https://doi.org/10.1016/j.eswa.2019.112903

Chai, J. Y and Ngai, EWT (2020), Decision-Making Techniques in Supplier Selection: Recent Accomplishments and What Lies Ahead *Expert Systems with Applications*. Vol. 140, 12903.

Decision-Making Techniques in Supplier Selection: Recent Accomplishments and What Lies Ahead

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Abstract

Supplier selection (SS) is deemed as sophisticated, application-oriented, decision-making (DM) problems, which has received considerable attention. In the past two decades, DM techniques and analytic methodologies continue to contribute and penetrate the development of SS applications. Keeping the pace of the rapid transitions in this field, this paper systematically reviews the relevant articles that appear between 2013 and 2018. We select the articles that orient various DM techniques and analyze them under a well-established framework. We summarize the state-of-the-art developments in the adoption of DM techniques in a SS process. We pay particular attention in promising directions that could dominate the future researches of this field. Towards methodological rather than application dimensions, we further extend the history of several interpenetrating fields including big data and economic theories. We discuss their potential for SS from an interdisciplinary perspective.

Keywords: supplier selection; decision making; big data; multiple criteria; artificial intelligence; literature review

1. Introduction

Supplier selection (SS) is the process in which companies identify, screen, evaluate, analyze and contract with suppliers. This process requires a large resource in finance and human for any company. Concurrently, companies expect suitable suppliers and their high-qualified services. SS has been widely studied in the context of operations management, decision sciences, and production economics. We witness the increasing interests on SS in the past two decade and numerous studies have been accumulated.

Chai et al. (2013) explored the profound development of decision making (DM) techniques in SS through a systematic review of the literature published between 2008 to 2012. Since then, a number of newly developed approaches were reported. In the past five years, at least three valuable academic surveys had well reviewed the literature on SS. Zimmer et al. (2016) capture sustainability and environmental influence in building criteria systems. Based on 143 articles published between 1997 and 2014, this paper points out that the dominating technique is Analytic hierarchy process (AHP), followed by Analytic network process (ANP) and fuzzy-based approach. This finding echoes the result of Chai et al. (2013). Fahimnia et al. (2015) review a broader scope of literature that involve 884 articles published between 1992 and 2013. Fahimnia et al. (2015) and Zimmer et al. (2016) are both concerned about sustainability and environmental influences in SS. Wetzstein et al. (2016) contribute general statistics in SS that contain 221 articles published between 1990 and 2015. Particularly, this study separates the literature into six research streams, which are (1) SS approach, (2) Criteria in SS, (3) Sustainability and Green SS, (4) Strategic SS, (5) R&D-oriented SS, and (6) Operations-oriented SS.

Although these reviews of literature provide insights for the future development of SS, none of them could be able to capture the transitions of the state-of-the-art development. For example, although they have paid enough attention in environmental influence, recent literature have illustrated the trend of using data mining techniques in SS. In addition, we are still missing a thorough summarization of DM techniques from a methodological perspective. This paper keeps the pace of Chai et al. (2013) and conduct the investigation within the time window of 2013 through 2018. The objectives of this paper include (a) systematically reviewing the occurrences since 2013, (b) summarizing the transitions of DM techniques in the field, and (c) identifying and promoting trends and possibilities in adopting DM techniques for SS purposes. This paper orients the methodological aspect rather than the application aspect. The generic methodological advances can be more significant because it can be employed across a broad spectrum of applications in supply chain management.

We consider almost all published articles between 2013 and 2018. Our target is not only providing an exhaustive survey but also uncovering the significant advancements and trends since our previous review of literature Chai et al. (2013) published. In the following, we highlight six aspects that will be specified in this paper.

(1) Transiting from handling uncertainty to risk analysis: Substantial growth in analysing risk factors in SS has happened. We witness a clear transition of research lines that is from dealing with various uncertainties to dealing with risks. Chai et al. (2013) summarize various profound models of uncertainty including fuzzy, rough and stochastic types. In the paper, we emphasize the recent attentions in supply chain disruption risk.

(2) Incorporating economic theories in SS: Incorporating theories in economics, such as game theory and several normative preference theories reveals the importance of behavioural aspects in SS has grown. Related behavioural and psychological researches under the paradigm of economics have been well recognised, particularly after recognised by the 2002 and 2017 Nobel Prize in Economics to Daniel Kahneman and Richard Thaler, respectively.

(3) Establishing supply base and their maintenance: Studies in supply base has been grown in its importance and also the quantity of articles. Investigating the relations of behaviours between buyers' side and sellers' side have been well explored.

(4) Adopting sorting techniques for SS: Sorting is a type of classification task, in which the predefined classes are preference-ordered. Domiance preference relation plays crucial role in sorting tasks.

(5) Developing Green and strategic SS: Environment protection has been a global issue. How to account for environmental factor and sustainability in selecting suppliers has been the most prominent trend in recent studies. Relevant articles are usually termed as green SS or strategic SS.

(6) Developing techniques for Group Negotiation: Multiple people involved in SS process remains the importance. The major challenge is how to design the method of preference aggregation. The solutions are to design proper mechanisms of negotiation and group argumentation.

These six aspects are major observations based on our collected literature. They will be specified in Section 5.1 through Section 5.6. Beyond the six aspects, we will elaborate an outstanding trend since 2013, which is the penetration of data mining techniques into SS approaches. This paper captures classification and clustering as two clear decision targets, which has not been emphasized enough before. The technical toolkit that is originally developed in fields of computer science and artificial intelligence can be implemented in SS processes. This direction is particularly needed to be investigated in the future.

This paper is organized as follows. Section 2 introduces our research methodology that describes the methods for selecting the articles to be included. In Section 3, we provide a bibliometric analysis. In Section 4, we provide a thorough and categorical review over our selected articles. In Section 5, we summarize key transitions of this field and emphasize exciting trends for the future researches. In Section 6, we put forward a discussion on necessities and principles when adopting the methodology of hybridizing DM techniques. We conclude this paper in Section 7.

2. Research Methodology

Two methodologies are frequently adopted in modelling a SS process. The first one is to characterize the needs of buyers and suppliers through using direct mathematical modelling, for example, Beil (2010). In this category, attempting to devise mechanisms for bridging buyers and suppliers are obviously a legitimate exercise. The second one is to develop a hybrid decision process or a combination of decision techniques. In this category, selecting suppliers is usually modelled as a mulit-stage process, which could involve group negotiation, dealing with risks or uncertainties, information fusion, and ranking or classifying suppliers. Hybridizing multiple techniques can well resolve the corresponding issues, for example, using rough set theory for dealding with uncertainties, or using fuzzy set theory for information fusion.

To the second category, Chai et al. (2013) conduct a thorough review of the literature published from 2008 to 2012. In this paper, DM techniques are boiled down to three streams including Multicriteria decision-making (MCDM), Artificial intelligence (AI), and Mathematical programming (MP). This paper establishes a methodological decision analysis framework for a standardized analysis of the literature. This framework contains four aspects, which are (a) the nature of problem, (b) the element of people involved, (c) the influence of environments, and (d) the suitable and adoptable problem-solving approach. We simply call this framework as a "Problem-People-Environment-Approach (PPEA)" framework. Under PPEA, Table 1 summarizes the differences between Chai et al. (2013) and the present paper.

Table 1. Comparisons between Chai et al. (2013) and the present paper

	The present paper	**Chai et al. (2013)**
Problem	Structural, Semi-Structural, and Non-Structural problems	Structural problems mainly
People	Individual or Group	Individual or Group
Environment	Deterministic, Uncertain, Risk	Uncertain mainly
Approach	Articles reported between 2013 and 2018	Articles reported between 2008 and 2013

We limit the scope of our survey in DM technique that has been used for SS. We search articles from databases including Science Direct, Emerald, Springer-Link Journals, IEEE Xplore, Academic Search Premier and World Scientific Net. We only select peer-reviewed articles that are published in respected international journal. We aim to achieve the hightest standard of quality in articles and relevance to our scope. We will not include conference articles, postgraduate theses, and editorial notes.

3. Bibliometric Analyses

3.1. Overview of Independent DM Techniques

DM techniques can be boiled down to three streams, MCDM, AI, and MP. This framework has been used in Chai et al. (2013) for analyse the collected 123 articles from 2008 to 2012. In this paper, we apply this framework to analyse the collected articles published after 2013. Table 2 shows the statistics in DM techniques used for SS between 2013 and 2018. We also provide a representative article that demonstrates the usage of the corresponding technique.

