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ORIGINAL PAPER

A strategy-based framework for supplier selection: a grey PCA-DEA approach

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Abstract
Supplier selection is one of the key competencies in the sourcing function. Considering the important role of suppliers in the strategy framework of supply chains, it is surprising that the sourcing function has not been subject to more focused research on the development of adequate decision support tools. The relatively simplified ranking systems that often have been presented on an ad hoc basis offer only partial information on the decision. This research attempts to develop a unified and integrated structure for supplier selection practices across a supply chain on the basis of strategic planning. Our evaluation is conducted by means of a multi-attribute efficiency analysis models and a multivariate statistical method, a so-called *principal component analysis-data envelopment analysis* (PCA-DEA) approach, to support supplier relationship management under uncertainty. The main contribution of this paper is to address the gap in the supply chain management (SCM) literature by proposing a strategy-based method for supplier selection problems when data are interrelated and interdependent. The proposed method in this study is applied to a real-world case study in agri-food industry to demonstrate the advantages and applicability of the proposed framework.

Keywords Supply chain management · Strategic sourcing · Supplier selection · Data envelopment analysis · Multivariate statistics

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1 Introduction

Beyond the acquisition and planning of raw materials and resources for the focal organisation, “sourcing and procurement” is described as increasingly important for the functioning of a supply chain (SC) in the recent past years. The planning reform and operational reshaping of the SC has put the focus on the effectiveness of the procurement[1] function (Chou and Chang 2008; Hatami-Marbini et al. 2017). As a consequence of recent improvements in organisational capabilities, quality control and logistics networks, procurement and supply base management have gained increasing attention (Monczka et al. 2015). Hence, sourcing and procurement have increasingly become a strategic issue in supply chain management (SCM) thanks to its great share of the total cost in most organisations (Alikhani et al. 2019). In the manufacturing sector the average percentage of purchases to sales is 55% showing that for every dollar of revenue gained from goods and services sales, more than half returns to suppliers (Monczka et al. 2015). More importantly, the relationship between organisational strategy and procurement strategy strongly affects SCM performance (Schütz et al. 2019). The strategic nature of the sourcing function becomes more apparent as organisations struggle to meet the ever-evolving tastes and preferences of customers (Kumar et al. 2018). Customer preferences can be effectively and optimally fulfilled by leveraging competitive advantages of suppliers such as production agility, flexible manufacturing and economies of scale, to name but a few (Kumar et al. 2018; Echchakoui 2018). Thereby, while single sourcing could minimise the respective cost and lead time in an uncertain environment multiple suppliers could be more reliable and mitigate risks occurred by an individual supplier (Kumar et al. 2018). In addition, building up a close and long-term relationship with suppliers could also be creating mutual value in line with sourcing strategy of the organisation.

Procurement departments at the heart of any successful SCs have responsibilities and functions pertinent to supplier evaluation, negotiation, selection, relationship and improvement which bring significant savings and values to the organisation and proactively minimise procurement risks (Boran et al. 2009). *Procurement management* takes a holistic view of sourcing by focusing on all functions, operations and relationships between the buyer and suppliers over time. That is, procurement management is defined as the communication, selection, negotiation, performance assessment and other relationship building activities that can help the organisation in developing and procuring required goods and services better, quicker, and at lower cost (Baily et al. 2008). Procurement has evolved into a more inclusive and strategic function in organisations and, resultantly, the focal organisation needs a strategic planning to manage the whole supplier base (Monczka et al. 2015). Supplier selection (SS) is a constituent of procurement management that can play a part in the sourcing satisfying the organisation’s demand consistently and cost-effectively

[1] The literature often uses the terms “procurement” and “purchasing” interchangeably even though there are some studies defining purchasing as a set of primarily transactional tasks, and procurement as the overarching services before, during and after a supplier relationship.

(Lawson et al. 2009; Wetzstein et al. 2018). However, in the contemporary operations management literature, the goal of procurement management is not only to select the right supplier but also to ensure proper supply through the strategic management of the whole supplier base (Wetzstein et al. 2018). The increasing focus on strategic sourcing is emphasising the fit between the strategic position of the supplier and the current and future position of the focal organisation making the sourcing problem highly qualitative. Although this vision is frequently advocated in applied and scientific literature, two other tendencies argue for a different focus to provide support to actual organisations. First, the procurement maturity level of the average organisation is relatively low compared to best practice, mostly focusing on operational decisions at a shorter time horizon. Second, the rapid restructuring of the supplier landscape with the hyper-connectivity, lowering barriers of entry and opening possibilities to source goods and services anywhere and anytime, can invariably lead to an overall increase in the sheer number of potential suppliers to evaluate and select, even within organisations with a higher maturity. Thus, our focus here is on the SS as a decision support problem, providing the organisation with relevant, timely and objective input for making a strategically aligned decision.

Needless to say, the literature has proposed numerous methodologies such as mathematical programming, multi-attribute decision making (MADM), data envelopment analysis (DEA), artificial intelligence, and statistical methods for the SS problem.[2] However, despite the extensive research on SS, further research needs to be undertaken to present methodologies that are appropriate, flexible and efficient for real-world applications in the field.

Obviously, the risk of selecting unsteady or unreliable supplier(s) is a matter of concern in the SS. In this regard, multi-sourcing is considered as a conventional risk mitigation way to be traded-off against the benefits accruing from more intensive long-term relationships with a smaller set of suppliers. However, establishing such relationships has become a challenge among a plethora of models in the SS literature, especially due to the lack of adequate attention to strategic supplier rationalisation and selection (Talluri et al. 2013; Dey et al. 2015). The gap between strategic management and its alignment with the SS has been also mentioned in several key SS studies (e.g. Wetzstein et al. 2016). This research gap will be theoretically and conceptually addressed in the present study by viewing the SS from a strategic perspective. The SS problem with regard to organisational strategy has the ability to provide a certain safety margin for suppliers for implementing the procurement process in a way that not only is compatible with the end consumers' requirements, but also achieves greater economies of scale. Furthermore, the strategic viewpoint in the SS strengthens managing the SC of the organisation using systematic coordination with strategies and long-term objectives. The organisation's strategies are normally determined on the basis of internal strengths and environmental opportunities that

[2] The main purpose of supplier evaluation is to improve the performance of suppliers while the objective of supplier selection is to select those suppliers that meet an organisation's needs. In the literature, the terms "supplier evaluation" and "supplier selection" are often used interchangeably. Notice that our focus in this paper is on supplier selection with respect to a strategic vision.

treat weaknesses and threats. It is naturally imperative that the decisions made by entire organisation's departments, such as the procurement department, should comply with the organisation's strategies.

The conventional SS process opts for the supplier(s) who excel in a certain number of criteria such as cost, design, manufacturability, and quality (Talluri et al. 2013). Noticeably, the presence of a large number of correlated criteria may lead to distortion of the SS evaluation, and the accuracy of the decisions made by managers cannot be reliable (Kasirian and Yusuff 2013). Therefore, data interrelation and interdependency between the evaluation criteria therefore play a crucial role, which needs to be elaborated and studied more in the SS context (Wetzstein et al. 2016). DEA is one of the most popular and powerful approaches used in the SS (Ho et al. 2010). The use of principal component analysis (PCA) and DEA simultaneously– which is called PCA-DEA– enables us to confront data interrelation and interdependency issue. Here, the focus is on the PCA-DEA model developed by Premachandra (2001). However, it is showed that a technical dilemma is still available in the PCA-DEA approach developed by Premachandra (2001). A small number of suppliers for building a long-term relationship can result in *data insufficiency* which creates difficulties in using many existing SS techniques. To deal with this problem, researchers have been trying to utilise grey PCA (GPCA) with the object of dealing with statistical deficiency of the conventional PCA. As far as we know, this is the first study that applies GPCA to PCA-DEA to address data insufficiency and data interrelation in the performance evaluation context. The GPCA-DEA approach proposed in this paper is also able to cope with a technical dilemma in PCA. As a basic assessment methodology, this study proposes a new unified MADM-DEA-based framework for evaluating a small number of potential suppliers competing closely on the basis of strategic planning. Due to the weakness of discriminatory power of conventional DEA models in assessing a small number of suppliers in the presence of many conflicting evaluation criteria, we apply grey relational analysis (GRA) in combination with the PCA technique to ameliorate the discrimination power of the analysis.

The rest of this paper is organised as follows: Sect. 2 provides a literature review on the SS models along with presenting detailed contributions of this study. Section 3 minutely describes a new two-phase framework in supplier relationship management with respect to the strategic and long-term viewpoint. We present a case study to demonstrate the efficacy and applicability of the developed framework in Sect. 4. In Sect. 5, we finally present our conclusions.

2 Related academic studies

The literature encompasses numerous approaches to SS. Several studies such as Ho et al. (2010), Chai et al. (2013), Karsak and Dursun (2016) and Wetzstein et al. (2016, 2018) tried to review the existing SS approaches from different angles. This section first lays emphasis on DEA as a mathematical programming approach to the SS problem and then describes the contributions of the present work in detail.

2.1 DEA for the SS problem

DEA is a data-driven technique for measuring the relative efficiencies of decision-making units (DMUs) such as hospitals, banks, suppliers and universities where multiple inputs and multiple outputs exist. Over the last two decades, DEA has been rapidly used and evolved in the areas of Operational Research and Management Science for solving both managerial and economic problems. In light of this growth, the use of DEA as a ranking tool has been also studied in the sourcing literature from both theoretical and modelling frameworks (Narasimhan et al. 2001; Talluri and Narasimhan 2004; Wu and Blackhurst 2009; Mahdiloo et al. 2015; Dobos and Vörösmarty 2019).

The seminal application of DEA to SS was carried out by Weber and Ellram (1992), Weber and Desai (1996) and Weber et al. (1998). Weber and Desai (1996) applied a combination of DEA and parallel coordinates representation to measure vendor efficiency in a just-in-time manufacturing environment. Later and based on the work of Baker and Talluri (1997) and Braglia and Petroni (2000) used DEA to measure the efficiencies of suppliers. The authors also applied both cross-efficiency and the so-called "Maverick index" to avoid selecting a sub-optimal or "false positive" supplier. Furthermore, Liu et al. (2000) extended Weber and Desai (1996)'s approach based upon DEA to evaluate suppliers for an individual product. In the light of increased global awareness of environmental concerns, Mahdiloo et al. (2015) presented a multiple objective linear programming DEA model to select green suppliers whereby their efficiency indicators were decomposed into technical, environmental and eco-efficiency scores. Dotoli et al. (2017) proposed a three-step technique to maximise supply chain network (SCN) efficiency under uncertainty. The first step evaluates and ranks all the actors in each SCN stage using a fuzzy cross-efficiency DEA approach, the second step uses a fuzzy linear integer programming model to identify the quantities required from each stakeholder and maximise the overall SCN efficiency while satisfying the demand, and the last step applies a heuristics approach to restrict the exchange of small quantities in the SCN. Jatuphatwarodom et al. (2018) focused on the Thai Silk industry and used DEA for measuring the efficiency of the existing suppliers and inventory departments. Of late, Dobos and Vörösmarty (2019) developed a DEA-based SS method to study the effect of inventory costs of the selected supplier in which green criteria and management criteria are the output and input variables, respectively.

