THE SELECTION OF COLLABORATION MODELS FOR R&D FIRMS IN THE INDUSTRIAL MARKET

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Abstract: This study considered a R&D firm how to select a collaboration model for maximizing its profit, and the model consisted of R&D, production, and marketing capabilities. R&D capability was the mainly concerned determinant of relative profitability performance in the industrial market in this study. This research measured R&D capability based on patent analysis and distinguishes R&D capability levels for firms in the target industry. The R&D levels could be taken as an index for decision makers as a suggestion to choose a production or business model. This research collected relative patent data of Aluminum Nitride product, and this case study could facilitate to verify the feasibility of this measurement procedure. The results provided evidence for the feasibility of measurement, and recognition by the importance of market demand.

Key word: collaboration, industrial market, R&D capability, patent analysis, fuzzy weighted average method

INTRODUCTION

Collaboration played an important role in research and development (R&D) activities, and had spurred research into their effects on firms' strategic decisions (Ge and Hu, 2008). Collaboration for R&D firms had outstanding advantages, by which firm can easily and faster gain skills and technologies, share costs and risks, and control competitive forces (Veugelers, 1998). R&D firms could be to be more owner-managed and smaller in size (Chang and Garen, 2004). They were usually more expert managed and high technologies such as, biotechnology or material industries. In addition, universities also could be defined R&D firms in this study because they were important R&D institutions for technology development. What's more, university commercialization strategies were popular in the R&D issues (Breznitz et al., 2008), and university spin-offs could be a kind of collaborations.

Through collaboration relationships, the firms could influence product demand by investing in demand-enhancing efforts. For example, a collaboration relationship was constructed by two firms. One firm invested in R&D to improve product quality, and the other firm invested in marketing to develop the market for the product. Here it should be noticed that the cost of the marketing effort was incurred by one firm that exerts effort but the benefit could improve demand potential which affected both firms (Gurnani et al., 2007). Similarly, investment in technology by R&D firm could benefit both firms in the industrial market. At the same time, the firms independently set prices in order to maximize their profits when products were sold to market. For instance, the R&D firm investing in product technology might prefer to charge a higher wholesale price to the other in collaboration, whereas the other partner exerting selling effort to develop the market might prefer a higher price in the end-market. Hence, both of them could gain the most profit for themselves. However, the power to make collaboration decisions was possession of the R&D firm because of its R&D capability (Wuyts et al., 2004). The R&D firm might make a decision not to collaborate with the other firm, and obtain the profits from production and marketing. Consequently, R&D capability was the critical decision factor to achieve collaboration for R&D firm (Wuyts et al., 2004).

R&D technology was one of the critical capabilities that needed to be improved and also could facilitate to enhance operation's performance and product quality (Singh, 2008). The R&D technology could reduce operation cost and increase potential demand to maximize the profit (Banker et al., 1998). Moreover, R&D capability has been suggested as one of the important characteristics that facilitate to differentiate successful from unsuccessful firms (Singh, 2008). Hence, R&D capability is the source of competitiveness for a R&D firm. How much level of R&D capability that R&D firm owned is the key issue to affect the decision for collaboration models. For this purpose, it's necessary to measure R&D capability well. Based on previous researches, patent analysis was an effective method to measure the impact of R&D technology and economic on a firm's performance (Albert et al., 1991; Ahuja, 2000; Choi et al., 2007). Moreover, patent data could be aggregated to patent information to measure the R&D technology impact on a firm (Bessen, 2008). Hence, patent data could be used to estimate the R&D capability which would be a decision factor to collaboration.

COLLABORATION MODEL CONSTRUCTION

This study considered a R&D firm to select one collaboration model for maximizing its profit, and the model constructed by three capabilities, such as R&D, production, and marketing. In order to analyze this, the model could be designed to represent the structure of the decision making process between a R&D firm A, selling a product through an independent firm B. There were three collaboration models for a R&D firm and exhibited in Figure 1.

In the model 1, Firm A developed R&D capability and firm B invested production and marketing capability. Firm A tried to improve the product quality and demand potential. Firm B invested production and marketing to reduce production cost and increase possible demand. At the same time, both firms independently set prices in order to maximize their profits; the firm A may prefer to charge a higher wholesale price to the firm B, whereas the firm B exerting marketing effort to develop the market may prefer a higher resale price in the end-mar … capability; firm B invested marketing capability to exp… …ed the quality and operation process to support productio… …t to sale them to end-market. In the model 3, firm A impro… …ltaneously. Hence, the R&D, production, marketing capal…

Following would const… …uction could be constructed and the notation would be sl…

(1)

D was defined the retai… …the end market. Let p be the resale price set in the end-… …t. The marketing capability effort was e, and the R&D … …arketing capability effort on demand, and λ measured th… …promotion or any action to improve the demand potenti… …f the R&D capability efforts to improve the demand pote… …ipment with high reliability, fast or flexible equipment, … …etc..

