (or more specifically, the year of the focal M&A prediction).

For each company (i.e., f_b or f_c), we also measure its *technological quality*, as follows:

- *Impact of Patents (IP): IP* measures the impact of a company's patents by counting the number of forward citations to them (Harhoff, Scherer, & Vopel, 2003; Kelley & Nakosteen, 2005; Grimpe & Hussinger, 2008). However, because earlier patents naturally tend to attract more forward citations, we attempt to avoid this possible bias by employing a *novel citation index* (NCI) (Sidiropoulos, Katsaros, & Manolopoulos, 2007) to estimate the *IP* of a company. The NCI of a patent j (i.e., NCI_j) is calculated as $NCI_j = \alpha \times (Y_c - Y_j + 1)^{\sigma} \times C_j$, where Y_c is the current year (or year of the focal M&A prediction), Y_j is the year patent j was published, C_j is the number of forward citations received by patent j, and α and σ are constant variables that adjust the weight. As suggested by Sidiropoulos et al. (2007), we set α to equal 4 and σ to -1. Accordingly, we can estimate the impact of the patents of a company i (f_b or f_c) by averaging *NCIs* across all patents by that company. Specifically, $IP_i = \frac{\sum_{j \in P_i} NCI_j}{|P_i|}$.

- *Technology Strength (TS): TS* offers another measure of the impact of a company's patents, typically estimated by the average of the current impact index (CII) of a company across all technological fields covered by the company's patents (Pegels & Thirumuthy, 1996; Kayal & Waters, 1999; Breitzman et al., 2002; Breitzman & Thomas, 2002; Schoenecker & Swanson, 2002). The *CII* of a company i in technological field d is defined as $CII_{id} = \frac{C_{id}/K_{id}}{C_d/K_d}$, where C_{id} is the total number of forward citations received by the patents of company i in technological field d in the current year (or year of the focal M&A prediction), K_{id} is the number of patents of company i in technological field d, C_d is the total number of forward citations received in the current year (or year of the focal M&A prediction) by all patents in technological field d, and K_d is the total number of patents in technological field d. Accordingly, the overall technology strength of a company i (f_b or f_c) can be estimated by averaging the *CII* values across all technological fields covered by the company. That is, $TS_i = \frac{\sum_{d \in F_i} CII_{id}}{|F_i|}$, where F_i is the set of technological fields covered by company i.

For this study, we determine the technological field of a patent by relying on the International Patent Classification (IPC) system (World Intellectual Property Organization, 2006). The IPC class of a patent can be specified at four levels: section, class, subclass, and subgroup. For example, a patent with an IPC class A01B/01 indicates the technological field at section A, class A01, subclass A01B, and subgroup A01B/01, respectively. To address the different classification levels when estimating the *TS* of a company, we differentiate *TS* into four variables according to classification levels. Thus, for a bidder company f_b, we use *TS*-S_b (section level), *TS*-C_b (class level), *TS*-SC_b (subclass level), and *TS*-G_b (subgroup level) for the M&A prediction. Likewise, we also include four variables that refer to the candidate target company f_c: *TS*-S_c, *TS*-C_c, *TS*-SC_c, and *TS*-G_c.

For each company (i.e., f_b or f_c), we measure its *technological innovation* as follows:

- *Link to Science (LS):* The link between patents and scientific articles reveals the extent to which a patent builds on scientific research, which often is used to measure the degree of technological innovation of a company (Narin, 1993; Deng et al., 1999; Breitzman et al., 2002; Breitzman & Thomas, 2002; Schoenecker & Swanson, 2002; Harhoff et al., 2003). Let ls_j be the number of links (i.e., backward citations) to scientific articles in patent j. The link to science of each company i (f_b or f_c) then can be calculated as the average link to scientific articles across all patents of the company: $LS_i = \frac{\sum_{j \in P_i} ls_j}{|P_i|}$.

- *Technology Cycle Time (TCT): TCT* measures the average median year of the patents cited by the patents of a company (Narin, 1993; Pegels & Thirumuthy, 1996; Deng et al., 1999; Kayal & Waters, 1999; Breitzman et al., 2002; Breitzman & Thomas, 2002; Schoenecker & Swanson, 2002). Companies whose patents cite relatively recent patents are likely to innovate faster than those whose patents cite older patents. Given a patent j with k (backward) citations ordered by their granting year (i.e., $<y_1, y_2, \ldots, y_k>$, where $y_h \leq y_{h+1}$ for all h where $1 \leq h < k$), we determine the technology cycle time of a patent j as $tct_j = y_{(k+1)/2}$ if k is an odd number and $tct_j = \frac{y_{k/2} + y_{(k/2)+1}}{2}$ if k is an even number. Therefore, the *TCT* of each company i (f_b or f_c) is computed as $TCT_i = \frac{\sum_{j \in P_i} tct_j}{|P_i|}$.

Furthermore, for each company (i.e., f_b or f_c), we measure its *technological diversity* as follows:

- *Concentration Rate (CR): CR* measures the concentration of patents of a company across all the technological fields covered by the patents of the company (Teichert & Ernst, 1999). For each company i (f_b or f_c), $CR_i = \frac{\sum_{d \in F_i} (\frac{K_{id}}{K_i} \times \log_2 \frac{K_{id}}{K_i})}{\log_2 |F_i|}$. Evidently, if a company concentrates only in one technological field, its *CR* value will be 0 (i.e., no diversity), whereas if the company's patents are evenly distributed across several technological fields, its *CR* value approaches 1.

As for technology strength, we determine the technological field of a patent according to the IPC classification system. Thus, when estimating *CR* for a company, we differentiate *CR* into four variables according to the classification levels. That is, we include $CR\text{-}S_b$ (section level), $CR\text{-}C_b$ (class level), $CR\text{-}SC_b$ (subclass level), and $CR\text{-}G_b$ (subgroup level) to measure the concentration rate of f_b and $CR\text{-}S_c$, $CR\text{-}C_c$, $CR\text{-}SC_c$, and $CR\text{-}G_c$, respectively, for f_c.

