Computers & Industrial Engineering 102 (2016) 58–68

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Assessment of corporate innovation capability with a data-mining approach: industrial case studies

Serkan Altuntas [a,*], Turkay Dereli [b,c], Andrew Kusiak [d]

[a] Yildiz Technical University, Department of Industrial Engineering, 34349 Istanbul, Turkey
[b] Iskenderun Technical University, Office of the President, 31200 Iskenderun, Hatay, Turkey
[c] Gaziantep University, Department of Industrial Engineering, 27310 Gaziantep, Turkey
[d] The University of Iowa, Department of Mechanical and Industrial Engineering, Iowa City, USA

A R T I C L E I N F O

Article history:
Received 27 May 2016
Received in revised form 10 September 2016
Accepted 23 October 2016
Available online 24 October 2016

Keywords:
Innovation capability
Data mining
Fuzzy association rules
Case studies

A B S T R A C T

The interest in assessment of innovation capability of manufacturing systems is fueled by the growing competition. At this time, there is no generally accepted model to evaluate innovation capability of manufacturing systems. In this paper, a fuzzy-logic based data-mining approach is proposed to assess innovation capability of manufacturing systems. The proposed algorithm is illustrated with two industrial case studies representing two different industry sectors. The results derived from these case studies demonstrate advantages of the proposed algorithm in assessing corporate innovation capability.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Assessing innovation capability of a corporation is important to remain competitive. Although the interest in assessment of innovation capability of organizations is growing, the literature on innovation capability is not extensive. This could be due to the lack of understanding of innovation. The need to create innovation science was outlined in Kusiak (2007a). The research related to innovation is interdisciplinary and has attracted numerous science and practice communities (Kusiak, 2007e). Due to its interdisciplinary nature, numerous definitions of innovation have appeared in the literature (e.g., see Martínez-Román, Gamero, & Tamayo, 2011). According to Kusiak (2009), innovation aims at the creation of new products, processes, services by the use of new and existing knowledge. Productivity and efficiency can be improved by application of methods and tools, such as: trial and error approach, lead user study, and innovation networks cited in Kusiak (2007c).

The literature offers different definitions of innovation capability. In this paper, innovation capability is defined as the ability to support and sustain innovation by using resources from diverse business areas ranging from marketing, research and development (R&D) and manufacturing to logistics, and human factors. An organization's capability is vital for sustaining its competitive advantage and implementation of new strategies (Guan & Ma, 2003). The innovation capability of an organization indicates its innovation potential and future technological power. Higher innovation capability implies stronger competitive power and long-term survival in a competitive environment. There is no widely agreed upon model for comprehensive assessment of innovation capability. The reason behind the latter is that the factors impacting innovation capability change from sector to sector and technology to technology. In addition, measuring such factors is difficult due to their imprecision and vagueness. However, assessing innovation capability of any organization is important.

Assessing innovation capability of any organization requires the considerations of multiple capabilities, such as organization innovation capability, process innovation capability, product innovation capability, marketing innovation capability etc. Considerations and evaluation of such capabilities needs the usage of data-mining driven methods to find out unknown pattern and meaningful results. Previous studies do not focus on associations among corporate innovation capabilities. No previous work also applies a fuzzy-logic based data-mining approach to assessment of innovation capability of corporations.

In this paper, a fuzzy-logic based data-mining approach is applied to assess innovation capability of organizations and to address imprecision and vagueness. The classic association rules

* Corresponding author.
E-mail addresses: serkan@yildiz.edu.tr, saltuntas2@gmail.com (S. Altuntas), dereli@gantep.edu.tr, turkay.dereli@iste.edu.tr (T. Dereli), andrew-kusiak@uiowa.edu (A. Kusiak).

http://dx.doi.org/10.1016/j.cie.2016.10.018
0360-8352/© 2016 Elsevier Ltd. All rights reserved.

cannot capture meaningful relationships among different types of innovation capabilities. To address this limitation, fuzzy association rules are used. The fuzzy rules are derived with data-mining algorithms, and they constitute a fuzzy-rule algorithm proposed in this paper. The fuzzy rules capture perceptions for decision makers. Knowing associations among different innovation capabilities offers great value to any organization in two ways: (1) making innovation capability of the competitive environment transparent and (2) organization's priorities become apparent. The major contribution of this paper is threefold. First, it proposes a fuzzy-logic based data-mining approach to assess corporate innovation capability in practice. Second, the study demonstrates a successful application of FGBRMA with industrial case studies. Third, a fuzzy-logic based data-mining approach is applied in this study to overcome the limitation of the classic association rule-based data mining algorithms and to address imprecision and vagueness in practice.

The remainder of this paper is organized as follows. The literature on innovation capability is presented in Section 2. The proposed approach for assessment of innovation capability is introduced in Section 3. To validate the proposed approach, applications in two different sectors are provided in Section 4. The final section offers future research directions and conclusions.

2. Literature review

The number of applications of formal methods in innovation science is rather limited. Engler and Kusiak (2010) proposed a novel text-mining approach to determine the authoritative entities involved in collaborative innovation. Engler and Kusiak (2008) proposed web mining for innovation. In addition, Kusiak (2007b) and Kusiak (2007d) discussed data mining in industrial applications and innovation. Guan and Ma (2003) conducted an empirical study to explore the relationship between innovation capability and export performance of Chinese exporting firms. The results demonstrated a relationship between the total improvement of innovation capability and export growth. It was determined that learning orientation impacts innovation capability of a corporation. In addition, organization's innovation capability and learning orientation affect firm performance (Calantone, Cavusgil, & Zhao, 2002). A range of internal and external factors may impact innovative performance of corporations. Details on these factors analyzed for electronics and software development firms are presented in Romijn and Albaladejo (2002). R&D positively affects innovation potential of a company. Higher R&D intensity and higher R&D manpower are important predictors of corporate performance (Sher & Yang, 2005). In addition, different types of technology sourcing impact innovative capability of corporations (Zhao, Tong, Wong, & Zhu, 2005). Koc and Ceylan (2007) documented factors impacting innovative capacity of large corporations.

Lawson and Samson (2001) proposed an innovation capability based model to achieve effective performance of organizations. Koc (2007) determined organizational factors of innovation capacity in software development companies. Yang, Zhang, and Ding (2015) proposed a method based on uncertain linguistic variables and analytical hierarchy process to study innovation capability. In addition, the impact of intellectual capital on radical and incremental innovative capability (Subramaniam & Youndt, 2005), national innovation capability (Sun, 2009), R&D project assessment with respect to innovation capability (Elmquist & Masson, 2009) has been reported in the literature. Martínez-Román et al. (2011) discussed innovation in small and medium enterprises, while Forsman (2011) analyzed innovation capacity and development of small enterprises. In addition, the impact of customer relationship management (Lin, Chen, & Chiu, 2010), tacit knowledge transfer (Cavusgil, Calantone, & Zhao, 2003), knowledge management (Yang, Rui, & Wang, 2006), knowledge sharing (Lin, 2007) of innovation capability have been researched in the literature. Ahmed and Abdalla (1999) discussed the role of innovation process in crafting the vision of the future.

The relationship between innovation capability and corporate knowledge management (Tasmin & Woods, 2007), and the knowledge creation process (Numprasertchai, Kanchanasanpetch, & Numprasertchai, 2009) have been studied.

Fuzzy logic based studies have been conducted to analyze innovation capability (see Dereli, Durmusoglu, & Daim, 2011; Lin, Tseng, Chen, & Chiu, 2011; Lu, Chen, & Wang, 2007; Wang, Lu, & Chen, 2008).

