Using qualitative reasoning to evaluate performance: An application in the retail sector

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Abstract

This paper offers a new method inspired by classic importance-performance analysis (IPA) that provides a global index of importance versus performance for firms together with a new version of the IPA diagram. The index compares two rankings of the same set of features regarding importance and performance, taking into account under-performing features. The marginal contribution of each feature to the proposed global index defines a set of iso-curves that represents an improvement in the IPA diagram. The defined index, together with the new version of the diagram, enables, by means of qualitative reasoning techniques, the assessment of a firm's overall performance and therefore enhance decision making in the allocation of resources. The proposed method has been applied to a Taiwanese multi-format retailer and managerial perceptions of performance and importance are compared to assess the firm's overall performance.

Introduction

In Importance-performance analysis (IPA), firm features are ranked regarding either their importance and their performance. Differences between importance and performance rankings of features are considered when assessing a firm's resource allocation. Initial approaches in the late 70s were based on simple and intuitive graphic techniques (Martilla and James 1977). The traditional IPA methodology basically consists of representing ratings of importance and performance for several features on a two-dimensional chart. The resulting importance-performance grid is divided into four quadrants. To interpret the results, Martilla and James give a name to each quadrant to help managers determine the highest and lowest priorities for improvement, as shown in Figure 1 (Martilla and James 1977).

We present in this paper a new similarity index to compare the importance and performance rankings of the same set of features. The proposed index is based on induced ordered weighted averaging (IOWA) operators (Yager and Filev 1999), and importance and performance rankings are obtained by means of qualitative assessments of the different features considered in a firm evaluation. These assessments, given by a set of experts, are expressed using order-of-magnitude models, allowing the experts to use different levels of precision for each feature. Differences between the importance and performance ordered lists are considered to define the index of similarity. This index, when applied to a firm's features rankings for both importance and performance, enables a firm's global performance to be assessed. There are two main differences between our index and existing indexes such as Kendall's Tau and Spearman's Rho correlation coefficients. On the one hand, the asymmetry of the features treatment, i.e., it just takes into account under-performing features, and, on the second hand, the specific relation between the weights and the importance, i.e., the more important an under-performing feature, the greater its weight is considered in the similarity index.

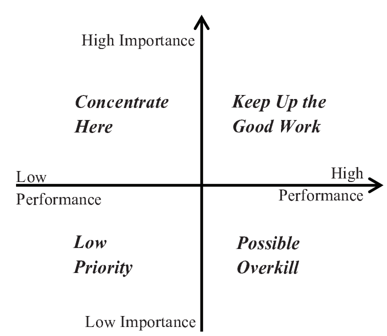

Figure 1: IPA diagram (Martilla and James 1977)

In addition, in this paper, a new IPA diagram, based on the proposed similarity index is presented to select features where resource allocation is necessary. The new IPA diagram is defined via the iso-curves obtained when considering the marginal contribution of the features to the proposed similarity index.

An application of the presented method to the retail sector has been conducted. The starting point of our application is a set of 44 features used in the retail sector that were selected by expert managers as the main performance variables. The similarity index is applied to compare the two rankings of this set of features. Whilst the proposed similarity index could have broader applications, the specific application in this paper throws light on company resource allocation (Deng 2007).

Theoretical framework

Several authors have conducted various analytical measures to compare the gap between performance and importance in the features that describe a firm. The index considered in this paper is based, on the one hand, on a ranking method that uses qualitative linguistic descriptions, and, on the other hand, on IOWA operators.

A ranking method using qualitative linguistic descriptions

In the proposed ranking method, each feature is characterized by the judgments of k evaluators, and each evaluator makes his/her judgements by means of qualitative labels belonging to an order-of-magnitude space $\mathbb{S}_{m_h}$ with granularity m_h for $h = 1, \dots, k$. The evaluations are then synthesized by means of the distance to a reference k-dimensional vector of labels. In this way, the process considered for ranking features assessed by k expert evaluators can be split in the following four steps:

Step 1. Feature representation as k-dimensional vectors of labels Features are represented by a k-dimensional vectors of labels belonging to the set $\mathbb{X}$, which is defined as:

$$\mathbb{X} = \mathbb{S}_{m_1} \times \cdots \times \mathbb{S}_{m_k} = \{\mathbf{X} = (X_1, \dots, X_k) \mid X_i \in \mathbb{S}_{m_h} \ \forall h = 1, \dots k\}.$$

For every component monotonicity is assumed, i.e., $X_h \leq X'_h$ indicates that the evaluation made by the evaluator h corresponding to the feature X' is better or equal to the one corresponding to X. The order relation defined in each $\mathbb{S}_{m_h}$ is extended to the Cartesian product $\mathbb{X}$:

$$\mathbf{X} = (X_1, \dots, X_k) \leq \mathbf{X}' = (X'_1, \dots, X'_k) \iff X_h \leq X'_h \ \forall h = 1, \dots, k.$$

This order relation in $\mathbb{X}$ is partial, since there are pairs of non-comparable k-dimensional vectors of labels. And $\mathbf{X} < \mathbf{X}'$, that is to say, $\mathbf{X} \leq \mathbf{X}'$ and $\mathbf{X} \neq \mathbf{X}'$, means that feature $\mathbf{X}$ is preferred to feature $\mathbf{X}'$ by all the evaluators.