Finally, we adopt 17 variables to measure the *technological compatibility* between the bidder company (f_b) and the candidate target company (f_c).

- *Compatibility of Technological Fields (CTF): CTF* measures the cosine similarity of the patent distributions of f_b and f_c across all technological fields covered by the two companies (Grimpe & Hussinger, 2008). Specifically, $CTF_{bc} = \frac{\sum_{d \in F_{bc}} R_{bd} \times R_{cd}}{\sqrt{\sum_{d \in F_{bc}} R_{bd}^2} \times \sqrt{\sum_{d \in F_{bc}} R_{cd}^2}}$, where R_{id} is the percentage of patents of company i in technological field d (i.e., $R_{id} = \frac{K_{id}}{|P_i|}$), and F_{bc} is the union of technological fields covered by f_b and those covered by f_c.

According to the IPC classification system, we again consider four possible levels of technological fields and use four variables to measure the *CTF* between f_b and f_c: $CTF\text{-}S_{bc}$ (section level), $CTF\text{-}C_{bc}$ (class level), $CTF\text{-}SC_{bc}$ (subclass level), and $CTF\text{-}G_{bc}$ (subgroup level).

- *Relative Strength of Technological Quantity:* The relative strength of technological quantity refers to the ratio of the two technological quantity measures defined previously (i.e., number of patents and number of recent patents) between f_b and f_c. The relative strength in the number of patents (*NP*) therefore is defined as $RNP_{bc} = \frac{NP_b}{NP_c}$, and the relative strength in the number of recent patents (*NRP*) is $RNRP_{bc} = \frac{NRP_b+0.5}{NRP_c+0.5}$. We add the constant 0.5 to avoid the possibility that the denominator could be 0.
- *Relative Strength of Technological Quality:* For the relative strength of technological quality, we calculate the ratio of the two technological quality measures defined previously (i.e., impact of patents and technology strength) between f_b and f_c. Thus, the relative strength in the impact of patents (*IP*) is $RIP_{bc} = \frac{IP_b+0.5}{IP_c+0.5}$. For technology strength (*TS*), we again define four variables for different IPC classification levels: $RTS\text{-}S_{bc} = \frac{TS\text{-}S_b+0.5}{TS\text{-}S_c+0.5}$ (section level), $RTS\text{-}C_{bc} = \frac{TS\text{-}C_b+0.5}{TS\text{-}C_c+0.5}$ (class level), $RTS\text{-}SC_{bc} = \frac{TS\text{-}SC_b+0.5}{TS\text{-}SC_c+0.5}$ (subclass level), and $RTS\text{-}G_{bc} = \frac{TS\text{-}G_b+0.5}{TS\text{-}G_c+0.5}$ (subgroup level).
- *Relative Strength of Technological Innovation:* The relative strength of technological innovation entails the ratio of the two technological innovation measures defined previously (i.e., link to science and technology cycle time) between f_b and f_c. Specifically, the relative strength of the link to science (*LS*) is measured as $RLS_{bc} = \frac{LS_b+0.5}{LS_c+0.5}$, and the relative strength of the technology cycle time (*TCT*) is defined as $RTCT_{bc} = \frac{TCT_b}{TCT_c}$.
- *Relative Strength of Technological Diversity:* The relative strength of technological diversity calculates the ratio of the two concentration rates (*CR*) between f_b and f_c. Specifically, we define four variables according to the four IPC classification levels: $RCR\text{-}S_{bc} = \frac{CR\text{-}S_b+0.5}{CR\text{-}S_c+0.5}$ (section level), $RCR\text{-}C_{bc} = \frac{CR\text{-}C_b+0.5}{CR\text{-}C_c+0.5}$ (class level), $RCR\text{-}SC_{bc} = \frac{CR\text{-}SC_b+0.5}{CR\text{-}SC_c+0.5}$ (subclass level), and $RCR\text{-}G_{bc} = \frac{CR\text{-}G_b+0.5}{CR\text{-}G_c+0.5}$ (subgroup level).

Table 1 summarizes all 43 variables (technological indicators) we adopt in our technology M&A prediction technique.

Detailed Design of Our Technology M&A Prediction Technique

Because we formulate technology M&A prediction as a dichotomous classification problem (i.e., M&A versus non-M&A), we follow the supervised learning approach to develop our technology M&A prediction technique. As Figure 1 shows, the proposed technique includes a learning phase and a prediction phase. The input to the learning phase is a set of training instances, each denoting a bidder–target dyad with a known M&A decision (i.e., whether the dyad is in the "M&A" or "non-M&A" category). On the basis of the training instances, the learning phase induces or trains one or more technology M&A prediction models, depending on the specific learning method employed. To predict the M&A decision for a dyad of a bidder and a candidate target, the prediction phase performs deductive reasoning on the technology M&A prediction model(s) induced previously and determines if the candidate target company is likely to be acquired or merged by the focal bidder

Table 1: Summary of variables for our technology M&A prediction technique.

