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Performance evaluation of technological innovation capabilities in uncertainty

Yuan-Hsu Lin[1], Ming-Lang Tseng[2,3]*, Yi-Li Cheng[4], Anthony S. F. Chiu[5] and Yong Geng[3]

[1]Department of Finance, Ming Dao University, Taiwan.
[2]Graduate School of Business and Management, Lunghwa University of Science and Technology, Taiwan.
[3]Shenyang Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110016, China.
[4]Department of Information Management, Wu-Feng University of ST, Taiwan.
[5]Department of Industrial Engineering, De La Salle University, Manila, Philippines.

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The evaluation of technological innovation capabilities (TICs) depends on determining multiple criteria and on building a performance and implementation plan. There are intensive studies on the issues of TICs which have been dealt with extensively by practitioners and academicians, however, studies on the implementation and performance evaluation are few. This study proposes the approach of adopting trapezoid fuzzy numbers and extending a technique for ordering performance by similarity to address the evaluation of TICs. An empirical case of a printed circuit board firm was evaluated using a proposed hybrid method. The results indicate that the hybrid method is a suitable and effective method for identifying and analyzing the competitiveness in the context of uncertainty.

Key words: Technological innovation capability, trapezoid fuzzy numbers, technique for order performance by similarity to ideal solution (TOPSIS).

INTRODUCTION

The Printed Circuit Board (PCB) manufacturing sector has more than 30 years of experience, along with good experienced staff, a mature industrial supply chain and top quality engineering to develop a PCB layout design and to fulfill the requirements of one-stop manufacturing production lines. Particularly while facing rapidly changing environments, the firms require continual technological innovation to constantly maintain their competitiveness. It is necessary for a company to enhance its competitiveness and to harmonize with external resources. Hence, the firms must integrate organizational resources and technological innovation to ensure corporate sustainability. Technological innovation capabilities (TICs) engender multi-criteria difficulties that involve multi-organizational functions and resource integration among various criteria (Betz, 1998; Agarwal et al., 2007; Wang et al., 2008; Tseng, 2011). These capabilities are important for the firm's continuous improvement, while placing strong emphasis on a rapidly changing environment in a competitive and sustainable market due to mandated environmental orders from the European Union such as directives on waste electrical and electronic equipment (WEEE) and the restriction of hazardous substances (ROHS). An effective and structured TIC evaluation for original equipment manufacturing (OEM) firms needs to be developed. The major cause for continued deterioration of technological innovation development is the pattern of corporate survival, especially in industrialized nations such as Taiwan (Lin et al., 2011).

In real situations, numerous TIC criteria are interactive when evaluating OEM firms. A traditional statistical approach is no longer suited to evaluate the proposed multi-criteria decision-making (MCDM)

*Corresponding author. E-mail: tsengminglang@gmail.com.

problem. There are always multiple choices for alternatives with a set of specific criteria concerning the industrial supply chain (Tseng et al., 2009b). Hence, this study utilizes a hybrid MCDM method to determine the important weights of the proposed criteria and to extend a technique called “order performance by similarity to an ideal solution” (TOPSIS) in order to obtain the performance ratings of the feasible alternatives. This method uses linguistic preferences parameterized with trapezoid fuzzy numbers (TFNs) and is a suitable modeling technique for analyzing the MCDM problem (Chen, 2000; Chen and Tzeng, 2004). The proposed hybrid method helps to impose order and direction on the complexity of existing relationships and composes a system for an evaluation framework. In addition, measurements of implementation and performance are necessary for future developments.

There is a growing consensus that for sustainability, it is necessary to move toward developing TICs to promote and measure achievements. Many firms are beginning to realize the importance of technological innovation capabilities. Nevertheless, only a few studies have determined TIC evaluation criteria with a qualitative assessment. The biggest challenge of this study is that evaluations are always performed in the face of uncertainty. In addition, there are dependence relations and multiple criteria because of rapid changes in the natural behavior of multi-criteria measures. Hence, a desirable evaluation tool is to hybridize fuzzy set theory, making an extension of TOPSIS to fulfill the requirements of an uncertain environment. In the literature, Afuah and Bahram (1995) proposed that technological innovation involves three uncertainties, namely, technological, market and enterprise-based uncertainties. There are numerous sources of uncertainty, and ambiguities are embedded within each phase of the technological innovation process. Garcia-Muina and Navas-Lopez (2007) defined the phrase “degree of uncertainty”, to mean each phase of a technological growth trajectory to which successful technological innovation requires increased amounts of information. The required information regards a firm’s organizational innovation decisions and its research and development (R&D) capability to fully represent the firm’s TIC. Wang et al. (2008) presented the evaluation, which is based on multiple criteria such as R&D, innovation decisions, marketing, manufacturing and capital capabilities. Since the TICs of a firm are typically subjective and because measurements are typically imprecise, this construct increases the complexity of the implementation and performance evaluation process. Therefore, evaluators of TICs are likely to perceive objectives and criteria differently.

Evaluators generally depend on subjective judgment, previous experience and professional knowledge and information, all of which are difficult to define and interpret accurately. Hence, fuzzy set theory is helpful in dealing with the vagueness of human thought and expression when making decisions. In particular, fuzzy set theory tackles a beneficial way to convert these linguistic preferences into trapezoid fuzzy numbers (TFNs) (Wang et al., 2008; Tseng et al., 2009b; Tseng, 2011). Most recent studies do not mention a source for building a set of TIC criteria and do not propose a suitable approach for assessing a firm’s status in their supply chain. However, this study focuses on the composition of TIC criteria. The most remarkable contribution is to provide a systematic insight into a complicated system by establishing preferences that are linguistic in nature. For the purpose of this approach, the innovation is a dynamic capability, that is - a learned and stable pattern of collective activity through which the organization systematically generates and modifies its operating routines in pursuit of improved effectiveness (Yam et al., 2011). The company’s innovation system can be defined as an interactive process that involves the generation, adoption, implementation, and incorporation of new ideas and practices within the firm (Carlsson et al., 2002; Guan and Ma, 2003). The main feature is the ability of the actors to generate, diffuse, and utilize innovations that have economic value, collectively known as the firm’s TICs. The primary argument is that the competitiveness of a firm is based on a set of complex capabilities.

A conventional single performance criterion, whether it measures profitability or finance, is insufficient to determine the excellence of an enterprise. In addition, Guan et al. (2006) argued that TICs depend not only on technological capability, but also on critical capability in the area of manufacturing, marketing, organization, strategy planning, learning and resource allocation. These authors also stated that this approach is a complex interactive process that involves many different resources. Therefore, TICs are multi-dimensional and have indicators that reflect the TICs of a firm.

Hence, this study applies TFNs to be evaluated with subjective judgment and requires dependence relations among the criteria to be built into an evaluation framework (Zadeh, 1965; Tseng, 2010). Therefore, a hybrid method is appropriate to achieve the study objectives. This study attempts to develop a set of TIC criteria that is sufficiently general and that can be applied to different homogeneous firms. To date, few studies have adopted such a hybrid method to model and evaluate a practical field. Consequently, resolving problems in evaluating a firm is fundamentally important to both researchers and practitioners. This study begins with a brief introduction of the definition of TICs and a description of the study objectives. Subsequently, a discussion of the literature on TICs and related literatures, the proposed hybrid method (specifically, the linguistic preferences applied to fuzzy set theory and the extension of TOPSIS), and an empirical case study are presented. The measures are provided with measurement guides. A summary of the findings of the method, as well as recommendations for its further development and practical applications were also presented.