Step 2. A distance between k-dimensional vectors of labels The method presented in (Agell et al 2012) via a codification of the labels in each $\mathbb{S}_{m_h}$ given by a location function is considered. The location function codifies each element $X_h = [B_i, B_j]$ in $\mathbb{S}_{m_h}$ by a pair of integers $(l_1(X_h), l_2(X_h))$, where $l_1(X_h)$ is the opposite of the number of basic elements in $\mathbb{S}_{m_h}$ that are "between" B_1 and B_i, that is, $l_1(X_h) = -(i-1)$, and $l_2(X_h)$ is the number of basic elements in $\mathbb{S}_{m_h}$ that are "between" B_j and B_{m_h}, i.e., $l_2(X_h) = m_h - j$.

The extension of the location function to the set $\mathbb{X}$ of k-dimensional vectors of labels is defined as:

$$L(\mathbf{X}) = L(X_1, \dots, X_k) = (l_1(X_1), l_2(X_1), \dots, l_1(X_k), l_2(X_k)).$$

A distance d between labels $\mathbf{X}, \mathbf{X}'$ in $\mathbb{X}$ is then defined via a weighted Euclidian distance in $\mathbb{R}^{2k}$ between their codifications:

$$d(\mathbf{X}, \mathbf{X}') = \sqrt{\sum_{h=1}^{k} w_h[((l_1(X_h) - l_1(X'_h))^2 + (l_2(X_h) - l_2(X'_h))^2]}.$$

where w_i are considered to be the weights assigned to the k evaluators and $\sum_{h=1}^{k} w_h = 1$. This function inherits all the properties of the weighted Euclidian distance in $\mathbb{R}^{2k}$.

Step 3. Building a reference k-dimensional vector of labels The reference k-dimensional vector of labels considered in this ranking method is the supreme with respect to the order relation $\leq$ of the set of feature representations.

Let $\{\mathbf{X}^1, \dots, \mathbf{X}^n\} \subset \mathbb{X}$ be the set of n features representations to be ranked, then the supreme of the set $\mathbf{X}^{\text{sup}}$, i.e., the minimum label in $\mathbb{X}$ which satisfies $\mathbf{X}^r \leq \mathbf{X}^{\text{sup}}, r = 1, \dots, n$, is computed as follows:

Given $\mathbf{X}^r = (X_1^r, \dots, X_k^r)$, with $X_h^r = [B_{i_h}^r, B_{j_h}^r]$ for all $h = 1, \dots, k$, and for all $r = 1, \dots, n$, then,

$$\mathbf{X}^{\text{sup}} = \sup\{\mathbf{X}^1, \dots, \mathbf{X}^n\} = (\tilde{X}_1, \dots, \tilde{X}_k),$$

where:

$$\tilde{X}_h = [\max\{B_{i_h}^1, \dots, B_{i_h}^n\}, \max\{B_{j_h}^1, \dots, B_{j_h}^n\}].$$

Step 4. Obtaining the features ranking from the values $d(\mathbf{X}, \mathbf{X}_{sup})$ Let d and $\mathbf{X}^{\text{sup}}$ be respectively the distance and the reference label defined in Steps 2 and 3. Then the following binary relation in $\mathbb{X}$:

$$\mathbf{X} \ll \mathbf{X}' \iff d(\mathbf{X}', \mathbf{X}^{\text{sup}}) \leq d(\mathbf{X}, \mathbf{X}^{\text{sup}})$$

is a pre-order, i.e., it is reflexive and transitive. This pre-order relation induces an equivalence relation $\equiv$ in $\mathbb{X}$ by means of:

$$\mathbf{X} \equiv \mathbf{X}' \iff [\mathbf{X} \ll \mathbf{X}' \ , \ \mathbf{X}' \ll \mathbf{X}] \iff d(\mathbf{X}', \mathbf{X}^{\text{sup}}) = d(\mathbf{X}, \mathbf{X}^{\text{sup}}).$$

In the quotient set $\mathbb{X}/\equiv$ the following relation between equivalence classes:

$$\text{class}\,(\mathbf{X}) \trianglelefteq \text{class}\,(\mathbf{X}') \iff \mathbf{X} \ll \mathbf{X}' \iff d(\mathbf{X}', \mathbf{X}^{\text{sup}}) \leq d(\mathbf{X}, \mathbf{X}^{\text{sup}})$$

is an order relation. It is trivially a total order.

In this way, a set of features $\mathbf{X}^1, \dots, \mathbf{X}^n$ can be ordered as a chain with respect to their proximity to the supreme: $\text{class}\,(\mathbf{X}^{i_1}) \trianglelefteq \cdots \trianglelefteq \text{class}\,(\mathbf{X}^{i_n})$.

