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An integrated fuzzy QFD framework for new product development

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Abstract An important source of competitive advantage, survival and renewal for firms is the successful new product development (NPD). Quality function deployment (QFD) aims to facilitate the NPD process from product conceptualization to production requirements; however, conventional QFD has its shortcomings. Even though modified QFD models have been proposed in literature, a comprehensive model is necessary. In this paper, factors in each phase of the QFD is prepared first through literature review and interview with domain experts. Fuzzy Delphi method is adopted to select the critical factors, and fuzzy interpretive structural modeling is applied to determine the relationships among the critical factors. The results are then used to construct houses of quality for QFD, which is incorporated by fuzzy analytic network process. A case study of a thin film transistor liquid crystal display firm is carried out to verify the practicality of the proposed framework.

Keywords New product development (NPD) · Quality function deployment (QFD) · Analytic network process (ANP) · Interpretive structural modeling (ISM)

1 Introduction

Under a globally competitive business environment, technological innovation and satisfaction of customer needs are the keys to survival and success for firms, especially for high-tech firms. The success of new product development (NPD) is important to

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maintain a competitive edge and to make a decent profit for a firm because new products are usually a source of new sales and profits (Lee et al. 2010a). Thus, a good NPD process is required to develop products successfully. Quality function deployment (QFD) is a popular tool to fulfill the task in different phases in NPD.

Despite of its benefits, QFD does have some drawbacks (Büyüközkan et al. 2004; Ertay et al. 2005; Kahraman et al. 2006; Kumar et al. 2007; Lee et al. 2010a). Therefore, some improved QFD approaches have been proposed to tackle the issues such as the generalization of the opinions of multiple decision makers, the large amounts of subjective data, the burden of a large dimensional comparison, and the ambiguity and uncertainty in human decision making.

While there are many hybrid QFD models available, the incorporation of fuzzy sets theory and analytic network process (ANP) in QFD is one of the new trends. Nevertheless, a simple FANP-QFD model may not be adequate to solve such a complicated process in real practice. Thus, this research proposes a comprehensive framework that applies fuzzy Delphi method (FDM) to select the critical factors, fuzzy interpretive structural modeling (FISM) to determine the relationship among factors, and FANP with QFD to complete the process. Fuzzy set theory is incorporated into the framework to consider the uncertainty and fuzziness of experts' opinions. Because of limited resources, a firm cannot consider all factors in developing a product. Therefore, FDM is adopted to select the more important factors in each house of quality (HOQ). Due to the fact that there may be an interrelationship among the factors, FISM is applied next to determine whether the interrelationship exists or not. Based on the results of FISM, a FANP-QFD questionnaire can be prepared so that the questionnaire will not be unnecessarily lengthy. The proposed framework can facilitate decision makers to have an extensive examination of the problem and can carry out the QFD process systematically and more comprehensively. To examine its practicality, the proposed framework is applied to the four phases of QFD in a TFT-LCD manufacturer.

The rest of this paper is organized as follows. Section 2 reviews the methodologies adopted in this research. Section 3 constructs an integrated fuzzy QFD model for new product development. A case study of TFT-LCD product design is presented in Sect. 4 to examine the practicality of the proposed framework. Some concluding remarks are made in the last section.

2 Methodologies

2.1 Quality function deployment (QFD)

In a complete QFD system, there are typically four phases: product planning, part deployment, process planning and production planning (Zhang et al. 1999; Chen et al. 2004). Each phase contains a matrix, called HOQ. The systematic procedure for the first HOQ contains seven steps (Chan et al. 1999; Wang 1999; Ramasamy and Selladurai 2004; Lin and Lee 2008):

1. Obtain customer attributes (CAs).
2. Develop engineering characteristics (ECs).
3. Build relationship between CAs and ECs.

4. Complete competitive survey and calculate relative importance of CAs.
5. Perform the competitive technical benchmarking.
6. Determine the relationships among ECs.
7. Calculate the importance of ECs and additional goals.

QFD has been applied abundantly. For example, Wang and Lin (2007) constructed a defects tracking matrix (DTM) based on the HOQ to directly connect manufacturing technologies with quality defects inside a mass customization production (MCP) module. Lu et al. (2007) suggested the use of QFD to match customer desires with design configurations in proposing a framework for simulation modeling of a transporter-constrained supply chain of customized products.

Because of the interrelationships among CAs and among ECs, ANP is used in some works (Partovi 2001, 2006, 2007; Karsak et al. 2002; Partovi and Corredoira 2002; Yoon et al. 2006; Pal et al. 2007; Raharjo et al. 2008; Parra-López et al. 2008). There are basically two types of ANP-QFD approaches: simple matrix manipulation and supermatrix approach (Raharjo et al. 2008; Lee et al. 2010a). The first type, which is based on the network model described in Saaty and Takizawa (1986), has some limitations (Raharjo et al. 2008). The second type, a general supermatrix approach, can tackle more complicated problems (Saaty 1996). Nevertheless, the input variables are assumed to be precise and are treated as numerical data under the two approaches. However, human decision making often contains ambiguity and uncertainty, and conventional ANP is inadequate to explicitly capture the importance assessment of CAs and ECs. To confront this problem, a new trend of studies is to incorporate fuzzy set theory into the ANP-QFD approach. Büyüközkan et al. (2004), Ertay et al. (2005) and Kahraman et al. (2006) incorporated fuzzy set theory into the simple matrix manipulation approach. Ertay et al. (2005) also prioritized ECs by implementing QFD based on ANP with linguistic data. Kahraman et al. (2006) proposed an integrated product design framework based on fuzzy QFD and a fuzzy optimization model. The fuzzy ANP is incorporated to consider the inner dependence among CAs and among ECs with the consideration of impreciseness and vagueness in human judgments' subjectivity. A mixed integer linear programming model is next applied to optimize target improvements of the ECs. Büyüközkan et al. (2007), by applying fuzzy triangular number and using ANP to determine the interdependence between CAs and ECs and the inner dependences among CAs and among ECs, calculated the priorities of ECs. The only fuzzy ANP-QFD with supermatrix approach was done by Lee et al. (2010a). A two-phase framework is constructed for facilitating the selection of engineering characteristics (ECs) for product design. The first phase contains QFD with the supermatrix approach of FANP to calculate the priorities of ECs. The second phase applies multi-choice goal programming model to select the most suitable ECs for design. To summarize, because the supermatrix approach is the authentic and acknowledged ANP methodology and fuzzy set theory can deal with vagueness or ambiguity, fuzzy supermatrix approach in QFD is adopted in this study.