2.2 Research gaps and contributions

How to deal with the dearth of strategic vision, rapid and frequent changes and uncertainty such as incomplete and interrelated data in decision-making procedures is a big challenge in real-life SS problems. A large number of developed models for SS are based on rather simplified perceptions of the decision-making process and most of these methods do not seem to address the complex and unstructured nature of many procurement problems (Chen et al. 2006). Therefore, some properties involving uncertainty, incompleteness and interrelation of data along with the strategic viewpoint are worth considering when solving the SS problem. The research strand of strategic vision in the context of SS has evolved at a slow pace since Masella and Rangone (2000)'s study. In particular, strategic decision-making under uncertainty in the context of SS has received less attention (Wetzstein et al. 2016, 2018; Alikhani et al. 2019). Thus, this study offers the following features to address the aforesaid research gaps:

(i) Establishing an effective SS approach with respect to competitive advantages in organisational strategy and long-term objectives,
(ii) Evaluating a limited potential number of suppliers in the presence of many influential criteria,
(iii) Encountering interrelated and interdependent criteria,
(iv) Tackling the lack of sufficient information for statistical analysis.

To the best of our knowledge, this study is the first attempt to consider the above-mentioned features all together in the SS context. Let us delineate each of these features herein.

Feature (i) The gap between organisational strategy of the organisation and long-term relationship with suppliers is a concern in the literature. This has been initiated by viewing many potential risks such as selecting unreliable supplier(s), setting aside *chain liability effects*, the monopoly of a single supplier, losing economies of scale, and lacking flexible manufacturing (Kumar et al. 2018; Lechler et al. 2019). The well-structured and strategy-based approach proposed by Chen (2011) inspires us to take the feature (i) into account in our framework. In addition, Dey et al. (2015) concluded that more studies need to be carried out for the area of supplier performance evaluation with an organisational strategy perspective. A considerable advantage of DEA is focusing on efficiency rather than outputs of the system which can be an underpinning and persuasive factor in bolstering and assessing strategic objectives of the organisation (Talluri et al. 2013). Therefore, DEA as a powerful and accepted methodology for SS is applied in this study to embed this feature within our framework.

Feature (ii) The basic results derived from the conventional DEA models classify the units into two sets; the *efficient* and *inefficient* units. In the SS process, the procurement manager is often interested in a complete ranking of suppliers to go beyond the dichotomy of units with the aim of making a final procurement decision. However, more than one supplier is often evaluated as efficient and cannot be discriminated further. In DEA, the discriminatory power between the efficient suppliers in practice requires that the number of suppliers (n) is considerably higher than the number of criteria (the sum of m input and s output indicators). The minimum of required units is often considered as twice the product of number of inputs and number of outputs, $n \geq 2(m \times s)$, or three times the sum of number of inputs and number of outputs, $n \geq 3(m+s)$ (Cooper et al. 2004). The present study shows that the condition for reaching a complete ranking comes into conflict with feature (ii). This is because the strategy-based SS seeks to create a long-term relationship with a few suppliers only while a considerable number of various criteria are usually required in the SS process in order to achieve organisational strategies and conflicting objectives. As a result, we can put the *DEA ranking methods* in place to embed feature (ii) within our framework.

Owing to the fact that the sourcing function is forced to consider a multitude of criteria to assess a few potential suppliers, it seems important to take data interdependencies in DEA under advisement as detailed in Feature (iii).

Feature (iii) It is essential to consider data interdependencies in the SS process since ignoring criteria interrelations often results in a distorted decision (Kasirian and Yusuff 2013). This issue has been slightly discussed by the literature as expounded in Wetzstein et al. (2016). Among multivariate statistical methods, PCA is a well-known ranking method being capable of dealing with data interrelation to some extent. The main idea of PCA is to describe the variation of a multivariate data set through linear combinations using a data reduction technique (Bolch and Huang 1974). Obviously, a small set of variables often renders the interpretation of a multivariate data matrix simple in a complicated data analysis. Loosely speaking, PCA is searching for a small and non-interrelated set of linear combinations with the largest variances. Therefore, the combination of PCA and DEA can provide an appropriate tool to the SS problem. In this regard, Zhu (1998) proposed a PCA-DEA approach for ranking DMUs and used Spearman and Kendall's Tau correlation tests to show that SE-DEA and PCA-DEA rankings have a high correlation. Premachandra (2001) modified Zhu (1998)'s model to remove the plausible inconsistency between PCA and DEA rankings in certain cases. Later, Adler and Golany (2002) developed three models by utilising PCA within the DEA context so as to improve the discriminatory power of the DEA model. Their first model presented assurance regions using PCA weights, and their second and third models utilised PCA across all inputs and outputs separately.

All in all, evaluating suppliers using interrelated criteria may lead to overestimated or underestimated results while feature (iii) of our DEA-based framework for SS comes into effect to attend to interrelated and interdependent criteria. In this paper, we deal with the difficulty resulted from features (ii) and (iii) by adopting Premachandra (2001)'s PCA-DEA method.

Feature (iv) The conventional multivariate statistical methods such as discriminant analysis, factor analysis (FA) and PCA, often require a large set of data, underlying hypotheses and given probability distributions (e.g. a normal distribution) while these prerequisites and assumptions may not be realistic in many systems including social, economic, agricultural, production and education systems (Betts and Belhoul 1987; Canbas et al. 2005). The incompleteness and inadequacy of information are an underlying characteristic of uncertain systems thanks to the dynamical systems, constrains of economic conditions and technological accessibilities, etc. In the 1980s, Deng developed *grey theory* as a systematic analysis methodology for dealing with problems involving poor, insufficient, and uncertain information (Deng 1984, 1985a, b, 1989). Where statistical methods seem inapplicable, grey incidence analysis yields a solution since it is independent of the sample size and probability distribution of variables. In the past three decades, grey systematic analysis has been quickly developed in a wide variety of areas due to its advantages (Liu and Lin 2010). Recently, Tung and Lee (2009) proposed grey PCA by combining the merits of grey theory and PCA. The authors revised the calculation of grey absolute degree of incidence (GADI) along with applying the matrix constructed by GADI instead of the conventional PCA correlation matrix. Then, Tung and Lee (2010) developed a ranking technique, so-called grey FA, by integrating the merits of grey theory and FA. After revising the computation procedure of GADI, they used the revised GADI matrix—entitled absolute degree of grey incidence (ADGI)—instead of the correlation matrix.

According to feature (iv), in the existing SS problem the lack of statistical assumptions is truly observable due to the small amount of available information and that is why making use of PCA-DEA method developed by Premachandra (2001) seems to be also problematic and controversial. We hence take advantage of Tung and Lee (2010)'s grey FA method to develop a new SS method based on the PCA and DEA techniques when the SS criteria and indicators are determined based on organisational strategy formulation.

3 Proposed framework

In this section, we propose a new framework including two major phases for evaluating and selecting appropriate suppliers with a long-term relationship from the strategic standpoint in a SC. Phase 1 of the proposed framework entails a strategic analysis within a group of procurement managers, strategists, top-level managers and CEO to build a consensus on the appropriate indicators to support the selection of the right supplier(s) with particular emphasis on the organisation's competitive strategy and long-term objectives, and Phase 2 embraces a modified grey PCA method within DEA framework, so-called *GPCA-DEA*, for evaluating the potential suppliers where interrelated and insufficient data are available in the evaluation procedure.

3.1 Phase 1: determining strategy-based evaluation criteria

In this subsection, we first provide an overview of various studies which have contributed to the procurement context. Our central focus is on various SS criteria, which can be taken into account by the decision maker when making procurement decisions. Then, we wish to develop a new approach for taking proper criteria into account in supplier relationship management with emphasis on the organisation's competitive strategy.

3.1.1 SS criteria in related studies

Dickson (1966), Roa and Kiser (1980) and Bache et al. (1987) are the seminal contributions for identifying the evaluation criteria through the SS process. Weber et al. (1991) conducted a comprehensive study by reviewing 74 relevant papers to derive that price, delivery, and quality were the most influential factors in the SS. Weber and Current (1993), Weber and Desai (1996), and Weber et al. (1998) also took alternative influential criteria such as geographical location into account.

Şen et al. (2008) undertook another overarching research to define the SS criteria based on the existing studies whose focus was on the levels of buyer–supplier relationship, the company's competitive situation and its organisational strategies. Then, Ho et al. (2010) provided an overview on supplier evaluation and selection techniques during 2000–2008 and Chai et al. (2013) studied a systematic literature review on articles published through 2008–2012. Their research showed that *quality* was the most common criterion, followed by delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment. Lately, Wetzstein et al. (2016) provided a structured review of studies conducted from 1990 to 2015 and categorised SS criteria as one of main research streams. The key literature trend of this stream shows that it has not played an important role for the last 8 years, i.e. after the study of Huang and Keskar (2007). Furthermore, Wetzstein et al. (2016) argued that the research emphasis is no longer placed on generic criteria since key criteria have been extensively explored, but the study on strategically oriented SS criteria is at the early stage of research.

In the current competitive market, it does not suffice to make strategic SS decisions solely based on traditional evaluation criteria such as cost, quality and delivery. Hence, the first step of the strategic evaluation of suppliers is to identify a set of evaluation criteria in a way that contributes to close and long-term relationships (Mandal and Deshmukh 1994; Dowlatshahi 2000; De Toni and Nassimbeni 2001; Narasimhan et al. 2001; Choy et al. 2002, 2003; Dulmin and Mininno 2003; Talluri and Narasimhan 2004; Araz and Ozkarahan 2007; Talluri et al. 2013; Osiro et al. 2014). According to Wetzstein et al. (2016), investigating profoundly on criteria for strategy-oriented SS still remains as a niche stream for future study.