Variables	Scope	Description
NP_b, NP_c	f_b or f_c	Number of patents
NRP_b, NRP_c	f_b or f_c	Number of patents in recent three years
IP_b, IP_c	f_b or f_c	Impact of patents
$TS\text{-}S_b$, $TS\text{-}C_b$, $TS\text{-}SC_b$, $TS\text{-}G_b$, $TS\text{-}S_c$, $TS\text{-}C_c$, $TS\text{-}SC_c$, $TS\text{-}G_c$	f_b or f_c	Technology strength at four IPC levels (i.e., section, class, subclass, and subgroup)
IS_b, IS_c	f_b or f_c	Link to science
TCT_b, TCT_c	f_b or f_c	Technology cycle time
$CR\text{-}S_b$, $CR\text{-}C_b$, $CR\text{-}SC_b$, $CR\text{-}G_b$, $CR\text{-}S_c$, $CR\text{-}C_c$, $CR\text{-}SC_c$, $CR\text{-}G_c$	f_b or f_c	Concentration rate at four IPC levels
$CTF\text{-}S_{bc}$, $CTF\text{-}C_{bc}$, $CTF\text{-}SC_{bc}$, $CTF\text{-}G_{bc}$	Both	Compatibility of technological fields between f_b and f_c at four IPC levels
RNP_{bc}	Both	Relative strength in number of patents between f_b and f_c
$RNRP_{bc}$	Both	Relative strength in number of recent patents between f_b and f_c
RIP_{bc}	Both	Relative strength in impact of patents between f_b and f_c
$RTS\text{-}S_{bc}$, $RTS\text{-}C_{bc}$, $RTS\text{-}SC_{bc}$, $RTS\text{-}G_{bc}$	Both	Relative strength in technology strength between f_b and f_c at four IPC levels
RLS_{bc}	Both	Relative strength in link to science between f_b and f_c
$RTCT_{bc}$	Both	Relative strength in technology cycle time between f_b and f_c
$RCR\text{-}S_{bc}$, $RCR\text{-}C_{bc}$, $RCR\text{-}SC_{bc}$, $RCR\text{-}G_{bc}$	Both	Relative strength in concentration rate between f_b and f_c at four IPC levels

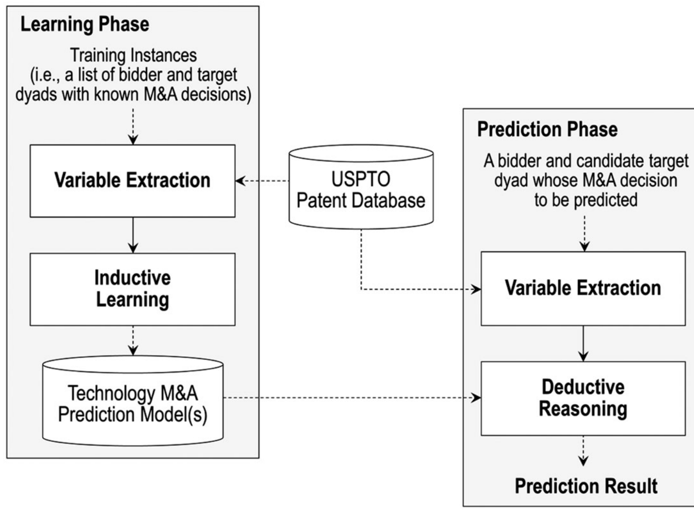
company. In the following subsections, we detail the design of each phase of our proposed technology M&A prediction technique.

Learning phase

The learning phase involves two main steps: variable extraction and inductive learning. The variable extraction step entails extracting the values of the 43 independent variables (see Table 1) for each training instance. In this study, we implement a Web crawler to automatically collect patent documents pertaining to the two companies involved in each training instance (i.e., the bidder company and the candidate target company) from the U.S. Patent and Trademark Office (USPTO) database (http://www.uspto.gov/main/patents.htm). Subsequently, we then extract the values of all independent variables for each training instance.

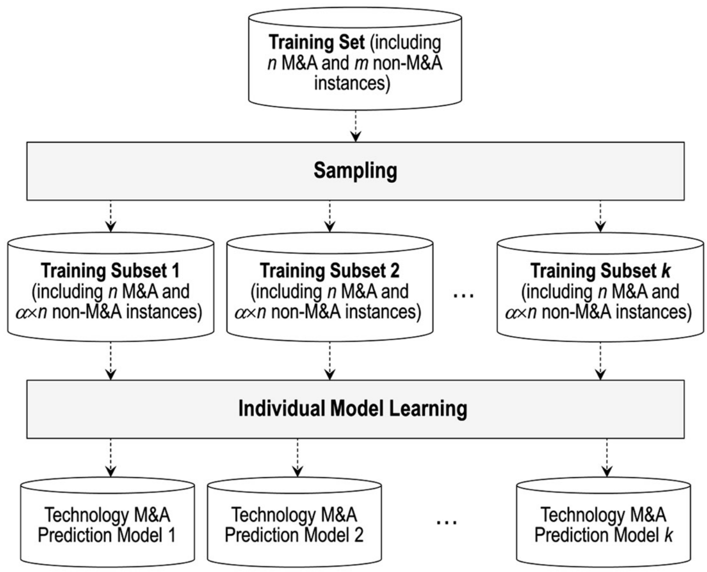
Following variable extraction is the inductive learning step. Depending on the learning method employed, the inductive learning step then induces one or

Figure 1: Overall process of the proposed technology M&A prediction technique.



multiple technology M&A prediction models from the set of training instances. In this study, we consider two learning methods: single learner and ensemble learning. For the former, we choose C4.5 (Quinlan, 1986; Quinlan, 1993), a supervised learning technique that offers computational efficiency and advantageous interpretability, as the underlying learning algorithm for constructing the technology M&A prediction model, which then will be used by the prediction phase to determine the likely M&A decision for a particular bidder–target dyad. C4.5 follows a divide-and-conquer strategy to construct a decision tree and generally prefers simple to complex trees, because simple trees are more accurate classifiers for new instances (Quinlan, 1986; Quinlan, 1993). Given a set of training instances, C4.5 evaluates the information gain (or gain ratio) for each input attribute (independent variable) and selects the one that yields the greatest information gain (or gain ratio) to create branches for a target node of the tree. The root node is the initial target node before the start of the decision tree construction process (i.e., empty tree). As construction proceeds, the decision tree grows by creating child nodes—one for each value of the selected branching attribute that emanates from the target node—and then classifying the training instances into appropriate, newly created child nodes. For each child node, the branching attribute selection and tree-construction process continues recursively as long as the training instances associated with the node do not belong to the same category or the prespecified termination condition is not satisfied; otherwise, the node becomes a decision node, assigned to a category according to the majority category of the training instances associated with the node. Similar to other decision-tree induction techniques, C4.5 is popular and widely adopted because of its uncomplicated tree construction process and interpretable and verifiable prediction model. In this study, we adopt J48 (an open

Figure 2: Process of our ensemble learning method.



source Java implementation of C4.5 in the Weka data mining tool) and use the gain ratio as the attribute selection criterion.