2.2 Delphi method

The Delphi method, first proposed by Dalkey and Helmer in 1963, can facilitate forecasting by converging a value through the feedback of experts after several rounds (Lee et al. 2010b). This popular method has been widely applied in many research and practical areas, but it has some shortfalls, such as repetitive questionnaires and evaluations, declining response rate of experts, inappropriate convergence, ambiguity and uncertainty in survey questions and in response, lengthy time and high cost (Chang et al. 2000; Chang and Wang 2006; Lee et al. 2010b). The incorporation of fuzzy set theory is one of the approaches to tackle the problems. Some of the attributes of the fuzzy Delphi method (FDM) include: the decrease in the number of rounds of questionnaire survey, and thus improvement in the response rate, time and cost; the reduction in the distortion of individual expert opinion; a clear expression of the semantic structure of predicted items; and the incorporation of fuzziness in the information contents of the respondents (Chang et al. 2000; Chang and Wang 2006; Hsiao 2006; Lee et al. 2010b).

Recent works that applied the FDM are reviewed here. Liu and Chen (2007) presented a systemic procedure to combine the AHP and the FDM for assessing slope rock mass quality estimates, and the FDM was used to synthesize the responses of the questionnaires from the experts. Wey and Wu (2007) proposed a transportation infrastructure selection methodology which reflects interdependencies among evaluation criteria and candidate projects using the FDM and the ANP and formulates a zero–one goal programming model. Büyüközkan and Ruan (2008) used a weighted FDM to determine the aggregated fuzzy weight of criteria and proposed a fuzzy multi-criteria decision approach in evaluating software development projects. Kuo and Chen (2008) based on the four perspectives of the balanced scorecard and applied the FDM to select key performance appraisal indicators for mobility of the service industries. Wang and Lin (2008) applied the FDM and ranking methods to extract the key performance indicators through expert questionnaires, and constructed a fuzzy regression model to monitor production loss. Wei and Chang (2008) constructed a systematic methodology that applied the FDM to determine the evaluation criteria and integrated the ANP and the zero–one goal programming (ZOGP) to select an optimal product design solution. Liu and Wang (2009) proposed an integrated fuzzy approach for the evaluation and selection of third-party logistics providers, and the FDM was applied to identify the important evaluation criteria and to obtain their weights for provider selection. Wang et al. (2010) applied the FDM to extract the factors for the sustainable development of a housing community and used ANP to evaluate different development projects. Lee et al. (2010b) applied the FDM to extract factors under the benefits, opportunities, costs and risks (BOCR) merits and adopted the FANP to evaluate various production strategies for a manufacturer. Lee et al. (2010c) used the FDM to select the critical factors for technology transfer of new equipment in high technology industry.

2.3 Interpretive structural modeling (ISM)

Interpretive structural modeling (ISM), proposed by Warfield (Warfield 1974a, b, 1976), is often used to provide fundamental understanding of complex situations and to put together a course of action for solving a problem. The ISM is a process that enables individuals or groups to develop a map of the complex relationships among elements in a complex situation and to calculate binary matrix, called adjacency matrix, to present the relations of the elements (Huang et al. 2005). Its basic idea is to use experts' practical experience and knowledge to decompose a complicated system into several subsystems (elements) and to construct a multilevel structural model (Warfield 1974a, b).

The ISM has been applied in various fields, such as assisting government bodies to prioritize activities, facilitating companies to select projects, and aiding researchers in relevant works. For example, Kannan and Haq (2007) used the ISM to understand the interactions of criteria and sub-criteria that are used to select the supplier for the built-in-order supply chain environment in the original equipment manufacturing company. However, the ISM is usually used as a tool for imposing order and direction on the complexity of relationships among the element, and it does not give any weighting associated with the elements (Kannan and Haq 2007). Therefore, other methodology can be incorporated with the ISM in research works. Huang et al. (2005) proposed a method which combined the ISM and the ANP to deal with the problem of the subsystems' interdependence and feedback. Yang et al. (2008) studied vendor selection by integrated fuzzy MCDM techniques, and the ISM was applied to map out the relationships among the sub-criteria. Feng et al. (2010) proposed a hybrid fuzzy integral decision-making model for selecting locations of high-tech manufacturing centers in China through integrating factor analysis, ISM, Markov chain, fuzzy integral and the simple additive weighted method. Lee et al. (2010b) proposed an evaluation framework for technology transfer of new equipment in high technology industry. The ISM was employed first to determine the interrelationship among the critical factors, and the FANP was applied next to evaluate the technology transfer performance of equipment suppliers.

The ISM requires the assumption of a binary relation between each two elements, that is, whether there is definitely a relation or there is no relation between two elements. However, a fuzzy relation with a degree of strength often exists, and the adoption of the fuzzy sets theory can provide a system with no sharp boundaries. Therefore, some scholars combined the ISM with the fuzzy sets theory to solve the problem (Tazaki and Amagasa 1979; Mitamura and Ohuchi 1997; Yamashita 1997; Raghuvanshi and Kumar 1999). The principle behind is to change the traditional binary value into a fuzzy binary relation. The FISM, thus, provide interviewers the opportunity to express the strength or fuzziness of the relationship among elements.

2.4 Analytic network process (ANP)

Analytic network process (ANP), introduced by Saaty, is a generalization of analytic hierarchy process (AHP) and is a multi-criteria decision support methodology to decompose a complex problem into a network (Saaty 1996; Lee et al. 2010c). A good decision-marking model needs to tolerate vagueness or ambiguity, thus, fuzzy set theory can be introduced to the conventional ANP, and it is called

FANP. The procedure for the FANP can be summarized as follows (Lee et al. 2010c):

1. Decompose the problem into a network.
2. Prepare a questionnaire based on the constructed network, and ask experts to fill out the questionnaire.
3. Transform the scores of pairwise comparison into linguistic variables, and aggregate the results of the experts' questionnaires.
4. Obtain crisp numbers by defuzzying the synthetic triangular fuzzy numbers.
5. Calculate the maximum eigenvalues and eigenvectors.
6. Check the consistency property of the matrix.
7. Form an unweighted supermatrix.
8. Form a weighted supermatrix.
9. Obtain the limit supermatrix and the priority weights of the alternatives.

3 An integrated fuzzy QFD model for new product development

A systematic process that incorporates FDM, FISM and FANP into QFD for product design is proposed here. There are three stages: the selection of factors using the FDM, the relationships among factors using the FISM, and the ranking of factors using the FANP-QFD. The procedures for selecting the factors for the first HOQ, the product planning phase, are explained as follows.