LITERATURE REVIEW

As a result of mandated environmental orders from the European Union, such as the WEEE and the ROHS Directives, and the increasing green competitive pressures, firms must continue to maintain competitiveness through TICs. Increased green competitive pressures are also forcing firms to continuously adopt and develop to enhance their competitiveness. TICs have become the primary basis of market competition (Watkins et al., 1999; Garcia-Muina and Navas-Lopez, 2007; Perdomo-Ortiz et al., 2006; Prašnikar et al., 2008). A firm must develop and evaluate the TICs rapidly and must facilitate the capabilities within its organization to strengthen its competitiveness. However, Ranganathan (1998) clearly pointed out that without any agreement on the fundamentals of what criteria to measure concerning TICs and how to measure these criteria, the management will be awash in a sea of confusing, contradictory, incomplete and incomparable information. Hence, the capabilities are relatively important for a firm’s sustainable development.

Technological innovation capabilities

Increased global competition pressures are also forcing firms to continuously develop and innovate to enhance green product competitiveness such as product design and quality, technological service and reliability. A firm must integrate its innovation capabilities for developing and commercializing new technologies and must facilitate the creation and dissemination of technological innovations within its organization, to strengthen its competitive advantage. Afuah and Bahram (1995) argued that radical, incremental and architectural aspects are applied to innovation at different stages in the innovation value-added chain and also proposed changes in high-tech firms. Most of the literatures discussing innovation system failure tend to focus on perceived weaknesses in structural composition. Yam et al. (2004) introduced a study framework reflecting the relevance of seven TICs to building and sustaining the competitiveness of Chinese firms. The findings verify that R&D and resource allocation capabilities are the two most important TICs. A strong R&D capability could safeguard the innovation rate and product competitiveness in large and medium-sized firms, whereas a resource allocation capability would enhance the sales growth in small firms. However, the impact of learning and organizing capabilities on a firm’s innovation performance has yet to be investigated. This type of investigation is needed to maintain the firm’s sustainable development and to effectively plan and implement its innovation strategies, as well as to enhance its whole innovation capability (Garcia-Muina and Navas-Lopez, 2007).

Woolthuis et al. (2005) indicated that all of the four types of innovation failures identified in their recent synthesis are related to structural components: infrastructure, institution, interaction and capability failures. However, it is difficult to evaluate the implementation and performance of a particular structural element without referring to its effects on the innovation process. Elements such as the planning and commitment of the management need to be identified. Generally, this work needs to be aligned with a new technology because firms compete not only in the market, but also over the nature of the institutional set-up (Jacobsson and Lauber, 2006). In addition, Guan et al. (2006) developed an innovation framework to provide a benchmark for auditing the quantitative relationship between competitiveness and TICs based on a traditional DEA approach to enhance the competitiveness of a firm. The study of Perdomo-Ortiz et al. (2006) found that there is a positive relationship between total quality management and business innovation capability, and shows that a firm that focuses more on quality activities such as promoting team work, empowering workers, training personnel in matters of quality, and designing a system of incentives for good performance all lead to a better innovation capability (Prašnikar et al., 2008).

Moreover, Yam et al. (2011) developed an important framework for evaluating innovation performance. This study found that utilizing sources of information available within their regional innovation system caused better performance because of effects that enhance the firm’s TICs. The different innovation capabilities of a firm are considered key components of a firm’s innovation system (Tan, 2011), and the results show that externally available information affects all innovation capabilities of the firm. In contrast, external expert organizations affect only the firm’s R&D and resource allocation capabilities and contribute to the innovation literature by providing empirical evidence on how firms can enhance their TICs and achieve global competitiveness. This study proposed that TIC evaluation could assist firms to build up their competitive advantages from valuable cues identified during intensive reviews. This study raises the topic of TIC implementation and performance, which deals with supplier assessments with subjective human preferences and dependence relations.

Proposed method

The traditional multi-criteria approach is not suited to evaluate TIC implementation and performance. The traditional approach assumes independence of criteria.

However, in real world systems, this assumption is not suitable for many applications. Because technological innovation related activities have inherent and high uncertainty and imprecision, innovation processes are uncertain, unpredictable and difficult to assess accurately (Wang et al., 2008). Triantaphyllou and Lin (1996) developed a fuzzy version of the TOPSIS method on the basis of fuzzy arithmetic operations, which led to a fuzzy relative closeness for each alternative. Chen (2000) extended the TOPSIS method to fuzzy group decision-making situations by defining a crisp Euclidean distance between any two fuzzy numbers. Chen and Tzeng (2004) also transformed a fuzzy MCDM problem into a non-fuzzy MCDM using fuzzy integrals and TOPSIS. Instead of using distance, this study employed dependence matrix to define the relative closeness of each alternative. In TOPSIS, measures are always assumed to be independent among the proposed criteria. To overcome the independent shortcomings, the criteria always involve the dependence relations in nature; to justify the shortcoming, the dependence parameters need to be involved in an extension of TOPSIS computation.

Humphreys et al. (2003) proposed a hierarchical fuzzy system with scalable fuzzy membership functions to facilitate the incorporation of environmental criteria during the selection process. Chen et al. (2006) used TOPSIS to rank suitable suppliers using quantitative and qualitative factors that they identified, such as quality, price, flexibility and delivery performance. Li (2007) proposed a compromise ratio method for MCDM under conditions of uncertainty. Owing to fuzziness being inherent in decision data and group decision making processes, the crisp values are inadequate to model real-life situations. The computation principle and the procedure of the compromise ratio method are described in detail. Moreover, the TOPSIS method, which was developed for multi-attribute decision making with crisp decision data, is analyzed under conditions of uncertainty. Tseng (2011) proposed a set of qualitative and quantitative measurements in environmental practice for knowledge management capability and addressed the dependence relationships of criteria in the context of uncertainty.

Tan (2011) proposed a multi-criteria interval-valued intuitionistic fuzzy decision-making technique, to resolve dependent characteristics among criteria and to take into account the preference of decision makers. To get a broad view of the techniques used, the Choquet integral-based Hamming distance between interval-valued intuitionistic fuzzy values is defined. This extension of the TOPSIS method is developed to deal with multi-criteria interval-valued intuitionistic fuzzy group decision-making problems. In conclusion, this study proposed a technique to deal with subjective human preferences in TIC evaluation. There are very few studies that have applied this proposed technique to solving specific management solutions. Fuzzy set theory accounts for the vagueness of language used to express qualitative criteria, whereas TOPSIS and the dependence relation matrix deal with the multi-criteria and attributes of the decision-making problem. The contribution of this proposed method is to involve a dependence matrix as the adjustment parameter for trapezoid fuzzy numbers and for the TOPSIS application.

Supplier selection

There are many studies that focused on the development of a selection model for suppliers. A green supplier is expected to achieve environmental compliance, design efficient, green products and perform life cycle analyses and there is a need for firms to possess extensive supplier selection and performance evaluation processes. Tseng et al. (2009b) studied the selection of appropriate suppliers in supply chain management strategy using an analytical network process and Choquet integral. The proposed framework included in several uncertainties, attributers of SCM strategy and criteria of organization appropriateness. Lee and Ou-Yang (2009) presented that the supplier selection negotiation is a sophisticated and challenged job due to the diversity of intellectual backgrounds of the negotiating parties, the many variables involved in supply–demand relationship, the complex interactions and the inadequate negotiation knowledge of project participants. It is therefore necessary to develop an intelligent system for negotiation support in supplier selection process; an artificial neural network-based predictive model with application for forecasting the supplier’s bid prices in supplier selection negotiation process (SSNP) is developed.

A recent study by Aksoy and Öztürk (2011) proposed just-in-time manufacturers in selecting the most appropriate suppliers and in evaluating supplier performance using neural network and supplier performance evaluation systems. Many manufacturers employ the JIT philosophy in order to be more competitive in today’s global market. The supplier selection and performance evaluation in long-term relationships have became more critical in JIT production environments. The supplier selection strategy is always an issue in a supply chain management. The selection outcomes impact relationships, profitability and reputation of businesses and whole supply chain. Most of supplier selection processes are based on multi-criteria and other mechanism. In uncertainty, it is necessary to propose a multi-criteria system to support in supplier selection process to reduce subjective judgment, forecast the preference of opponents and improve negotiation decision quality (Cakravastia et al., 2002; Murthy et al., 2004). The performance evaluation based on multi-criteria was used for the current study.