Table 2. Statistics in DM Techniques used for SS

The adopted DM Techniques		**Abbreviations**	**Representative**	**Frequency**
A. Multiattribute Decision Making (MCDM) Techniques				
Multiattribute Utility method	Analytic Hierarchy Process	AHP	Dong et al. (2017)	13
	Analytic Network Process	ANP	Abdollahi et al. (2015)	6
Outranking method	Preference Ranking Organization Method for Enrichment Evaluation	PROMETHEE	Govindan et al. (2017)	2
	* Qualitative Flexible Multiple Criteria Method	QUALIFLEX	Zhang & Xu(2015)	1
	** Elimination and Choice Expressing Reality	ELECTRE	---	0
Compromise method	Technique for Order Performance by Similarity to Ideal Solution	TOPSIS	Hague et al. (2015)	8
	Multicriteria Optimization and Compromise Solution	VIKOR	Awasthi et al. (2018)	2
Other method	Decision Making Trial and Evaluation Laboratory	DEMATEL	Abdollahi et al. (2015)	2
	The Best Worst Method	BWM	Rezaei (2015)	1
	** Simple Multiattribute Rating Technique	SMART	---	0
B. Mathematical Programming (MP) Techniques				
Classical programming techniques	Linear programming	LP	Purohit et al. (2016)	19
	Stochastic programming	SP	Manerba et al. (2018)	11
	Nonlinear programming	NLP	Adeinat & Ventura (2018)	9
	Goal programming	GP	Hu and Yu (2016)	7
	Multiobjective programming	MOP	Babic & Peric (2014)	6
	Data Envelopment Analysis	DEA	Talluri et al. (2013)	4

* Mixed programming	Mixed integer linear programming	MILP	Arampantzi et al. (2018)	9
	Mixed integer nonlinear programming	MINLP	Adeinat & Ventura (2015)	6
	Stochastic mixed integer linear programming	MILP+SP	Amorim et al. (2016)	3
	Stochastic mixed integer nonlinear programming	MINLP+SP	Amin & Zhang (2013)	1
	Multiobjective mixed integer linear programming	MILP+MOP	Babic and Peric (2014)	2
	Multiobjective mixed integer nonlinear programming	MINLP+MOP	Konur et al. (2017)	2
	Multiobjective stochastic mixed integer programming	MIP+MOP+SP	Sawik (2016)	2
C. Data Mining and Artificial Intelligence (DMAI) Techniques				
Classification Methods	Neural Networks	NN	Tavana et al. (2016)	2
	Bayesian Networks	BN	Hosseini & Barker (2016)	3
	Decision Tree	DT	Nepal & Yadav (2015)	2
	Support Vector Machine	SVM	Medhi & Mondal (2016)	2
	Genetic Algorithm	GA	Du et al. (2015)	2
	Rough Set Theory	RST	Chai & Liu (2014)	1
	** Association rule	AR	---	0
	** Case-Based Reasoning	CBR	---	0
Clustering Method	* K-means clustering		Jabbarzadeh et al. (2018)	3
Other DMAI Method	Grey System Theory	GST	Memon et al. (2015)	3
	** Ant Colony Algorithm	ACA	---	0
	** Dempster Shafer Theory of evidence	DST	---	0
	** Particle Swarm Optimization	PSO	---	0

* means the emerging techniques since our 2013 paper.

** means the technique has not been found in our pool of collected articles.

As illustrated in Table 2, most listed DM techniques in Chai et al. (2013) are still active after 2013. We highlight several transitions below.

- As an outranking method, ELECTRE method is not reported after 2013. QUALIFLEX as a new outranking method is reported as a component of hybridized approach such as Zhang & Xu (2015).

- The SMART method appeared in Chai et al. (2013) is not appeared in our collected pool of this paper.
- In the MP classes, the frequency of using Data envelopment analysis (DEA) has been reduced from 10.65% according to Chai et al. (2013) to 3.4% of this paper. The frequency of using basic linear programming of this paper (16.1%) is flat with the previous 5-year stage (15.44%). Beyond that, the more complicated combination of multiple MP techniques has been an obvious tendency. The relevant frequency has been increased from 8.9% of Chai et al. (2013) to the current 21.7% in this paper.
- Some AI techniques reported before 2013 are not reproduced including Association rule (AR), Case-based reasoning (CBR), Particle swarm optimization (PSO), Ant coloy algorithm (ACA), and Dempster Shafer theory of evidence (DST). Alternatively, more standardized AI techniques are evidenced its key role in combination of DM techniques, for example, Support vector machine (SVM) and K-nearest neighbour classifer (KNN).
- In incorporating with recent developments of AI, several techniques for "big data" analysis are penetrating the SS field. We therefore advance the AI class presented in Chai et al. (2013) by renaming it as Data mining and artificial intelligence (DMAI) techniques. We note that the literature tend to focus on the functions of AI tehniques such as classficiation and clustering. The detailed reviews over each class are outlined in Section 4.

3.2. Summarisation of DM Techniques

A decision approach is deemed as a complete problem-solving process for certain decision target(s). Some literature also term an approach as a scheme or a solution. Generally, a decision approach in SS processes must provide the process of transition from the known to targeted unknown. From the perspective of information system, the known is the input that can be various sources, personnel or financial information. The unknown refers to several certain, predetermined and mostly fixed decision goals. Such goals can be ranking candidate suppliers (i.e. the task of ranking), choosing the most appropriate suppliers for contracting (i.e. the task of choice), assigning candidate suppliers into several (predefined or non-predefined) classes with different labels (i.e. the tasks of classification, clustering and sorting), and establishing or maintaining a supplier base.

However, the problem-solving process in SS can be highly complex. Objective or subjective factors can upgrade the level of complexity. We outline several aspects in the following.

1. The complexity may come from the problem per se. For example, the problem is not well structured formulations, or does not have clear boundaires and decision goals. Such problems must be analyzed and contructed. Chai et al. (2013) advocate to formulate all SS decisions into three types: structural, non-structural and their intermediate zone called semi-structural.

2. The complexity may come from decision environments (e.g. uncertainty of information, supply disruption risk, nonquantitative judgements of decision makers, or people's intangible perception). Based on our review, environment complexity is the dominating issue, in which the literature for the last 10 years (2008-2018) are trying to figure out.
3. The complexity may be from people's decision, for example, how to select qualified evaluators (personnel selection), how to blend information from different sources (i.e. the task of information fusion), how to reconcile different or conflict opinions of decision makers (i.e. the task of group negotiation), how to elicit decision makers' perception that could be rather ambiguous, undetermined and even intangible (i.e. the task of preference representation and elicitation).
4. The complexity may be from the problem-solving process. The process from decision source to decision goals could contain a number of stages that aims to resolve a single problem, for example, construction of decision makers, information fusion, disruption risk analysis, establishment of evaluation criteria, and the stage of ranking or classification. Each stage or decision task has its sub-goals, different inputs and outputs. How to design and develop such a multi-stage process must be a big challenge due to complexities.

To resolve the complexity is the main incentive and essential motivation of designing and developing an approach in a SS process. Table 3 provides the detailed summarization of reviewed articles. As Chai et al. (2013), we consider three classes here including MCDM, MP, and AI. We particularly focus on the hybridization of DM techniques. We list the outstanding DM techniques of each article in the last column. Note that we only list the most core DM techniques and some of articles can be overlapping in this table.