3.1 Stage I: The selection of factors by the FDM

Because of limited resources, a firm can only focus on certain factors in developing a product. Therefore, the FDM is applied to select the most important CAs and ECs from the candidate lists. The steps are as follows (Ishikawa et al. 1993; Chang and Wang 2006; Hsiao 2006; Lin and Lee 2008; Wang et al. 2010; Lee et al. 2010b):

1. Form a committee of experts to define the product design problem in a TFT-LCD manufacturer. List all possible CAs and ECs in the product planning phase through interview, questionnaire or brainstorming.
2. Employ a questionnaire to ask experts for their most pessimistic (minimum) value and the most optimistic (maximum) value of the importance of each CA (EC) in the possible factor set $S_C(S_E)$ in a range from 1 to 10. A score for a CA (EC) is denoted as:

$$c_i = \left(l_k^i, h_k^i\right), \quad i \in S_C \tag{1}$$

$$e_v = \left(l_k^v, h_k^v\right), \quad v \in S_E \tag{2}$$

where l_k^i $\left(l_k^v\right)$ is the pessimistic index of factor i (v) and h_k^i $\left(h_k^v\right)$ is the optimistic index of factor i (v), rated by expert k.
3. Determine the triangular fuzzy number for the most pessimistic index and the most optimistic index for each factor. For each factor i (v), the minimum value

$\left(l_l^i \text{ and } l_l^v\right)$, the geometric mean $\left(l_m^i \text{ and } l_m^v\right)$, and the maximum value $\left(l_u^i \text{ and } l_u^v\right)$ of the experts' opinions on the most pessimistic index are obtained, and the triangular fuzzy number is $l^i = \left(l_l^i, l_m^i, l_u^i\right)$ $l^v = \left(l_l^v, l_m^v, l_u^v\right)$. The triangular fuzzy number for the most optimistic index is also obtained, $h^i = \left(h_l^i, h_m^i, h_u^i\right)$ $h^v = \left(h_l^v, h_m^v, h_u^v\right)$.

4. Examine the consensus of experts' opinions, and calculate the consensus significance value of each factor. The gray zone, as shown in Fig. 1, is the overlap section of l^i and h^i and is used to examine the consensus of experts in each factor. The consensus significance value of the factor i, s^i, is calculated by the following rules:

   4.1 If there is no overlap between l^i and h^i, i.e., $l_u^i \leq h_l^i$ and no gray zone exists, experts' opinions in factor i are in consensus. The consensus significance value of the factor is:

$$s^i = \frac{l_m^i + h_m^i}{2}. \tag{3}$$

   4.2 If a gray zone exists and the gray zone interval value $g^i\left(g^i = l_u^i - h_l^i\right)$ is less than the interval value of l^i and h^i $\left(d^i = h_m^i - l_m^i\right)$, i.e., $g^i \leq d^i$, the consensus significance value of the factor is calculated by Eqs.4 and 5:

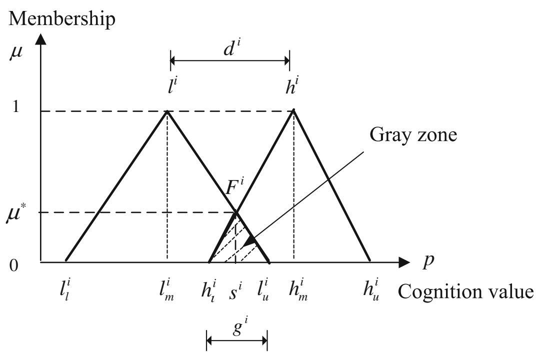
$$F^i(p) = \left\{ \int_p \left\{ \min\left[l^i(p),\, h^i(p)\right] \right\} dp \right\}, \quad i \in S \tag{4}$$

$$s^i = \{p \mid \max \mu_{F^i}(p)\}, \quad i \in S \tag{5}$$

   where $F^i(p)$ is the area of the intersection of l^i and h^i, and s^i is the cognition value (p) with the highest degree of membership (μ^*) of the intersection of l^i and h^i.

   4.3 If a gray zone exists and $g^i > d^i$, this implies a great discrepancy among the experts' opinions. *Step 1* to *Step 3* need to be repeated until a convergence is obtained.
   The same procedure is carried out to calculate the consensus significance value of factor v, s^v.

Fig. 1 Gray zone of l^i and h^i (Lin and Lee 2008; Lee et al. 2010b)



5. Select factors from the candidate list. Select factor i (v) if its consensus significance value is greater than or equal to the threshold value T_C (T_E) which is determined by experts subjectively based on the mean of all s^i (s^v). That is, select factor $i(v)$ if $s^i \geq T_C$ ($s^v \geq T_E$).

3.2 Stage II: The relationships among factors by the FISM

Because a CA may have an impact on other CAs, so is an EC on other ECs, the interdependence among CAs and among ECs must be studied. In addition, a CA can be fulfilled if one or more ECs are achieved. FISM is applied to determine the relationship. The procedures of the FISM in determining the interdependence among CAs are as follows:

1. List factors selected from Stage I, and define each CA as x_i, $i = 1,2,3,\ldots,n$.
2. Employ a questionnaire to ask experts the relation between each two CAs. The relationship between any two CAs can be from x_i to x_j, from x_j to x_i, in both directions between x_i and x_j, or x_i and x_j unrelated. Five levels of relation from one CA to another are set, namely, "unrelated", "low related", "fairly related", "strongly related", and "completely related". The linguistic variables are transformed into triangular fuzzy numbers, as shown in Table 1.
3. Aggregate experts' responses. By applying the geometric mean approach to aggregate experts' opinions, the relation from CA$_i$ to CA$_j$ can be represented by a triangular fuzzy number, $\tilde{x}_{ij}$.
4. Establish an aggregated fuzzy relation matrix. By applying α-cuts, an aggregated fuzzy relation matrix can be formed (Kang and Lee 2007):

$$\mathbf{D}_\alpha = \begin{bmatrix} 0 & \left[x_{12L}^\alpha, x_{12U}^\alpha\right] & \cdots & \left[x_{1nL}^\alpha, x_{1nU}^\alpha\right] \\ \left[x_{21L}^\alpha, x_{21U}^\alpha\right] & 0 & \cdots & \left[x_{2nL}^\alpha, x_{2nU}^\alpha\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[x_{n1L}^\alpha, x_{n1U}^\alpha\right] & \left[x_{n2L}^\alpha, x_{n2U}^\alpha\right] & \cdots & 0 \end{bmatrix} \tag{6}$$

   where $0 \leq \alpha \leq 1$.
5. Establish an aggregated defuzzified relation matrix with α-cuts and the degree of satisfaction of the experts on judgment, $\mathbf{X}_\alpha^\beta$. When α is fixed, the index of optimism β can be set to represent the degree of the optimism of decision makers (Kang and Lee 2007). A larger β indicates a higher degree of optimism,

