CHAPTER 3

Research Methodology

The main aim of this research is to synthesize the new performance measurement model for evaluating the effectiveness of the frozen shrimp supply chain for using specifically in Thailand. The conclusion of literature reviews in Chapter 2 is recommended that the effective performance measurement in supply chain for the Thai's frozen shrimp is required the integrating of the PM with significant evaluation methods and multi-confirming factors. Then, the new performance measurement model will be developed based on recommendation from Chapter 2. The research methodology in this chapter is designed to response on the research objectives. The model is composed of two conceptual ideas (see Figure 3.1).

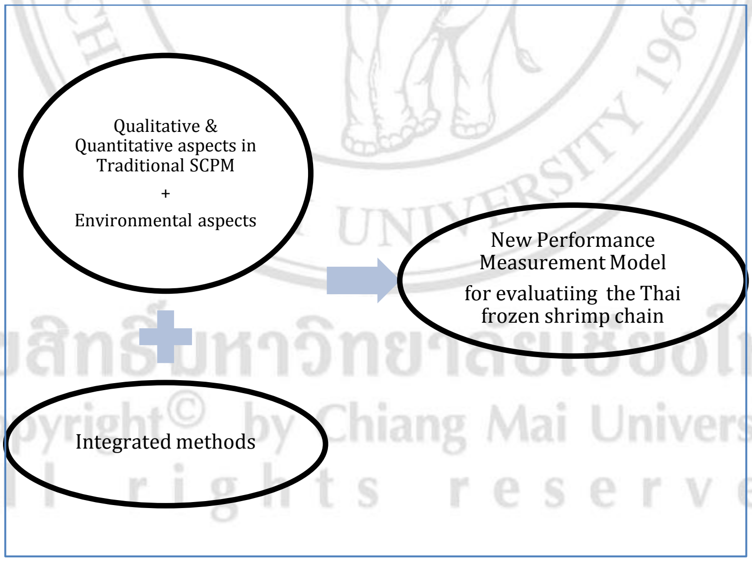

Figure 3.1 The new Performance Measurement Model

Chapter 3, based on the new Performance Measurement Model (PMM) presents above (Figure 3.1), the integrating dimension and the synthesized conceptual idea can explain as follow;

Integrating dimensions (SCM dimensions and environmental management dimensions). In order to fulfill the effectiveness of the new performance measurement model, the environmental dimension will be integrated into the PM model. The new model will be formulated with five dimensions; Financial Efficiency, Flexibility Responsibility, Innovativeness and Quality (product quality and process quality including environmental aspects).

The synthesized conceptual ideas and the new performance measurement model, the researcher integrates the conceptual ideas by using technique of Structural Equation Modeling (SEM) based on the multiple decisions making. The Confirmatory Factor Analysis (CFA) is used to analyze the model and use to test reliability and a validity of the research instrument for the adequacy and feasibility of the model. The confirming structure of the model and the explicit of the correlation among KPIs will be presented in term of casual relationship by using CFA method. SEM suggests the importance and the significance among the relationship of the indicators. Then, the research will apply the AHP for synthesizing and prioritizing the important dimensions and KPIs. The research methodology and research design apply in the collecting data process and analysis process are continues to explain in the main body this chapter.

In order to gain the better understanding on how the new model was developed, the research methodology and procedures were summarized in Figure 3.2 and Figure 3.3.

