2019

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ARTICLE INFO

Keywords:

Supplier selection
Sustainability
Risk
Type-2 fuzzy sets
VIKOR
DEA

ABSTRACT

Supplier selection is a multi-faceted strategic decision but there is no research that considers factors like sustainability and risk, simultaneously. Moreover, when selection criteria are subjective and require decision makers' judgment, and each candidate supplier dominates a separate selection criterion, the decision-making process becomes more complex and traditional DEA models cannot differentiate between potential candidates. In this paper, we propose a multi-method approach based on quantitative empirical investigations, and analytical modeling. We utilize interval type-2 fuzzy sets to quantify decision makers' inputs and propose an extended super-efficiency DEA model, which includes both desirable and undesirable inputs and outputs to evaluate suppliers. This approach simultaneously incorporates sustainability and suppliers' risk factors into the supplier selection problem. The model is developed for both risk-neutral and risk-averse decision-makers. The efficiency and applicability of the proposed framework is demonstrated through a real case. Results show that considering sustainability criteria or risk factors separately results in inappropriate decisions.

1. Introduction

Finding eligible suppliers with which one can form long-lasting, deep relationships is a strategic problem. A firms' competitiveness highly depends on its suppliers increasing the strategic role they play in the supply chain (SC) (Narasimhan and Talluri, 2009). Therefore, supplier selection and evaluation is pivotal to managing and developing an effective, and efficient supply chain (Wu and Blackhurst, 2009). Organizations need structured and well-developed methods to evaluate candidate suppliers. Taking into account the various sources of complexity in SCs, achieving the right path of analysis with a sound framework is not a trivial task. This paper proposes one such framework that is rigorous and unbiased.

SCs are prone to various sources of uncertainty (e.g. supply disruptions, political instability, natural disasters, etc.) (Chopra and Sodhi, 2012; Torabi et al., 2015; Fahimnia et al., 2015b). In a tightly connected network, a small supply disruption can ripple along the whole supply chain leading to significant losses. While most studies in the literature focus on cost-based competition (Baskaran et al., 2012) some argue that an emphasis on just minimizing supply chain costs can make that chain more fragile and susceptible to risks (Madadi et al., 2014). This paradox highlights the need for considering the problem not only based on a risk-neutral approach, which aims to minimize costs to

achieve competitiveness, but also ponder it under a risk-averse policy.

There is also an emerging consensus amongst researchers and practitioners that SCs need to shift their focus from merely considering internal criteria (such as quality and cost) to include broader, social and environmental dimensions of sustainability (Nematollahi et al., 2017; Chen et al., 2017). Economic benefit and social corporate responsibility in supply chain management (SCM) can be achieved through proactive sustainability (Lin and Tseng, 2016). Sustainability cannot be attained when a focal firm behaves isolated from the other members of the supply chain. Buyers should then select suppliers by applying three - often contrasting - dimensions of sustainability (i.e. social, environmental and economic) and find the right balance between sustainability and other relevant factors. This task is nontrivial and not having adequate knowledge about suppliers' production environment, processes and capabilities, purchasing managers may show bias towards one dimension (e.g. cost) and may be inclined to select an otherwise unqualified supplier (Jiang, 2009).

According to the resource-based view of the firm, a supply base with resources and capabilities that could support the focal company's sustainability efforts could actually become a competitive advantage for the focal firm (Barney, 1991). Selecting capable suppliers for strategic long-term relationships can lead to competitive advantage for the focal company (Chen and Wu, 2013; Talluri and Narasimhan, 2004).

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However, the role of core competencies of suppliers in the supplier selection problem has not been properly studied (Houshmandi et al., 2013).

Supplier selection may have side-effects like complexity and fragmentation (Awasthi et al., 2018), which can lead to unsustainable production in the supply side (Fahimnia et al., 2015a,b). Sustainable sourcing practices suggest purchasing from and outsourcing to sustainable suppliers only (Fahimnia and Jabbarzadeh, 2016). The most sustainable suppliers, however, may not necessarily be the best performing suppliers. Other factors such as supplier risk should also be considered.

Without using a structured supplier risk assessment method, supplier sustainability can only be achieved randomly, which may result in adverse effects on corporate reputation (Foerstl et al., 2010). Previous studies did not integrate different dimensions of sustainability with supply chain risks (Chopra and Sodhi, 2012). In fact, current risk management structures neglect how sustainability issues are materialized as risk in the supply chain (Hofmann et al., 2014). Moreover, sustainable supplier selection literature does not properly consider supplier risks in real-world applications (Azadnia et al., 2015; Vahidi et al., 2018). This gap has been noted as one of the prevalent limitations in the sustainable supplier selection and risk management research (Govindan et al., 2013b). To the best of our knowledge, the recent studies of Awasthi et al. (2018) and Vahidi et al. (2018) are the only ones that considered sustainability and risk factors for sustainable supplier selection but treated risk and sustainability criteria as independent factors. We believe that risk factors are the outcome of the supplier selection decisions, so, it is unrealistic to treat sustainability criteria and risk factors in the same way. Furthermore, it is inappropriate to assume all sustainability criteria and risk factors as independent due to the uncertainty of the operations environment. This makes the problem really complex and intertwined. We propose that risk and sustainability criteria are correlated concepts. Our study aims to close this research gap by considering sustainability and risk factors in supplier selection, simultaneously. Unlike common applied methods in the literature, instead of concentrating on a single risk attitude or adding a risk factor to the equation, the proposed method in this study provides a more holistic view for DMs, having both a risk-averse attitude in the first step and a risk-neutral attitude in the second step, that common decision methods often lack the capability to bring such insights for managers.

The following research questions motivate and guide our study. First, what does a proper sustainable supplier selection process look like considering the potential risks in an uncertain environment? Second, if in a competitive market each firm must have at least one core competency to survive, then how would one determine the most suitable suppliers based on their strategic capabilities? To answer the above questions, this paper develops a decision-making framework that integrates the risks associated with the sustainable supplier selection problem with the suppliers' core competencies. Our main contribution lies in the integration of selection criteria, namely the intersection of sustainability, risk and suppliers' core competencies.

To tackle the strategic supplier selection problem under sustainability and risk criteria, we develop a multi-method approach that jointly employs direct observations, empirical surveys, and analytical modeling techniques. First, we ask experts to rate suppliers based on the three dimensions of sustainability and identify potential suppliers that are the best in each of these dimensions based on their core competencies. Then, using a fuzzified version of VIKOR (a multi-criteria decision-making method developed to handle conflicting criteria), we rank the candidate suppliers in terms of risk. For the final step of selecting the right suppliers, we develop an extension for the super-efficiency DEA model in which the sustainability criteria act as inputs while the risk measure is an output.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature and identifies research gaps. Section 3 presents the

proposed methodology, which includes a description of the basic concepts of Interval Type-2 Fuzzy Sets (IT2FSs) and Tra-IT2F VIKOR, and the proposed super-efficiency DEA model. Section 4 discusses an illustrative case application. Section 5 provides the numerical results and sensitivity analyses, which is followed by a discussion of managerial implications in Section 6. Finally, Section 7 provides concluding remarks and directions for future research.

2. Literature review

There is a large and growing body of literature on the supplier selection problem (Ghadimi et al., 2016; Govindan et al., 2013b; Karsak and Dursun, 2016). Unlike most prior studies that typically applied a single tool for supplier selection, hybrid methods have been gaining popularity (Blackhurst et al., 2008). Since the techniques and approaches for supplier selection are very broad, we mainly focus on the decision-making techniques more relevant to this study. The literature presented in this paper relates to three streams of previous research: sustainable supplier selection, supplier risk management, and supplier performance evaluation using DEA. In the following sections, we provide a concise review of these three strands and ascertain the research gaps that motivate our research.

2.1. Sustainable supplier selection

The synthesis of economic, environmental and social development is frequently interpreted as sustainability and sustainable development, which is also known as the triple-bottom-line approach (Bai and Sarkis, 2010; Dai and Blackhurst, 2012). Monitoring of sustainability in SCM encompasses self-managed activities such as specifying supplier selection criteria, gathering information related to the candidate suppliers, and assessment of the environmental and social performances of incoming goods as well as suppliers' operations (Gualandris et al., 2015). In other words, supplier selection and purchasing are ways to reach sustainability goals, not only for the focal company but also for the entire supply chain.

The challenge for integrating environmental and social issues with the economic aspect of SCM has been receiving increased attention (Gualandris et al., 2015). Awasthi et al. (2018) proposed a model for global supplier selection assessing the sustainability of suppliers and their sub-suppliers simultaneously. Amindoust et al. (2012) developed a model for evaluating and ranking a set of suppliers according to some sustainability criteria and their sub-criteria concurrently. Ghadimi et al. (2018) applied a multi-agent system for sustainable supplier selection, which facilitates communications and structured information exchange between all members of the supply chain. Recent reviews on sustainable supplier selection models report that economic and environmental dimensions of sustainability are highlighted more than the social dimension (Zimmer et al., 2015; Azadnia et al., 2015). Goebel et al. (2012) found that the majority of previous research on sustainable supplier selection focused on one aspect of sustainability and rarely considered multiple dimensions simultaneously.