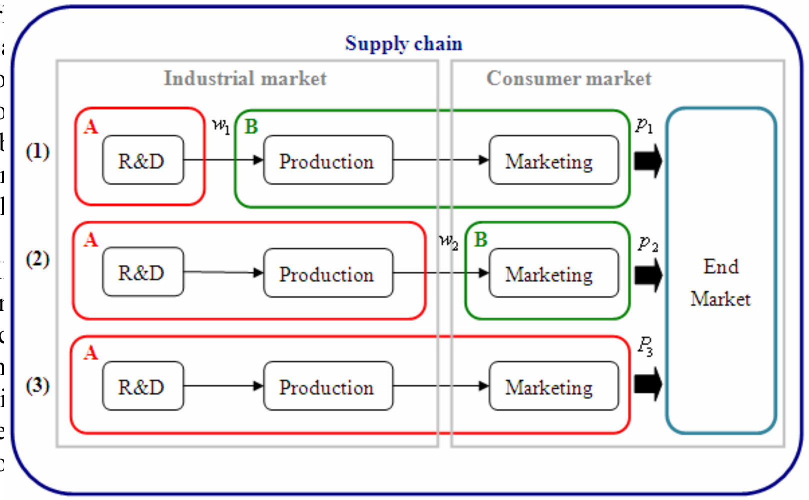


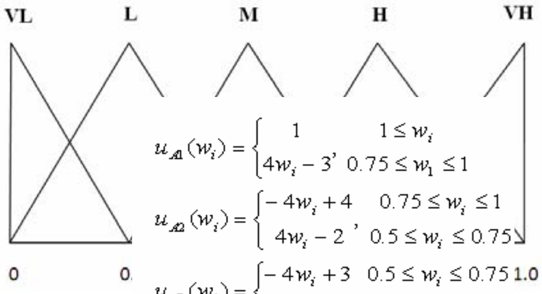
Figure 1 Collaboration models

Supposed that there were forth factors to affect the potential demand in this study, and ζ was the error term on demand with mean 0 and standard deviation σ. Thus, the ζ could be regarded as the other impact factors on demand, and the demand uncertainty was caused by those unconsidered factors. Here, ζ did not assume any specification distribution but noted that the lower support was such that the demand was always non-negative. Because the demand was impossible to be negative in the real world, ζ would be contributed to the various demand uncertainty level. Similar demand model had been used in the literature by Gurnani et al. (2007).

Patent Information Aggregation Procedure

This … …rated on the … …ed averages during the …

For e… …nd consequen… …idence and engineering… …patent exper… …minology of decision an… …to require th… …ts about the likelihood … …erefore, fuzz… …cepted and adopted by … …relative imp… …e linguistic terms defin… …s study were …



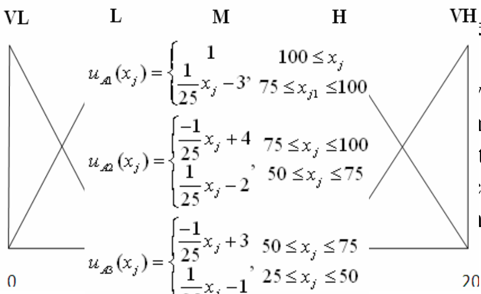


Figure … Figur… …ating

In this study, the v… …iables …uzzy numbers as follow

(2)

The criterions of th… …nt number, and self-cit… …ngular fuzzy numbers were used for the values… …lting factors.

$$u_{A1}(w_i)=\begin{cases}1 & 1\le w_i\\ 4w_i-3, & 0.75\le w_1\le 1\end{cases}$$

$$u_{A2}(w_i)=\begin{cases}-4w_i+4 & 0.75\le w_i\le 1\\ 4w_i-2, & 0.5\le w_i\le 0.75\end{cases}$$

$$u_{A3}(w_i)=\begin{cases}-4w_i+3 & 0.5\le w_i\le 0.75\\ 4w_i-1, & 0.25\le w_i\le 0.5\end{cases}$$

$$u_{A4}(w_i)=\begin{cases}-4w_i+2 & 0.25\le w_i\le 0.5\\ 4w_i, & 0\le w_i\le 0.25\end{cases}$$

$$u_{A5}(w_i)=\begin{cases}-4w_i+1 & 0\le w_i\le 0.25\\ 1, & w_i\le 0\end{cases}$$

$i=1,2,3$

effect of No. of patent ci…

$\frac{\ldots+w_2x_{i2}+w_3x_{i3}}{w_1+w_2+w_3}$

effect of No. of patent

effect of No. of self − cit…

…nt citations by others of j…

…atent of firm i

$$u_{A1}(x_j)=\begin{cases}1 & 100\le x_j\\ \frac{1}{25}x_j-3, & 75\le x_{j1}\le 100\end{cases}$$

$$u_{A2}(x_j)=\begin{cases}\frac{-1}{25}x_j+4 & 75\le x_j\le 100\\ \frac{1}{25}x_j-2, & 50\le x_j\le 75\end{cases}$$

$$u_{A3}(x_j)=\begin{cases}\frac{-1}{25}x_j+3 & 50\le x_j\le 75\\ \frac{1}{25}x_j-1, & 25\le x_j\le 50\end{cases}$$

$$u_{A4}(x_j)=\begin{cases}\frac{-1}{25}x_j+2 & 25\le x_j\le 50\\ \frac{1}{25}x_j, & 0\le x_j\le 25\end{cases}$$

$$u_{A5}(x_j)=\begin{cases}\frac{-1}{25}x_j+1, & 0\le x_j\le 25\\ 0 & x_j\le 0\end{cases}$$

$j=1,2,3$

And then, the method proposed by Gun et al. (2008) would be applied to solve the desired criteria weights (w_1, w_2, w_3).