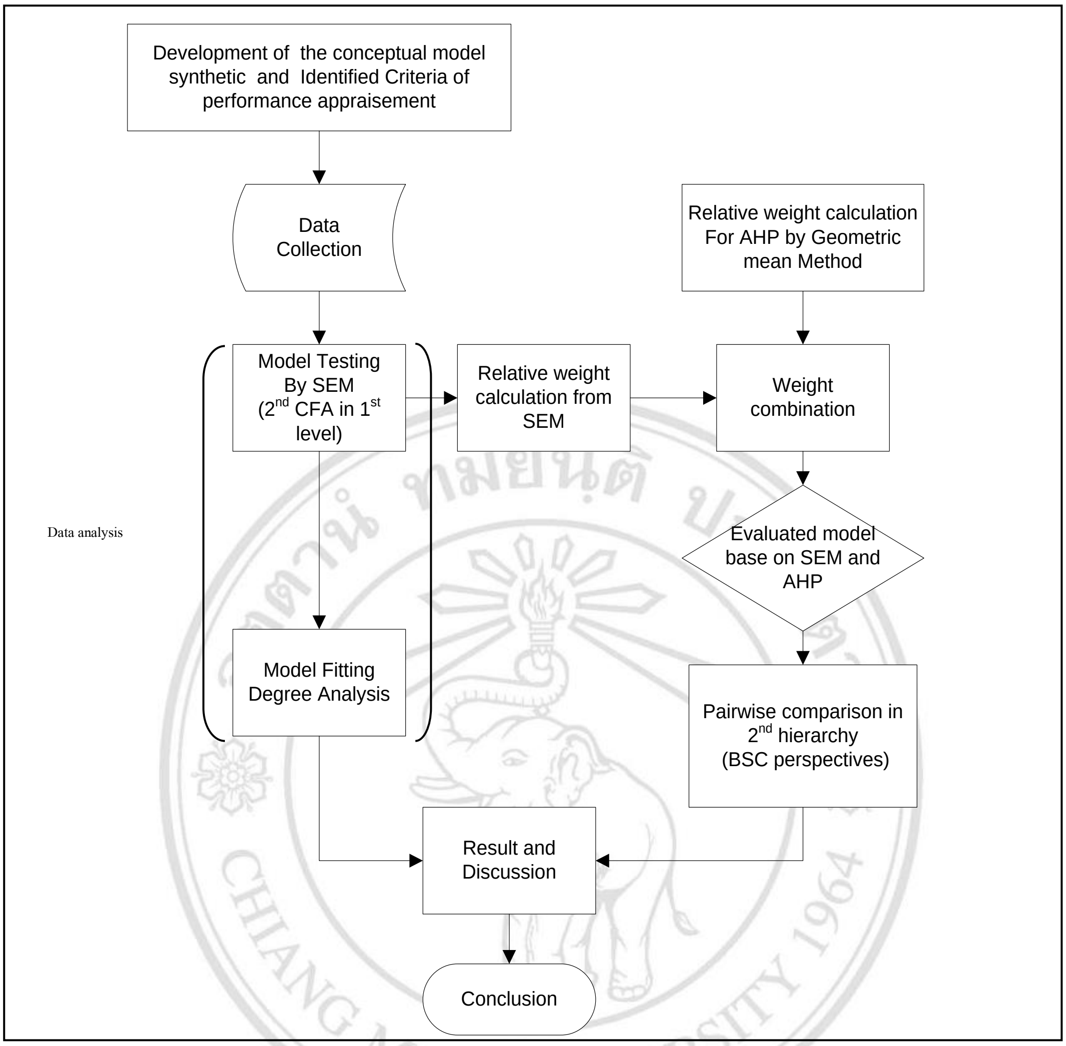

Figure 3.2 Research Methodology

The Figure 3.2 which describes a process of CFA that it is adopted from the six-stage process for structural equation modeling (Hair et al., 2010). The process of CFA method can be described in four steps in figure 3.3 as below.

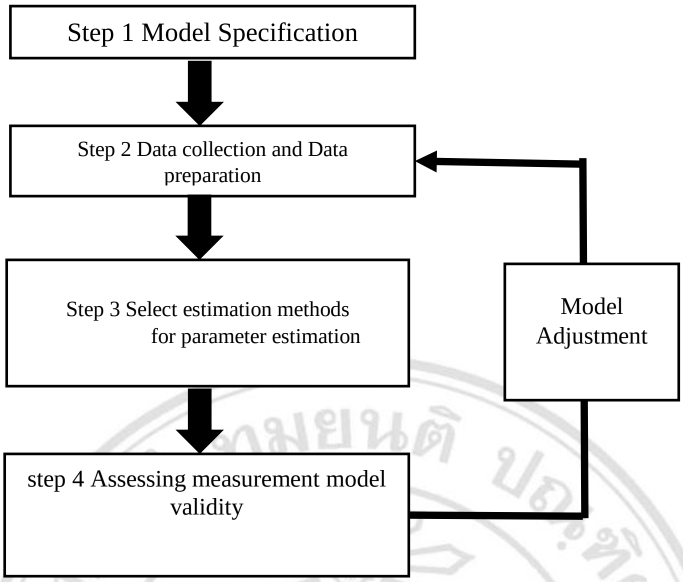

Figure 3.3 CFA process

To achieve our research methodology, the processes is explained step by step as follow;