If each class $(\mathbf{X}^{i_j}), j = 1, \dots n$, contains only a feature representation $\mathbf{X}^{i_j}$, the process is finished and we obtain the ranking $\mathbf{X}^{i_1} \trianglelefteq \cdots \trianglelefteq \mathbf{X}^{i_n}$. If there is some class $(\mathbf{X}^{i_j})$ with more than one feature representation, then the same ranking process is applied to the set of the feature representations belonging to class $(\mathbf{X}^{i_j})$, and continued until an iteration of the process gives the same ranking as the previous iteration. The final ranking $\mathbf{X}^{m_1} \trianglelefteq \cdots \trianglelefteq \mathbf{X}^{m_n}$ is then obtained.

IOWA operators

As rankings are generated for both importance and performance when measuring the same set of features, the definition of a suitable indicator of their differences is a relevant issue. A comparison of rankings may be undertaken with different techniques, but most techniques do not take into account the relative importance of the ranked items, and only consider their relative ranked position. The index considered in this paper, based on induced ordered weighted averaging (IOWA) operator's concept (Chiclana et al 2007; Yager and Filev 1999) enables importance and performance rankings to be compared more sensitively. IOWA operators were introduced in (Yager and Filev 1999) as an extension of ordered weighted averaging (OWA) operators (Yager 1988).

The OWA operators are a type of weighted mean that enables tuning the weights by means of the relative importance of the considered variable. To this end, values of the considered variable are ordered before being weighted.

Definition 1 *(Yager 1988) An OWA operator of dimension n is a mapping $f : \mathbb{R}^n \to \mathbb{R}$ such that:*

$$f(x_1, \dots, x_n) = \sum_{i=1}^{n} w_i x_{(i)},$$

where $x_{(i)}$ are the same values as x_i ordered from the largest to the smallest, and w_i are a set of weights such that $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$.

On the other hand, IOWA operators consider two related variables: First, the order inducing variable, and second, the argument variable. The argument variable values are aggregated using a set of weights based on the order of the values of the first variable.

Definition 2 *(Yager and Filev 1999) An IOWA operator of dimension n is a mapping $\Phi : (\mathbb{R} \times \mathbb{R})^n \to \mathbb{R}$ such that:*

$$\Phi((u_1, x_1), \dots, (u_n, x_n)) = \sum_{i=1}^{n} w_i x_{\sigma(i)},$$

where $\sigma : \{1, \dots, n\} \to \{1, \dots, n\}$ is a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall i = 1, \dots, n-1$, and w_i are a set of weights such that $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$.

Both OWA and IOWA operators have been deeply studied and applied in multi-criteria and group decision-making literature (Chiclana et al 2007). In addition, several extensions of the above-mentioned operators have been introduced in other studies to deal with situations where fuzzy or linguistic variables are considered in the decision-making process (Herrera and Herrera-Viedma 1997; Herrera-Viedma et al 2006).

An index for comparing importance and performance

The following definitions consider differences between performance and importance in features ordered from the most important to the least. The global index proposed in this paper is a convenient weighted mean of these differences, i.e., an IOWA operator, with importance as order inducing variable and these differences as argument variable.

Let n be the number of features considered to describe a firm and I_i and P_i be the importance and performance positions in the rankings of the ith feature respectively. I_i and P_i are numbers from 1 to n such that the feature corresponding to $I_i = 1$ is the most important and the feature corresponding to $P_j = 1$ is the best performed.

Note that from now on, the features are considered ordered with respect to their importance position in the ranking, i.e., the $(i)th$ feature is the feature with importance position in the ranking $I_{(i)} = i$, and so $I_{(1)} = 1 \dots, I_{(n)} = n$.

Definition 3 *The importance-performance vector of a firm F is the vector:*

$$IPR(F) = ((1, P_1), \dots, (n, P_n))$$

whose components are the pairs of ranking values of its considered features with respect to importance and performance, ordered with respect to their importance position in the ranking.

The n components of the $IPR(F)$ vector of a firm F can be represented as points in the IPA diagram, each point (x, y) corresponding to one of the n considered features. To include all these n points in the classical IPA diagram, the reverse positions in the ranking with respect to performance and importance, centered in $(\frac{n+1}{2}, \frac{n+1}{2})$, have to be computed, i.e., $x = \frac{n+1}{2} - P_i$ and $y = \frac{n+1}{2} - i$.

Note that the ranking values (i, P_i) of the considered features with respect to importance and performance can be obtained via any ranking method. Agell et al (2012) proposes a ranking method based on the absolute order-of-magnitude qualitative model.

From now on, let us denote by IPR^* the importance-performance vector of the ideal best performed firm, i.e., $IPR^* = ((1, 1), \dots, (i, i), \dots, (n, n))$ and IPR_* the importance-performance vector of a firm in the opposite situation, i.e., $IPR_* = ((1, n), \dots, (i, n-i+1), \dots, (n, 1))$.

To focus on the features in which resources must be allocated, and from the importance-performance vector of a firm $IPR(F) = ((1, P_1), \dots, (n, P_n))$, the next definition introduces a new vector that takes into account only under-performing features, i.e., those features where their performance position in the ranking is worse than their importance position in the ranking.