Although data mining algorithms usually call for large data sets, fuzzy association rules can be derived based on small data sets, e.g., provided by a few decision makers. For example, Vinodh, Prakash, and Selvan (2011) used data from five different decision makers to evaluate leanness in manufacturing with fuzzy association rules. Similarly, Hu, Chen, and Tzeng (2003) used data from ten different resources, which can be considered decision makers, to utilize fuzzy association rules. Although a few decision makers are enough to employ fuzzy association rules, the number of rules derived by fuzzy association rules is generally high. Fuzzy association rules provides only meaningful results among these rules derived.

Fuzzy association rules express relationships among items under fuzziness. In this paper, the items are referred to as factors. The relationship among factors is expressed with association rules. The rules indicate that if condition "A" occurs, then condition "B" may also occur. Details on the association rules are provided in Hipp, Güntzer, and Nakhaeizadeh (2000), Zhao and Bhowmick (2003), Kotsiantis and Kanellopoulos (2006), Sowan, Dahal, Hossain, Zhang, and Spencer (2013), and Altuntas, Dereli, and Kusiak (2015).

Association rules are widely used tools in data mining. Jain, Benyoucef, and Deshmukh (2008) applied association rules to evaluate agility of supply chains. Vinodh et al. (2011) used fuzzy association rules based approach to evaluate leanness. We are not aware of any study using association rules to evaluate innovation capability.

Most publications related to the innovation capability report empirical research based on surveyed data. They focus on identification of factors impacting innovation capability, relationship between innovation capability and these factors, and validation of various hypothesis. This paper presents application of the fuzzy-grids based rule-mining algorithm (FGBRMA) to assess innovation capability of organizations. Details of the proposed approach introduced in the next section.

3. Fuzzy-grid based rule-mining algorithm (FGBRMA)

Hu et al. (2003) proposed fuzzy-grid based rule-mining algorithm (FGBRMA) to find associations in a relational database. The algorithm proposed in this paper is based on data mining. It includes two stages, generation of the large fuzzy grids and generation of fuzzy association rules (Hu et al., 2003).

Overview of the proposed methodology is illustrated in Fig. 1.

The steps of the FGBRM algorithm (Hu et al., 2003) applied to assess corporate innovation capability are presented next. The proposed FGBRMA application is new.

Step 1:	Determine factors impacting innovation capability.
Step 2:	Determine fuzzy partitioning of factors and fuzzy sets with membership functions.
Step 3:	Specify the minimum support value.
Step 4:	Specify decision makers.

(*continued on next page*)

Step 5: Perform decision maker's assessment (points, between 0 and 10, are given) for each factor.
Step 6: Compute a fuzzy grid data and the fuzzy support values.
Step 7: Eliminate fuzzy grids if support value is less than the determined minimum support value. If there are at least two fuzzy grids remaining, go to Step 8, otherwise go to Step 9.
Step 8: Use the remaining fuzzy grids to form multi-dimensional grids and go to Step 7.
Step 9: Combine fuzzy grids to obtain different fuzzy association rules in the form "Antecedent" and "Consequent" by using the remaining fuzzy grids. Calculate *fuzzy confidence* of each combination (rule) [*Generation of fuzzy association rules*]
Step 10: Sort all rules in descending order with respect to *fuzzy confidence value*.

The following definitions are used in the FGBRMA.

- *Minimum support* is specified by a decision maker and takes the value between 0 and 1.
- *Fuzzy grid:* Every fuzzy set is called a candidate fuzzy *grid*. There may be n-dimensional *grid*. For example, PS(L).PR(M) is a two-dimensional *grid* and it implies "low process innovation capability and medium product innovation capability". It should be noted that it is not possible to construct a fuzzy grid using two factors, the low process innovation capability and the medium process innovation capability denoted by PS(L).PS(M).
- *Fuzzy support* (FS) = ($\sum$all elements in a fuzzy *grid*)/(number of elements in the fuzzy *grid*).
- *Fuzzy confidence of an association rule* (FC) = Fuzzy support of all elements constructing association rule/Fuzzy support of the consequent.

The above definitions are illustrated with an example. We will use two factors, X and Y, two linguistic values (Small(S) and Large (L)), and three decision makers (A, B, C). Table 1 presents a *one*-dimensional fuzzy grid. FS for Y(S) = (0.2 + 0 + 0.3)/3 = 0.166. Assume that value of FS of the *one*-dimensional fuzzy grid is higher than the *minimum support value.* X(S).X(L) is invalid fuzzy grid because of the fact that the same factor is used to construct different fuzzy grids. *Fuzzy confidence value* of X(S) → Y(S) = FS (X(S).Y (S))/FS (Y(S)) = (0.1 × 0.2 + 0.5 × 0 + 0.2 × 0.3)/0.166 = 0.482.

4. Applications of the proposed algorithm

Two industrial case studies illustrate viability of the proposed approach.

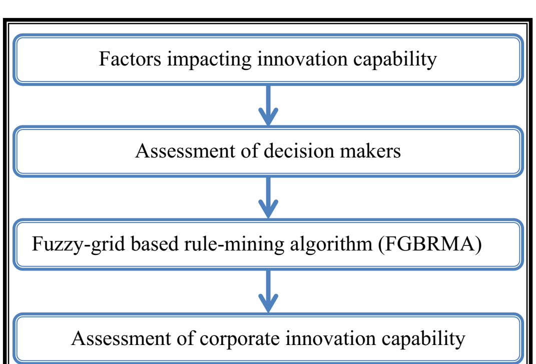

Fig. 1. Overview of the proposed methodology.

Table 1
One-dimensional fuzzy grid.

	A	B	C
X(S)	0.1	0.5	0.2
X(L)	0.5	0.2	1
Y(S)	0.2	0	0.3
Y(L)	0.3	0.4	0

4.1. Case study 1

The first case study was conducted in a company producing roof facade insulation systems in Erzincan City, Turkey. The firm was established in 2004 and it manufactures different products for roof waterproofing, insulation, screed concrete, ceramic adhesive, perlite, plaster and flooring systems. The company sells their products in domestic and overseas markets. Face to face interviews were conducted to obtain the data needed to demonstrate the proposed approach.

Implementation of the FGBRM algorithm is presented next.

Step 1: Five levels of innovation capability (attributes), namely organization innovation capability, process innovation capability, service innovation capability, product innovation capability, and marketing innovation capability, were proposed by Wonglimpiyarat (2010) to assess innovation efficiency in an industrial innovation system. In this paper, all levels of innovation capability are considered, except of the service innovation capability due to the fact that service innovation capability applies to the service oriented/based firms.

Step 2: Fuzzy partitioning of an attribute and fuzzy sets X(L), X (M) and X(H) with the membership functions used by Vinodh et al. (2011) is applied in this study (see Fig. 2). The crisp set and fuzzy set for each capability is provided in Table 2.

Each capability consists of fuzzy sets (X(L), X(M) and X(H)) with the membership functions presented in Vinodh et al. (2011):

$$X(L) = \mu(x) = (-X/5) + 1$$
$$X(M) = \mu(x) = (X/5);\ x \leqslant 5$$
$$\qquad 2 - (X/5);\ x \geqslant 5$$
$$X(H) = \mu(x) = (X/5) - 1$$

where X is the crisp set, such that x ε X, μ(x) ε (0,1). Zero value is assigned, if $x \geqslant 5$ for X(L) and $x \leqslant 5$ for X(H). Here, each of X(L), X (M) and X(H) is a candidate for a *one*-dimensional grid.