3.1 Development and Confirming a New Performance Measurement Model (Model Specification in CFA process)

In the first step to develop a new performance measurement model, the researcher focused on the literature review of the performance measurement supply chain, determining KPIs and the way to construct a performance measurement model. In addition, the researcher considered developing the specific instrument or questionnaire for collecting the data. The researcher identified criteria and sub-criteria, which are used to be the components of the model, to investigate particular aspects of Thailand's frozen shrimp industry and to create the conceptual model. The model was formulated based on the five criteria; 1) Financial efficiency, 2) Flexibility, 3) Responsibility, 4) Quality, and 5) Innovativeness. The model was implemented to test the research hypothesis by applied with SEM method. Researcher converted all KPIs into the Y model as variables. The Y model included of the endogenous dependent observed which these variables linked to the latent variables: efficiency (E1-E5), flexibility (F1-F5), responsiveness

(R1-R5), quality (Q1-Q10), innovativeness (I1-I2) (see Table 3.1). The BSC perspectives were used to design the new performance measurement model within both financial and non-financial factors. All variables were classified into 1) financial perspective, 2) customer perspective, 3) internal business perspective and innovative and 4) learning perspective.

Table 3.1 The observed variables and the latent variables in the performance measurement model

Latent variable	**Observed variables**	**Definitions**
Financial Efficiency	1. Manufacturing costs (E1)	Combined costs of raw materials and labor used to produce goods
	2. Distribution costs (E2)	Transportation and handing costs, safety stock costs, and duties
	3. Inventory costs (E3)	Work in process and inventories of finished goods
	4. Profit (E4)	The positive gain from investment, after subtracting all expenses
	5. Return on investments (E5)	A measure of a firm's profitability and how effectively the firm uses its capital to generate profit
Flexibility	6. Volume flexibility (F1)	The ability to change the output levels of the products produced
	7. Delivery flexibility (F2)	The ability to change the planned delivery dates
	8. Customer satisfaction (F3)	The degree to which the customers are satisfied with the products or services
	9. Backorders (F4)	An order that is currently not in stock, but is being re-ordered and will be available at a later time
	10. Lost sale (F5)	An order that was lost due to a lack of stock and because the customer was not willing to wait or permit a backorder.
Responsiveness	11. Full rate (R1)	Percentage of units ordered that are shipped on a given order
	12. Product lateness (R2)	The amount of time between the promised product delivery date and the actual product delivery date
	13. Customer response time (R3)	The amount of time between completing an order and its corresponding delivery
	14. Lead time (R4)	Total amount of time required to produce a particular product or service
	15. Customer complaints (R5)	The registered complaints from customers about a product or service

Table 3.1 (continued)

Latent variable	Observed variables	Definitions
Qualities	16. Appearance (Q1)	All attributes of the products
	17. Product safety (Q2)	Whether the product exceeds an acceptable level of risk associated with pathogenic organisms or chemical and physical hazards, such as microbiological or chemical contaminants in products or micro-organisms
	18. Product reliability (Q3)	Refers to compliance of the actual product composition with the product description
	19. Traceability (Q4)	The ability to trace the history, application, or location of a product using recorded identifications
	20. Storage and transport Conditions (Q5)	Standard conditions required for transportation and storage of products that ensures good quality
	21. Working condition (Q6)	Standards that ensure a hygienic, safe working environment, with correct handling and good conditions
	22. Energy use (Q7)	The content of energy used in all productions
	23. Carbon credit (Q8)	Greenhouse gasses that each plant can reduce to be sold as credits to developed countries
	24. Water use (Q9)	The water content used in all productions
	25. Chemical use (Q10)	The chemical contents used in all productions
Innovativeness	26. Launch of a new product (I1)	The number of products launched by a particular company within a given period
	27. New technology use (I2)	The percentage decrease in time necessary for producing the same product