Table 3. Summarization of DM Techniques Used for SS

Techniques	**Literature**	**Features of Decision Approach**
A. Multiattribute Decision Making (MCDM) Techniques		
1. Multiattribute Utility Method		
AHP	Dong et al. (2017)	Considering decision group
	Awasthi et al. (2018)	Integrated fuzzy VIKOR with AHP
	Dweiri et al. (2016)	Aided by system approach called Expert Choice software
	Lee et al. (2015)	Integrated fuzzy TOPSIS with fuzzy AHP
	Azadnia et al. (2015)	Using fuzzy AHP
	Rezaei et al. (2014)	Consider the case of KLM airline
	Kar (2014)	Integrated fuzzy GP and Geometric mean method with AHP
	Theiben & Spinler (2014)	Using Case-based derived decision criteria
	Deng et al. (2014)	Considering D number as elements

	Ghorbani et al. (2013)	Integrated fuzzy Kano questionnaire with fuzzy AHP
	Parthiban & Abdul Zubar (2013)	Integrated MISM and MICMAC[1] with AHP
	Rodriguez et al. (2013)	Integrated fuzzy TOPSIS with fuzzy AHP
	Kasirian & Yusuff (2013)	Integrated TOPSIS with AHP
ANP	Govindan et al. (2016)	Integrated fuzzy Delphi and DEMATEL with ANP
	Abdollahi et al. (2015)	Integrated DEMATEL with ANP
	Bodaghi et al. (2018)	Integrated GP with ANP
	Hashemi et al. (2015)	Integrated Grey system with ANP
	Lin, et al. (2015)	Using Triple Bottom Line
	Asadabadi (2017)	Integrated QFD and Markov Chain simulation with ANP
2. Outranking Method		
PROMETHEE	Govindan et al. (2017)	Using linear programming
	Segura & Maroto (2017)	Integrated AHP with PROMETHEE, and consider group decisions
QUALIFLEX	Zhang & Xu (2015)	Consider Hesitant fuzzy elements
3. Compromise Method		
TOPSIS	Hague et al. (2015)	Typical Usage
	Khemiri et al. (2017)	Using fuzzy TOPSIS
	Lima-Junior & Carpinetti (2016)	Using a Supply Chain Operations Reference (SCOR@) model
	Beikkhakhian et al. (2015)	Using fuzzy TOPSIS
	Igoulalene et al. (2015)	Using fuzzy TOPSIS
	Yayla et al. (2015)	Integrated fuzzy TOPSIS with fuzzy AHP
	Venkatesh et al. 2018	Integrated fuzzy AHP with TOPSIS
	Kannan et al. (2014)	Using fuzzy TOPSIS
VIKOR	Awasthi et al. (2018)	Integrated fuzzy AHP with VIKOR
	You et al. (2015)	Considering interval 2-tuple fuzzy elements under VIKOR
4. Other MCDM method		
DEMATEL	Govindan et al. (2016)	Using fuzzy Delphi; ANP; PROMETHEE
	Abdollahi et al. (2015)	Using ANP
BWM	Rezaei et al. (2015)	Using Best worst method for criteria analysis
B. Mathematical Programming (MP) Techniques		
1. Basic and Independent MP Techniques		
DEA	Dobos & Vorosmarty (2018)	Typical usage of DEA
	Talluri et al. (2013)	Typical usage of DEA
	Mahdiloo et al. (2015)	Integrated multi-objective LP with EDA

[1] MISM refers to Modified interpretive structural modelling. MICMAC refers to impact matrix cross-reference multiplication applied to a classification.

	Kumar et al. (2014)	Consider green SS
LP	Sodenkamp et al. (2016)	Using a tradeoff mechanism
	Purohit et al. (2016)	Using integer LP under non-stationary stochastic demand
	Dotoli et al. (2017)	Integrated fuzzy DEA with LP
	Irawan et al. (2018)	Integrated AHP with Integer LP
	Andrade-Pineda et al. (2017)	Using Integer LP
SP	Manerba et al. (2018)	Typical usage of SP
	Yoon et al. (2018)	Integrated AHP with SP
	Babbar & Amin (2018)	Integrated QFD with SP with considering trapezoidal fuzzy elements
	Balcik and Ak (2014)	Consider uncertainty of demand
	Torabi et al. (2015)	Integrated with MOP for building supply base
GP	Jatuphatwarodom et al. (2018)	Integrated DEA and AHP with GP
	Bodaghi et al. (2018)	Integrated fuzzy ANP with GP
	Guarnaschelli et al. (2017)	Using lexicographic goal programming
	Sheikhalishabi & Torabi (2014)	Using lexicographic goal programming
	Jadidi et al. (2014)	Considering crisp cases and fuzzy case
	Hu & Yu (2016)	Integrated a voting method with GP
	Hong & Lee (2013)	Using Monte Carlo simulation
2. Mixed integer programming		
MILP	Arampantzi et al. (2018)	Typical usage of MILP
	Cunha et al. (2018)	Typical usage of MILP
	Sali & Sahin (2016)	Typical usage of MILP
	Von Massow & Canbolat (2014)	Typical usage of MILP
	Kamalahmadi & Parast (2017)	Considering risk factor
	Dupont et al. (2018)	Considering risk and loss aversion
	Zouadi et al. (2018)	Considering green SS
	Chen et al. (2018)	Using heuristic method
MINLP	Ventura et al. (2013)	Typical usage of MINLP
	Guo & Li (2014)	Considering stochastic demand
	Adeinat & Ventura (2015)	Typical usage of MINLP
	Adeinat & Ventura (2018)	Typical usage of MINLP
	Negahban & Dehghanimohammadabadi (2018)	Typical usage of MINLP
	Ahmad & Mondal (2016)	Integrated Taguchi method with MINLP
MILP+SP	Amorim et al. (2016)	Typical usage of MILP+SP

	Hammami et al. (2014)	Considering risk and uncertainty
	Sawik (2014)	Considering risk factor
MINLP+SP	Amin & Zhang (2013)	Integrated QFD with NINLP+SP
MILP+MOP	Mota et al. (2018)	Integrated life cycle analysis with MILP+MOP
	Babic & Peric (2014)	Integrated AHP with MILP+MOP
MINLP+MOP	Konur et al. (2017)	Considering green SS
	Ware et al. (2014)	Typical usage of MINLP+MOP
MIP+MOP+SP	Sawik (2016)	Considering risk factor
	Torabi et al. (2015)	Considering risk factor
C. Data Mining (DM) and Artificial Intelligence (AI) Techniques		
1. Classification Methods		
BN	Hosseini & Barker (2016)	Considering risk factors
	Nepal & Yadav (2015)	Integrated DT with BN
	Sarkis & Dhavale (2015)	Using Monte Carlo Markov Chain
NN	Tavana et al. (2016)	Using adaptive neuro fuzzy inference system
	Medhi & Mondal (2016)	Integrated SVM, Kohonen's self organizing map (SOM) with NN
SVM	Guo et al. (2014)	Integrated CCEA[2] and Kernel clustering algorithm with SVM
	Medhi & Mondal (2016)	Integrated NN, Kohonen's self organizing map (SOM) with SVM
GA	Du et al. (2015)	Integrated MOP with GA and consider a life cycle analysis
	Cao et al. (2014)	Considering risk factor and sorting problem
DT	Kamalahmadi & Parast (2017)	Integrated MIP with DT
	Nepal & Yadav (2015)	Integrated DT with BN
RST	Chai & Liu (2014)	Developing a believable rough set approach
2. Clustering Methods		
K-Means (K-Modes K-Medoids)	Jabbarzadeh et al. (2018)	Integrated SP with K-means
	Keskin (2015)	Integrated fuzzy DEMATEL with fuzzy C-means algorithm
	Jula et al. (2015)	Integrated PROCLUS with a K-Medoids-like cluster method
3. Other DMAI Method		
GST	Memon et al. (2015)	Considering fuzzy elements
	Hashemi et al. (2015)	Integrated ANP with GA and consider green SS
	Pitchipoo et al. (2013)	Using fuzzy AHP

[2] CCEA refers to a cooperative coevolution algorithm

4. Categorical Reviews of Articles

In this section, we provide a categorical review on the collected articles. Most of these techniques appeared in Chai et al. (2013) are still active till now, while some are declining. Meanwhile, several new DM techniques are reported in the previous 5 years. In Section 4.1-4.3, we review outstanding techniques from three categories: MCDM, MP and DMAI. In section 4.4, we review the emerging techniques beyond the three categories above.

4.1 MCDM Techniques

4.1.1. Multiattribute Utility Methods

MAUM is used to assign a value to each alternative where the value is a quantitative representation of people's preferences. The term 'utility' is borrowed from economics fields where human preference can be formulated by a utility (or value) function. The value of a utility function is comparable thus it is the proper measurement for ranking (choosing) alternatives. AHP and ANP are two representative MAUMs. In AHP, people's evaluations are pairwise compared. ANP as the extension of AHP applies the networking for comparisons over multiple attributes.

According to Chai et al. (2013), AHP and ANP are dominating DM techniques (i.e. 24.4% and 12.2%, respectively). These percentages between 2013 and 2018 are declined (around 10.0% and 5.0%, respectively). We observe that AHP and ANP tend to be a component in hybridization or to be a solution for one stage in a multi-stage process (e.g. Hashemi et al. 2015). In our pool of articles, AHP/ANP has been integrated with fuzzy set (Yayla et al. 2015; Lee et al. 2015; Rezaei et al. 2014; Pitchipoo et al. 2013), TOPSIS (Beikkhakhian et al. 2015), D numbers (Deng et al. 2014), QFD (Asadabadi 2017, Scott et al. 2013, Scott et al. 2015), VIKOR (Awasthi et al. 2018) and a fuzzy Kano model (Ghorbani et al. 2013). Independent usage of AHP/ANP can be found in Irawan et al. (2018), Dweiri et al. (2016) and Tavana et al. (2016).