Step 3: The minimum support value of 0.25 is used in this case study.

Step 4: The total number of decision makers is five. Decision makers represent the sales and marketing department, R & D department, production planning department, quality control

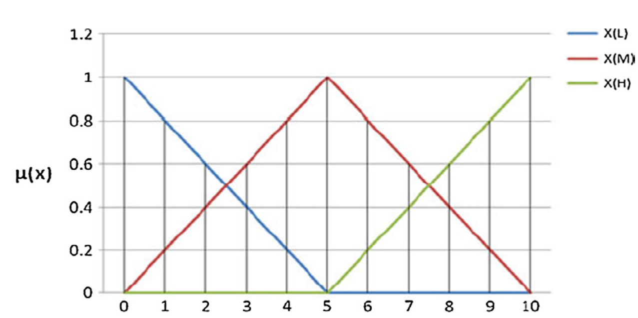

Fig. 2. Fuzzy partitioning of an attribute (Vinodh et al., 2011).

Table 2
Crisp and fuzzy sets.

Capability	Crisp set	Fuzzy set
1. Organization innovation capability	O	O(L), O(M), O(H)
2. Process innovation capability	PS	PS(L), PS(M), PS(H)
3. Product innovation capability	PR	PR(L), PR(M), PR(H)
4. Marketing innovation capability	M	M(L), M(M), M(H)

Table 3
The scores provided by five decision makers in case study 1.

Capability		Decision maker				
		1	2	3	4	5
1. Organization innovation capability	(0 – 1 0)	7	8	6	7	8
2. Process innovation capability	(0 – 1 0)	8	8	5	8	9
3. Product innovation capability	(0 – 1 0)	6	7	9	8	8
4. Marketing innovation capability	(0 – 1 0)	6	8	4	8	9

Table 4
One-dimensional fuzzy operation support data in case study 1.

No.	1DFW	1	2	3	4	5	Support
1	O(L)	0	0	0	0	0	0
2	O(M)	0.6	0.4	0.8	0.6	0.4	0.56[a]
3	O(H)	0.4	0.6	0.2	0.4	0.6	0.44[a]
4	PS(L)	0	0	0	0	0	0
5	PS(M)	0.4	0.4	1	0.4	0.2	0.48[a]
6	PS(H)	0.6	0.6	0	0.6	0.8	0.52[a]
7	PR(L)	0	0	0	0	0	0
8	PR(M)	0.8	0.6	0.2	0.4	0.4	0.48[a]
9	PR(H)	0.2	0.4	0.8	0.6	0.6	0.52[a]
10	M(L)	0	0	0.2	0	0	0.04
11	M(M)	0.8	0.4	0.8	0.4	0.2	0.52[a]
12	M(H)	0.2	0.6	0	0.6	0.8	0.44[a]

1DFW: one dimensional grid.
[a] indicates value that is not less than the minimum support value of 0.25.

Table 5
The eliminated *one*-dimensional fuzzy grids in case study 1.

No.	1DFW	1	2	3	4	5	Support
1	O(M)	0.6	0.4	0.8	0.6	0.4	0.56
2	O(H)	0.4	0.6	0.2	0.4	0.6	0.44
3	PS(M)	0.4	0.4	1	0.4	0.2	0.48
4	PS(H)	0.6	0.6	0	0.6	0.8	0.52
5	PR(M)	0.8	0.6	0.2	0.4	0.4	0.48
6	PR(H)	0.2	0.4	0.8	0.6	0.6	0.52
7	M(M)	0.8	0.4	0.8	0.4	0.2	0.52
8	M(H)	0.2	0.6	0	0.6	0.8	0.44

department, and an administrative office. The average employment time of the decision makers in the company is about 3 years.

Step 5: Decision maker assessments are provided (scores between 0 and 10) in Table 3.

Step 6: The computed fuzzy operation support is provided in Table 4.

Step 7: The eliminated *one*-dimensional fuzzy grids are shown in Table 5. There are six *fuzzy grids* remaining. Therefore, go to Step 8.

Step 8: The computed *two*-dimensional fuzzy operation support data is provided in Table 6. Go to Step 7.

Step 7: The eliminated *two*-dimensional fuzzy grids are shown in Table 7. There are twelve *fuzzy grids* remaining. Therefore, go to Step 8.

Step 8: The computed *three*-dimensional fuzzy operation support data is provided in Table 8 which is given in Appendix A. All of the *three*-dimensional fuzzy grids are eliminated due to the fact that their support value is less than 0.25.

Steps 9 and 10: The generated fuzzy association rules and their fuzzy confidence values are listed in the descending order in Table 9. The minimum confidence value is 0.55. In total, 177 association rules have been generated in case study 1. Of those, 27 association rules listed in Table 9 are important due to the fact that the remaining rules are trivial, i.e., have low fuzzy confidence value. The most important association rules from based on Table 9 are illustrated in Fig. 3. A circle and a square indicates *one* or *two*-dimensional fuzzy grid, respectively. The link between two fuzzy grids shows points to an association. Interestingly, there are no associations among *two*-dimensional fuzzy grids in Fig. 3. As can be seen from Table 9, the most important rule is PS(M).M(M) → O(M). This rule states that If the firm has "Medium process innovation capability" AND "Medium marketing innovation capability", THEN it will have "Medium organization innovation capability" in near future. Therefore, to improve the corporate innovation capability potential, the managers should pay attention to these 27 associations as have the relatively high fuzzy confidence.

4.2. Case study 2

The second case study was conducted in a company operating in defense industry in Trabzon city, Turkey. The firm was established in 1993 and it manufactures 30 different products for defense industry. Most of these products are related to weapon systems. The firm manufactures 45,000 products a year sold domestically and in 30 different countries. Face to face interviews were conducted to obtain the data needed to demonstrate the proposed approach. One decision maker provided data by email. In this case study, the first three steps of the algorithm are the same as in case study 1. Hence, application of the proposed approach in case study 2 begins at Step 4 as presented next.

Step 4: The total number of decision makers in case study 2 is eight. Decision makers work mostly in the production department. The average employment time of the decision makers in the company is about 6 years.

Step 5: The assessment values of the decision makers are provided (scores, between 0 and 10, are given) in Table 10.

Step 6: The computed fuzzy operation support values are provided in Table 11.

Step 7: The eliminated *one*-dimensional fuzzy grid are shown in Table 12. There are six *fuzzy grids* remaining. Therefore, go to Step 8.

Step 8: The computed *two*-dimensional fuzzy operation support data is provided in Table 13. Therefore, go to Step 7.

Step 7: The eliminated *two*-dimensional fuzzy grids are shown in Table 14. There are six *fuzzy grids* again remaining. Therefore, go to Step 8.

Step 8: The computed *three*-dimensional fuzzy operation support data in this case study is provided in Table 15. The eliminated *three*-dimensional fuzzy grids and the computed *four*-dimensional fuzzy operation support data are given in Tables 16 and 17, respectively. As can be seen from Table 17, there is only one association rule remaining with 0.352 support value in the *four*-dimensional fuzzy operation support case.

Steps 9 and 10: The generated fuzzy association rules and their calculated fuzzy confidence values are listed in descending order in Table 18. The minimum confidence value is 0.55. In total, 42 association rules have been generated in case study 2. As can be seen from Table 18, there are *one, two* and *three*-dimensional association rules in this case study. The most important association rules from Table 18 are illustrated in Fig. 4. A circle, a square, and a triangle indicates *one*, *two* or *three*-dimensional fuzzy grid, respectively. The link between two fuzzy grids shows points to an

Table 6
Two-dimensional fuzzy operation support data in case study 1.