X : the rating of No. of self − citations of firm i

N : No. of firms in the market that develope the ralitive producti

Consistent with the empirical R&D literature (Trajtenberg, 1990; Dutta et al., 1999; Dutta et al., 2005), the output of R&D capability could be measured using weighted average with citations. This concept was constructed by the quality of the patent data. Therefore, this research would apply the averaging method to calculate the estimated value for measuring the relative R&D capability (RRDC):

$$\theta_i = \frac{w_1 A_{i1} + w_2 A_{i2} + w_3 A_{i3}}{w_1 + w_2 + w_3} \tag{3}$$

θ_i : the relative R & D capability effort of firm i
w_1 : the weight to measure the effect of No. of patent citations by others
w_2 : the weight to measure the effect of No. of patent
w_3 : the weight to measure the effect of No. of self − citations
A_{i1} : the number of citation of patents of firm i
A_{i2} : technology strength
A_{i3} : the number of No. of self − citations of firm i

Model Formulation

The notations that used in the model construction would be exhibited in the Table 1. The following section would indicate the relation between these dependent variables and R&D capability θ.

Table 1 Notation Table

Π_{Ai} :profits for firm A in model i, i=1, 2,3 Π_{Bi} :profits for firm A in model i, i=1, 2,3 α : Market size γ : Measure the impact of marketing capability effort on demand λ : Measure the impact of R&D capability level on demand c : unit cost v : the impact of R&D capability on variable cost σ: standard deviation of demand uncertainty η : the impact of marketing cost φ: the impact of R&D cost f : facilities cost θ: relative R&D capability effort	w : the wholesale price set by firm A in the industrial market p : the resale price set in the end-market D : Retail demand e: Market capability effort

Model 1: Developing R&D capability

In this model, firm A's objective function was:

$$\text{Max } [\Pi_{A1} = (w_1)(D) - \varphi\theta_1^2 / 2\,] \tag{4}$$

Where the cost of R&D capability was assumed to be $\varphi\theta^2/2$. Assume the variable cost made by operation process was $c(1+v\theta)$, where v might be less than or greater than zero. Allowing v to be negative to model the case when the variable production costs actually decline due to improvement in R&D capability (Banker et al., 1998). Then, firm B's objective function was:

$$\text{Max } [\Pi_{B1} = (p_1 - w_1 - c(1+v\theta_1))(D) - \eta e_1^2 / 2\,] \tag{5}$$

Where the cost of marketing capability was assumed to be $\eta e^2/2$.

Then, from the first order condition:

$$\frac{\partial \prod_{B1}}{\partial p} = 0 \Rightarrow p_1 = \frac{\alpha + \gamma e_1 + \lambda\theta_1 + \omega_1 + \zeta + c(1+v\theta)}{2} \tag{6}$$

Use the expression of p_1 from above, the expected profit of the firm B as followed:

$$E[\prod_{B1}] = [\frac{\alpha + \gamma e_1 + \lambda\theta_1 - \omega_1 - c(1+v\theta)}{2}]^2 + \frac{\sigma^2}{4} - \frac{\eta e_1^2}{2} \tag{7}$$

Next, find the optimal marketing capability level that maximized the firm B's profit:

$$\frac{\partial E[\prod_{B1}]}{\partial e_1} = 0 \Rightarrow e_1^* = \frac{\gamma}{2\eta - \gamma^2}[\alpha + \lambda\theta_1 - \omega_1 - c(1+v\theta)] \tag{8}$$

Use the expression of e_1 from above, p_1 of the firm B as followed:

$$p_1^* = \frac{(\alpha + \lambda\theta_1)\eta + \omega_1(\eta - \gamma^2) + (\eta - \gamma^2)c(1+v\theta)}{(2\eta - \gamma^2)} + \frac{\zeta}{2} \tag{9}$$

Then, the demand function could rewrite by the expression of p_1^* :

$$D_1(\omega_1, \theta_1) = \frac{\eta[\alpha + \lambda\theta_1 - \omega_1 - c(1+v\theta)]}{(2\eta - \gamma^2)} + \frac{\zeta}{2} \tag{10}$$

Find the optimal wholesale price level that maximized the firm A's profit:

$$\frac{\partial \prod_{A1}}{\partial \omega_1} = 0 \Rightarrow \omega_1 = \frac{\alpha + \lambda\theta_1 - c(1+v\theta_1)}{2} \tag{11}$$

Finally, the expected profit of firm A could be rewrite by the expression form above functions:

$$e_1 = \frac{\gamma}{4\eta - \gamma^2}[\alpha + \lambda\theta_1 - c(1+v\theta_1)] \tag{12}$$

$$p_1 = \frac{1}{4}[3\alpha + 3\gamma e_1 + 3\lambda\theta_1 + c(1+v\theta_1)] + \frac{3}{8}\sigma^2 \tag{13}$$

$$E[\Pi_{A1}^*] = \frac{\eta}{4(2\eta - \gamma^2)}[\alpha + \lambda\theta - c(1+v\theta)]^2 - \frac{\varphi\theta_1^2}{2} \tag{14}$$