We also develop an ensemble learning method to address the possible imbalance sample problem (Lee & Zhu, 2011) in our technology M&A prediction. As we mentioned previously, the input to the learning phase is a set of training instances. Because obtaining non-M&A instances generally is easier than obtaining M&A instances, the set of training instances tends to be asymmetric or skewed, such that non-M&A is the majority category and M&A is the minority category. To deal with this possible skewness in a training set, our ensemble learning method first samples k "more balanced" training subsets from the original training set and then induces k prediction models from these k training subsets. To predict the M&A decision for a bidder–target dyad, each prediction model first makes its individual prediction, and then the k predictions are combined to arrive at an overall prediction for the focal dyad (we will describe the specific combination scheme in the next section).

Assume that we have n M&A instances and m non-M&A instances (where $n < m$) in the training set. As Figure 2 illustrates, for each training subset, our ensemble learning method includes all n M&A instances (because they belong to the minority category) and $\alpha \times n$ randomly sampled non-M&A instances (from the majority category), where α is the value used to adjust the ratio between non-M&A and M&A instances in the training subset. Subsequently, a supervised learning algorithm then applies to learn a technology M&A prediction model for each training subset. As with the single learner method, we adopt C4.5 as the underlying learning algorithm. Accordingly, our ensemble learning method produces k technology M&A prediction models.

Prediction phase

In the prediction phase, given a dyad of a bidder company and a candidate target company, the values of the 43 independent variables need to be extracted from the USPTO patent database for the focal dyad. The variable extraction step of the prediction phase is identical to that of the learning phase. When the single learner method is adopted by the learning phase (i.e., only one prediction model induced), the deductive reasoning step traverses the decision tree (i.e., prediction model) induced by C4.5, using the values of the independent variables for the focal dyad, to arrive at an M&A prediction for the focal dyad.

In contrast, if the learning phase relies on the ensemble learning method, the deductive reasoning step must perform multiple deductive reasoning tasks, one for each technology M&A prediction model, to attain k individual predictions. These k predictions are then combined to reach an overall prediction for the focal dyad. The simplest prediction combination method involves the voting scheme: We assign the focal dyad to the category that receives most of the votes from the k prediction models. The voting scheme gives an equal weight to each prediction model. However, the k prediction models may not have identical prediction power, which implies the need to use a weighted voting scheme.

With a weighted voting scheme, we assign the focal dyad to the category that receives most of the weighted votes from the k prediction models. We estimate the weight of each prediction model by its prediction effectiveness, across the entire set of training instances. Several common metrics, including accuracy and F_1 (Baeza-Yates & Ribeiro-Neto, 1999), can be considered to measure the effectiveness of a prediction model. Accuracy refers to the predictive power of a prediction model (i.e., percentage of instances correctly assigned to their true categories). Because accuracy involves all categories, this metric cannot reliably reflect the prediction performance of a particular category of interest; in the presence of data skewness, it tends to be biased toward the majority category (i.e., non-M&A in this study). In the context of M&A target selection, the prediction effectiveness of the M&A category is more important than that of its counterpart. Therefore, using a prediction model's F_1 for the M&A category as the weight of the prediction model appears more appropriate than using the accuracy metric, and we adopt it as the weighted voting scheme for our ensemble learning method. The F_1 measure of a prediction model with respect to the M&A category is the harmonic average of its precision and recall, defined as $\frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$, where the precision of a prediction model for the M&A category is calculated as the percentage of instances predicted as M&As that are truly M&A cases, whereas recall refers to the percentage of true M&A instances correctly predicted by the prediction model.

EMPIRICAL EVALUATIONS

In this section, we describe our data collection and evaluation design, and then discuss some important results from our evaluation of the proposed technology M&A prediction technique.

Data Collection

We collect M&A cases from the SDC Platinum database (available at http://www.thomsonreuters.com/products_services/financial/sdc). We identify M&A cases between January 1997 and May 2008 in six industries (electronics, communications, computer equipment, machinery, prepackaged software, and chemical) that involve companies in Japan and Taiwan. In addition, for each M&A case selected, we require that the bidder and target companies be from the same country (i.e., Japan or Taiwan), because motivations for multinational M&As often go beyond technological concerns and may not represent technology M&A cases. After collecting the initial set of M&A cases from the SDC Platinum Database, we conduct several filtering tasks to restrict our data set to only those cases that appear likely to be technology M&As.

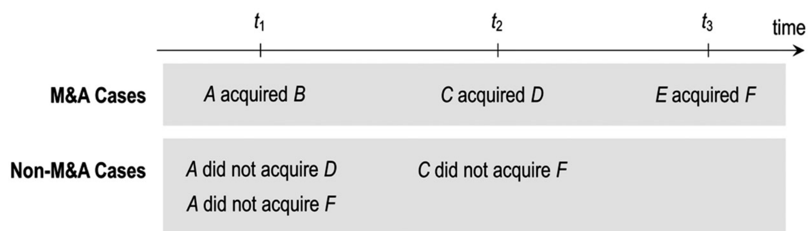
First, a bidder or target in any M&A case in the SDC Platinum Database could be a department of a company. Because the analysis unit for our study is the company level, we exclude any M&A cases whose bidder or target is a department rather than the whole company.