No.	2DFW	1	2	3	4	5	Support
1	O(M).PS(M)	0.24	0.16	0.8	0.24	0.08	0.304[a]
2	O(M).PS(H)	0.36	0.24	0	0.36	0.32	0.256[a]
3	O(M).PR(M)	0.48	0.24	0.16	0.24	0.16	0.256[a]
4	O(M).PR(H)	0.12	0.16	0.64	0.36	0.24	0.304[a]
5	O(M).M(M)	0.48	0.16	0.64	0.24	0.08	0.320[a]
6	O(M).M(H)	0.12	0.24	0	0.36	0.32	0.208
7	O(H).PS(M)	0.16	0.24	0.2	0.16	0.12	0.176
8	O(H).PS(H)	0.24	0.36	0	0.24	0.48	0.264[a]
9	O(H).PR(M)	0.32	0.36	0.04	0.16	0.24	0.224
10	O(H).PR(H)	0.08	0.24	0.16	0.24	0.36	0.216
11	O(H).M(M)	0.32	0.24	0.16	0.16	0.12	0.200
12	O(H).M(H)	0.08	0.36	0	0.24	0.48	0.232
13	PS(M).PR(M)	0.32	0.24	0.2	0.16	0.08	0.200
14	PS(M).PR(H)	0.08	0.16	0.8	0.24	0.12	0.280[a]
15	PS(M).M(M)	0.32	0.16	0.8	0.16	0.04	0.296[a]
16	PS(M).M(H)	0.08	0.24	0	0.24	0.16	0.144
17	PS(H).PR(M)	0.48	0.36	0	0.24	0.32	0.280[a]
18	PS(H).PR(H)	0.12	0.24	0	0.36	0.48	0.240
19	PS(H).M(M)	0.48	0.24	0	0.24	0.16	0.224
20	PS(H).M(H)	0.12	0.36	0	0.36	0.64	0.296[a]
21	PR(M).M(M)	0.64	0.24	0.16	0.16	0.08	0.256[a]
22	PR(M).M(H)	0.16	0.36	0	0.24	0.32	0.216
23	PR(H).M(M)	0.16	0.16	0.64	0.24	0.12	0.264[a]
24	PR(H).M(H)	0.04	0.24	0	0.36	0.48	0.224

2DFW: two dimensional grid.
[a] indicates value that is not less than minimum support value (0.25).

Table 7
The eliminated *two*-dimensional fuzzy operation support data in case study 1.

No.	2DFW	1	2	3	4	5	Support
1	O(M).PS(M)	0.24	0.16	0.8	0.24	0.08	0.304
2	O(M).PS(H)	0.36	0.24	0	0.36	0.32	0.256
3	O(M).PR(M)	0.48	0.24	0.16	0.24	0.16	0.256
4	O(M).PR(H)	0.12	0.16	0.64	0.36	0.24	0.304
5	O(M).M(M)	0.48	0.16	0.64	0.24	0.08	0.320
6	O(H).PS(H)	0.24	0.36	0	0.24	0.48	0.264
7	PS(M).PR(H)	0.08	0.16	0.8	0.24	0.12	0.280
8	PS(M).M(M)	0.32	0.16	0.8	0.16	0.04	0.296
9	PS(H).PR(M)	0.48	0.36	0	0.24	0.32	0.280
10	PS(H).M(H)	0.12	0.36	0	0.36	0.64	0.296
11	PR(M).M(M)	0.64	0.24	0.16	0.16	0.08	0.256
12	PR(H).M(M)	0.16	0.16	0.64	0.24	0.12	0.264

Table 9
Fuzzy association rules generated in case study 1.

No.	Fuzzy association rules	FC	No.	Fuzzy association rules	FC
1	PS(M).M(M) → O(M)	0.6811	15	O(H).PS(H) → M(H)	0.6000
2	PS(M).PR(H) → O(M)	0.6743	16	O(H) → PS(H)	0.6000
3	PR(H).M(M) → PS(M)	0.6727	17	PR(H) → O(M)	0.5846
4	M(H) → PS(H)	0.6727	18	PR(M) → PS(H)	0.5833
5	O(M).PS(M) → M(M)	0.6632	19	PS(M) → PR(H)	0.5833
6	PR(H).M(M) → O(M)	0.6545	20	O(M).PR(M) → M(M)	0.5750
7	PS(M).PR(H) → M(M)	0.6343	21	PR(M).M(M) → O(M)	0.5750
8	PS(M) → O(M)	0.6333	22	O(M) → M(M)	0.5714
9	O(M).M(M) → PS(M)	0.6300	23	M(M) → PS(M)	0.5692
10	O(M).PS(M) → PR(H)	0.6211	24	PS(H) → M(H)	0.5692
11	O(M).PR(H) → PS(M)	0.6211	25	O(M).PR(H) → M(M)	0.5684
12	PS(M) → M(M)	0.6167	26	O(M).PS(H) → PR(M)	0.5500
13	M(M) → O(M)	0.6154	27	O(M).PR(M) → PS(H)	0.5500
14	PS(M).M(M) → PR(H)	0.6000			

association. Interestingly, most of the associations are between *one* and *two*-dimensional fuzzy grids in the Figure. Unlike in case study 1, there are associations among both *one* and *two*-dimensional fuzzy grids in Fig. 4. However, no association exists among *three*-dimensional fuzzy grids. *Three*-dimensional fuzzy grids impact only *one*-dimensional fuzzy grids but not the other way around. Furthermore, *four*-dimensional fuzzy operation support data is constructed, but there is no *four*-dimensional fuzzy grid in the generated fuzzy association rules.

As can be seen from Table 18, the most important rule is O(M) → M(M). This rule states that If the firm has "Medium organization innovation capability", THEN it will also has "Medium marketing innovation capability" in near future. Association rules that have the lowest fuzzy confidence value in Table 18 are: [O(M) → PS

