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# Analysis and Evaluation for Core Competence of Insurance Company Based on SEM

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## ABSTRACT

*Evaluation the core competence reasonably plays an important role in the insurance company, it is related to whether the insurance can maintain a stable long-term competitive advantage or not, and whether obtain a stable long-term excess profits or not. In this paper, we select* 6 *first-degree indexes* (*including the core competence*) *and* 28 *second-degree indexes to evaluate the core competence of insurance company by Structural Equation Model* (*SEM*), *and analysis the relationships among the first-degree indexes. Besides, we use a new algorithm proposed by us to improve the calculation of SEM.*

***Keywords:*** *Core Competence, Insurance, SEM, Algorithm*

## 1. Introduction

The essential of competition among enterprises is scramble for the required resources of their survival and development of enterprises, the competitiveness of enterprises is the ability of enterprises to compete for resources [1]. Traditional competitive theory still can not make a satisfactory answer of the long-term ups and downs of Enterprise. However, the theory of the core competitiveness study the ability of optimal allocation of resources of enterprises from the short-term extends to long-term. And point out that in order to make sure the survival and development of corporate sustainability, we must have more ability of optimal allocation of resources. In other words, companies must have strong core competitiveness.

The core competence was first proposed by C. K. Prahalad and Gary Hamel [2]. This theory is a kind of business strategy concept and paradigm which has great vitality; it opened the real password of the modern business success in a sense. Enhance the core competitiveness have great strategic significance for the development of the insurance business. Insurance companies operate with the characteristics of debt, once the insurance companies have poor core competitiveness, poor operating performance and unable to bear the compensation or payments, they will harm the vital interests of the insured, and even affect the stability of the whole society. So it is very significant to study the core competence of insurance company.

The core competence of insurance company is different from the general company. Professor J. P. Jan believes that the following 3 reasons account for this phenomenon. First, the insurance company cannot establishment the core competence rely on market segmentation or monopoly. Second, insurance products cannot apply for a patent. Third, regulatory authorities require the insurance company provide the transparent and open information of the insurance products for financial supervision [3]. Based on this features, many scholars establish the model to evaluate the core competence of insurance company. Such as DEA data envelopment analysis model, BSC (Balanced Score Card model) [4] and so on. Among the most important and most widely recognized model is FCEM (Fuzzy Comprehensive Evaluation Model) [5]. However, all of the above models are very subjective in a sense. In this paper, we introduce a model in which the coefficients and weights are calculated by samples, so it is more objective and convincing, and could offer more deep analysis for the index systems.

## 2. SEM for the Core Competence of Insurance Company

SEM is a rapid-developing embranchment of Application Statistics, which has a wide application in the area of Psychology, Economics and Sociology [6,7], especially in Customer Satisfaction Index (CSI) [8] model which is required by a series of ISO9000 criterions. This model

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not only studies the interior relationship among various factors, but also the relative and causal relations among latent variables. As we know, we cannot observe the value of the core competence directly. So it is a latent variable, and we can use the SEM to research.

Different companies have different competitive advantages; it may be different with the company's industrial environment and strength. For example, Intel's core competence is the chip manufacturing technology; Coca-Cola Company's core competence is a trademark and formula, while Galanz's core competence is the large-scale and low-cost production capacity. The difference of the external environment and internal resources among the different industry is very large, so the constituent elements and cultivation methods of the core competence would be different with each other. Therefore, with the basic principles of selected index [9], we consider the specificity of the insurance enterprise; identified 5 first-degree indexes which have relate to the enterprise's core competence, all of them are latent variables. In order to study the core competence, we have to seek the observed variables for each latent variable. The variables are listed in **Table 1** as follows:

There exists 13 relationships among the 6 structural variables (latent variables), which are expressed in **Figure 1** (The relationships among variables are $\gamma_1 \sim \gamma_5$, expressed with dashed arrowheads; the relationships among independent variables are $\beta_{ij}$, expressed with real-line arrowheads). The structural relationship among the latent variables (structural model) can be put as follows:

As shown in the **Figure 1**, we can see the path relationships or causalities among these variables. Next we can express these causalities among the structural variables as equations as below:

$$\begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 & 0 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 0 & 0 \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & 0 \end{pmatrix} \begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{pmatrix} + \begin{pmatrix} \gamma_{11} \\ \gamma_{12} \\ \gamma_{13} \\ \gamma_{14} \\ \gamma_{15} \end{pmatrix} \xi_1 + \begin{pmatrix} \varepsilon_{\eta_1} \\ \varepsilon_{\eta_2} \\ \varepsilon_{\eta_3} \\ \varepsilon_{\eta_4} \\ \varepsilon_{\eta_5} \end{pmatrix} \quad (1)$$