2.2. Supplier risk assessment and mitigation

The origin of many supply chain risks stems from the supplier selection problem. However, literature lacks adequate integrated approaches for the quantification of risk variants (Fang et al., 2015). Supplier risk evaluation is imperative to reduce the uncertainty in supply, and purchasing managers should construct an effective assessment system for this purpose (Tang, 2006). A comprehensive literature review on sourcing strategies and supplier risk assessment in SCs is provided by Hamdi et al. (2018).

Supply chain risk management literature classifies risks into two broad classes: operational and disruption risks (Torabi et al., 2015). According to Tang (2006), any threat or event which may cause a major

Table 1
Classification of sustainable supplier selection and risk assessment approaches.

References	Solution approaches and tools	Research case area	Sustainability aspects			Uncertainty mitigation approach			Scope and description
			Economic	Environmental	Social	Fuzzy	Stochastic	Others	
Blackhurst et al. (2008)	MCSP	Automotive industry	✓						Measuring, tracking, and analyzing supplier and part specific risk over time
Wu & Blackhurst (2009)	DEA	Aviation industry	✓						Evaluating and selecting supplier
Azadeh & Alem (2010)	DEA, Simulation	Illustrative example	✓	✓		✓	✓		Supplier selection under uncertainty
Bai & Sarkis (2010)	Rough set and grey system	Illustrative example	✓		✓			✓	Evaluation of the supplier selection decision with the recommendation of using sustainability factors
Amindoust et al. (2012)	FIS	Illustrative example	✓	✓	✓	✓			Sustainable supplier selection
Goebel et al. (2012)	Survey and structural modeling	Mixed		✓	✓				Relationship between ethical culture and sustainable supplier selection
Dai & Blackhurst (2012)	AHP-QFD	Retail industry	✓	✓	✓				Determining the sustainable purchasing competitive priority, developing sustainable supplier assessment
Baskaran et al. (2012)	Grey approach	Textile industry		✓	✓			✓	Suppliers sustainability evaluation
Sun et al. (2012)	MP	Automotive industry	✓						Supply chain coordination, supplier risk management
Govindan et al. (2013a)	TOPSIS	Illustrative example	✓	✓	✓	✓			Sustainable supplier selection
Ruiz-torres et al. (2013)	MP	Appliances industry	✓						Supplier selection and order allocation with contingency planning and minimizing network costs
Chen and Wu (2013)	AHP-FMEA	Semiconductor industry	✓					✓	Supplier selection and risk assessment
Silbermayr & Minner (2014)	SMDP	Illustrative example	✓				✓		The trade-off between single and multiple-sourcing, as well as keeping inventory and having a back-up supplier
Trapp & Sarkis (2014)	MP	Illustrative example		✓					Supplier selection, supplier development, and sustainability considerations simultaneously
Kumar et al. (2014)	DEA	Automotive industry	✓	✓					Supplier selection in green supply chain management
Dobos & Vörösmarty (2014)	DEA, MCDM	Illustrative example	✓	✓					Supplier selection and evaluation in non-strategic items with a focus on green issues.
Azadi et al. (2014)	DEA	Petrochemical industry	✓	✓	✓	✓			Sustainable supplier selection under uncertainty
Azadnia et al. (2015)	AHP, MODM	Food industry	✓	✓	✓	✓			Supplier selection and order allocation
Shi et al. (2014)	DEA	Appliances industry	✓	✓	✓	✓			Propose a process for sustainable supplier selection
Karsak & Dursun (2014)	DEA, QFD	Healthcare	✓	✓	✓	✓			Supplier selection under imprecise data
Sarkis & Dhavale (2015)	Bayesian framework and simulation	Illustrative example	✓	✓	✓	✓			Ranking and selection of suppliers using specific selection objectives.
Jia et al. (2015)	TOPSIS	Fashion industry	✓	✓	✓	✓			Investigating the optimal supplier selection problem for sustainable materials supply
Fang et al. (2015)	MCDM	Illustrative example	✓			✓	✓		Order allocation and risk mitigation by modeling both supply chain operational risks and disruption risks
Käkit et al. (2015)	Simulation								
	GRA								
	BN	Automotive industry	✓				✓		Assessing risks triggered by supplier disruptions in a supply network
	PRA								
Hosseininasab & Ahmadi (2015)	MCDM	Illustrative example	✓						Supplier selection based on development and the overall trend of fit to the buyer throughout time and risk consideration.
Shu et al. (2015)	MP	Retail industry	✓				✓		Developing an optimal strategy for managing procurement problem in the presence of unreliable supply and stochastic demand
Paul (2015)	FIS	Illustrative example	✓	✓	✓	✓			To develop supplier selection model for managing supply risk
Nekooie et al. (2015)	MCDM	Illustrative example	✓			✓			Supplier selection and order allocation under risks consideration.
Rajesh & Ravi (2015)	GRA, AHP, ANP	Electronic industry	✓	✓		✓		✓	Supplier selection in a resilient supply chain
Ross et al. (2016)	CCDEA	Telecommunications industry	✓	✓					Supplier performance risk, supplier segmentation, and evaluation
Mahdilo et al. (2015)	DEA, MOLP	Steel Company	✓	✓					Green supplier selection by decomposing their efficiency indicators into technical, environmental and eco-efficiency scores
Dotoli et al. (2015a)	DEA	Healthcare	✓			✓			Performance evaluation under uncertainty of suppliers in terms of efficiency
Dotoli et al. (2015b)	DEA, Simulation	Automotive industry	✓				✓		The optimal selection of suppliers under uncertainty, ranking, and multiple sourcing

(continued on next page)

Table 1 (continued)

References	Solution approaches and tools	Research case area	Sustainability aspects			Uncertainty mitigation approach			Scope and description
			Economic	Environmental	Social	Fuzzy	Stochastic	Others	

Visani et al. (2016)	DEA, TCO	Mechanical company	✓						To empirically explore the effectiveness of TCO-based DEA in approximating supplier TCO
Lintukangas et al. (2016)	Survey, Regression	Mixed	✓	✓					Mitigation of supply risk as driver of green supply chain management
Hallikas & Lintukangas (2016)	Survey, MA	Mixed							Exploring the influential risk factors in supply risk performance and determining risk drivers in purchasing

Abbreviations: Mathematical Programming (MP); Multi-Objective Decision-Making (MODM); Multi-Criteria Decision-Making (MCDM); Multi-Objective Linear Programming (MOLP); Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS); Analytical Hierarchy Process (AHP); Analytic Network Process (ANP); Fuzzy Inference System (FIS); Quality Function Deployment (QFD); Failure Mode and Effects Analysis (FMEA); Semi-Markov Decision Process (SMDP); Grey Relational Analysis (GRA); Bayesian Networks (BN); Probabilistic Risk Assessment (PRA); Multi-Criteria Scoring Procedure (MCSP); Multivariate Analysis (MA); Chance-Constraint Data Envelopment Analysis (CCDEA); Total Cost of Ownership (TCO).

disruption in the organization, such as an earthquake, flood or terror attack, are called disruption risks. On the other hand, operational risks refer to any inherent uncertainty such as uncertainty in demand, supply, and environmental data that may hinder operations. Typically, disruption risks are low-occurrence high-impact events, while operational risks have medium to high likelihood and low impact.

2.2.1. Suppliers as a source of risk

There are various definitions for supply risk. Zsidisin (2003) defined supply risk as “the potential occurrence of an incident associated with inbound supply from individual supplier failures or the supply market, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety.” Chen and Wu (2013) also view supply risk as a failure caused by suppliers. However, Ellis et al. (2010) claim that the definition by Zsidisin (2003) portrays an incomplete interpretation of supply risk. Their empirical findings lend new insight to the depiction of supply risk by highlighting the severity and magnitude of disruption risk as a major determinant along with the primary role of potential occurrence. Talluri et al. (2006) consider supply risk as the vendors' performance variability risk, which greatly affects vendor selection decisions. For retail SCs, Oke and Gopalakrishnan (2009) define sources of supply risk as events which could disrupt the products and services that a retail supply chain provides to its customers (e.g. imports, climate change, man-made and natural disasters, socio-economic issues, and loss of key suppliers).