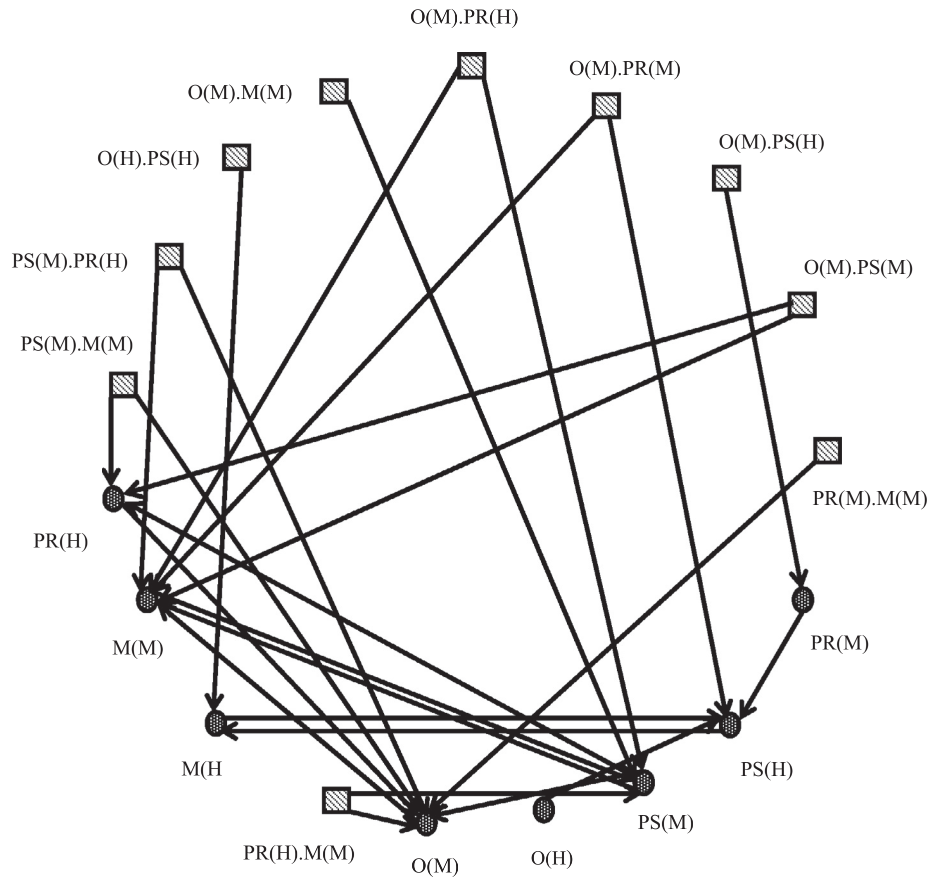

Fig. 3. Most important association rules generated in case study 1.

Table 10
The scores provided by eight decision makers in case study 2.

Capability		Decision maker							
		1	2	3	4	5	6	7	8
1. Organization innovation capability	(0 –1 0)	6	3	5	7	5	7	5	8
2. Process innovation capability	(0 –1 0)	3	7	6	5	4	6	9	8
3. Product innovation capability	(0 –1 0)	5	8	6	5	5	8	8	6
4. Marketing innovation capability	(0 –1 0)	5	5	5	5	6	6	5	7

Table 11
One-dimensional fuzzy operation support data in case study 2.

No.	1DFW	1	2	3	4	5	6	7	8	Support
1	O(L)	0	0.4	0	0	0	0	0	0	0.050
2	O(M)	0.8	0.6	1	0.6	1	0.6	1	0.4	0.750[a]
3	O(H)	0.2	0	0	0.4	0	0.4	0	0.6	0.200
4	PS(L)	0.4	0	0	0	0.2	0	0	0	0.075
5	PS(M)	0.6	0.6	0.8	1	0.8	0.8	0.2	0.4	0.650[a]
6	PS(H)	0	0.4	0.2	0	0	0.2	0.8	0.6	0.275[a]
7	PR(L)	0	0	0	0	0	0	0	0	0
8	PR(M)	1	0.4	0.8	1	1	0.4	0.4	0.8	0.725[a]
9	PR(H)	0	0.6	0.2	0	0	0.6	0.6	0.2	0.275[a]
10	M(L)	0	0	0	0	0	0	0	0	0
11	M(M)	1	1	1	1	0.8	0.8	1	0.6	0.900[a]
12	M(H)	0	0	0	0	0.2	0.2	0	0.4	0.100

1DFW: one dimensional grid.
[a] indicates value that is not less than minimum support value (0.25).

(M); O(M).M(M) → PS(M); O(M).PR(M) → PS(M).M(M); PR(M) → PS(M).M(M) and PS(M).M(M) → O(M).PR(M)]

As can be seen from Fig. 4, the success of M(M) and O(M) capabilities is mostly effected by the other innovation types. Managers or decision makers should pay attention to these 42 associations as have relatively high fuzzy confidence value in order to improve corporate innovation capability potential and sustain the organization' competitive position.

Table 12
The eliminated *one*-dimensional fuzzy grids in case study 2.

No.	1DFW	1	2	3	4	5	6	7	8	Support
1	O(M)	0.8	0.6	1	0.6	1	0.6	1	0.4	0.750
2	PS(M)	0.6	0.6	0.8	1	0.8	0.8	0.2	0.4	0.650
3	PS(H)	0	0.4	0.2	0	0	0.2	0.8	0.6	0.275
4	PR(M)	1	0.4	0.8	1	1	0.4	0.4	0.8	0.725
5	PR(H)	0	0.6	0.2	0	0	0.6	0.6	0.2	0.275
6	M(M)	1	1	1	1	0.8	0.8	1	0.6	0.900

Table 13
Two-dimensional fuzzy operation support data in case study 2.

No.	2DFW	1	2	3	4	5	6	7	8	Support
1	O(M).PS(M)	0.48	0.36	0.8	0.6	0.8	0.48	0.2	0.16	0.485[a]
2	O(M).PS(H)	0	0.24	0.2	0	0	0.12	0.8	0.24	0.200
3	O(M).PR(M)	0.8	0.24	0.8	0.6	1	0.24	0.4	0.32	0.550[a]
4	O(M).PR(H)	0	0.36	0.2	0	0	0.36	0.6	0.08	0.200
5	O(M).M(M)	0.8	0.6	1	0.6	0.8	0.48	1	0.24	0.690[a]
6	PS(M).PR(M)	0.6	0.24	0.64	1	0.8	0.32	0.08	0.32	0.190
7	PS(M).PR(H)	0	0.36	0.16	0	0	0.48	0.12	0.08	0.150
8	PS(M).M(M)	0.6	0.6	0.8	1	0.64	0.64	0.2	0.24	0.590[a]
9	PS(H).PR(M)	0	0.16	0.16	0	0	0.08	0.32	0.48	0.150
10	PS(H).PR(H)	0	0.24	0.04	0	0	0.12	0.48	0.12	0.125
11	PS(H).M(M)	0	0.4	0.2	0	0	0.16	0.8	0.36	0.240
12	PR(M).M(M)	1	0.4	0.8	1	0.8	0.32	0.4	0.48	0.650[a]
13	PR(H).M(M)	0	0.6	0.2	0	0	0.48	0.6	0.12	0.250[a]

2DFW: two dimensional grid.
[a] indicates value that is not less than the minimum support value of 0.25.

Table 14
The eliminated *two*-dimensional fuzzy operation support data in case study 2.

No.	2DFW	1	2	3	4	5	6	7	8	Support
1	O(M).PS(M)	0.48	0.36	0.8	0.6	0.8	0.48	0.2	0.16	0.485
2	O(M).PR(M)	0.8	0.24	0.8	0.6	1	0.24	0.4	0.32	0.550
3	O(M).M(M)	0.8	0.6	1	0.6	0.8	0.48	1	0.24	0.690
4	PS(M).M(M)	0.6	0.6	0.8	1	0.64	0.64	0.2	0.24	0.590
5	PR(M).M(M)	1	0.4	0.8	1	0.8	0.32	0.4	0.48	0.650
6	PR(H).M(M)	0	0.6	0.2	0	0	0.48	0.6	0.12	0.250

Table 15
Three-dimensional fuzzy operation support data in case study 2.

No.	3DFW	1	2	3	4	5	6	7	8	Support
1	O(M).PS(M).PR(M)	0.480	0.144	0.640	0.600	0.800	0.192	0.080	0.128	0.383[a]
2	O(M).PS(M).M(M)	0.480	0.360	0.800	0.600	0.640	0.384	0.200	0.096	0.445[a]
3	O(M).PS(M).PR(H)	0.000	0.216	0.160	0.000	0.000	0.288	0.120	0.032	0.102
4	O(M).PR(M).PS(M)	0.480	0.144	0.640	0.600	0.800	0.192	0.080	0.128	0.383[a]
5	O(M).M(M).PR(M)	0.800	0.240	0.800	0.600	0.800	0.192	0.400	0.192	0.503[a]
6	O(M).M(M).PR(H)	0.000	0.360	0.200	0.000	0.000	0.288	0.600	0.048	0.187
7	PS(M).M(M).PR(M)	0.600	0.240	0.640	1.000	0.640	0.256	0.080	0.192	0.456[a]
8	PS(M).M(M).PR(H)	0.000	0.360	0.160	0.000	0.000	0.384	0.120	0.048	0.134

3DFW: three-dimensional grid.
[a] indicates value that is not less than the minimum support value of 0.25.

