CHAPTER 3

RESEARCH METHODOLOGY

3.1 Methodology

This research was split in three phrases as follows:

Phase 1: An identification of critical success factors and performance indicators (criteria) for functional upgrading

With a comprehensive review of performance indicators through the four BSC perspectives: financial, customer, internal process, and learning and growth perspective, and success factors through the lenses of three theoretical perspectives: RBV, relational view, and institutional theories, the all potential success factors and performance indicators were first extracted. After that, the fuzzy Delphi method – a method of expert consensus building, has been applied to screen the key critical success factors and performance indicators for functional upgrading in electronic industry through experts' consensus as follows:

An anonymous (fuzzy Delphi-based) questionnaire was prepared, and fourteen experts consisting of two senior managers, eight middle managers and four consultants, with more than ten years experience in upgrading process practices in the electronics industry in Thailand, were asked to evaluate the most pessimistic (minimum) value and the most optimistic (maximum) value of the importance of each potential success factor and each potential performance indicator in a range from 1 to 10. A convergence of their opinions was obtained, and the key critical success factors and performance indicators were extracted. A higher consensus significance value indicates a higher degree of importance. Therefore, we subjectively set 8 as the threshold value for the geometric mean of experts' consensus significance values. The factors and indicators with the consensus significance value, g_i greater than the threshold of 8 were selected to be critical success factors and key performance indicators for functional upgrading process.

Phase 2: A prioritization of critical success factors through fuzzy AHP

Based on the critical success factors and key performance indicators, a hierarchical model was developed by using the dynamic capabilities which were considered as mediating factors in the relationship between critical success factors and performance. The fuzzy AHP-based group decision making, based on the fuzzy AHP evaluation method of Calabrese et al. (2013) was applied to determine the relative importance of critical success factors as follows:

The group of experts consisted of twenty persons: six senior-level managers, seven middle-level managers, and seven consultants in electronics industry in Thailand with more than ten years experience in implementing upgrading practices. The fuzzy AHP-based questionnaires were provided to collect information from the experts. Each expert was asked to assign linguistic terms based on his/her subjective judgment, to the pair-wise comparisons by asking which one of two elements was more important and how much more important it was with respect to their upper level. In decision-making, each expert gave his/her preference on the elements using fuzzy judgment matrix. After getting the answers from experts in linguistic terms, these linguistic judgments were then converted to triangular fuzzy sets as defined in Table 3-1. The opinions from several experts were then combined by using geometric mean. Based on the Calabrese et al.'s (2013) fuzzy AHP evaluation method, the local priority weights for all levels in hierarchy were calculated. Finally, the global priority weight of each element was calculated by multiplying its local weight with its corresponding weight along the hierarchy. The final priority results of the elements were ranked based on their own global weights.

Phase 3: A validation of the fuzzy AHP results via sensitivity analysis

To verify how robust the ranking results are, or to analyze how changing the indicator weights influence on the ranking results, a sensitivity analysis was carried out by exchanging the weights of two performance indicators among themselves, while the weights of other performance indicators remain unchanged. Due to the five key performance indicators identified, ten different scenarios were created based on the combination of performance indicator weights, and then, ten different calculations for re-determining the weights of critical success factors for each scenario were performed. The sensitivity analysis was conducted to observe how the overall rankings of critical success factors change with respect to the priority weights of each performance indicator under the different scenarios. By using the Spearman's rank correlation coefficient, we measured the degree of correspondence between two rankings: the original ranking achieved by the base scenario (S0) which had no exchanging of weights and the ranking gained from each of ten scenarios (S1, S2… S10). Finally, the important implications for both practitioners and researchers were derived based on the findings.