2.2.2. Modeling risk into supplier selection

Generally, there are three approaches to model risk and uncertainty for supplier selection (Hamdi et al., 2018). The first approach employs fuzzy sets theory to incorporate inherent uncertainty to the decision model (Azadnia et al., 2015; Govindan et al., 2013a; Paul, 2015; Vahidi et al., 2018). Combined models of fuzzy multi-criteria decision making (MCDM) benefiting from the advantages and capabilities of different methods are very common in the supplier selection literature (Azadnia et al., 2015; Govindan et al., 2013a; Ju and Wang, 2013). Second most common modeling approach is scenario-based modeling, which welcomes randomness and utilizes stochastic problem parameters (Scott et al., 2015; Xanthopoulos et al., 2012; Vahidi et al., 2018). Finally, the third approach is using quantitative risk measures including the value at risk (VaR) and conditional value at risk (CVaR) (Fang et al., 2015; Sawik, 2013, 2014).

Table 1 presents the results of our literature review. It is clear that the main strand of the literature has been MCDM techniques, especially AHP (Azadnia et al., 2015; Dai and Blackhurst, 2012; Rajesh and Ravi, 2015) to deal with risk, followed by Mathematical Programming (MP) (Sun et al., 2012; Trapp and Sarkis, 2014) and FMEA (Chen and Wu, 2013). Fuzzy programming is also a common method to handle uncertain input data (Nekooie et al., 2015; Paul, 2015). Stochastic programming (Silbermayr and Minner, 2014), grey theory (Rajesh and Ravi, 2015), bootstrapping (Io Storto, 2013), chance-constrained DEA (Azadeh and Alem, 2010), and Monte Carlo simulation (Dotoli et al., 2015b) are other methodologies that have been utilized to cope with uncertainty in supplier selection.

2.3. Application of DEA in supplier selection

Due to its potential in dealing with conflicting criteria without the need of a decision-maker's intuitive judgment and preferences about the inputs and outputs, DEA has become one of the most popular decision-making tools for supplier selection. DEA's robustness and flexibility are key factors for its extensive use in supplier selection and supply risk management (Kumar et al., 2014). For a comprehensive description of the DEA method, we refer the reader to Section 4.3.

Research is abundant in various aspects of supplier selection and performance evaluation using DEA. Dyson and Shale (2010)

categorized four main classes of DEA models under uncertainty. Supplier performance evaluation under imprecise DEA, addressed by Toloo (2014), predominates research using interval or fuzzy numbers. In general, the first premise of DEA in supplier selection is performance evaluation and distinguishing efficient and inefficient suppliers through a simple segmentation (Dotoli et al., 2015a, 2015b; Wu and Blackhurst, 2009). The second premise is the consideration of uncertainty and risk in suppliers' inputs or outputs (Azadi et al., 2014; Karsak and Dursun, 2014).

Previous studies have accounted for desirable inputs and outputs in their models. However, although DEA researchers allowed outputs to be desirable or undesirable, when it comes to inputs only desirable inputs were included in DEA models (Mahdiloo et al., 2015; Motevali Haghighi et al., 2016). Our research contributes to the DEA literature by ranking efficient suppliers with both, desirable and undesirable inputs because some real-world problems include what could be considered undesirable inputs.

2.4. Research gaps and our contributions

The literature lacks an integrated multi-methodological perspective for both sustainable supplier selection and supply risk management. This study attempts to bring together the two fields by proposing a unified analytical framework for the supplier selection problem under sustainability and risk. Moreover, supplier selection models in the literature generally assume that purchasing managers are risk-neutral, and therefore prefer to find opportunities for optimizing expected profit or cost. Risk-averse decision-makers (DMs) on the other hand, prefer to minimize risk and consider the implications of their decisions.

Our multi-method approach benefits from Interval Type-2 Fuzzy Set (IT2FS) VIKOR for the assessment of suppliers' risks and proposes an extended super-efficiency DEA model which includes both, desirable and undesirable inputs and outputs simultaneously, to rank candidate suppliers. We focus more on the total value of reliable purchases rather than following the conventional approach of minimizing total purchasing cost. The area covered in this research is depicted in Fig. 1.

Our literature review also showed that the majority of papers in this area applied their models only on theoretical examples rather than real-world instances (Dobos and Vörösmarty, 2014; Trapp and Sarkis, 2014; Nekooie et al., 2015). Specifically, almost all of the studies which considered all three facets of sustainability simultaneously, have only utilized hypothetical examples rather than real-case applications (Bai and Sarkis, 2010; Amindoust et al., 2012; Govindan et al., 2013a; Sarkis

and Dhavale, 2015). In this study, we use a real-case scenario from Iran to demonstrate the applicability of the proposed selection method in practice.

3. Proposed framework

Examining a phenomenon from two or more perspectives and within a broader domain can reveal much more reliable findings compared to using just one perspective or a narrow domain (Singhal and Singhal, 2012). Multi-perspective research in Operations Management (OM), and using qualitative exploratory research methods (e.g. interviews and case studies) along with quantitative methods and theory development, can bring about the creation of the “science” of OM (Choi et al., 2016). In this paper, we conduct a two-step research design: (1) qualitative empirical investigations, and (2) analytical modeling. We now explain these steps in more detail.

Step 1: To collect the qualitative data, semi-structured interviews are conducted with purchasing managers who are the DMs in our context. They are asked about the diversity of supplier risks as well as the sustainability criteria they use in their purchasing practices. Next, exhaustive lists of sustainability criteria and risk factors gathered from the literature are revealed to the DMs to allow them to revise their preferences, if deemed necessary. Then the purchasing managers are asked to describe what they understand from each of the sustainability criterion and risk factor. We do this to check the consistency between their descriptions and those explained in the literature. In addition, external validity is also checked by asking the same questions to another set of decision makers. The qualitative data collected are then quantified. This quantification process is explained in detail in Section 5.

Step 2: The analytical model is developed in two ways:

2a. For a *risk-averse* DM, we first apply Interval Type-2 Fuzzy Sets (IT2FSs) to handle vague and imperfect information and overcome the ambiguity around the risk profile of suppliers. We interpret the DM's intuitive judgment into crisp numbers using IT2FSs. These numbers are fed as inputs into VIKOR. VIKOR is a well-known multi-attribute decision-making (MADM) tool to rank a number of candidates while considering various criteria (here risk-related factors). **2b.** For a *risk-neutral* DM, we use an extended super-efficiency DEA model to evaluate candidate suppliers. We introduce the sustainability criteria obtained from Step 1 as inputs and the risk measures of each supplier retrieved from Step 2a as outputs of the DEA model. A schematic overview of the proposed methodology is depicted in Fig. 2. Next, we explain the analytical processes involved in each of the above steps in detail.

3.1. Interval type-2 fuzzy sets (IT2FS)

The concept of classical fuzzy sets, also known as “type-1 fuzzy sets” was introduced by Zadeh (1965). Type-1 fuzzy sets yield a membership value that is a real crisp in the interval [0,1]. Although interval type-1 fuzzy sets (IT1FSs) are an efficient tool to deal with subjective uncertainty and have been applied to various disciplines, determining the exact membership value of an object to the universe of discourse is rarely possible (Torshizi et al., 2015). To overcome this shortcoming of type-1 fuzzy sets, type-2 fuzzy sets provide a measure of dispersion to better capture the inherent uncertainty (Mendel, 2007). Therefore, type-2 fuzzy sets are arguably more capable than type-1 when dealing with the intuitive judgment of a DM especially when making a strategic decision such as supplier selection. In this section, we briefly review relevant definitions and operations of trapezoidal interval type-2 fuzzy sets (Tra-IT2FS) (Chen et al., 2012; Mendel et al., 2006):

Definition 1. A type-2 fuzzy set A in the universe of discourse X can be

Fig. 1. The area of this research.

Fig. 2. A schematic overview of the proposed methodology.

represented by a membership function μ_A , shown as follows:

$$A = \{((x, u), \mu_A(x, u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1], 0 \leq \mu_A(x, u) \leq 1\} \quad (1)$$

where J_x denotes an interval $[0,1]$. The type-2 fuzzy set A also can be represented as follows:

$$A = \int_{x \in X} \int_{u \in J_x} \frac{\mu_A(x, u)}{(x, u)} \quad (2)$$

where $J_x \subseteq [0,1]$ and $\int \int$ denotes union over all admissible x and u .