Table 16
The eliminated *three*-dimensional fuzzy operation support data in case study 2.

No.	3DFW	1	2	3	4	5	6	7	8	Support
1	O(M).PS(M).PR(M)	0.480	0.144	0.640	0.600	0.800	0.192	0.080	0.128	0.383
2	O(M).PS(M).M(M)	0.480	0.360	0.800	0.600	0.640	0.384	0.200	0.096	0.445
3	O(M).PR(M).PS(M)	0.480	0.144	0.640	0.600	0.800	0.192	0.080	0.128	0.383
4	O(M).M(M).PR(M)	0.800	0.240	0.800	0.600	0.800	0.192	0.400	0.192	0.503
5	PS(M).M(M).PR(M)	0.600	0.240	0.640	1.000	0.640	0.256	0.080	0.192	0.456

Table 17
Four-dimensional fuzzy operation support data in case study 2.

No.	4DFW	1	2	3	4	5	6	7	8	Support
1	O(M).PS(M).PR(M).M(M)	0.480	0.144	0.640	0.600	0.640	0.154	0.080	0.077	0.352[a]

4DFW: four-dimensional grid.
[a] indicates value that is not less than minimum support value (0.25).

Table 18
Fuzzy association rules generated in case study 2.

No.	Fuzzy association rule	FC	No.	Fuzzy association rule	FC
1	O(M) → M(M)	0.9200	22	PR(H) → O(M)	0.7273
2	O(M).PS(M).PR(M) → M(M)	0.9191	23	O(M).PS(M) → PR(M).M(M)	0.7258
3	O(M).PS(M) → M(M)	0.9175	24	M(M) → PR(M)	0.7222
4	O(M).PR(M) → M(M)	0.9145	25	PS(M) → PR(M).M(M)	0.7015
5	PR(H) → M(M)	0.9091	26	PR(M).M(M) → PS(M)	0.7015
6	PS(M) → M(M)	0.9077	27	O(M).M(M).PR(M) → PS(M)	0.6998
7	PR(M) → M(M)	0.8966	28	O(M).PR(M) → PS(M)	0.6964
8	PS(H) → M(M)	0.8727	29	PR(M) → O(M).M(M)	0.6938
9	O(M).PS(M).M(M) → PR(M)	0.7910	30	PS(M) → O(M).M(M)	0.6846
10	O(M).PS(M) → PR(M)	0.7897	31	PR(H) → O(M).M(M)	0.6800
11	PR(M).M(M) → O(M)	0.7738	32	PS(H) → O(M).M(M)	0.6727
12	PS(M).M(M) → PR(M)	0.7729	33	O(M) → PR(M).M(M)	0.6707
13	PS(M).M(M).PR(M) → O(M)	0.7719	34	M(M) → PS(M)	0.6556
14	M(M) → O(M)	0.7667	35	O(M) → PS(M)	0.6467
15	PR(M) → O(M)	0.7586	36	O(M).M(M) → PS(M)	0.6449
16	PS(M).M(M) → O(M)	0.7542	37	O(M).PR(M) → PS(M).M(M)	0.6400
17	PR(H).M(M) → O(M)	0.7480	38	PR(M) → PS(M).M(M)	0.6290
18	PS(M) → O(M)	0.7462	39	PS(M).M(M) → O(M).PR(M)	0.5966
19	O(M) → PR(M)	0.7333	40	O(M) → PS(M).M(M)	0.5933
20	O(M).M(M) → PR(M)	0.7290	41	PS(M) → O(M).PR(M)	0.5892
21	PS(H) → O(M)	0.7273	42	M(M) → O(M).PR(M)	0.5589

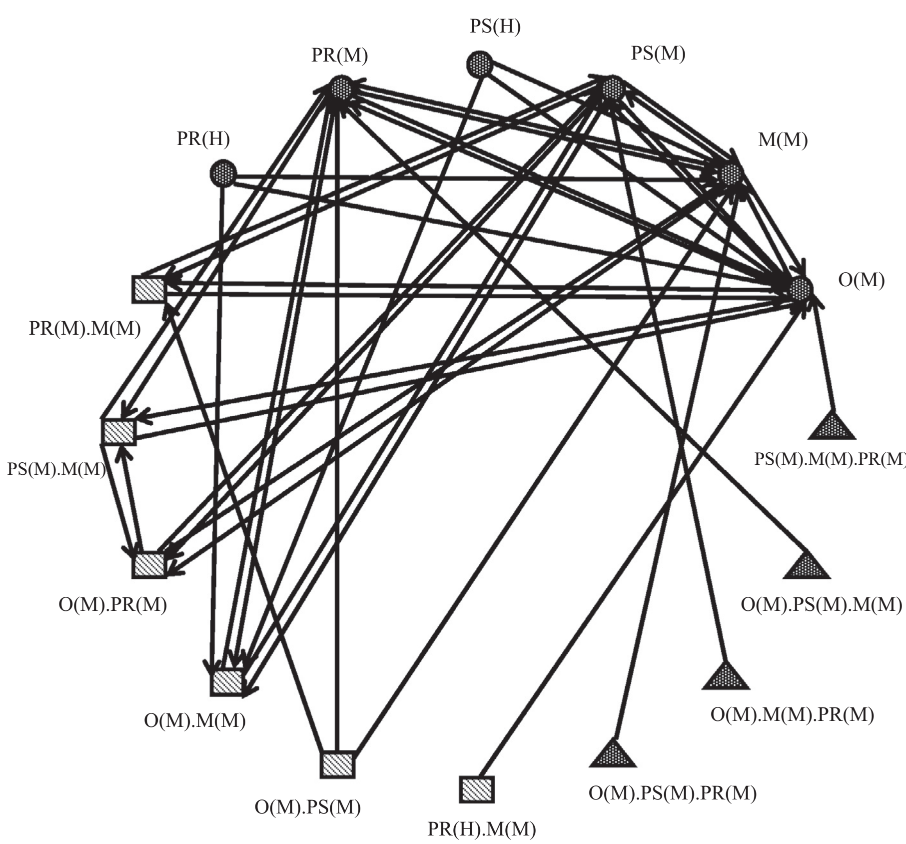

Fig. 4. Most important association rules generated in case study 2.

Table 19
A comparison of case studies.

	a	b	c	d	e	f	g
Case study 1	5	8	12	NA	NA	27	16.4698
Case study 2	8	6	6	5	1	42	31.0503

NA: Not Assigned. a: The number of decision makers. b: The number of eliminated one-dimensional grid. c: The number of eliminated two-dimensional grid. d: The number of eliminated three-dimensional grid. e: The number of eliminated four-dimensional grid. f. Total number of fuzzy association rules generated. g. Sum of FC values.