Proposed criteria

Sun and Gertsen (1995) explored the causes for the formation of competitiveness. These tools not only involve technological factors in their research field, but also bring the organization management, manufacturing, marketing and industry environment into consideration. Guan et al. (2006) argued that TICs depend not only on operational capability but also on critical capability in the area of manufacturing, marketing, organization, strategy planning, learning and resource allocation and so forth. In addition, TICs involve complexity and interaction processes of many different resources; as a result, multi-dimensional and corresponding indicators reflect the TICs of a firm. Additionally, numerous constructs are interdependent when evaluating TICs. A traditional multi-criteria approach is not suited to evaluate TICs. There are seven primary interactive aspects that engender difficulty in evaluating TICs: planning and commitment of the management capability; marketing capability; innovative capability; R&D capability; operations capability; knowledge and skills capability; information and communication capability and external environment capability (Huber et al., 2001; Garcia-Muina and Navas-Lopez, 2007; Perdomo-Ortiz et al., 2006; Prašnikar et al., 2008; Wang et al., 2008; Tseng, 2011). For example, a firm that has outstanding R&D capabilities to perform advanced research and to create unique designs often possesses good operations capabilities such as advanced manufacturing technology for producing and improving high-quality products. Such an R&D capability is also related to information and communication capabilities, which are required to bring information to R&D activities (Garcia-Muina et al., 2007). High-quality products depend on good marketing capabilities to monitor the degree of new product competitiveness and for market forces to acquire the preferences and exchange of product information and knowledge (Wang et al., 2008). The planning and commitment of the management capability need to refer to related capabilities such as cooperation with innovation centers or universities to confirm technological comparisons of the competition and to make certain of new product competitiveness. These resources are called external environment capabilities (Prašnikar et al., 2008; Tseng, 2011).

Moreover, industrial competitiveness is vital for an enterprise in its formulation of R&D capabilities, in its design of process flows and in its marketing capabilities (Pun et al., 2004). Betz (1998) categorizes innovation into three types, namely: (1) product innovation, which is the launching of significantly improved or new products to the market, (2) process innovation, which is the implementation of new processes and technologies for firms and markets, and (3) service innovation, which is the introduction of new technology-based services to the market. In addition, Watkins (1999) defined multiple innovations as partial changes that are made when adopting new technologies, new management practices, new administrative activities, or organizational culture for creating innovative products and services. In conclusion, it is necessary to integrate the criteria into a systematic evaluation framework. Table 1 presents the proposed seven main criteria in this study.

METHODOLOGY

This study conducts a hybrid MCDM method to provide an overall view of implementation and performance evaluation of technological innovation capabilities under conditions of uncertainty.

Fuzzy set theory

For the purpose of reference, some important definitions and notations of fuzzy set theory from Chen and Tzeng (2001) and Cheng and Lin (2002) are reviewed. The group of evaluators is usually important to any organization in achieving a favorable solution. An effective fuzzy aggregation method is required to deal with research problems in a fuzzy environment. Usually, many qualitative measures that involve imprecision, constraints and possible actions are not precisely described (Bellman and Zadeh, 1970). Study results in an uncertain environment are highly affected by subjective judgments that are vague and imprecise. To solve this imprecise and uncertain problem, fuzzy logic was first introduced by Zadeh (1965) as a mathematical way to represent and handle vagueness in an evaluation process. In fuzzy logic, each number between 0 and 1 indicates a partial truth, whereas crisp sets correspond to binary logic [0, 1]. Hence, fuzzy logic can express and handle vague or imprecise judgments mathematically (Al-Najjar and Alsyouf, 2003). To deal with the vagueness of human thought and expression in processes, fuzzy logic is very helpful. Specifically, to tackle the ambiguities involved in the process of linguistic estimation, fuzzy logic is a beneficial way to convert these linguistic terms into TFNs.

A fuzzy number $\tilde{m}$ is a special fuzzy subset on the set R of real numbers that satisfies the following conditions: There exists a $x_0 \in R$ so that the degree of its membership $u_{\tilde{m}}\left(x_0\right)$ = 1 and the membership function $u_{\tilde{m}}\left(x\right)$ is left and right continuous. Let $\tilde{m} = \left(a,b,c,d\right)$ be a trapezoid fuzzy number, where the membership function of $\mu_{\tilde{m}}$ is $\tilde{m}$ given by:

$$\mu_{\tilde{m}}(x)=\begin{cases}\dfrac{x-a}{b-a} & \left(a \le x \le d\right)\\ 1 & \left(b \le x \le c\right)\\ \dfrac{d-x}{d-c} & \left(c \le x \le d\right)\end{cases} \tag{1}$$

Where $\left[b,c\right]$ is called a mode interval of $\tilde{m}$, while a and d are called the lower and upper limits of $\tilde{m}$, respectively. If $\left[b=c\right]$, then $\tilde{m}=\left(a,b,c,d\right)$ is called a triangular fuzzy number, denoted $\tilde{m}=\left(a,m,d\right)$, where $m=b=c$. Obviously, the membership function $\mu_{\tilde{m}}$ of a triangular fuzzy number $\tilde{m}=\left(a,m,d\right)$ is:

Table 1. Technological innovation capability.

Goals	Criteria	Description
Implementation and performance evaluation of technological innovation capability	Planning and commitment of the management capability (C1)	Definition of technological innovation strategy such as R& D staffs, Specific budget for innovative activities and proportion of successful R& D to entire organization.
	Marketing capability (C2)	This capability is related to degree of new product competitiveness, monitoring market forces, firm awareness of customer requirements and preferences and exchange of product information and knowledge among team groups.
	Innovative capability (C3)	Promote projects help to reduce the risk of innovation, evaluation of technical, economic and commercial feasibility of innovative ideas, which are suitable programming and resources for future development.
	Knowledge and skills capability (C4)	Innovativeness knowledge protection systems, periodical evaluations of the practices and routines and the operational processes require skills that are difficult to acquire.
	Information and communication capability (C5)	This criterion is mentioned permanent information flow and utilizes the information system as a stimulus for new ideas, well management the documents and supervision system and technology transfer.
	External environment capability (C6)	The innovation projects in cooperation with innovation centers or universities to confirm the technological comparison of competition and make sure the new product competitiveness.
	Operations capability (C 7)	Overall quality and technological innovation matching market requirements, which might success in technology transfer, product development and commercialization. The fund raising ability to pursue technology innovation.

$$\mu_{\tilde{m}}(x)=\begin{cases}\dfrac{x-a}{b-a} & (a\le x\le m)\\ \dfrac{d-x}{d-c} & (m\le x\le d)\end{cases} \qquad (2)$$

Therefore, a triangular fuzzy number is a special case of the trapezoid fuzzy number. In other words, a triangular fuzzy number $\tilde{m}=(a,m,d)$ can also be written as a trapezoid fuzzy number $\tilde{m}=(a,m,m,d)$. It is easy to see that a trapezoid fuzzy number $\tilde{m}=(a,b,c,d)$ is reduced to a real number if $a=b=c=d$. Conversely, a real number m can be written as a trapezoid fuzzy number $\tilde{m}=(m,m,m,m)$. For the sake of simplicity and without loss of generality, it is assumed that all fuzzy numbers are trapezoid fuzzy numbers throughout the paper unless otherwise stated (Figure 1). The notation $\tilde{m}=(a,b,c,d)$ is called a positive trapezoid fuzzy number if $a\ge 0$ and a,b,c and d are not identical. Thus, it could be assumed that $\tilde{m}=(m_1,m_2,m_3,m_4)$ and $\tilde{n}=(n_1,n_2,n_3,n_4)$ are two positive trapezoid fuzzy numbers and that $r>0$ is a positive real number.