3.2 Data Collection and Data preparation

The data collecting process is performed in the study. The sampling method is mentioned to use a convenience sampling in each sub-sample group of the shrimp agents. For instance, shrimp feeds & shrimp equipment manufacturer, and frozen and processor in Chanthaburi province, Chachoengsao province, Suratthani province, Nakhon Si Thammarat province, and Songkhla province. Because it has a limitation to access to the area for data collecting, the convenience sampling is fast inexpensive and easy to find out interviewees especially shrimp farmers. Therefore the sample size, the total number of respondents who participated in this study, was 120 subjects. In this study, the random sampling principle for selecting the sample size is needed, and the relevance advanced statistical analysis is required to provide the trustworthiness of the results. CFA and SEM were used to find a ratio between a sample size and number of parameters or variables that should be assigned about 3-20 times per parameter. There were 27 performance measurement indicators in this research; therefore, the ratio of 4:1 at least is applied (Robert et al., 2001). The potential final participants (120 subjects) are engaged in this data collecting process. The part of the questionnaire development, data was collected by applying the survey questionnaires (see in Appendix A). The researcher conducted the structure interviewing technique with 120 participants. Then, questions of the questionnaires were measured by using the 5- points Likert scale (1= not agree at all, 5= strongly agree) (Satty, 1980). Moreover, the researcher conducted the in-depth interview technique with participants and provided them with more opportunities to explain their thought about the model. The close and open-end questions were used to ask participants. The depth data from the interviewing will support the result of the study on how to the new integrating performance measurement model can be fully effective developed.

3.3 Data Analysis

The data analysis process of this study was divided into three parts: 1) testing of the model, 2) analyzing the causal relationships among factors and 3) ranking the factors. First of all, the model was tested for validity, reliability, and confirmed by using confirmatory factor analysis (CFA). According to Zhu et al. (2008) CFA will be used to assess how well the observed variables can reflect the unobserved or latent variables. This is because the CFA focuses on the correlation between factors rather than the causal relationship among factors. The CFA model represents the first-order, second-order and higher order factor models. In this research, the researcher applied the first-order and second-order factor models. The first-order factor models are the main criteria that are correlated among the sub-criteria (the observed variables) in the performance measurement model. Second-order factor models are correlated among the-first order factors.

3.4 Select estimation methods for parameter estimation

Previously, Ordinary Least Squares (OLS) regression, Unweight Least Squares (ULS), Two State Least Squares (2SLS) and Tree State Least Squares (3SLS) used to perform SEM. The advantage of them is 3 SLS has not been very thoroughly investigated, and 2SLS does not rely on normal assumptions. However, all of them provide poor estimation and use within seldom error assumption (Hair et al., 2010). Maximum Likelihood Estimation (MLE) this technique was quickly supplanted all old methods above. MLE is more efficient and unbiased while the hypothesis model is correct. Furthermore, all variables in the model are multivariate normal (Hair et al., 2010; Olsson et al., 2000). Incidentally, MLE is very sensitivity when variables are nonnormality. For this reason, many methods such as Weighted Least Squares (WLS), General Least Square (GLS) and Asymptotically Distribution-Free (ADF) estimation have overcome on MLE. Olsson et al. (2000) pointed out the investigation of performance between GLS and MLE in terms of empirical fit and theoretical fit under a nonnormality condition. The Olsson et al. found the GLS incline to produce better empirical fit than MLE but lower in term of theoretic fit. Moreover, ADF and WLS is used to perform model when data or variables in the model are nonnormal distribution. ADS requires large sample size than MLE. However ADS is not much practical as general estimation above, and Olsson et al. (2000) suggested ADF estimation method performs poorly when the model is misspecified an unattractive technique when nonnormality exists. WLS is a quadratic form and is mentioned when the data are nonnormal distribution. The WLS also supposed when data are peaked or skewness is vary. Besides, WLS, MLE, and GLS will be closed when kurtosis is negligible.

In generally, the CFA method bases on a maximum likelihood estimation (MLE) method because MLE is an efficiency technique and unbiased. MLE is used to estimate parameter when assumptions of multivariate are a normality distribution. In contrast, to receive and to proceed a CFA analysis of nonnormality data, parameter estimation technique should be changed from maximum likelihood estimation (MLE) method to Generalized least square (GL)

In this research, our data are nonnormality and have varied both of skewness and kurtosis. However, skewness and kurtosis are not sufficient conditions for multivariate distribution therefore GLS can used to perform the model (Olsson et al., 2010). For this reason, GLS is selected. For the reason, GLS have an efficiency than MLE, GLS can handle nonnormality assumption and can estimate parameters of an assessment measurement model validity such as Goodness-of-fit, absolute fit model, and goodness-of-fit index as well (Hair et al., 2010).

3.5 Assessing measurement model validity

The Assessing measurement process of this study is divided into three parts: 1) testing of the model, 2) analyzing the causal relationships among factors and 3) ranking the factors. First of all, the model was tested for validity, reliability, and confirmed by using confirmatory factor analysis (CFA). According to Zhu et al. (2008) CFA will be used to assess how well the observed variables can reflect the unobserved or latent variables. Since the CFA focuses on the correlation between factors are rather than the causal relationship among factors. The CFA model represents the first-order, second-order and higher order factor models. In this research, the researcher applied the first-order and second-order factor models. The first-order factor models are the main criteria that related to the sub-criteria (the observed variables) in the performance measurement model. Second-order factor models correlated with the first order factors.

