APPLYING TECHNOLOGICAL RESOURCE-BASED VIEW FOR STRATEGIC ALLIANCE FORMATION PREDICTION

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Abstract

Strategic alliance represents an important business activity for firms to access desirable resources and to enhance their competitive advantages. An important task concerning strategic alliance is alliance formation prediction, which can help a firm anticipate possible alliance actions of its rivals and accordingly develop strategies to prevent their partnering opportunities or neutralize the advantages the rivals can gain from these alliance actions. Previous studies on alliance formation prediction investigate various factors affecting the likelihood of alliance formation but incur some limitations. Among them, the most critical limitation is that most of prior studies concentrated on factors pertaining to financial and managerial factors and seldom exploited the utility of technological factors for alliance formation prediction. The growing importance of technology and innovation for competitive advantages makes it critical for firms to consider and assess technological factors in their strategic alliance partner selection. In response, we propose a technological-based strategic alliance formation prediction technique, which employs multiple dimensions of technological resource as the predictors to predict whether two firms will form a strategic alliance. On the basis of 201 strategic alliance cases and 392 non-strategic alliance cases, our empirical evaluation shows our proposed technique can achieve promising prediction effectiveness.

Keywords: Strategic Alliance, Alliance Formation Prediction, Technological Resource, Patent Analysis.

1 INTROUDCTION

Forming strategic alliances has become a popular strategy for many contemporary firms (Hitt et al. 2000). Strategic alliances are defined as voluntary arrangements between firms to exchange, share, or co-develop products, technologies, or services (Gulati 1998). The general benefits of strategic alliances include accessing knowledge, skills, and resources (e.g., Kogut 1988), reducing environmental uncertainty (e.g., Burgers et al. 1993), enhancing legitimacy and status (e.g., Baum and Oliver 1991), and so on. According to a report of Global Business Insights, more than 600 biotech pharmaceutical alliances were formed in 2007, and their value was increased from $30 billion to more than $90 billion between 2004 and 2007 (Global Business Insights 2008; Xiao and Xu 2012). Hughes and Weiss's (2007) study also indicated that the number of alliances increases by 25% per year.

Particularly, strategic alliances are critical for firms that have limited resources. According to the resource-based view, a firm forms a strategic alliance to access desirable resources from its strategic partners and to enhance its competitive advantage (Das and Teng 2000; Eisenhardt and Schoonhoven 1996). A focal firm can further enhance its competitive advantage by predicting its rivals' potential alliances (i.e., strategic alliances the rivals may develop in the future). With such prediction, a focal firm can initiate some competitive actions to mitigate the rivals' prospective competitive advantages or enhance its own competitive advantages. For example, the focal firm can attempt to foreclose the rivals' partnering opportunities and thus prevent the rivals from gaining access to their desirable resources (Gomes-Casseres 1996; Silverman and Baum 2002) or can form an alliance with the rivals' potential partners ahead of the rivals. Given the importance of competitive advantages to a firm's survival, performing this prediction effectively is critical for firms in increasingly competitive business environments. This raises the questions of how a focal firm can effectively predict its rivals' potential partners and which information can be used to support this prediction.

Previous studies on alliance formation prediction have investigated various factors affecting the likelihood of alliance formation, including trust (Gulati 1995; Ireland et al. 2002), commitment (Shah and Swaminathan 2008), transaction cost (Hennart 1988), risk sharing (Elmuti and Kathawala 2001), alliance experience (Chung et al. 2000), top management team (Eisenhardt and Schoonhoven 1996), and firm resources (Das and Teng 2000). For instance, Ireland et al. (2002) argued that the trust between firms facilitates alliance formation because trust reduces the threat of opportunism in alliances. Thus, firms are likely to form alliances with partners they trust. However, previous studies have some limitations. First, the models developed in prior studies may not be applied to the scenario in which a focal firm attempts to predict its rivals' strategic alliance, because these models involve some factors that require information private to its rivals. For example, to sustain their competitive advantages, the rivals have no intention to reveal all information (e.g., trust with other firms) to the focal firm. In this case, the firm cannot utilize existing models for predicting possible strategic alliances of its rivals. Second, most of prior studies concentrated on factors pertaining to financial and managerial factors and seldom exploited the utility of technological factors for alliance formation prediction. The growing importance of technology and innovation for competitive advantages makes it essential for firms to pay attention to technological factors in their strategic alliance partner selection. Third, most of existing studies investigated alliance formation from either the perspective of a firm or the perspective of a dyadic relationship between a firm and its potential partner, but relatively few studies have considered both perspectives together. Because these perspectives influence alliance formation differently, considering both perspectives should increase our understanding of alliance formation.

