Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 9 (21): 3792-3803, 2009
ISSN 1812-5654

Modified IPA for Order-Winner Criteria Improvement: A MICMAC Approach

[1,2]Hsiu-Yuan Hu, [3]Shao-I, Chiu and [4]Tieh-Min Yen
[1]Department of Food Science, Taipei College of Maritime Technology,
212, Yen Ping N. Rd., Sec. 9, Taipei, Taiwan, Republic of China
[2]Teaching Director of Da Chien Health Medical System, 6, Shin-Guang Street,
Miaoli City Taiwan, Republic of China
[3]The Center for General Education, Taipei College of Maritime Technology,
212, Yen Ping N. Rd., Sec. 9, Taipei, Taiwan, Republic of China
[4]Department of Technology Management, Chung-Hua University, 707,
Sec. 2, WuFu Rd., HsinChu, Taiwan 300, Republic of China

Abstract: The goal of the study is to establish a new decision analysis methodology from a systematic perspective, in order to help business build market strategies and make improvements that win more orders. The Importance-Performance Analysis (IPA) model has been extensively applied to the consumer satisfaction analysis. However, the conventional IPA model implied some key assumptions, that the quality characteristics are mutually independent variables; thus, it failed to analyze how the types of quality characteristics affect the whole system from a systematic point of view. Under that assumption, if the quality characteristics do correlate, the conventional IPA model could not accurately analyze the importance and priority of improvement and may lead to a wrong decision. We propose a new decision analysis methodology, the M-IPA model. By using Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (MICMAC) to calculate the correlation (influences) between quality characteristics, the model finds the core driving factor to the order-winner criteria and uses it to modify the importance of quality characteristics in the IPA model. We use a case study on the air conditioning technology industry to illustrate the applications and benefits of the M-IPA model. In this study, we get the conclusion that the MICMAC model failed to discuss the decision model for the market strategy of order-winner criteria. Thus, by integrating the MICMAC and IPA models, we establish a new decision analysis methodology and find out the core improvement items in an order-winner criteria system.

Key words: Importance-performance analysis, Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (MICMAC), order-winner criteria, customer satisfaction

INTRODUCTION

Since 1980s, various quality control systems were developed and the customer satisfaction has been a major indicator for organizational performance evaluation in many theoretical and empirical studies. Lots of research works study the importance and satisfaction of service quality characteristics. A main tool for these studies is the Importance-Performance Analysis (IPA). Importance-Performance Analysis (IPA) is very efficient; moreover, it directly evaluates advantages and disadvantages of an organization using market survey data. The basic idea of the method is to approach customers' recognition of the importance of quality characteristics through market survey; after a customer experiences the service, the model measures his/her actual satisfaction for quality characteristics. By building a two dimensional (importance and performance) matrix, it divides quality characteristics into four types, based on their importance and performance, in order to assist organizations adopt corresponding market strategy based on quality characteristics types. The four quadrants are defined as follows: (1) concentrate here: the customers suggest that the importance of the product or service quality characteristics is high; however, the organizational performance is low, (2) keep up the good work: the customers suggest that the importance of the product or service quality characteristics is high and the organizational performance is also high, (3) low priority: organizational performance on the product service quality characteristic is low and the customers' cognitive importance is also low and (4) possible overkill:

Corresponding Author: Tieh-Min Yen, Department of Technology Management, Chung-Hua University, 707, Sec. 2, WuFu Rd.HsinChu, Taiwan 300, Republic of China Tel: +886-3-4024298 Fax: +886-3-4026145

organizational performance on the product or service quality characteristic is high; however, the customers' cognitive importance is low. Bacon (2003) and Eskildsen and Kristensen (2006), they pointed out that IPA's primary goal is to give organizations an opportunity to improve the product or service quality characteristics. Bacon (2003) and Martilla and James (1977) claimed that managers can use the two dimensional matrix of importance and performance to determine which quality characteristics need to be maintained, improved or reduced inputs and then develop an action plan for the organization.

Martilla and James (1977) was the first to develop a market strategy for organizations by using IPA; this method has been broadly adopted in many industries. For example, in a recent study, Levenburg and Magal (2005) applied IPA on e-business strategies and resource allocation. Zhang and Chow (2004) used IPA to improve the service quality of travel guides. Matzler *et al*. (2003) used IPA to improve service quality and strategically development for banks. Aigbedo and Parameswaran (2004) used IPA to enhance the quality of campus food service. Matzler *et al*. (2004) took automobile industry for example and reconsidered IPA's applications. Matzler *et al*. (2005) applied IPA to trend studies on recent management methods and tools. Huang *et al*. (2006) applied IPA to approach long-distance travelers' satisfaction for the service quality on national highways. Tonge and Moore (2007) used IPA and gap analysis to estimate how visitors to Marine-Park coast-line evaluate the service quality, which effectively improved environment protection management. Lee *et al*. (2008b) applied the IPA model on suppliers' performance evaluation, etc. As Martilla and James (1977) pointed out, the advantages of IPA, for example low costs, easy to apply and offering more focused and strategic advices, are the major reasons it has been widely accepted and applied.

In recent years, many scholars tried to modify the conventional IPA model to enhance its accuracy and expressibility. Matzler *et al*. (2003) used empirical studies on bank service quality to demonstrate that customer satisfaction is a linear component of the quality characteristics and that the conventional IPA model may lead to wrong organizational decisions. Sampson and Showalter (1999) proved that there is a negative correlation between importance and performance; as a result, the importance shall not be expressed by point estimation, rather, it shall be a causal function of the performance. Yavas and Shemwell (2001) multiplied the performance difference between the organization and competitors by the relative importance to adjust the IPA model; and they used the medical industry as an example to illustrate the application. In a customer satisfaction study on the quality characteristics of outdoor recreational facilities. Tarrant and Smith (2002) used mean and standard error to adjust the IPA model, in order to compensate the shortcoming of conventional mean point estimation. Matzler *et al*. (2004) claimed that customer recognized importance could not truly reflect the relative importance of quality characteristics; the study also proved that the customer recognized importance is not a function of the quality characteristics satisfaction; instead, implied importance is the function of the quality characteristics satisfaction. The result was deducted from a multiple regression, with performances of k quality characteristics as independent variables (X_i) and the overall satisfaction as the dependent variable (Y); the function can be shown as $Y = \beta_0+\beta_1X_1+\beta_2X_2+...+\beta_kX_k+\epsilon$, where ϵ is the error term. Since the regression coefficient β_i represents the extent of influence the i-th quality characteristic has on the overall satisfaction, Matzler and Sauerwein (2002) claimed that the measure for customer-recognized importance on quality characteristics shall be the coefficient deducted from a multiple regression.