3.5.1 Reliability Testing

The measurement properties of SCPM construct was firstly tested by using reliability and correlation analysis. Then, CFA was followed. The Cronbach coefficient has been used to evaluate reliability. A scale was found to be reliable if □ is 0.70 or higher (Li et al., 2005). However, Mueller (1996) observed that the traditional definitions of the reliability did not allow for the correlating measurement error of items or scales. Within CFA, the reliability could be tested. Bollen (1989) proposed the proportion of variance (R^2) which was an observed variable to test the CFA. It accounts all latent constructs. The coefficient will be readily and easily determined using by LISREL software and LISREL analysis. The primary data analysis, reliability and validity test of the tool were necessary. The Cronbach α coefficient was applied, using the SPSS software version 20 and the result of was 0.828. This result indicated a good reliability. The factor loading gained the high loading level, which also indicated convergent validity. The variables were normally distributed and proved by the $Z_{skewness}$ value that was less than 1.96 at 95% confidential interval (CI).

3.5.2 Validity Testing

1) Convergent Validity

To assess the convergent validity of constructs, Li et al. (2005) suggested to use the Bentler-Bonett coefficient (Δ) which was the ratio of the difference between the chi-square value of the null measurement model and the chi-square value of the specified measurement model to the chi-square value of the null model. This meant that If a value is 0.90 or higher, the model has a strong convergent validity.

2) Discriminant Validity

Discriminant validity refers to the uniqueness and independence of the measures (Mueller, 1996). A series of pairwise CFA was conducted to assess the discriminant validity of the factors using the chi-square test. This step of the analysis had been conducted by measurement item of each pair of factors into a single underlying factor. If there provide significant deterioration of the model fit about a two-factor model, then the result would imply the presence of discriminant validity between the pair of factors. Likewise, discriminant validity was performed on all possible pairs of factors.

3.5.3 Model Testing (goodness of fit) and The Statistics for Evaluating the Goodness of Fit

CFA had been applied to confirm constructs and variables that fitted the model. CFA was used to reduce irrelevant constructs or variables from practitioner's perspectives. Correlations between constructs and variables can also use to interpret the relationship.

Traditional statistical methods normally utilize on the one statistical test to determine the significance of the analysis. However, Structural Equation Modeling (SEM), CFA specifically relies on several statistical tests to determine the adequacy of model fit to the data.

The chi-square test (χ^2) indicates the amount of the difference between expected and observed covariance matrices. A chi-square value close to zero indicates little difference between the expected and observed covariance matrices. In addition, the probability level must be greater than 0.05 when chi-square is close to zero.

The Comparative Fit Index (CFI) is equal to the discrepancy function that was adjusted for the sample size. CFI ranges from 0 to 1 with a larger value will indicate the better model fit. The acceptable model fit is indicated by a CFI value at 0.90 or greater.

Root Mean Square Error of Approximation (RMSEA) is related to residual in the equation model. RMSEA values have a range from 0 to 1. A smaller RMSEA value indicates a good model fit. If the model fit is accepted, RMSEA value is 0.06 or less. (Dianna, 2008)

Normed Fit Index (NFI) was proposed by Bentler and Bonnett (1980). *NFI* values have a range from 0 to 1, with higher values indicating that it is better to fit with the model. If *NFI* equals one, the authors mentioned above suggested that the target model is the best possible improvement over the independence model. Although the theoretical boundary of *NFI* is one, *NFI* may not reach this upper limit even if the specified model is correct, especially in small samples. (Schermelleh-Engel & Moosbrugger, 2003)

Goodness-of-Fit-Index (GFI) the *GFI* typically ranges between zero and one with higher values indicating better fit, but in some cases a negative *GFI* may occur. The usual rule for this index is that at 0.95 is indicated as a good fit relate to the baseline model, while values greater than 0.90 are usually interpreted as the indicating an acceptable fit. In addition, Adjusted Goodness-of-Fit-Index (AGFI) is used to adjust about a bias resulting from the complexity of the model.