In general, suppose that $\eta_1 \sim \eta_m$ are $m$ dependent variables, arranging them as a vector $\eta$ by column as (1), that is $\eta' = \left(\eta_1', \eta_2', \cdots, \eta_{m-1}', \eta_m'\right)$, we called it as endogenous latent variables; and $\xi_1 \sim \xi_k$ are $k$ independent variables, arranging them as a vector $\xi$ by column also, $\xi' = \left(\xi_1', \xi_2', \cdots, \xi_{k-1}', \xi_k'\right)$, we call it as exogenous latent variables. Then $m \times m$ square matrix $B$ is the coefficient matrix of $\eta$, and $m \times k$ matrix $\Gamma$ is the coefficient matrix of $\xi$, let $\varepsilon_\eta$ is the residual vector, then Equation (1) may be extended as:

$$\eta = B\eta + \Gamma\xi + \varepsilon_\eta \quad (2)$$

where $m = 5$ and $k = 1$.

**Table 1. Index of variables**

| Structural variables | Observed variables | | | | |
|---|---|---|---|---|---|
| Organizational capacity $\xi_1$ | Employ satisfaction $x_{11}$ | Employee turnover $x_{12}$ | Enterprise cohesion $x_{13}$ | Staff training input rate $x_{14}$ | |
| Quality of service $\eta_1$ | Customer Satisfaction $y_{11}$ | Corporate reputation $y_{12}$ | Customer loyalty $y_{13}$ | Corporate social image $y_{14}$ | Emergency Management capacity $y_{15}$ |
| Innovation capacity $\eta_2$ | New insurance development rate $y_{21}$ | New insurance development cycle $y_{22}$ | R & D investment rate $y_{23}$ | New insurance premium income rate $y_{24}$ | Patents possess rate $y_{25}$ |
| Market capacity $\eta_3$ | Market possess rate $y_{31}$ | Insurance depth $y_{32}$ | Insurance density $y_{33}$ | Market reaction speed $y_{34}$ | Explore new market capacity $y_{35}$ |
| Risk management $\eta_4$ | Solvency $y_{41}$ | Capital adequacy rate $y_{42}$ | Investment Income rate $y_{43}$ | Insurance funds efficiency $y_{44}$ | |
| Core competence $\eta_5$ | ROE $y_{51}$ | Sales profit rate $y_{52}$ | Profit growth rate $y_{53}$ | Per capita profit $y_{54}$ | Financial stability factor $y_{55}$ |