Model 2: Developing R&D and operation capabilities

In this model, firm B's objective also could be presented as:

$$\text{Max } [\Pi_{B2} = (p_2 - w_2)(D_2) - \eta e_2^2/2 \,] \tag{15}$$

It was easy to see that the profit function was concave in p. Then, from the first order condition:

$$\frac{\partial \Pi_{B2}}{\partial p_2} = 0 \Rightarrow p_2 = \frac{\alpha + \gamma e_2 + \lambda\theta_2 + \omega_2 + \zeta}{2} \tag{16}$$

Use the expression of p from above, the expected profit of the firm B as followed:

$$E[\Pi_{B2}] = [\frac{\alpha + \gamma e_2 + \lambda\theta_2 - \omega_2}{2}]^2 + \frac{\delta^2}{4} - \frac{\eta e_2^2}{2} \tag{17}$$

Next, find the optimal marketing capability level that maximized the firm B's profit:

$$\frac{\partial E[\Pi_{B2}]}{\partial e_2} = 0 \Rightarrow e_2^* = \frac{\gamma}{2\eta - \gamma^2}[\alpha + \lambda\theta_2 - \omega_2] \tag{18}$$

In order to ensure concavity and that there were no pathological cases of negative marketing capability effort, $2\eta > \gamma^2$ was the required condition. Hence, using e^*_2 from above could get:

$$p_2^* = \frac{(\alpha + \lambda\theta_2)\eta + \omega_2(\eta - \gamma^2)}{(2\eta - \gamma^2)\,\eta} + \frac{\zeta}{2} \tag{19}$$

$$E[\Pi^*_{B2}(\omega_2, \theta_2)] = \frac{\eta}{2(2\eta - \gamma^2)}[\alpha + \lambda\theta_2 - \omega_2]^2 + \frac{\delta^2}{4} \tag{20}$$

$$D_2(\omega_2, \theta_2) = \frac{\eta(\alpha + \lambda\theta_2 - \omega_2)}{(2\eta - \gamma^2)} + \frac{\zeta}{2} \tag{21}$$

Let $K = \frac{\eta}{(2\eta - \gamma^2)}$ (22)

Get $E[\Pi^*_{B2}(\omega_2, \theta_2)] = \frac{K}{2}[\alpha + \lambda\theta_2 - \omega_2]^2 + \frac{\delta^2}{4}$ (23)

$$D_2(\omega_2, \theta_2) = K(\alpha + \lambda\theta_2 - \omega_2) + \frac{\zeta}{2} \tag{24}$$

Then, firm A's objective function was:

$$Max\left[\Pi_{A2} = (w_2 - c(1 + v\theta_2))(D_2) - \varphi\theta_2^2/2 - sf\right]$$
$$\Pi_{A2} = \left[w_2 - c(1 + v\theta)\right]\left[K(\alpha + \lambda\theta_2 - \omega_2) + \frac{\zeta}{2}\right] - \varphi\theta_2^2/2 - sf \tag{25}$$

Since firm A both developed R&D and invested operation capability, not only the R&D cost but also variable cost by production should join into the objective function. The firm A's profit function was concave if $\left(2\varphi - K(\lambda - cv)^2 > 0\right)$. Assume that above condition was valid, then from the first order conditions and noting that E[ζ]=0, get:

$$\frac{\partial \Pi_{A2}}{\partial \omega_2} = 0 \Rightarrow \omega_2 = \frac{\alpha + \lambda\theta_2 + c(1 + v\theta_2)}{2} \tag{26}$$

Solving above function for ω and θ, get:

$$\omega_2 = \frac{1}{2}[\alpha + \gamma e + \lambda\theta + c(1 + c\theta)] \tag{27}$$

$$e_2 = \frac{\gamma}{4\eta - \gamma^2}[\alpha + \lambda\theta_1 - c(1 + v\theta_1)] \tag{28}$$

$$p_2 = \frac{1}{4}[3\alpha + 3\gamma e_1 + 3\lambda\theta_1 + c(1 + v\theta_1)] + \frac{3}{8}\sigma^2 \tag{29}$$

$$E[\Pi^*_{A_2}](\theta_2) = \frac{1}{8}[\alpha + \gamma e + \lambda\theta - c(1 + v\theta)]^2 + \frac{1}{16}\sigma^2 - \frac{\varphi\theta^2}{2} - sf \tag{30}$$

$$E[\Pi^*_{B_2}](\theta_2) = \frac{\varphi\theta_2^2}{2K(\lambda - cv)} + \frac{\sigma^2}{4} \tag{31}$$

Form the above functions, the expected profits could be observed were independent of level of R&D capability level, market size, and uncertainty in demand. Therefore, changing the value of R&D capability level θ , market size α, and demand uncertainty σ could affect the value of expect profits. The selection of collaboration models could be changed by the different profits for R&D firms. Also, the different uncertainty level on demand could affect the decision making by R&D firms.