The concept of linguistic preference is very useful in situations where decision problems are too complex or too ill-defined to be described properly using conventional quantitative expressions. For example, the importance ratings on qualitative criteria could be expressed using linguistic terms. Such linguistic values can be represented using positive TFNs. For example, ''low'' and ''Extreme high'' can be represented by positive TFNs (0.2, 0.3, 0.4, 0.5) and (0.8, 0.9, 1.0, 1.0), respectively. Taking $\tilde{m}=(m_1,m_2,m_3,m_4)$ and $\tilde{n}=(n_1,n_2,n_3,n_4)$ as two trapezoid fuzzy numbers, then the distance measure between them is defined using the Minkowski distance

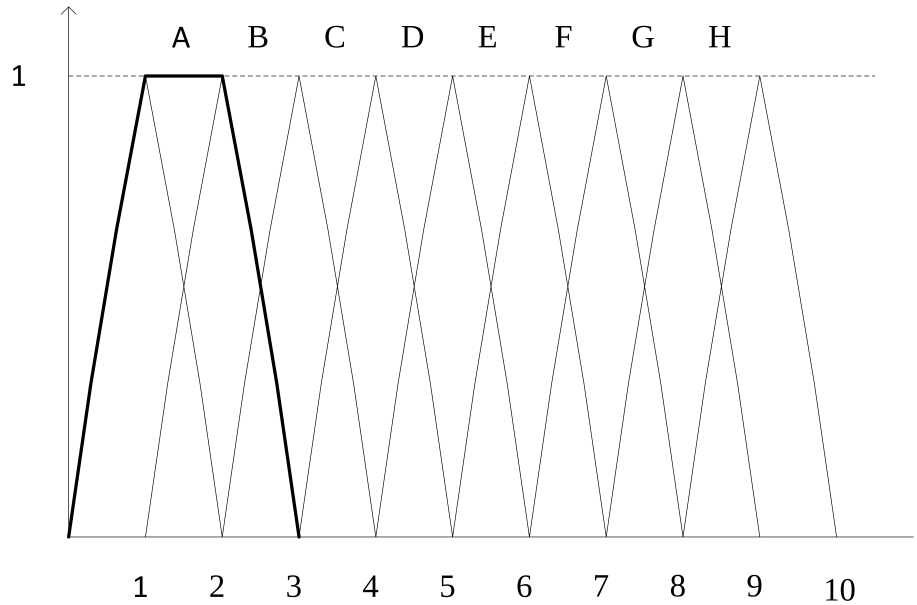

Figure 1. Trapezoidal fuzzy numbers.

(or L_P - metric), as follows:

$$d_p(\tilde{m},\tilde{n}) = \sqrt[p]{\frac{(m_1-n_1)^p + (m_2-n_2)^p + (m_3-n_3)^p + (m_4-n_4)^p}{6}} \quad (3)$$

Where $p \geq 1$ is a distance parameter. From this equation of weighted distance, which considers different levels of importance for the lower limit, the left and right points of the mode interval, and the upper limit of the trapezoid fuzzy numbers are considered. For $p = 1,$ this equation can be rewritten as follows:

$$d_1 = (\tilde{m},\tilde{n}) = \frac{|m_1-n_1| + 2|m_2-n_2| + 2|m_3-n_3| + |m_4-n_4|}{6} \quad (4)$$

This is a weighted Hamming distance. Also, for $p = 2,$ this can be rewritten as follows:

$$d_2(\tilde{m},\tilde{n}) = \sqrt{\frac{(m_1-n_1)^2 + 2(m_2-n_2)^2 + 2(m_3-n_3)^2 + (m_4-n_4)^2}{6}} \quad (5)$$

This is a weighted Euclidean distance. In addition, if $q \to \infty,$ this equation can be rewritten as follows:

$$d_\infty(\tilde{m},\tilde{n}) = \max\left\{\frac{m_1-n_1}{6}, \frac{m_2-n_2}{3}, \frac{m_3-n_3}{3}, \frac{m_4-n_4}{6}\right\} \quad (6)$$

This is the weighted Chebyshev distance. Note that if both $\tilde{m}$ and $\tilde{n}$ are real numbers, then the distance measurement $dp(\tilde{m},\tilde{n})$ is identical to the Euclidean distance. In fact, suppose that both $\tilde{m} = (m_1, m_2, m_3, m_4)$ and $\tilde{n} = (n_1, n_2, n_3, n_4)$ are two real numbers, then $m_1 = m_2 = m_3 = m_4 = m$ and $n_1 = n_2 = n_3 = n_4 = n$. The distance measurement $dp(\tilde{m},\tilde{n})$ can be calculated as follows:

$$\begin{aligned} d_p(\tilde{m},\tilde{n}) &= \sqrt[p]{\frac{(m_1-n_1)^p + 2(m_2-n_2)^p + 2(m_3-n_3)^p + (m_4-n_4)^p}{6}} \\ &= \sqrt[p]{\frac{(m-n)^p + 2(m-n)^p + 2(m-n)^p + (m-n)^p}{6}} \\ &= \sqrt[p]{(m-n)^p} = |m-n| \end{aligned} \quad (7)$$

Furthermore, it is easily seen that two TFNs $\tilde{m}$ and $\tilde{n}$ are identical if and only if the distance measurement $dp(\tilde{m},\tilde{n}) = 0$. After the initial linguistic interrogation of each individual, each subsequent interrogation is accompanied by a linguistic preference regarding the preceding round of replies, usually presented anonymously. The defuzzified crisp numbers are the dataset for extension of TOPSIS.

Extension of TOPSIS

The TOPSIS method was proposed by Hwang and Yoon (1981), and the logic of TOPSIS is intended to define the ideal solution and the negative ideal solution. In short, the ideal solution consists of all of the best values attained for attributes, whereas the negative ideal solution is composed of all of the worst values attained for criteria. The optimal alternative is the one that has the shortest distance from the ideal solution and the farthest distance from the negative ideal solution, based on the TOPSIS concept of the degree of optimality. These considerations provide the ranking of the alternatives by the observation group. Since TOPSIS is a well-known method for classical MCDM, many researchers have applied TOPSIS to solve MCDM problems in the past.

In classical methods, the ratings and the weights of the criteria are known precisely. Abo-sinna and Amer (2004) extended the TOPSIS approach to solve multi-objective nonlinear programming problems. Jahanshahloo et al. (2006) also extended the concept of TOPSIS to develop a methodology for solving MCDM problems with interval data. In real-world situations, because of incomplete or non-obtainable information, for example, human judgments including preferences are often vague and cannot estimate preferences with exact numerical data, the data often are not very deterministic. As a result, there is usually vagueness and imprecision. It is generally understood that customer perceptions are usually judged by human perception measurements (Tseng et al., 2008; 2009a). Hence, since some of the evaluation criteria and alternatives are subjective and because the description of linguistic information is qualitative in nature, it is very difficult for the customer to express preferences using exact numerical values. As a result, it is more desirable for researchers to use fuzzy logic evaluation.