3.2 Fuzzy Delphi Method

As the conventional Delphi method fails to deal with the fuzziness (or uncertainty) in expert opinions (Chang, Chang, & Lee, 2014) and it needs repetitive surveys of the experts (Chang, Huang, & Lin, 2000; Ishikawa et al., 1993; Kuo & Chen, 2008; Wey & Wu, 2007). Thus, this study adopted the fuzzy Delphi method which combines the fuzzy set theory and the conventional Delphi method (Murray, Pipino, & van Gigch, 1985) to identify applicable critical success factors and to establish a series of applicable success criteria based on Thai experts' perspective, and consequently to develop a hierarchical structure model, a fuzzy AHP-based model, to find the most significant factors of functional upgrading process.

According to Zadeh (1965), a fuzzy set is characterized by a membership function ranging within the interval [0, 1]. The triangular fuzzy sets of lower (l), medium (m) and upper (u) values can be used to capture a range of numerical values, and a triangular fuzzy number (TFN) can be expressed as a triplet (l, m, u). A triangular membership function of x in $\tilde{A}$ is defined as

$$\mu_{\tilde{A}}(x)=\begin{cases} 0, & \text{for } m < l, \\ (x-l)/(m-l), & \text{for } l \le x \le m, \\ (u-x)/(u-m), & \text{for } m \le x \le u, \\ 0, & \text{for } x > u \end{cases}$$

Thus, the triangular type membership function is as in Figure 3-1.

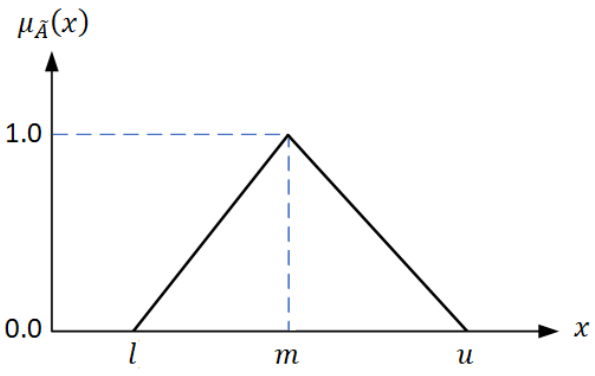

Figure 3-1 The membership function of triangular fuzzy number

The procedure for executing the fuzzy Delphi method is as follows (Chang et al. 2014; Dzeng & Wen, 2005; Kuo & Chen, 2008; Lee, Wang, & Lin, 2010; Somsuk & Laosirihongthong, 2016; Parameshwaran, Baskar, & Karthik, 2015; Wang, 2015):

Step 1: Conducting a fuzzy Delphi-based questionnaire and asking experts for their most pessimistic value and the most optimistic value of the importance of each factor in the possible factor set S in a range from 1 to 10. A score is denoted as $p_{ik} = (l_{ik}, u_{ik}),\ i \in S,$ where l_{ik} and u_{ik} are the pessimistic index and the optimistic index of factor i rated by expert k respectively.

Step 2: Organizing expert opinion collected from questionnaires and determining the TFNs for the most pessimistic index $p_i = (l_{pi}, m_{pi}, u_{pi})$ and the most optimistic index $o_i = (l_{oi}, m_{oi}, u_{oi})$ for each factor i. Taking $p_i = (l_{pi}, m_{pi}, u_{pi})$ as an illustrative example, l_{pi} and u_{pi} indicate the minimum and maximum of all the experts' most pessimistic value respectively. The m_{pi} is the geometric mean of all the experts' most conservative value of factor, It is obtained through Eq. (1)

$$m_{pi} = \sqrt[k]{l_{i1} \times l_{i2} \times \ldots \times l_{ik}} \tag{1}$$

In the same way, the minimum (l_{oi}), geometric mean (m_{oi}), and the maximum (u_{oi}) of the group's most optimistic values for factor i can be obtained.

Step 3: Calculating the TFNs for the most pessimistic index $p_i = (l_{pi}, m_{pi}, u_{pi})$ and the most optimistic index $o_i = (l_{oi}, m_{oi}, u_{oi})$ for the remaining strategies, $A_i, i \in S$.

Step 4: Examining the consistency of experts' opinions and calculating the consensus significance value, g_i for each factor. The gray zone (Hsiao 2006; Lee et al. 2010), the overlap section of p_i and o_i in Figure 3-2, is used to examine the consensus of experts in each factor and calculate its consensus significance value, g_i.