Definition 2. Let A be a type-2 fuzzy set in the universe of discourse X represented by the type-2 membership function μ_A . If all $\mu_A(x, u) = 1$, then A is called as interval type-2 fuzzy set (IT2FS). An IT2FS A can be considered a special case of a type-2 fuzzy set, represented as follows:

$$A = \int_{x \in X} \int_{u \in J_x} \frac{1}{(x, u)}, \text{ where } J_x \subseteq [0,1] \quad (3)$$

A Tra-IT2FS is shown in Fig. 3. The upper membership function (UMF) and the lower membership function (LMF) of an IT2FS are type-1 membership functions, respectively. The bounded region between the UMF and the LMF is called the footprint of uncertainty (FOU). Next, we explain the arithmetic operations between two Tra-IT2FSs. Let A_1 and A_2 be two Tra-IT2FSs described as follows:

Fig. 3. A trapezoidal interval Type-2 fuzzy set A .

$$\begin{aligned} A_1 &= (A_1^U, A_1^L) \\ &= ((a_{11}^u, a_{12}^u, a_{13}^u, a_{14}^u; H_1(A_1^U), H_2(A_1^U)), \\ &\quad (a_{11}^l, a_{12}^l, a_{13}^l, a_{14}^l; H_1(A_1^L), H_2(A_1^L))) \end{aligned} \quad (4)$$

$$\begin{aligned} A_2 &= (A_2^U, A_2^L) \\ &= ((a_{21}^u, a_{22}^u, a_{23}^u, a_{24}^u; H_1(A_2^U), H_2(A_2^U)), \\ &\quad (a_{21}^l, a_{22}^l, a_{23}^l, a_{24}^l; H_1(A_2^L), H_2(A_2^L))) \end{aligned} \quad (5)$$

Definition 3. The addition operation between A_1 and A_2 is defined as follows:

$$\begin{aligned} A_1 + A_2 &= (A_1^U, A_1^L) + (A_2^U, A_2^L) \\ &= ((a_{11}^u + a_{21}^u, a_{12}^u + a_{22}^u, a_{13}^u + a_{23}^u, a_{14}^u + a_{24}^u); \\ &\min(H_1(A_1^U), H_1(A_2^U)), \min(H_2(A_1^U), H_2(A_2^U))), (a_{11}^L + a_{21}^L, a_{12}^L + a_{22}^L, a_{13}^L \\ &+ a_{23}^L, a_{14}^L + a_{24}^L); \\ &\min(H_1(A_1^L), H_1(A_2^L)), \min(H_2(A_1^L), H_2(A_2^L))). \end{aligned} \quad (6)$$

Definition 4. The subtraction operation between A_1 and A_2 is defined as follows:

$$\begin{aligned} A_1 - A_2 &= (A_1^U, A_1^L) - (A_2^U, A_2^L) \\ &= ((a_{11}^u - a_{21}^u, a_{12}^u - a_{22}^u, a_{13}^u - a_{23}^u, a_{14}^u - a_{24}^u); \\ &\min(H_1(A_1^U), H_1(A_2^U)), \min(H_2(A_1^U), H_2(A_2^U))), (a_{11}^L \\ &- a_{21}^L, a_{12}^L - a_{22}^L, a_{13}^L - a_{23}^L, a_{14}^L - a_{24}^L); \\ &\min(H_1(A_1^L), H_1(A_2^L)), \min(H_2(A_1^L), H_2(A_2^L))). \end{aligned} \quad (7)$$

Definition 5. The multiplication operation between A_1 and A_2 is defined as follows:

$$\begin{aligned} A_1 \otimes A_2 &= (A_1^U, A_1^L) \otimes (A_2^U, A_2^L) \\ &= ((a_{11}^u \times a_{21}^u, a_{12}^u \times a_{22}^u, a_{13}^u \times a_{23}^u, a_{14}^u \times a_{24}^u); \\ &\min(H_1(A_1^U), H_1(A_2^U)), \min(H_2(A_1^U), H_2(A_2^U))), (a_{11}^L \\ &\times a_{21}^L, a_{12}^L \times a_{22}^L, a_{13}^L \times a_{23}^L, a_{14}^L \times a_{24}^L); \\ &\min(H_1(A_1^L), H_1(A_2^L)), \min(H_2(A_1^L), H_2(A_2^L))). \end{aligned} \quad (8)$$

Definition 6. The multiplication operation between A_1 and a real number k is defined as follows:

$$\begin{aligned} k \times A_1 &= k \times (A_1^U, A_1^L) \\ &= ((k \times a_{11}^u, k \times a_{12}^u, k \times a_{13}^u, k \times a_{14}^u; H_1(A_1^U), H_2(A_1^U)), \\ &(k \times a_{11}^L, k \times a_{12}^L, k \times a_{13}^L, k \times a_{14}^L; H_1(A_1^L), H_2(A_1^L))) \end{aligned} \quad (9)$$

Definition 7. The ranking value of A_1 is defined as (Kahraman et al., 2014):

$$\begin{aligned} \text{Rank}(A_1) &= \frac{1}{2} \times \left(\frac{(a_{14}^u - a_{11}^u) + (H_1(A_1^U) \times a_{12}^u - a_{11}^u) + (H_2(A_1^U) \times a_{13}^u - a_{11}^u)}{4} + a_{11}^u \right. \\ &\left. + \frac{(a_{14}^L - a_{11}^L) + (H_1(A_1^L) \times a_{12}^L - a_{11}^L) + (H_2(A_1^L) \times a_{13}^L - a_{11}^L)}{4} + a_{11}^L \right). \end{aligned} \quad (10)$$

3.2. Interval type-2 fuzzy VIKOR methodology

VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje, in Serbian) method was introduced by Opricovic (1998) to deal with MCDM problems in complex systems. This method strives to rank and select from a set of alternatives and determines a compromise solution under the presence of some conflicting criteria (Opricovic and Tzeng, 2004). The compromise solution is a feasible solution closest to the ideal solution, where the word compromise refers to mutual concessions. This compromise solution makes a ranking index based on the proximity to the ideal solution. According to Opricovic and Tzeng (2007), the advantage of multi-criteria analysis with compromise ranking is based on the L_p -metric concept applied in compromise programming (Zeleny and Cochrane, 1973).

Suppose that in a group MCDM problem there exist K decision-makers DM_k ($k=1, 2, \dots, K$), m alternatives A_i ($i=1, 2, \dots, m$), and n decision criteria C_j ($j=1, 2, \dots, n$). Each alternative is assessed with respect to these n criteria. In addition, the fuzzy rating x_{ij}^k of each DM and the importance weight w_j^k of each criterion can be represented as a positive Tra-IT2FS. In this section, we propose a new IT2F-VIKOR and present the algorithm step-by-step:

Step 1. Construct the decision matrix Y_k of the k th DM, where $1 \leq k \leq K$ and the average decision matrix $\bar{Y}$ as shown below:

$$Y_k = (x_{ij}^k)_{m \times n} = \begin{bmatrix} x_{11}^k & x_{12}^k & \dots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \dots & x_{2n}^k \\ \vdots & \vdots & \dots & \vdots \\ x_{m1}^k & x_{m2}^k & \dots & x_{mn}^k \end{bmatrix} \text{ and } \bar{Y} = (x_{ij})_{m \times n} \quad (11)$$

where $x_{ij} = (\frac{x_{ij}^1 \oplus x_{ij}^2 \oplus \dots \oplus x_{ij}^K}{K})$, $1 \leq i \leq m$, $1 \leq j \leq n$ and K shows the number of DMs. It is obvious that x_{ij} is a Tra-IT2FS.

Step 2. Construct the weighting matrix W_k of the k th DM against each criterion where $1 \leq k \leq K$ and the average weighting matrix $\bar{W}$ as shown below:

$$W_k = (w_j^k)_{1 \times n} = [w_1^k \ w_2^k \ \dots \ w_n^k] \text{ and } \bar{W} = (w_j)_{1 \times n} \quad (12)$$

where $w_j = (\frac{w_j^1 \oplus w_j^2 \oplus \dots \oplus w_j^K}{K})$, $1 \leq j \leq n$, and K shows the number of DMs. In addition, w_j is a Tra-IT2FS.

Step 3. Construct the weighted decision matrix by multiplying the importance weight of each evaluation criteria with its rating in the decision matrix:

$$\bar{Y}_w = (f_{ij})_{m \times n} = \begin{bmatrix} A_1 & f_{11} & f_{12} & \dots & f_{1n} \\ A_2 & f_{21} & f_{22} & \dots & f_{2n} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ A_m & f_{m1} & f_{m2} & \dots & f_{mn} \end{bmatrix} \quad (13)$$

where $f_{ij} = x_{ij} \otimes w_j$, $1 \leq i \leq m$, $1 \leq j \leq n$ and f_{ij} represents a Tra-IT2FS.

Step 4. Specify the best (f_j^*) and the worst (f_j^-) rating values of alternatives with respect to each criterion as described below:

$$f_j^* = \begin{cases} \max\{\text{Rank}(f_{ij})\} & \text{if } C_j \in F_1 \\ 1 \leq i \leq m \end{cases} \quad (14)$$

$$f_j^- = \begin{cases} \min\{\text{Rank}(f_{ij})\} & \text{if } C_j \in F_1 \\ 1 \leq i \leq m \end{cases} \quad (15)$$

where F_1 denotes the set of benefit attributes (the higher the better), F_2 denotes the set of cost attributes (the lower the better), and $1 \leq j \leq n$.