Definition 4 *Let $IPR(F) = ((1, P_1), \cdots, (n, P_n))$ be the importance-performance vector of a firm F. The non-negative performance-importance differences vector of the firm is the n-dimensional vector $DV(F) = (X_1, \dots, X_n)$, where $X_i = \max(P_i - i, 0)$, for all $i = 1, \dots, n$.*

Note that for any firm F, the components of $DV(F)$, are $X_i \geq 0$ for all $i = 1, \dots, n$ and nonzero components correspond to under-performing features.

In the two cases described above, corresponding to the ideal best performed firm and its opposite situation, the associated non-negative performance-importance differences vectors are respectively:

$DV^* = (0, \dots, 0)$ and $DV_* = (n-1, \dots, \max(n - 2i + 1, 0), \dots, 0)$.

Based on the usual partial order in $\mathbb{R}^n$, the next definition establishes a preference relation between differences vectors introduced in Definition 4, and therefore between the importance-performance status of firms.

Definition 5 *Let $DV(F^1) = (X_1^1, \dots, X_n^1)$ and $DV(F^2) = (X_1^2, \dots, X_n^2)$ be two differences vectors, then $DV(F^1)$ is preferred to $DV(F^2)$, $DV(F^1) \preceq DV(F^2)$,* *when $DV(F^1) \leq DV(F^2)$ with the usual order in $\mathbb{R}^n$, i.e., $X_i^1 \leq X_i^2$ for all $i = 1, \ldots, n$.*

In this way, $DV(F^1)$ is preferred to $DV(F^2)$ when F^1 performs better than F^2 for all under-performing features. Differences vectors introduced in Definition 4 enable us to define an index via an IOWA operator that preserves this preference relation:

Definition 6 *Let $DV(F) = (X_1, \ldots, X_n)$ be the differences vector of a firm, the Global Importance-Performance Index ($\mathcal{G}$) of the firm is:*

$$\mathcal{G}(X_1, \ldots, X_n) = \sum_{i=1}^{n} w_i X_i$$

where weights are computed using Borda-Kendall method (Kendall1962), i.e., $w_i = \dfrac{2(n-i+1)}{n(n+1)}$ for all $i = 1, \ldots, n$.

Note that $w_i \in [0,1]$ for all $i = 1, \ldots, n$ and $\sum_{i=1}^{n} w_i = 1$. These weights express the ratio between the reverse importance position in the ranking $n - I_i - 1 = n - i - 1$ of the ith feature and $\sum_{i=1}^{n} i$. Indeed, the weights decrease from $\dfrac{2n}{n(n+1)}$ to $\dfrac{2}{n(n+1)}$. In this way, features with greater importance have greater weights in the weighted mean defining the $\mathcal{G}(X_1, \ldots, X_n)$ of a given firm.

Note that $\mathcal{G}(X_1, \ldots, X_n)$ is an IOWA operator with importance as order inducing variable and the non-negative performance-importance differences as argument variable.

In the following proposition, some properties of $\mathcal{G}(X_1, \ldots, X_n)$ are provided.

Proposition 1 *$\mathcal{G}(X_1, \ldots, X_n)$ satisfies the following properties:*

1. *$\mathcal{G}(X_1, \ldots, X_n) \geq 0$.*
2. *$\mathcal{G}(X_1, \ldots, X_n) = 0$ if and only if $P_i = i$ for all $i = 1, \ldots, n$, i.e., $(X_1, \ldots, X_n) = (0, \ldots, 0) = DV^*$.*
3. *If n is even $\mathcal{G}(DV_*) = \dfrac{5n-2}{12}$, and if n is odd $\mathcal{G}(DV_*) = \dfrac{(n-1)(5n+3)}{12n}$.*
4. *$\mathcal{G}(X_1, \ldots, X_n)$ preserves the $\preceq$ relation.*

Proofs can be found in (Sayeras et al 2015)

The following proposition establishes an intuitive property for the $\mathcal{G}$ index, relating it with the partition of the IPA diagram in (Abalo et al 2007) (see Figure 2) and determining relevant importance-performance situations. Abalo et al (2007) use a partition that combines the quadrant and diagonal-based schemes, enlarging the top left quadrant as shown in Figure 2.

Proposition 2 *The features that contribute to the $\mathcal{G}$ index are all features above the principal diagonal of the IPA diagram, i.e., those classified as "Concentrate Here" in the partition of the IPA diagram in (Abalo et al 2007).*

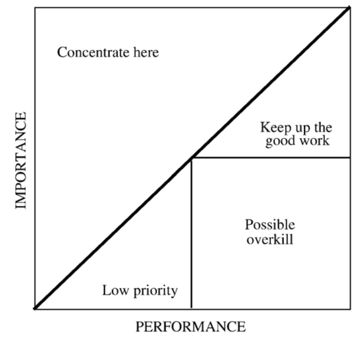

Figure 2: A partition of the IPA diagram, Abalo et al. (Abalo et al 2007)

PROOF. The proof is straightforward, because only features above the diagonal $I = P$ provide non-negative performance-importance differences.$\square$

The following proposition determines the level curves (iso-curves) of the marginal contribution of the features to the $\mathcal{G}$ index in the IPA diagram, giving decision makers a precise information about where to concentrate resources to improve performance.