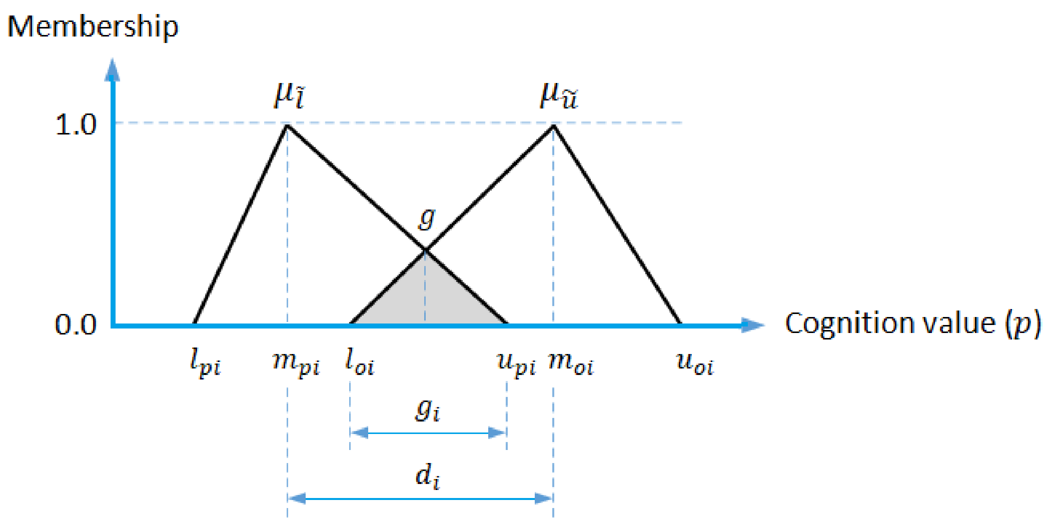

Figure 3-2 Gray zone of p_i and o_i

First, if the TFN pair does not overlap (or the value of $u_{pi} \leq l_{oi}$) and no gray zone exists, the expert options in factor i achieve consensus, the consensus significance value is calculated by Eq. (2):

$$g_i = (m_{pi} + m_{oi})/2. \tag{2}$$

Second, if there is an overlap (or the value of $u_{pi} > l_{oi}$) and the gray zone interval value g_i is equal to $u_{pi} - l_{oi}$, and g_i is less than the interval value of p_i and o_i $(d_i = m_{oi} - m_{pi})$ that is, $g_i \leq d_i$, then the consensus significance value g_i of each factor can be calculated by Eq. (3) (Wang, 2015):

$$g_i = \frac{(u_{pi} \times m_{oi}) - (l_{oi} \times m_{pi})}{(u_{pi} - m_{pi}) + (m_{oi} - l_{oi})} \tag{3}$$

Third, if the gray zone exists and $g_i > d_i$, then there are great discrepancies among the experts' opinions. Repeat Step 1 to Step 4 until a convergence is attained.

Step 5: Extracting factors from the candidate list. Comparing consensus significance value with a threshold value, T, which is determined by experts subjectively based on the geometric mean of all consensus significance value g_i (Hsiao 2006; Ishikawa et al. 1993; Lee et al. 2010). If $g_i > T$, factor i is then selected for further analysis.

3.3 Fuzzy Analytic Hierarchy Process

The analytic hierarchy process (AHP) is a multiple-criteria decision analysis technique used to derive the relative weights of alternatives based on some defined criteria (Saaty, 1980). The AHP enables the decision makers to structure a complex multi-criteria decision-making problem into a hierarchical manner (Dyer & Forman, 1992), with the goal at the top, above the lower levels of criteria and alternatives. In AHP analysis, the criteria and alternatives (or so-called elements) are compared pair-wise at each level of the hierarchy with respect to an upper level element (e.g. criterion). By using pair-wise comparisons, judgments are usually expressed on a numerical scale of 1–9 by decision maker based on their expertise and experiences.