A decision group has *k* members. The weight $\tilde{w}_j^k$ represents the fuzzy weight of the *j*th criterion assessed by *k* evaluators. Applying synthetic value notation integrates the different opinions of evaluators. This procedure aggregates the subjective judgment for *k* evaluators, given by:

$$\tilde{w}_j = \frac{1}{k}(\tilde{w}_j^1 + \tilde{w}_j^2 + \tilde{w}_j^3 + ... + \tilde{w}_j^k) \tag{8}$$

Given m alternatives, a criterion and *k* decision-makers, a typical fuzzy multi-criteria group for a decision-making problem can be expressed in matrix format as follows:

$$\tilde{D} = \begin{array}{c} \\ S_1 \\ S_2 \\ ... \\ S_m \end{array} \begin{array}{c} \mathrm{C}_1, C_2 ....C_n \\ \begin{bmatrix} \tilde{X}_{11} & \tilde{X}_{12} & ..... & \tilde{X}_{1n} \\ \tilde{X}_{21} & \tilde{X}_{22} & .... & \tilde{X}_{2n} \\ .... & ..... & ..... & .... \\ \tilde{X}_{m1} & \tilde{X}_{m1} & .... & \tilde{X}_{mn} \end{bmatrix} \end{array}, i = 1, 2, ..., m;\ j = 1, 2, ...n \tag{9}$$

Where $S_1, S_2, … S_m$ represent the alternatives to be chosen, while $C_1, C_2,...C_n$ denote the evaluation criteria. The variable $\tilde{x}_{ij}$ expresses the rating of alternative S_i with respect to criteria C_j assessed by *k* evaluators concerning the same evaluation criteria. Hence, we obtain the geometric mean of $\tilde{x}_{ij}^k$, where $\tilde{x}_{ij}^k$ is the rating of alternative S_i with respect to criterion C_j evaluated by the *k*th evaluator, and $\tilde{x}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k, d_{ij}^k)$. The linear scale normalization function applied here preserves the property that the ranges of normalized TFNs to be included are [0, 1]. Therefore, in the normalized fuzzy decision matrix,

$$\tilde{R} = [\tilde{r}_{ij}]_{mxn}, i = 1,2,........m;\ j = 1,2,........,n \tag{10}$$

Where $\tilde{r}_{ij} = (\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}, \frac{d_{ij}}{c_j^+})$ and $c_j^+ = \max_i c_{ij}$

With a different weight for each criterion, we obtained the weighted normalized decision matrix by multiplying the importance weights of the evaluation criteria and the value in the normalized fuzzy decision matrix. The weighted normalized decision matrix $\tilde{V}$ is defined as:

$$\tilde{V} = [\tilde{v}_{ij}]_{mxn}, i = 1,2,....m;\ j = 1,2,....n \tag{11}$$

Where $\tilde{w}_{cj}$ represents the importance weight of criterion C_j; $\tilde{w}_{dependence}$ represents the dependence weights. The positive TFNs are included in the interval [0,1]. Hence, the following definitions for the fuzzy positive ideal reference point (FPIRP, A^+) and the fuzzy negative ideal reference point (FNIRP, A^-) applies, as follows:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, ..., v_n^+)$$
$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, ..., v_n^-)$$

; where $\tilde{v}_j^+$ =(1,1,1,1) and $\tilde{v}_j^-$ =(0,0,0,0), j=1,2,…………..,n. (12)

The distances of alternatives from FPIRP and FNIRP are given by:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+)$$
$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1,2,.........,m; \quad j = 1,2,..........n \tag{13}$$

Respectively, where $d(\tilde{v}_a, \tilde{v}_b)$ denotes the measured distance between two fuzzy numbers, d_i^+ represents the distance of alternative S_i from FPIRP, and d_i^+ is the distance of alternative S_i from FNIRP, the closeness coefficient of each alternative is calculated as:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1,2,.....,m \tag{14}$$

An alternative with index CC_i approaching first indicates that the alternative is close to the FPIRP and far from the FNIRP. This statement means that a large value of index CC_i indicates a good performance of the alternative S_i.

RESULTS

In this study, the evaluation methodology for the evaluation of TICs was operationalized at a case firm. The firm continues to face challenges with how they manage their competitive advantages. In this study, the expert team was formed from four professors, one vice president and five management professionals with extensive consulting experience. This study is required to generate and establish evaluation criteria in the current scenario, which is a chain (of interrelations) of the criteria. The proposed 7 criteria were used and have been considered in TICs from the literature. A firm must have outstanding TICs to perform good management regarding sustainable development. As such, this study views TICs as a complex, interactive process of many different resources with multiple criteria and with dependence

Table 2. Linguistic preferences for importance of criteria.

Linguistic preferences	Trapezoid fuzzy numbers
Extreme low (EL)	(0, 0, 0.1, 0.2)
Very low (LV)	(0.1, 0.2, 0.3, 0.4)
Low (L)	(0.2, 0.3, 0.4, 0.5)
Medium low (ML)	(0.3, 0.4, 0.5, 0.6)
Medium (M)	(0.4, 0.5, 0.6, 0.7)
Medium high (MH)	(0.5, 0.6, 0.7, 0.8)
High (H)	(0.6, 0.7, 0.8, 0.9)
Very high (VH)	(0.7, 0.8, 0.9, 1.0)
Extreme high (EH)	(0.8, 0.9, 1.0, 1.0)

criteria in linguistic preferences.

Problem description

Under the prosperous electronic consumption products and network market, COM Co., LTD not only is the largest professional PCB manufacturer in Taiwan, but is also ranked as number five worldwide. To offer the best service by an electronic manufacturer, COM Co., LTD is continuing to develop new generation technology, enhancing its competitiveness, fully satisfying the market and customer demands and developing a closer relationship with suppliers and customers. COM Co., LTD has to spend substantial effort on improving processes and on developing TICs to meet their customer requirements. The capability of developing and researching new technologies is a global competition resource, which meets product demands from customers and explores new products on the market. Hence, TICs are relatively important for COM Co., LTD to sustain itself in such a competitive market.

The survey instrument was pre-tested for content validity in two stages. In the first stage, ten experienced researchers were asked to review the questionnaire for the ambiguity, clarity and appropriateness of items used to measure each criterion. On the basis of the feedback obtained, the instrument was modified to enhance clarity and appropriateness of the measures purporting to tap the criteria. In the second stage, the survey instrument was mailed to five academicians and professionals affiliated with PCB firms in Taiwan. These academicians and professionals were asked to review the questionnaire for structure, readability, ambiguity and completeness. The survey instrument incorporated feedback received from these executives, which enhanced the comprehensibility of the instruments. The process yielded a survey instrument that was judged to exhibit high content validity. This instrument has 7 criteria related to the importance of TICs. The expert group reviewed the criteria because they expected to remain as a long-term competitor in an intensive market. Hence, the TICs are one of the most prioritized issues of the management team. The intention is to evaluate the criteria in a more logical and persuasive way, as there is a growing need for an analytical and systematic way of solving management decision procedures. The 10 experts should adopt possible relative importance criteria for better handling of this problem. This study provides a criteria ranking, which would be useful for efficient and effective TIC implementation and performance.

Analytical results

The valid questionnaires contained the opinions of the respondents on the level of importance of each evaluation criterion using linguistic preferences based on the corresponding TFNs (Tables 2 and 3). This study utilized the best non-fuzzy performance (BNP) value to defuzzify the TFN and to understand the importance order of the criteria, using Equation (8). The BNP values reveal the important performance criteria sequence for initial TICs as follows: C7 (operations capability); C4 (knowledge and skills capability); C2 (marketing capability); C3 (innovative capability); C1 (planning and commitment of the management capability); C5 (information and communication capability); C6 (external environment capability). The completed result is shown in Table 4.

The fuzzy assessments provide for the inclusion of scientific criteria and provide a means for exhibiting a complex set of relations. Linguistic preferences are interpreted into a fuzzy linguistic scale. To convert the TFNs into a crisp score, the fuzzy assessments are defuzzified to a crisp value. Building the fuzzy decision matrix and normalizing the raw data eliminates anomalies with different measurement units and scales in several MCDM problems. However, the linear scale normalization function applied here preserves the property that the range of normalized TFNs to be included is [0, 1]. The normalized fuzzy decision matrix can be acquired, as follows: Given m alternatives, a set of criteria, and k decision-makers, a typical fuzzy multi-criteria group

Table 3. Linguistic variables for ratings of each alternative with respect to each criterion.

Linguistic preferences	Trapezoid fuzzy numbers
Extreme poor (EP)	(0, 0, 1, 2)
Very poor (LP)	(1, 2, 3, 4)
Poor (P)	(2, 3, 4, 5)
Medium poor (MP)	(3, 4, 5, 6)
Fair (F)	(4, 5, 6, 7)
Medium good (MG)	(5, 6, 7, 8)
High (H)	(6, 7, 8, 9)
Very good (VG)	(7, 8, 9, 10)
Extreme good (EG)	(8, 9, 10, 10)

Table 4. The fuzzy important weight, BNP and rank for each criterion.