Proposition 3 *The level curves of the marginal contribution of a feature to the $\mathcal{G}$ index in the IPA diagram are:*

$$\frac{n+1+2y}{n(n+1)}(y-x) = k,$$

for any $k \in \mathbb{R}^+$ (see Figure 3).

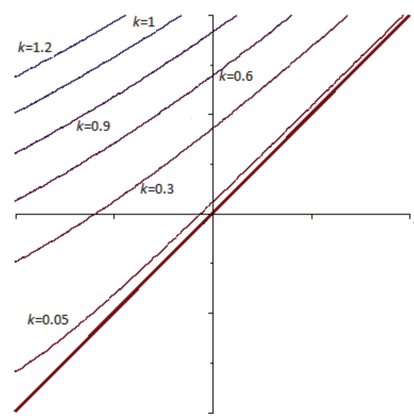

Figure 3: Level curves of the marginal contribution of the features to the $\mathcal{G}$ index

PROOF. Let us consider $x = \dfrac{n+1}{2} - P_i$ and $y = \dfrac{n+1}{2} - i$. From Definition 5, the level curves equations of the marginal contribution of the ith feature to the G index are:

$$\frac{2(n-i+1)}{n(n+1)}(P_i - i) = k,$$

for all features with non-negative performance-importance difference (otherwise the features do not contribute to the $\mathcal{G}$ index). By substituting P_i and i by their expressions in terms of x and y respectively, we obtain:

$$\frac{2(n-(\frac{n+1}{2}-y)+1)}{n(n+1)}((\frac{n+1}{2}-x)-(\frac{n+1}{2}-y))=k,$$

which is equivalent to:

$$\frac{2n-(n+1-2y)+2)}{n(n+1)}(y-x)=k,$$

Finally:

$$\frac{n+1+2y}{n(n+1)}(y-x)=k.\square$$

Figure 3 shows the level curves of the marginal contribution of the under-performing features to the $\mathcal{G}$ index over the IPA diagram partition in (Abalo et al 2007). Features in the same level curve are those with the same degree of under-performance, i.e., for each k the corresponding level curve contains features "with degree of under-performance k". In Figure 3, level curves corresponding to $k = 0.05, 0.3, 0.6, 0.9, 1$ and 1.2 are represented.

This representation clearly improves the approach in (Abalo et al 2007) to determine the target features for resource allocation. The "Concentrate Here" zone of the diagram can be dynamically selected depending on the available resources and the admitted level of under-performance.

Two are the main differences between the $\mathcal{G}$ index and other well known correlation coefficients defined to compare rankings. On the one hand, the $\mathcal{G}$ index takes into account only under-performing features. On the other hand, since the $\mathcal{G}$ index is defined through an IOWA operator applied to the non-negative performance-importance differences of a firm, not all the features contribute to it in the same way. The more under-performing and the more important a feature is, the greater its contribution to the $\mathcal{G}$ index.

Let us highlight the advantages and disadvantages of our proposal in comparison with other existing IPA approaches. The IPA framework has been widely accepted due to its simplicity of calculations and intuitive graphical representation. From a computational point of view, the proposed method represents an improvement since the marginal contribution of each feature to the $\mathcal{G}$ index is determined. These marginal contributions provide information about how the current performance of a firm can be improved giving decision makers information about where to concentrate resources. From a graphical point of view, the innovative contribution of the proposed approach is that features can be drawn in a new diagram with the level curves of the marginal contribution of each feature to the $\mathcal{G}$ index, so managers can easily capture different levels of intensity regarding under-performed features.

As a possible drawback of the proposed method, we can note that $\mathcal{G}$ index compares attributes' importance and performance within a particular company. In a situation of limited information about competitors, it provides managers a framework to work with and to explore the strengths and weaknesses of the company. Nevertheless, the proposed method including the $\mathcal{G}$ index could be improved by adding measures of attributes' performance based on comparisons of products and services of either competing companies or the sector. In this direction, some extensions of IPA are reviewed in (Kim and Oh 2011). In particular, some approaches modify the original IPA by considering three or more dimensions, being competitors' performance one of them. These studies consider, instead of the four quadrants in the original IPA grid, either eight octants or even more different outcomes' areas. However, adding dimensions in the IPA grid implies loosing simplicity of attribute display and data interpretation.

In general in decision-making aid systems, one should note that there is no single method which outperforms all other methods in all aspects. However, the simplicity in user-interaction is, indeed, one of the main values that share most of the IPA methods, and it is closely related to the grid dimensionality.

A real-case application to the retail sector

In this section, an application of the proposed method to assess importance-performance in a Taiwan retail company is presented, after a brief introduction to the performance evaluation framework for the retail sector.