Actually, people tend to express uncertainty or imprecision rather than single points (Moisiadis, 2002).

Although the AHP has been widely used for 'assessing multiple criteria and deriving priorities for decision-making purposes' (Liedtka, 2005), however, the AHP is criticized for its inability to deal with the inherent uncertainty and vagueness of the human decision-making process (Chan & Kumar, 2007; Kwong & Bai, 2003). To overcome this difficulty, fuzzy AHP was developed by combining traditional AHP with fuzzy set theory, to handle uncertainty and vagueness of human's subjective judgments to reach an effective decision (Chen & Hung, 2010; Chiou, Tzeng, & Cheng, 2005; Naghadehi, Mikaeil, & Ataei, 2009).

In this study, we employed fuzzy set theory introduced by Zadeh (1965), to deal with the uncertainty and subjective nature of human thinking in the prioritization process, in which the opinions of human in pair-wise comparison (linguistic judgments) will be converted into the fuzzy numbers that represent them. This study used triangular fuzzy numbers, a 9-point scale, to represent subjective pair-wise comparisons of prioritization process. This is due to the simplicity of the triangular fuzzy numbers in its implementation in practice and in its computation.

In this study, the conversion scale used to convert linguistic judgments (or linguistic scales) to triangular fuzzy numbers (or triangular fuzzy scales) is shown in Table 3-1.

Table 3-1

Triangular Fuzzy Conversion Scale

Linguistic scale	**Triangular fuzzy scale**	**Triangular fuzzy reciprocal scale**
Equally important	(1, 1, 3)	(1/3, 1, 1)
Moderately important	(1, 3, 5)	(1/5, 1/3, 1)

Linguistic scale	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Fairly important	(3, 5, 7)	(1/7, 1/5, 1/3)
Very strongly important	(5, 7, 9)	(1/9, 1/7, 1/5)
Absolutely important	(7, 9, 9)	(1/9, 1/9, 1/7)

Arithmetic operations on triangular fuzzy numbers: Dubois and Prade (1979) derive basic arithmetic operations on two triangular fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$ as follows:

Let $\widetilde{A} = (l_1, m_1, u_1)$ and $\widetilde{B} = (l_2, m_2, u_2)$ then

addition: $\widetilde{A} \oplus \widetilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$,

subtraction: $\widetilde{A} \ominus \widetilde{B} = (l_1 - l_2, m_1 - m_2, u_1 - u_2)$,

multiplication: $\widetilde{A} \otimes \widetilde{B} \cong (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2)$,

division: $\widetilde{A} \oslash \widetilde{B} \cong (l_1/u_2, m_1/m_2, u_1/l_2)$, and

reciprocal: $\widetilde{A}^{-1} \cong (1/u_1, 1/m_1, 1/l_1)$

There have been a number of methods introduced (cf., e.g. Buckley, 1985; Calabrese, Costa, & Menichini, 2013; Chang, 1996; Csutora & Buckley, 2001; Mikhailov, 2003; van Laarhoven & Pedrycz, 1983; Wang, Luo, & Hua, 2008) to handle fuzzy AHP to obtain relative weights from fuzzy comparison matrices. Among these methods, the extent analysis method of triangular fuzzy AHP developed by Chang (1996) is widely applied (Calabrese et al., 2013). Nevertheless, there are strong criticisms of Chang's method (1996) (Wang & Elhag, 2006; Wang et al., 2008; Zhü, 2014). Wang, Luo, and Hua (2008) have shown that Chang's method (1996) cannot estimate the true weights from a fuzzy comparison matrix as it may assign a zero weight to some elements (criteria, sub-criteria or alternatives/critical success factors) and such elements will not be considered, possibly leading to a wrong prioritization of the elements. Moreover, Chang's method (1996) is proved theoretically that why it yields zero-weight which may lead to poor robustness, unreasonable priorities and information loss (Zhü, 2014).