Step 5. Compute the values of utility index S_i and regret index R_i , using the following relations:

$$S_i = \sum_{j=1}^n \text{Rank}(w_j) \frac{(f_j^* - \text{Rank}(f_{ij}))}{(f_j^* - f_j^-)}, \quad i = 1, 2, \dots, m \quad (16)$$

$$R_i = \max_j \{\text{Rank}(w_j) \frac{(f_j^* - \text{Rank}(f_{ij}))}{(f_j^* - f_j^-)}\}, \quad i = 1, 2, \dots, m \quad (17)$$

Step 6. Compute the risk value of Q_i as described below:

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*}, \quad i = 1, 2, \dots, m \quad (18)$$

where $S^* = \min_i S_i$, $S^- = \max_i S_i$, $R^* = \min_i R_i$, $R^- = \max_i R_i$ and v is the weight of the strategy of maximum group utility, whereas $1 - v$ denotes the weight of the individual regret. In this study we use $v = 0.5$.

Step 7. Rank the alternatives by sorting the values of S , R and Q , in descending order, to obtain three ranking lists. The alternative with the minimum Q value is selected as the best alternative.

Step 8. The alternative $A^{(1)}$ is ranked the best by measure Q if the following two conditions are satisfied:

Condition 1. Acceptance advantage; where $A^{(2)}$ is the alternative with the second position in the ranking list by Q , and m is the number of alternatives.

$$Q(A^{(2)}) - Q(A^{(1)}) \geq \frac{1}{m-1} \quad (19)$$

Condition 2. Acceptable stability in the decision making; Alternative $A^{(1)}$ should also have the best rank by S and/or R . This compromise solution is stable regardless of the decision-making process (i.e. voting by majority rule when $v > 0.5$, or by consensus with $v \approx 0.5$, or even when $v < 0.5$).

Otherwise, if one of these two conditions is not satisfied, then a set of compromise solutions is proposed: If only Condition 2 is not satisfied the compromise solution consists of alternatives $A^{(1)}$ and $A^{(2)}$. If Condition 1 is not satisfied then the compromise solution includes all alternatives $A^{(1)}$, $A^{(2)}$, ..., $A^{(m)}$. Also, $A^{(m)}$ is determined by $Q(A^{(m)}) - Q(A^{(1)}) \geq \frac{1}{m-1}$ for maximum m (the positions of these alternatives are in closeness).

3.3. Data envelopment analysis

Initially, DEA, a nonparametric mathematical programming technique was introduced by Charnes et al. (1978) to measure the efficiency of similar Decision Making Units (DMUs). The basic DEA model is applied to evaluate the relative efficiency of DMUs in the presence of multiple inputs and outputs (Adler et al., 2002). The relative efficiency of each DMU can be obtained through the ratio of its total weighted outputs to its total weighted inputs. DEA assigns the best possible weights to each input and output of individual DMUs in order to maximize the DMUs efficiency subject to existing constraints. A DMU with an efficiency score equal to 1 is deemed an efficient DMU, while DMUs with efficiency scores less than 1 are deemed inefficient.

Although DEA is an efficient technique for ranking DMUs, it has been shown that basic DEA models could lack discrimination capability for supplier selection problems (Braglia and Petroni, 2000). This problem is exacerbated when a small number of suppliers are compared or the number of inputs and outputs (criteria) is large. The super-efficiency variant of DEA which was first introduced by Andersen and Petersen (1993) and reviewed by Adler et al. (2002), provides a framework for ranking both efficient and inefficient DMUs. In the super-efficiency approach, an efficient DMU can achieve an efficiency score equal to or greater than one in a linear combination of all other DMUs.

However, Thrall (1996) indicated that the Andersen-Petersen (AP) model may cause instability and infeasibility when some input values are close to zero. Also, Adler et al. (2002) pointed out that the AP model could result in excessively high ranking for specialized DMUs. To overcome these drawbacks of the AP model, extensions to super-efficiency models have been proposed by Amirteimoori (2005) and Mehrabian (1999), each of which has its own shortcomings. One of the best extensions is the LJK model introduced by Li et al. (2007). Thus, in this research we chose the LJK model since it never results in infeasibility and instability even when some inputs are close to zero, and is superior to both, the AP model as well as the extension proposed by Mehrabian (1999). The LJK model is also simple and easy to solve compared to other models. Furthermore, unlike classic DEA models, no extra steps are needed in the LJK model for ranking efficient DMUs. Now, we explain the LJK model we used in this paper:

Assume that there are n homogenous DMUs to be evaluated, such that each DMU consumes m inputs x_{ij} ($i = 1, \dots, m$) to process s outputs y_{rj} ($r = 1, \dots, s$). The LJK model is written as follows:

$$\text{Minimize } 1 + \frac{1}{m} \sum_{i=1}^m \frac{s_{i2}^+}{R_i^-} \quad (20)$$

Subject to:

$$\sum_{j=1}^n \lambda_j x_{ij} + s_{i1}^- - s_{i2}^+ = x_{i0} \quad i = 1, \dots, m \quad (21)$$

$$\sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = y_{r0} \quad r = 1, \dots, s \quad (22)$$

$$\lambda_j, s_{i1}^-, s_{i2}^+, s_r^+ \geq 0 \quad i = 1, \dots, m; r = 1, \dots, s; j = 1, \dots, n \quad (23)$$

where R_i^- is the maximum of all inputs including the i th input of a DMU (i.e. $R_i^- = \max_j(x_{ij})$). R_i^- is always positive and j_0 is the DMU under evaluation (also shown by DMU_0). For each DMU_0 under evaluation, the objective function of LJK model minimizes the average ratio of second input slacks to the maximum input among all DMUs. The first constraint relaxes the input i of DMU_0 to increase by s_{i2}^+ or decrease by s_{i1}^- . Although both slack variables s_{i2}^+ and s_{i1}^- can be replaced by s , using free variable s leads to the dual infeasibility of the super-efficiency model. The second constraint restricts the increase in output r of DMU_0 to s_r^+ . Note that the non-negative combinations of both the first and second constraints do not include DMU_0 . In this way, efficient DMUs obtain a super-efficiency score equal or greater than 1 and inefficient DMUs yield efficiency scores less than 1.

To formulate the Production Possibility Set (PPS) for DEA models it is generally assumed that all inputs are similar in nature. However, in reality not all inputs improve efficiency in the same direction. Quality and cost are good examples. While an increase in quality increases efficiency, an increase in cost will decrease efficiency. Therefore, cost can be considered as a desirable input (less is better) while quality would be an undesirable input (more is better), and in a real scenario, it makes sense to expect some desirable and undesirable inputs to appear in the same model (Liu et al., 2010). The LJK model requires a further extension to be able to deal with both desirable and undesirable inputs and outputs simultaneously. The extended LJK model is presented below:

$$\text{Minimize } 1 + \frac{1}{m} \left(\sum_{i \in I_D} \frac{s_{i2}^+}{R_i^-} + \sum_{i \in I_U} \frac{s_{i2}^+}{R_i^-} \right) \quad (24)$$

Subject to:

$$\sum_{j=1}^n \lambda_j x_{ij} + s_{i1}^- - s_{i2}^+ = x_{i0}^D \quad i \in I_D \quad (25)$$

$$\sum_{j=1}^n \lambda_j (-x_{ij} + w_i) + s_{i1}^- - s_{i2}^+ = -x_{i0}^U + w_i \quad i \in I_U \quad (26)$$

$$\sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = y_{r0}^U \quad r \in O_D \quad (27)$$

$$\sum_{j=1}^n \lambda_j (-y_{rj} + w_r) - s_r^+ = -y_{r0}^U + w_r \quad r \in O_U \quad (28)$$

$$\lambda_j, s_{i1}^-, s_{i2}^+, s_r^+ \geq 0 \quad i = 1, \dots, m; r = 1, \dots, s; j = 1, \dots, n \quad (29)$$

where I_D , O_D are desirable inputs and outputs, and I_U , O_U are undesirable inputs and outputs respectively. Also $w_i = \max_j(x_{ij})$, and $w_r = \max_j(y_{rj})$.

4. Real-case application

Our empirical analysis focuses on a well-known Iranian supermarket chain, Shahrvand Goods & Servicing Company (www.shahrvand.ir). Shahrvand is arguably the most advanced supermarket chain in Iran that cares about sustainability. The company operates 35 stores in the capital city of Tehran, offering about 30,000 to 50,000 items at each store. Because they carry a large variety of products in each store, Shahrvand has a massive supply network exposing them to significant supply-side risks. Therefore, the company needs to implement a

systematic approach to evaluate its suppliers based on their risk profile while also considering the three, often-contrasting pillars of sustainability. Moreover, all of their suppliers claim that they have a core competency that gives them a competitive advantage in the marketplace. This means that each supplier has at least one criterion in which they are better than other suppliers.