Second, we submit the name of each company (bidder or target) in our data set to the Derwent innovation index database (http://scientific.thomsonreuters.com/products/dii/) to search for possible assignee terms in the USPTO database. The purpose of this assignee term search is to find possible alternative company names listed in patent documents, such that we can search for all patents granted to this company. For example, "Taiwan Semiconductor Manufacturing Company Ltd." is listed in the SDC Platinum database as "Taiwan Semiconductor Mnfr Co." This company has three possible assignee terms according to the Derwent innovation index database: "Taiwan Semiconductor Mfg Co Ltd," "Taiwan Semiconductor Mfg Co," and "Taiwan Semiconductor Mfg Corp Ltd." If we cannot find any assignee term for a company involved in an M&A case in our data set, the company likely does not have any issued patents. In this case, it is unlikely that the M&A is technology-oriented, and we remove it from our data set.

Third, we check whether either the bidder or the target company involved in each M&A case in our data set had any issued patents before the year of the focal M&A event. If not, we remove this M&A from our data set, because it likely is not a technology M&A. As a result of these three filtering efforts, we retain 90 M&A cases in our data set, which will be used for our empirical evaluation purpose.

Following the collection of these M&A cases, we need to generate non-M&A cases to serve as the instances of the non-M&A category. We consider that representative non-M&A cases should be those having the opportunity for being M&A cases. A non-M&A case with bidder and target companies from different industries may be driven by considerations other than technological ones and thus may not be a representative non-M&A case. As a result, we perform our non-M&A case generation process intraindustrially with the following constraints. First, bidder companies are usually large companies and, thus, have little chance of being acquired or merged. Therefore, our non-M&A cases should not include instances in which target companies are the bidder companies of known M&A

Figure 3: Example non-M&A case generation.



cases. Second, the target company of a known M&A case is unlikely to be a bidder company before it is acquired or merged. Thus, our non-M&A cases will not include instances in which bidder companies are the target companies of known M&A cases. Third, an M&A event results in either the absorption of the respective target company, which ceases to be a trade name after the operation, or a totally new company built from the bidder and target companies (Giacomazzi, Panella, Pernici, & Sansoni, 1997). Therefore, a target company acquired or merged by a bidder company in an M&A case at a specific time will never again be a target afterward. That is, a target company involved in a known M&A case can only appear in non-M&A cases before the focal M&A case.

The following example illustrates our non-M&A case generation process. As Figure 3 shows, we assume there are three M&A cases in the same industry: *A* acquired *B* at time t_1, *C* acquired *D* at time t_2, and *E* acquired *F* at time t_3, where t_1 is earlier than t_2, and t_2 is earlier than t_3. Accordingly, we generate three non-M&A cases: *A* did not acquire *D* at time t_1, *A* did not acquire *F* at time t_1, and *C* did not acquire *F* at time t_2. We do not include such non-M&A cases as "*A* did not acquire *C* at time t_1" or "*C* did not acquire *E* at time t_2," because they violate the first constraint. Nor do we include "*D* did not acquire *F* at time t_1," because it violates the second constraint. Finally, due to the third constraint, our non-M&A cases do not include "*C* did not acquire *B* at time t_2" or "*E* did not acquire *B* at time t_3."

Following this non-M&A case generation process, we create from the 90 M&A cases 689 non-M&A cases. That is, our complete data set includes 90 instances of the M&A category and 689 instances of the non-M&A category.

Evaluation Design

We evaluate the effectiveness of our proposed technology M&A prediction technique in terms of overall accuracy and area under ROC curve (AUC) (Fawcett, 2006) as well as recall, precision, and F_1 measures with respect to the M&A category. We use a tenfold cross-validation strategy to estimate the effectiveness of our proposed technology M&A prediction technique. That is, we divide all instances in our data set randomly into ten mutually exclusive subsets of approximately equal size. In turn, we designate each subset as the testing instances while the others serve as the training instances. To minimize the potential sampling biases, we perform the tenfold cross-validation process 30 times and estimate overall effectiveness by averaging the performance estimates obtained from these trials.

In our empirical evaluations, we first include two technological-based benchmarks. As we depicted previously, most existing studies of M&A prediction depend solely on information about the focal candidate target company, without considering the profile of the bidder. Therefore, our first technological-based benchmark (denoted Benchmark TB1) uses only the 13 technological variables pertaining to the focal candidate target company (i.e., NP_c, NRP_c, IP_c, $TS\text{-}S_c$, $TS\text{-}C_c$, $TS\text{-}SC_c$, $TS\text{-}G_c$, IS_c, TCT_c, $CR\text{-}S_c$, $CR\text{-}C_c$, $CR\text{-}SC_c$, and $CR\text{-}G_c$; Table 1) to learn the technology M&A prediction model(s). For the second benchmark (denoted Benchmark TB2), we include only the 17 technological compatibility variables between the bidder and the candidate target company (i.e., $CTF\text{-}S_{bc}$, $CTF\text{-}C_{bc}$, $CTF\text{-}SC_{bc}$, $CTF\text{-}G_{bc}$, RNP_{bc}, $RNRP_{bc}$, RIP_{bc}, $RTS\text{-}S_{bc}$, $RTS\text{-}C_{bc}$, $RTS\text{-}SC_{bc}$, $RTS\text{-}G_{bc}$, RLS_{bc}, $RTCT_{bc}$, $RCR\text{-}S_{bc}$, $RCR\text{-}C_{bc}$, $RCR\text{-}SC_{bc}$, and $RCR\text{-}G_{bc}$; Table 1) to induce the technology M&A prediction model(s).

As mentioned, prior studies mainly consider financial variables as predictors for M&A prediction. Therefore, we further develop some benchmarks that take the traditional financial-based approach for M&A prediction. Specifically, we consider 18 financial indicators (Table 2) that are commonly employed in prior studies to implement our financial-based benchmarks. As with our technology M&A prediction technique, our first financial-based benchmark (denoted Benchmark FB1) takes into account the financial profiles of both bidder and candidate target companies and their financial compatibility. In this study, we calculate the financial compatibility with respect to a specific financial indicator as the ratio between the bidder and candidate target companies. For example, for the indicator of total assets (i.e., the first indicator in Table 2), the respective financial compatibility is the total assets of the bidder company divided by those of the candidate target company. Accordingly, Benchmark FB1 uses a total of 54 financial variables: 18 for the bidder company, 18 for the candidate target company, and 18 for financial compatibility. For the second financial-based benchmark (denoted Benchmark FB2), we include only the 18 financial variables pertaining to the candidate target company. Our third financial-based benchmark (denoted Benchmark FB3) considers only the 18 financial compatibility variables between the bidder and candidate target companies.