Scholars mentioned above all made great contributions to the IPA studies. However, the IPA model is built on an assumption that quality characteristics are mutually independent variables; if quality characteristics are not independent, the conventional IPA model could not accurately analyze the importance and priority of improvements. As a result, our goal is to establish a new decision analysis methodology, M-IPA, from the systematic perspective. By using Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (MICMAC) to calculate the correlation between quality characteristics, we modify the importance of quality characteristics in the IPA model. Lastly, we use a case study on the air conditioning technology industry to illustrate the applications and benefits of the M-IPA model.

MATERIALS AND METHODS

To build our M-IPA methodology, we discuss the following four issues respectively: (1) a briefing of the order-winner criteria, (2) the conventional IPA model, (3) MICMAC and (4) to integrate MICMAC and IPA and establish the M-IPA decision analysis methodology.

Order-winner criteria: Hill (2000) created the concept of order-winner criteria in his manufacturing strategy studies. He claimed that the reason to set order-winner criteria for different products is to enhance a company's understanding in its market, which helps company to win more orders. As for the definition of order-winner criteria, Hill (2000) claimed the qualifiers are that companies must conform to customers' requests, in order to become a qualified supplier. However, to offer or to possess those criteria does not necessarily win orders. Defined by Hill (2000), order-winners are the ones with a value exceeding what components offered to customers and the ones that help win the orders. Therefore, companies must outperform competitors to provide order winners.

According to Hill (2000), the order-winner criteria can be divided into 14 items, under three major categories. The three categories are: manufacture-related and exclusive manufacture order-winner and order-qualifying criteria, manufacture-related yet non-exclusive order-winner and order-qualifying criteria and non-manufacture related order-winner and order-qualifying criteria. We describe the items and their definitions as follows:

- **Price:** Hill (2000) claimed that in different market stages of a product lifecycle, e.g., product introduction, growth, maturity, decline, etc., the importance of price will gradually increase and become an order-winner criterion
- **Delivery reliability:** The major indicator for delivery reliability is on-time delivery, which shows suppliers' capacity to deliver products based on agreed delivery schedule
- **Delivery speed:** An organization may satisfy customer needs and win orders by delivering faster than competitors or delivering at a requested time that competitors cannot deliver
- **Quality conformance:** Since the mid 1970s, quality has become a market competition factor. The reason many organizations failed to gain advantages in market competition was because they lack a clear definition for quality. Hill (2000) adopted the eight quality competition dimensions in Garvin (1987) as order-winner criteria
- **Demand increases:** In certain markets, organizations have the capacity to react to increased customer needs fast, which is a crucial order-winner criterion. Increased market demands often result form market growth, seasonal needs, unexpected needs, or an increase in certain customer's specific needs
- **Product range:** The market will differentiate as need features differ; as a result, manufactures must gradually change the mass production process to small and diversified production
- **Design:** Hill (2000) claimed that design is a key order-winner criterion; besides, the design, manufacture and market must come together completely and intensely, because it is a basic strategic requirement for organizational operation
- **Distribution:** The key to distribution is a fast and reliable devilry; and the costs, quality and speed of distribution will directly affect the competitiveness of the organization. Hence, Hill (2000) believed that distribution is an order-qualifying criterion for non-manufacture orders
- **Design leadership:** The key factor in product design or development is to meet or exceed customer needs. If the feature and quality characteristics of product design exceed other competitors, the organization will become the design leader in the market. In addition, the frequency an organization launch new products represents its design leadership
- **Being an existing supplier:** If being a qualified supplier for existing customers, the organization will continue to get orders from customers
- **Marketing and sales:** The key to marketing and sales lies in how to handle different customer needs or segment different markets. As a result, the key issue for an organization is to understand market price, identify opportunities and threats and the growth and reduction of the current segmented markets
- **Brand name:** Organizations could build a product's brand awareness through different activities like the design, advertisements and the increase or maintenance of market share. It will guarantee the organization's capacity to win orders. Once you build customers' brand awareness or image in the market, it guarantees the organizations' market status and helps them get orders constantly
- **Technical liaison and support:** In some markets, customers request supplier to provide supports ranging from product design to manufacture techniques before signing the contract; those are important competition factors in the market
- **After-sales support:** In some markets, needs for product usage, warranty, maintenance service and waste disposal occur after product sales; hence, Hill (2000) listed after-sales support as one of the order-winner criteria

The conventional IPA model: The IPA model was proposed by Martilla and James (1977) to develop effective market strategies. By collecting customer perception on quality characteristics, including customer recognized importance and organizational performance, the IPA builds a two-dimensional matrix for decision-making. By estimating the central tendency of importance and performance, IPA divides the two-dimensional matrix into four quadrants to show the status of quality characteristics. An IPA matrix can be defined by the four quadrants respectively: (1) concentrate here: the customers suggest that the importance of the product or service quality characteristics is high; however, the organizational performance is low, (2) keep up the good work: the customers suggest that the importance of the product or service quality characteristics is high and the organizational performance is also high, (3) low priority: organizational performance on the product service quality characteristic is low and the customers' cognitive importance is also low and (4) possible overkill: organizational performance on the product or service quality characteristic is high; however, the customers' cognitive importance is low. As pointed out in the studies of Bacon (2003) and Eskildsen and Kristensen (2006), the primary purpose of IPA is to create an opportunity for improvement regarding quality characteristics of product and service rendered by organization. Even though the IPA model is easy to apply and interpret, it failed to consider the causal relationship between quality characteristics and their influence.