Table 1 Triangular fuzzy numbers for FISM

Linguistic variables	Triangular fuzzy numbers
Completely related	(0.75,1,1)
Strongly related	(0.05,0.75,1)
Fairly related	(0.25,0.05,0.75)
Low related	(0.01,0.25,0.05)
Unrelated	(0.01,0.01,0.01)

and vice versa. The index of optimism is a linear convex combination and is defined as:

$$x_{ij}^{\alpha\beta} = (1-\beta)x_{ijL}^{\alpha} + \beta x_{ijU}^{\alpha}, \quad \forall \beta \in [0,1] \tag{7}$$

The aggregated defuzzified relation matrix with α-cuts and index of optimism β is:

$$\mathbf{D}_{\alpha}^{\beta} = \begin{bmatrix} x_{11}^{\alpha\beta} & x_{12}^{\alpha\beta} & \dots & x_{1n}^{\alpha\beta} \\ x_{21}^{\alpha\beta} & x_{22}^{\alpha\beta} & \dots & x_{2n}^{\alpha\beta} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1}^{\alpha\beta} & x_{n2}^{\alpha\beta} & \dots & x_{nn}^{\alpha\beta} \end{bmatrix} \tag{8}$$

6. Determine a binary relation matrix. A threshold value is set to determine whether the there is a relation between each two CAs. If $x_{ij}^{\alpha\beta}$ is higher than the threshold value, x_j is deemed reachable from x_i, and we let $\pi_{ij} = 1$, otherwise, $\pi_{ij} = 0$ (Yang et al. 2008). The binary relation matrix is:

$$\mathbf{D} = \begin{array}{c} \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{array} \begin{array}{c} \begin{array}{cccc} x_1 & x_2 & \dots & x_n \end{array} \\ \begin{bmatrix} 0 & \pi_{12} & \dots & \pi_{1n} \\ \pi_{21} & 0 & \dots & \pi_{2n} \\ \vdots & \vdots & 0 & \vdots \\ \pi_{n1} & \pi_{n2} & \dots & 0 \end{bmatrix} \end{array}, \quad i = 1,2,\dots,n;\ j = 1,2,\dots,n \tag{9}$$

where π_{ij} denotes the relation between the ith row and jth column CAs.

7. Develop a reachability matrix. The initial reachability matrix $\mathbf{M}$ is calculated by adding $\mathbf{D}$ with the identity matrix $\mathbf{I}$:

$$\mathbf{M} = \mathbf{D} + \mathbf{I} \tag{10}$$

8. Calculate the final reachability matrix. In the final reachability matrix, $\mathbf{M}^*$, a convergence can be met to reflect the transitivity of the contextual relation among CAs.

$$\mathbf{M}^* = \mathbf{M}^b = \mathbf{M}^{b+1}, \quad b > 1 \tag{11}$$

$$\mathbf{M}^* = \begin{array}{c} \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{array} \begin{array}{c} \begin{array}{cccc} x_1 & x_2 & \dots & x_n \end{array} \\ \begin{bmatrix} \pi_{11}^* & \pi_{12}^* & \dots & \pi_{1n}^* \\ \pi_{21}^* & \pi_{22}^* & \dots & \pi_{2n}^* \\ \vdots & \vdots & \vdots & \vdots \\ \pi_{n1}^* & \pi_{n2}^* & \dots & \pi_{nn}^* \end{bmatrix} \end{array}, \quad i = 1,2,\dots,n;\ j = 1,2,\dots,n \tag{12}$$

where π_{ij}^* denotes the relation between the ith row and jth column CAs.

The same procedures are repeated for determining the interdependence among ECs and the influences of CAs on ECs.

3.3 Stage III: The ranking of factors using the FANP-QFD

Using the information from Stage II, a HOQ is constructed first, and a questionnaire is prepared to pairwise compare the relationships between CAs and ECs, the inner dependence among CAs and the inner dependence among ECs. The final ranking of the ECs can be calculated by applying FANP. The procedures of the FANP-QFD are as follows:

1. Construct a HOQ. Use the relationship between CAs and ECs, inner dependence among CAs and among ECs obtained from Stage II to fill in the rectangle, left-hand triangle and top triangle of the HOQ. A check is entered if there is an influence of one factor to another factor.
2. Prepare questionnaire and receive feedback from experts. A questionnaire using Satty's nine-point scale of pairwise comparison for ANP is prepared, and related personnel are asked to fill out the questionnaire. In the questionnaire, the relationship between CAs and ECs, the inner dependence among CAs and the inner dependence among ECs based on the HOQ are asked. Pairwise comparison matrix of each part of the questionnaire from each expert is examined for consistency first by calculating the consistency index (*CI*) and consistency ratio (*CR*). If an inconsistency is present, the expert is asked to revise the part of the questionnaire.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{13}$$

$$CR = \frac{CI}{RI} \tag{14}$$

   where n is the number of items being compared in the matrix, and RI is random index (Saaty 1980).
3. Construct fuzzy pairwise comparison matrices. The pairwise comparison matrix of each part of the questionnaire from each expert is transformed into a fuzzy pairwise comparison matrix using Table 2. For instance, with pairwise comparison of the importance of CAs, we can obtain a matrix $(\tilde{A}_k)$ for expert k:

Table 2 Triangular fuzzy numbers for FANP (Lee et al. 2010c)

Linguistic variables	Positive triangular fuzzy numbers	Positive reciprocal triangular fuzzy numbers
Extremely strong	(9,9,9)	(1/9,1/9,1/9)
Intermediate	(7,8,9)	(1/9,1/8,1/7)
Very strong	(6,7,8)	(1/8,1/7,1/6)
Intermediate	(5,6,7)	(1/7,1/6,1/5)
Strong	(4,5,6)	(1/6,1/5,1/4)
Intermediate	(3,4,5)	(1/5,1/4,1/3)
Moderately strong	(2,3,4)	(1/4,1/3,1/2)
Intermediate	(1,2,3)	(1/3,1/2,1)
Equally strong	(1,1,1)	(1,1,1)

$$\tilde{A}_k = \begin{array}{c|c} & \begin{array}{cccccccc} CA_1 & CA_2 & \cdots & \cdots & CA_j & \cdots & CA_n \end{array} \\ \begin{array}{c} CA_1 \\ CA_2 \\ \vdots \\ CA_i \\ \vdots \\ \vdots \\ CA_n \end{array} & \begin{bmatrix} 1 & \tilde{a}_{12k} & \cdots & \cdots & \cdots & \cdots & \tilde{a}_{1nk} \\ 1/\tilde{a}_{12k} & 1 & \cdots & \cdots & \cdots & \cdots & \tilde{a}_{2nk} \\ \vdots & \vdots & 1 & \cdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & 1 & \tilde{a}_{ijk} & \cdots & \vdots \\ \vdots & \vdots & \vdots & 1/\tilde{a}_{ijk} & 1 & \cdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & 1 & \vdots \\ 1/\tilde{a}_{1nk} & 1/\tilde{a}_{2nk} & \cdots & \cdots & \cdots & \cdots & 1 \end{bmatrix} \end{array} \tag{15}$$

where n is the number of CAs.