We collect the financial data required to calculate the 54 financial variables from the Compustat database in the Wharton Research Data Services (WRDS, available at http://wrds-web.wharton.upenn.edu/wrds/). Because some companies in our evaluation data set are not publicly traded, their financial data are unavailable in the Compustat database. The cases (M&A or non-M&A) involving any of these companies are thus removed from our evaluation data set when we conduct the comparative evaluation between the three financial-based benchmarks and our proposed technology M&A prediction technique. Accordingly, this reduced data set consists of 69 M&A cases and 505 non-M&A cases. The ratio between M&A cases and non-M&A cases in the reduced data set is 69/505 = 0.1366, similar to that in the complete data set (i.e., 90/689 = 0.1306).

Table 2: Summary of financial indicators for M&A prediction.

Indicator	Definition
Total assets	Sum of current and long-term assets
Net sales	Gross sales minus sales returns, sales allowances, and sales discounts
Market to book value ratio	Market value per share/book value per share
Tobin's Q	Sum of short-term and long-term debt/total assets
Cash flow to total assets ratio	Cash flow/total assets
Cash flow to sales ratio	Cash flow/net sales
Return on assets	Net income/total assets
Sales to total assets ratio	Net sales/total assets
Debt to equity ratio	Sum of long-term and short-term debt/book value of equity
Long-term debt to equity ratio	Long-term debt/book value of equity
Price to earnings ratio	Market value per share/earning per share
Current ratio	Current assets/current liabilities
Return on equity	Net income/book value of equity
Debt to assets ratio	Sum of long-term and short-term debt/total assets
Long-term debt to assets ratio	Long-term debt/total assets
Capital expenditures to total asset ratio	Current assets − current liabilities/total assets
Two-year growth in sales	Net sales in current year − net sales in previous year
Two-year growth in total assets	Total assets in current year − total assets in previous year

Tuning Experiments and Results

Our proposed technology M&A prediction technique can feature either a single learner or an ensemble learning method. We therefore need to conduct an experiment to choose a better learning method for our proposed technique. Because the ensemble learning method involves two parameters, k (i.e., number of technology M&A prediction models induced) and α (ratio between non-M&A and M&A instances in each training subset), we thus first need to determine the proper parameter values for the ensemble learning method. In this study, we set k to 31 and, on the basis of the complete data set that includes 90 M&A cases and 689 non-M&A cases, investigate the effectiveness of the proposed technology M&A prediction technique across different values for α, ranging from 1 to 5 in increments of 1.

Table 3 lists the results pertaining to the effectiveness of our technology M&A prediction technique with the ensemble learning method for different values for α. An increase of α means the inclusion of more non-M&A cases into each training subset, so each resultant M&A prediction model gradually will favor the minority category (i.e., M&A) less. We can observe this effect in Table 3; the increase of α from 1 to 5 deteriorates the recall rate of the M&A category but

Table 3: Tuning results of the technology M&A prediction technique with ensemble learning.

			M&A Category		
α	Accuracy	AUC	Recall	Precision	F_1
1	79.75%	87.50%	74.81%	33.27%	46.06%
2	87.92%	88.74%	57.96%	47.15%	52.00%
3	90.39%	89.16%	52.44%	59.70%	55.83%
4	90.98%	88.82%	48.22%	64.78%	55.27%
5	91.28%	88.61%	45.04%	68.83%	54.45%

Table 4: Evaluation of different learning methods.

			M&A Category		
Learning Method	Accuracy	AUC	Recall	Precision	F_1
Single learner	89.83%	73.23%	47.92%	57.26%	52.18%
Ensemble learning	90.39%	89.16%	52.44%	59.70%	55.83%

improves its precision rate. Moreover, the increase of α from 1 to 3 enhances the overall accuracy and F_1 of the M&A category. Specifically, when we set α to 3, the accuracy, AUC, recall, precision, and F_1 are 90.39%, 89.16%, 52.44%, 59.70%, and 55.83%, respectively. However, moving α beyond 3 impairs the AUC as well as the F_1 of the M&A category. Overall, setting α to 3 appears to produce the highest AUC and the best trade-off between the recall and precision of the M&A category. We therefore adopt this value for our subsequent evaluations.

With the proper parameter values for the ensemble learning method, we then conduct an experiment to determine the better learning method (i.e., single learner or ensemble learning) for our technology M&A prediction technique. As Table 4 illustrates, the proposed technique with the ensemble learning method outperforms the single learner method on all performance metrics. We further perform two-tailed t-tests to assess the statistical significance of these differences; the differences in AUC, recall, and F_1 are statistically significant at the 0.001 level, the difference in accuracy is significant at the 0.01 level, and the difference in precision is significant at the 0.05 level. Therefore, this experiment suggests that the ensemble learning method is capable of addressing the imbalance sample problem in technology M&A prediction and represents a better learning strategy for our proposed technique. Thus, we adopt the ensemble learning method for our subsequent evaluations.

Evaluation Results: Our Technique versus Technological-Based Benchmarks

We compare the effectiveness of our proposed technology M&A prediction technique (involving all 43 technological variables) with that of the two

Table 5: Evaluation results (our technique versus technological-based benchmarks).