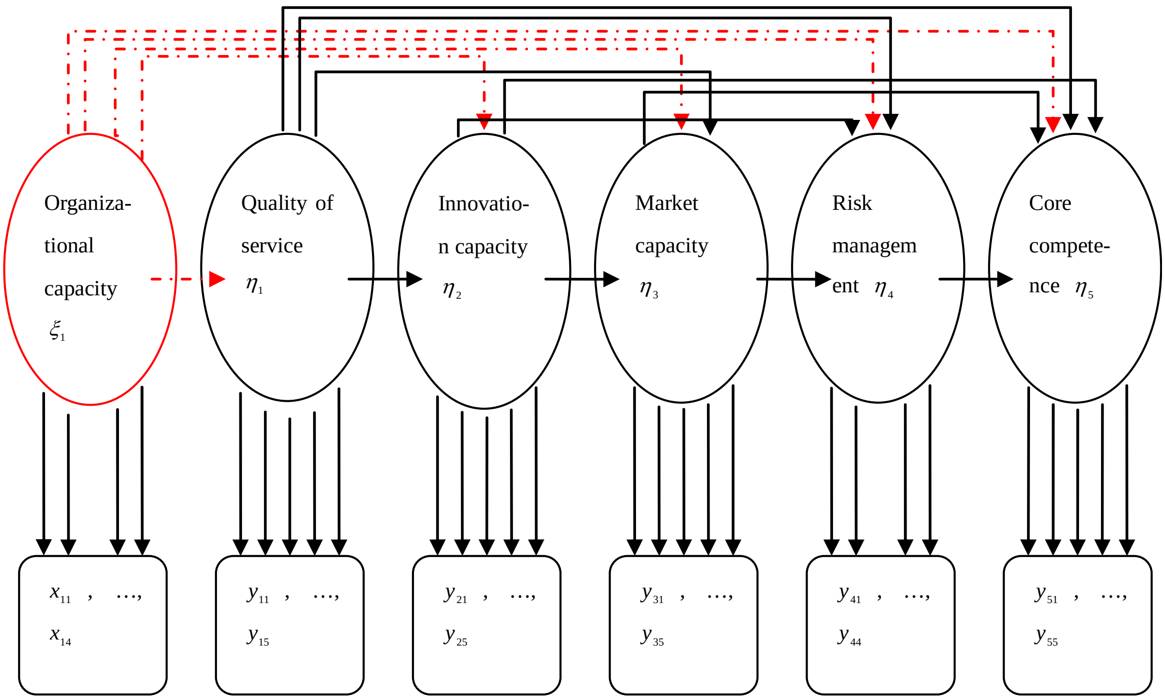


**Figure 1. Path relationships among variables**

There are always two systems of equations in a SEM. One is a structure system of equations among structural variables, and the other one is a measurement system of equations between structural variables and observed variables. From the above narrative, we can know the Equation (2) is the structure system of equations. And the structural variables are always implicit and cannot be observed directly. So there must have many observed variables to reflect the structural variables. And the relationships between the latent variables and the observed variables are the other equations of SEM, which are measurement system equations.

From the above, we know there are $k$ exogenous latent variables and $m$ endogenous latent variables. Generally the observed variables corresponding to $\xi_i$ are denoted as $x_{ij}$, $i=1,\cdots,k$; $j=1,\cdots,h(i)$, here $h(i)$ is the number of observed variables corresponding to $\xi_i$. Similarly, the observed variables corresponding to $\eta_t$ are denoted as $y_{ts}$, $t=1,\cdots,m$, $s=1,\cdots,g(t)$, here $g(t)$ is the number of observed variables corresponding to $\eta_t$. Then the observation equations in the **Figure 1** can be expressed as the relationship from the observation variables to the structural variables:

$$\xi_i=\sum_{j=1}^{h(i)}\psi_{ij}\,x_{ij}+\varepsilon_{xi},\quad i=1,\cdots,k \tag{3}$$

$$\eta_t=\sum_{s=1}^{g(t)}\omega_{ts}\,y_{ts}+\varepsilon_{yt},\quad t=1,\cdots,m \tag{4}$$

Where $\psi_{ij}$, $\omega_{ts}$ are the summarizing coefficients, and $\varepsilon$ with subscripts are random error items. Let $X_i'=\left(x_{i1}',\cdots,x_{ih(i)}'\right)$, $Y_t'=\left(y_{t1}',\cdots,y_{tg(t)}'\right)$, $\psi_i'=(\psi_{i1},\cdots,\psi_{ih(i)})$, $\omega_t'=(\omega_{t1},\cdots,\omega_{tg(t)})$. Then combining the Equations (2), (3) and (4) as:

$$SEM^+=\begin{cases}\eta=B\eta+\Gamma\xi+\varepsilon_\eta\\ \xi_i=\psi_i'X_i+\delta_{xi},\quad i=1,\cdots,k\\ \eta_t=\omega_t'Y_t+\delta_{yt},\quad t=1,\cdots,m\end{cases} \tag{5}$$

here $SEM^+$ is the structural equations model with positive observation.

On the other hand, the measurement equations can be also expressed as follows:

$$\begin{pmatrix}x_{i1}\\x_{i2}\\\vdots\\x_{ij}\end{pmatrix}=\begin{pmatrix}\upsilon_{i1}\\\upsilon_{i2}\\\vdots\\\upsilon_{ij}\end{pmatrix}\xi_i+\begin{pmatrix}\varepsilon_{x_{i1}}\\\varepsilon_{x_{i2}}\\\vdots\\\varepsilon_{x_{ij}}\end{pmatrix} \tag{6}$$

$i=1,\cdots,k;\ j=1,\cdots,h(i)$

$$\begin{pmatrix}y_{t1}\\\vdots\\y_{ts}\end{pmatrix}=\begin{pmatrix}\lambda_{t1}\\\vdots\\\lambda_{ts}\end{pmatrix}\eta_t+\begin{pmatrix}\varepsilon_{y_{t1}}\\\vdots\\\varepsilon_{y_{ts}}\end{pmatrix} \tag{7}$$

$t=1,\cdots,m;\ s=1,\cdots,g(t)$

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here, $\upsilon_{ij}$ and $\lambda_{ts}$ are the loading coefficients, and $\varepsilon$ with subscripts are random error items yet.