4. Construct fuzzy aggregated pairwise comparison matrices. Combine fuzzy pairwise comparison matrices from all experts by a geometric mean approach. With k experts, there are a total of k sets of pairwise comparison matrices to represent the relationship between CAs and ECs, and also for the inner dependence among CAs and for the inner dependence among ECs. For each pairwise comparison between two elements, there are k triangular fuzzy numbers. A synthetic triangular fuzzy number is obtained by geometric mean approach:

$$\tilde{a}_{ij} = \left(\tilde{a}_{ij1} \otimes \tilde{a}_{ij2} \otimes \cdots \otimes \tilde{a}_{ijk}\right)^{1/k} \tag{16}$$

where $\tilde{a}_{ijk} = (l_{ijk}, t_{ijk}, u_{ijk})$
The fuzzy aggregated pairwise comparison matrix is:

$$\tilde{\mathbf{A}} = \begin{bmatrix} 1 & \tilde{a}_{12} & \ldots & \ldots & \ldots & \ldots & \tilde{a}_{1j} \\ 1/\tilde{a}_{12} & 1 & \ldots & \ldots & \ldots & \ldots & \tilde{a}_{2j} \\ \vdots & \vdots & 1 & \ldots & \ldots & \ldots & \ldots \\ \vdots & \vdots & \vdots & 1 & \tilde{a}_{ij} & \ldots & \ldots \\ \vdots & \vdots & \vdots & 1/\tilde{a}_{ij} & 1 & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & 1 & \ldots \\ 1/\tilde{a}_{1j} & 1/\tilde{a}_{2j} & \ldots & \ldots & \ldots & \ldots & 1 \end{bmatrix} \tag{17}$$

where $\tilde{a}_{ij} = (l_{ij}, t_{ij}, u_{ij})$.

5. Construct defuzzified aggregated pairwise comparison matrices. The fuzzy aggregated pairwise comparison matrices are transformed into defuzzified aggregated pairwise comparison matrices using the center of gravity (COG) method. The comparison between element i and j can be defuzzified as (Yager 1978; Klir and Yuan 1995):

$$a_{ij} = \frac{\left[\left(u_{ij} - l_{ij}\right) + \left(t_{ij} - l_{ij}\right)\right]}{3} + l_{ij} \tag{18}$$

The defuzzified aggregated pairwise comparison matrix is:

$$\mathbf{A} = \begin{bmatrix} 1 & a_{12} & \cdots & \cdots & \cdots & \cdots & a_{1j} \\ 1/a_{12} & 1 & \cdots & \cdots & \cdots & \cdots & a_{2j} \\ \vdots & \vdots & 1 & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & 1 & a_{ij} & \cdots & \cdots \\ \vdots & \vdots & \vdots & 1/a_{ij} & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & 1 & \cdots \\ 1/a_{1j} & 1/a_{2j} & \cdots & \cdots & \cdots & \cdots & 1 \end{bmatrix} \tag{19}$$

6. Calculate priority vectors and check the consistency of the defuzzified aggregated pairwise comparison matrices. A local priority vector is derived for each defuzzified aggregated comparison matrix as an estimate of the relative importance of the elements (Saaty 1980, 1996):

$$\mathbf{A} \cdot w = \lambda_{\max} \cdot w \tag{20}$$

   where $\mathbf{A}$ is the defuzzified aggregated pairwise comparison matrix, w is the eigenvector, and $\lambda_{\max}$ is the largest eigenvalue of $\mathbf{A}$.
   The consistency property of each defuzzified aggregated pairwise comparison matrix can be examined by *CI* and *CR* if necessary.
7. Form an unweighted supermatrix. Priority vectors are entered in the appropriate columns of a matrix, known as an unweighted supermatrix, to represent the relationships in the HOQ.

$$\mathbf{M}_1^{\text{unweighted}} = \begin{array}{c} \\ \text{G1} \\ \text{CA} \\ \text{EC} \end{array} \begin{array}{c} \begin{array}{ccc} \text{G1} & \text{CA} & \text{EC} \end{array} \\ \begin{bmatrix} \mathbf{I} & & \\ w_{\text{CG}} & \mathbf{W}_{\text{CC}} & \\ & \mathbf{W}_{\text{EC}} & \mathbf{W}_{\text{EE}} \end{bmatrix} \end{array} \tag{21}$$

   where w_{CG} is a vector that represents the impact of the goal on CAs, $\mathbf{W}_{\text{EC}}$ is a matrix that represents the impact of CAs on ECs, $\mathbf{W}_{\text{CC}}$ indicates the interdependency of CAs, $\mathbf{W}_{\text{EE}}$ indicates the interdependency of ECs, $\mathbf{I}$ is the identity matrix, and entries of zeros correspond to those elements that have no influence (Saaty 1996; Lee et al. 2010a).
8. Calculate a weighted supermatrix. The unweighted supermatrix must be transformed first to be stochastic, that is, each column of the matrix sums to unity (Saaty 1996). In this study, equal weights are given to the blocks in the same column to make each column sums to unity (Lee et al. 2010a).
9. Calculate the limit supermatrix and obtain the final priorities of ECs. By raising the weighted supermatrix to the power of $2k + 1$ (where k is an arbitrarily large number), the limit supermatrix, which has a convergence on the importance weights, can be obtained (Saaty 1996). The priority weights of ECs can be found in the EC-to-goal block, i.e., block (3,1), in the limit supermatrix (Lee et al. 2010a).

Through the above three stages, the priority weights of ECs in the first HOQ can be calculated. The same procedures can be taken for the next three HOQs.

4 Case study of TFT-LCD NPD

As global demand of information technology increases, the demand of TFT-LCD panels with low weight, slender profile, low power consumption, high resolution, high brightness and low radiance also increases. However, as more and more firms enter the global TFT-LCD production, an extremely competitive and cost-cutting war is foreseeable. TFT-LCD industry is currently one of the most brilliant industries in Taiwan, and its production value is one of the highest in the world. NPD is essential for TFT-LCD manufacturers to maintain a competitive edge and to make a decent profit in a longer term. Thus, developing products that deliver the quality and functionality customers demand while generating the desired profits becomes an important task for the manufacturers. The case study is carried out in an anonymous TFT-LCD manufacturer in Taiwan, and the proposed model is applied in the firm's four-phases of QFD, i.e., product planning, part deployment, process planning and production planning. Seven experts from the firm are asked to contribute their expertise in the study. In this paper, the first phase of QFD is presented.