In this study, we propose a technological-based strategic alliance formation prediction technique to address the aforementioned limitations. We focus on the biotechnology industry, because firms in this industry often form strategic R&D alliances to obtain desirable technological resources (Grabowski and Kyle, 2008). Although it is challenging to measure a firm's technological resource accurately, prior studies have suggested that the firm's patents are a good proxy of this resource (Mowery et al. 1998; Zhang et al. 2007). To predict whether two firms will engage in strategic alliance, our prediction technique takes into account multiple dimensions of technological resource pertaining to each firm and to this dyadic relationship as the predictors. We collect 201 strategic R&D alliance events to examine our proposed technique and find that the use of our proposed technological predictors can achieve satisfactory prediction effectiveness.

Our study has significant implications for researchers and managers. This study contributes to the literature on alliance formation prediction. We extend the existing research by investigating the utility of technological predictors (covering multiple dimensions of technological resource) for alliance formation prediction. Our study has several managerial implications. First, publicly available technological information is useful for managers to predict alliance formation. Second, firms can increase their competitive advantages by not only ally with superior partners ahead of their rivals but also block their rivals' from accessing desirable resources.

2 LITERATURE REVIEW

Strategic alliance formation has received considerable research attention. Previous studies have used several theories to explain alliance formation, including resource-based view (Das and Teng 2000), transaction cost theory (Hennart 1988), game theory (Parkhe 1993), matching theory (Mitsuhashi and Greve 2009), and social network theory (Gulati 1995). Resource-based view is especially useful when researchers attempt to understand how a firm's resources influence its alliance formation. According to the resource-based view, a firm is likely to form an alliance when the alliance helps the firm create value by pooling the resources of the focal firm and the partner (Das and Teng 2000; Eisenhardt and Schoonhoven 1996). Firm's value can be enhanced if alliance partners complement each other's weakness (Chung et al. 2000; Hamel et al. 1989; Harrison et al. 2001; Shah and Swaminathan 2008). Specifically, a firm in an alliance can access complementary resource from its partner.

Firms' resources can be classified into four categories: financial resource, physical resource, managerial resource, and technological resource (Barney 1991). Financial resource refers to capital availability, which is crucial for firms to develop new products or services (Glaister and Buckley 1996; Hamel et al. 1989). Product/service development can be costly and risky. In this case, firms usually prefer to share these financial cost and risk among alliance partners (Elmuti and Kathawala 2001). Therefore, financial resource becomes one of important criteria for firms to select their potential alliance partners (Hitt et al. 2000; Park et al. 2002). For instance, a study by Park et al. (2002) demonstrated that the sum of capital funding positively influences the likelihood of alliance formation because a firm with more funding is attractive to other firms.

Second, physical resource includes firm's production capacity, distribution channels, and access to raw materials (Barney 1991; Chi 1994; Das and Teng 1998). Although Reed and DeFillippi (1990) argued that obtaining only physical resources may not enhance firm's value significantly, such resources still are considered influential on the likelihood of alliance formation. For instance, a firm with strong distribution capability is likely to form an alliance with a firm having strong manufacturing skill, because such alliance can reduce the cost and risk of entering new business or markets (Hamel et al. 1989).

Third, managerial resource of a firm refers to its top management team and its ability to run a business (Das and Teng 1998). Prior studies have explored how the characteristics of a top management team (e.g., team size, team members' experience, team members' reputation, and team members' status) influence the likelihood of alliance formation (Eisenhardt and Schoonhoven 1996; Stern et al. 2013). For instance, Eisenhardt and Schoonhoven (1996) found that a large size of a top management team is more likely to form an alliance than a smaller size because a larger top management team has more business connections with potential alliance partners.