Let $\upsilon'_i = \left(\upsilon_{i1}, \cdots, \upsilon_{ih(i)}\right)$ and the same time let $\Lambda'_t = \left(\lambda_{t1}, \cdots, \lambda_{tg(t)}\right)$. Then (5) and (6) can be expressed as:

$$X_i = \upsilon_i \xi_i + \varepsilon_{xi}, \quad i = 1, \cdots, k \tag{8}$$

$$Y_t = \Lambda_t \eta_t + \varepsilon_{yt}, \quad t = 1, \cdots, m \tag{9}$$

Combine the Equations (2), (8) and (9), then we can get:

$$SEM^- = \begin{cases} \eta = B\eta + \Gamma\xi + \varepsilon_\eta \\ X_i = \upsilon_i \xi_i + \delta_{xi}, \quad i = 1, \cdots, k \\ Y_t = \Lambda_t \eta_t + \delta_{yt}, \quad t = 1, \cdots, m \end{cases} \tag{10}$$

here $SEM^-$ the structural equations model with converse observation.

## 3. Modular Constraint Least Squares Solution (MCLS)

We can skillfully use the least squares method in regression between each structural variable and its corresponding observation variables, and obtain the least squares solution of structural variable by the modular constraint of structure vector if we analyzing the observation equations of SEM carefully [10,11]. The algorithm for MCLS can be expressed as follows:

**Algorithm 1**. The MCLS of structural vector in $SEM$.

**Step 1** In $SEM^-$, suppose $\xi_i, \eta_t$ all are unit vectors, we can calculate the least square estimates of the coefficients between each structural variable and its corresponding observation variables:

$$\upsilon_{ij}^2 = x_{ij} x'_{ij} - \hat{\varphi}_{ij}^2$$
$$j = 1, \cdots, h(i); i = 1, \cdots, k \tag{11}$$

where

$$\hat{\varphi}_{ij}^2 = \hat{\phi}_{ij}^{-1}, \hat{\Sigma}_{ix} = x_i x'$$
$$diag(\phi_{i1}^2, \phi_{i2}^2, \cdots, \phi_{ih(i)}^2) = \hat{\Sigma}_{ix}^{-1} \tag{12}$$

Similarly we have

$$\hat{\lambda}_{ts}^2 = y_{ts} y'_{ts} - \hat{\vartheta}_{ts}^2$$
$$s = 1, \cdots, g(t); t = 1, \cdots, m \tag{13}$$

where

$$\hat{\vartheta}_{ts}^2 = \hat{\theta}_{ts}^{-1}, \hat{\Sigma}_{ty} = y_t y'$$
$$diag(\hat{\theta}_{t1}^2, \hat{\theta}_{t2}^2, \cdots, \hat{\theta}_{tg(t)}^2) = \hat{\Sigma}_{ty}^{-1} \tag{14}$$

**Step 2** In $SEM^-$, calculate the least square estimates of structural variables by using of $\hat{\upsilon}_{ij}, \hat{\lambda}_{ts}$:

$$\hat{\xi}_{il} = \frac{\hat{\upsilon}'_i X_{il}}{\hat{\upsilon}_i \hat{\upsilon}'_i}, \hat{\eta}_{tl} = \frac{\hat{\lambda}' Y_{tl}}{\hat{\lambda}_t \hat{\lambda}'_t}$$
$$i = 1, \cdots, k; t = 1, \cdots, m; l = 1, \cdots, N \tag{15}$$

**Step 3** In $SEM^+$, make use of $\hat{\xi}_i, \hat{\eta}_t$ obtained in Step 2 to calculate the estimates of regression coefficients $\psi_{ij}, \omega_{ts}$ according to common linear regression method.

**Step 4** In $SEM^+$, make use of $\hat{\xi}_i, \hat{\eta}_t$ obtained in Step 2 to calculate the estimates of coefficient matrix $B, \Gamma$.

Notice that (2) is a common linear regression equations, we can use the two-stage least squares method to calculate it.