Evaluating performance in the retail sector

In recent years, the role of knowledge within strategic management has become the subject of substantial advances in research (Braz et al 2011; Chini 2004; Gherardi2006; Nonaka and Teece 2001; Teece 2000). Nevertheless, most of these studies relate to aspects of the transfer of knowledge rather than the application of knowledge in the evaluation of performance.

Despite the relative paucity of research in a retail context, the use of expert knowledge by managers is an important factor at a micro-level in the success of retailers and at the macro-level for sectorial re-structuring. Managers bring to bear their individual expert knowledge to solve problems at operational and strategic levels in the retail firm. The knowledge they hold and apply depends mainly on their perceptions of the levels of current performance and the levels of importance of specific features. An issue that arises, deriving from this view of the diversity of knowledge held by retail managers, is how to synthesize the individual perceptions of managers in ways that can be useful in strategic management. Thus, aggregating managerial opinions on the relative performance of some specific features and analyzing the contribution of these different features to the overall performance of the retailer are considered crucial.

In this research context, these individual and differing perceptions of the relevance of the various resources can be gathered through qualitative data collection. Given that managers will view differently the relative importance of the various features, a method to compare the opinions of managers and synthesize these qualitatively framed opinions would be useful.

In the next subsections, we conduct a full experiment that first includes the selection of relevant performance related

Table 1: The resource attributes used as variables in the evaluation procedures

Resource area	Resource concept	Number of features
Physical resource	Reach ability	2
Legal resource	Brand strength	2
Human resource	Human management	2
Organizational resources	Expansion ability	2
	Productivity	2
	General management	2
	Technology management	2
	Organizational management	2
	Inventory management	2
	Marketing management	2
	Financial management	2
	Product innovation	2
	Loan repay ability	3
	Diversification	1
Informational resources	Market segment risk	2
	Strategic vision	2
Relational resources	Stakeholder relations	3
External factors	Actions from outside stakeholders	3
	Political environmental	2
	Technological environmental	2
	Socio-culture environmental	2

variables. Secondly, we present a survey of senior managers that measures their perceptions of the importance and performance of the selected variables, based on an order-of-magnitude qualitative model. Thirdly, the ranking method detailed in (Agell et al 2012), is applied to obtain rankings of the selected variables, aggregating expert opinions with respect to importance and performance respectively. Finally, the global index $\mathcal{G}$, together with the iso-curves of the feature contribution to the index introduced in Section 3, is used to summarize the differences in these rankings and identify features to which resources should be allocated.

Design of the empirical study and data collection

A study involving senior managers as experts was undertaken in a major chain store organization. President Chain Store Corporation is a multinational retailer based in Taiwan that operates a multi-format strategy through a range of organizational structures. It is the largest retailer in Taiwan. Using literature surveys and 25 in-depth interviews with a cross-section of retailer stake-holders, 170 performance-related variables relevant to retailing were identified. From this list, after rationalization and classification in terms of the nature of the resource, 44 features or variables related to resources used in retailing were selected as the main performance variables. The selection was undertaken by reference to the views of interviewees and research literature on resource based theories of the firm. Seven resource areas were established within these 44 features, as shown in Table 1.

A survey was then undertaken with managers in the Taiwan head office. Data was collected from 84 senior managers across all the managerial functions. Managers were divided into five main groups depending on broad functional area: marketing (15); operations and store operations (17); accounting, finance and audit (24); R&D and information systems (14); and other (e.g. human resources, law) (14).

Managers were asked to use their expertise to assess each of the 44 variables in terms of their perceived importance to the performance of the firm. An ordinal scale of 1 to 4 was used as: (1) extremely important; (2) very important; (3) moderately important; (4) not very important; with (5) as ”don’t know”. The managers were asked to repeat the exercise in terms of the perceived performance of the firm based on the same variables, with the scale being: (1) extremely good (or extremely strong); (2) very good (or very strong); (3) moderately good (or moderately strong); (4) not very good (or not very strong); with (5) again used as ”don’t know”.

Data analysis and results

This subsection is devoted to analyzing and comparing the evaluations of importance and performance of the 44 features in Table 1. Using the ranking method described in (Agell et al 2012) the features were ranked with respect to their importance and with respect to their performance from the responses from all 84 experts.

In this case, the non-negative performance-importance differences vector of the firm is the 44-dimensional vector:

$$DV(F) = (10, 12, 1, 4, 10, 13, 13, 0, 3, 16, 0, 0, 10, 27, 14, 0, 0, 12, 3, 0, 6, 11, 1, 0, 0, 10, 16, 0, 0, 1, 0, 7, 0, 3, 0, 0, 0, 0, 3, 0, 0, 0, 1, 0).$$

Then, weights are computed using Borda-Kendall law, obtaining $w_i = \dfrac{45 - i}{990}$ for all $i = 1, \ldots, 44$. With these values, the $\mathcal{G}$ index introduced in Section 3 to compare rankings with respect to importance and performance is computed and produces a global importance-performance index $\mathcal{G}(DV(F)) = 6.329$. Taking into account that the ideal best performing firm has $\mathcal{G}(DV^*) = 0$ and the firm in the opposite situation has $\mathcal{G}(DV_*) = 18.167$, as proven in Proposition 1, there is therefore a significant divergence between the two considered rankings (corresponding to about one third of the range of variation, precisely a 34.8%). This fact shows that there is room for resource allocation improvement. Note that, similar conclusions can be obtained when we compute other well-known correlation coefficients, such as Kendall’s Tau or Spearman’s Rho, for the same pairs of importance-performance rankings. In these two cases we obtain 0.378 and 0.506 respectively.