AGFI values typically range between zero (0) and one (1) with the larger values indicates, the better fit, but it is also possible that a large *N* in combination with small df can result in a negative *AGFI*. If the number of degrees of freedom for the target model approaches the number of degrees of freedom for the null model, the *AGFI* will approach the *GFI*. A rule of thumb for this index is that 0.90 is indicative of good fit relate to the baseline model while values greater than 0.85 may be considered as an acceptable fit (Schermelleh-Engel & Moosbrugger, 2003)

If the model fit is accepted, the parameter estimates are examined. The ratio of each parameter estimate to its standard error that is distributed as a Z statistic and is significant at the 0.05 level if its value exceeds 1.96 and at the 0.01 level if its value exceeds 2.56. Unstandardized parameter estimates the retain scaling information of variables and can only be interpreted with the referencing to the scales of the variables. Standardized parameter estimates are transformations of unstandardized estimates that remove scaling and can be used for informal comparisons of parameters throughout the model. Standardized estimates correspond to effect-size estimates.

3.6 Determine Relative Weighting Score for Applying in AHP Process

According to papers of Pungchompoo and Sopadang in 2012 and 2014, the generic model has the statistics and the MCDM approaches as a referencing, regarding that the CFA model can confirm the relationship between the latent variable and observed variables within the framework of SEM by using a loading factor value. The notation of their sub-criteria and measurement errors, variables is explained by the measure equation Y-model. The measure equation can be summarized as:

$$Y = \Lambda_y \eta + \varepsilon \tag{3.1}$$

Where;

Λ_y is the first order factor loading

η is criteria (the latent endogenous variables)

ε is used as the measurement error term

Moreover, the higher order structure can summarized as:

$$\eta = \Gamma \xi + \varsigma \tag{3.2}$$

Where;

Γ is the second order the factor loading.

ξ is the BSC perspectives.

ς is used the residual error term.

The factor loading from CFA linked into weight method for AHPand also this combined weight method has strongly supported in the literature (Punniyamoorthy, Mathiyalagan, & Lakshmi, 2012; Zhu et al., 2008). Therefore, the relative weight (*RW*), which is from the average weight method, for each criterion (η) was applied in this study to evaluate performance measurement model by using AHP.

$$RWj = \Gamma_j \;/\, \Sigma\Gamma_j \tag{3.3}$$

Where;

Γ_j is the second order factor loading.

$\Sigma\Gamma_j$ is the sum of all the second-order factor loadings.

j is 1,2…,5

The preference BSC perspectives (BSC) for i=1 to 4:

$$BSC_i = \Sigma^m{}_{j=1}\, RW_j b_{ij} \tag{3.4}$$

Where;

b_{ig} is relative weighting for BSC_i with respect *to jth* criterion.

RW_j is relative weighting for the criterion.

BSC_i is BSC perspectives *i* for performance evaluation.

For b_{ij}, the researcher applied Geometric Mean Method to normalize geometric mean. The researcher also computed the normalized geometric mean to estimate the eigenvector between four BSC perspectives and the five main criteria. The weight can be expressed in form of;

$$W_i = (\Pi^n{}_{j=1}\, a_{ij})^{1/n} \tag{3.5}$$

Where;

a_{ij} is a pair-wise comparison score in each criterion with respect to BSC perspectives.

W_i is the relative weights of criteria.

The factor loading from CFA mode can be linked into weight method for AHP, this combined weight method which had been strongly recommended from the study of Zhu et al. (2008) and Puuniyamoorthy et al. (2012). Therefore, the researcher applied the relative weight (RW) for each criterion (η) to ranks the alternatives by AHP. Then, the factor loadings were used as relative weights in the AHP process.

3.7 Synthesize the New Performance Measurement and Prioritizing Performance Measurement Indicators

There are four steps to conducting the AHP process, which can be summarized as follows.

Step 1: Break the problem down into a hierarchy of significant levels. There are three significant main levels: 1) the goal, 2) objective, and 3) alternatives. This study aims to evaluate the performance measurement of the Thai's frozen shrimp chain by using the BSC in the first level, which is expressed in Figure 3.4.