4.1.2 Outranking Methods

Outranking methods use binary relations to compare alternatives through weak preference like 'as least' and 'as good as'. ELECTRE methods use such a preference relation straightforward, while PROMETHEE advances ELECTRE by further using the pairwise comparisons. In our reviewed period of time, ELECTRE is not reported whereas PROMETHEE is reported in two articles including Govindan et al. (2017) and Segura and Maroto (2017).

QUALIFLEX (qualitative flexible multiple criteria method) as a new outranking method is reported in Zhang and Xu (2015). This technique is developed by Paelinck (1976, 1977, 1978). It uses pairwise comparisons over each criterion under all possible permutations of the alternative and select the optimal permutations that could maximize the value of concordance or discordance index (Martel and Matarazzo 2005). This method is particularly suitable for handling cardinal and ordinal mixed information and the case where the number of criteria considered is more than the number of alternatives (Chen et al. 2013).

4.1.3 Compromise Methods

Compromise methods are attempting to find the closest to the ideal solution. TOPSIS and VIKOR are the representative compromise methods, which applies aggregating functions to formulate the closeness to the ideal point. TOPSIS uses linear normalization to eliminate the units of criteria function. Differently, VIKOR uses vector normalization to do so. Based on our reviews, TOPSIS is used in eight articles, which is the dominating technique in the MCDM class. Because the TOPSIS formulation is simple to construct and the values of TOPSIS are comparable for ranking, it can be easy to integrate it into a multi-stage SS process, for example, Beikkhakhian et al. 2015. The typical usage of VIKOR can be found in Awasthi et al. (2018).

4.1.4 Other MCDM Methods

DEMATEL and SMART have been highlighted in Chai et al. (2013). DEMATEL is to analyze the relations among multiple criteria. We found two articles that apply DEMATEL as a component of integration. Govindan et al. (2016)'s hybridization contains fuzzy Delphi, ANP, PROMETHEE and DEMATEL. Abdoliahi et al. (2015) integrate DEMATEL and ANP. The use of SMART is not found in our pool of literature.

Rezaei (2015) proposes a best-worst method (BWM) for criteria analysis that can be an alterantive of AHP. Decision makers firstly identify the pair of criteria that is the best one and the worst one, and then conduct pairwise comparisons in each pair among other criteira. This method has been used in supplier segmentation (Rezaei et al., 2015) and has the potential for SS analysis.

4.2 MP Techniques

MP are typical techniques of optimization. Wallenius et al. (2008) suggest two categories including multiple criteria discrete alternative problems and multiple criteria optimisation problems. Int he first category, examples of discrete choice include choosing the location or choosing a research program for graduates. Typically, this kind of problem involves a reasonably-sized collection of alternatives (also called options, choices, items among literature). Multiple criteria sorting problems advocated in Doumpos and Zopounidis (2002) also belong to this category.

In the second category, multiple criteria optimization problems typically include planning, scheduling, and portfolio selection. The collection of alternatives is usually far larger than that in discrete choice problems. The constraints in optimization are defined by a system of equations and inequalities. This category generally requires more resources of computation when compared with discrete choice problems.

Six basic MP techniques emphasized in Chai et al. (2013) are reported after 2013. Linear programming is still the dominating technique, followed by Stochastic programming, Nonlinear programming, Goal programming, Multiobjective programming, and DEA. The frequency of using DEA is reduced from 10.65% (in 2008-2012) to 10.65% (in 2013-2018). The frequency of mixed using multiple optimization techniques is increased dramatically. We provide a detailed review as follows.

(a) Mixed integer linear programming (MILP):

The dominating mixed MP technique is Mixed integer linear programming (MILP). We found nine articles that use this most basic mixture. The independent usages are exhibited in Arampantzi et al. (2018), Cunha et al. (2018), Sali and Sahin (2016) and Von Massow and Canbolat (2014). Kamalahmadi and Parast (2017) and Dupont et al. (2018) further incorporate the influence of risk factor. Zouadi et al. (2018) further consider environment factor so as to a green SS process. Chen et al. (2018) develop a heuristic method that integrates MILP.

(b) Mixed integer nonlinear programming (MINLP):

Mixed integer nonlinear programming (MINLP) advances MILP by using a nonlinear function. Its typical usages appear in four articles including Ventura et al. (2013), Guo and Li (2014), Adeinat and Ventura (2015) and Negahban and Dehghanimohammadabadi (2018).

The Taguchi (Taguchi 1990) method aims to find optimal parameter setting when the variables are not independent. Though it is not a typical DM technique, the Taguchi's optimal parameter settings can decrease the sensitivity of a system to the changes of sources and thus improve the robustness of systems. Several studies adopt the Taguchi method to examine the robustness of proposed MINLP models, for example, Ahmad and Mondal (2016). The Taguchi method is not new to the SS applicaitons. As reviewed by Chai et al. (2013), Ordoobadi (2010) integrates the Taguch mehtod with AHP for SS purposes.

(c) Stochastic mixed integer linear/nonlinear programming (MILP+SP or MINLP+SP):

Stochanstic mixed integer linear or nonlinear programming is the mixture that considers the stochastic conditions in MIP. This mixture is typically applied in Amorim et al. (2016). Hammami et al. (2014) and Sawik (2014) consider its integration with risk and uncertainty. Further, Amin and Zhang (2013) integrates this mixture with the QFD method.

(d) Multiobjective mixed integer linear/nonlinear programming (MILP+MOP/MINLP+MOP):

Multiobjective mixed integer linear or nonlinear programming considers the condition of multiple objectives. This mixture has been integrated with AHP in Babic and Peric (2014) and the life cycle analysis in Mota et al. (2018). It is typically used in Ware et al. (2014) and is used in Konur et al. (2017) with particular concerns in green SS.

(e) Multiobjective stochastic mixed integer programming (MIP+MOP+SP):

Multiobjective stochastic mixed integer programming considers both stochastic conditions and multiobjective conditions. According to our pool of literature, this mixture has been used in two articles including Sawik (2016) and Torabi et al. (2015). The independent usage of SP as the modelling approach remains its effectiveness. For example, Balcik and Ak (2014) develop a scenario-based stochastic programming model that can capture demand uncertainty by representing them as a set of disaster scenarios.

4.3 DMAI Techniques

In Chai et al. (2013), AI techniques are roughly classified as the major techniques and the minor techniques. In the last decade, we witness rapid developments in data science. To meet the needs of big data analysis, many new approaches are reported, which are penetrated by toolkits of data mining. In this paper, we rename the third category as Data mining artificial intelligence (DMAI). We further emphasize the functional purposes of data analysis like classification and clustering. Therein, classification methods contain six techniques including BN, ANN, SVM, GA, DT and RS. Clustering methods contain C-means and Kernel. In addition, grey system theory is an approach for handling imprecise information. It is neither a classification nor a clustering method. Therefore, we place it into the 'other' category.

Classification aims to extract models for depicting important data classes, where the models can be called classifiers. Normally, data classification contains two stages. The first is called the learning stage or a training phase. A classifier needs to be established for describing a predetermined set of data classes or modules. It is based on a classification algorithm for analyzing a training set consisting of database tuples and their associate class labels. The second stage is to use the established model for classification.

Clustering departures from classification tasks in the learning stage. If providing the class label of each training tuple, we call it as a supervised learning. The learning is supervised because it is particularized to which class each training tuple belongs. In contrast, we have unsupervised learning in which the class label of each training tuple is unknown and the quantity or set of classes to be learned may be unknown in advance. Using unsupervised learning in the first step is called clustering.

In this section, we firstly review the classification methods in Section 4.3.1, the clustering methods in Section 4.3.2, and the other DMAI method in Section 4.3.3.