4.1 Stage I: The selection of factors by the FDM

Through literature review and interview with experts, a list of candidate CAs and a list of candidate ECs are prepared. Because the number of important CAs, according to the experts' opinions, is rather limited in this case study, there is no need to apply the FDM. On the other hand, there are numerous ECs, and it is not worthwhile and nor possible to include all the ECs in the NPD process. Therefore, the FDM is applied first to collect the opinions of the experts and to select the most important ECs for further analysis. The results of the FDM are as shown in Table 3. With T_E is set arbitrarily at 8, five out of 20 ECs are selected. These selected factors are used in the construction of the HOQ as in Fig. 2.

4.2 Stage II: The relationships among factors by the FISM

FISM is applied next to determine the interdependence among CAs, the interdependence among ECs, and relationship of CAs and ECs. Using the CAs (ECs) selected from the FDM, a questionnaire is prepared to ask the contextual relationship between any two CAs (and any two ECs) and the associated direction of the relation, and the importance of each EC to each CA. The experts' opinions are transformed into triangular fuzzy numbers first, and the geometric mean method is applied to calculate the aggregated triangular fuzzy numbers. With $\alpha = 0.5$ and $\beta = 0.3$, α-cut method is adopted to obtain the crisp values. The results of CAs are shown in Table 4.

Table 3 FDM for ECs

EC Candidates	Pessimistic value			Optimistic value			$d^v - g^v$	Consensus significance value (s^v)[a]
	l_l^v	l_m^v	l_u^v	h_l^v	h_m^v	h_u^v		
High color saturation	3	6.0343	8	6	8.5200	10	0.4857	7.1236
High contrast ratio	6	7.0649	8	9	9.4868	10	3.4219	*8.6576*
Low display blur	5	7.4712	10	8	9.6768	10	0.2056	*8.7974*
High image resolution	6	6.7595	8	8	9.3641	10	2.6046	*8.0000*
Wide viewing angle	4	5.1646	6	7	8.2514	10	4.0869	6.4003
High refresh rate	4	5.8633	8	7	8.4271	10	1.5638	7.4004
Fast response time	6	6.7456	8	8	9.4751	10	2.7294	*8.0000*
No scratch on glass substrate	1	2.8958	8	4	6.8978	10	0.0020	5.4486
Low contamination in TFT-LCD module	5	6.4359	8	8	9.2660	10	2.8301	*8.0000*
No short-circuit	2	4.5954	7	6	8.5200	10	2.9246	6.5117
No damage in TFT-LCD module	1	4.1760	7	5	7.7585	10	1.5825	5.9883
No exterior defect in TFT-LCD module	1	4.3488	7	5	7.8663	10	1.5175	6.0390
Good packaging	5	5.8750	7	7	8.9413	10	3.0663	7.0000
Low design variations with common materials	3	4.1121	6	6	6.7735	8	2.6614	6.0000
Size	2	3.1943	4	5	6.3458	7	4.1515	4.3745
Ultra-thin design	4	4.7623	6	6	8.0075	10	3.2452	6.0000
Regulatory certification	2	4.8204	7	5	7.6337	10	0.8133	6.0943
Eco-friendly materials	2	4.9493	7	5	7.6553	10	0.7059	6.1285
After-sales service	3	4.5251	10	7	7.7550	10	0.2299	7.3636
Low power consumption	2	6.1377	8	7	8.6280	10	1.4903	7.4664

[a] Threshold value T_E is set at 8, and the values in italics are greater than or equal to 8. The factors are selected

The integrated relation matrix between CAs is calculated and is as shown in Table 5. A threshold value of 0.5 is used to determine whether the two CAs are dependent or not (Yang et al. 2008). If the value between two CAs, i.e., $x_{ij}^{\alpha B}$, in the relation matrix is higher than the threshold value, x_j is deemed reachable from x_i, and we let $\pi_{ij}^{\alpha B} = 1$ (Yang et al. 2008). The adjusted relation matrix **D** is:

$$\mathbf{D} = \begin{array}{c} \\ CA_1 \\ CA_2 \\ CA_3 \\ CA_4 \\ CA_5 \end{array} \begin{array}{c} \begin{array}{ccccc} CA_1 & CA_2 & CA_3 & CA_4 & CA_5 \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

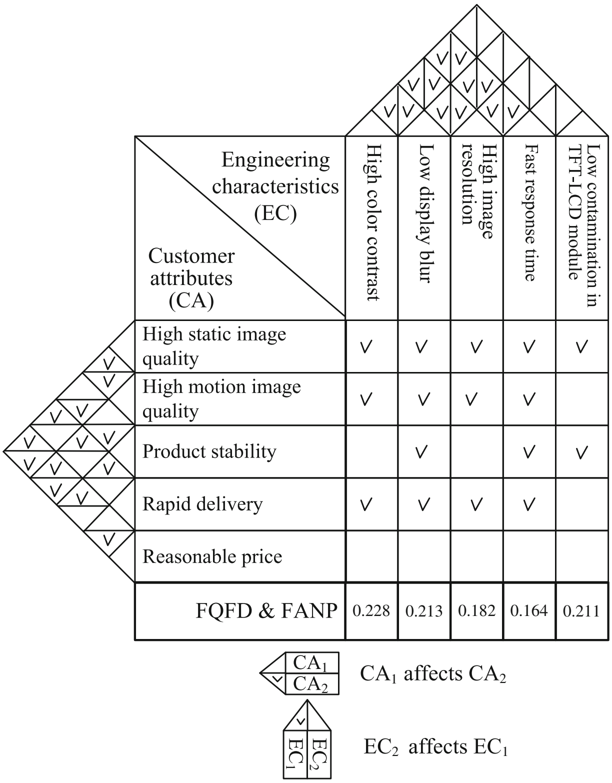


Fig. 2 HOQ for the first phase

The initial reachability matrix **M** for CAs is:

$$\mathbf{M} = \mathbf{D} + \mathbf{I} = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix}$$

The final reachability matrix $\mathbf{M}^*$ for CAs is:

$$\mathrm{M}^* = \mathbf{M}^3 = \mathbf{M}^4 = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 \end{bmatrix}$$

Based on $\mathbf{M}^*$, the inner dependence among the five CAs can be depicted as in Fig. 2. A checkmark is shown for the presence of a relationship from one CA to another CA. The same procedure can be carried out for determining the inner dependence among ECs, and the influence of CAs on ECs.