Several studies (see e.g. Narasimhan et al. 2001; Talluri and Narasimhan 2004; Araz and Ozkarahan 2007; Talluri et al. 2013 and Osiro et al. 2014) opted for strategic SS criteria based on expert judgments as well as the criteria presented in the literature. In addition, there exist some studies in the literature providing techniques and algorithms for determining appropriate evaluation criteria in the SS problem. For example, Lee (2009) and Lee et al. (2009) developed a framework involving four hierarchical structures of BOCR (benefits, opportunities, costs and risks) to define a number of multi-perspective supplier evaluation criteria with the aim of establishing long lasting relationships between the organisation and suppliers. Also, SWOT (strengths, weaknesses, opportunities and threats) is known as a distinct supporting framework in the strategic planning context (see e.g. Weihrich 1982; Wenerfelt 1984; Grant 1991; Miser 1995). As far as we know, SWOT in SS was initially adopted by Amin et al. (2011) based on organisational strategies, and followed by Ghorbani et al. (2012) as a categorisation basis for defining the evaluation criteria. Chen (2011) also used SWOT to determine the SS criteria with regard to the strategic and long-term organisation objectives. To the best of our knowledge, the work of Chen (2011) is the only research that developed an integrated structure to evaluate the suppliers on the basis of organisational strategies. Below, we draw on the framework developed in Chen (2011) to identify the SS criteria and sub-criteria (indicators) using a strategy-based model.

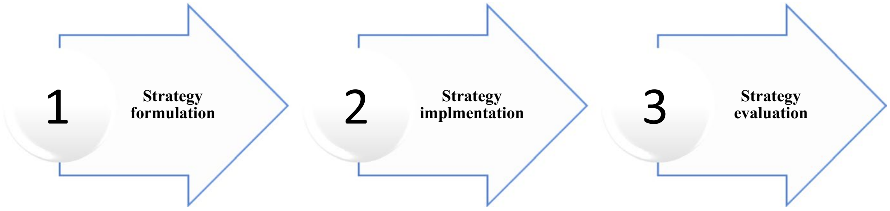

Fig. 1 The process of strategic management

Table 1 EFE (IFE) matrix

Key External (Internal) Factors	Weight (between 0.0 and 1.0)	Rating (1,2,3, or 4)	Weighted score
Opportunities (Strengths) Threats (Weaknesses)	Relative importance of factors in the organisation's industry	Relative importance of factors in the organisation	Multiplication of the *Weight* and *Rating* columns
Total	1.0		Total weighted score

3.1.2 Strategy-based model to identify SS criteria and indicators

We first present the organisation strategy formulation for an organisation to discern its competitive position in the industry. This is a standard practise taken from the strategic management literature to be complemented the framework of Chen (2011). Subsequently, we determine the evaluation criteria and performance indicators for the SS. We hence struggle to contribute to the SS literature by utilising the organisation strategy formulation to determine SS criteria.

3.1.2.1 Organisation strategy formulation Strategic management involves formulating, implementing and evaluating strategies that can help organisations align policies and achieve the objectives (see Fig. 1). The first stage of strategic management is strategy formulation (strategic planning) involving: (i) developing vision and mission, (ii) building long-term objectives, (iii) generating, evaluating and selecting strategies using External/Internal Factor Evaluation (EFE/IFE). Strategists take advantage of EFE/IFE matrices to sum up and evaluate organisations' "external opportunities and threats" and "internal strengths and weaknesses". Indeed, organisations strive to pursue strategies that capitalise on internal strengths and improve on internal weaknesses (David 2011).

The structure of an EFE/IFE matrix is shown in Table 1 consisting of a list of key external/internal factors. The relative importance of factors for being successful in the organisation's industry is expressed by *weights* that range from 0.0 (not important) to 1.0 (all important) whereas the *rating* indicates the relative importance of each factor in the organisation that can be a considerable threat/weakness (rating = 1), an inconsiderable threat/weakness (rating = 2), an inconsiderable opportunity/strength (rating = 3), or a considerable opportunity/strength (rating = 4). Note that the ratings are evaluated based on the focal organisation's perspective while the

The EFE Total Weighted Score	The IFE Total Weighted Score →	*Strong* 3.0 to 4.0 (4.0–3.0)	*Average* 2.0 to 2.99 (3.0–2.0)	*Weak* 1.0 to 1.99 (2.0–1.0)
	High 3.0 to 4.0 (4.0–3.0)	**G&B Aggressive**	**G&B Progressive**	**H&M Conservative**
	Medium 2.0 to 2.99 (3.0–2.0)	**G&B Growth**	**H&M Maintenance**	**H|D Defence**
	Low 1.0 to 1.99 (2.0–1.0)	**H&M Competitive**	**H|D Protect**	**H|D Liquidate**

Business Strategy	Tactical Strategies
Aggressive	Integration*, Intension**, Cost Leadership–Best Value, Related/Unrelated Diversification
Progressive	Intension, Joint Venture
Growth	Integration, Intension, Cost Leadership–Best Value/Low Cost, Related Diversification, Differentiation
Conservative	Market Penetration, Product Development, Focus–Best Value
Maintenance	Market Penetration, Product Development, Focus–Best Value/ Low Cost, Joint Venture
Competitive	Market Penetration, Product Development, Cost Leadership–Low Cost, Differentiation, Focus– Low Cost, Acquisition
Defence	Retrenchment, Divestiture, Merger
Protect	Retrenchment, Divestiture, Cooperation among Companies
Liquidate	Wind-up the Assets and Exit from the Industry

* Integrative Strategies: Backward, Forward, and Horizontal Integration
** Intensive Strategies: Market Penetration, Market Development, Alternative Sales Channels, Product Development

Fig. 2 Business strategy matrix

weights are evaluated based on the focal industry's perspective (i.e., Table 1) which are often determined by expert judgments. A weighted score for each factor is calculated as the multiplication of each factor's weight by its rating as reported in the last column of Table 1. The *EFE (IFE) total weighted score* for the organisation that varies within [1, 4] is the sum of the weighted scores of factors. A larger EFE (IFE) total weighted score implies a better performance for the organisation by exploiting external opportunities (internal strengths) and averting external threats (internal weaknesses). In terms of the EFE and IFE total weighted scores, the apt strategy of an organisation, involving "*Grow and Build*" (G&B), "*Hold and Maintain*" (H&M) or "*Harvest or Divest*" (H/D), can be chosen as shown in Fig. 2 (David 2011).

The main goal of the G&B strategy is to strengthen the business aggressively to provide the competitive foundation. The G&B strategy can be divided into the *aggressive*, *progressive* and *growth* business strategies based on the EFE/IFE total weighted score (see Fig. 2). Organisations with a weaker competency position choose H&M strategies to discover a practical competitive position. Consequently, the organisation struggles to defend its competitive position in the marketplace. The EFE/IFE total weighted score aids in classifying the H&M strategy into *conservative*, *maintenance* and *competitive* business strategies as shown in the main diagonal of Fig. 2. Finally, an organisation with a weak competency position can employ the H/D strategy to limit the investment as far as possible, exit the industry or merge with a stronger organisation. The EFE/IFE total weighted score can be used to build *defence*, *protect* and/or *liquidate* business strategies for the H/D strategy; (see Fig. 2). To apply these business strategies, we can consider one or several relevant tactical strategies mentioned in Fig. 2. Let us consider the *aggressive business strategy* as an example; the emphasis of "an intensive tactical strategy" in an organisation is on investing resources to increase the market share by the use of *market penetration*, *market development*, *alternative sales channels*, and/or *product development*, whereas "an integrative tactical strategy" attempts to develop a marketing competency by using *horizontal*, *backward*, and/or *forward* extension methods. Note that we do not often utilise *integrative tactical strategies* for an organisation deploying H&M and H/D strategies since the implementation of these strategies in practice is costly and complicated, in particular for an organisation unable to increase its market share.

3.1.2.2 Criteria and indicators identification Quite often, a ranking based on quantitative criteria only makes sense to apply to a given application. The appropriate definition of SS criteria is important since irrelevant criteria can lead to inappropriate procurement decision-making. Dickson (1966) initially provided a comprehensive overview through the selection criteria often used by procurement practitioners. The author collected 23 significant criteria for SS that have been considered by purchasing managers, and as a result of the survey, quality and delivery were the two most important criteria. Weber et al. (1991) provided an alternative survey of the SS literature so as to derive the most important criteria. They concluded that price was the highest-ranked criterion, followed by delivery and quality. A recent study by Chen (2011) divided evaluation criteria for SS into "competition" and "organisation" groups. The former group contains "quality", "cost", "delivery time", and "service" criteria, and the latter group encompasses "technical and production capability", "relation combination", and "organisational management".

The organisation strategy formulation helps decision makers such as procurement managers to greatly focus on a specific set of criteria for SS. In this paper, the assessment criteria are chosen based on the organisation strategy formulation selected by the EFE/IFE analysis as described in the preceding subsection. This is because the literature lacks decision support systems for using internal and external strategic analysis in the SS process. Accordingly, the EFE/IFE analysis serves to perform procurement activities in terms of strategy-based criteria so that the supplier management process helps the organisation to achieve its long-term goals. The resulting EFE and IFE scores can set the scene to locate the appropriate business strategy amongst *aggressive*, *progressive*, *growth*, *conservative*, *maintenance*, *competitive*, *defence*, *protect*, and *liquidate*. Then, the potential tactical strategies pertinent to each chosen business strategy are advisable and even vital to be opted for the organisation (see Fig. 2). The most relevant and generic set of evaluation criteria for SS in relation to each tactical strategy is showed in Table 2.[3] For instance, assume that the G&B strategy is thoroughly implemented across the organisation and its top management and shareholders opt for an *aggressive business strategy* with both integration and intension tactical strategies (see Fig. 2). Consequently, this organisation

[3] It should be noticed that these criteria can be changed in different organisations and situations as emphasised in Wetzstein et al. (2016, p. 319). For instance, in the banking sector, the criteria such as *safeguarding*, *safekeeping*, and *regulatory compliance* play an important part in evaluating the service suppliers' performance.

Table 2 Evaluation criteria for supplier selection

Tactical strategy	Evaluation criteria
Integration	Cost; organisational management
Intension	Delivery time; service; relation combination
Cost leadership	Cost; technical and production capability
Diversification	Service; relation combination
Joint venture	Quality; service; relation combination
Differentiation	Quality; technical and production capability
Focus	Cost; delivery time; relation combination
Acquisition	Cost; delivery time; technical and production capability
Retrenchment Divestiture Merger Cooperation	Cost

can take "cost", "organisational management", "delivery time", "service" and "relation combination" criteria into account through the SS process (see Table 3). Each criterion listed in Table 2 includes some performance indicators that can be used in evaluating the suppliers as presented and defined in Table 3.

It is noteworthy that Chen (2011)'s study inspires us to provide Tables 2 and 3 as a big picture of the most relevant and generic evaluation criteria and indicators related to each tactical strategy. Let us interpret the rationale behind the development of Table 2 that shows the link between criteria and strategy.