Finally, technological resource refers to a firm's knowledge and capability relevant to the development of new products/services or the improvement of existing products/services. Firms can use a strategic alliance to obtain access to the technological capability of other firms. Previous studies have investigated how the likelihood of strategic alliance formation is affected by the level of and diversity of a firm's technological capability (Mowery et al. 1998; Sakakibara 2002). For example, Zhang et al. (2007) found that a firm with high technological diversity is more likely to form an alliance than a firm with low technological diversity, because high technological diversity increases a firm's ability to absorb other firm's technological resource.

In addition to these four resources, social capital also influences the likelihood of alliance formation (Chung et al. 2000; Eisenhardt and Schoonhoven 1996). Social capital refers to relationships between a focal firm and other firms in their business network. Because, in addition to values and resources, alliances also bring risks to firms, social relationship helps firms to learn about the reliability and capability of potential partners and to reduce the possibility of their opportunistic behaviors. Prior studies have investigated several aspects of social capital that may influence the likelihood of alliance formation, including the number of past alliances between two firms (Chung et al. 2000; Gulati 1995), the number of common third-party ties between two firms (Chung et al. 2000; Gulati 1995), combined network centrality of two firms (Ahuja et al. 2009), and structural holes (Walker et al. 1997).

3 OUR TECHNOLOGICAL RESOURCE-BASED TECHNIQUE FOR STRATEGIC ALLIANCE FORMATION PREDICTION

Because prior studies have suggested that firm's patents represent a good proxy to measure a firm's technological resource (Mowery et al. 1998; Zhang et al. 2007), we exploit a patent analysis to design the technological predictors for strategic alliance formation prediction. According to our review of existing patent data analysis studies, we develop and employ four types of technological predictors, namely technological quantity, technological quality, technological attractiveness, and technological similarity. For a dyad of firms (i.e., a firm f and its potential partner p) involved in a focal strategic alliance formation prediction, seven predictors are employed to measure each individual firm's technological resource and eight predictors are applied to estimate the dyadic relationship between f and p. We detail these technological predictors in the following.

<u>*Technological Quantity*</u>: A firm with a higher number of patents (*NP*) is expected to have greater technological resource. Accordingly, for each firm (i.e., f or p) involved in an alliance formation prediction, we measure the firm's technological quantity by the number of patents granted (Ali-Yrkkö et al. 2005; Breitzman and Thomas 2002; Breitzman et al. 2002; Deng et al. 1999; Ernst 2003; Pegels and Thirumuthy 1996; Schoenecker and Swanson 2002).

- Number of patents (*NP*) is estimated by counting the number of patents granted to a specific firm of interest. For each firm i (i.e., f or p), $NP_i = |P_i|$, where P_i is the set of patents granted to firm i. Moreover, we measure the relative strength of technological quantities between firm f and firm p by a relative strength of *NP*s as $RNP_{f,p} = NP_f / NP_p$.

<u>*Technological Quality*</u>: We measure the technological quality of each firm (i.e., f or p) with four common patent quality indicators: number of forward citation (*NFC*), current impact index (*CII*), technology cycle time (*TCT*), and science linkage (*SL*) (Chiu and Chen 2007; Hirschey and Richardson 2001; Reitzig 2004; Yang et al. 2014).

- Number of forward citations (*NFC*) is a measure of the impact of a firm's patents. If a patent is cited by many patents, it is likely a foundation of many other inventions. When a firm's patents have a greater average number of forward citations, the technological quality of the firm should be greater. *NFC* of a firm i (i.e., f or p) is estimated as $NFC_i = \sum_{j \in P_i} fc_j / |P_i|$, where fc_j is the number of forward citations to patent j. We also consider the relative strength of the average number of forward citations (*RNFC*) between firm f and firm p, defined as $RNFC_{f,p} = NFC_f / NFC_p$.
- Current impact index (*CII*) measures the impact of a firm's patents by estimating the relative number of *novel* forward citations to them (Breitzman and Thomas 2002; Breitzman et al. 2002; Karki 1997; Kayal and Waters 1999; Pegels and Thirumuthy 1996; Schoenecker and Swanson 2002). It is common that earlier patents attract more forward citations. Thus, the *CII* value of a firm i (i.e., f or p) in the current year is estimated as $CII_i = \frac{|C_i| / |K_i|}{|C| / |K|}$, where K_i is the set of patents granted to firm i in the previous five years, C_i is the set of forward citations received by patents in K_i in the current year, K is the set of patents granted in the previous five years, and C is the set of forward citations received by patents in K in the current year. The dyadic relationship of *CII*

between firm f and firm p is also considered and defined as the relative strength of current impact index $RCII_{f,p} = CII_f / CII_p$.