In most cases, when making improvements based on quality characteristics, we assume independence between those characteristics, directly apply the IPA matrix to identify which quality characteristics need to be improved and then improve them one by one. However, if there is a causal relationship between quality characteristics, improving certain quality characteristic may simultaneously affect other characteristics; as a result, highly influential quality characteristics shall be prioritized when improvements are to be made. To discuss the causal relationship between quality characteristics and its impacts on decision-making and improvement, we describe the MICMAC method and the M-IPA results in the following two sections respectively, as a basis for decision-making and improvements.

Cross-impact matrix multiplication applied to classification (MICMAC): Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) was developed by Duperrin and Godet (1973). It is a systematic analysis for complex issues; it categorized variables based on the relationship and the extent they influence one another to find out the key variable in the system. In recent years, scholars applied MICMAC wildly in various fields; for example, Wang *et al*. (2008) used ISM and MICMAC to identify and classify obstacles affecting energy conservation in China, how they affect one another and the primary cause. Qureshi *et al.* (2008) integrated ISM and FMICMAC to identify and classify the key criteria for evaluating logistics service suppliers. Arya and Abbasi (2001) integrated ISM and FMICMAC to identify and classify key factors in an environmental impact assessment. Ravi and Shankar (2005) used ISM and MICMAC to analyze obstacles for the reverse logistics and how they affect one another in the automobile industry. Jha and Devaya (2008) used ISM and MICMAC to analyze risks business face when contracting international projects in India. Qureshi *et al.* (2007) used ISM and MICMAC to build a relationship model for variables in logistics service outsourcing in order to make shipping suppliers more efficient and productive. Kannan and Haq (2007) used ISM and MICMAC in the build-to-order supply chain, to analyze the relationship between supplier choice and evaluation standards. Georgantzas and Hessel (1995) applied MICMAC to estimate the intensity between customer needs and product features in Quality Function Deployment (QFD) and they designed the product quality based on the relationship between those features. Agarwal *et al.* (2007) applied ISM and MICMAC to build level structure in an agile supply chain and the relationship between variables. Faisal *et al.* (2006) adopted ISM and MICMAC to analyze the dynamic of variables and figure out the key factor that reduces risks in the supply chain. Faisal *et al.* (2007) focused on information risk management in the supply chain; the work used ISM and MICMAC to build a conceptual framework which identifies key factors and resolves issues such as group decisions. Therefore, MICMAC has been applied to many fields successfully. The MICMAC model deals with complex systems. Based the direct impacts of variables, MIMAC used matrix to calculate outcomes in a system after mutual influence, then impacts of visual structure/dependency map were used to identify the types of variables in a system, in order to get the key variable in a complex system and then determine the directions for system control or improvement.

A MICMAC analysis contains the following three steps, (1) identify relevant variables: usually through brain-storming or based on expert opinions, variables related to the research topic are identified. A complete variable list is crucial for future studies and analysis, (2) build the causal relationship between variables: causal relationship between the variables is built in this stage, (3) identify key variables: this step is mainly about identifying key variables and factors that are important to overall system changes. We briefly illustrate MICMAC's structure and process.

Define variables and set up measurement scale: Based on literature review, brain-storming, or expertise opinions, variables influencing a certain complex system could be listed and defined. Assume there are n variables influencing a complex system, to understand the causal relationship between variables and how they affect one another, the measurement scale for influence needs to be determined; the scale will be divided into four levels, 0, 1, 2 and 3, which represents no influence, weak influence, moderate influence and strong influence, respectively. In addition, since variables may have influence in the future, thus a measurement scale p is designed to capture potential influences

Matrix of direct influence (MDI): If there are n variables, an n×n Matrix of Direct Influence (MDI), X, can be derived from a pair-wise comparison of variable's relationship and extent of influence. In a MDI (X), x_{ij} denotes to the extent variable i influences variable j; and the diagonal variables, x_{ii}, in MDI are set to 0.

$$X = \begin{bmatrix} 0 & x_{12} & \cdots & x_{1n} \\ x_{21} & 0 & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & 0 \end{bmatrix} \quad (1)$$

Each MDI must reach a stable convergence after continuous matrix multiplication; the matrix product is shown in Eq. 2. Generally speaking, a matrix with less than 30 variables will converge after 6 to 7 matrix multiplications. To understand the influence and dependency of variables in MDI, we compute the sum of rows in matrix X (D_i) and sum of columns in matrix X (R_i) in Eq. 3 and 4, respectively; then we get the extent of influence and dependency between variables. Next, based on MDI, we get a direct influence/dependency map, which is a two-dimensional graph, with the horizontal axis representing the extent of dependence and the vertical axis representing the extent of influence. We then use the mean to divide the direct influence/dependency map into four areas for variable classification. If the system is too complex, you can build a direct influence map first to capture impacts of highly influential variables.

$$X^k = \prod^{k} X = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \quad (2)$$

$$D_i = \sum_{j=1}^{n} x_{ij} \; (I = 1,2,3,...,n) \quad (3)$$

$$R_j = \sum_{i=1}^{n} x_{ij} \; (j = 1, 2, 3,..., n) \quad (4)$$

Matrix of potential direct influence (MPDI): In a MDI, some variables may have potential influence on other variables. For those with a potential influence in the future, we denote p to represent the potential influence and the extent of influence is fixed to 3. Incorporate the potential relationship and influence into Eq. 1 and we get MPDI, X_p. Similarly, by computing the sum of rows in matrix X_p (D_i) and the sum of columns in matrix X_p (R_i) in Eq. 3 and 4, respectively, we get the extent of influence and dependency between variables and build a potential direct influence/dependency map and potential direct influence map.

Matrix of indirect influence (MII): When MDI reaches stable convergence after matrix multiplications specified in Eq. 2, we get the MII, X^k. By computing the sum of rows in matrix X^k (D_k^i) and sum of columns in matrix X^k (R_k^i) in Eq. 5 and 6, we get the extent of indirect influence and dependency between variables and build an indirect influence/dependency map and indirect influence map.

$$D_i^k = \sum_{j=1}^{n} a_{ij} \quad (5)$$

$$R_j^k = \sum_{i=1}^{n} a_{ij} \quad (6)$$

Matrix of potential indirect influence (MPII): When MPII reaches stable convergence after matrix multiplications specified in Eq. 2, we get the MPII, X_p^k. By computing the sum of rows in matrix X^k (D_j^k) and sum of columns in matrix X^k (R_j^k) in Eq. 5 and 6, we get the extent of potential indirect influence and dependency between variables and build a potential indirect influence/dependency map and indirect influence map.