To assist Shahrvand's procurement department in selecting reliable and sustainable suppliers while reducing Shahrvand's risk exposure, we conducted interviews with Shahrvand's procurement experts. The process of obtaining information through semi-structured interviews is illustrated in the schematic view of the research in Fig. 2. The experts were first asked to identify the sustainability criteria and risk factors in the Iranian retail sector. They were then shown a list of sustainability criteria and risk factors identified from the literature to allow them to revise their preferences if they so desire. The experts were also asked to define each criteria they have selected. Their definitions were compared to the definitions in the literature to check the validity of their answers. When discrepancies were found we revealed them to the interviewees and through iterative discussions we were able to reach to a common understanding for each criterion. The list and descriptions of risk factors and sustainability criteria obtained from the interviews as well as the references to corresponding literature are provided in Tables 2 and 6, respectively. Supplier risk factors are the potential for losses due to failures of suppliers in the future while the sustainability criteria refer to qualitative and quantitative criteria applied to assess opportunities and challenges deriving from economic, environmental and social dimensions. These are quite different concepts. For example, the quality of a product purchased from a supplier can be "Good", but the risk of quality for that supplier can be "High" or "Very Low".

Since the share of meat products is a significant part of food spend at Shahrvand, we considered the suppliers of meat products for our illustrative case. Meat is highly perishable and becomes worthless at expiration. Also, sustainable meat production is an important issue since meat products are among the most energy-intensive, ecologically burdensome, and ethically concerned foods (Dagevos and Voordouw, 2013). Livestock sector is one of the largest sources of greenhouse gases' emissions, a major stressor on many ecosystems, one of the main reasons of loss of biodiversity, and maybe the leading source of water pollution in the developed and developing countries (Steinfeld et al., 2006). All these factors highlight the strategic importance of sustainable meat production.

Table 2
Risk factors and their descriptions.

No.	Risk Factor	Description	Applied references
1	Quality	The desired product qualification ratio or the product rejection rate. It is deemed that low level of product quality can adversely affect the reputation of a company.	Chen and Wu (2013); Xiao et al. (2012)
2	Cost	It includes the sources of risk related to product price fluctuations, product recall requirements by the supplier, procurement related costs and any other sources of tangible cost which caused by the supplier.	Chen and Wu (2013)
3	Long-term cooperation	It includes the risk, which exists in mutual trust and commitment to relationships, joint actions, ill structured cooperation, frequent unexpected events and not proper information sharing.	Xiao et al. (2012)
4	Bankruptcy	It includes the sources of risk, which a supplier will become insolvent and fail to meet its commitment because of its inability to payback its debt.	Valverde and Talla (2013)
5	On-time delivery	The risk of delayed-delivery due to issues like a complex network of the supply chain that postpone the timely delivery of raw materials and commodities, which ultimately leads to financial losses.	Lee (2009)
6	Supply constraints	Generally, supply constraint risk is related to limitations of the abilities of a supplier to meet its commitments. These constraints broadly include legal, political and geographical limitations.	Lee (2009)
7	Supplier's profile	The contingent risk with regard to supplier's past performance, financial status, manufacturing facilities and customer-oriented approach.	Xiao et al. (2012); Lee (2009)
8	Continuity	It includes the sources of risk related to natural disasters, man-made disruptions, geographical diversity, biological or geo-political events.	Norrman and Jonsson (2004)
9	Second-tier supplier	The second-tier supplier failure that results in the inability of the vendor to meet customer demand or jeopardizes customer life cycle and safety.	Kull and Closs (2008)
10	Contractual and opportunism	Contractual risk includes where supplier creates liability for the buyer but is financially unable to cover the damages or buyer has not adequately protected the entity against the threat of financial loss. Also, the risk of opportunism refers to the situation where supplier with regard to the legal actions strives to exploit of the contract, unilaterally.	Wathne and Heide (2000)

To consider the competitiveness of suppliers, all suppliers that had a core competency in at least one of the sustainability criteria, were chosen from a pool of 21 potential suppliers, resulting in five candidate suppliers. Each of the three purchasing managers (i.e. DMs) were asked to first rate the importance of risk factors, and then rate the five candidate suppliers for each risk factor using their own words. The DMs could apply the linguistic terms presented in Table 3 to rate each supplier based on ten risk factors: "Very Low" (VL), "Low" (L), "Medium Low" (ML), "Medium" (M), "Medium High" (MH), "High" (H), "Very High" (VH) and their corresponding IT2 FSs. Table 4 shows the assessment of each DM for each supplier and the importance of each risk factor (RF) using Tra-IT2FSs. The DMs also rated each supplier based on eight sustainability criteria using the linguistic terms shown in Table 3: "Very Poor" (VP), "Poor" (P), "Medium Poor" (MP), "Medium" (M), "Medium Good" (MG), "Good" (G), "Very Good" (VG) and their corresponding IT2 FSs. The ninth sustainability criterion, product cost was the only factor for which quantitative data was available based on the bids received from these suppliers. The DMs were not asked to assign importance weights to sustainability criteria since those are calculated by the super-efficiency DEA.

To rank suppliers based on their risk factors, we applied VIKOR to the data in Table 4 and the weighted decision matrix in Table 5. The eight-step Tra-IT2F VIKOR process described in section 3.2 was implemented to rank candidate suppliers based on risk factors and obtain their respective risk measure Q . For the risk-averse approach, however, the supplier with the minimum risk was selected. DMs ratings of suppliers based on sustainability criteria were also quantified using VIKOR. Since the applied method is group decision-making, we used the average decision matrix which is a common approach in the literature to treat deviations among DMs. Table 7 shows the quantified sustainability criteria and risk measures Q .

Since due to the "dominance concept", those suppliers that are best in at least one criterion (i.e. have a core competency) would be efficient, we used super-efficiency DEA to rank suppliers. We considered sustainability criteria as inputs and the risk measure Q as output. We treat criteria such as cost as undesirable inputs (the lower the better) while desirable inputs (the bigger the better) would be quality, technological capabilities, green design, environmental management system, environmental competencies, employee rights, stakeholder rights, and commitment to social management. The undesirable output is the risk measure Q (the lower the better).

Table 3
Linguistic terms and their corresponding interval type-2 fuzzy sets.

Linguistic terms (For risk factors)	Interval type-2 fuzzy sets	Linguistic terms (For sustainability criteria)
Very Low (VL)	((0,0,0.05; 1,1), (0,0,0.05; 0.9, 0.9))	Very Poor (VP)
Low (L)	((0,0.1, 0.1, 0.3; 1,1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9))	Poor (P)
Medium Low (ML)	((0.1, 0.3, 0.3, 0.5; 1,1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9))	Medium poor (MP)
Medium (M)	((0.3, 0.5, 0.5, 0.7; 1,1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9))	Medium (M)
Medium High (MH)	((0.5, 0.7, 0.7, 0.9; 1,1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9))	Medium Good (MG)
High (H)	((0.7, 0.9, 0.9, 1; 1,1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9))	Good (G)
Very High (VH)	((0.9, 1,1,1; 1,1), (0.95, 1,1,1; 0.9, 0.9))	Very Good (VG)

Table 4
Evaluation of suppliers and risk factors importance with respect to different risk factors.

Risk Factors	DM ₁						DM ₂						DM ₃					
	S ₁	S ₂	S ₃	S ₄	S ₅	RF	S ₁	S ₂	S ₃	S ₄	S ₅	RF	S ₁	S ₂	S ₃	S ₄	S ₅	RF
Quality	MH	L	H	VL	M	VH	H	L	MH	L	ML	H	H	ML	MH	VL	L	H
Cost	H	ML	VH	L	MH	H	MH	M	H	L	M	H	H	M	H	L	M	H
Long-term cooperation	M	M	M	M	M	H	M	ML	M	MH	M	M	M	M	VH	ML	MH	MH
Bankruptcy	ML	ML	VH	L	VH	MH	M	ML	MH	VL	MH	M	VH	L	H	L	M	ML
On-time delivery	M	M	H	VL	ML	H	MH	M	VH	L	M	M	H	ML	MH	L	MH	M
Supply constraints	H	ML	MH	MH	H	ML	H	M	ML	M	M	M	M	MH	VH	ML	H	M
Supplier's profile	VH	ML	H	VL	ML	VH	H	M	M	L	M	H	MH	M	M	ML	ML	MH
Continuity	H	M	H	M	M	H	VH	ML	MH	ML	MH	M	H	L	MH	M	M	M
Second-tier supplier	M	MH	H	M	M	ML	M	MH	VH	M	H	M	H	H	H	ML	MH	ML
Contractual and opportunism	M	M	MH	L	M	ML	H	M	H	VL	ML	M	M	ML	VH	ML	M	M

Table 5
Weighted fuzzy performance values of suppliers.