4.3.1 Classification methods

Classification method can be divided into two categories: Eager learners and Lazy learners. Given a training set of objects, eager learners will establish a general classification model before receiving new objects. If we consider a learning process from the seen to the unseen world, using eager learners that have been trained in the seen world are also ready for recognising the unseen world and 'eager' to classify new objects (i.e suppliers). Eager learners include Decision tree (DT), Bayesian networks (BN), Neural networks (NN), Association rule (AR), and Support vector machine (SVM) methods. On the contrary, a lazy learner algorithm simply stores the training object or conducts a minor processing in the seen world and waits until a new object is given. Lazy learners require an efficient storage technique and can be computationally expensive. Case-based reasoning (CBR) classifier is a typical lazy learner. K-nearest-neighbour classifiers (KNN) is close to CBR classifer, where the training tuples are stored as points in Euclidean space rather than the form of 'cases'. Based on our review, four classification methods including DT, BN, NN, and SVM have been reported for SS, which will be reviewed from Section 4.3.1.1 to Section 4.3.3.4. In Section 4.3.1.5, we capture three potential classification methods including AR, CBR, and KNN, which have not been reported for SS until now and get the potential for SS applications in the future.

4.3.1.1 Decision Tree (DT)

Quinlan (1986) develop a decision tree algorithm called ID3 (Iterative Dichotomiser) that is an advanced version of Concept learning systems suggestged by Hunt et al. (1966). After that, Quinlan (1993) present a successor of ID3 called the C4.5 algorithm that became the benchmark of newer classification algorithms since then. Breiman et al. (1984) create a new generation of binary decision tree named as Classification and Regression Tree (CART). ID3, C4.5 and CART commonly use a greedy approach where decision trees are built in a top-down recursive divide-and-conquer manner. Wu et al. (2008) systematically summarize the top ten most influential data analysis algorithm, where C4.5 and CART are in the list.

In the past 5-year stage, DT has been frequently applied for dealing with supply disruption risk directly or else selecting suppliers under different scenarios of risks. Kamalahmadi and Parast (2017) use a DT model to capture disruption scenarios. Nepal and Yadav (2015) formulate a DT model by incorporating the probability.

4.3.1.2 Bayesian Networks (BN)

Bayesian classifiers are short for Bayes theorem-based statistical classifiers that can predict class membership probabilities. Naive Bayesian classifier is the simplest Bayesian classifier that allows representation of dependencies among subsets of attributes. After assuming conditional independence of classes, Navie Bayesian classifier performs the best among all other classifiers according to Han et al. (2011). Since the dependencies in the real world exist between variables, the assumption faces great challenges. As an advanced version, Bayesian belief networks specify join conditional probability distributions, so that the assumption of class conditional independencies can hold among subsets of variables. Among literature, Bayesian belief networks are also called as Bayesian networks (BN), or Belief and Probabilistic networks.

In the past 5-year stage, Hosseini and Barker (2016) use BN as a ranking tool to evaluate the quality of suppliers under green criteria systems. Sarkis and Dhavale (2015) integrate BN with Monte Carlo-Markov Chain simulation to rank suppliers. Nepal and Yadav (2015) use BN to quantify supply disruption risk.

4.3.1.3 Neural Networks (NN)

Neural networks learning algorithm simulates the mechanism of biological neural network that is initially generated by neurobiologists. The network is a set of connected input and output units in which each connection has a weight associated with it. In the learning stage, the network learns by changing the weights that aim to predict the correct class label of the input tuples. Medhi and Mondal (2016) define NN algorithm as a self-organizing map (SOM) for a non-typical clustering analysis. Tavana et al. (2016) develop an adaptive neuro fuzzy inference system in which NN analysis is as a component for integration.

4.3.1.4 Support Vector Machine (SVM)

SVM is a well-established, typical classifier for both linear and nonlinear data. SVM preliminarily adopts a nonlinear mapping to transform the original training data into a higher dimension. In this dimension, SVM aims to search a decision boundary separating the tuples of one class from another. By using a proper nonlinear mapping to a sufficiently high dimension, data from two classes can always be separated by a decision boundary. SVM finds this boundary through using training tuples (i.e. support vectors) and margins defined by the vectors. Guo et al. (2014) typically use SVM for multi-classification problem. Medhi and Mondal (2016) integrates three DMAI components including NN, SVM, and Kohonen's self organizing map (SOM).

4.3.1.5 Potential Classification Methods for SS

(a) Association Rule (AR)

AR method belongs to rule-based classifiers. It includes two stages. The first stage, frequent itemset mining, searches for relations of attribute-value pairs that appear repeatedly in a dataset. Each pair is known as an item, which constitute frequent item sets. The second stage, rule generation, analyszes the frequent item sets to induce associate rules. These rules are characterized by the confidence (their accuracy) and the support (the proportion of the dataset that they truly represent). Until now, there is no article reported the adoption of AR for SS. Due to its effecitivenss of classification, we expect this blank will be filled soon.

In addition, Classification based on multiple association rules (CMAR) and Classification based on predictive association rules (CPAR) are two well-established generation of AR classifiers. Beyond the basic usage of AR, these two advanced AR techinques get the potential to be investigated for the applications of selecting suppliers.

(b) Case-Based Reasoning (CBR)

CBR classifiers use a collection of problem solutions to solve new problems and store straining tuples (called cases) as complex symbolic descriptions. To classify a new case, a CBR classifier will first check if an identical training case exists. If one is found, the accompanying solution to that case then output. If no identical case can be found, CBR classifier will search for training cases having components similar to those of the new case. Using CBR classifers for SS could be an interesting direction for future studies.

(c) K-Nearest Neighbor Classifier (KNN)

Firstly introduced by Fix and Hodges (1951), KNN technique is based on the idea of analogy. Given a large training set of objects, KNN classifier compares a given, new object with simple training objects. Each object (e.g. supplier) is described by *n* attributes (also known as criteria) and each object represents a point stored in an n-dimensional space. After receiving a new object, a KNN classifier searches the space for the *k* training objects that can be the closest to the new object. These k training objects are the k 'nearest neighbours' of this new object, where the closeness is defined as a distance metric and can be measured by Euclidean distance. Related technical developments in KNN can be referred to Dasarathy (1991) and Duda et al. (2001).

The paradigm of KNN fits much for SS under multiple criteria. MCDM techniques are also suitable for multiple criteria. Differently, the target of MCDM is mainly for ranking, whereas the target of KNN is for classification and prediction, especially when the known training set of suppliers is very large. In addition, the KNN paradigm can be a proper technique for establishment and maintenance of a supply base. This direction will be reviewed in Section 5.3.

4.3.2 Clustering Methods

Clustering analysis is another central filed in data analysis. Clustering is a process of partitioning a collection of data objects into subsets. A subset is called a cluster. Data objects in a cluster are similar to each other but not in other clusters. While the subset (classes) in classification must be predetermined, a subset in clustering is not predefined. On the same dataset, using different clustering methods may generate different clusters. Partition on a dataset depends on the use of clustering algorithm rather than human settings. Therefore, it offers the opportunity of uncovering the previously unknown clustering (groups and patterns) within the data. Cluster analysis has been used widely in business intelligence, information retrieval, pattern recognition, web search, and artificial intelligence. In web search, for example, clustering techniques help to cluster extremely large number of online documents into topics, thereby allowing the search results to be grouped into topic clusters and presenting to users in a concise and easily accessible manner.

Based on our review, the community has not paid enough attention on the approach of using clustering methods for SS. We found only two articles that give such an attempts. Jabbarzadeh et al.

(2018) try to use K-means clustering method for assessing the quality of candidate suppliers. Guo et al. (2014) apply the concept of Kernel for clustering. In this subsection, we summarize releveant clustering techniques and promote their potential in serving the target of SS for future studies.

4.3.2.1 Partitioning Method (e.g. K-means, K-modes and K-Medoids)

The basic task in clustering is partitioning that is to assign the objects of a set into several non-predefined clusters. The simplest partitioning is to assume that the number of *c* clusters is known. Considering a data set D with *n* objects and the parameter K (i.e. the number of clusters to form), the objects are assigned into K clusters where K ≤ n. The clusters are formed to optimize an objective partitioning criterion similar to a dissimilarity function based on distance. The object thus can be similar to any other within the same cluster, but dissimilar to objects in other clusters in terms of the data set attributes. We emphasize three kinds of partitioning methods including K-means, K-modes, and K-medoids algorithms as below.

K-Means method is a centroid-based partitioning technique that uses the concept of centroid of a cluster to represent that cluster. Centroid can be generally deemed as the centre point of a cluster. The difference between the objects and a centroid is measured by Euclidean distances. The objective function is to make the k clusters as separate as possible. K-means technique only defines the centroid of a cluster as the mean value of the points within the cluster. K-means was introduced by Lloyd (1957) and is followed by the recent works of Arthur and Vassilvitskii (2007) and Kanungo et al. (2002). For SS tasks, Jabbarzadeh et al. (2018) advocates a c-means method in their fuzzy approach and has mentioned its origin from Dunn (1973). Keskin (2015) proposes a two-stage process that uses fuzzy DEMATEL followed by fuzzy K-means technique. This paper attempts to suggest a well-established and high-structured framework in knowledge background of classification and clustering, which will benefit for future development in SS.