The strategic *integration* aims to achieve economies of scale. To this end, the total *cost* of goods and services procured from suppliers is the imperative, and *organisational management* capabilities of suppliers are a requisite for organisational integration. For the strategic intension, the *delivery time* and *service* level take part in intensification of markets, distributions or products, and the readiness of suppliers for *relation combination* might be a game-changing factor to create values in the focal organisation's target markets. The aim of the *cost leadership* strategy is to reach the long-term goals of an organisation that is aligned with the capability of suppliers in controlling *cost* and managing *technical and [mass] production* processes in-house. Where product or service *diversification* is the main strategy of an organisation, evidence from suppliers for providing better *service* levels and the readiness for *relation combination* can be a matter of the focal organisation to address the plausible difficulties in creating diversified outcomes. Generally, the aim of the joint venture strategy is to seek to enter a new market, gain economies of scale, mitigate risks for major investments or acquire skills and capabilities. For the SS process, product or service *quality*, *service levels*, and *relation combination* might be imperative to reduce the risk of a clash of organisational objectives brought into the venture by the different partners. In addition to the *cost leadership strategy*, the *differentiation* and *focus* strategies are the main sources of gaining competitive advantage observed in Porter's generic strategies (David 2011). Organisations that use *differentiation* strategies lay emphasis on providing products or services with distinctive attributes

Table 3 Definition of performance indicators for each criterion

Criteria	Evaluation criteria	Performance indicators	Description
Competition factor	Quality	Return rate	Sales return/gross sales (smaller return rate means sales of better quality products and higher customer acceptance)
		Discount rate	Sales discount/gross sales (smaller discount rate means sales of better quality products and higher customer acceptance)
	Cost	Gross profit rate	(Net sales–cost of goods sold)/sales (larger supplier gross profit rate indicates stronger cost control ability)
		Quantity discount	Suppliers offer discounts based on purchase quantity (bigger quantity discount indicates higher cost ability)
	Delivery time	Lead time	Average days each supplier needs to deliver an order (smaller lead time indicates further agility of a supplier)
		On-time delivery rate	The proportion of orders delivered on-time (higher on-time delivery rate denotes more dependability)
		Delivery flexibility	The proportion of orders accepted by the supplier to be delivered sooner than default or contract (more delivery flexibility leads to wider corporate customisation ability)
	Service	Service standard	The proportion of organisation requested services accepted by the supplier to be presented (higher service standard leads to more compatibility to customer-defined quality)
		Responsiveness	The proportion of times accepted by the supplier to take the responsibility for low quality services or corrupted materials (further responsiveness indicates more dependability)
		Improvement capability	The proportion of other than ordinary and non-contracted services accepted by the supplier to be fulfilled on the request of corporation (larger improvement capability means further supplier flexibility in offering various types of services or goods)

Table 3 (continued)

Criteria	Evaluation criteria	Performance indicators	Description
Organisation factor	Technical and production capability	R&D rate	R&D expense/sales; (higher supplier R&D rate denotes stronger technology ability)
		Process capability (productivity)	The proportion of products successfully customised by the supplier according to the organisation requirements (higher supplier productivity means greater supply ability)
	Relation combination	Technique cooperation	Cost of goods sold as the result of technical cooperation (further technique cooperation leads to stronger technical alliances and higher customer acceptance)
		Market cooperation	Cost of goods sold as the result of market-required modifications made to the supplied materials or services (further market cooperation brings about stronger marketing alliances and more compatibility to customer-defined quality)
		Cooperative time	Duration of cooperation in months (more cooperative time denotes further relation compatibility)
	Organisational management	Inventory turnover ratio	Cost of goods sold/average inventory (larger supplier inventory turnover ratio indicates stronger production/marketing control ability)
		Operating expense rate	Operating expense/net sales (smaller supplier operating expense rate expresses higher operating management efficiency)

that are different from those of competitors. In this respect, the quality of goods or services and the *technical and production capability* of the suppliers are paramount to attain unique features, functionality, durability, support, and also brand image. *Focus* strategies target a specific niche market and leverage the dynamics feature of that market and the unique needs of customers to produce low-cost or well-specified products. Hence, focus strategies compel the procurement team to concentrate on *cost*, *delivery time*, and *relation combination* capability of suppliers to minimise the total cost and increase differentiation. In *acquisition* strategies, organisations acquire other organisations to gain economies of scale, diversification, greater market share, increased synergy, cost reductions, or new niche markets. So, organisations develop strategies for the SS problem to ensure that the acquiring organisation selects the appropriate suppliers based on the cost, delivery time, and technical and production capability factors. The *cost* criterion is the most pivotal driver in choosing suppliers when the focal organisation has *retrenchment*, *divestiture*, *merger*, or *cooperation* strategies due to its internal and external weak and unstable situations. We here draw the attention to the fact that there is no need to perform SS when a organisation adopts a *liquidation* business strategy since this strategy limits or eliminates the investment as far as possible and the organisation should then gather all the sales revenue before it winds up the organisation and exits the industry.

It should be noted that Table 3 also includes indicators such as *discount rate*, *gross profit rate* and *inventory turnover ratio* that can be often used for measuring organisational performance. This range of indicators may be particularly applicable to situations of direct suppliers (e.g. raw materials). We point out that, due to the fact that indirect suppliers that supply direct suppliers are close to the markets, long-term relationships need to be established for indirect suppliers as well as direct suppliers (Choi and Hartley 1996).

3.2 Phase 2: GPCA-DEA methodology (SS)

In multi-input multi-output systems, DEA is a powerful non-parametric, axiomatic and mathematical programming approach for efficiency analysis developed by Charnes et al. (1978), which can be also utilised for the SS problem. Though the DEA model is well established and extensively used in the literature, it is criticised for the lack of discriminatory capability as the results divide the units into *efficient* and *inefficient* sets. In some cases, an excessive number of units is considered as efficient, particularly when a small number of units are assessed. To present a complete ranking, beyond the dichotomised classification observed in basic DEA models (e.g. CCR), a classification of DEA ranking methods in the literature are introduced by Adler et al. (2002) and Aldamak and Zolfaghari (2017). Amongst these classes, our methodology in this research is placed in "ranking methods with statistics" and "DEA and MCDM methods" classes.

Although super-efficiency DEA (SE-DEA) models are often able to enhance the discriminatory power of [non-parametric] efficiency analysis models, they suffer from its non-statistical nature in the estimation.[4] Hence, PCA as a popular multivariate technique was applied to DEA by Zhu (1998), and improved by Premachandra (2001), with the aim of presenting an alternative ranking model with the parametric and statistical basis. The main objective of Zhu (1998)'s study (hereafter called PCA-DEA) was to take advantage of PCA to improve the discriminatory power of DEA model. Zhu (1998) used a specific example to show that the ranking results of his method and SE-DEA were consistent.[5]

The need for the explicit distributional assumption as an underlying pre-requisite is the main weakness of PCA as a parametric approach. On the other hand, grey theory is a systematic analysis methodology for handling situations with poor, insufficient, and uncertain information (Deng 1984, 1985a, b, 1989) and ADGI—stemming from grey theory and factor analysis—is a measure equivalent to the statistical correlation coefficient and was developed on the basis of geometric similarity between the curves of two sequence data (Tung and Lee 2010). ADGI is entirely independent of the number of observations (sample size) and data distribution and is able to deal with the aforesaid weakness of PCA. As such, a grey extension of PCA (GPCA) was therefore developed by Tung and Lee (2009, 2010) as given in "Appendix C". It is worth noting that we accommodate some adjustments based on the general concept of the standard PCA approach.

Relying on the semi-statistical characteristics of GPCA, in this phase we develop a GPCA-DEA approach to evaluate the suppliers with regard to the strategy of organisations along with avoiding overestimated or underestimated results. Our approach is capable of improving the discriminatory power especially in cases where a small number of suppliers and a large number of inputs (cost criteria) and outputs (benefit criteria) are present. In addition, our findings show a higher consistency between the rankings obtained from DEA and GPCA-DEA.

3.2.1 GPCA-DEA algorithm

Let us continue with the notations presented in the Appendices. Assume that there exist n suppliers where each supplier has $m+s$ performance indicators. In DEA, we minimise "inputs" and maximise "outputs" at large. Therefore, each supplier's performance indicator can be either an input, denoted by x_{kj} ($k=1,\ldots,m;\ j=1,\ldots,n$), or an output, denoted by y_{lj} ($l=1,\ldots,s;\ j=1,\ldots,n$). When the smaller levels of an indicator represent better performance, this indicator is discerned as an *input*, while when the larger levels of an indicator represent better performance this indicator is discerned as an *output*. We develop a GPCA-DEA approach in which its procedure can be summarised in the following series of steps:

(1) Generate $p=(m\times s)+1$ partial efficiency measures ($\boldsymbol{C}_i=(c_{i1},\ldots,c_{in})$, $i=1,\ldots,p$) similar to steps (1–2) of PCA-DEA in "Appendix B".

[4] For the purpose of convenience, CCR and SE-DEA models are reviewed in "Appendix A".

[5] We make a brief recall of PCA and PCA-DEA techniques in "Appendix B".

(2) Apply steps (1–5) of GPCA, presented in "Appendix C", to the matrix $\mathbf{C}=(\boldsymbol{C}_1,\ldots,\boldsymbol{C}_p)$ to obtain r standardised PCs, i.e., $\boldsymbol{F}_t$, $t=1,\ldots,r$.
(3) Calculate the efficiency of each supplier using Eq. (8) in "Appendix B".