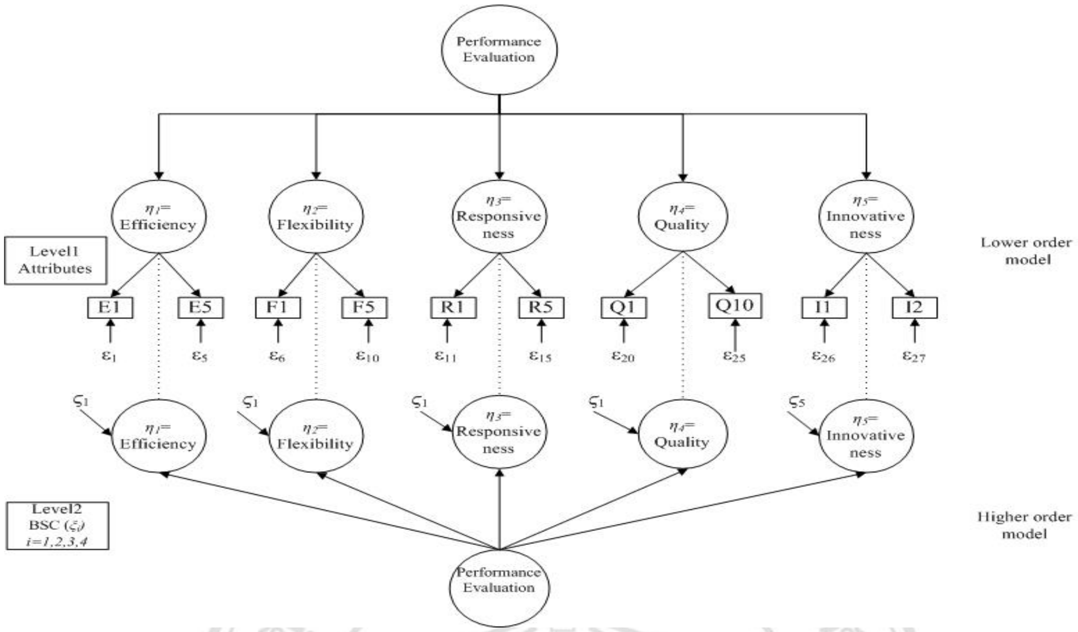

Figure 3.4 Breakdown a Decision Problem

Step 2: Formulating a pairwise comparison matrix for the elements at a single level of the hierarchy, with respect to each of the elements at the level above.

Step 3: Pairwise matrix estimation is the way to calculate weight and rank elements. According to Gao et al. (2009), the geometric mean method was derived from the Logarithmic Least-Squares method (LLS) which is defined the objective function of the optimization problem as follows:

$$min \sum_{i=1}^{n} \sum_{j>1}^{n} \left[ln a_{ij} - \left(ln w_i - ln w_j\right)\right]^2$$

Subject to

$$\prod_{j=1}^{n} w_i = 1$$

Therefore, the geometric mean method is defined as;

$$w_i > 0,\ i=1,2,\ldots,n \tag{3.7}$$

$$w_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n} \Big/ \sum_{k=1}^{n}\left(\prod_{j=1}^{n} a_{kj}\right)^{1/n} \tag{3.8}$$

Step 4: The final step is to calculate a Consistency Ratio (CR) for measuring how consistent the judgments have been related to the large samples of random judgments. Usually, the CR should not exceed 0.1; if CR value is more than 0.1, the judgments would not be strong enough for the trustworthiness because they are too close for comforting to randomness, and the research will need to be repeated.

The researcher determined the consistency ratio by using the equation CR=CI/ mean random CI. The consistency index (CI) was the difference ratio between λ_{max}- n and n-1. Because λ_{max} was closely related to n, it could be suggested as the more consistent judgments. Thus, the difference λ_{max} - n could be used as the measurement of inconsistency (if the difference is zero, this would be the best judgment). The researcher also discovered the mean random CI for differently sized matrices by using a random consistency index (RI).

3.8 Conclusion

In this chapter, the research methods involved in the quantitative interview data collection, including purposive sampling and convenience sampling, the recruitment process, structured interviews, and the developing of survey questionnaire of performance measurement in the Thai frozen shrimp supply chain have been discussed. The data analysis was implemented to 1) testing of the model by using the CFA, 2) analyzing the causal relationships among factors by applying the CFA and 3) ranking the factors is proved by AHP. The connection between chapter 2 and chapter 3 is interpreted in Figure 8: Summary of the connection between literature reviews (Chapter 2) and the research methodology (Chapter 3).