One drawback of the *K-means* algorithm is its sensitivity to outliers since the objects departure from the majority of the data. After being assigned to a cluster, outliers can distort the centroid (mean value or mode) of the cluster undesirably. As an advanced K-means, *K-Medoids* technique (Kaufman and Rousseeuw 1990) chooses actual objects to represent the clusters rather than taking the mean value as a reference point like K-means. Jula et al. (2015) adopt PROCLUS that a top-down and K-medoid-like clustering method.

K-modes technique independently proposed by Huang (1998) and Chaturvedi et al. (2001) as a variant of K-means. This method replaces the means of clusters with the modes when the mean of a set of objects is not defined. Integrating K-modes or K-Medoids Clustering with other DM techniques can be a promising direction for future studies.

4.3.2.2 Other Clustering Methods

Decision problems can be structural, semi-structural, and non-structural. The latter two types partially depend on qualtitative analysis, less-organized inforamtion, or intuitions including human perception and judgments (Chai et al. 2013). Different from classification that is learning from examples, cluster analysis can be learning from observation and does not rely on label information of classes. Therefore, cluster analysis could be suitaible for resolving semi-structural and non-structural SS since it could be more convenient to incorporate people's subjective judgements. In the following, we recommend two clustering techniques that can be suitable for SS.

(a) Density-based Cluster Methods

The centroid-based clusters such as K-means, K-modes and K-Medoids algorithms are based on the distance between objects. The formed clusters thus have to be spherical-shaped. Density-based cluster methods can find arbitrary shapes of clusters. It thus can be more flexible for analyzing the subjects (e.g. alternative suppliers). The basic idea is to grow a searched cluster iteratively until the density (i.e. the number of objects) in the neighbourhood exceeds a predefined threshold. This method can form clusters of any shape and benefits for decreasing the influence of outlier subjects or noisy information. Interested readers can refer to several sophisticated toolkits including DBSCAN (Ester et al. 1996), OPTICS (Ankerst et al. 1999), DENCLUE (Hinneburg and Gabriel 2007) among other literature such as Breunig et al. (2000), Fraley and Raftery (2002) and Kim and Han (2009).

(b) Grid-based Cluster Methods

The grid-based clusters are to transfer the space of objects for a finite number of cells under a grid structure. This method process clustering on this quantized space. Using such techniques is reasonable since clustering process only depends on the number of cells and is independent of the number of objects. When the number of alternative suppliers is large, this method is more efficient than either centroid-based or density-based cluster methods as it requires less processing time. Two examples of sophisticated and noteworthy grid-based techniques are STING (Wang et al. 1997) and CLIQUE (Agrawal et al. 1998). They get the potential as a component of DM integration for semi-structural or non-structural SS processes.

4.3.3 Other DMAI Methods

In this section, we review several DMAI methods that typically cannot affiliate to either classification or clusteringb. Genetic Algorithm (GA) incorporates the idea of natural transition. Rough set approach (RSA) is based on the concept of equivalence classes. Both GA and RSA show their classification ability in certain applications. Grey system approach (GSA) is based on interval values (i.e. grey number) to represent imprecise or noisy data.

Based on our reviews, Cao et al. (2014) and Du et al. (2015) use GA to resolve multi-objective problems. Chai and Ngai (2014) develop a new rule-based sorting technique based on dominance-based rough set approach (Greco et al. 2001). Memon et al. (2015), Hashemi et al. (2015) and Pitchipoo, et al. (2013) adopt GSA to handle information ambiguity in their SS process.

Three minor AI techniques summarized in Chai et al (2013) are disappeared in our pool of articles. They include Particle swarm optimization (PSO) that simulates birds' behaviours, Ant colony algorithm that simulates ants' behaviours, and Dempster-Shafer theory of evidence. Notwithstanding, we overview several emerging techniques that can be recognized after 2013.

4.4. Emerging DM Techniques beyond the three-class framework

Table 4 shows the techniques that are beyond Chai et al. (2013), which are not typically used based on our reviews. Quality function deployment (QFD) is the most frequently used, which is followed by heuristic methods, Monte Carlo methods, Markov chain simulation, Triple Bottom Line, among others. We will overview them in this section.

Table 4. Emerging Techniques Used in SS Since 2013

Emerging Techniques	Representative Literature	Frequency
1. Quality Function Deployment (QFD)	Scott, Ho, & Dey (2013)	7
2. Monte Carlo Methods	Hong & Lee (2013)	3
3. Multi-Agent Systems	Yu & Wong (2015)	2
4. Markov Chain simulation	Sarkis & Dhavale (2015)	2
5. Triple Bottom Line	Mota et al. (2018)	2

4.4.1 Quality Function Deployment (QFD)

QFD developed by Akao (1972) can transfer the requirements of customers into the requirements of production and service. QFD can be a proper method of information pre-processing where the transferred information are inputs for the next-stage decision process. QFD is popular for SS since it can be the bridge between a structural DM problem and the real world. Based on our reviews, QFD has been integrated with AHP (Scott et al. 2013; Scott et al. 2015), ANP (Asadabadi 2017), SP and trapezoidal fuzzy elements (Babbar and Amin 2018), MINLP+SP (Amin and Zhang 2013), and DEA (Karsak and Dursun 2014).

4.4.2 Multi-Agent Systems

A multi-agent system, also known as a self-organised system, is an information system composed of multiple interacting intelligent agents. Agents are partially independent, self-aware and autonomous, which fit for carrying a decision task. Similar usages of multi-agent systems in our collected pool can be found in Yu and Wong (2015) and Ghadimi et al. (2018).

4.4.3 Monte Carlo Methods

Monte Carlo method (known as Monte Carlo simulation or probability simulation) is a computerized mathematical technique that allows people to see all possible decision outcomes and to assesse the influences of risk and uncertainty. This method provides people with a range of possible outcomes and the probabilities. This technique has been established in many reported approaches as a component after integration with Bayesian network (Sarkis and Dhavale 2015), Goal programming (Hong & Lee 2013; Moghaddam 2015) and a Lagrangian relaxation approach (Benyoucef et al. 2013).

4.4.4 Markov Chain Methods

The Markov chains, named after Andrey Markov, is a dynamic model that is based on the idea of "memorylessness". The next state of the process depends only on the previous state rather than the sequence of states. This assumption allows conditional probability to be calculated in a simple manner. Chai et al. (2013) summarized the usage of this method for SS problems including the integration with DEA in Wu and Olson (2008). Since then, Asadabadi (2017) uses Markov Chain in supporting QFD analysis and further develops an ANP-QFD method. Sarkis and Dhavale (2015) develop a highly integrated Monte Carlo Markov Chain method for a robust analysis in suppliers.

4.4.5 Triple Bottom Line Model

Triple bottom line (TBL) is a framework of sustainable operations. It suggests the three aspects including social development, environmental protection and economic development (Sridhar and Jones 2013). This framework has been well-implemented in Hewlett-Packard (Gmelin and Seuring 2014), and further is advocated to the community. In MCDM, TBL helps to establish the system of multiple criteria. Lin et al. (2015) provide a detailed TBL-based framework on the account of sustainability, where ANP is the main decision tool in their approach. Mota et al. (2018) use TBL as a preliminary framework and integrate a multi-objective MILP model into their approach.

5. Trends for Future Researches

Based on our review, we found clearly transitions of DM techniques. This section summarizes six important aspects, which could shed light on several promising directions in this field.

5.1 From Uncertainty Analysis to Risk Analysis

Chai et al. (2013) emphasized the uncertainty environment in SS including stochastic information, grey numbers, fuzzy variables and its diversified family such as triangular, trapezoidal, intuitionistic and internal valued fuzzy variables. It concludes that fuzzy integrated methodology dominates DM techniques. Most of them are still adopted frequently in the literature. Table 5 illustrates the status quo of fuzzy integrated approach for SS.