3.2.2 A technical dilemma

Step 3 of the PCA technique that determines the eigenvectors of the correlation matrix $\boldsymbol{\Gamma}$ (see "Appendix B"), affects Step 2 of the proposed GPCA-DEA algorithm where the correlation matrix is replaced with ADGI (see Step 5 of GPCA in "Appendix C"). In this regard, assume that $\boldsymbol{V}_i$ ($i=1,\ldots,p$) is an eigenvector of matrix $\boldsymbol{\Gamma}$, i.e., $\boldsymbol{V}_i(\boldsymbol{\Gamma}-\lambda_i\mathbf{I})=0$. It is simple to show that $-\boldsymbol{V}_i$ is also an eigenvector of matrix $\boldsymbol{\Gamma}$ because $(-\boldsymbol{V}_i)(\boldsymbol{\Gamma}-\lambda_i\mathbf{I})=0$. Analogous to $\boldsymbol{V}_i$, $-\boldsymbol{V}_i$ is a unit vector, i.e., $\sum_{b=1}^{p}(-v_{ib})^2=1$. Furthermore, given $\left(-\boldsymbol{V}_i\right)\boldsymbol{V}_q^{\mathrm{T}}=0$ $(\forall i,q=1,\ldots,p; i\neq q)$, $-\boldsymbol{V}_i$ and $\boldsymbol{V}_q$ are orthogonal vectors. As a result, $-\boldsymbol{V}_i$ $(-\boldsymbol{V}_t)$ can be used as a substitute eigenvector for $\boldsymbol{V}_i$ $(\boldsymbol{V}_t)$ in order to determine the ith (tth) principal component (PC). In the light of this substitution, $\boldsymbol{F}_t$ may be changed to $-\boldsymbol{F}_t$ when obtaining r standardised PCs, that is, a cost criterion may be changed to a benefit one and vice versa. Hence, it is crucial to propose a generalised method that allows us to select the appropriate eigenvectors. Here, we draw the attention to the fact that PCs ($\boldsymbol{F}_t$s) derived from PCA preferably have benefit (cost) characteristic when we have benefit (cost) variables ($\boldsymbol{D}_i$s), i.e., PCs preferably have the same characteristic as original variables. We plan to address this issue with the aid of a concept called "positive impact".

The positive or negative correlation of $\boldsymbol{D}_i$s ($i=1,\ldots,p$) with $\boldsymbol{F}_t$ (see Eq. (6) in "Appendix B" and $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$[6] in "Appendix C") is remarkable since the coefficients of $\boldsymbol{D}_i$s (v_{ti}s) in (6) can take either positive or negative sign. The standardised PC $\boldsymbol{F}_t$ includes positive (negative) impact when all its corresponding coefficients take positive (negative) values. However, in most cases, there exist simultaneously both positive and negative coefficients for a given PC and this issue complicates the recognition of positive or negative impact of $\boldsymbol{D}_i$s on each $\boldsymbol{F}_t$.

Thus far, it is argued that the positive impact of $\boldsymbol{D}_i$s on $\boldsymbol{F}_t$s is indispensable because it makes PCs that have identical cost/benefit characteristic with the original variables ($\boldsymbol{D}_i$s). In GPCA, this feature can be satisfied for each $\boldsymbol{F}_t$ when a direct (positive) grey correlation exists between each $\boldsymbol{F}_t$ and *all* $\boldsymbol{D}_i$ variables, i.e., when for every i, $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)>0$. However, as earlier mentioned, it rarely occurs for a PC to have a positive grey correlation with all variables. Accordingly, we utilise the sum of the grey correlation coefficients between $\boldsymbol{F}_t$ and $\boldsymbol{D}_i$s as:

[6] The value of $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$ is such that $-\lambda_t^{1/2}\leq\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)\leq+\lambda_t^{1/2}$. The + and − signs indicate positive and negative correlations, respectively (Proof. see Appendix D). *Positive grey correlation:* If $\boldsymbol{F}_t$ and $\boldsymbol{D}_i$ have a strong positive correlation, the value of $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$ is positive and close to $+\lambda_t^{1/2}$. A $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$ value of exactly $+\lambda_t^{1/2}$ presents a perfect positive correlation. *Negative grey correlation:* If $\boldsymbol{F}_t$ and $\boldsymbol{D}_i$ have a strong negative correlation, the value of $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$ is negative and close to $-\lambda_t^{1/2}$. A $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$ value of exactly $-\lambda_t^{1/2}$ presents a perfect positive correlation. *No grey correlation:* If there is no correlation, $\mathrm{GCorr}\left(\boldsymbol{F}_t,\boldsymbol{D}_i\right)$ is equal to close to 0.

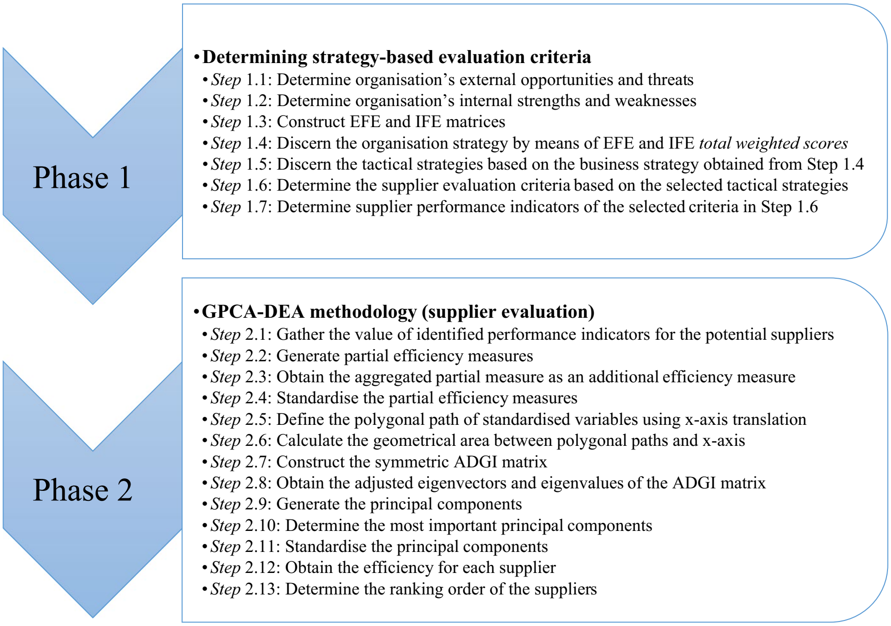

Fig. 3 The proposed framework

- If $\sum_{i=1}^{p} \mathrm{GCorr}\left(\boldsymbol{F}_t, \boldsymbol{D}_i\right) > 0$, then $\boldsymbol{F}_t$ $(t = 1,\ldots,r)$ entails positive impact from $\boldsymbol{D}_i$s.
- If $\sum_{i=1}^{p} \mathrm{GCorr}\left(\boldsymbol{F}_t, \boldsymbol{D}_i\right) < 0$, then $-\boldsymbol{F}_t$ entails positive impact from $\boldsymbol{D}_i$s.

Hence, in the procedure of GPCA (see "Appendix C"), for any $\boldsymbol{F}_t$ $(t = 1,\ldots,r)$, if $\sum_{i=1}^{p} \mathrm{GCorr}\left(\boldsymbol{F}_t, \boldsymbol{D}_i\right) < 0$, we substitute $\boldsymbol{V}_t$ with $-\boldsymbol{V}_t$ and repeat Step (5). We also take this adjustment into account while executing Step (2.8) of the proposed GPCA-DEA procedure in this study.

In sum, the proposed framework is presented in Fig. 3 consisting of two main phases, (1) determination of strategy-based evaluation criteria, and (2) SS via GPCA-DEA.

4 Case study

The agri-food industry is one of the most competitive business sectors of economy, particularly in emerging markets. Considering the complexity of the food SC, originating from agricultural labour to the end-user/consumer, the market requirements could not be simply achieved unless a comprehensive SC system is constructed by stakeholders. To outline such a rigorous system, we need to account for the strategic (long-term) goals and objectives within the business for boosting productivity growth and creating shared value throughout an organisation.

In this research, we first set out to perform the strategic analysis to formulate strategies for a confectionery medium-sized organisation in Iran[7] and then, on the basis of this analysis, multiple evaluation criteria are identified to evaluate the suppliers from the organisation strategy viewpoint (see Phase 1 in Fig. 3). Since there are some strategies that are not directly linked to the SS criteria, we limit our focus on those strategies of the organisation connected to evaluation criteria to some extent. To enhance the suppliers' alignment with organisation strategies, more tactics can be defined.

Phase 1 of the proposed framework enables the organisation to evaluate and select the appropriate and long-term suppliers. In what follows, two experienced consultants who had more than 9 years of experience in the strategic sourcing and procurement were hired to assist us in implementing the strategic analysis. In addition to the consultants, we directly collaborated with three top level managers from the procurement, manufacturing and also financial departments of the organisation. The present strategic SS approach is developed on the basis of a data set collected from the suppliers' balance sheet and income statement of 2013–2014 in addition to the historical records of collaboration with suppliers.

As a primary action, the strategic team well devised an EFE/IFE analysis which resulted in the formation of an EFE matrix including 10 and 5 key external opportunity and threat factors respectively, as well as an IFE matrix including 12 and 4 key internal strength and weakness factors respectively. The weights of these factors in the industry and their rating in the organisation determined by the strategic team's judgments are reported in Tables 4 and 5.

EFE and IFE total weighted scores are 2.930 and 3.170 here, respectively. Hence, the corresponding business strategy of the organisation is located in *growth* subdivision according to the "Business Strategy Matrix" (see Fig. 2). In this case, a number of tactical strategies such as *integration, intension, cost leadership–best value/low cost,* etc. are viable to meet the strategic objectives of the organisation. To opt for the appropriate tactical strategy (strategies), the strategic team solicited the managerial preferences of the procurement, manufacturing, quality, financial and engineering departments. This process gave rise to the selection of *Integration* and *Intension* strategies. According to these tactical strategies, the assessment team chosen and used the most appropriate and relevant criteria to systematically assess the potential suppliers. These are *cost, delivery time, service* as competition factors and *organisational management, relation combination* as organisation factors. The strategy-based criteria assist the organisation to render a long-term perspective for synchronising with the selected suppliers. The performance indicators associated with each criterion and their descriptions can be found in Table 3.

By analysing the procurement process of a specific product, we realised that it is necessary to assess six candidate suppliers located in the same geographical region. Apropos of available historical data, these suppliers were in collaboration with the

[7] The name of the organisation is not indicated to preserve confidentiality.