Criteria	Fuzzy important weight				Dependence $\tilde{w}_{cj}$	BNP	Ranking
C 1	(0.471,	0.671,	0.731,	0.829)	0.1338	0.657	5
C 2	(0.529,	0.729,	0.748,	0.886)	0.1445	0.714	3
C 3	(0.471,	0.671,	0.686,	0.843)	0.1398	0.662	4
C 4	(0.586,	0.786,	0.795,	0.943)	0.1420	0.771	2
C 5	(0.443,	0.643,	0.742,	0.829)	0.1553	0.638	6
C 6	(0.386,	0.586,	0.686,	0.786)	0.1465	0.586	7
C 7	(0.614,	0.814,	0.905,	0.957)	0.1380	0.795	1

decision-making problem can be expressed in matrix format as in Equation (9). Normalizing the raw data eliminates anomalies with different measurement units and scales in several MCDM problems. However, the linear scale normalization function applied here preserves the property that the range of normalized TFNs to be included is [0, 1]. The normalized fuzzy decision matrix can be acquired. Table 5 presents the Fuzzy decision matrix of performance. The weighted normalized fuzzy decision matrix arises from the following procedure. Considering the different weights for each criterion, we obtained the weighted normalized decision matrix by multiplying the importance weights of the evaluation criteria and the value in the normalized fuzzy decision matrix, using Equation (10). The weighted normalized decision matrix $\tilde{V}$ is presented in Table 6.

Using Equation (11), Table 7 presents the weighted normalized fuzzy decision matrix to present the involvement of interactive relations among criteria, which multiplied the dependence matrix. For example, the fuzzy numbers are 0.56, 0.77 and 0.79, 0.95, and the C1 of alternative S1 from Table 6 are 0.092, 0.180 and 0.220 0.274 with respect to criterion S1. The Table 6 figures in the first row are presented as the following by using Equation (2): 0.092 = 0.56 × 0.164, 0.18 = 0.77 × 0.233, 0.22 = 0.79 × 0.28 and 0.274 = 0.95 × 0.288, respectively. To determine the FPIRP and FNIRP, the positive TFNs are included in the interval [0, 1]. Hence, the following definition of the fuzzy positive ideal reference point (FPIRP, A^+) and the fuzzy negative ideal reference point (FNIRP, A^-) applies: The positive TFNs are within the range [0, 1]. Using Eq.(12), the FPIRP and FNIRP are defined as: A^+ = [(1,1,1,1), (1,1,1,1), (1,1,1,1), (1,1,1,1), (1,1,1,1), (1,1,1,1), (1,1,1,1)]; A^- = [(0,0,0,0), (0,0,0,0), (0,0,0,0), (0,0,0,0), (0,0,0,0), (0,0,0,0) , (0,0,0,0)] for seven criteria.

When calculating the distances of each alternative to FPIRP and FNIRP, $d(\tilde{v}_a, \tilde{v}_b)$ denotes the measured distance between two fuzzy numbers, d_i^+ represents the distance of alternative S_i from FPIRP, and d_i^+ is the distance of alternative S_i from FNIRP. To obtain the distance of each alternative to the FPIRP and FNIRP, the following calculation is the S_1 used in Equation (13) to arrive at d^+ and d^-; the completed result can be obtained for S_1 to S_7 by repeating the computational process.

$$d^+ = \{[(0.092-1)^2 + (0.18-1)^2 + (0.222-1)^2 + (0.274-1)^2]/4\}^{0.5} + \{[(0.111-1)^2 + (0.208-1)^2 + (0.258-1)^2 + (0.296-1)^2]/4\}^{0.5} \ldots\ldots\ldots\ldots + \{[(0.106-1)^2 + (0.201-1)^2 + (0.221-1)^2 + (0.287-1)^2]/4\}^{0.5} = 2.254$$

Table 5. Fuzzy decision matrix of performance.

Criteria	S1				S2				S3				S4			
C1	(5.29,	7.29,	7.58,	9.00)	(5.86,	7.86,	8.66,	9.43)	(6.14,	8.14,	8.54,	9.43)	(6.71,	8.71,	8.85,	9.86)
C2	(6.43,	8.43,	8.68,	9.71)	(5.57,	7.57,	7.77,	9.00)	(5.86,	7.86,	8.16,	9.43)	(5.57,	7.57,	7.86,	9.29)
C3	(5.29,	7.29,	7.78,	9.00)	(5.86,	7.86,	8.56,	9.14)	(4.43,	6.43,	7.53,	8.14)	(5.57,	7.57,	7.86,	9.29)
C4	(5.57,	7.57,	7.96,	9.29)	(4.43,	6.42,	7.45,	8.29)	(5.57,	7.57,	7.85,	9.00)	(5.29,	7.29,	8.28,	9.14)
C5	(5.29,	7.29,	7.53,	9.00)	(5.29,	7.26,	8.46,	8.86)	(6.43,	8.43,	8.88,	9.71)	(5.29,	7.29,	8.56,	9.00)
C6	(5.86,	7.86,	7.99,	9.29)	(4.71,	6.71,	7.53,	8.57)	(5.57,	7.57,	7.86,	9.14)	(5.00,	7.00,	7.63,	8.86)
C7	(6.14,	8.14,	8.53,	9.43)	(5.86,	7.85,	8.25,	9.43)	(5.00,	7.00,	7.55,	8.71)	(5.86,	7.86,	7.99,	9.43)

Table 6. Fuzzy normalized decision matrix.

Criteria	S1				S2				S3				S4			
C1	(0.56,	0.77,	0.79,	0.95)	(0.62,	0.83,	0.88,	1.00)	(0.65,	0.86,	0.86,	1.00)	(0.681,	0.84,	0.88,	1.00)
C 2	(0.68,	0.89,	0.92,	1.00)	(0.59,	0.82,	0.88,	0.95)	(0.62,	0.83,	0.83,	1.00)	(0.565,	0.76,	0.78,	0.92)
C 3	(0.56,	0.77,	0.78,	0.95)	(0.62,	0.83,	0.86,	0.97)	(0.47,	0.62,	0.68,	0.86)	(0.565,	0.78,	0.79,	0.92)
C 4	(0.59,	0.82,	0.82,	0.98)	(0.47,	0.68,	0.78,	0.87)	(0.51,	0.83,	0.80,	0.95)	(0.536,	0.73,	0.79,	0.98)
C 5	(0.56,	0.77,	0.79,	0.95)	(0.56,	0.77,	0.79,	0.93)	(0.68,	0.84,	0.89,	1.00)	(0.536,	0.79,	0.82,	0.93)
C 6	(0.62,	0.83,	0.85,	0.98)	(0.50,	0.71,	0.77,	0.99)	(0.59,	0.83,	0.88,	0.97)	(0.507,	0.71,	0.78,	0.89)
C 7	(0.65,	0.86,	0.88,	1.00)	(0.62,	0.83,	0.88,	1.00)	(0.53,	0.72,	0.74,	0.92)	(0.594,	0.77,	0.77,	0.97)

Table 7. Fuzzy weighted normalized decision matrix.

