



Measuring entrepreneurship: Expert-based vs. data-based methodologies

Jafar Rezaei ^{*}, Roland Ortt ¹, Victor Scholten ²

Section Technology, Strategy and Entrepreneurship, Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, 2628 BX Delft, The Netherlands

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ABSTRACT

The concept of entrepreneurial orientation (EO) has become essential in research into the degree of entrepreneurial behavior at firm level. It is relevant to managers to be able to assess explicitly the level of entrepreneurship of a firm. Incubators, venture capitalists, corporate venturing units, angel investors, investment banks and governments need solid measures that go beyond expert intuition to assess the entrepreneurial nature of firms before they invest in them. Researchers have examined EO and consider innovativeness, risk taking, and proactiveness are important dimensions of this concept. Although the concept is seen as a multidimensional construct, there has been a great deal of debate among scholars on how to analyse it. The traditional statistical methodology has a number of drawbacks. In this article, we extend the debate and assess the construct of EO using four different methodologies: the traditional statistical methodology, a fuzzy-logic methodology, a DEA-like methodology and a naïve methodology. As an expert-based methodology, fuzzy logic compensates some of the limitations of the statistical methodology. Drawing on a sample of 59 start-ups in a self-administered questionnaire, we measure innovativeness, risk taking and proactiveness and subsequently compare the resulting EO scores using the four methodologies. We found several differences, the most prominent of which are discussed in greater detail. The EO score from a naïve methodology yields a value that lies between the other results, while the entrepreneurial score from a fuzzy logic methodology is most different from the other results.

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1. Introduction

Entrepreneurship has become the engine of economic and social development throughout the world (Audretsch, 2002). Entrepreneurial firms that are able to sustain continuous innovation are more likely to survive in a dynamic environment (D'Aveni, 1994). To measure the degree of entrepreneurial behavior, researchers have introduced the concept of entrepreneurial orientation (EO). The concept of EO refers to the strategy-making processes that underlie a firm's entrepreneurial decisions and actions (e.g., Lumpkin & Dess, 1996; Wiklund & Shepherd, 2003). Since its introduction (Covin & Slevin, 1989; Miller, 1983), the concept has received substantial conceptual and empirical attention and has contributed significantly to the area of entrepreneurship (Covin, Green, & Slevin, 2006). A meta-analysis of the relationship between EO and performance among a sample of 53 research projects indicated that the correlation is moderately large and robust with respect to different operationalizations and cultural contexts (Rauch, Wiklund, Lumpkin, & Frese, 2009).

Despite the large consensus among researchers about the value of the EO construct, several researchers argue that there are some problems with the EO construct, most of which have to do with the nature of the construct (Zahra, 1993), the redundancy in the items (Zahra, 1993), the debate on reflective or formative constructs (George, 2006; Stetz, Howell, Stewart, Blair, & Fottler, 2000) and the effect of different types of environments (i.e., external factors) (Knight, 1997; Wiklund & Shepherd, 2005). Although previous studies have adopted traditional statistical analysis to assess the level of EO of a firm, one could wonder whether such a methodology can control for the problems identified, which is why this paper focuses on the effect of the analytical approach being used on the possibility of making interpretations at the level of EO in a given dataset of small and new ICT firms. Usually, the analytical approach to construct development is based on three steps. Firstly, the meaning of entrepreneurial character has to be defined and different dimensions of the construct have to be identified. Secondly, the measurement of the construct has to be described, for example in terms of the items used to measure the dimensions. Thirdly, the algorithm used to assess the overall entrepreneurial character of a firm, using the scores on separate items, has to be selected. In this article, we focus on the third step, which means that we will use a particular conceptualization of entrepreneurship and we adopt a standard list of items to measure the construct. Our focus is on the algorithm used to assess the overall entrepreneurial character

* Corresponding author. Tel.: +31 15 27 82985; fax: +31 15 27 83177.

E-mail addresses: j.rezaei@tudelft.nl (J. Rezaei), j.r.ortt@tudelft.nl (R. Ortt), v.e.scholten@tudelft.nl (V. Scholten).

¹ Tel.: +31 15 27 84815; fax: +31 15 27 83177.

² Tel.: +31 15 27 89596; fax: +31 15 27 83177.