Also, noted that $\frac{\partial \Pi_{A2}}{\partial \eta}$, $\frac{\partial \Pi_{B2}}{\partial \eta} < 0$, and $\frac{\partial \Pi_{A2}}{\partial \varphi}$, $\frac{\partial \Pi_{A2}}{\partial \varphi} < 0$, that was, the Firm A's and B's profits were decreasing in increasing cost of marketing selling effort and in the cost of building R&D quality. Observed form $E[\Pi^*_{A_2}]$ and $E[\Pi^*_{B_2}]$ that while expected profits were independent of level of uncertainty in demand, expected firm B's profits increased in σ, but firm A's was not.

Model 3: Developing R&D, operation, and marketing

In this model, firm A should develop the product by himself and set the only price to end-market. Hence, the firm A's objective function was:

$$\text{Max } [\Pi_{A3} = (P_3 - c(1 + v\theta_3))(D) - \varphi\theta_3^2/2 - \eta e_3^2/2 - sf \,] \tag{32}$$

It was easy to see that the profit function was concave in w_3. Then, from the first order condition for w_3:

$$\frac{\partial \Pi_{A3}}{\partial \omega_3} = 0 \Rightarrow P^*_3 = \frac{\alpha + \gamma e_3 + \lambda\theta_3 + \omega_3 + \zeta + c(1 + v\theta_3)}{2} \tag{33}$$

Then the demand function could be rewrite as:

$$D^* = \frac{\alpha + \gamma e_3 + \lambda\theta_3 + \omega_3 + \zeta + c(1 + v\theta)}{2} \tag{34}$$

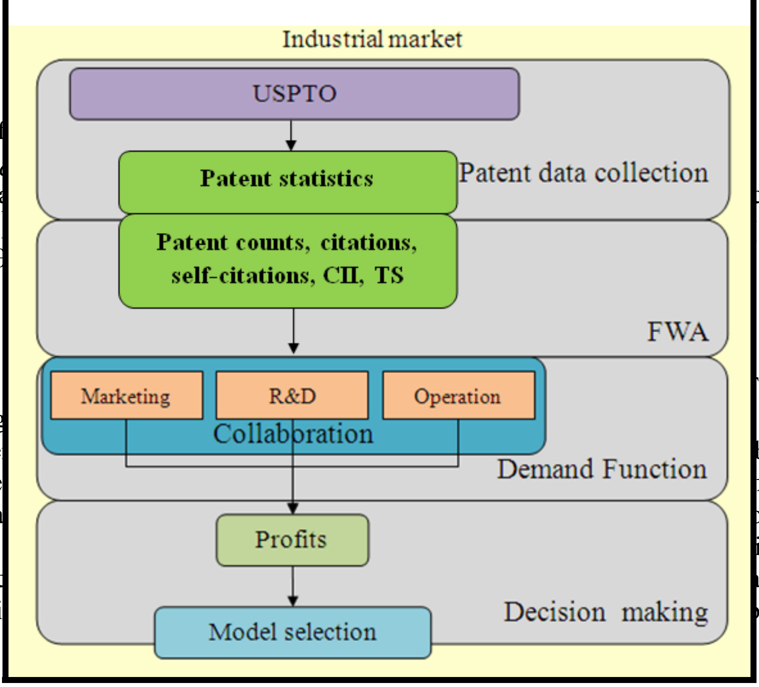
Therefore, the expected profit could get form above solutions;

$$E[\Pi^*_{A3}] = \frac{1}{4}[\alpha + re_3 + \lambda\theta_3 - c(1 + v\theta_3)]^2 + \frac{\sigma^2}{8} - \frac{\eta e_3^2}{2} - \frac{\varphi\theta_3^2}{2} - sf \tag{35}$$

Then, from the first order condition for e_3:

$$\frac{\partial E[\Pi_{A3}]}{\partial e_3} = 0 \Rightarrow e^*_3 = \frac{\gamma[\alpha + \lambda\theta_3 - c(1 + v\theta_3)]}{2\eta - \gamma^2} \tag{36}$$

Solving above function f
$p_3 = \frac{1}{2}[\alpha + \gamma e + \lambda\theta +$ (37)
We noted from above tha
, as expected. Further,
observed that the e^*_3 and $E[$
$_{A3}{}^*]$ could have liner relation
with relative R&D capability θ



CASE STUDY

The research framework
igure 4. The first step was to
analyze the patent data throug
(USPTO). The three criteria
would be collected, which we
be used to obtain the weighted
sum of those criteria evaluate
from the FWA method could
measure the R&D capability a
on would be constructed based
on the capability impacts on
ilities. And then, the demand
function could contribute to c
lysis with different simulated
parameter settings would be i
bility. According to the profits
resulted from R&D capability

Sample and Patent Data

The data of this research
ch as previous researches in the
nanotechnology-related field (H
's patent data could be collected
from 2003 to 2008. The data se
ysis software, Patent Guider, to
facilitate the search for the pater

Measured using a citation
as a current impact index (CII)
(Breitzman et al., 2002). CII wa
's most recent 5 years of patents,
divided by the expected numbe
ilar technology companies. The
technology strength (TS) was de
npact index. Patent counts could
be modulated to the technology
ogical activity, the patent counts
measure, and the quality of the
of patent counts would be the
company's the technology stren

For evaluating the applic
nplement the case study for the
Aluminum Nitride related pater
rd-based search in the USPTO.
Some of the collected data did n
ignee would be not taken in. The
patents were issued by 720 firm
II was zero would be excluded.
Hence, 720 firms would be adju