Table 4 The EFE matrix

	Key external factors	Weight	Rating	Weighted score
	Opportunities			
1.	A fundamental societal need	0.050	3	0.150
2.	Governmental supports for non-oil exports	0.020	3	0.060
3.	Domestic preference to consume nuts, nibbles and sweets	0.020	3	0.060
4.	Societal tendency to consume foods with high nutritional value	0.120	4	0.480
5.	Domestic confidence to consume national foodstuff productions	0.040	3	0.120
6.	The lack of domestic substituted products with high quality, low cost, and on-time delivery	0.050	3	0.150
7.	Competitive costs for domestic processing of confectionary raw materials including dairy products and other agricultural commodities	0.090	4	0.360
8.	Passive, dependent and non-innovative performance of domestic competitors	0.140	4	0.560
9.	Existence and abundance of domestic skilled and unskilled workforces	0.080	4	0.320
10.	Poor and regressing performance of some domestic well-known competitors	0.040	3	0.120
	Threats			
1.	Temporary and abrupt decision from government on pricing policies for raw materials and tariffs	0.100	2	0.200
2.	Poor domestic packaging industry and the shortage of world-class experts in this field	0.050	2	0.100
3.	Poor sentiment of domestic products in the regional markets and the lack of governmental supports to solve the existing hurdles	0.100	1	0.100
4.	Severe competition of foodstuff local producers and abundant global competitors	0.050	1	0.050
5.	Experimental weakness of suppliers and cooperators in the world-class production milieu	0.050	2	0.100
	Total	1.000		2.930

Table 5 The IFE matrix

	Key internal factors	Weight	Rating	Weighted score
	Strengths			
1.	Paying special attention to innovation in products; the company's ability in market leadership by adopting horizontal diversification, concentric diversification, and product development strategies	0.100	4	0.400
2.	Credibility, prominence, and stable position of the company in numerous regional markets	0.080	4	0.320
3.	Sustainable relationship with customers	0.030	3	0.090
4.	Cost leadership subject to high efficiency	0.060	3	0.180
5.	On-time delivery and high availability of product in domestic market; the creation of a powerful supply chain with local and global distribution networks	0.120	4	0.480
6.	Cautious about public health	0.030	3	0.090
7.	Broad horizontal and vertical integration for establishing a full corporation	0.120	4	0.480
8.	Adopting appropriate marketing policies	0.060	3	0.180
9.	Cautious about human capital	0.050	3	0.150
10.	Effective relationship with the government and other companies	0.050	4	0.200
11.	Investment in other markets	0.020	3	0.060
12.	Cautious about social responsibility	0.080	3	0.240
	Weaknesses			
1.	Dependency on the talented leaders and managers	0.100	1	0.100
2.	Marketing and selling practice using umbrella branding	0.050	2	0.100
3.	Dependency on some strategic and subsidized materials	0.020	2	0.040
4.	Potential risk of the ignition of the oilseed processing factories	0.030	2	0.060
	Total	1.000		3.170

Table 6 Decision matrix

Criterion	Delivery Time			Service			Relation Combination			Cost		Organisational Management	
Indicator	Lead Time	On-Time Delivery Rate	Delivery Flexibility	Service Standard	Responsiveness	Improvement Capability	Technique Cooperation	Market Cooperation	Cooperative Time	Gross Profit Rate	Quantity Discount	Inventory Turnover Ratio	Operating Expense Rate
Type	Input	Output	Output	Output	Output	Output	Output	Output	Output	Output	Output	Output	Input
Supplier													
A	22	0.667	0.273	0.750	0.667	0.750	19,850	38,400	111	0.115	10	8.536	0.047
B	10	0.818	0.583	0.833	0.895	0.850	62,800	71,200	120	0.004	10	5.358	0.120
C	14	0.591	0.350	0.667	0.625	0.375	8950	8950	58	0.209	4	1.409	0.079
D	29	0.615	0.214	0.667	0.636	0.727	22,500	22,500	116	0.143	8	5.287	0.029
E	5	0.818	0.385	0.667	0.778	0.857	51,500	68,500	152	0.258	8	10.677	0.031
F	9	0.733	0.375	0.583	0.750	0.708	18,550	32,850	141	0.322	6	4.462	0.050

organisation for 3–5 years and their capacity were sufficient to serve the present and growing needs. It is notable that the performance evaluation procedure is based on quantitative and precise decision data (see Table 6), which was extracted from the existing historical or financial reports.

Given that this SS problem was composed of poor, insufficient, and uncertain data on the one hand, and considering the importance of high discriminatory power for the procurement managers on the other hand, we were promoted to apply the proposed GPCA-DEA method in this research to evaluate the six suppliers (see Sect. 3.2). We considered the 13 indicators under the five main criteria (i.e., *cost, delivery time, service, organisational management,* and *relation combination*) that were concluded from the above strategic analysis. The associated ratings for the six suppliers with respect to the 13 performance indicators are presented in Table 6.

Among the performance indicators, we regarded *Lead time* and *Operating expense rate* as inputs since their smaller amounts have better performance while the remaining indicators that their larger levels improve the performance were considered as outputs, i.e., $m=2$ inputs and $s=11$ outputs with $n=6$ suppliers. We implemented Phase 2 of the proposed framework in Fig. 3, i.e. GPCA-DEA procedure, to evaluate the six candidate suppliers:

Step 2.1 Generate the decision matrix using the performance indicators obtained from Phase 1, i.e., see Table 6.

Step 2.2 Generate $m \times s = 2 \times 11 = 22$ partial efficiency measures:

$$\boldsymbol{C}_i = \left(c_{i1}, \dots, c_{i6}\right); c_{ij} = y_{lj}/x_{kj}; i = 1, \dots, 22; j = 1, \dots, 6; k = 1, 2; l = 1, \dots, 11.$$

For instance, $\boldsymbol{C}_1 = (0.030, 0.082, 0.042, 0.021, 0.164, 0.081)$.

Step 2.3 Obtain the aggregated partial measure, C_{23}, as an additional efficiency measure to matrix $\boldsymbol{C}$ as follows:

$$\boldsymbol{C}_{23} = \left(c_{(23)1}, \dots, c_{(23)6}\right); c_{(23)j} = \sum_{i=1}^{22} c_{ij}; j = 1, \dots, 6,$$

$$\boldsymbol{C}_{23} = (1247455.454, 1133734.407, 228987.839, 1561467.819, 3944529.992, 1037110.719).$$

Step 2.4 Standardise the variables $\boldsymbol{C}_1, \dots, \boldsymbol{C}_{23}$ using Eq. (9) presented in "Appendix C", denoted by $\boldsymbol{D}_1, \dots, \boldsymbol{D}_{23}$ where $\boldsymbol{D}_i = (d_{i1}, \dots, d_{i6})$, $i = 1, \dots, 23$. For instance, $\boldsymbol{D}_1 = (0.064, 0.426, 0.147, 0, 1, 0.423)$.

Step 2.5 Define the polygonal path $\boldsymbol{D}_i^0 = \left(d_{i1}^0, \dots, d_{i6}^0\right)$ $\left(d_{ij}^0 = d_{ij} - d_{i1}; i = 1, \dots, 23; j = 1, \dots, 6\right)$ using x-axis translation. For instance, $\boldsymbol{D}_1^0 = (0, 0.362, 0.084, -0.064, 0.936, 0.359)$.

Step 2.6 Calculate the geometrical area between $\boldsymbol{D}_i^0$ and the x-axis ($\delta_i; i = 1, \dots, 23$), and also between $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$ ($\delta_{iq}; i, q = 1, \dots, 23$) using Eqs. (10) and (11) presented in "Appendix C", respectively. For instance, $\delta_1 = 1.805$ and $\delta_{(1)23} = 1.525$.

Step 2.7 Construct the symmetric ADGI matrix $\boldsymbol{\Gamma}_{23\times 23} = \left[\gamma_{iq} : i, q = 1, \dots, 23\right]$ using Eq. (12) in "Appendix C". For instance, $\gamma_{(1)23} = 0.723$.

Step 2.8: Calculate the eigenvalues (λ_i) and eigenvectors ($\boldsymbol{V}_i$) of matrix $\boldsymbol{\Gamma}$ using the equation $\boldsymbol{V}_i\left(\boldsymbol{\Gamma} - \lambda_i \mathbf{I}\right) = 0, i = 1, \dots, 23$. For instance, $\boldsymbol{V}_1 = (0.214, 0.209, \dots, 0.210)$

Table 7 Comparison of the ranks obtained from super-efficiency DEA (SE-DEA), PCA-DEA and GPCA-DEA

Supplier	Efficiency			Rank		
	SE-DEA	PCA-DEA	GPCA-DEA	SE-DEA	PCA-DEA	GPCA-DEA
A	0.804	24.348	0.275	3	4	4
B	0.757	11.048	0.196	5	6	5
C	0.392	21.416	0.046	6	5	6
D	1.069	38.223	0.407	2	3	2
E	4.273	89.367	0.881	1	1	1
F	0.774	53.826	0.312	4	2	3

is the first eigenvector corresponding to the greatest eigenvalue, $\lambda_1 = 17.817$. Also, note that $\sum_{i=1}^{23} \lambda_i = 23$.

Based on the proposed adjustment in Sect. 3.2.2 and the properties of GPCA, for any $(\boldsymbol{V}_i = v_{i1}, v_{i2}, \ldots v_{i23})$ $(i=1,\ldots,23)$ if $\sum_{b=1}^{23} \lambda_i^{1/2} v_{ib} < 0$, we substitute $\boldsymbol{V}_i$ with $-\boldsymbol{V}_i$. Notice here that we have $\sqrt{17.817}(0.214 + 0.209 + \cdots + 0.210) \geq 0$ for $\boldsymbol{V}_1$, therefore, the substitution is not required.

Step 2.9 Generate the PCs via Eq. (5) presented in "Appendix B". The first PC is described as:

$$\begin{aligned}\boldsymbol{PC}_1 &= 0.214\boldsymbol{D}_1 + 0.209\boldsymbol{D}_2 + \cdots + 0.210\boldsymbol{D}_{23}\\ &= (1.125, 1.257, 0.325, 1.596, 4.764, 1.756).\end{aligned}$$

Step 2.10 Consider the first $r=4$ out of $p=23$ PCs that are able to preserve at least 90% of the total data variance as computed below:

$$\begin{aligned}&\mathrm{Var}(\boldsymbol{PC}_i) = \lambda_i,\\ &\lambda_1 = 17.817, \lambda_2 = 2.065, \lambda_3 = 0.617, \lambda_4 = 0.483,\\ &\sum_{t=1}^{4} \lambda_t/23 = 0.912 \geq 0.9.\end{aligned}$$

Step 2.11 Standardise the PCs by means of Eq. (6) presented in "Appendix B". For example:

$$\begin{aligned}\boldsymbol{F}_1 &= \left(0.214\boldsymbol{D}_1 + 0.209\boldsymbol{D}_2 + \cdots + 0.210\boldsymbol{D}_{23}\right)/\sqrt{17.817}\\ &= (0.267, 0.298, 0.077, 0.378, 1.129, 0.416).\end{aligned}$$

Step 2.12 Calculate the final efficiency measure of each supplier j $(j=1,\ldots,6)$ via (8) presented in "Appendix B" as follows:

$$z_j = 0.775f_{1j} + 0.090f_{2j} + 0.027f_{3j} + 0.021f_{4j}.$$

Step 2.13 Determine the ranking order of the six suppliers as presented in the last column of Table 7.