Variable classification and identification: Duperrin and Godet (1973) categorized and defined different types of variables in a system (Fig. 1). The following is a brief introduction:

- **Influential variables (I):** Those variables have high driving power yet low dependency; they can explain or affect system behaviors
- **Relay variables (R):** Those variables are also called Linkage Variables. They have high influence and high dependency and they are unstable; any actions towards those variables may relay back through other variables. The feedbacks caused by Relay Variables will increase or lower the signal-input of the original variables

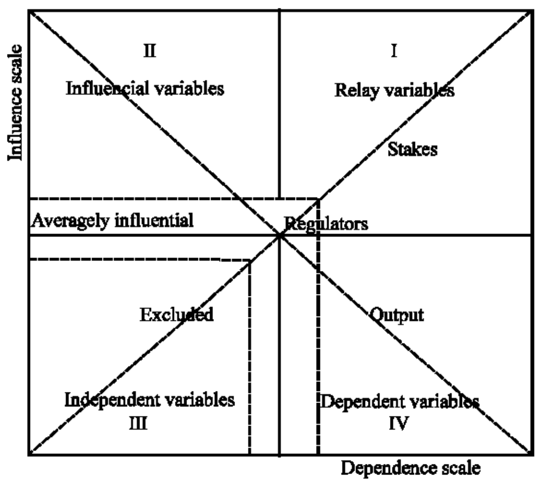

Fig. 1: MICMAC influence-dependence map

- **Dependent variables (D):** Those variables are also called resultant variables. They have low driving power and high dependency; they are influenced by both Influential Variables and Relay Variables
- **Excluded variables (E):** Those variables are close to the origin of the matrix; as a result, they are also called Independent Variables or Autonomous Variables. They have low driving power and low dependency. They have a weaker link to the system, with only a few relationships with the system. Those variables are highly antonymous and may develop in their own way; moreover, they do not determine the future of the system; thus, we do not need to pay too much attention to these variables. They could be excluded in the analysis
- **Averagely influential and/or dependent variables (A):** Variables in this middle group are also called regulating variables. They are adjustable and controllable; usually, we do not need to discuss or deal with their priority

Mandal and Deshmukh (1994) claimed that the primary goal of MICMAC analysis is to analyze the driving power and dependency of variables. The driving power is defined as the power to influence the way other variables change; and the dependency is defined as the extent of changes the variable is influenced by other variables. By Ravi *et al.* (2005), the study applied MICMAC analysis to classify variables in a logistics support system into four types, using a matrix with dependence as the horizontal axis and driving power as the vertical axis. As shown in Fig. 1, the III quadrant is composed of Autonomous (or Independent) Variables with low driving power and low dependency; relatively, this type of variables is highly independent and has a weak link to the system, so they are not very influential. The IV quadrant is composed of Dependent Variables with low driving power yet high dependency. The I quadrant is composed of Linkage Variables with high driving power and high dependency; these variables are quite unstable, because when changes are made to these variables, other variables will also be affected; once other variables change, the feedbacks will have influence on variables in this category. The II quadrant is composed of Independent Variables with high driving power and low dependency.

In the MICMAC theory, some variables may affect other variables, causing a dramatic change to the entire system. Even though some variables have a weaker influence on other variables, the influence may be magnified by high influential variables. To include the above effect, MICMAC not only considers the direct variable influences, indirect influences to the system are also measured. Besides, the MICMIAC results can reflect system features under the dynamic conditions. As a result, decision-makers can find out the driving quality characteristics of key issues in a complex system based on the causal relationship and influence scale of quality characteristics. Then, proper decisions could be made according to the influence type and extent.

Integrate MICMAC and IPA: The conventional way to improve quality characteristics is to use the IPA matrix to find out quality characteristics that need to be improved and then make individual improvements. However, if there is a causal relationship between quality characteristics, an improvement targeting certain quality characteristic may cause other characteristics to change simultaneously. Therefore, quality characteristics with high influence shall be given priority when improvements are made. To comprehend the causal relationship between quality characteristics, we divided the two-dimensional cause-and-effect diagram into four quadrants by the mean value obtained from the MICMAC results. The I quadrant represents high influence and high dependency; quality characteristics in this area are Relay Variables and they are unstable in the system. The II quadrant represents high influence yet low dependency; quality characteristics in this area are Influential Variables and they will affect other quality characteristics. The III quadrant represents low influence and low dependency; quality characteristics in this area have high independence; they do not affect and are not affected by other quality characteristics much. The IV quadrant represents low influence yet high dependency; this means that quality characteristics in this area are the key problems that are affected by other quality characteristics. As a result, we know that the causal relationship between quality characteristics may affect the results of an IPA matrix. To assess the driving power of quality characteristics, we must consider the direct, indirect and potential relationship. Thus, our study integrated the direct, indirect and potential matrices into MICMAC; with Eq. 7 and 8, we compute the Total Influence Matrix, T.

$$N = \frac{1}{\underset{1 \le i \le n}{\text{Max}} \left(\sum_{j=1}^{n} x_{ij} \right)} \times X_p \tag{7}$$

$$T = \lim_{k \to \infty} \left(N + N^2 + \cdots + N^k \right) = N(I - N)^{-1} \tag{8}$$

where, I is the Identity Matrix.