4.3. A comparison of case studies

The proposed approach and case studies show that the assessment of corporate innovation capability of any organization is based on subjectivity and decision makers' perception due to uncertainties. Different approaches may results different outcomes from each other based on decision makers' assessment because of vagueness. Experiences, background and departments where decision makers work affect the assessment. Therefore, we could not compare the results of proposed approach to the ones of other method in this study. However, a comparison of case studies is given in Table 19. It should be noted that we set minimum support to 0.25 and minimum confidence to 0.55 in case studies to generate fuzzy association rules. It also should be highlighted that decision makers work in different departments ranging from R & D department to quality control department and average employment time is 3 years in Case study 1 although decision makers work mostly in the production department and the average employment time of the decision makers in the company is about 6 years in case study 2. As can be seen from Table 19, the number of decision makers and total number of fuzzy association rules generated in Case study 2 are higher than those of Case study 1. Therefore, the sum of fuzzy confidence values in Case study 2 (31.0503), is higher than that of Case study 1(16.4698) and there is no three and four-dimensional in Case study 1. The results reveal that the proposed approach can be effectively and straightforwardly applied in practice under uncertainty.

5. Conclusion

Assessing corporate innovation capability is complex and the measuring factors impacting innovation capability is difficult due to its inherent vagueness. There is no widely agreed upon model for comprehensive assessment of innovation capability in the literature. Fuzzy association-rules are applicable in decision-making involving vagueness which makes them suitable for assessment of corporate innovation capability discussed in this paper. The studies related to innovation capability presented in the literature are usually conducted using data from large sample sizes. The fuzzy-grid based rule-mining algorithm (FGBRMA) applied to assess corporate innovation capability of organizations allows any number of samples or decision makers. The research reported in the paper was demonstrated with industrial case studies involving successful application of FGBRMA to assess corporate innovation capability.

The proposed approach offers insights into decision making of interest to managers, practitioners, and decision makers. For example, low level of innovation can be improved by focusing on the innovation capability derived by the proposed research approach. The proposed method provides answers to questions such as: (i) which innovation capabilities should be improved? (ii) which innovation capabilities are associated with other capabilities? and (iii) which innovation capabilities have strong associations? The results support decisions related to the distributions of resources with respect to innovation.

The results of the industrial case studies show that the most important rules for Case study 1 and Case study 2 are PS(M).M(M) → O(M) and O(M) → M(M), respectively. The first rule states that If the firm has "Medium process innovation capability" AND "Medium marketing innovation capability", THEN it will have "Medium organization innovation capability" in near future. The second rule states that If the firm has "Medium organization innovation capability", THEN it will also have "Medium marketing innovation capability" in near future. These rules show direct association. In Case study 1, antecedent part (the left part of the rule), composed of two dimensional grid and consequent part (the right part of the rule) has one dimensional grid. In Case study 2, both antecedent and consequent parts have one dimensional grid in the rule. As can be seen from the results of the industrial case studies, it is clear that there may be different combination of these grids in practice. Indirect relations among the levels of innovation capability can be also easily assessed based on the results of fuzzy association rules generated. To improve the corporate innovation capability potential in Case study 1, the managers should consider 27 associations. In Case study 2, the managers should pay attention to 42 associations in order to improve corporate innovation capability potential and sustain organization's competitive position. The sum of fuzzy confidence values for Case study 2 (31.0503), is higher than that of Case study 1 (16.4698). The success of M(M), O(M) and PS(M) capabilities is mostly effected by the other innovation types in Case 1. In addition, the success of M(M) and O(M) capabilities is also mostly effected by the other innovation types in Case 2. It is important for decision makers to assess innovation activities and identify gaps in innovation.

In this study, a methodology to assess corporate innovation capability is presented. The methodology uses data provided by the decision makers. The fuzzy association rules are highly dependent on the decision maker assessments. Therefore, the assessment is organization specific. Assessment of corporate innovation capability with the proposed methodology provides great value to the decision makers or engineers in manufacturing systems. For example, the proposed methodology offers great value to any organization in two ways: (1) making innovation capability of the competitive environment transparent and (2) organization's priorities become apparent.

There are some limitations of the proposed approach. First, it was assumed that the capabilities related to innovation were of equal importance. The differences among types of innovation capabilities could be taken into account using fuzzy-weighted association-rules in the future research. A weight could be assigned to each innovation capability for deriving fuzzy-weighted association-rules. Second, sensitivity analysis could be conducted with respect to different *minimum support* and *minimum confidence values*. Decision makers from different departments evaluated innovation capabilities in this study. Hence, decision makers could evaluate only the innovation capability of interest to them in the future research. For example, the process innovation capability could be evaluated by a process engineer. Similarly, marketing innovation capability and product innovation capability could be evaluated by a marketing manager and a production engineer, respectively.

Acknowledgements

The authors would like to thank the two anonymous reviewers for their insightful comments and suggestions.

Appendix A

Table 8

Table 8
Three-dimensional fuzzy operation support data of case study 1.

No	3DFW	1	2	3	4	5	Support
1	O(M).PS(M).PR(M)	0.192	0.096	0.160	0.096	0.032	0.115
2	O(M).PS(M).PR(H)	0.048	0.064	0.640	0.144	0.048	0.189
3	O(M).PS(M).M(M)	0.192	0.064	0.640	0.096	0.016	0.202
4	O(M).PS(M).M(H)	0.048	0.096	0.000	0.144	0.064	0.070
5	O(M).PS(H).PR(M)	0.288	0.144	0.000	0.144	0.128	0.141
6	O(M).PS(H).PR(H)	0.072	0.096	0.000	0.216	0.192	0.115
7	O(M).PS(H).M(M)	0.288	0.096	0.000	0.144	0.064	0.118
8	O(M).PS(H).M(H)	0.072	0.144	0.000	0.216	0.256	0.138
9	O(M).PR(M).M(M)	0.384	0.096	0.128	0.096	0.032	0.147
10	O(M).PR(M).PS(H)	0.288	0.144	0.000	0.144	0.128	0.141
11	O(M).PR(M).PS(M)	0.192	0.096	0.160	0.096	0.032	0.115
12	O(M).PR(M).M(H)	0.096	0.144	0.000	0.144	0.128	0.102
13	O(M).PR(H).M(M)	0.096	0.064	0.512	0.144	0.048	0.173
14	O(M).PR(H).PS(H)	0.072	0.096	0.000	0.216	0.192	0.115
15	O(M).PR(H).PS(M)	0.048	0.064	0.640	0.144	0.048	0.189
16	O(M).PR(H).M(H)	0.024	0.096	0.000	0.216	0.192	0.106
17	O(M).M(M).PS(H)	0.288	0.096	0.000	0.144	0.064	0.118
18	O(M).M(M).PS(M)	0.192	0.064	0.640	0.096	0.016	0.202
19	O(M).M(M).PR(H)	0.096	0.064	0.512	0.144	0.048	0.173
20	O(M).M(M).PR(M)	0.384	0.096	0.128	0.096	0.032	0.147
21	O(H).PS(H).PR(H)	0.048	0.144	0.000	0.144	0.288	0.125
22	O(H).PS(H).M(M)	0.192	0.144	0.000	0.096	0.096	0.106
23	O(H).PS(H).PR(M)	0.192	0.216	0.000	0.096	0.192	0.139
24	O(H).PS(H).M(H)	0.048	0.216	0.000	0.144	0.384	0.158
25	PS(M).PR(H).M(M)	0.064	0.064	0.640	0.096	0.024	0.178
26	PS(M).PR(H).M(H)	0.016	0.096	0.000	0.144	0.096	0.070
27	PS(M).M(M).PR(M)	0.256	0.096	0.160	0.064	0.016	0.118
28	PS(M).M(M).PR(H)	0.064	0.064	0.640	0.096	0.024	0.178
29	PS(H).PR(M).M(H)	0.096	0.216	0.000	0.144	0.256	0.142
30	PS(H).PR(M).M(M)	0.384	0.144	0.000	0.096	0.064	0.138
31	PS(H).M(H).PR(H)	0.024	0.144	0.000	0.216	0.384	0.154

References

Ahmed, A. M., & Abdalla, H. S. (1999). The role of innovation process in crafting the vision of the future. *Computers & Industrial Engineering, 37*, 421–424.