The comparison of the two rankings given by our method and shown in Figure 4 also points out the directions for this improvement. The added value of our contribution to the comparison of both rankings is the combination of the $\mathcal{G}$ index and the level curves of the marginal contribution of the features to this index. In Figure 4 an example of the level curve corresponding to $k = 0.3$ is depicted (see Proposition 3).

As detailed in Proposition 2, among the 44 features selected, the 24 features that plot above the principal diagonal are those that contribute to the $\mathcal{G}$ value of the firm. These are

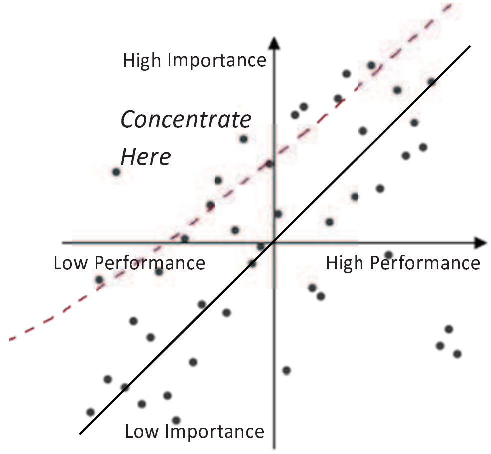

Figure 4: Representation of features with respect to managers' perceptions of importance and performance

aspects of the firm that are perceived by managers as under-performing and coincide with aspects in the "Concentrate Here" region defined in (Abalo et al 2007). Similarly, Figure 4 shows the region labeled as "Concentrate Here" in the Martilla's classical IPA diagram, which contains *seven* features.

In addition, in this paper, as explained in Section 3, we propose a step forward in understanding which features may be improved. Beyond the IPA diagram, we suggest concentrating resources in those features that contribute most to the $\mathcal{G}$ value of the firm. In Figure 4, these features have been visualized over the dotted line for the case $k = 0.3$. This line is the iso-curve of the marginal contribution of the features to the $\mathcal{G}$ index in the IPA diagram corresponding to $k = 0.3$ (see Proposition 3). Visually, most of the contribution to the $\mathcal{G}$ index can be seen as focussing on a limited number of features. These 10 extreme values are listed in Table 2.

Table 2: Variations in the ranking of expert managers when importance is ranked much higher than performance

Features	Ranking of importance	Ranking of performance	Contribution to $\mathcal{G}$
Market positioning	1	11	0.444
Number of customer visits	2	14	0.521
Customer complaints management	5	15	0.404
Sales per store	6	19	0.512
Store opening strategy	7	20	0.499
Franchise system	10	26	0.566
Spending-per-visit rate	13	23	0.323
Staff training	14	41	0.845
Quality of data collection and process system	15	29	0.424
Innovation of new technology equipment	18	30	0.327

Most are directly or indirectly associated with firm growth. Six out of the ten relate directly to organizational resources, three relate to physical, human, and relational resources respectively, and the final one relates to external factors. Note that in this case, the value $k = 0.3$ has been used, however depending on the available resources, different values of k could be considered.

Discussion and managerial implications

Hansen and Bush pointed out that IPA is a simple and effective technique that can assist in identifying improvement priorities (Hansen and Bush 1999). IPA has been applied as an effective means of evaluating a firm's competitive position in the market, identifying improvement opportunities, and guiding strategic planning efforts. However, typically, managers must work with limited resources in competitive business environments. For this reason, the proposed method, able to decide how to best allocate scarce resources in order to maximize importance-performance, is very helpful.

The results of the empirical testing of the method show how to identify areas of perceived under-performance of the firm. In our real case, 44 features related to resources used in retailing were selected as main performance variables. Managers in the President Chain Store Corporation then evaluated the perceived importance and the perceived performance of the firm for these 44 features. From these evaluations, the features were ranked with respect to these two concepts. The proposed $\mathcal{G}$ index is computed, and the iso-curves of the marginal contribution of the features to the $\mathcal{G}$ index enabled recognition of the perceived under-performing features of the firm. The method used, by taking into account the qualitative perceptions held by managers, provides a useful tool for decision making for the retailer.

Considering the iso-curve of the marginal contribution to the $\mathcal{G}$ index as corresponding to a contribution of $k = 0.3$, ten features appeared as being under-performing in that firm, thus they can potentially be improved. This level of contribution ($k = 0.3$) corresponds, as a percentage, to 4.7% of the $\mathcal{G}$ index. As we can see in Table 2, the "staff training" feature, which belongs to the human resources area, is perceived as the most under-performing feature, contributing more than 13% (0.13351 = 0.845/6.329) to the $\mathcal{G}$ index. There are seven features whose contribution to the $\mathcal{G}$ index varies between 6.4% and 9%, with two features contributing about 5.1% each. The remaining under-performing features, below the considered iso-curve, contribute less than 4.7% each to the $\mathcal{G}$.