Let t_{ij} be a quality characteristic in the Total Influence Matrix, T and i, j = 1, 2,..., n. We can derive the sum of rows and columns in the Total Influence Matrix, T, from Eq. 9 and 10. Let D_{Ti} be the sum of the i-th row, which represents the total influence caused by quality characteristic i to other quality characteristics; and let R_{Tj} be the sum of the j-th column, which represents the total influence caused by quality characteristic j to other quality characteristics. The D_{Ti} and R_{Tj} values derived from the Total Influence Matrix, T, include direct, indirect and potential influences.

$$D_{Ti} = \sum_{j=1}^{n} t_{ij} \quad (i = 1, 2, \cdots, n) \tag{9}$$

$$R_{Tj} = \sum_{i=1}^{n} t_{ij} \quad (j = 1, 2, \cdots, n) \tag{10}$$

To compute the driving power of a quality characteristic, we define the Driving Power Coefficient (DP value) with the same principle MICMAC used to classify variables in Fig.1. Claimed that core variables which can affect and control changes in the system are those that have high influence yet low dependency (Fig. 1, II), suggesting that a high driving power implies high importance. Variables making the system unstable are those with a high influence and high dependency (Fig. 1, I); then suggested that changes to those variables shall be avoided; therefore, a low driving power implies low importance. The more independent variables are excluded variables (Fig. 1, III); they do not affect the system much; therefore, a low driving power also implies low importance. Lastly, dependent variables are hardly affected by other variables; thus the lowest driving power implies the lowest importance. As a result, we derive the Driving Power Coefficient, DP_i, for quality characteristic i from Eq. 11.

$$DP_i = \begin{cases} \dfrac{D_{Ti}}{R_{Tj}} & R_{Tj} > 0 \\[2ex] \dfrac{D_{Ti}}{\text{Min}(R_T)} & R_{Tj} = 0 \end{cases} \tag{11}$$

The study proposes a Combinative Importance (CI), I_{ci}, by integrating MICMAC and IPA. The Combinative Importance is the product of customer-recognized importance, I and the driving power coefficient of the quality characteristic in MICMAC, DP_i. The Combinative Importance of the i-th quality characteristic is shown in Eq. 12.

$$I_{ci} = DP_i \times I_i \ (i = 1, 2, 3, \ldots, n) \tag{12}$$

Therefore, this study transforms the axis of the conventional two-dimensional importance-performance matrix into the Combinative Importance (CI), I_{ci}. This integrated the M-IPA model under MICMAC and IPA, as shown in Fig. 2. We use mean to estimate the central tendency of importance, which divided the two-dimensional importance-performance matrix into four quadrates. The definition and strategy for the four quadrates remain the same as the conventional IPA method proposed by Martilla and James (1977). Hence, our study preserves the comprehensibility and strategy interpretation of the original model.

Case study: We use the air conditioning technology industry in Taiwan for case study. By using the M-IPA model to analyze order-winner criteria, we offer a basis for market strategy and manufacturing strategic decision to help enhance customer satisfaction. The head office of the case study, the King Sun Group, is located in Taiwan. It is the second largest air condition equipment manufacturer in Taiwan, with an approximate 30% of

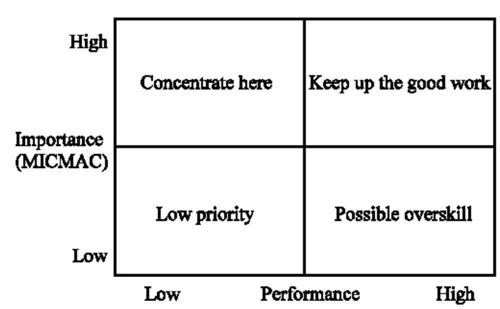

Fig. 2: The M-IPA matrix which integrated MICMAC and IPA

market share. It acquires certification from the ISO 9001 quality management system and enjoys a stable business growth. The study was conducted in 2008; we surveyed the company's customers and developed a questionnaire about order-winner criteria. The analysis adopted the M-IPA model to find out core problems and ways to make improvements, which could be used as a basis for market strategy decisions and make the company more competitive.

Present study targeted customers that had business with the company in the past. In 2008, we conducted a survey about the satisfaction on order-winner criteria for air conditioning technology products. A scalogram with 9 satisfaction degrees by Slack (1994) was used to determine the customers' perception of this company's performance in order to evaluate the company's actual performance. For organizational performance questions, the scale 1 = very unsatisfied and 9 = very satisfied. For questions related to the importance of quality characteristics, the scale 1 = very unimportant and 9 = very important. The questionnaire design used the 14 order-winner criteria in Hill (2000) as quality characteristics; we also interviewed 20 customers and 10 senior managers in the company to make sure that the 14 order-winner criteria are suitable measures for customer satisfaction. Griffin and Hauser (1993) held that in an interview with 20 to 30 customers could determine 90-95% of the quality characteristics in homogeneous markets. The basis for customer selection is to choose the ones that have their transaction and service completed in 2007. A total of 540 questionnaires were mailed and faxed to the customers' designated personnel. 177 effective questionnaires were collected by IPA, constituting a 32.78% recovery rate.

The design of MICMAC questionnaire adopted the 14 order-winner criteria in Hill (2000) as the basis; then 10 senior managers used the expertise opinion method to develop a direct influence matrix with the 14 order-winner criteria. A scalogram with 4 direct influence degrees by researcher was used; 0 represents no influence and 3 represents highly influential. After collecting the questionnaires, the company adopted MICMAC to build the relationship between order-winner criteria features and the total influence. The company then adopted the M-IPA model to find out core problems and ways to make improvements, which could be used as a basis for market strategy decision and make the company more competitive.

RESULTS AND DISCUSSION

According to the conventional IPA analysis, as shown in Fig. 3 and Table 1, order-winner criteria in the Concentrated here area, including Price (OW1), Quality Conformance (OW4), Delivery Reliability (OW2), Delivery Speed (OW3) and After-Sales Support (OW14); these are the ones that need to be improved immediately. The order-winner criteria in the keep up the good work area, including Design (OW7) and Being an Existing Supplier (OW10), shall preserve their competitive advantages. The order-winner criteria in the possible overkill area, including Product Range (OW6), Distribution (OW8) and Design Leadership (OW9), could have less resource inputs. The order-winner criteria in the low priority area,