Implementation Procedure

The proposed measureme
ction collaboration plan. The
measurement procedure of the p
was shown in Figure 5. The
implementation procedure conta

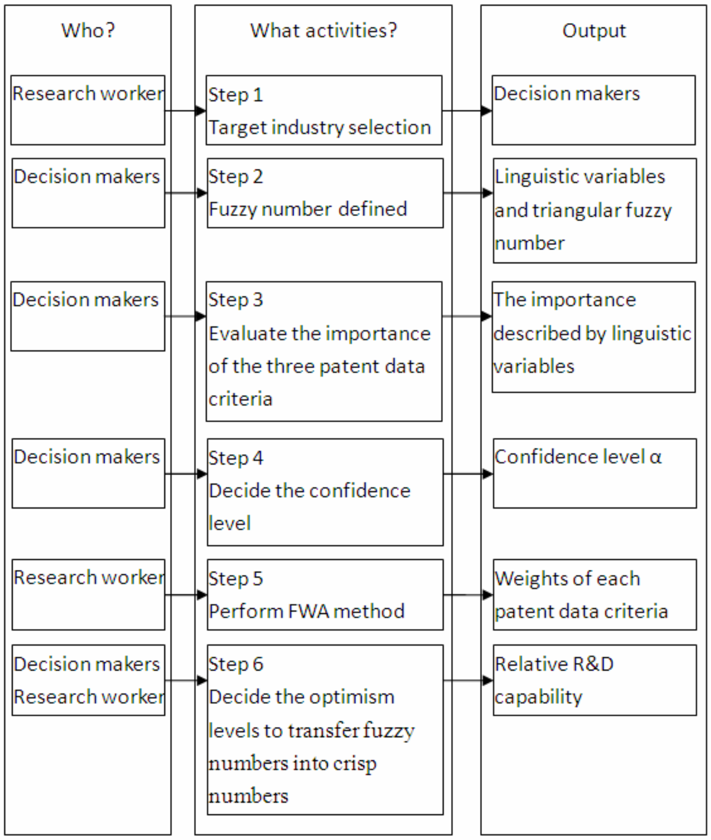


Figure 5 The implementation procedure of the measurement approach

First, the case company was selected from the target industry. The case firm's patent manager or R&D manager could be invited to perform the evaluation, regard as the decision makers (DM) which could provide the relative importance for each patent data criteria. The decision makers could provide the evidence and numerical judgments to evaluate the likelihood and consequences of each patent data criteria. Second, the decision makers defined their linguistic variables and corresponding triangular fuzzy numbers. The DM's definition of linguistic variables and corresponding triangular fuzzy numbers in a graph could be exhibited in Figure 2 and Figure 3. Third, the decision makers used linguistic variables to evaluate the three patent data relative importance on relative R&D capability. The linguistic variables contained five levels which were very high, high, medium, low, and very low. The decision makers should decide the linguistic variables for the three patent data criteria according to their experience and knowhow for the target industry. Fourth, the decision makers decided upon the confidence levels. The confidence level decided the range of the fuzzy numbers which were evaluated by linguistic variables. The high value of confidence level meant that the decision makers had more confidence for the determined linguistic value. Fifth, because this was the first time they were using this approach, the managers decided to simplify the arithmetical process of FWA by using confidence level $\alpha = 0.5$ to calculate the weighted scores of those criteria. As an example, we had Manager evaluate chemistry industry for the Aluminum Nitride product. The evaluation results of the feasibility factors and their corresponding importance rates, presented in linguistic values, were [very high, high, high] for the patent data criteria [Citations, patent counts, self-citation], respectively. The linguistic values could be replaced with triangular fuzzy numbers according to the Manager's definition of linguistic variables and triangular fuzzy numbers. After the computational procedure of FWA, the weights for the patent data criteria were [0.9375, 0.75, 0.5] which could be obtained. Sixth, the decision makers decided the optimism levels that were used to transfer fuzzy numbers into crisp numbers. The weighted average method could be used to aggregate the evaluated weights and patent data to relative R&D capability (RRDC). Finally, the different case companies from different industries all could apply the step 1 to step 6 for the relative R&D capabilities of different industries. The case study could help to examine the application of the measurement for different industries.

Model Comparisons and Case Analysis

How the R&D firm's profit and price changed could be illustrated with R&D relative capability using the following simulation example. The parameter setting was exhibited in Table 2.

Table 2 Parameters setting

Control variable	Parameters simulation setting
α : Market size	100
γ : Measure the impact of marketing capability effort on demand	0.9
λ : Measure the impact of R&D capability level on demand	2
c : unit cost	7
v : the i	
σ: stand	
η:the im	
ψ:the im	
s : firm	
f : facil	

The effect of R… …rofits of model 1 and
model 2 increased at f… …reased. We could find
that the interaction ha… …split into three levels:
low, medium, and high… …f model 3 smaller than
model 2. The medium… …smaller than model 1.
The high level meant…