$f_{11} = ((0.49, 0.78, 0.78, 0.97; 1,1)(0.62, 0.78, 0.78, 0.87; 0.9, 0.9))$	$f_{36} = ((0.16, 0.38, 0.38, 0.61; 1,1)(0.26, 0.38, 0.38, 0.49; 0.9, 0.9))$
$f_{12} = ((0.44, 0.75, 0.75, 0.97; 1, 1)(0.59, 0.75, 0.75, 0.86; 0.9, 0.9))$	$f_{37} = ((0.30, 0.55, 0.55, 0.77; 1, 1)(0.42, 0.55, 0.55, 0.66; 0.9, 0.9))$
$f_{13} = ((0.15, 0.35, 0.35, 0.61; 1, 1)(0.24, 0.35, 0.35, 0.47; 0.9, 0.9))$	$f_{38} = ((0.25, 0.49, 0.49, 0.75; 1, 1)(0.36, 0.49, 0.49, 0.61; 0.9, 0.9))$
$f_{14} = ((0.13, 0.30, 0.30, 0.51; 1, 1)(0.21, 0.30, 0.30, 0.40; 0.9, 0.9))$	$f_{39} = ((0.13, 0.34, 0.34, 0.57; 1, 1)(0.23, 0.34, 0.34, 0.45; 0.9, 0.9))$
$f_{15} = ((0.25, 0.49, 0.49, 0.75; 1,1)(0.36, 0.49, 0.49, 0.61; 0.9, 0.9))$	$f_{310} = ((0.16, 0.38, 0.38, 0.61; 1,1)(0.26, 0.38, 0.38, 0.49; 0.9, 0.9))$
$f_{16} = ((0.13, 0.33, 0.33, 0.57; 1, 1)(0.22, 0.33, 0.33, 0.44; 0.9, 0.9))$	$f_{41} = ((0.00, 0.03, 0.03, 0.12; 1, 1)(0.01, 0.03, 0.03, 0.10; 0.9, 0.9))$
$f_{17} = ((0.44, 0.69, 0.69, 0.87; 1, 1)(0.56, 0.69, 0.69, 0.78; 0.9, 0.9))$	$f_{42} = ((0.00, 0.09, 0.09, 0.30; 1, 1)(0.04, 0.09, 0.09, 0.19; 0.9, 0.9))$
$f_{18} = ((0.33, 0.59, 0.59, 0.80; 1, 1)(0.45, 0.59, 0.59, 0.69; 0.9, 0.9))$	$f_{43} = ((0.15, 0.35, 0.35, 0.61; 1, 1)(0.24, 0.35, 0.35, 0.47; 0.9, 0.9))$
$f_{19} = ((0.07, 0.23, 0.23, 0.45; 1, 1)(0.14, 0.23, 0.23, 0.33; 0.9, 0.9))$	$f_{44} = ((0.00, 0.03, 0.03, 0.14; 1, 1)(0.01, 0.03, 0.03, 0.13; 0.9, 0.9))$
$f_{110} = ((0.10, 0.27, 0.27, 0.51; 1, 1)(0.18, 0.27, 0.27, 0.38; 0.9, 0.9))$	$f_{45} = ((0.00, 0.05, 0.05, 0.17; 1, 1)(0.02, 0.05, 0.05, 0.17; 0.9, 0.9))$
$f_{21} = ((0.03, 0.16, 0.16, 0.37; 1, 1)(0.09, 0.16, 0.16, 0.26; 0.9, 0.9))$	$f_{46} = ((0.07, 0.22, 0.22, 0.44; 1, 1)(0.13, 0.22, 0.22, 0.32; 0.9, 0.9))$
$f_{22} = ((0.16, 0.39, 0.39, 0.63; 1,1)(0.27, 0.39, 0.39, 0.51; 0.9, 0.9))$	$f_{47} = ((0.02, 0.12, 0.12, 0.30; 1, 1)(0.06, 0.12, 0.12, 0.20; 0.9, 0.9))$
$f_{23} = ((0.12, 0.30, 0.30, 0.55; 1, 1)(0.20, 0.30, 0.30, 0.42; 0.9, 0.9))$	$f_{48} = ((0.10, 0.27, 0.27, 0.51; 1, 1)(0.18, 0.27, 0.27, 0.38; 0.9, 0.9))$
$f_{24} = ((0.02, 0.12, 0.12, 0.30; 1, 1)(0.06, 0.12, 0.12, 0.20; 0.9, 0.9))$	$f_{49} = ((0.04, 0.16, 0.16, 0.36; 1, 1)(0.09, 0.16, 0.16, 0.25; 0.9, 0.9))$
$f_{25} = ((0.12, 0.30, 0.30, 0.55; 1, 1)(0.20, 0.30, 0.30, 0.42; 0.9, 0.9))$	$f_{410} = ((0.01, 0.06, 0.06, 0.18; 1, 1)(0.03, 0.06, 0.06, 0.12; 0.9, 0.9))$
$f_{26} = ((0.07, 0.22, 0.22, 0.44; 1, 1)(0.13, 0.22, 0.22, 0.32; 0.9, 0.9))$	$f_{51} = ((0.10, 0.28, 0.28, 0.50; 1, 1)(0.18, 0.28, 0.28, 0.39; 0.9, 0.9))$
$f_{27} = ((0.16, 0.38, 0.38, 0.61; 1,1)(0.26, 0.38, 0.38, 0.49; 0.9, 0.9))$	$f_{52} = ((0.26, 0.51, 0.51, 0.77; 1, 1)(0.37, 0.51, 0.51, 0.63; 0.9, 0.9))$
$f_{28} = ((0.06, 0.19, 0.19, 0.40; 1, 1)(0.12, 0.19, 0.19, 0.29; 0.9, 0.9))$	$f_{53} = ((0.22, 0.44, 0.44, 0.72; 1, 1)(0.32, 0.44, 0.44, 0.57; 0.9, 0.9))$
$f_{29} = ((0.09, 0.28, 0.28, 0.53; 1, 1)(0.18, 0.28, 0.28, 0.40; 0.9, 0.9))$	$f_{54} = ((0.17, 0.37, 0.37, 0.61; 1, 1)(0.26, 0.37, 0.37, 0.48; 0.9, 0.9))$
$f_{210} = ((0.05, 0.19, 0.19, 0.40; 1, 1)(0.11, 0.19, 0.19, 0.28; 0.9, 0.9))$	$f_{55} = ((0.15, 0.35, 0.35, 0.61; 1, 1)(0.24, 0.35, 0.35, 0.47; 0.9, 0.9))$
$f_{31} = ((0.43, 0.72, 0.72, 0.93; 1, 1)(0.57, 0.72, 0.72, 0.82; 0.9, 0.9))$	$f_{56} = ((0.13, 0.33, 0.33, 0.57; 1, 1)(0.22, 0.33, 0.33, 0.44; 0.9, 0.9))$
$f_{32} = ((0.54, 0.84, 0.84, 1.00; 1, 1)(0.68, 0.84, 0.84, 0.92; 0.9, 0.9))$	$f_{57} = ((0.12, 0.32, 0.32, 0.55; 1, 1)(0.21, 0.32, 0.32, 0.43; 0.9, 0.9))$
$f_{33} = ((0.23, 0.47, 0.47, 0.78; 1, 1)(0.35, 0.47, 0.47, 0.68; 0.9, 0.9))$	$f_{58} = ((0.16, 0.36, 0.36, 0.61; 1, 1)(0.25, 0.36, 0.36, 0.48; 0.9, 0.9))$
$f_{34} = ((0.21, 0.43, 0.43, 0.68; 1, 1)(0.31, 0.43, 0.43, 0.55; 0.9, 0.9))$	$f_{59} = ((0.08, 0.26, 0.26, 0.49; 1, 1)(0.16, 0.26, 0.26, 0.37; 0.9, 0.9))$
$f_{35} = ((0.35, 0.61, 0.61, 0.84; 1, 1)(0.47, 0.61, 0.61, 0.72; 0.9, 0.9))$	$f_{510} = ((0.05, 0.19, 0.19, 0.40; 1, 1)(0.11, 0.19, 0.19, 0.28; 0.9, 0.9))$

5. Results

The super-efficiency DEA models are solved using Lingo software and the Tra-IT2F VIKOR is solved using Microsoft Excel. Results are provided in Table 8. The rank of each supplier is given in terms of the values of S , R and Q , for the Tra-IT2F VIKOR and super-efficiency DEA. The ranking of suppliers based on DEA is $S_2 > S_4 > S_1 > S_5 > S_3$. The ranking based on just risk factors is $S_4 > S_2 > S_5 > S_1 > S_3$. Clearly, the ranking based on the risk factors using Tra-IT2F VIKOR and based on the DEA model

are not the same and there is no supplier holding the same position in both lists. As Table 8 shows, Supplier 4 has the lowest risk and Supplier 2 is the most efficient. Because each supplier is best in at least one criteria (their core competency), all suppliers achieve super-efficiency scores greater than or equal to 1. Supplier 2 dominates Supplier 4 in terms of sustainability and competitiveness, however, it has a higher risk performance from the viewpoint of DMs.

We check the sensitivity of our results in two different ways. First, in the Tra-IT2F VIKOR method, the parameter ν is introduced as the

Table 6
Sustainability criteria and their descriptions.