Altuntas, S., Dereli, T., & Kusiak, A. (2015). Analysis of patent documents with weighted association rules. *Technological Forecasting and Social Change, 92*, 249–262.

Calantone, R. J., Cavusgil, S. T., & Zhao, Y. (2002). Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management, 31*, 515–524.

Cavusgil, S. T., Calantone, R. J., & Zhao, Y. (2003). Tacit knowledge transfer and firm innovation capability. *Journal of Business & Industrial Marketing, 18*, 6–21.

Dereli, T., Durmusoglu, A., & Daim, T. U. (2011). Buyer/seller collaboration through measurement of beliefs on innovativeness of products. *Computers in Industry, 62*, 205–212.

Elmquist, M., & Masson, P. L. (2009). The value of a 'failed' R&D project: An emerging evaluation framework for building innovative capabilities. *R&D Management, 39*, 136–152.

Engler, J., & Kusiak, A. (2008). Web mining for innovation. *ASME Mechanical Engineering, 130*, 38–40.

Engler, J., & Kusiak, A. (2010). Mining authoritativeness of collaborative innovation partners. *International Journal of Computers, Communications & Control, 5*, 42–51.

Forsman, H. (2011). Innovation capacity and innovation development in small enterprises. A comparison between the manufacturing and service sectors. *Research Policy, 40*, 739–750.

Guan, J., & Ma, N. (2003). Innovative capability and export performance of Chinese firms. *Technovation, 23*, 737–747.

Hipp, J., Güntzer, U., & Nakhaeizadeh, G. (2000). Algorithms for association rule mining-A general survey and comparison. *ACM SIG KDD Explorations, 2*, 58–64.

Hu, Y. C., Chen, R. S., & Tzeng, G. H. (2003). Discovering fuzzy association rules using fuzzy partition methods. *Knowledge-Based Systems, 16*, 137–147.

Jain, V., Benyoucef, L., & Deshmukh, S. G. (2008). A new approach for evaluating agility in supply chains using fuzzy association rules mining. *Engineering Applications of Artificial Intelligence, 21*, 367–385.

Koc, Y. (2007). Organizational determinants of innovation capacity in software companies. *Computers & Industrial Engineering, 53*, 373–385.

Koc, T., & Ceylan, C. (2007). Factors impacting the innovative capacity in large-scale companies. *Technovation, 27*, 105–114.

Kotsiantis, S., & Kanellopoulos, D. (2006). Association rules mining: A recent overview. *GESTS International Transactions on Computer Science and Engineering, 32*, 71–82.

Kusiak, A. (2007a). Innovation science: a primer. *International Journal of Computer Applications in Technology, 28*, 140–149.

Kusiak, A. (2007b). Innovation: From data and knowledge. *BONEZone, 6*, 24–26.

Kusiak, A. (2007c). Innovation of products and services: Bridging world's economies. In *19th International conference on production research, ICPR 19, Valparaiso Chile, 1–6 August*. .

Kusiak, A. (2007d). Data mining in industrial applications and innovation. *ICS News*, 17–21. INFORMS Computing Society.

Kusiak, A. (2007e). Innovation: The living laboratory perspective. *Computer-Aided Design & Applications, 4*, 863–876.

Kusiak, A. (2009). Innovation: A data-driven approach. *International Journal of Production Economics, 122*, 440–448.

Lawson, B., & Samson, D. (2001). Developing innovation capability in organizations: A dynamic capabilities approach. *International Journal of Innovation Management, 5*, 377–400.

Lin, H. F. (2007). Knowledge sharing and firm innovation capability: An empirical study. *International Journal of Manpower, 28*, 315–332.

Lin, R. J., Chen, R. H., & Chiu, K. K. S. (2010). Customer relationship management and innovation capability: An empirical study. *Industrial Management & Data Systems, 110*, 111–133.

Lin, Y., Tseng, M. L., Chen, C. C., & Chiu, A. S. F. (2011). Positioning strategic competitiveness of green business innovation capabilities using hybrid method. *Expert Systems with Applications, 38*, 1839–1849.

Lu, L. Y., Chen, C. B., & Wang, C. H. (2007). Fuzzy multi attribute analysis for evaluating firm technological innovation capability. *International Journal of Technology Management, 40*, 114–130.

Martínez-Román, J. A., Gamero, J., & Tamayo, J. A. (2011). Analysis of innovation in SMEs using an innovative capability-based non-linear model: A study in the province of Seville (Spain). *Technovation, 31*, 459–475.

Numprasertchai, S., Kanchanasanpetch, P., & Numprasertchai, H. (2009). Knowledge creation and innovation capability in the public university. *International Journal of Innovation and Learning, 6*, 568–580.

Romijn, H., & Albaladejo, M. (2002). Determinants of innovation capability in small electronics and software firms in southeast England. *Research Policy, 31*, 1053–1067.

Sher, P. J., & Yang, P. Y. (2005). The effects of innovative capabilities and R&D clustering on firm performance: The evidence of Taiwan's semiconductor industry. *Technovation, 25*, 33–43.

Sowan, B., Dahal, K., Hossain, M. A., Zhang, L., & Spencer, L. (2013). Fuzzy association rule mining approaches for enhancing prediction performance. *Expert Systems with Applications, 40*, 6928–6937.

Subramaniam, M., & Youndt, M. A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Academy of Management Journal, 48*, 450–463.

Sun, H. (2009). A meta-analysis on the influence of national culture on innovation capability. *International Journal of Entrepreneurship and Innovation Management, 10*, 353–360.

Tasmin, R., & Woods, P. (2007). Relationship between corporate knowledge management and the firm's innovation capability. *International Journal of Services Technology and Management, 8*, 62–79.

Vinodh, S., Prakash, N. H., & Selvan, K. E. (2011). Evaluation of leanness using fuzzy association rules mining. *The International Journal of Advanced Manufacturing Technology, 57*, 343–352.

Wang, C. H., Lu, I. Y., & Chen, C. B. (2008). Evaluating firm technological innovation capability under uncertainty. *Technovation, 28*, 349–363.

Wonglimpiyarat, J. (2010). Innovation index and the innovative capacity of nations. *Futures, 42*, 247–253.

Yang, J., Rui, M., & Wang, J. (2006). Enhancing the firm's innovation capability through knowledge management: A study of high technology firms in China. *International Journal of Technology Management, 36*, 305–317.

Yang, C., Zhang, Q., & Ding, S. (2015). An evaluation method for innovation capability based on uncertain linguistic variable. *Applied Mathematics and Computation, 256*, 160–174.

Zhao, Q. & Bhowmick, S. S. (2003). *Association rule mining: A survey*. Technical Report, CAIS, Nanyang Technological University, Singapore, No. 2003116.

Zhao, H., Tong, X., Wong, P. K., & Zhu, J. (2005). Types of technology sourcing and innovative capability: An exploratory study of Singapore manufacturing firms. *Journal of High Technology Management Research, 16*, 209–224.