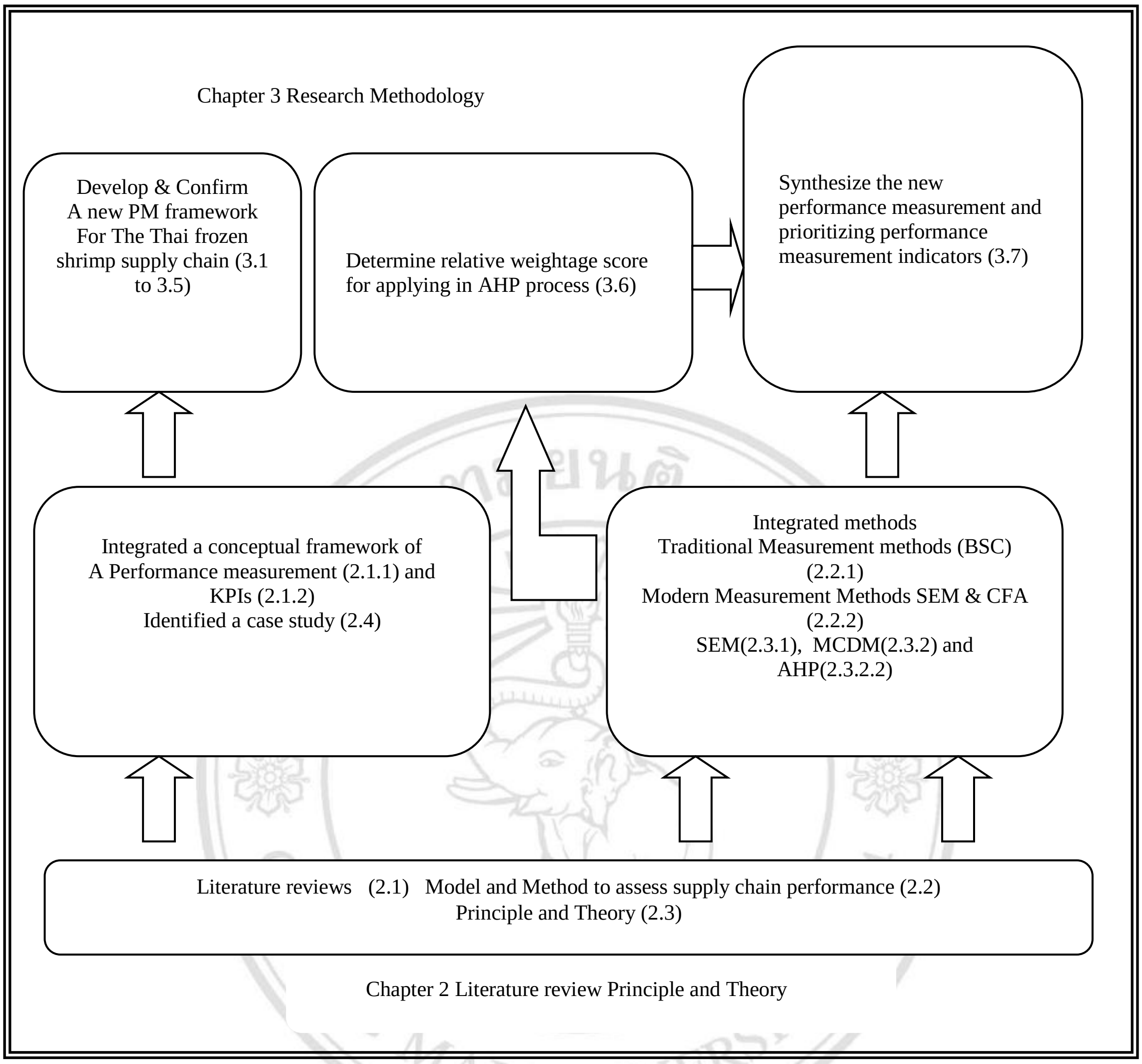

Figure 3.5 Summary of the connection between literature reviews (Chapter 2) and research methodology (Chapter 3)

Figure 3.5, this connection is also focused on the integrated concept idea emerged from literature reviews. Then, it guided to conduct the research methodology of the study. In the bottom level of the framework shows the literature review from chapter 2 that lead to integrating the principles of PM, SEM and CFA and MCDM theory. Next, at the middle level of the framework, the researcher draws the new integrating performance measurement model by identifying KPIs and the main criteria specific to evaluate the PM of Thai's frozen shrimp supply chain. The top level of the framework provides the key processes performed in term of the research methodology including the process of developing and confirming of the new PM, applying AHP to determine relative weightage score and synthesis and prioritizing the new PM. Moreover, it's indicators. The results of the study will be explored and explained in the next chapter.