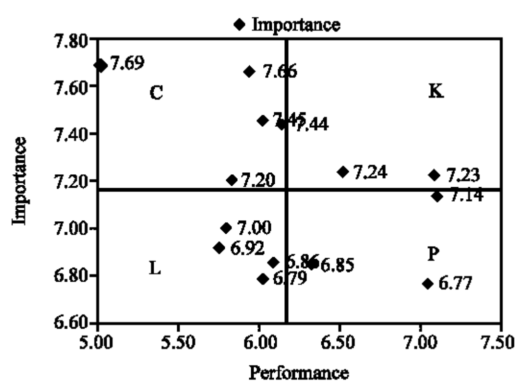

Fig. 3: Conventional IPA map for order-winner criteria

Table 1: Conventional IPA analysis for order-winner criteria

Notation	Order-winner criteria	Performance	Importance	Strategy
OW1	Price	5.94	7.66	C
OW2	Delivery reliability	6.02	7.45	C
OW3	Delivery speed	5.82	7.20	C
OW4	Quality conformance	5.01	7.69	C
OW5	Demand increases	5.75	6.92	L
OW6	Product range	7.04	6.77	P
OW7	Design	6.51	7.24	K
OW8	Distribution	7.10	7.14	P
OW9	Design leadership	6.32	6.85	P
OW10	Being an existing supplier	7.08	7.23	K
OW11	Marketing and sales	6.02	6.79	L
OW12	Brand name	6.08	6.86	L
OW13	Technical liaison and support	5.79	7.00	L
OW14	After-Sales support	6.14	7.44	C

Table 2: Influence and dependency coefficients for order-winner criteria

Notation	Order-winner criteria	R_{Tj}	D_{Ti}	D_{Ti}/R_{Tj}	Classification
OW1	Price	1.52	0.68	0.45	D
OW2	Delivery reliability	1.03	0.53	0.52	D
OW3	Delivery speed	1.35	1.00	0.74	R
OW4	Quality conformance	1.54	1.47	0.95	R
OW5	Demand increases	0.27	0.84	3.10	A
OW6	Product range	0.34	1.35	4.03	I
OW7	Design	1.13	1.83	1.62	R
OW8	Distribution	0.35	0.37	1.05	E
OW9	Design leadership	0.35	1.00	2.87	A
OW10	Being an existing supplier	1.23	1.02	0.83	R
OW11	Marketing and sales	1.28	0.78	0.61	D
OW12	Brand name	0.67	0.38	0.57	E
OW13	Technical liaison and support	0.39	0.36	0.92	E
OW14	After-Sales support	0.57	0.41	0.72	E

including Demand Increases (OW5), Marketing and Sales (OW11), Brand Name (OW12) and Technical Liaison and Support (OW13) shall be given low improvement priority.

We adopt MICMAC analysis on the order-winner criteria to understand the causal relationship between these order-winner criteria. First, we build a Direct Influence Matrix according to Eq. 1; then substitute the potential relationship by 3 to form a Potential Direct Influence Matrix X_p. Use Eq. 7 to compute the normalized influence matrix N; then use Eq. 8 to get the Total Influence Matrix T. Use Eq. 9 and 10 to compute the D_{Ti} value for each row and the R_{Tj} value for each column, which represent the influence and dependency respectively. In addition, the driving power coefficient DP_i is shown in Table 2. Take Delivery Speed (OW3) for example, $R_{tj} = 0.07+0.10+\ldots+0.03 = 1.52$, $D_{ti} = 0.16+0.14+\ldots+0.03 = 0.68$; thus, $D_{ti}/R_{Tj} = 0.68/1.52 = 0.74$.

By summing up the influence, D_{Ti} and dependency, R_{Tj} and then divided them with the 14 order-winner criteria, we get an average of 0.86 and 0.86, respectively; the value is an estimate for the central tendency of the cause and effect matrix. This value divides the influence-dependence map into four quadrants, as shown in Fig. 4. According to the analysis in Fig, 4, the order-winner criteria that belong to Influential Variables (I) include Product Range (OW6). The Relay Variables (R) are Delivery Speed (OW3), Quality Conformance (OW4), Design (OW7) and Being an Existing Supplier (OW10). The Excluded Variables (E) are Distribution (OW8), Brand Name (OW12), Technical Liaison and Support (OW13) and After-Sale Support (OW14). The Averagely Influential and/or Dependent Variables (A) are Demand Increases (OW5) and Design Leadership (OW9). The Dependent Variables (D) are Price (OW1), Delivery Reliability (OW2) and Marketing and Sales (OW11).

According to the M-IPA model, we multiply customer-recognized importance, I, by the driving power coefficient of the quality characteristic in MICMAC, DP_i; then the importance axis is transformed into the

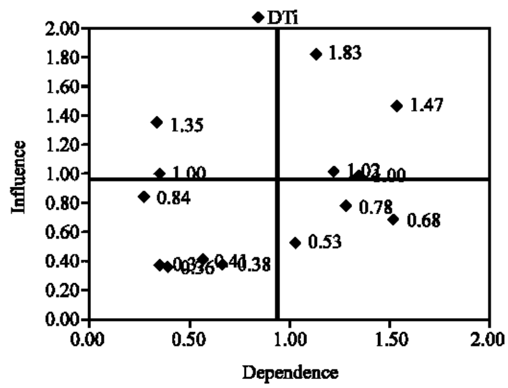

Fig. 4: Impacts of order-winner criteria, influence-dependence map

Combinative Importance (CI), I_{ci}; the M-IPA matrix is shown in Table 3 and Fig. 5. Take Delivery Speed (OW3) for example, the Combinative Importance (CI), $I_{ci} = 0.74\times7.20 = 5.32$.

According to the M-IPA analysis, as show in Fig. 5 and Table 3, the order-winner criteria located in the concentrate here area, which is Demand Increases (OW5), shall be improved immediately. The order-winner criteria located in keep up the good work area, including Produce Range (OW6), Design (OW7) and Design Leadership (OW9), shall remain the competitive advantages. The order-winner criteria in possible overkill, including Distribution (OW8), Being an Existing Supplier (OW10) and Design Leadership (OW9), can have less resource inputs. The order-winner criteria in low priority, including Price (OW1), Quality Conformance (OW4), Delivery reliability (OW2), Delivery Speed (OW3), Marketing and Sales (OW11), Brand Name (OW12), Technical Liaison and Support (OW13) and After-sales Support (OW14), shall be given low improvement priority.