- Technology cycle time (*TCT*) is the average median year of the patents cited by the patents of a firm (Breitzman and Thomas 2002; Breitzman et al. 2002; Deng et al. 1999; Kayal and Waters 1999; Pegels and Thirumuthy 1996; Schoenecker and Swanson 2002). A firm whose patents cite more recent patents is likely to innovate faster. For each firm i (i.e., f or p), TCT_i is measured as: $\sum_{j \in P_i} m_j / |P_i|$, where m_j is the median year of the patents cited by patent j. Furthermore, we also take into account the relative strength of technology cycle time (*RTCT*) between firm f and firm p, calculated by $RTCT_{f,p} = TCT_f / TCT_p$.
- Science linkage (*SL*), which captures the link between patents and scientific articles, is often used to measure the degree of technological innovation of a company (Breitzman and Thomas 2002; Breitzman et al. 2002; Deng et al. 1999; Schoenecker & Swanson, 2002). A patent cites more scientific articles is considered to build more on scientific research and thus should be more innovative. The *SL* of each firm i (i.e., f or p) is estimated as: $\sum_{j \in P_i} ls_j / |P_i|$, where ls_j is the number of links to scientific articles in patent j. We then estimate the relative strength of science linkage (*RSL*) between firm f and firm p as $RSL_{f,p} = SL_f / SL_p$.

Technological Attractiveness: The technological resource of a firm can also be measured by the attractiveness of the firm's patents granted. Specifically, we adopt two predictors: family size and technological scope. Kim and Vonortas (2006) suggested that the density of a patent, which is generally estimated by its family size, is an important indicator about whether the claimed technology will be protected well. On the other hand, technological scope is an indicator that measures the width of technological areas, often calculated by counting the number of classification classes, covered by a patent (Ernst 2003).

- Family size (*FS*) measures the patent density of a firm. A higher density means that the firm has more attractive patents. The family size of each firm i (i.e., f or p) is computed as: $FS_i = \sum_{j \in P_i} fp_j / |P_i|$, where fp_j is the number of foreign patents relevant to patent j. The relative strength of family size (*RSL*) between firm f and firm p is estimated by $RFS_{f,p} = FS_f / FS_p$.
- Technological scope (*TS*) of a patent is measured by the number of classification codes covered by the patent. If a patent has a wider scope (i.e., more classification codes), it should be more general and valuable. Accordingly, the technological scope of each firm i (i.e., f or p) is calculated as: $TS_i = \sum_{j \in P_i} c_j / |P_i|$, where c_j is the number of classification codes assigned to patent j. International patent classification (IPC) (World Intellectual Property Organization 2014) and United States patent classification (USPC) (United States Patent and Trademark Office 2012) are two well-known patent classification systems and can be adopted to estimate the technological scope of a firm. In this study, the IPC classification system is employed. We also consider the relative strength of technological scope (*RTS*) between firm f and firm p, which is estimated by $RTS_{f,p} = TS_f / TS_p$.

Technological Similarity: The similarity of the technological profiles between a dyad of firms is an important indicator of strategic alliance. If the similarity is high, the two firms have similar technological resources and accordingly may be able to learn faster from each other during the period of strategic alliance.

- Technological similarity (*TSI*) between a dyad of firms is estimated by the similarity between their patent profiles. The profile of a firm's patents is represented as a vector of distribution of patent classification classes. Specifically, the profile of firm i is defined as: $PR_i = \langle v_{i1}, v_{i2}, \ldots v_{im} \rangle$, where v_{ij} is the number of patents of firm i assigned to class j and m is the total number of classes involved in the analysis. Accordingly, the technological similarity (TSI) between firm f and firm p is calculated as: $TSI_{f,p} = \cos(PR_f, PR_p) = \frac{\sum_{j \in C_{fp}} v_{fj} \times v_{pj}}{\sqrt{\sum_{j \in C_{fp}} v_{fj}^2} \times \sqrt{\sum_{j \in C_{fp}} v_{pj}^2}}$.