As stated, when modifying the value of k, a different number of features for focus would be obtained. The strength of the method proposed is its adaptable nature, which helps managers to improve the efficiency of the firm. Therefore, the $\mathcal{G}$ index could be considered as a valuable decision-support tool to better allocate resources within the firm.

Conclusions and future research

This paper contributes to improving importance-performance analysis by providing a new measure that captures the overall relationship between importance and performance. This measure is obtained by considering the relevant features that describe a firm and so enable a firm's managers to improve decision-making in resource allocation. The developed method, together with a new version of the classical IPA diagram, enables managers to assess a firm's overall performance and detect features where resources should be allocated. The presented global importance-performance index ($\mathcal{G}$), inspired by OWA operators, is a weighted sum of the non-negative performance-importance differences, where weights depend on the importance of the feature.

Moreover, the $\mathcal{G}$ index also leads to an enhancement of the IPA diagonal-based scheme with a new representation: Contribution-to-$\mathcal{G}$ iso-curves. These level curves show a more accurate picture of the most-needed-investment features, and determine a new "Concentrate Here" zone in the classical IPA diagram. A real-case application in the retail sector has been used to show that the presented method can lead to a more accurate importance-performance analysis of a firm's situation. The real-case application gives us an example of how $\mathcal{G}$ could benefit managerial decision-making processes in resource allocation.

As future work, a marginal sensitivity analysis of the $\mathcal{G}$ index incorporating changes in resource allocation would be a major future contribution for decision-making processes. It could be of interest in a more advanced study of $\mathcal{G}$ properties to determine the upper-boundary of the index for relative comparisons of company performances. Additional analysis that separately considers the functional area of managers could be performed to infer how the area of expertise influences perceptions and modifies the $\mathcal{G}$ index.

References

Abalo, J., Varela, J. and Manzano, V. (2007). Importance values for importance-performance analysis: A formula for spreading out values derived from preference rankings. *Journal of Business Research* 60, 115-121.

Agell, N., Sánchez, M., Prats, F. and Roselló, L. (2012), Ranking multi-attribute alternatives on the basis of linguistic labels in group decisions. *Information Sciences* 209: 49-60.

Braz, R., Scavarda, L. and Martins, R. (2011). Reviewing and improving performance measurement systems: An action research. *International Journal of Production Economics* 133(2): 751-760.

Chiclana, F., Herrera-Viedma, E., Herrera,F., Alonso, S.(2007). Some Induced Ordered Weighted Averaging Operators and Their Use for Solving Group Decision-Making Problems based on Fuzzy Preference Relations. *European Journal of Operational Research* 182(1): 383-399.

Chini, T. (2004). *Effective Knowledge Transfer in Multinational Companies*. Palgrave Macmillan, Basingstoke, U.K.

Deng, W. (2007). Using a revised importanceï¿$\frac{1}{2}$performance analysis approach: The case of Taiwanese hot springs tourism. *Tourism Management* 28: 1274-1284.

Gherardi, S. (2006). *Organizational Knowledge*. Blackwell, Oxford, U.K.

Hansen, E. and Bush, R.J. (1999). Understanding customer quality requirements. Model and Application. *Industrial Marketing Management* 2: 119-130.

Herrera, F., Herrera-Viedma, E. (1997). Aggregation Operators for Linguistic Weighted Information. *IEEE Transactions on Systems, Man and Cybernetics* 27: 646-656.

Herrera-Viedma, E., Pasi, G., López-Herrera, A.G., Porcel, C. (2006) Evaluating the Information Quality of Web Sites: A Methodology Based on Fuzzy Computing with Words. *Journal of American Society for Information Science and Technology* 57(4): 538-549.

Kim, B-Y. and Oh, H. (2011). An Extended Application of Importance-Performance Analysis. *Journal of Construction Engineering and Management* 137(12): 1142-1152.

Kendall, M. (1962) *Rank Correlation Methods*, Hafner, New York, USA.

Martilla, J.A. and James, J.C. (1977). Importance-Performance Analysis. *Journal of Marketing* 41(1): 77-79.

Nonaka, I. and Teece, D. (2001). *Managing Industrial Knowledge*. Thousand Oaks: Sage.

Sayeras, J.M., Agell, N., Rovira, X., Sánchez, M., Dawson, J.A. A measure of perceived performance to assess resource allocation*Soft Computing*. DOI 10.1007/s00500-015-1696-3

Teece, D. (2000). *Managing Intellectual Capital: Organizational, Strategic and Policy Dimensions*. Oxford: Oxford University Press.

Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multi-criteria decision making. *IEEE Transactions on Systems Management, Cybernetics* 18: 183-190.

Yager, R. R., Filev, D.P.(1999). Induced ordered weighted averaging operators, *IEEE Transaction on Systems, Man and Cybernetics* 29: 141-150.