Table 4 Influence of a CA on another CA

CA_i	Influence on CA_j	Geometric mean ($\tilde{x}_{ij}$)			α-Cut		$x_{ij}^{\alpha B}$
		ι	μ	υ	x_{ijL}^{α}	x_{ijU}^{α}	
High static image quality	High motion image quality	0.5880	0.8415	1.0000	0.7148	0.9207	0.7765
	Product stability	0.5422	0.7944	1.0000	0.6683	0.8972	0.7370
	Rapid delivery	0.0910	0.4457	0.7155	0.2683	0.5806	0.3620
	Reasonable price	0.5880	0.8415	1.0000	0.7148	0.9207	0.7765
High motion image quality	High static image quality	0.0792	0.4109	0.6755	0.2451	0.5432	0.3345
	Product stability	0.3299	0.5880	0.8415	0.4590	0.7148	0.5357
	Rapid delivery	0.0690	0.3789	0.6377	0.2240	0.5083	0.3093
	Reasonable price	0.3789	0.6377	0.8913	0.5083	0.7645	0.5852
Product stability	High static image quality	0.2872	0.5422	0.7944	0.4147	0.6683	0.4908
	High motion image quality	0.2500	0.5000	0.7500	0.3750	0.6250	0.4500
	Rapid delivery	0.1991	0.5552	0.8219	0.3771	0.6885	0.4705
	Reasonable price	0.0362	0.3299	0.5880	0.1831	0.4590	0.2658
Rapid delivery	High static image quality	0.0987	0.4720	0.7155	0.2854	0.5938	0.3779
	High motion image quality	0.0792	0.4109	0.6755	0.2451	0.5432	0.3345
	Product stability	0.3789	0.6377	0.8913	0.5083	0.7645	0.5852
	Reasonable price	0.2480	0.7944	1.0000	0.5212	0.8972	0.6340
Reasonable price	High static image quality	0.3789	0.6377	0.8913	0.5083	0.7645	0.5852
	High motion image quality	0.3299	0.5880	0.8415	0.4590	0.7148	0.5357
	Product stability	0.1733	0.5119	0.7759	0.3426	0.6439	0.4330
	Rapid delivery	0.1509	0.4720	0.7325	0.3114	0.6023	0.3987

Table 5 Integrated relation matrix among CAs

	CA_1	CA_2	CA_3	CA_4	CA_5
CA_1	0	0.7765	0.7370	0.3620	0.7765
CA_2	0.3345	0	0.5357	0.3093	0.5852
CA_3	0.4908	0.4500	0	0.4705	0.2658
CA_4	0.3779	0.3345	0.5852	0	0.6340
CA_5	0.5852	0.5357	0.4330	0.3987	0

4.3 Stage III: The ranking of factors using the FANP-QFD

Based on the relationship among factors shown in the HOQ in Fig. 3, a pairwise comparison questionnaire is prepared, and the seven experts are asked to do the questionnaire. The consistency test is performed to check all the pairwise comparison matrices from the experts, and a revision of the inputs to the

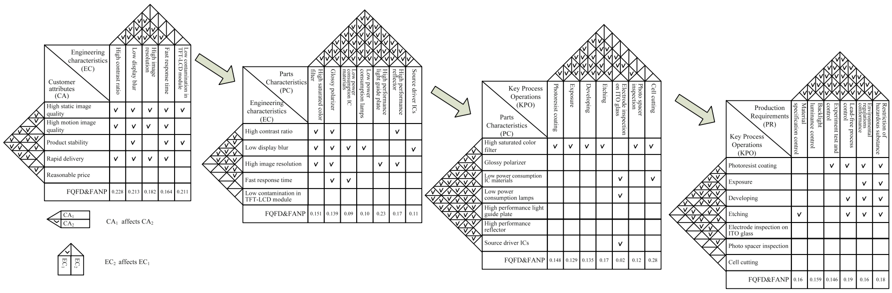


Fig. 3 The four HOQs for the case study

questionnaire is requested if necessary. The opinions are aggregated, and aggregated pairwise comparison matrices are prepared. Use the comparison of the importance of high static image quality (CA_1) and high motion image quality (CA_2) as an example. The experts' opinions are transformed into triangular fuzzy numbers, i.e., (1/6,1/5,1/4), (3,4,5), (1,1,1), (1,1,1), (1/4,1/3,1/2), (1/6,1/5,1/4) and (1/6,1/5,1/4). Geometric mean approach is employed to aggregate experts' responses, and the synthetic triangular fuzzy number for the comparison between CA_1 and CA_2 is (0.4553,0.5227,0.6292). The same procedure is carried out for all pairwise comparisons of other CAs. The fuzzy aggregated pairwise comparison matrix for the CAs is:

$$\tilde{W}_{21} = \begin{array}{c} \\ CA_1 \\ CA2 \\ CA_3 \\ CA_4 \\ CA_5 \end{array} \begin{array}{c} \begin{array}{ccccc} \text{CA1} & \text{CA2} & \text{CA3} & \text{CA4} & \text{CA5} \end{array} \\ \left[\begin{array}{ccccc} 1 & (0.4453, 0.5227, 0.6292) & (0.2225, 0.2624, 0.3320) & (0.4202, 0.5742, 0.7430) & (0.3048, 0.3712, 0.4640) \\ & 1 & (0.2225, 0.2669, 0.3441) & (0.4283, 0.5870, 0.7626) & (0.2876, 0.3451, 0.4202) \\ & & 1 & (0.6454, 0.8824, 1.1266) & (0.3598, 0.4602, 0.5656) \\ & & & 1 & (0.2714, 0.3173, 0.3743) \\ & & & & 1 \end{array} \right] \end{array}$$

To prepare a defuzzified comparison matrix, the center of gravity (COG) method is applied next. For example, with the synthetic triangular fuzzy number for the comparison between CA_1 and CA_2, the defuzzified comparison between CA_1 and CA_2 is 0.5324. The defuzzified aggregated pairwise comparison matrix is:

$$\mathbf{W}_{21} = \begin{array}{c} \\ CA_1 \\ CA_2 \\ CA_3 \\ CA_4 \\ CA_5 \end{array} \begin{array}{c} \begin{array}{ccccc} CA_1 & CA_2 & CA_3 & CA_4 & CA_5 \end{array} \\ \left[\begin{array}{ccccc} 1 & 0.5324 & 0.2723 & 0.5791 & 0.3800 \\ & 1 & 0.2778 & 0.5926 & 0.3510 \\ & & 1 & 0.8848 & 0.4619 \\ & & & 1 & 0.3210 \\ & & & & 1 \end{array} \right] \end{array}$$

The priority vector of the defuzzified aggregated pairwise comparison matrix for CAa is calculated.

$$w_{21} = \begin{array}{c} CA_1 \\ CA_2 \\ CA_3 \\ CA_4 \\ CA_5 \end{array} \begin{bmatrix} 0.0883 \\ 0.1124 \\ 0.2473 \\ 0.1738 \\ 0.3783 \end{bmatrix}$$

The consistency test is performed by calculating the consistency index (CI) and consistency ratio (CR):

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{5.3355 - 5}{5-1} = 0.08388, \text{ and}$$
$$CR = \frac{CI}{RI} = \frac{0.08388}{1.12} = 0.07489.$$

Since CR is less than 0.1, the experts' judgment is consistent. If the consistency test fails, the experts are required to fill out the specific part of the questionnaire again until a consensus is met.