In this study, we employ the IPC classification system to measure the technological similarity between a dyad of firms. IPC is a hierarchical classification system with four levels, namely section, class, subclass, and subgroup (World Intellectual Property Organization 2014). For example, given the IPC class "G05L 12/21," its section, class, subclass, and subgroup codes are "G," "G05," "G05L," and "G05L 12/21" respectively. In this study, the first three levels are adopted to represent the patent profile of a firm. In addition, a patent could be assigned with multiple classes in which the first one is considered as main class and the remaining as secondary classes. Therefore, two scenarios can be considered. The first one is the "main class" scenario in which only the main class of a patent is adopted to construct the patent profile of a firm, while the second one is the "all classes" scenario in which all the classes (not the main class only) of a patent are employed. Considering the three classification hierarchy levels and the two classification class scenarios, six variables can be derived. They are TSI-M-S, TSI-M-C, TSI-M-SC, TSI-A-S, TSI-A-C, and TSI-A-SC, where M and A denote the "main class" and "all classes" scenarios and S, C, and SC represent the "section," "class," and "subclass" hierarchical levels respectively. Either part or all of the six variables can be adopted to measure the technological similarity between a dyad of firms.

A summary of the predictors adopted for our desired technological resource-based strategic alliance prediction is provided in Table 1.

Category	**Predictor**	**Scope**	**Description**
Technological Quantity	NP_f, NP_p	Individual	Number of patents granted to firm *i* (i.e., *f* or *p*)
	$RNP_{f,p}$	Dyadic	Relative strength of *NP*s between firm *f* and firm *p*
Technological Quality	NFC_f, NFC_p	Individual	Average number of forward citations to the patents of firm *i*
	$RNFC_{f,p}$	Dyadic	Relative strength of *NFC*s between firm *f* and firm *p*
	CII_f, CII_p	Individual	Average current impact index of the patents of firm *i*
	$RCII_{f,p}$	Dyadic	Relative strength of *CII*s between firm *f* and firm *p*
	TCT_f, TCT_p	Individual	Average technology cycle time of the patents of firm *i*
	$RTCT_{f,p}$	Dyadic	Relative strength of *TCT*s between firm *f* and firm *p*
	SL_f, SL_p	Individual	Average science linkage of the patents of firm *i*
	$RSL_{f,p}$	Dyadic	Relative strength of *SL*s between firm *f* and firm *p*
Technological Attractiveness	FS_f, FS_p	Individual	Average family size of the patents of firm *i*
	$RFS_{f,p}$	Dyadic	Relative strength of *FS*s between firm *f* and firm *p*
	TS_f, TS_p	Individual	Average technological scope of the patents of firm *i*
	$RTS_{f,p}$	Dyadic	Relative strength of *SL*s between firm *f* and firm *p*
Technological Similarity	$TSI_{f,p}$	Dyadic	Technological similarity of the patent profiles between firm *f* and firm *p*

Table 1. Summary of the Technological Predictors for Strategic Alliance Formation Prediction.

In addition to the technological predictors developed for strategic alliance formation prediction, an inductive learning algorithm is also essential to the prediction effectiveness. Naïve bayes classifier has been applied to many application domains and shows its relative effectiveness. Consequently, we adopt Naïve bayes classifier as our underlying learning algorithm.

Given a dyad D of firms f and p (described by h predictors $x_1, x_2, \ldots, x_h$), the probability that firms f and p will form a strategic alliance (i.e., SA event occurs) is computed via Bayes rule as:

$$p(SA \mid D) = \frac{p(D \mid SA)\, p(SA)}{p(D)}.$$

As $p(D)$ is constant for all events, only $p(D|SA)p(SA)$ needs to be considered. Moreover, assuming the statistical independence of the predictors, the statistics is transformed into:

$$p(SA \mid D) = p(SA) \prod_{j=1}^{h} p(x_j \mid SA).$$

The values of $p(SA)$ and $p(x_j|SA)$ can be estimated on the basis of a set of training instances. After the probabilities of $p(SA|D)$ and $p(\sim SA|D)$ are estimated, we can arrive at an final prediction of whether the dyad of firms will form a strategic alliance or not.