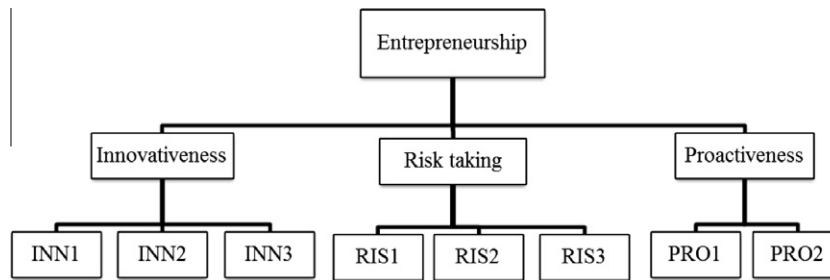


Fig. 1. Dimensions and items of entrepreneurial firm (adapted from Miller, 1983 and Covin & Slevin, 1989).

of a firm. We compare the results for four different algorithms: the traditional statistical methodology, a fuzzy-logic methodology, a DEA-like methodology and a naïve methodology.

In the next section, we review existing literature on how to define and measure entrepreneurship and we choose a particular definition and measurement methodology that will be used in the remainder of the article. In Section 3, the methodologies used to assess the entrepreneurial character of a firm are introduced. Applications of the proposed methodologies in real-world situations and a comparison of the results are presented in Sections 4 and 5, respectively. The discussion and conclusions are discussed in Section 6.

2. Literature review

Different groups of authors have defined the entrepreneurial character of firms and distinguished the relevant dimensions. To develop a construct to measure the level of entrepreneurial behavior of a firm, there are three steps. Firstly, we examine the meaning of the entrepreneurial character and the different dimensions of the EO construct. Secondly, we describe the construct in terms of the items to measure the dimensions. And thirdly, we assess various algorithms that can be used to identify the overall EO of a firm.

Based on the work by Miller and Friesen (1982), Covin and Slevin (1989) define the concept of EO as a strategic posture at firm level. Firms with a high level of EO are seen as having a higher competitive advantage that improves their performance. Firms that score high on EO are believed to be engaged in innovation frequently, to be more willing to take risks and to act more proactively when opportunities arise. Accordingly, Covin and Slevin (1989) distinguish three dimensions in the entrepreneurial-conservation orientation of a firm: innovativeness, aggressiveness and risk taking. They call a firm entrepreneurial if its managers have innovative, aggressive and risk-taking management styles. Otherwise, the management styles and the firms are considered to be more conservative. To measure this orientation, Covin and Slevin (1989) provide a nine-item scale (three items for each dimension). The mean rating on items determines the entrepreneurial-conservative orientation of the firm.

In this paper we adopt the model suggested by Miller (1983) and Covin and Slevin (1989). To gather the data, we use the instrument provided by Covin and Slevin (1989) with some modifications. We decided to adopt this model because it is used most frequently in the field of entrepreneurship and use it to compare four different algorithms to assess the overall degree of entrepreneurship of firms.

Despite its popularity (e.g., Rauch et al., 2009), several researchers have reported problems with the above-mentioned scale. These problems have to do with different aspects of the scale, such as the choice of dimensions (Lumpkin & Dess, 1996; Zahra, 1993), the choice of the items used to assess the dimensions (Brown,

Davidsson, & Wiklund, 2001), the self-report assessment (Brown et al., 2001) and the lack of contingency effects of the environment on the relationship between the EO construct and firm performance (Knight, 1997; Wiklund & Shepherd, 2005).

In this article, we assess the extent to which the algorithm being used affects the calculation of the overall entrepreneurial behavior of a firm, focusing on two types of criticism, the first of which refers to redundancy in the items (Zahra, 1993). According to Zahra, several items of a particular dimension may be related to other dimensions. Zahra illustrates this with an example: “entrepreneurial posture is positively related to the ability of a firm to quickly bring new products to market”. Zahra indicates that this may refer to the dimension of innovativeness as well as to the dimension of proactiveness.

The second criticism refers to the debate on reflective or formative constructs (George, 2006; Stetz et al., 2000). A reflective construct is a latent construct that is assessed in terms of observable items that are a consequence or reflection of that construct. A formative construct is a latent construct that is assessed by combining observable items that together create or cause that construct (Diamantopoulos & Winklhofer, 2001). Originally, Covin and Slevin (1986) described the EO construct as unidimensional, where each dimension of EO should co-vary. Later, scholars have reached a consensus and argued that the construct is theoretically a more multidimensional one (Kreiser, Marino, & Weaver, 2002; Lumpkin & Dess, 1996). The three dimensions are considered to co-vary, which means that a change in EO also results in a change in innovativeness, risk taking and proactiveness (George, 2006; Rauch & Frese, 2009). Although most researchers use a statistical methodology and assess the construct by means of factor analyses, two studies indicate that a formative approach may be more appropriate (George, 2006; Stetz et al., 2000).