Criteria	S1				S2				S3				S4			
C1	(0.092,	0.180,	0.220,	0.274)	(0.108,	0.206,	0.286,	0.304)	(0.113,	0.213,	0.245,	0.304)	(0.118,	0.218,	0.225,	0.304)
C2	(0.111,	0.208,	0.258,	0.296)	(0.102,	0.198,	0.228,	0.291)	(0.108,	0.206,	0.222,	0.304)	(0.098,	0.190,	0.221,	0.287)
C3	(0.092,	0.180,	0.260,	0.274)	(0.108,	0.206,	0.246,	0.295)	(0.081,	0.168,	0.225,	0.263)	(0.098,	0.190,	0.225,	0.287)
C4	(0.097,	0.187,	0.217,	0.283)	(0.081,	0.168,	0.258,	0.268)	(0.102,	0.198,	0.207,	0.291)	(0.093,	0.182,	0.260,	0.282)
C5	(0.092,	0.180,	0.220,	0.274)	(0.097,	0.191,	0.241,	0.286)	(0.118,	0.221,	0.251,	0.314)	(0.093,	0.182,	0.259,	0.278)
C6	(0.101,	0.194,	0.244,	0.283)	(0.087,	0.176,	0.226,	0.277)	(0.102,	0.198,	0.228,	0.295)	(0.088,	0.175,	0.248,	0.274)
C7	(0.106,	0.201,	0.221,	0.287)	(0.108,	0.206,	0.256,	0.304)	(0.092,	0.183,	0.203,	0.281)	(0.103,	0.197,	0.220,	0.291)

$d^{-} = \{[(0.092-0)^2 + (0.18-0)^2 + (0.222-1)^2 + (0.274-0)^2]/4\}^{0.5} + \{[(0.111-0)^2 + (0.208-0)^2 + (0.258-1)^2 + (0.296-0)^2]/4\}^{0.5} + \ldots\ldots\ldots\ldots\ldots\ldots + \{[(0.106-0)^2 + (0.201-0)^2 + (0.221-0)^2 + (0.287-0)^2]/4\}^{0.5} = 0.164$

Equation (14) provides the closeness coefficient. The index CC_j for the first alternative hotel is calculated as $CC_j = 0.164/(2.254+0.164) = 0.068$. An alternative with a closeness coefficient close to 1 has the shortest distance from the FPIRP, and the largest distance from the FNIRP. A large closeness coefficient of an alternative indicates good performance. Table 8 shows the

Table 8. The closeness coefficient and rank of alternatives.

Alternatives	d^+	d^-	CC_J	Rank
S1	2.254	0.164	0.0680	3
S2	1.925	0.143	0.0690	1
S3	1.616	0.116	0.0669	4
S4	1.287	0.094	0.0681	2

closeness coefficient of the seven alternatives. The ranking is as follows:

S_2(0.0690)> S_4(0.0681)> S_3(0.0680)> S_4(0.0669)

The result indicates that S_2 is the best out of four green suppliers prior to the TIC multi-criteria. An alternative with index CC_i approaching first indicates that the alternative is close to the FPIRP and far from the FNIRP. This statement means that a large value for the index CC_i indicates a good performance of the alternative S_i.

Managerial implications

Management should pay attention to the results to improve the TICs in their future supply chain strategy. This empirical study plans to enhance their current performance through the seven TIC criteria. This study is important to identify strategic preferences for TICs and also provides management with a guide for improvement in aligning TICs and supplier choices. Apart from the academic dimension, this study has an important managerial facet. First, practitioners are offered new insights into how to measure TICs. Here, the proposed methodological tool brings important benefits for practitioners, which can be summarized, as follows: First, among the seven criteria, the operations capability (C7) is the most important criterion because it has the highest importance weight (that is - overall quality and technological innovation matching market requirements, which might bring success in technology transfer, product development and commercialization). To enhance its competitive advantages, the firm should be aware of what the technology innovation does and should continue to improve a value-added process that encompasses a continuum of the range of the related firms' activities from laboratory innovation to market requirements. Intra-organizational technology between firms and suppliers should be integrated to meet the market requirements. However, knowledge and skills capabilities (C4) should be recognized because of the innovativeness of knowledge protection systems, and periodical evaluations of practices and routines require operational process skills.

Secondly, the ranking of BNP values reveals the important criteria ranking for the initial perception of TICs as follows: Operations capability (C7), knowledge and skills capability (C4), marketing capability (C2), innovative capability (C3), planning and commitment of the management capability (C1), information and communication capability (C5) and external environment capability (C6). In particular, the marketing capability of a firm is reflected in its ability to differentiate products and services from competitors and to build successful brands with strong brand names. This success can allow a firm to charge premium prices in foreign markets to enhance their profitability. The firm develops a market orientation that facilitates the generation and utilization of market information and that facilitates the coordinated application of resources focused on delivering superior customer value. Hence, the TICs are really one overall process encompassing multiple criteria that collectively transform the capabilities of their firm. The operations capabilities comprising technology transfer, product development and commercialization are routinely viewed as discrete activities, but it is more constructive to treat these capabilities as a continuous process from technology discovery through market orientation.

Thirdly, the identification of TICs and the marketing capabilities were substantial inputs for the planning and commitment of the management capability (C1). To design a customer driven firm, investments were directed into the enhancement of marketing capabilities and the knowledge and skills capabilities (C4) that contribute to the development of high-end products. Moreover, the majority of firms in the industry builds competitive advantages on marketing requirements and employs radical technological innovations. Differentiation therefore relies on a unique portfolio of technological and marketing capabilities and their effective integration. A methodological tool that promotes the periodic scrutiny of existing capabilities is highly valuable for firms.

Fourthly, the hybrid method enables managers to identify their firm's technological innovation capabilities systematically and integrally, thereby providing managers with relevant information for strategizing about the development and deployment of the firm's capabilities. The proposed method allows the pinpointing of areas that are most critical and that deserve priority action. The methodology can be applied repeatedly in a firm, thus facilitating longitudinal capability analyses. In fact, the measurement process can be performed internally without the need to hire external consultants. This benefit found the methodological tool to be very simple and with feasible evaluation. In addition, this study requires the active participation of all important holders of TICs in a firm. The involvement of technology and marketing experts identify and measure capabilities by increasing the level of understanding and acceptance of its current strategy's implementation and performance evaluation.

Finally, as TICs are taking on an important strategic role, this empirical study measures the importance of performance weights to be obtained effectively, to transform cases into benchmarks for firms and other settings. More importantly, the successful TICs start with the evaluation of the current status, which is produced by a robust evaluation method. However, this problem requires a consideration of a large number of complex criteria as multiple evaluation criteria. Although numerous creditable works are devoted to the study of how to build a decision model and to execute the TICs strategy successfully, few of these have provided methods that can systematically evaluate and model complex characteristics in criteria measurements.

Conclusion

Several alternatives must be considered and evaluated in terms of many different dependence relations in an optimal selection problem, leading to subjective judgment. This study makes two major contributions to the literature. The first contribution is related to the use of linguistic preferences, dependence relations and TOPSIS as a hybrid method to evaluate a TIC implementation and performance. The second contribution is related to the TIC criteria to approach the suppliers' selection problem. Through the expert evaluation, this study establishes criteria and develops a more suitable evaluation method for its TIC implementation and performance. When experts consider alternatives, evaluations of TICs have a set of criteria for subjective judgment, allowing comparisons with the alternative ranking problem. Most current measures rely on statistical analysis, disregarding human subjectivity, dependency and environmental uncertainty. Hence, an effective evaluation approach is essential to improve the quality of computational procedures. The TICs utilizing TFNs to express linguistic preferences consider the subjective judgments of expert evaluations. Extending the applications of TOPSIS to a fuzzy environment influences the overall value and rank of the suppliers. However, because of the need to consider the dependence relations among the evaluation criteria, the proposed method was applied in solving the objective.

The final ranking shows that the performance of S_2 in general, is better in the TICs implementation as benchmarking. The identification of experts' perception on the TICs is essential to better tailor marketing efforts to ensure that customer needs are found. Since the overall indicators can be analyzed dynamically, once a lower performance level appears, management can recognize, prioritize and improve operational areas where important weaknesses are presented. This study enables an evaluator to utilize quantitative measures with inherent imprecision in the weighting implementation and performance criteria related to qualitative evaluation by transforming linguistic preferences into crisp values. This study employed trapezoid fuzzy numbers to represent linguistic preferences in dealing with fuzzy subjective judgments by evaluators and reduced the evaluator cognitive burden during TIC evaluations. However, this study also suffers two major limitations. First, the survey is conducted without having in mind the treatment of fuzzy set theory methodology, and for this reason, each expert does not have the option of defining the TFNs to be more concordant with their perceptions. Secondly, the perception of TICs might be biased because additional effects could exist. Therefore, the sample is important and the findings can be robust.