4 EMPIRICAL EVALUATION

In this section, we describe our evaluation design, including data collection, evaluation criteria and procedure, and discuss important evaluation results of our proposed strategic alliance formation prediction technique.

4.1 Data Collection

For empirical evaluation purposes, the strategic alliance events from January 1, 2004 to December 31, 2008 are collected from the SDC Platinum database. Because a strategic alliance event may consist of more than two firms, we combine each pair of firms in the event to form a candidate strategic alliance case. For example, if three firms A, B, and C are involved in a specific strategic alliance event, we will generate three dyads of strategic alliance cases, namely 'A and B,' 'A and C,' and 'B and C.' Moreover, to avoid the ambiguity caused by the fact that a firm with possible name variations, we submit the name of each firm to the Delphion database 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. Initially, we obtain 609 strategic alliance cases from the strategic alliance events collected. However, some of the strategic alliance cases may not be appropriate for our study. We apply two filtering rules to clean the dataset. First, because we only focus on the biotechnology industry, we only retain those cases whose related firms are in biotechnology industry and register in United States. Second, we are interested in how technological resources influence alliance formation. Because previous studies (Mowery et al. 1998; Zhang et al. 2007) suggested that patents are a good proxy of firm's technological capacity, we filter out those cases involving firms that do not have any granted patents before the date of the strategic alliance event. After the filtering process, our dataset is reduced to 201 strategic alliance cases.

In addition to the positive strategic alliance cases described previously, we need to generate negative strategic alliance instances for inductive learning purposes. There exist a huge amount of candidate negative strategic alliance cases (i.e., any pairs of firms not in our positive case dataset). However, not all pairs are representative. We consider a representative negative case should involve two firms who might be willing to but did not participate in any strategic alliance event in our collection. We follow and extend the procedure developed in a study by Yang et al. (2014) to generate negative strategic alliance cases. Specifically, for each positive strategic alliance case, we employ all other positive cases occurred within a three-month time window to generate negative cases. Figure 1 is an example of our negative case generation process. Assume A and B form a strategic alliance on t_2, C and D form a strategic alliance on t_1, E and F form a strategic alliance on t_3, and the interval between t_2 and t_1 and that between t_3 and t_2 are no more than three months. Eight negative cases (i.e., A and C, A and D, A and E, A and F, B and C, B and D, B and E, and B and F) can be generated. After this negative strategic alliance case generation process, there are still too many negative cases (i.e., 21,895) that make the dataset highly skewed and could not be handled appropriately by general inductive learning algorithms. Consequently, we further prune the negative cases by retaining only two negative cases (i.e., one for each of the involved firm) for each positive case. Pointwise mutual information (PMI) (Church and Hanks 1989), which is a measure of association between two items, is adopted for negative case selection. Specifically, for each negative case comprising of, for example, firm A and firm C, we generate three queries (i.e., A, C, and A $\wedge$ C), submit them to the Google search engine, and then calculate its PMI value on the basis of the number of webpages relevant to each query as: $\mathrm{PMI}(\mathrm{A}, \mathrm{C}) = \log \dfrac{p(\mathrm{A} \wedge \mathrm{C})}{p(\mathrm{A})\, p(\mathrm{C})} = \log \dfrac{N \times \mathrm{hits}(\mathrm{A} \wedge \mathrm{C})}{\mathrm{hits}(\mathrm{A})\, \mathrm{hits}(\mathrm{C})}$, where hits(*query*) is the number of results of *query* returned by the Google search engine. For each firm involved in a positive strategic alliance case, only the candidate case with top-ranked PMI value is selected as our final negative strategic alliance case. Using Figure 1 as an example, firm *A* has four candidate negative cases. Assume the PMI values of the four cases “A and C,” “A and D,” “A and E,” and “A and F,” are 0.51, 0.32, 0.18, and 0.66 respectively. Only “A and F” (with the highest PMI value) is selected as a negative strategic alliance case for subsequent analysis. Since our dataset consists of 201 positive cases, we should generate 402 negative cases. After duplicate removal, there are 392 negative cases retained. In summary, our strategic alliance dataset consists of 593 cases (i.e., 201 positive cases and 392 negative cases).