Table 5. Status Quo of Fuzzy integrated Approach

	Fuzzy related Decision Approach	**Representative Articles**
Using Fuzzy Element	Using Fuzzy independently	none
	Fuzzy VIKOR	Leng et al. (2014)
	Fuzzy AHP	Pitchipoo et al. (2013)
	Fuzzy TOPSIS	Rodriguez et al. (2013)
	Fuzzy GP	Kar (2014); Moghaddam (2015)
	Fuzzy Delphi	Govindan et al. (2016)
	Fuzzy MIP	Babic & Peric (2014)
	Fuzzy ANP	Bodaghi et al. (2018)
	Fuzzy MOP	Jadidi et al. (2014)
	Fuzzy DEMATEL	Keskin (2015)
	Fuzzy C-Means	Keskin (2015)
	Fuzzy SVM	Guo et al. (2014)
	Fuzzy LP	Ulutas et al. (2016)
	Fuzzy DEA	Karsak & Dursun (2014)
	Fuzzy QFD	Babbar & Amin
	Fuzzy NN	Tavana et al. (2016)
	Fuzzy GS	Memon et al. (2015)
Using Extension of Fuzzy Element	Intuitionistic Fuzzy (IF)	Chang (2017); Wan & Li (2013)
	IF-VIKOR	You et al. (2015)
	Hesitant Fuzzy (HF)	Chai & Ngai (2015); Liao et al. (2018)
	HF-QUALIFLEX	Zhang & Xu (2015)
	Type-2 Fuzzy	Turk et al. (2017); Qin et al. (2017)

We found a significant transition that is from uncertainty analysis to risk analysis. Based on our review, 44 articles take the risk factor into account, which can be boiled down to two aspects. First, Risks in manufacturing and operations are from demand uncertainty, equipment failure, quality and delay problems. Second, random disruption risks are from natural disasters, strikes, supplier bankruptcy even war and terrorism (Dupont et al. 2018). In the first aspect, typical methods assume that people's risk-taking behaviour situates in a quantified degree of risk aversion. An optimal solution can be found through a predefined objective function. In this process, translating these risks into a quantified and measurable attribute is a challenging problem. Value-at-risk (VaR) and conditional value-at-risk are introduced in Fang et al. (2016), Merzifonluoglu (2015) and Sawik (2014). Firouz et al. (2017) provides a discrete-event simulation type in evaluating disruptions in supply chains. Yoon et al. (2018) parameterize consumers' risk attitudes into their retailer's sourcing strategy.

Loss aversion is one of the key feature incorporated in the prospect theory (Kahneman and Tversky 1979; 1992). Before 1980, most decision theories are founded in Expected utility theory (von Neumann and Morgenstern 1944) and its generalized formulation Subject expect utility theory (Savage 1954). The descriptive validity of both theories has been challenged substantially by Allais (1953)'s paradox and Ellsberg (1961)'s paradox. The 1979 version of prospect theory is motivated to resolve the fourfold pattern of risk attitude that cannot by captured by classical theories. Loss aversion, preference dependence, and diminishing sensitivity are incorporated into this version of prospect theory. The 1992 version of prospect theory distinguishes between the gain and the loss in both utility function and probability weighting function. Related literature before 1990 were well reviewed by Camerer and Weber (1987; 1992). Modern decision theories since 1990 can be found in Wakker (2010) and Barberis (2013). An updated study in measuring prospect theory probability weighting function can be found in Chai and Ngai (2019). Loss aversion, together with risk aversion, has been reported for resolving SS, for example Dupont et al. (2018) and Merzifonluoglu (2015). Beyond that, uncertainty is also considerable. For example, Balcik and Ak (2014) capture demand uncertainty after using a set of disaster scenarios.

5.2 Incorporating Economic Theories in SS

Existing economic theories have penetratred for modelling SS process such as game theory and normative preference theories. Game theories can be motivated to resolve existing competition and cooperation between suppliers. Sheu (2016) formulates buyer's behaviours by using a Nash bargaining game normative analyses. Wang and Li (2014) propose an improved Nash bargaining game DEA model based on Wu et al. (2009)'s cross-efficiency evaluation method. Ji et al. (2015) formulate a game model to capture the cooperation tendency of relationship between buyers and suppliers through interactions among different game players. Mohammaditabar et al. (2016) adopt cooperative and non-operative game models to examine the selected supplier and total costs in supply chains. Noori-Daryan et al. (2018) use cooperative game model by assuming a coalition attitude among game players in which all the players' decisions are known by any other player when making decisions at the same time. Leng et al. (2014) use a Stackelberg game model for parts machining outsourcing problem after the integration with a fuzzy VIKOR method.

Normative preference theories refer to the normative model of using a value or utility function to represent human preference. The additive model such as Fishburn (1967), Keeney (1972) and Keeney and Raiffa (1976) provides the theoretical foundation of modern Multiattribute utility theory (MAUT). A detailed survey ican be found in Stewart (1992) and Wallenius et al. (2008). de Almeida et al. (2016) develop a flexible and interactive trade-off method for eliciting the weights of attributes under an additive utility structure where priori information are not required. Methodologically, their idea is similar with the trade-off method (Wakker and Deneffe 1996). Based on an additive structure

(Keeney and Raiffa 1976), Rezaei (2018) advocates the use of a set of piecewise linear value functions to represent the preference of people involved in SS. Notwithstanding, the value function in this way must be determined by a priori and must be linear.

MAUM includes AHP/ANP, which has been emphasized in Chai et al. (2013). According to Gass (2005), MAUM also includes Multiattribute utility theory (MAUT) developed by Keeney and Raiffa (1976). MAUT is imposed by the axioms of von Neumann and Morgenstern (1944) on lotteries. In the past decade, there is no study that uses MAUT for SS. We note that uncertainties addressed in MAUT is associated with probabilities, while the uncertainties in classical SS is related to the unqualified representation of information.

5.3 Establishment and Maintenance of a Supply Base

Supply base is considered as a pool of qualified suppliers managed by a buying company. The selected suppliers are eligible for contract award with buyers. Two scenarios are considered. If buyers apply short-term contracts and re-buy the same raw material frequently, it makes sense to establish a collection of previously evaluated suppliers who are eligible for these contracts. If buyers apply long-term contracts for individual items that do not need to be re-bid frequently, the maintenance of such a supply base still makes sense because this mechanism offers a completion between the long-term supply base members and the potential alternative new suppliers. Therefore, using a supply base can reduce the cost of SS processes, can benefit for development of an optimized contracting process with selected suppliers, standardize the conditions and evaluation criteria of selecting suppliers.

In a base while more suppliers are needed, the problem is maintaining this base from the buyer's end, thereby is controlling the high cost of finding and qualifying new suppliers. Relevant topics can be categorised as follows. First, when suppliers in the base are preference-ordered on how to select alternative suppliers to join in this base while maintaining existing order relation. Supplier A dominates B in preference with respect to a criterion (e.g. price). The new supplier C should not be inferior to B and superior to A at the same time. Considering multiple criteria on this topic would be very challenging. Second, how to sort alternative suppliers into existing classes. This topic addressing preference-ordered or interdependent classes can be challenging and non-trivial. Third, selecting alternative suppliers under multiple criteria should be considered, expecically when the existing feature of the supplier base must be maintained.

Based on our review, Torabi et al. (2015) propose a mixed usage of stochastic and multi-objective programming for base establishment under risk environments. Supply base management is also concerned about the designs of base (Wan and Beil, 2014), auction mechanism (Chaturvedi et al. 2014), pricing (Li, 2013) and its complexity (Choi and Krause, 2006; Vanpoucke et al. 2014). Hu and Motwani (2014) attempt to minimize downside risks in supply base.

Recent literature put forward a concept of supplier segmentation. The basic task is to group suppliers in a supply base by their impact on the business. The target is to build a portfolio of supplier relationships with varying characteristics that support the firm in different manners (Gulati and Kletter, 2005). Essentially, supplier segmentation is a process of dividing suppliers into distinct groups, which in the perspective of DMAI can be boiled down to a clustering problem if the group is not identified, or a classification problem if the group has been identified, or a sorting problem if the group is identified as well as preference-ordered. In this sense, the rich toolkit of DMAI as reviewed in this paper can be adopted. In our pool of articles, Segura and Maroto (2017) use the outranking method PROMETHEE and MAUT to construct the criteria for supplier segmentation. Rezaei et al. (2015) apply a Best-worrst method to determine the criteria for segmenting the suppliers. How to use the DMAI tookit for directly grouping or classifying suppliers is a valuable direction for future studies.