As was the aim of this study, the proposed trapezoid fuzzy number, the dependence matrix and the TOPSIS method worked smoothly in tackling the issue of segmenting the TICs into meaningful portions. This method is relatively useful for handling the effects of dependencies and makes the evaluation result more reasonable. Additionally, this study has contributed to extend practical applications in the TIC field, and using the suggested analytical procedure, the method here can effectively handle any problem of selection with multi-faceted dependency criteria. However, there are some limitations; for example, if the study involves large samples, then the combined methodology might be too complicated. Therefore, to promote and deepen continuing research in the future, it is worthwhile to investigate more studies to uncover invaluable new study issues. Finally, to enhance the overall performance and its current implementation, the results provide the PCB industry with directions for future improvement.

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REFERENCES

Abo-Sinna MA, Amer AH (2004). Extensions of TOPSIS for multi-objective large-scale nonlinear programming problems. Appl. Math. Comput. 162:243-256.

Afuah A, Bahram N (1995). The hypercube of innovation. Res. Pol. 24:51-76.

Agarwal A, Shankar R, Tiwari MK (2007). Modeling agility of supply

chain. Ind. Market. Manage. 36:443-457.
Aksoy S, Öztürk N (2011). Supplier selection and performance evaluation in just-in-time production environments. Expert Syst. Appl., 38(5):6351-6359.
Al-Najjar B, Alsyouf I (2003). Selecting the most efficient maintenance approach using fuzzy multiple criteria decision making. Int. J. Prod. Econ. 84(1):85–100.
Bellman RE, Zadeh LA (1970). Decision making in a fuzzy environment. Manage. Sci. 17(4):141-164.
Betz F (1998). Managing Technological Innovation, NY: John Wiley and Sons.
Cakravastia A, Toha IS, Nakamura N (2002). A two-stage model for the design of supply chain networks. Int. J. Prod. Econ. 80:231–248.
Carlsson B, Jacobsson S, Holmén M, Rickne A (2002). Innovation system: Analytical and methodological issues. Res. Pol. 31(2):233-245.
Chen CT (2000). Extension of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets Syst. 114:1-9.
Chen CT, Lin CT, Huang SF (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. Int. J. Prod. Econ. 102:289-301.
Chen MF, Tzeng GH (2004). Combining grey relation and TOPSIS concepts for selecting an expatriate host country. Math. Comput. Modell. 40:1473-1490.
Cheng CH, Lin Y (2002). Evaluating the best main battle tank using fuzzy decision theory with linguistic criteria evaluation. Eur. J. Oper. Res. 142(1):174-186.
Garcia-Muina FE, Navas-Lopez JE (2007). Explaining and measuring success in new business: the effect of technological capabilities on firm results. Technovation 27(1-2):30-46.
Guan J, Ma N (2003). Innovative capability and export performance of Chinese Firms. Technovation 23(9):737-747.
Guan JC, Yam RCM, Mok CK, Ma N (2006). A study of the relationship between competitiveness and technological innovation capability based on DEA models. Eur. J. Oper. Res. 170:971-986.
Huber F, Herrmann A, Morgan RE (2001). Gaining competitive advantage through customer value oriented management." J. Consum. Mark. 18(1):41-51
Humphreys PK, Wong YK, Chan FTS (2003). Integrating environmental criteria into the supplier selection process. J. Mater. Process. Technol. 138:349-356
Hwang CL, Yoon K (1981). Multiple attribute decision making methods and applications: A state-of-the-art survey. New York: Springer-Verlag.
Jacobsson S, Lauber V (2006). The politics and policy of energy system transformation - Explaining the German diffusion of renewable energy technology. Energy Pol. 34:256-276.
Jahanshahloo GR, Hosseinzadeh LF, Izadikhah M (2006). An algorithmic method to extend TOPSIS for decision-making problems with interval data. Appl. Math. Comput. 175(2):1375-1384 DATE
Lee CC, Ou-Yang C (2009). A neural networks approach for forecasting the supplier's bid prices in supplier selection negotiation process. Expert Syst. Appl. 36(2):961-2970
Li DF (2007). Compromise ratio method for fuzzy multi-attribute group decision making. Appl. Soft Comput. 7:807-817
Lin YH, Tseng ML, Chen CC, Chiu ASF (2011). Positioning strategic competitiveness of green business innovation capabilities using hybrid method. Expert Syst. Appl. 38(3):1839-1849.
Murthy NN, Soni S, Ghosh S (2004). A framework for facilitating sourcing and allocation decisions for make-to-order items. Decis. Sci. 35:609–637.
Perdomo-Ortiz J, Gonza' lez-Benito J, Galende J (2006). Total quality management as a forerunner of business innovation capability. Technovation 26(10):1170-1185
Prašnikar J, Lisjak M, Buhovac AJ, Štembergar M (2008). Identifying and Exploiting the inter relationships between Technological and Marketing capability. Long-Range Plan. 41(5):530-554.
Pun KF, Chin KS, White AS, Gill R (2004). Determinants of manufacturing strategy formulation: A longitudinal study in Hong Kong. Technovation: Int. J. Tech. Innovat. Entrep. 24(2):121–137.
Ranganathan J (1998). Sustainability Rulers: Measuring Corporate Environmental and Social Performance. Sustainable Enterprise Perspectives, World Resource Institute: Washington, DC. http://www.wri.org/meb/pdf/janet/pdf.
Sun H, Gertsen F (1995). Organizational changes in production area with advanced manufacturing technologies. Int. J. Prod. Econ. 41:369–375.
Tan C (2011). A multi-criteria interval-valued intuitionistic fuzzy group decision making with Choquet integral-based TOPSIS. Expert Syst. Appl. 38(4):3023-3033
Tan H (2011). The empirical analysis of enterprise scientific and technology innovation. Energy Procedia 5:1258-1263
Triantaphyllou E, Lin CT (1996). Development and evaluation of five fuzzy multi-attribute decision-making methods. Int. J. Approx. Reason. 14:281-310.
Tseng ML (2010). Using linguistic preferences and grey relational analysis to evaluate the environmental knowledge management capacities. Expert Syst. Appl. 37(1):70-81.
Tseng ML (2011). Using a hybrid MCDM model to evaluate firm environmental knowledge management in uncertainty. Appl. Soft Comput. 11(1):1340-1352.
Tseng ML, Chiang JH, Lan LW (2009b). Selection of optimal supplier in supply chain management strategy with analytic network process and choquet integral. Comput. Ind. Eng. 57(1):330-340.
Tseng ML, Divinagracia L, Divinagracia R (2009a). Evaluating firm's sustainable production indicators in uncertainty. Comput. Ind. Eng. 57:1393-1403
Tseng ML, Lin YH, Chiu ASF, Liao CH (2008). Using FANP approach on selection of competitive priorities based on cleaner production implementation: A case study in PCB manufacturer, Taiwan. Clean Technol. Environ. Pol. 10(1):17-29
Wang CH, Lu LY, Chen CB (2008). Evaluating firm technological innovation capability under uncertainty. Technovation 28:349-363
Watkins KE, Ellinger AD, Valentine T (1999). Understanding support for innovation in a large-scale change effort: The manager-as-instructor approach. Hum. Resour. Dev. Qual. 10(1):63-78
Woolthuis KR, Lankhuizen M, Gilsing V (2005). A system failure framework for innovation policy design. Technovation 25:609-619.
Yam RCM, Guan JC, Pun KF, Tang EPY (2004). An audit of technological innovation capabilities in Chinese firms: Some empirical findings in Beijing, China. Res. Pol. 33(8):1123-1140
Yam RCM, Lo W, Tang EPY, Lau AKW (2011). Analysis of sources of innovation, technological innovation capabilities, and performance: An empirical study of Hong Kong manufacturing industries. Res. Pol. 40:391-402
Zadeh LA (1965). Fuzzy set. Inform. Control 18:338-353.