These two issues, the redundancy in the items and the debate on reflective or formative constructs, can be tackled by using different algorithms to assess the EO construct even when the same data are used on the same items. In the following section, we therefore discuss the role different algorithms used to analyze the EO construct can have on its interpretation in a dataset.

3. Methodologies

As mentioned above, in the model under study there are three general dimensions for entrepreneurship, each of which can be measured using different items (see Fig. 1).

Different methodologies can be applied to assess the overall value for the construct. The goal of a typical methodology is to calculate the degree of the top box (entrepreneurship) using the underlying dimensions and items. The methodologies vary, for example, in terms of the weights being assigned to the different items and dimensions. In this section, we describe four different methodologies to calculate the level of entrepreneurship of the firm: a naïve, statistical, fuzzy logic and DEA-like methodology,

which are all based on expert knowledge or data. The naïve methodology applies the same weights to all elements at each level, the statistical methodology extracts the weights from the data, the fuzzy logic methodology calculates the weights using experts knowledge and the DEA-like methodology makes the highest flexibility to determine the weights, allowing a firm to select its own weights to maximize its level of entrepreneurship compared to other firms. This means we have a set of methodologies that operate differently when assigning weights to the items and dimensions. There are similarities and differences, which we discuss in greater detail below.

3.1. Naïve

Using this methodology we simply use an average of the item scores as the level of entrepreneurship of the firm. This methodology is straightforward and is used in most real-world cases.

3.2. Statistical

The latent constructs in the conceptual model were measured on multi-item scales, excepting the construct diversity. To use the data, the items must be reduced and combined into the latent constructs they are intended to measure. For this purpose, a factor analysis³ is used.

First of all, it is important to determine whether a factor analysis is allowed, which we did by conducting two different tests: Bartlett's test of Sphericity,⁴ Kaiser–Meyer–Olkin measure of sampling adequacy.⁵ A principal component analysis is more commonly used, which is why we use it in this research. The principal component analysis explains total variance as opposed to common factor analysis, which explains common variance and specific and error variance. What followed was the rotation of the initial solution, which was executed according to the Orthogonal Rotation method.⁶ The advantage of rotation is that it makes proper interpretation possible. The rotated solution clearly shows a distinction between factors. The method we used for rotation is the varimax procedure.⁷ What followed was the determination of factors underlying the data; which could be found in the output of SPSS. After the underlying factors have been determined, communalities should be examined to see whether the different items actually correlate with each other. If communality is very low (<0.30), and the degree of correlation between an item and other items is relatively low (which means it is 'quite unique') such an item should be removed, as it is definitely measuring 'something else'. Also, when the loading of an item was <0.45, the item was automatically deleted, after which the investigation started over again until the proper items were selected. The last step was to determine the reliability of the factors, which was done via the Cronbach alpha test.⁸ For fundamental research, a Cronbach

$\alpha > 0.70$ is acceptable. In this research, a Cronbach $\alpha > 0.60$ is acceptable, because the sample of this research was not big ($N = 59$ firms). It is important to realize that the statistical procedure proceeds in two steps. Firstly, dimensions are assessed by adding weighted scores of the items, in which the weights are derived using a factor analysis. Secondly, the scores for these dimensions are simply added. In a full structural equation model, the effect of the dimensions on the overall construct would also be derived statistically. However, data limitations do not allow us to use these types of models.