In order to overcome some weaknesses of Chang's method (1996), Calabrese et al. (2013) introduced a modified (row sum) method based on the modified normalization formula which has been proposed by Wang and Elhag (2006) and Wang et al. (2008) to resolve the zero weight issue. Therefore, in this study, we adopted the fuzzy AHP evaluation method proposed by Calabrese et al. (2013) to avoid possibly obtaining zero-weight elements to obtain the correct prioritization of the elements.

3.4 Calabrese et al.'s (2013) Fuzzy AHP Evaluation Method

The modified Fuzzy AHP evaluation method developed by Calabrese et al. (2013) can be summarized as the following steps:

Step 1: Construct fuzzy pair-wise comparison matrices

According to Chang's method (1996), for each decision maker, the fuzzy pair-wise comparison matrices are constructed at each level of the hierarchy relative to each element at the next higher level. A triangular fuzzy comparison matrix $\widetilde{A}$ is constructed as shown below.

$$\widetilde{A} = (\tilde{a}_{ij})_{n\times n} = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \dots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \dots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \dots & (1,1,1) \end{bmatrix}$$

where $(l_{ij}, m_{ij}, u_{ij}) = (1/u_{ji}, 1/m_{ji}, 1/l_{ji})$, for $i = i, \dots, n,\ j = 1, \dots, n$ and $i \neq j$.

Individual judgments can be aggregated in one consolidated matrix by using the geometric mean of their preferences.

Step 2: Examine the consistency of the fuzzy pairwise comparison matrices.

After the aggregation of the judgments of all decision makers in one consolidated matrix, the consistency of the fuzzy pair-wise comparison matrices is examined by defuzzifying (or conversing) the fuzzy number $\tilde{A} = (l, m, u)$ in the fuzzy pairwise comparison matrices into a form of crisp number using $a_{ij}(\tilde{a}_{ij}) = (m + l + u)/3$. The consistency ratio (index) can be then computed using the crisp AHP method (Saaty 1980). The consistency ratio value for each of the crisp comparison matrices should be maintained ≤ 10%. Nevertheless, the judgments from decision makers as inputs of the matrix need to be reviewed until the satisfactory consistency is obtained.

Step 3: Sum each row of the fuzzy pair-wise comparison matrix $\tilde{A}$ as follows:

$$\widetilde{RS}_i = \sum_{j=1}^{n} \tilde{a}_{ij} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right), \quad i = 1, \ldots, n.$$

Step 4: Normalize the rows by the row sums

The correct normalization formula as proposed by Wang et al. (2008) for local fuzzy weights is as follows:

$$\tilde{S}_i = \frac{\widetilde{RS}_i}{\sum_{j=1}^{n} \widetilde{RS}_j} = \left(\frac{\sum_{j=1}^{n} l_{ij}}{\sum_{j=1}^{n} l_{ij} + \sum_{k=1,k\neq i}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{j=1}^{n} u_{ij} + \sum_{k=1,k\neq i}^{n} \sum_{j=1}^{n} l_{kj}}\right) = (l_i, m_i, u_i)$$

for $i = 1, \ldots, n$

Step 5: Define the priority vector of the fuzzy comparison matrix

Ultimately, by converting fuzzy weights to the crisp weights, the local weight is given by the following equation (Calabrese et al., 2013):

$$w_i = S_i(\tilde{S}_i) = \frac{l_i + m_i + u_i}{3}, \quad \text{for } i = 1, \ldots, n$$

By normalizing the crisp weight, the normalized crisp weight (w') is described by the following equation:

$$w_i' = \frac{S_i(\tilde{S}_i)}{\sum_{i=1}^{n} S_i(\tilde{S}_i)}, \quad \text{for } i = 1, \ldots, n.$$

The normalized crisp vector (W) of weights is as follows:

$$W = \left(w_1', w_2', \ldots, w_n'\right)$$

Concluding Remark

This chapter presented the research design, methodology employed in this study, and the justification of the use of research methods: fuzzy Delphi, fuzzy AHP, and the Calabrese et al.'s (2013) fuzzy AHP evaluation method. The details of data collection and analysis were described.