With the assumption that the CAs are independent, the attributes of a TFT-LCD that should be focused on to achieve customer satisfaction can be seen from the ranking of the CAs. Among the CAs, reasonable price (CA_5) has the largest priority with 0.3783, followed by product stability (CA_3), rapid delivery (CA_4), high motion image quality (CA_2), and high static image quality (CA_1) with priorities of 0.2473, 0.1738, 0.1124 and 0.0883, respectively. Based on the questionnaires, a similar procedure is done to calculate the priority vectors of the inner dependence among ECs and the impact of CAs on ECs. These priorities are entered into the designated places in the supermatrix, as shown in Table 6.

After the unweighted supermatrix is transformed into a weighted supermatrix, the weighted supermatrix is raised to powers to capture all the interactions and to obtain a steady-state outcome. The resulting supermatrix, the limit supermatrix, shows the priority weights of the ECs the (3,1) block and are:

$$w^{ANP} = \begin{array}{c} \\ EC1 \\ EC2 \\ EC3 \\ EC4 \\ EC5 \end{array} \begin{array}{c} G1 \\ \begin{bmatrix} 0.2288 \\ 0.2137 \\ 0.1823 \\ 0.1642 \\ 0.2110 \end{bmatrix} \end{array}$$

The priorities of ECs calculated by FANP-QFD are also shown in the bottom part of Fig. 2. High color contrast (EC_1) is the most important EC with priority of 0.2288, followed by low display blur (EC_2) and low contamination in TFT-LCD module (EC_5) with priorities of 0.2137 and 0.2110, respectively. This is the end of the calculations for the first phase of QFD.

The integrated fuzzy QFD model is executed for the other three phases of QFD. Figure 3 depicts the results of the entire QFD process. The outcome from the first HOQ is input to the second HOQ for calculating the importance of the parts characteristics (PCs), and so on. The second HOQ shows that the most important PCs, in descending order, are high performance light guide plate, high performance

Table 6 Unweighted supermatrix

	G_1	CA_1	CA_2	CA_3	CA_4	CA_5	EC_1	EC_2	EC_3	EC_4	EC_5
G_1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CA_1	0.0883	0.2329	0.3297	0.0000	0.2538	0.1809	0.0000	0.0000	0.0000	0.0000	0.0000
CA_2	0.1124	0.1980	0.2282	0.0000	0.2073	0.1492	0.0000	0.0000	0.0000	0.0000	0.0000
CA_3	0.2473	0.3057	0.2365	1.0000	0.2149	0.4009	0.0000	0.0000	0.0000	0.0000	0.0000
CA_4	0.1738	0.0000	0.0000	0.0000	0.1795	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CA_5	0.3783	0.2634	0.2057	0.0000	0.1445	0.0707	0.0000	0.0000	0.0000	0.0000	0.0000
EC_1	0.0000	0.1475	0.2948	0.0000	0.2646	0.2646	0.3191	0.2339	0.3621	0.2426	0.0000
EC_2	0.0000	0.1453	0.2317	0.2696	0.2578	0.2578	0.2422	0.3252	0.2068	0.3111	0.0000
EC_3	0.0000	0.1857	0.2120	0.0000	0.2449	0.2449	0.2487	0.2008	0.2758	0.1959	0.0000
EC_4	0.0000	0.1983	0.2615	0.3222	0.2327	0.2327	0.1900	0.2401	0.1554	0.2504	0.0000
EC_5	0.0000	0.3231	0.0000	0.4082	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

reflector and high saturated color filter, with priorities of 0.23, 0.17 and 0.151, respectively. The third HOQ calculates the priorities of key process operations (KPOs), and the top three KPOs are cell cutting, etching and photoresist coating with priorities of 0.28, 0.17 and 0.148, respectively. In the last HOQ, the critical production requirements (PRs) are lead-free process control (0.198) and restriction of hazardous substances (0.18). The other four PRs are relatively equally important. The accumulated priority of lead-free process control, restriction of hazardous substances and environmental regulations conformance is 0.53, and this indicates that environmental protection is an important issue in production. With the proposed comprehensive QFD model, the firm can understand which CAs, ECs, PCs, KPOs and PRs should be focused on in each step of the NPD process.

Because conventional QFD approaches have some drawbacks, the proposed framework can tackle some of the issues, including the generalization of the opinions of multiple decision makers, the large amounts of subjective data, the burden of a large dimensional comparison, and the ambiguity and uncertainty in human decision making. In the authors' knowledge, there has not been many works that adopt fuzzy set theory to the supermatrix approach of ANP in QFD. Since the supermatrix approach is the authentic and acknowledged ANP methodology, a fuzzy supermatrix approach in QFD is superior to the simple matrix manipulation approach. In addition, through the first two stages in the proposed framework, the more importance factors can be selected in advance and the interrelationship among the factors can be determined before the FANP-QFD is carried out. Therefore, the decision makers will not have too much hassle in going through the QFD process.

5 Conclusion

With limited resources, including time, cost and human power, a firm can only focus on a certain parts of its research and design. Therefore, how to develop and manufacture a product that can acquire the highest expected benefits for the firm is an important task. In this research, a systematic framework that incorporates FDM, FISM and FANP into QFD is proposed for new product development. Through literature review and interview with experts, lists of factors are prepared, including customer attributes, engineering characteristics, parts characteristics, key process operations and production requirements. The critical factors from each list are selected by the FDM. The FISM is applied next to determine the relationship among factors. The results are used to construct the four houses of QFD, and the priorities of the factors can be calculated through FANP. The proposed framework is examined by a case study in a TFT-LCD manufacturer in Taiwan. The results show the important customer attributes, engineering characteristics, parts characteristics, key process operations and production requirements in designing a new product. Those factors with higher priorities should especially be focused on. In conclusion, the proposed model can help a firm systematically consider relevant NPD information and effectively determine key factors for designing and manufacturing of new products.

Green supply chain has become an important topic these days due to pollution, global warming, extreme climatic events, etc. A green product is manufactured with the goal of reducing the damage to the environment and limiting the use of energy and other resources at any stage of its life, including raw materials, manufacture, use and disposal. A good measure of the impact that a product has on the environment, especially in climate change, in the entire lifetime of the product, is carbon footprint. Therefore, for future research direction, a systematic model based on QFD can be constructed for developing green and low-carbon products. In addition, other factors such as cost budget and time constraint may need to be considered in developing products; therefore, mathematical programming approach, such as zero–one goal programming and fuzzy multiple objective programming, can be incorporated into the framework.

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