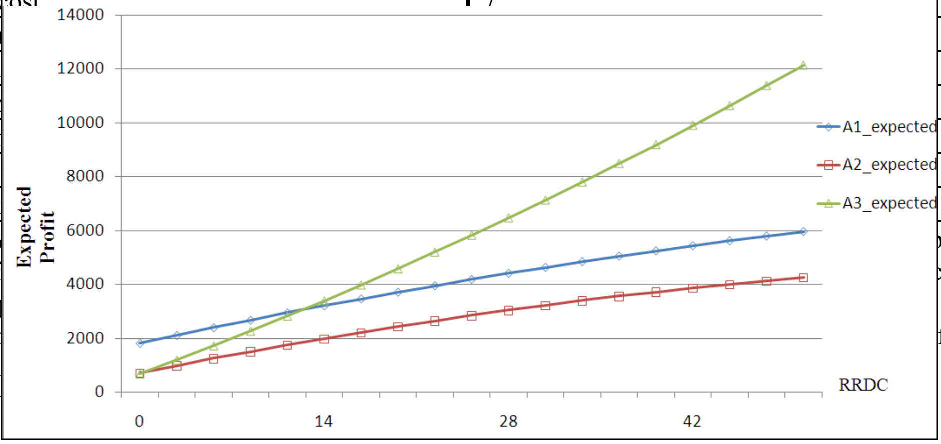


Figure 6 Effect of R&D capability effort on expected profit (RRDC = 0~50)

This research would apply decision trees to construct decision rules and predict the feasible options. A decision tree was a well-known tool to model and to evaluate a decision process which consisted of an alternating sequence of actions and uncertain consequences (Lootsma, 1997; Reyck et al., 2008). Decision trees analysis was one of the different approaches to build a classification model. Focusing on the data provided, decision trees produced a model of tree-shaped structure using inductive reasoning. To classify all input data, each node of the tree was a distinguish equation. The equation would focus on a certain variable and determine whether the imported data was greater than, equal to, or less than a certain value. Each node of such could classify the imported data into different category afterwards (Chien et al., 2005). Decision tree was a common method that provided both classification and predictive functions simultaneously. With a sequence of questions and rules, data was classified to predict the feasible the value of each options. Featuring the use of similar models to predict similar outcomes, the decision tree theory was very suitable for conducting plan selection and data analysis explanations for decision making (Chang and Chen, 2009). The decision tree of this case was exhibited Figure 4-7.

In the Aluminum Nitride case of the decision tree, when relative R&D capability was lower than 12.343, the model 1 was most feasible. Figure 4-8 and Table 4-6 were histogram of each RRDC level counts and Accumulated table of RRDC separately. It could be observed that RRDC of 73.6% companies were lower than 12.343. Hence, if the company's RRDC was the top 26.4% in the

Aluminum Nitride industry, with model 1 could increase
its R&D capability until th ompany could switch from
model 1 or model 2 to mode npanies had low RRDC and
the highest RRDC firm had evealed that few companies
owned the most technolog increasing R&D capability
quickly to improve the R&

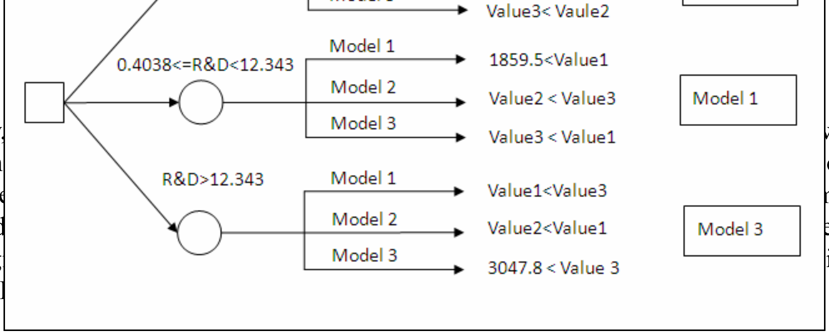


Figure 7 Decision tree for model selections

Sensitivity Analysis

Sensitivity analysis investigated how the decision value might change given a change in the problem parameter setting. The result of the changed might cause different decision making outcome. This research would investigate the impacts of the parameters value changed for final price and R&D firm's profits. The investigated parameters of this research were exhibited same as Table 1, and the θ was 51. To conduct sensitivity analysis, we first simply change the value of one parameter and fix all others and see the effects on the final price, and the expected profit for each model. The value of the parameter would be changed by the range {-50%, -30%, -10%, +10%, +20%, +50%}. If the range of the value was too wide, the original value would lose its sense. If the range of the value was too narrow, the difference of the numerical analysis would be hard to distinguish. Hence, this research would adopt the range {±50%} to implement the sensitivity analysis. Following sections would present sensitivity analysis for each model. The results of above sensitivity analysis could be concluded in Table 3.

Table 3 The results of sensitivity analysis

Model 1	**α**	**γ**	**λ**	**c**	**v**	**σ**	**η**	**ψ**	**f**
Profit	High	High	High	High	High	No	High	High	No
Price	High	High	High	Low	Low	High	High	No	No
Model 2	**α**	**γ**	**λ**	**c**	**v**	**σ**	**η**	**ψ**	**f**
Profit	High	High	High	High	High	Low	High	High	High
Price	High	High	High	Low	Low	High	High	No	No
Model 3	**α**	**γ**	**λ**	**c**	**v**	**σ**	**η**	**ψ**	**f**
Profit	High	High	High	High	High	Low	High	High	High
Price	High	High	High	Low	Low	High	High	No	No

The results of sensitivity for the three models were the consistent. It could be observed from those charts that the expected profits increased when the values of α, γ, λ, c, v and σ increased, but decreased as the η, ψ, and f increased. Moreover, the model 2 was more highly sensitive than the other two models because the model 2 had the highest sensitivity to change in parameter α, λ, c, v, ψ, σ, and f. Therefore, the profit the model 2 could be considered the one which was more easily to be affected by possible factors. In a reasonable decision process, the model 2 could be a plan with highly risk comparative to the other models.