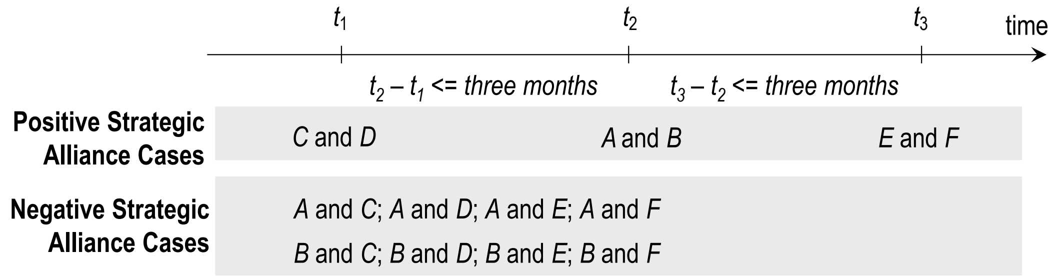

Figure 1. Illustration of Negative Strategic Alliance Case Generation.

4.2 Evaluation Procedure and Criteria

To evaluate the effectiveness of our proposed technological resource-based strategic alliance formation prediction technique, a tenfold cross-validation strategy is employed. That is, given a dataset, we divide all cases in the dataset randomly into ten mutually exclusive subsets of approximately equal size. In turn, we designate each subset as the testing subset while the others serve as the training subset. Moreover, we evaluate the effectiveness of our proposed technique in terms of overall accuracy and area under ROC curve (AUC) as well as recall, precision, and F_1 measures with respect to the strategic alliance and non-strategic alliance classes respectively.

4.3 Evaluation Results

We first evaluate the prediction effectiveness of the proposed technique using the set of PMI-selected balanced dataset (i.e., 201 positive cases and 392 negative cases) and the original skewed dataset (i.e., 201 positive cases and 21,895 negative cases). The evaluation results are shown in Table 2. The proposed prediction technique has higher overall accuracy (i.e., 0.868) in the original skewed dataset than that (i.e., 0.654) in the PMI-selected balanced one. However, the PMI-selected dataset has better overall AUC value (i.e., 0.670 vs. 0.649) than that of the original dataset. Considering the performance in the strategic alliance (SA) class and the non-strategic alliance (non-SA) class respectively, the proposed technique performs well in the non-SA class in the original dataset but extremely poor in the SA class. On the other hand, the performance in the PMI-selected dataset is relatively balanced between the SA and the non-SA classes. Considering the difficulty of strategic alliance formation prediction, we believe that our proposed technique achieves satisfactory prediction effectiveness, although it needs further extension and improvement.

			Strategic Alliance Class			Non-Strategic Alliance Class		
Dataset	**Accuracy**	**AUC**	**Precision**	**Recall**	F_1	**Precision**	**Recall**	F_1
PMI-selected	0.654	0.670	0.492	0.577	0.531	0.762	0.694	0.726
Original	0.868	0.649	0.019	0.269	0.035	0.992	0.874	0.929

Table 2. Evaluation Results of Strategic Alliance Formation Prediction.

As mentioned in Section 3, the technological similarity (TSI) predictor can be further divided into six variables depending on the three classification hierarchical levels of the IPC classification system and the two classification class scenarios (i.e., main class and all classes scenarios) examined. The evaluation results shown in Table 2 are produced by the use of all six TSI variables for learning and prediction. We further investigate the prediction effectiveness of our proposed technique when only a subset of the TSI variables is included. On the basis of the PMI-selected dataset, Table 3 shows the effect of IPC hierarchical levels on our prediction model. “Full” means that all six TSI variables are examined, while “Section” indicates that only the two section-level TSI variables (i.e., TSI-M-S and TSI-A-S) are involved, “Class” indicates that only the two class-level TSI variables are employed (i.e., TSI-M-C and TSI-A-C), and “Class” denotes that only the two subclass-level TSI variables are adopted (i.e., TSI-M-SC and TSI-A-SC). We can observe that the inclusion of all TSI variables outperforms other settings with respect to the overall accuracy and AUC as well as the precision, recall, and F_1 of the SA class but slightly worse in terms of the recall and F_1 of the non-SA class.