No.	Inputs	Description	Applied references
1	Cost/Price (C/P)	The various sources of cost which mainly include purchase cost of products, transportation cost, inventory cost, maintenance cost, buyer-supplier coordination and controlling cost.	Kuo et al. (2010); Azadnia et al. (2015)
2	Quality (Qu)	Quality products provision, consistent conformance to required specifications settled by the buyer, and quality stability in long-term cooperation.	Kuo et al. (2010); Grisi et al. (2010); Azadnia et al. (2015)
3	Technology Capabilities (TC)	The capability of suppliers to adjust themselves towards innovations, adopt advanced process technologies and react to technological turbulence promptly.	Lee et al. (2009)
4	Green Design (GD)	The design of products in which issues such as reuse, recycle, recovery, reduced consumption of material and energy and avoiding the use of hazardous materials are taken into consideration.	Chen et al. (2010)
5	Environmental Management System (EMS)	Environmental standards and certifications like ISO 14000, planning, performing, monitoring and control of environmental activities, and staff training for environmental objectives.	Chiou et al. (2008)
6	Environmental Competencies (EC)	Using cleaner production systems; Ability to change and amend manufacturing process into green and environmentally friendly products.	Grisi et al. (2010); Humphreys et al. (2006)
7	Interests and Rights of Employees (IRE)	This includes workers' pay, benefits and safe working condition, force labor, working hours, compensation and disciplinary practices.	Kuo et al. (2010)
8	Rights of Stakeholders (RS)	Stakeholder rights, including informing them about business activities, hearing them, identify and satisfy their requirements and respect them.	Kuo et al. (2010)
9	Social Management Commitment (SMC)	The commitment to ensure compliance and continuous improvement in delivering important social aspects such as child labor, health, safety, discrimination and etc.	Klassen and Vereecke (2012)

Table 7
Quantitative values of inputs and the output.

Inputs									Output	
Suppliers	C/P (Iranian Rial)	Qu	TC	GD	EMS	EC	IRE	RS	SMC	Risk measure Q
1	55	0.56	0.82	0.50	0.59	0.69	0.75	0.79	0.98	0.915
2	51	0.85	0.76	0.91	0.69	0.75	0.79	0.91	0.62	0.268
3	52	0.82	0.50	0.59	0.69	0.75	0.79	0.91	0.62	0.977
4	50	0.82	0.43	0.24	0.43	0.50	0.43	0.30	0.56	0
5	56	0.73	0.50	0.75	0.36	0.56	0.88	0.43	0.62	0.522

Table 8
The collective comprehensive values and ranking orders of suppliers.

Value					Rank			
Suppliers	S_i	R_i	Q_I	DEA	S_i	R_i	Q_I	DEA
1	4.984	0.913	0.915	1.003838	4	5	4	3
2	1.749	0.387	0.268	1.253257	2	2	2	1
3	5.940	0.879	0.977	1.00	5	4	5	5
4	0.314	0.181	0	1.073448	1	1	1	2
5	3.405	0.542	0.522	1.003525	3	3	3	4

weight of the strategy for maximum group utility. It has a crucial role in the ranking of suppliers based on their risks. The parameter v can take a value between 0 and 1, however in this paper we used $v = 0.5$. We analyze the sensitivity of our results against changes in v . Fig. 4 shows that changing v value does not have a significant impact on the order of suppliers and the rank of three suppliers remains unchanged. This indicates that the suppliers' risks are the same in terms of both the maximum group utility and the minimum individual regret. Thus, we can conclude that the obtained results are relatively robust and independent of the maximum group utility strategy. We should also mention that while the top three suppliers do not change their rank, at around $v = 0.25$ Suppliers 1 and 3 switch places in their rank orders. However, since $v < 0.5$ means a minority rule for any "fair" decision-making scenario (i.e. group consensus $v = 0.5$ or majority rule $v > 0.5$) the rank order of the five suppliers remains unchanged.

Second, we validated the super-efficiency model by running it with different values of the risk measure Q . As shown in Table 9, changing the risk measure Q changes the super-efficiency DEA scores for all the candidate suppliers. Moreover, the rank of all the suppliers change except for Supplier 5 whose super-efficiency score decreased. Our

Fig. 4. Results of sensitivity analysis.

results show that the performance of all suppliers depends on their risks and the model is very sensitive to the risk measure Q of suppliers.

6. Discussion and managerial implications

At the beginning of this paper we proposed two research questions. The results of our study indicate that ranking suppliers based on only their risk factors or sustainability practices may not yield the best decision. Our proposed framework not only ranks the suppliers using sustainability and risk simultaneously, but also identifies the correlation between sustainability and risk. Furthermore, our super-efficiency DEA model is able to differentiate suppliers with various core competencies while also dealing with supplier risk.

Our results indicate that dominating each input may not necessarily mean a supplier will be the best amongst the candidate group. For example, as shown in Table 7, Supplier 2 ranks best in the highest

Table 9
The values and ranking orders in sensitivity analysis.

Suppliers	Value		Rank	
	Q_I	DEA	Q_I	DEA
1	0	1.283	1	1
2	0.522	1.0256	3	3
3	0.268	1.064	2	2
4	0.977	1.000001	5	5
5	0.915	1.00001	4	4

number of sustainability criteria, but loses its dominance when its risk measure Q is changed (see Table 9). Likewise, despite having the best risk measure, Supplier 4 places second in the optimal solution. Supplier 3, on the other hand, ranks second in terms of core competencies but has not been able to achieve a rank better than last. Nevertheless, having the second rank in terms of the number of core competencies and the risk measure as shown in Table 9, Supplier 3 could achieve the second rank if the decision-makers' risk tolerance changes. These results indicate that devising models that can tackle multiple dimensions of the supplier selection problem simultaneously are worthwhile.

Another notable issue is that while all MCDM techniques depend on assigning subjective weights to criteria this could be a daunting task for DMs but DEA does not have this shortcoming. Risk-averse DMs prefer to obtain the highest outcome based on various risks, whereas risk-neutral DMs care more about the trade-offs among the risk and sustainability criteria. Instead of concentrating on a single risk attitude (such as AHP and TOPSIS), our approach takes on a more holistic view, considering both, a risk-averse approach in the first step and a risk-neutral one in the second. For example, although Supplier 4 is excellent from a risk-averse perspective, it is seldom the best supplier when the rest of the sustainability criteria are considered. The proposed model can be used for any multi-faceted selection problem when the concerns include sustainability and risk. For example, our model could be useful in selecting third-party logistics (3PL) providers, or resource allocation to a set of facilities.

The focus of this study is supplier selection under sustainability and risk criteria. Clearly, the selection of appropriate and relevant criteria is important but is not the core idea of this paper. In this paper, the sustainability criteria and risk factors are selected by the decision makers from a list obtained from the literature (we refer the interested readers to Luthra et al. (2017); Vahidi et al. (2018); and Ghadimi et al. (2016) for sustainability criteria and Hamdi et al. (2018); and Ikediashi et al. (2012) for risk factors in the supplier selection literature). That said, there are some recently developed systematic methods to choose appropriate criteria for the supplier selection problem. For instance, Vahidi et al. (2018) developed a hybrid SWOT-QFD framework for choosing the most influential sustainability criteria. Although such approaches can be systematic and comprehensive, simplicity and ease of use are of interest to DMs.

7. Conclusion

In this paper, we consider a supplier selection problem where the criteria include the triple bottom line (economic, social and environmental dimensions of sustainability) and supplier risks. We develop a framework that considers both, a risk-averse as well as a risk-neutral approach to the selection problem. We first apply an extension of a group MCDM tool (i.e. Tra-IT2F VIKOR) to quantify decision-maker inputs and outputs and then select the best supplier using a variant of super-efficiency DEA. We also highlight the importance of suppliers' core competencies in the selection decision, and the fact that traditional DEA models fail to distinguish between suppliers when each of them excels in at least one criteria.

We illustrate our multi-method approach on a real case of a supermarket chain in Iran. We demonstrate that subjectivity is inherent to most real-life problems and through our quantification process and the DEA model, decision makers can still make smart and objective selections. Our results and sensitivity analysis show that considering sustainability criteria and risk factors separately versus simultaneously highly affects the selection process.

The main limitation of our research is the shortage of experts who are well-versed in both, sustainability and risk management issues. In most companies, these topics are tasked to different departments or people. Additionally, in this study we quantified risk factors using the gathered qualitative data (i.e. the intuitive judgment of DMs). However, the reliability of results would of course improve if risk measures are based on objective historical data when available.

Two potential future research directions arise from the results of this study. First, suppliers, based on given benchmarks, can evaluate their strengths and weaknesses and invest into change. Hence, it is would be interesting to investigate how supplier development activities would affect the selection process. Secondly, how the inter-dependencies and correlations between selection criteria impact the selection process should be explored.

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