5.4 Sorting Techniques Adoption

Classification aims to assign suppliers to several predefined classes. Clustering can be separated from classification when the classes are not determined. Differently, sorting aims to assign alternatives to the classes that is not only predefined but also preference-ordered. Sorting can be important for several senarios of SS processes but its application is rarely been reported. Main challenges come from a lack of proper toolkit to deal with the alternatives who violate the dominance of preference relations. Mature classifiers like DT, BN, NN and SVM cannot incorporate people's subjective judgements. And, mature preference structures like MAUT and Prospect Theory (Bleichrodt, Schmidt, and Zank, 2009) cannot be applied for classification. Bridging this gap must be desirable in the future.

Dominance-based rough set approach (Greco et al. 2001, Slowinski et al. 2009) is a mature DM technique for sorting. Its preference model is based on a sample of past decisions through ‘if-then’ rules. It can uncover inconsistencies from past samples. Chai and Liu (2014) proposed a DRSA-based approach for supply base maintenance. In the base, supplier members are sorted into several grades according to their qualifications. The challenge is to increase this base by accepting new, potential suppliers that must be sorted into the graded levels within the base. Maintaining a base abide by preference transitivity and preference dominance principle. The practical implication is for those large-scale multi-supplier companies such as retail enterprises or assembly enterprises.

5.5 Green and Strategic Supplier Selection

Green supplier selection considers environmental protection and sustainablity in SS processes. The mainstream of green SS attempts to establish a system of criteria, some of which represent sustainabilities. For example, Kannan et al. (2014) establish a criteria system for the Brazilian electronics industry by using a Fuzzy TOPSIS approach. Mahdiloo et al. (2015) create a system for Hyundai steel company by integrating multiple objective LP and DEA approach. Similar usages can be found in Hashemi et al. (2015) for automotive industries and Lin et al. (2015) for Taiwanese electronics companies. Sheu (2016) considers green supply chains by incorporating qualified attitudes and procurement decisions of buyers. Also, Dobos and Vorosmarty (2018) adopt DEA in green SS.

Strategic supplier selection derives from the concept of strategic sourcing. Yet, some past articles under the strategic SS label have nothing to do with environmental factors, for example, Dey et al. (2015) and Chai and Ngai (2015). The usage of terms in literature could confuse people. We found that green SS refers to criteria settings that is concerned about environments, whereas strategic SS emphasizes organizational and human factors such as strategies of companies, influences of stakeholders, and policy environments. In this sense, green SS can be regarded as a component of strategic SS.

5.6 Group and Negotiation Process

The process of SS normally involves more than one decision maker. The core of group SS is preference aggregation (PA). When PA happens in an earlier stage, it is easy to operate but individual's judgements may not be preserved completely. When PA happens later, it become more complicated. A valuable direction is to develop negotiation mechanisms in which subjective judgmments of people can be preserved. In literature, Baucells and Sarin (2003) and Baucells and Shapley (2008) suggest building methodologically a number of coalitions in the group in order to reach final decisions by pursuing an agreement of these coalitions. Keeney (2013) proves fundamentally that the relations between the groups expecting utility and individuals expecting utility can be a weighted sum. It allows PA from the individual to the group, which can happen in the later stage.

Based on our review, Chai and Ngai (2016) provide a framework for group argumentation mechanism that considers opinion interaction and metasynthesis process for SS. Govindan et al. (2017) use the PROMETHEE method to induce a group compromise ranking. Dong et al. (2017) develop a convergent group AHP consensus reaching model. In this model, the importance of evaluators in a group are adjustable and compatible through a weighting feedback mechanism. Sodenkamp et al. (2016) design a trade-off mechanism that can synthesize suppliers' synergistic performance characteristics. Also, multi-person factor is incorporated in several non-group-focused decision approaches such as Qin et al. (2017), You et al. (2015), Karsak and Dursun (2014), Kar (2014) and Wan and Li (2014).

6. Discussions

Why do we need to hybrid DM techniques? A SS decision process usually involves multiple stages. In buyers' end, general processes could involve (1) collecting suppliers, (2) shortlisting suppliers, (3) establishing criteria, (4) organizing and selecting qualified decision makers (group), (5) eliciting, refining, and modelling preference of people, (6) normalization of decision information, (7) finding solutions for choosing, ranking, or classifying alternatives, (8) managing established supply bases, and so on. Methodologically, Baucells and Sarin (2003) point out "decision analysis has a strong tradition of breaking down complex problems into simple parts and then combining the information collected on these parts to reach a decision." It explains that why we understand a SS process as a complex decision and would like to break it down into several separated tasks. The main challenges are to find the most suitable solutions for each of these stages with considering various organizational or environmental purposes. The target is to take the advantages of adopted DM techniques for a better outcome in each stage, so as to a better outcome in the next or final stage. A contribution of this paper is just to summarize the state-of-the-art development of adopted DM techniques in the last half decade.

Hybridization of DM techniques should be "organic" rather than a simple combination. For example, ranking suppliers may need multiple preference operations including elicitation, refinement, modelling, and standardization. They all strongly rely on the preference information provided by people. This information could be incomplete, inaccurate, or perhaps involving subjective incentive or bias (Chai and Ngai, 2016). A successful hybridization should ensure being unique and superior to other possible hybridizations. Simply, any adopted DM technique shouldn't be for an ad hoc purpose. The chosen technique in hybridization cannot be replaced easily by other alternative techniques if decision conditions are unchanged.

Echoing Chai et al. (2013)'s result, AHP/ANP still dominate other DM techniques (around 10.0%/5.0%, respectively) between 2013 and 2018. Recently, AHP/ANP start to be a component of the hybridization rather than a relatively independent usage of SS. As illustrated in Wallenius et al. (2008, Figure 3), AHP/ANP have been very popular since Saaty (1980), especially after 1990. Saaty (1986) provided the axiomatic foundation of AHP that is actually against the axioms of expected utility theory (Smith and von Winterfeldt, 2004). Dyer (1990) argues that AHP/ANP generates arbitrary outcomes. The crux of this debate is whether the performance of AHP can be tested or repeatable. Winkler (1990) made an analogy with utility theory. The reason for the popularity is that AHP/ANP is intuitional and can reflect people's daily thinking. Another truth is that it indeed lacks supports of a normative foundation. We agree that AHP/ANP must be a suitable tool for relatively independent usages in SS processes. Yet, we have reservations on using them for overladen hybridization. For instance, AHP/ANP use pairwise comparisons for ranking, which could be incompatible with other chosen techniques in other stages. Any incompatibility in hybridization is highly unexpected and must be avoided.

Echoing Chai et al. (2013)'s results, until now the family of fuzzy theories plays a heavy role in hybridization as shown in Table 5. Fuzzy theory and many of its variations are to convert people's natural languages (e.g. linguistic terms) into the quantified, computable, corresponding numbers. These numbers carrying people's preference are the fundamental information for evaluating suppliers. The reason of their popularity is that using fuzzy for information fusion can be relatively independent with other stages. The advantages are the rich fuzzification toolkit that can be used for preference modelling. The disadvantages are the loss of information occurred more or less in fuzzy calculation. For SS, once assuming the natural language as decision inputs, one can usually establish more than one fuzzifications for it, e.g. basic fuzzy numbers, IF numbers, or HF numbers. That is why we can find a fuzzy version of the most of the independent DM techniques as shown in Table 5. Also, it is easy to extend a fuzzy version to other fuzzy variations. Nevertheless, if the assumption of inputting natural language in SS, all fuzzy-integrated approaches are all disabled. This could motivate the transition of recent attentions from uncertainty (fuzzy) analyses to risk analyses as concluded in Section 5.1.

7. Conclusions

In this paper, we provide a state-of-the-art survey of literature on applications of DM techniques for supplier selection. We elaborately analyse the articles that has published between 2013 and 2018, which can be deemed as the succeeding study of Chai et al. (2013) that study articles published between 2008 and 2013 with the similar methodology. In this paper, we exhibit clearly the full picture of this field including transitions of the development. We emphasize the core trend that is the penetration of data mining and analysis such as classification and clustering. We further specify the six aspects of transitions including uncertainty and risk, economic theories, supply bases, sorting techniques, green and strategic SS, and group and negotiation issues. We witness that this field benefits from other disciplines including computer science, data science, and economic science. Although SS is an application domain, its development relies strongly on the development of methodology, especially generic methodological innovations. This paper provides valuable knowledge accumulation on current studies and clear recommendations for future works.

Acknowledgments

The authors are grateful for the constructive and insightful comments of the referees on an earlier version of this paper. The first author gratefully acknowledges financial supports from Beijing Normal University-Hong Kong Baptist University United International College Research Grant under Grant R201917. The second author thanks xxx

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