			M&A Category		
Technique	Accuracy	AUC	Recall	Precision	F_1
Our technique (using all 43 technological variables)	**90.39%**	**89.16%**	**52.44%**	**59.70%**	**55.83%**
Benchmark TB1 (13 technological variables on candidate target companies)	89.29%	80.50%	32.59%	56.37%	41.30%
Benchmark TB2 (17 technological compatibility variables)	89.65%	86.62%	36.67%	58.27%	45.01%

Note 1: The evaluation is based on the complete data set.
Note 2: The bolded number in each column indicates the highest value across the different prediction techniques investigated.

technological-based benchmarks (i.e., Benchmark TB1 and TB2) on the basis of the complete data set. All the techniques employ the ensemble learning method as their underlying learning algorithm, with α equal to 3 and k equal to 31. As Table 5 shows, our proposed technique outperforms the two technological-based benchmarks on all performance metrics. Specifically, the precision attained by the proposed technique is 3.33% and 1.43% higher than that of Benchmark TB1 and TB2, respectively. Our proposed technique is particularly more effective than the two benchmarks in the recall measure: It achieves a recall 19.85% and 15.77% higher than the two benchmarks. Consequently, the F_1 of the proposed technique is 14.53% and 10.82% higher than that of the two benchmarks. Moreover, the proposed technique also outperforms the two benchmarks in the AUC measure with a differential of 8.66% and 2.54%, respectively. Our statistical significance tests indicate that the differences in accuracy, AUC, recall, precision, and F_1 between our proposed technique and Benchmark TB1 are statistically significant at the 0.001 level. Moreover, the differences in accuracy, AUC, recall, and F_1 between our proposed technique and Benchmark TB2 again are statistically significant at the 0.001 level, though their difference in precision is not statistically significant. Overall, the comparative evaluation results suggest that technology M&A prediction based solely on the technological profiles of the candidate target companies is insufficient to account for many technology M&A cases (recall is only 32.59%). Moreover, technology M&As often go beyond the considerations of technological compatibility (recall and precision of Benchmark TB2 are only 36.67% and 58.27%, respectively). The incorporation of the bidder's and the candidate target companies'

Table 6: Evaluation results (our technique versus financial-based benchmarks).

			M&A Category		
Technique	Accuracy	AUC	Recall	Precision	F_1
Our technique (using all 43 technological variables)	**89.79%**	**90.24%**	**57.79%**	**56.55%**	**57.16%**
Benchmark FB1 (using all 54 financial variables)	85.75%	75.61%	35.31%	39.58%	37.32%
Benchmark FB2 (18 financial variables on candidate target companies)	85.53%	66.45%	18.70%	32.35%	23.70%
Benchmark FB3 (18 financial compatibility variables)	83.55%	72.87%	22.61%	27.69%	24.89%

Note 1: The evaluation is based on the reduced data set.
Note 2: The bolded number in each column indicates the highest value across the different prediction techniques investigated.

technological profiles and technological compatibility as predictors instead significantly improves the effectiveness of technology M&A prediction.

Evaluation Results: Our Technique versus Financial-Based Benchmarks

In this evaluation, we compare the effectiveness of our proposed technology M&A prediction technique (involving all 43 technological variables) with that of the three financial-based benchmarks on the basis of the reduced data set. All the techniques employ the ensemble learning method as their underlying learning algorithm, with α equal to 3 and k equal to 31. As we show in Table 6, the financial-based approach achieves its best prediction performance when all variables are adopted (i.e., Benchmark FB1 outperforms Benchmark FB2 and FB3). This finding is comparable to that observed from the technological-based benchmarks. That is, M&A prediction based only on the financial profiles of the candidate target companies (i.e., Benchmark FB2) or on the financial compatibility (i.e., Benchmark FB3) is insufficient. Using the financial profiles and financial compatibility of both companies as predictors improves the effectiveness of relevant predictions.

As Table 6 also illustrates, our proposed technology M&A prediction technique outperforms all financial-based benchmarks on all performance metrics. Specifically, the accuracy, AUC, recall, precision, and F_1 of our proposed technology M&A prediction technique are 4.04%, 14.63%, 22.48%, 16.97%, and 19.84% higher than those of the best financial-based benchmark (i.e., Benchmark FB1). Our statistical significant tests also indicate that the differences in accuracy, AUC, recall, precision, and F_1 between our proposed technique and Benchmark FB1 are statistically significant at the 0.001 level. This comparative evaluation result suggests that technology M&As likely go beyond the financial considerations. When predicting technology M&As, the technological variables adopted by our proposed technique represent more effective predictors than the financial variables.

In addition to the performance improvement, the use of our technological variables for technology M&A prediction is also considered more appealing than the use of financial variables in terms of data availability and prediction coverage. All of our technological variables can be extracted or derived from patent documents that are publicly available in the patent databases provided by official patent offices (e.g., USPTO in this study). However, given a dyad of a bidder company and a candidate target company, the financial data required to calculate the financial variables may not be readily available if any of the two companies is not publicly listed. In this case, the M&A decision of the focal dyad cannot be predicted or additional effort is required for collecting the needed financial data from other sources. Using our collected M&A cases as an example, all 90 M&A cases can be included for evaluation purposes if the technological variables are employed as predictors. In contrast, only 69 M&A cases (76.67% of all M&A cases) can be included when taking the financial-based approach. That is, compared to our proposed technique that uses the technological variables, the financial-based approach likely suffers from its relative lower prediction coverage.

Effects of Different Ensemble Learning Algorithms

For our proposed technology M&A prediction technique, we adopt an ensemble learning method to deal with the problem of skewness between the M&A and non-M&A categories. In this subsection, we perform another evaluation to examine its effectiveness in comparison with two prevailing ensemble learning algorithms: bagging (Breiman, 1996; Quinlan, 1996; Bauer & Kohavi, 1999) and boosting (Quinlan, 1996; Freund & Schapire, 1997; Bauer & Kohavi, 1999). Bagging employs bootstrap sampling to generate multiple training subsets from the entire original training data set. Each resulting training subset is then used to construct a prediction model. In each iteration, bagging randomly samples the entire original training data set with replacements to create a distinct subset that contains the same number of training instances as in the original data set. Each subset derived from bootstrap sampling provides training cases to construct a prediction model that is based on a specific learning algorithm (i.e., C4.5 in our study). This process continues until it reaches the prespecified number (i.e., k) of iterations. To predict the output category for a new instance, an overall prediction emerges from voting over the individual predictions made by the k prediction models constructed previously.