Table 8 Spearman rank correlation for DEA vs. PCA-DEA, and DEA vs. GPCA-DEA

	DEA
PCA-DEA	0.771 Spearman correlation is not significant at the 0.010 level
GPCA-DEA	0.943 Spearman correlation is significant at the 0.010 level

The efficiency scores of the suppliers obtained from the SE-DEA model (see model (2) in "Appendix A") and the PCA-DEA method proposed by Premachandra in 2001 (see "Appendix B") are reported in Table 7. These efficiency scores are utilised to compare and validate the proposed GPCA-DEA method (see Table 7). As a result, the supplier *E* is the superior candidate while the supplier *C* is an inferior candidate in both SE-DEA and GPCA-DEA methods.

To provide a more transparent comparison, Spearman rank correlation test as a non-parametric statistical test is implemented between these methods, involving SE-DEA with PCA-DEA and SE-DEA with GPCA-DEA. Table 8 concludes that SE-DEA and GPCA-DEA approaches yield the consistent rankings. Indeed, the Spearman correlation of SE-DEA and PCA-DEA rankings is not significant at the 1% level while the Spearman correlation of SE-DEA and GPCA-DEA rankings is significant at the 1% level.

It is worth elaborating the advantages of the proposed GPCA-DEA approach in this study. The approach provides a full ranking as well as being consistent with the results obtained from DEA model. In addition, our GPCA-DEA approach avoids generating overestimated or underestimated results in the case of interrelated criteria (see Table 7). For example, the efficiency score of supplier *E* ranked 1st is approximately quadrupled compared to that for supplier *D* ranked 2nd in SE-DEA while more reasonable results can be viewed in GPCA-DEA by virtue of semi-statistical characteristics. The reliable and accurate results of GPCA-DEA can create values for the organisation and shareholder as the result of the SS process.

Referring to the recent review study conducted by Wetzstein et al. (2016), it is concluded that the efficiency and effectiveness of SS approaches is a matter of concern and concerted effort is needed to consider these characteristics in SS approaches. The efficiency of GPCA-DEA has been here examined in comparison with SE-DEA with the aid of the Spearman rank correlation test. The effectiveness of our SS approach is reflected by the fact that the performance indicators in relation to suppliers are identified based upon the strategy-based model. The achievement of organisation strategies is heavily dependent on the internal performance in terms of strategy implementation and evaluation stages (see Fig. 1) and our new approach does not cast doubt on the failure of strategies fulfilment through the SS processes.

5 Conclusion

Supplier selection (SS) is at the heart of the sourcing function in a supply chain. Today, uncertainty and complexity of data are the overriding concerns of the procurement managers of each organisation. Still most sourcing departments operate without integrated quantitative support tools, partly because the proposed methods have a partial or too operational focus and the selection problem is deemed as an abstract matching exercise. This research attempted to present a systematic strategy-based methodology for the SS problem in order to generate sustained growth and competitive advantages over the long term for a supply chain. We leveraged the organisational strategic plan as a basis to identify key performance indicators impacting long-term relationships with the suppliers. We then proposed a modified grey PCA within DEA framework, so-called *GPCA-DEA*, for evaluating the suppliers in situations where interrelated and insufficient data are available.

We also presented a case study in agri-food industry to ascertain the applicability of the proposed framework for the selections problem. As a result of this real-world case study, the *growth strategy* was concluded as an appropriate strategic action after analysing the strategic plan of the organisation involving its internal and external environmental considerations. The application was composed of a detailed study to assess six suppliers considering five influential and conflicting criteria derived from the strategic plan of the organisation. Using the method, the sourcing managers obtained a comprehensive and strategically relevant ranking of the six candidate suppliers. Moreover, our numerical results showed that the proposed approach yielded a ranking that was statistically consistent with the SE-DEA ranking.

Conceptually, the proposed SS framework in this paper has the advantage of being rooted in strategic planning rather than in a priori operational criteria. Given the proposed methodology, PCA yields a deeper awareness of criteria based on a statistical nature where an ordinary non-parametric efficiency analysis model stalls at ranking few potential suppliers in the presence of many criteria. Also, the novel application of grey theory allows the approach to handle the complexity and uncertainty resulting from incomplete and scarce data. As such, GPCA-DEA is able to address statistical limitations and challenges in the SS.

There is scope for further work on implementation of strategic sourcing systems. In particular, when the focal organisation needs to make sourcing decisions in multiple functions, it is an open question at what level or in which form criteria and their values should be selected and measured. Though there are numerous techniques and algorithms in the literature for determining appropriate evaluation criteria in the SS problem, there is a valid concern about the complexity of pinpointing a direct link between organisational strategies and SS criteria. It would also be interesting to investigate empirically how procurement teams ascertain a direct link between the organisational strategy and the selected SS criteria. Another crucial aspect in real-world SS problems that could be further studied is concerned with the integration level of the decision-making tool into the organisation information system.

Appendix A (DEA models)

CCR model

Assume that there exist n suppliers (DMU$_j$: $j=1,\ldots,n$), where each supplier consumes m inputs, denoted by x_{kj} ($k=1,\ldots,m$), to produce s outputs, denoted by y_{lj} ($l=1,\ldots,s$). The CCR input oriented model evaluates the efficiency of DMU$_o$, DMU under consideration, by solving the following linear program (Charnes et al. 1978):

$$\begin{aligned} \max \quad & h_o = \sum_{l=1}^{s} u_l y_{lo}, \\ \text{s.t.} \quad & \sum_{k=1}^{m} v_k x_{kj} - \sum_{l=1}^{s} u_l y_{lj} \geq 0; \quad j = 1, \ldots, n, \\ & \sum_{k=1}^{m} v_k x_{ko} = 1; \\ & u_l, v_k \geq \varepsilon; \quad k = 1, \ldots, m; \quad l = 1, \ldots, s, \end{aligned} \tag{1}$$

where u_l and v_k are the weights associated with the l^{th} output and kth input, respectively. Also, ε is a positive non-Archimedean infinitesimal. The above DEA model divides the DMUs into two sets, DMUs that are efficient when $h_o = 1$ and inefficient when $h_o \neq 1$.

Super-efficiency DEA (SE-DEA) model

For ranking the efficient units, the following SE-DEA model is formulated based upon the CCR model in which a DMU being evaluated is excluded from the reference set (Andersen and Petersen 1993):

$$\begin{aligned} \max \quad & E_o = \sum_{l=1}^{s} u_l y_{lo}, \\ \text{s.t.} \quad & \sum_{k=1}^{m} v_k x_{kj} - \sum_{l=1}^{s} u_l y_{lj} \geq 0; \quad j = 1, \ldots, n; \quad j \neq o, \\ & \sum_{k=1}^{m} v_k x_{ko} = 1; \\ & u_l, v_k \geq \varepsilon; \quad k = 1, \ldots, m; \quad l = 1, \ldots, s. \end{aligned} \tag{2}$$

The super-efficiency model is also referred as a "radial super-efficiency" model.

Appendix B

PCA technique

PCA is a popular multivariate technique that uses an orthogonal linear transformation to simplify the information complexity by converting several interrelated variables into fewer non-interrelated and independent principal components (PCs) where the first coordinate, so-called the first PC, has the largest possible variance, the second coordinate has the second largest possible variance, and so on. Put differently, a simpler data set is generated from the initial observations representing their main specifications. The number of PCs is always less than or equal to the number of original variables.

Assume a data set that is represented in terms of a $p \times n$ matrix, denoted by $\mathbf{C}$, where the n columns are the observations and the p rows are the variables. In other words, there are p variables, $\mathbf{C}=(\boldsymbol{C}_1,\ldots,\boldsymbol{C}_i,\ldots,\boldsymbol{C}_p)^{\mathrm{T}}$ where $\boldsymbol{C}_i=(c_{i1},\ldots,c_{in})$, $i=1,\ldots,p$ and T stands for transpose. The main procedure for PCA can be described in a series of steps (Manly 2004):

(1) Standardise the variable vector $\boldsymbol{C}_i$ as:

$$\boldsymbol{D}_i = \left(\boldsymbol{C}_i - \mu\left(\boldsymbol{C}_i\right)\right)/\sigma\left(\boldsymbol{C}_i\right); \quad i = 1, \ldots, p, \tag{3}$$

where $\mu\left(\boldsymbol{C}_i\right)$ and $\sigma\left(\boldsymbol{C}_i\right)$ are the mean and the standard deviation of the i^{th} variable vector.

(2) Construct the correlation matrix ($\boldsymbol{\Gamma}$):

$$\boldsymbol{\Gamma}_{p\times p} = \left[\gamma_{iq} : \gamma_{iq} = \mathrm{Corr}\left(\boldsymbol{D}_i,\boldsymbol{D}_q\right) = \frac{\mathrm{Cov}\left(\boldsymbol{D}_i,\boldsymbol{D}_q\right)}{\sigma\left(\boldsymbol{D}_i\right)\sigma\left(\boldsymbol{D}_q\right)}; \quad i = 1, \ldots, p; \quad q = 1, \ldots, p\right], \tag{4}$$

where $\mathrm{Corr}\left(\boldsymbol{D}_i,\boldsymbol{D}_q\right)$ and $\mathrm{Cov}\left(\boldsymbol{D}_i,\boldsymbol{D}_q\right)$ are the correlation coefficient and covariance of variables $\boldsymbol{D}_i$ and $\boldsymbol{D}_q$, respectively.

(3) Calculate the eigenvalues and eigenvectors from matrix $\boldsymbol{\Gamma}$ as:

$$\boldsymbol{V}_i\left(\boldsymbol{\Gamma} - \lambda_i\mathbf{I}\right) = 0,$$

where $\boldsymbol{V}_i=(v_{i1},v_{i2},\ldots,v_{ip})$, $i=1,\ldots,p,$ is an eigenvector, $\mathbf{I}$ is an identity matrix of size $p,$ and λ_i $(\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0)$ is a scalar, called the *eigenvalue* corresponding to $\boldsymbol{V}_i$ where $\sum_{i=1}^{p} \lambda_i = p$. Note that $\boldsymbol{V}_i$ is a unit vector, viz., $\sum_{b=1}^{p} (v_{ib})^2 = 1, i = 1, \ldots, p$. The eigenvectors $\boldsymbol{V}_i$ and $\boldsymbol{V}_q$ $(i, q = 1, \ldots, p; i \neq q)$ corresponding to the eigenvalues of a symmetric matrix are orthogonal denoted by $V_i \perp V_q$, i.e., $\boldsymbol{V}_i\boldsymbol{V}_q^{\mathrm{T}} = 0$.