3.3. Fuzzy logic

In most practical problems, precise data are not available (Rezaei & Dowlatshahi, 2010), for two possible reasons. In some cases, we are faced with inherent imprecision in *what* we try to measure, while in other cases, the lack of a robust *measurement tool* causes the imprecision. In most cases, we are faced with both kinds of imprecision. Fuzzy logic, which was first introduced by Zadeh (1965), is a precise logic of imprecision and approximate reasoning. Unlike classical logical systems, the purpose of fuzzy logic is to model and formalize the imprecise modes of reasoning based on two fundamental human abilities; the ability to make rational decisions in an environment of uncertainty and imperfect information, and the ability to do a wide variety of physical and mental tasks and make rational decisions without any computations (Zadeh, 1988, 1999, 2001, 2008). As Ragin (2000) pointed out, however, most scholars have not recognized the potential of fuzzy logic for transforming social science methodologies. Although fuzzy logic has great potential for dealing with ambiguous problems in the field of innovation and entrepreneurship as a social science, as yet we find few applications in existing studies. For instance Wu, Chen, and Chen (2010), in assessing the performance of the intellectual capital of Taiwanese universities, applied Fuzzy Analytic Hierarchy Process (FAHP) to determine the weights of the innovation capital indicators. Cheng, Chen, and Wu (2009) applied trend-weighted fuzzy time-series model to predict innovation diffusion of ICT products. Wang (2009) considered a hierarchy of four criteria, each of them containing some elements to measure the new product development performance using a 2-tuple fuzzy linguistic computing approach.

In this paper, due to the ambiguities of entrepreneurial dimensions and items, we design and apply a rule-based system to measure the level of entrepreneurship of a firm. In practice, experts start by determining the model by indicating how item scores can be transformed to verbal labels and subsequently how the item scores can be combined into dimensions and an overall score. Item scores for separate firms can then be determined (in some cases this can also be done by experts, and in our case a questionnaire was used to gather this data). So, in fuzzy logic, the development of the model is separated from the evaluation of the firms.

When experts indicate how item scores can be transformed to verbal labels, they indicate, for each separate item in the construct (in the case of EO these items are INN1–3, RIS1–3 and PRO1–2), at which numerical values the item is considered to be low, moderate or high. Because this approach is relatively subjective, a distribution of values with some overlap is assessed. If this assessment is completed for all items, experts discuss how low, moderate and high values for the items can be combined into low, moderate or high values for the dimensions and in turn, how dimensions can be combined into the overall construct. In the next section, we briefly describe a fuzzy inference system that is required to conduct the calculations.

³ A factor analysis is a class of procedures primarily used for data reduction and summarization.

⁴ The Bartlett's test of Sphericity shows if the correlation matrix is different from the identity matrix (significantly) which is essential for the factor analysis. Test statistic should be high ($p < 0.05$).

⁵ The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is an index used to examine the appropriateness of factor analysis. The KMO checks the sufficiency of intercorrelations between variables. High values (between 0.5 and 1.0) indicate that factor analysis is appropriate. Values below 0.5 imply that factor analysis may not be appropriate.

⁶ Orthogonal Rotation Method makes proper interpretation possible, because this method does not change the total variance extracted and it does change distribution of extracted variance over factors.

⁷ This is an orthogonal method of rotation that minimises the number of variables with high loadings on a factor, thereby enhancing the interpretability of the factors.

⁸ Cronbach α represents the average of all possible split-half coefficients computed as the mean correlation over all possible split half reliabilities and with this the reliability of a factor.

3.3.1. Fuzzy inference system

A Fuzzy inference system (FIS), or fuzzy-rule-based system, is basically composed of four functional blocks (Jang, 1993).

3.3.1.1. *Fuzzification interface.* The fuzzification interface consists of the following functions (Lee, 1990):

- Measures the values of input variables.
- Performs a scale mapping that transfers the range of values of input variables into corresponding universes of discourse.
- Performs the function of fuzzification to convert input data into suitable linguistic values that may be viewed as labels of fuzzy sets.

3.3.1.2. *Knowledge base.* The knowledge base refers to the rule base (IF-THEN rules) and the database. The knowledge acquisition phase comprises expert knowledge of the application domain and the decision rules governing the relationships between input and output.

3.3.1.3. *Decision-making unit.* The decision-making unit is in fact simulating human decision-making processes based on the rules of inference in fuzzy logic. The evaluation of a rule is based on computing the truth value of its premise and applying it to its conclusion. This results in assigning one fuzzy subset to each output variable of the rule. This component interacts with the knowledge base and performs mathematical computations based on the above-mentioned fuzzy numbers.

3.3.1.4. *The defuzzification interface.* As the final operation of a fuzzy inference system, the fuzzy output produced by the system is converted to a crisp number. This is necessary because the decision-maker cannot decide based on a fuzzy output. In literature, there are different methods of defuzzification (see for example, Yen & Langari, 1999).