Hierarchical Level	**Accuracy**	**AUC**	**Strategic Alliance Class**			**Non-Strategic Alliance Class**		
			Precision	**Recall**	F_1	**Precision**	**Recall**	F_1
Full	0.654	0.670	0.492	0.577	0.531	0.762	0.694	0.726
Section	0.639	0.653	0.468	0.478	0.473	0.729	0.722	0.725
Class	0.648	0.654	0.481	0.502	0.491	0.739	0.722	0.730
Subclass	0.653	0.655	0.487	0.478	0.482	0.735	0.742	0.738

Table 3. Effect of IPC Hierarchical Levels on Prediction Effectiveness

Table 4 illustrates the effects of different classification class scenarios on prediction effectiveness. The “main class” scenario indicates that only the main class of a patent is adopted and thus includes three TSI variables (i.e., TSI-M-S, TSI-M-C, TSI-M-SC), while the “all classes” scenario involves the other three TSI variables (i.e., TSI-A-S, TSI-A-C, TSI-A-SC). The evaluation results show that the “main class” scenario performs worse than the “all classes” scenario. Thus, for strategic alliance formation prediction, TSI variables are better estimated by using all the classification classes of a patent.

Scenarios	**Accuracy**	**AUC**	**Strategic Alliance Class**			**Non-Strategic Alliance Class**		
			Precision	**Recall**	F_1	**Precision**	**Recall**	F_1
Full	0.654	0.670	0.492	0.577	0.531	0.762	0.694	0.726
Main Class	0.654	0.653	0.490	0.468	0.479	0.733	0.750	0.741
All Classes	0.664	0.660	0.505	0.498	0.501	0.744	0.750	0.747

Table 4. Effect of Classification Class Scenarios on Prediction Effectiveness

5 CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In response to the limitations of existing studies on strategic alliance formation prediction, we propose a technique that employs multiple dimensions of technological resource pertaining to individual firm and to the dyadic relationship as the predictors for predicting whether the two firms will form an alliance. Specifically, we exploit a patent analysis to design a set of technological resource-based predictors for strategic alliance formation prediction. For a dyad of firms (i.e., a firm and its potential partner) involved in a focal strategic alliance formation prediction, seven predictors are employed to measure the individual firm’s technological resource and eight predictors are applied to measure the dyadic relationship between them. 201 strategic alliance cases and 392 non-strategic alliance cases in the biotechnology industry were collected for empirical evaluation purposes. The evaluations results show that our proposed technological resource-based alliance formation prediction technique achieves an accuracy of 0.654 and AUC of 0.670.

In addition to the theoretical contribution to the literature on alliance formation, our study offers several practical implications. First, a focal firm can increase its competitive advantages as well as reduce its rivals’ competitive advantages by predicting and then preventing the rivals’ potential alliances. Because an alliance formation brings in desirable resources to the alliance partners, a focal firm can prohibit its rivals from receiving valuable resources by establishing an alliance with the rivals’ potential partners ahead of the rivals. Second, the search and selection process of alliance partners for a firm is time consuming and costly, because the firm typically needs to investigate many potential candidates to select a potential partner. Our study provides possible guidelines to facilitate this selection process. Specifically, our findings suggest that technological capability can be used to predict the likelihood of forming an alliance between two firms.

Some ongoing and future research directions are summarized as follows. First, our proposed technique only includes technological predictors. It is critical to include other categories of predictors, such as financial resource and social relationship, to investigate their comparative effectiveness in alliance formation prediction. Second, the technological predictors derived from a patent analysis in this study can also be expanded. It is desired to design and include additional technological predictors from patent analysis into our proposed technique. Third, we employ Naïve bayes classifier as our underlying learning algorithm. Empirical comparison of the effectiveness of alliance formation prediction using different induction learning algorithms would be interesting and valuable. Last but not least, we only collect strategic alliance cases from the biotechnology industry for the evaluation purposes. To extend the scope and generalizability of our study, empirical evaluations covering diverse industries, such as semiconductor, photonics, and ICT, represent an interesting and important future research direction.

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