## 4. Definite Linear Algorithm with Prescription Constraint

According to the above algorithm, we can get the modular constraint least squares solution based on the constraints of the unit structural vector. But the solutions are not unique, and irrelevant to the modular length of the latent variables. As we know, it is not reasonable to stipulate that modular length of each structural variable is 1. If each modular length of the structural variable is not equal in possibly existing optimal solution set, then MCLS is not good.

An exploring way to improve the algorithm is to find a more reasonable constraint to replace modular constraint. After getting MCLS, we can change the modular length of structural variable in measurement system of equations to make the path coefficient between each structural variable and its corresponding observation variables satisfying prescription condition. That is:

$$\sum_{j=1}^{h(i)} \psi_{ij} = 1, \ \psi_{ij} \geq 0, \ i = 1, \cdots, k \tag{16}$$

$$\sum_{s=1}^{g(t)} \omega_{ts} = 1, \ \omega_{ts} \geq 0 \ t = 1, \cdots, m \tag{17}$$

Next, we compute the prescription condition from two cases.

If the corresponding path coefficients of MCLS are all non-negative at the beginning, we just need to divide a constant at the two sides of the Equation (3) and (4). This constant should be the sum of corresponding path coefficients in MCLS.

If the corresponding path coefficients of MCLS have negative at the beginning, we can not completely use the method of prescription regression [12]. However, we can change prescription condition and let $\psi_{ij} \geq \delta$, $\omega_{ts} \geq \delta$, here $\delta > 0$ but not $\delta = 0$, and $\delta$ may be decided by

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user according to the actual problem. That is:

$$\sum_{j=1}^{h(i)} \psi_{ij} = 1, \quad \psi_{ij} \geq \delta, \quad i = 1, \cdots, k \tag{18}$$

$$\sum_{s=1}^{g(t)} \omega_{ts} = 1, \quad \omega_{ts} \geq \delta, \quad t = 1, \cdots, m \tag{19}$$

If some initial regression coefficients are less than $\delta$, they are all changed as $\delta$, and the corresponding independent variables multiplied by coefficient $\delta$ should be removed to the left of the equation in regression process.

Under on these conditions we can continue to improve the algorithm of MCLS.

**Algorithm 2**. Improvement on Step 3 of the Algorithm 1

**Step 3*** After getting the estimated values as $\hat{\xi}_i, \hat{\eta}_t$ of the structural variables $\xi_i, \eta_t$ in Step 2 of Algorithm 1, we calculate the summarizing coefficients $\psi_{ij}, \omega_{ts}$ by prescription regression, and next calculate the estimated values of $\xi_i, \eta_t$ again.

**Step 3*.1** Define $\hat{\xi}_i, \hat{\eta}_t$ in Step 2, and calculate $\hat{\psi}_{ij}, \hat{\omega}_{ts}$ in $SEM^+$ by common regression.

**Step 3*.2** For any $i$, if $\hat{\psi}_{tj} \geq \delta$ ($\delta \geq 0$) and $\sum_{j=1}^{h(t)} \psi_{ij} = c_i$ for all $j$. Then the both sides of Equation (3) are divided by $c_i$. In the same way, the both sides of Equation (4) are divided by $c_t$ on the conditions.

After checking all $i, t$, go to Step 4 in Algorithm 1.

**Step 3*.3** For any $i, t$, if there is $j$ or $s$ to make $\hat{\psi}_{ij} < \delta$ or $\hat{\omega}_{ts} < \delta$ ($\delta \geq 0$), then let corresponding item be fixed, that is $\hat{\psi}_{ij} = \delta$ or $\hat{\omega}_{ts} = \delta$. The corresponding observation variables $x_{ij}$ or $y_{ts}$ with its coefficient $\delta$ should be removed to the left of the equation, and combined with the latent variable $\hat{\xi}_t$ or $\hat{\eta}_i$ to regress, that is go to Step 3*.1 and Step 3*.2. After regression, the corresponding observation variable $x_{ij}$ or $y_{ts}$ with its coefficient $\delta$ should be removed to the right of the equation.

## 5. Final Remarks

In this paper, we propose SEM to analysis and evaluate the core competence of insurance company, and improve the algorithm of the SEM. It is more objective and scientific to use SEM in the evaluation of the core competence of insurance company compared with traditional methods, such as AHP, FCEM and so on, because the coefficients of this evaluation system are calculated by samples rather than designed arbitrarily. Therefore, we can have a better understanding the relationships among the indexes, which will do a great favor to decision-making analysis and evaluate for the core competence of insurance company.

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