Boosting (specifically, AdaBoost) constructs a sequence of prediction models. It first constructs an initial prediction model using a specific learning algorithm (i.e., C4.5 in our study) and the entire original training data set. This (initial) prediction model then predicts all instances, initially assigned equal weights, in the training data set. When the model's prediction of a training instance differs from its known output category, the weight of this instance increases. A new training subset is then randomly selected with replacements from the resulting set of weighted instances. Because the instances incorrectly predicted by the initial prediction

Table 7: Technology M&A prediction results using different ensemble learning methods.

			M&A Category		
Ensemble learning method	Accuracy	AUC	Recall	Precision	F_1
Our ensemble learning method	90.39%	**89.16%**	**52.44%**	59.70%	**55.83%**
Bagging method	**91.78%**	86.00%	38.89%	**79.55%**	52.24%
AdaBoost method	**91.78%**	81.90%	44.44%	74.07%	55.55%

Note 1: The evaluation is based on the complete data set.
Note 2: The bolded number in each column indicates the highest value across all ensemble learning methods examined.

model have greater weights, they are more likely to be included in the new training subset. As a result, the learning of the next prediction model is forced to focus more on these challenging instances—that is, on those incorrectly predicted by the predecessor prediction model. This process continues until it reaches a specified number (i.e., k) of iterations or a predefined termination condition is satisfied, thus creating a sequence of prediction models. To classify a new instance, a weighted voting scheme generally is used to obtain an overall prediction that combines the respective predictions made by the sequence of prediction models. The weight of a prediction model typically depends on its effectiveness in correctly predicting all instances in the entire training data set.

For this evaluation, we use the complete data set and adopt 31 for k for all the three ensemble learning methods examined. As we show in Table 7, the proposed ensemble learning method achieves greater AUC, recall, and F_1 than its counterparts. Both the bagging and AdaBoost methods attain higher precision on the M&A category than our proposed ensemble learning algorithm does. The higher precision and lower recall of the bagging and AdaBoost methods for the M&A category suggest that both tend to assign unseen instances to the non-M&A (i.e., majority) category. That is, neither ensemble learning method can handle the data skewness problem associated with technology M&A prediction. Because to support technology M&A target selection, the prediction effectiveness of the M&A category is more important than that of the non-M&A category, our proposed ensemble learning method appears more favorable than the two prevailing ensemble learning methods.

CONCLUSION AND FURTHER RESEARCH

In this study, we propose a technology M&A prediction technique that not only encompasses technological variables but also takes into account the technological profiles of both bidder and candidate target companies. Specifically, we derive 43 technological variables from patent documents and develop an ensemble learning method for our proposed technology M&A prediction technique. Our empirical evaluation results suggest that technology M&A prediction cannot consider only the technological profiles of the candidate target companies or the technological compatibility between the bidder and candidate target companies. Rather, the incorporation of the technological profiles of both bidder and candidate target companies, as well as their technological compatibility, as predictors significantly improves the effectiveness of technology M&A prediction. Furthermore, the use of technological variables for technology M&A prediction achieves greater prediction effectiveness than that attained by the use of financial variables. Our empirical evaluation also shows that our proposed ensemble learning method for technology M&A prediction is more effective (in terms of AUC, recall, and the F_1 measure) than two prevalent ensemble learning methods (i.e., the bagging and AdaBoost methods).

This study makes several contributions to technology M&A prediction and patent mining research. First, existing M&A prediction research mainly takes financial and managerial variables into account and few prior studies consider the technological aspect. Our study thus contributes to M&A prediction research by addressing an underexplored area (i.e., technology M&A prediction) and proposing a promising technique for technology M&A prediction. Second, we perform systematic evaluations using real-world M&A cases and generate empirical evidence that suggests the viability and utility of the proposed technique, as well as its relative effectiveness compared with two technological-based benchmarks and three financial-based benchmarks. Third, we also contribute to patent mining research by broadening its scope. Existing patent mining research mainly concentrates on patent document classification (Lai & Wu, 2005; Liu & Shih, 2011) and patent map construction (Yoon, Yoon, & Park, 2002; Wu & Liu, 2006). Our study provides an appealing illustration of patent mining research that moves beyond patent document management and should serve as a foundation for continued patent mining research.

Our study contains several limitations that warrant additional research attention. First, this study only concentrates on the selection (prediction) of M&A targets for a given bidder company. However, M&A deals may result in negative outcomes, such as market share losses, declining profits, lower R&D intensity, and, in the long term, losses for shareholders (Hitt, Hoskisson, Ireland, & Harrison, 1991; Webber & Dholakia, 2000). Thus, the investigation of whether a specific technology M&A deal will be successful represents an interesting and essential future research direction. Second, our data set for the empirical evaluation consists of M&A cases from six industries in Japan and Taiwan. It is essential to collect a larger data set, covering more countries and industries, and then to perform similar evaluations to strengthen the validity and generalizability of the evaluation results reported in the current study. Third, we recognize that there is still room to improve the effectiveness of our proposed technique. One direction might be to develop and include additional technological variables for technology M&A prediction. Fourth, an M&A event pertaining to a particular bidder company may have effects on the probability of the focal company being involved in subsequent M&A events. Because our study concentrates on the development of technological indicators and associated techniques for technology M&A prediction, it thus does not include the prior M&A history of a bidder company as predictors for the company's subsequent M&As. Incorporating M&A-history-related variables into our proposed technology M&A prediction technique would be desirable and would likely improve prediction effectiveness further. Fifth, the approach we have proposed might be applied to other patent mining tasks. For example, we can adopt and extend our technological variables to support R&D alliance selection decisions.

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