(4) Determine p PCs by:

$$\boldsymbol{PC}_i = v_{i1}\boldsymbol{D}_1 + v_{i2}\boldsymbol{D}_2 + \cdots + v_{ip}\boldsymbol{D}_p; \quad i = 1, \ldots, p, \tag{5}$$

where the first PC has the largest variance, the second PC has the second largest variance and so on. It is straightforwardly proved that $\mathrm{Var}(\boldsymbol{PC}_i) = \lambda_i$ and $\mu(\boldsymbol{PC}_i) = 0$. In addition, $\sum_{i=1}^{p} \mathrm{Var}(\boldsymbol{D}_i) = p = \sum_{i=1}^{p} \lambda_i$ because $\mathrm{Var}(\boldsymbol{D}_i) = 1, i = 1, \ldots, p$. The PCs has therefore the capability to describe the total variance of the original data, in particular, $\boldsymbol{PC}_i$ describes λ_i/p. Notice that there is no covariance between two different PCs, $\boldsymbol{PC}_i$ and $\boldsymbol{PC}_q$, since their corresponding eigenvectors, $\boldsymbol{V}_i$ and $\boldsymbol{V}_q$, are orthogonal, i.e., $\mathrm{Cov}(\boldsymbol{PC}_i, \boldsymbol{PC}_q) = 0$ because $\boldsymbol{V}_i \perp \boldsymbol{V}_q$.

(5) Select the first r out of p PCs such that at least 90%[8] of the total variance is considered, i.e., $\sum_{t=1}^{r} \lambda_t \geq 0.9p$.

(6) Obtain r standardised PCs by:

$$\boldsymbol{F}_t = \left(v_{t1}\boldsymbol{D}_1 + v_{t2}\boldsymbol{D}_2 + \cdots + v_{tp}\boldsymbol{D}_p\right)/\sigma\left(\boldsymbol{PC}_t\right); \quad t = 1, \ldots, r, \tag{6}$$

where $\sigma\left(\boldsymbol{PC}_t\right) = \lambda_t^{1/2}$.

PCA-DEA technique

The main goal of PCA-DEA is to take advantage of a multivariate statistical method, PCA, to improve the discriminatory power. Assume that there exist n DMUs (suppliers) where the jth supplier ($j = 1,\ldots,n$) consumes m positive inputs x_{kj} ($k = 1,\ldots,m$) to produce s positive outputs y_{lj} ($l = 1,\ldots,s$). The PCA-DEA procedure can be described in a series of steps:

(1) Generate $m \times s$ (ms for short) number of partial efficiency measures in terms of ratios of individual outputs to individual inputs.[9] On this basis, an $ms \times n$ data matrix, denoted by $\mathbf{C}$, can be created to present the values of ms partial efficiency measures in the rows of the matrix against n columns of DMUs. Let $\mathbf{C}_{ms \times n} = (\boldsymbol{C}_1,\ldots,\boldsymbol{C}_{ms})^{\mathrm{T}}$. Then, each row of matrix $\mathbf{C}$ is defined as $\boldsymbol{C}_i = (c_{i1},\ldots,c_{ij},\ldots, c_{in})$ where $c_{ij} = y_{lj}/x_{kj}; i = 1, \ldots, ms; j = 1, \ldots, n; k = 1, \ldots, m; l = 1, \ldots, s$, that is, each row is dedicated to a given output/input ratio and each column is dedicated to a DMU. For further clarification of the row indexing, we focus attention on the case of $i = 1$ which represents $k = 1$ and $l = 1$; also $i = 2$ can represent $k = 1$ and $l = 2$ or alternately $k = 2$ and $l = 1$, etc. Note that when x_{kj} has a value of zero, the corresponding c_{ij} value cannot be defined; to deal with this possible problem, we replace the input value of zero with a very small amount.

(2) Add the new efficiency measure $\boldsymbol{C}_p = \left(c_{p1}, \ldots, c_{pj}, \ldots, c_{pn}\right)$ to matrix $\mathbf{C}$ such that:

$$c_{pj} = \sum_i c_{ij}; j = 1, \ldots, n. \tag{7}$$

[8] This amount is subject to change in different studies.

[9] In a case with no input or no output in the model, we can employ a dummy input or output equal to the fixed value of 1.

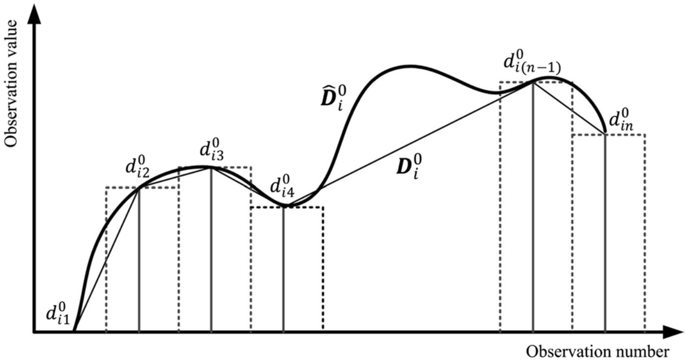

Fig. 4 Information curve ($\hat{\boldsymbol{D}}_i^0$) and polygonal path ($\boldsymbol{D}_i^0$) of variable $\boldsymbol{D}_i$ (Tung and Lee 2010)

(3) Apply Steps (1–6) of PCA presented in the first part of this Appendix to the following matrix:

$$\mathbf{C}_{(ms+1)\times n} = \left(\boldsymbol{C}_1, \dots, \boldsymbol{C}_{ms}, \boldsymbol{C}_p\right)^{\mathrm{T}}.$$

(4) Calculate the efficiency measure of each DMU_j by:

$$z_j = \sum_{t=1}^{r} w_t f_{tj}; j = 1, \cdots, n, \tag{8}$$

where $w_t = \lambda_t/(ms + 1)$ is the importance level of $\boldsymbol{F}_t = (f_{t1},\dots,f_{tn})$.

Appendix C (*Grey PCA*)

Let us assume there are p benefit variables, $\mathbf{C} = (\boldsymbol{C}_1,\dots,\boldsymbol{C}_i,\dots,\boldsymbol{C}_p)^{\mathrm{T}}$ where $\boldsymbol{C}_i = (c_{i1},\dots, c_{in})$, $i = 1,\dots,p$. We describe the procedure of GPCA in a series of steps:

(1) Standardise the variables, denoted by $\mathbf{D} = (\boldsymbol{D}_1,\dots,\boldsymbol{D}_i,\dots,\boldsymbol{D}_p)^{\mathrm{T}}$ where $\boldsymbol{D}_i = (d_{i1},\dots, d_{ij},\dots,d_{in})$ and:

$$d_{ij} = \frac{c_{ij} - \min_j c_{ij}}{\max_j c_{ij} - \min_j c_{ij}}; \quad i = 1, \dots, p, \quad j = 1, \dots, n. \tag{9}$$

Assume that $\hat{\boldsymbol{D}}_i$, $i = 1, \dots, p$, is the ith continuous curve and $d_{ij}, j = 1, \dots, n$, are the n observed data of the information curve $\hat{\boldsymbol{D}}_i$ (see Fig. 4 as a case where $d_{i1} = 0$).

(2) Convert the polygonal path of $\boldsymbol{D}_i$ to $\boldsymbol{D}_i^0 = \left(d_{i1}^0, \dots, d_{in}^0\right)$ using $d_{ij}^0 = d_{ij} - d_{i1}$.

(3) Calculate the geometrical area between $\boldsymbol{D}_i^0$ and the x-axis, denoted by δ_i, as follows:

$$\delta_i = \sum_{j=2}^{n} \left| d_{ij}^0 \right|. \tag{10}$$

In addition, the area between two sequence variables, $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$, is calculated by:

$$\delta_{iq} = \sum_{j=2}^{n} \left| d_{ij}^0 - d_{qj}^0 \right|; \quad i, q = 1, \dots, p. \tag{11}$$

(4) Obtain the symmetric ADGI matrix as:

$$\boldsymbol{\Gamma}_{p\times p} = \left[\gamma_{iq} \,:\, i, q = 1, \dots, p \right],$$

where γ_{iq} for two sequence variables $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$ is computed as:

$$\gamma_{iq} = \frac{1 + \delta_i + \delta_q}{1 + \delta_i + \delta_q + \delta_{iq}}, \tag{12}$$

where $\delta_i(\delta_q)$ and δ_{iq} are calculated from Eqs. (10) and (11). It should be noted that γ_{iq} has the following characteristics:
(a) $0 < \gamma_{iq} \leq 1$.
(b) $\gamma_{iq} = \gamma_{qi}$.
(c) $\gamma_{ii} = 1$.
(d) γ_{iq} depends on the geometric shapes of $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$. Therefore, γ_{iq} increases if $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$ have more similarity in their geometric shapes.
(e) $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$ are parallel iff $\gamma_{iq} = 1$.

(5) Consider the ADGI matrix instead of the correlation matrix ($\boldsymbol{\Gamma}$) in steps (3–6) of PCA technique in “Appendix B” to calculate r standardised PCs, denoted by $\boldsymbol{F}_t$ (see Eq. (6) in “Appendix B”). Note here that the vector variable $\boldsymbol{C}_i$ is standardised using Eq. (9) to obtain the PCs, while in PCA we use another standardisation method (see Eq. (3) in “Appendix B”).

In the GPCA procedure, the following properties exist:

i. $\mathrm{GVar}(\boldsymbol{D}_i) = 1$,

ii. $\mathrm{GVar}(\boldsymbol{F}_t) = 1$,

iii. $\mathrm{GCorr}(\boldsymbol{F}_t, \boldsymbol{D}_i) = \lambda_t^{1/2} v_{ti}$,

iv. $\mathrm{GCorr}(\boldsymbol{F}_t, \boldsymbol{F}_q) = 0; t, q = 1, \dots, r$,

where $\mathrm{GVar}(\cdot)$ and $\mathrm{GCorr}(x, y)$ present the grey variance and grey correlation coefficient of x and y variables, respectively. The more detailed formulations can be found in Tung and Lee (2010).

It is worthwhile to point out that the min–max standardisation technique in Step (1) is able to improve the discrimination power of γ_{iq} values because it directly projects the values of variables on $\boldsymbol{D}_i^0$ and $\boldsymbol{D}_q^0$. However, the effect of using other standardisation techniques in our GPCA-DEA method could be left as a further research topic.

Appendix D

Proof Since the eigenvector $\boldsymbol{V}_t(t = 1, \cdots, r)$ is unit, i.e., $\sum_{i=1}^{p} (v_{ti})^2 = 1$, it is concluded that $-1 \le v_{ti} \le +1$. Hence $-\lambda_t^{1/2} \le \lambda_t^{1/2} v_{ti} \le \lambda_t^{1/2}$, i.e., $-\lambda_t^{1/2} \le \mathrm{GCorr}\left(\boldsymbol{F}_t, \boldsymbol{D}_i\right) \le \lambda_t^{1/2}$.

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