From Fig. 3 and 5, we know that the results of M-IPA analysis significantly differ from the conventional IPA

Table 3: M-IPA coefficients for order-winner criteria

Notation	Order-Winner Criteria	DTi/RTj	Performance	Importance (Ici)	Strategy
OW1	Price	0.45	5.94	3.44	L
OW2	Delivery reliability	0.52	6.02	3.84	L
OW3	Delivery speed	0.74	5.82	5.32	L
OW4	Quality conformance	0.95	5.01	7.32	L
OW5	Demand increases	3.10	5.75	21.45	C
OW6	Product range	4.03	7.04	27.25	K
OW7	Design	1.62	6.51	11.71	K
OW8	Distribution	1.05	7.10	7.47	P
OW9	Design leadership	2.87	6.32	19.65	K
OW10	Being an existing supplier	0.83	7.08	6.01	P
OW11	Marketing and sales	0.61	6.02	4.13	L
OW12	Brand name	0.67	0.38	0.57	L
OW13	Technical liaison and support	0.39	0.36	0.92	L
OW14	After-Sales support	0.57	0.41	0.72	L

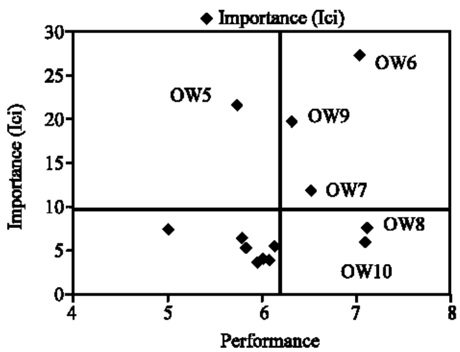

Fig. 5: M-IMP map for order-winner criteria

model. If the order-winner criteria belong to concentrate here (C), such as Demand Increases (OW5) improvement shall be proposed immediately. Price (OW1), Delivery Reliability (OW2), Delivery Speed (OW3), Quality Conformance (OW4) and After-sales Support (OW14) move from concentrate here (C) to low priority (L). On the other hand, Demand Increases (OW5) moves from low priority (L) to concentrate here (C); this is because Demand Increases (OW5) is an Averagely Influential and/or Dependent Variables (A), which can adjust and force Dependency Variables to improve.

Based on the M-IPA analysis, if the order-winner criteria belong to keep up the good work (K), which are Product range (OW6), Design (OW7) and Design Leadership (OW9), the organization must maintain or reinforce this competitive advantage. This result differs significantly from the conventional IPA analysis. Being an Existing Supplier (OW10) moved from keep up the good work (K) area to the possible overkill (P) area, while Product Range (OW6) and Design Leadership (OW9) moved from possible overkill (P) to keep up the good work (K). Since Design Leadership (OW9) is an Averagely Influential and/or Dependent Variables (A), it can adjust and prompt Dependent Variables to improve; meanwhile, Product range (OW6) is an Influential Variable, it can directly cause changes to other variables. The similar researches that factors have the cause-effect relationships will cause different results from the traditional IPA model in decision making have been proved by Lee *et al*. (2008a-c, 2009).

Lastly, if adopt the M-IPA decision model, order-winner criteria that are Influential Variables (I) or Averagely Influential and/or Dependent Variables (A) and located in concentrate here (C) or keep up the good work (K) area include Demand Increases (OW5), Product Range (OW6), Design (OW7) and Design Leadership (OW9). The organization shall determine the improvements and reinforce these order-winner criteria, in order to adopt a differentiated strategy for market segmentation and enhance market competitiveness.

CONCLUSIONS

Conventionally, customer satisfaction studies are conducted by surveys. All researchers use quantified ordinal scale data as variables; after calculating the average of quality characteristic importance and performance, a two-dimensional importance-performance matrix is built to determine which quality characteristics shall have fewer inputs, which still need to be improved and which shall maintain their competitive advantages, in order to enhance market competitiveness for the organization. The conventional IPA model and the following works all contribute significantly to this technique. However, those models still have some potential problems that need to be studied and solved. The potential problems include the following. The conventional IPA model assumes that quality characteristics are mutually independent variables; thus, it failed to analyze how the types of quality characteristics affect the whole system from a systematic point of view. If the quality characteristics do correlate and have a causal relationship, the conventional IPA model could not accurately analyze the importance and priority of improvement and may lead to a wrong decision. Our study used MICMAC to study the influence and dependency of quality characteristics; we successfully classify order-winner and order-qualifying criteria and make in-depth analysis on the benefits of order-winner criteria improvements. However, the MICMAC model failed to discuss the decision model for the market strategy of order-winner criteria. Thus, we use MICMAC to incorporate the influence and dependency of order-winner criteria. By integrating the MICMAC and IPA models, we establish a new decision analysis methodology, the M-IPA. By using M-IPA, we find out the core improvement items in an order-winner criteria system.

In this study, the M-IPA methodology combines the MICMAC and IPA model and from the case study we get some conclusions are as present study used MICMAC to study the influence and dependency of quality characteristics; we successfully classify order-winner and order-qualifying criteria and make in-depth analysis on the benefits of order-winner criteria improvements. M-IPA model not only solves potential problems in the conventional IPA model, but also keeps a comprehensible decision model under the IPA. This methodology requires the least inputs and focuses on key driving factors in the system, to help improve order-winner criteria. Finally, we analyze and discuss an actual case study on the air conditioning technology industry in Taiwan to illustrate the M-IPA decision analysis methodology built on MICMAC and IPA. Meanwhile, impacts of quality characteristics are considered in order to reasonably incorporate the importance of order-winner criteria with the least inputs and to solve the complex systematic problems when there is a causal relationship between order-winner criteria. This allows us to get the most out of customers' feedbacks; moreover, it provides the accurate and effective information an organization needs for decision-making.

REFERENCES

Agarwal, A., R. Shankar and M.K. Tiwari, 2007. Modeling agility of supply chain. Industrial Market. Manage., 36: 443-457.

Aigbedo, H. and R. Parameswaran, 2004. Importance performance analysis for improving quality of campus food service. Int. J. Qual. Reliab. Manage., 21: 876-896.

Arya, D.S. and S.A. Abbasi, 2001. Identification and classification of key variables and their role in environmental impact assessment: Methodology and software package intra. Environ. Monit. Assess., 72: 277-296.

Bacon, D.R., 2003. A comparison of approaches to importance-performance analysis. Int. J. Mar. Res., 45: 55-72.