For the requirement to conduct a robust sensitivity analysis which posit the need for an analysis more comprehensive than the static case that only changed a single parameter with others being constant, as discussed above. Therefore, the experimental design techniques proposed by Taguchi would be implemented in the following analysis (Taguchi, 1987) . Based on the Taguchi method, experimental designs could be conduct for three models. It consisted of the nine control factors: Market size, the impact of marketing capability effort on demand, the impact of R&D capability level on demand, unit cost, the impact of R&D capability on variable cost, standard deviation of demand uncertainty, the impact of marketing cost, the impact of R&D cost, and facilities cost. A $L_{12}2^9$ orthogonal table was selected for assigning the control variables, in which levels 1 and 2 represent +10% and -10% of the value of initial parameter setting, respectively. Based on the SN ratio proposed by Taguchi, which was used to measure the quality characteristic that deviated from the desired value, we derived the optimal conditions. The SN ratio calculated by the following equation was used to estimate the quality variation (Taguchi, 1987):

$$SN = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{38}$$

Where y_i was the performance response for the ith setting of the parameter combination, n was the number of samples of the performance response corresponding to the number of design parameter combinations. Because the expected profit the larger more better, in this case the larger the SN ratio the better(Taguchi, 1987).

Table 4 Design and experimental results

NO.	**A**	**γ**	**λ**	**c**	**v**	**σ**	**η**	**ψ**	**f**	Π_1	Π_2	Π_3	**SNR**
1	1	1	1	1	1	1	1	1	1	3538.2	2232.01	8830.6	70.0962

2	1	1	1	1	1	2	2	2	2	1714.1	389.70	6998.4	56.3541
3	1	1	2	2	2	1	1	1	2	6444.4	4793.87	12219.5	76.0619
4	1	2	1	2	2	1	2	2	1	4926.5	3152.80	11202.7	73.0169
5	1	2	2	1	2	2	1	2	1	8970.4	6015.01	14626.9	78.2642
6	1	2	2	2	1	2	2	1	2	7242.0	5165.54	12429.1	76.7766
7	2	1	2	2	1	1	2	2	1	5400.6	4161.33	13094.2	74.8649
8	2	1	2	1	2	2	2	1	1	6571.3	5329.86	13708.6	76.7311
9	2	1	1	2	2	2	1	2	2	5356.6	3709.72	12414.8	74.2020
10	2	2	2	1	1	1	1	2	2	10744.3	7339.08	16846.8	79.8925
11	2	2	1	2	1	2	1	1	1	9781.7	6859.06	15036.7	79.1926
12	2	2	1	1	2	1	2	1	2	7340.6	5254.51	13266.9	76.9566
Rank	3	1	2	7	6	9	4	5	8				

Based on the SN ratio, the optimal conditions for the three models were the NO. 10. Furthermore, Table 4 was response table for SN ratios which revealed that γ has a greater effect on the expected profit. It implied if the effect of marketing on demand increased the expected profit would increase more obviously than other parameters. Therefore, if the company wanted to increase its profit, how to increase demand by marketing was the most efficient. Moreover, the results of three models all presented same ranks of parameters. The rank 2 factor was λ which measured the R&D capability effect on demand. The rank 3 factor was α which measure the market size. It could be observed that those three factors all relate about market demand. Therefore, the market demand was a critical issue relative increase profit (Day, 1994). Obviously, the demand factors selected the high level because they had right proportion with profits. The cost factors selected the low level because they had inverse proportion with profits. There was a finding that demands uncertainty σ was low level. It revealed that low demands uncertainty could be an ideal environment situation (Kotler and Keller, 2006).

CONCLUSION REMARK

This research mainly accomplished two tasks: R&D capability measurement, and collaboration models constructing and selection. This research distinguished R&D capability levels for firms in the target industry through measuring R&D capability by patent analysis. The output of the measurement could be taken as an index for decision makers to choose a production or business model. This similarly concept also performed in the previous literatures (Dutta et al., 2005; Storto, 2006; Ma and Lee, 2008). They collected economical data to compare the critical capabilities' importance and the profit performance. This research investigated the R&D capability with patent data specifically. This research collected relative patent data of Aluminum Nitride product, and those empirical data could facilitate to verify the feasibility of this measurement. The results provided evidence for the feasibility of implementation in the case study, and recognition by the importance of market demand.

There are four research limitations which can deserve further attentions to future researches. The first one is FWA method application and which can be substituted for other methods to improve the effectiveness of weights setting. The second one is model construction and which can join more factors to improve the feasibility of collaboration models. The third one is R&D capability measurement. We might apply other indexes to improve the nature drawback of patent data. The fourth one is cases verification. More empirical cases can provide more evidences to verify the feasibility of this approach.

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