Duperrin, J.C. and M. Godet, 1973. Methode de hierarchisation des elements d'un systeme. Rapport Economique du CEA, R-45-41, Paris.

Eskildsen, J.K. and K. Kristensen, 2006. Enhancing importance-performance analysis. Int. J. Prod. Perf. Manage., 55: 40-60.

Faisal, M.N., D.K. Banwet and R. Shankar, 2006. Supply chain risk mitigation: Modeling the enablers. Bus. Process Manage. J., 12: 535-552.

Faisal, M.N., D.K. Banwet and R. Shankar, 2007. Information risks management in supply chains: An assessment and mitigation framework. J. Ent. Inform. Manage., 20: 1747-17398.

Garvin, D.A., 1987. Competing on the eight dimensions of quality. Harvard Bus. Rev., 65: 101-109.

Georgantzas, N.C. and M.P. Hessel, 1995. The intermediate structure of designs for quality. Int. J. Q. Reliabil. Manage., 12: 97-108.

Griffin, A. and J.R. Hauser, 1993. The voice of customer. Market. Sci., 12: 1-27.

Hill, T., 2000. Manufacturing Strategy: Text and Cases. 3rd Edn., The McGraw-Hill Companies Inc., Palgrave, Basingstoke, ISBN-13: 978-0256106664.

Huang, Y.C., C.H. Wu and C.J. Hsu, 2006. Using importance-performance analysis in evaluating Taiwan medium and long distance national highway passenger transportation service quality. J. Am. Acad. Bus., 8: 98-104.

Jha, K.N. and M.N. Devaya, 2008. Modelling the risks faced by indian construction companies assessing international projects. Construction Manage. Econ., 26: 337-348.

Kannan, G. and A.N. Haq, 2007. Analysis of interactions of criteria and sub-criteria for the selection of supplier in the built-in-order supply chain environment. Int. J. Prod. Res., 45: 3831-3852.

Lee, Y.C., C.C. Cheng and T.M. Yen, 2009. Integrate kanos model and ipa to improve order-winner criteria: A study of computer industry. J. Applied Sci., 9: 38-48.

Lee, Y.C., H.Y. Hu, T.M. Yen and C.H. Tsai, 2008a. Kanos model and decision making trial and evaluation laboratory applied to order-winners and qualifiers improvement: A study of computer industry. Inform. Technol. J., 7: 702-714.

Lee, Y.C., T.M. Yen and C.H. Tsai, 2008b. The study of an integrated rating system for supplier quality performance in the semiconductor industry. J. Applied Sci., 8: 453-461.

Lee, Y.C., T.M. Yen and C.H. Tsai, 2008c. Using importance-performance analysis and decision making trial and evaluation laboratory to enhance order-winner criteria: A study of computer industry. Inform. Technol. J., 7: 396-408.

Levenburg, N.M. and S.R. Magal, 2005. Applying importance-performance analysis to evaluate E-business strategies among small firms. E-Service J., 3: 29-48.

Mandal, A. and S.G. Deshmukh, 1994. Vender selection using interpretive structural modeling. Int. J. Operat. Prod. Manage., 14: 52-59.

Martilla, J.A. and J.C. James, 1977. Importance-performance analysis. J. Market., 41: 77-79.

Matzler, K. and E. Sauerwein, 2002. The Factor Structure of customer satisfaction: An empirical test of importance grid and the penalty-reward-contrast analysis. Int. J. Service Ind. Manage., 13: 314-332.

Matzler, K., E. Sauerwein and K.A. Heischmidt, 2003. Importance-performance analysis revisited: The role of factor structure of customer satisfaction. Service Ind. J., 23: 112-129.

Matzler, K., F. Bailom, H.H. Hinterhuber, B. Renzl and J. Pichler, 2004. The asymmetric relationship between attribute-level performance and overall customer satisfaction: A reconsideration of the importance-performance analysis. Ind. Market. Manage., 33: 271-277.

Matzler, K., M. Rier, H.H. Hinterhuber, B. Renzl and C. Stadler, 2005. Methods and concepts in management: Significance, satisfaction and suggestions for further research-perspectives from Germany, Austria and Switzerland. Strategic Change, 14: 1-13.

Qureshi, M.N., D. Kumar and P. Kumar, 2007. Modeling the logistics outsourcing relationship variables to enhance shipper's productivity and competitiveness in logistical supply chain. Int. J. Prod. Perform. Manage., 56: 689-714.

Qureshi, M.N., D. Kumar and P. Kumar, 2008. An integrated model to identify and classify the key criteria and their role in the assessment of 3pl services providers. Asia Pacific J. Market. Logist., 20: 227-249.

Ravi, V. and R. Shankar, 2005. Analysis of interactions among the barriers of reverse logistics. Tech. Forecast. Soc. Change, 72: 1011-1029.

Ravi, V., R. Shankar and M.K. Tiwari, 2005. Productivity improvement of a computer hardware supply chain. Int. J. Prod. Perform. Manage., 54: 239-255.

Sampson, S.E. and M.J. Showalter, 1999. The performance-importance response function: Observations and implications. Service Ind. J., 19: 1-25.

Slack, N., 1994. The importance-performance matrix as a determinant of improvement priority. J. Operat. Prod. Manage., 14: 59-75.

Tarrant, M.A. and E.K. Smith, 2002. The use of a modified importance-performance framework to examine visitor satisfaction with attributes of outdoor recreation settings. Manag. Leisure, 7: 69-82.

Tonge, J. and S.A. Moore, 2007. Importance-satisfaction analysis for marine-park hinterlands: A Western Australian case study. Tourism Manage., 28: 768-776.

Wang, G.H., Y.X. Wang and T. Zhao, 2008. Analysis of interactions among the barriers to energy saving in china. Energy Policy, 36: 1879-1889.

Yavas, U. and D.J. Shemwell, 2001. Modified importance-performance analysis: An application to hospitals. Int. J. Health Care Qual. Assurance, 14: 104-110.

Zhang, H.Q. and I. Chow, 2004. Application of importance-performance model in tour guides performance: Evidence from mainland Chinese outbound visitors in Hong Kong. Tourism Manage., 25: 81-91.