3.4. Data envelopment analysis (DEA)-like

Here, we introduce a new methodology to measuring the level of entrepreneurship of the firm. It is similar to the data envelopment analysis (DEA) first introduced by Charnes, Cooper, and Rhodes (1978). DEA is a useful tool to measure the relevant efficiency of a set of decision making units (DMUs), which use input to generate output. Because the amount of input and output varies, they are supposed to be different in terms of their efficiency. This methodology is mostly used to measure the relative efficiency of banks (e.g., Sherman & Gold, 1985; Sherman & Ladino, 1995), hospitals (e.g., Banker, Conrad, & Strauss, 1986) and other decision-making units (e.g., public schools by Ray (1991); suppliers by Celebi and Bayraktar (2007)). For more information on this subject, please see Charnes, Cooper, Lewin, and Seiford (1994) and Cooper, Seiford, and Tone (2007).

Mimicking DEA methodology, we introduce a mathematical programming model to measure the relative level of entrepreneurship of firms.

Suppose we have N firms (DMUs). The level of entrepreneurship of firm i (E_i) is considered as the sum product of its items measures $d_{ij}, j = 1, \dots, J$ by their weights $w_{ij}, j = 1, \dots, J$ ($\sum_{j=1}^J w_{ij} d_{ij}$). We can measure the level of entrepreneurship of other firms in the same formulation. Now, if firm i (DMU i) is allowed to maximize its level of entrepreneurship providing the level of entrepreneurship of other firms do not exceed than 1, then the calculated maximum level of entrepreneurship of this

firm denotes its relative entrepreneurship. The mathematical programming model for firm i is as follow:

$$\begin{aligned} \max(E_i) &= \sum_{j=1}^J w_{ij} d_{ij}, \\ \text{s.t.} \quad &\sum_{j=1}^J w_{ij} d_{nj} \leq 1, \quad n = 1, \dots, i, \dots, N, \\ &w_{ij} \geq 0, \quad j = 1, \dots, J. \end{aligned} \quad (1)$$

The programming models of other firms are formed similar. Solving N models, the relative level of entrepreneurship of all N firms is obtained. It has to be mentioned that this methodology allows total flexibility in the selection of weights such that each firm could maximize its own level of entrepreneurship. In DEA based on their relative efficiency score, DMUs are usually divided into two categories: *efficient* (those who have efficiency score equal to 1) and *non-efficient* (those who have efficiency score less than 1). Here, however, we rank them based on their relative level of entrepreneurship, which logically lies between 0 and 1. However, it is possible for more than one DMU to have a relative level of entrepreneurship of 1. Although these firms are more entrepreneurial than those with a lower level of entrepreneurship, we cannot compare them by themselves. For example if the relative level of entrepreneurship of firms l , m and p is 1, 1, and 0.8, it is clear that firms l and m are more entrepreneurial than firm p , but we cannot assess the level of entrepreneurship of firm l compared to m or vice versa. To deal with this issue, we modify model (1) as follows:

$$\begin{aligned} \max(E_i) &= \sum_{j=1}^J w_{ij} d_{ij}, \\ \text{s.t.} \quad &\sum_{\substack{j=1 \\ j \neq i}}^J w_{ij} d_{nj} \leq 1, \quad n = 1, \dots, N, \\ &w_{ij} \geq 0, \quad j = 1, \dots, J, \quad j \neq i. \end{aligned} \quad (2)$$

This modification is similar to the model suggested by Andersen and Petersen (1993) for ranking efficient DMUs. Here, we in fact excluded the DMUs under study from the constraint set, allowing it to maximize its relevant level of entrepreneurship if it can. We therefore will have the relevant level of entrepreneurship of more than 1 for most of the entrepreneurial firms, which is useful for ranking them.

4. Application

In this section, we first describe the data used to apply and compare the above-mentioned methodologies, after which we discuss the application procedures.

4.1. Description of the real-world case and data collection

We collected data on EO from a sample of Dutch ICT firms. To be included in our sample, firms needed to meet three requirements. Firstly, they had to be operating in the Dutch ICT industry. Secondly, they must have been established between 2002 and 2004, to make we were dealing with start-up firms. And thirdly, they needed to be relatively small, with a maximum of 65 full-time employees. The reason we selected the ICT industry was that start-ups in this industry are facing a hostile environment, where rapid change is a way of life. There have been substantial changes in information technology in recent years. Computers and software have evolved a rapid, complex and almost chaotic way, with implications for competition and strategy. As such, the new competitive landscape requires a significantly different approach to strategy compared to the past (Bettis & Hitt, 1995). As a result, the ICT

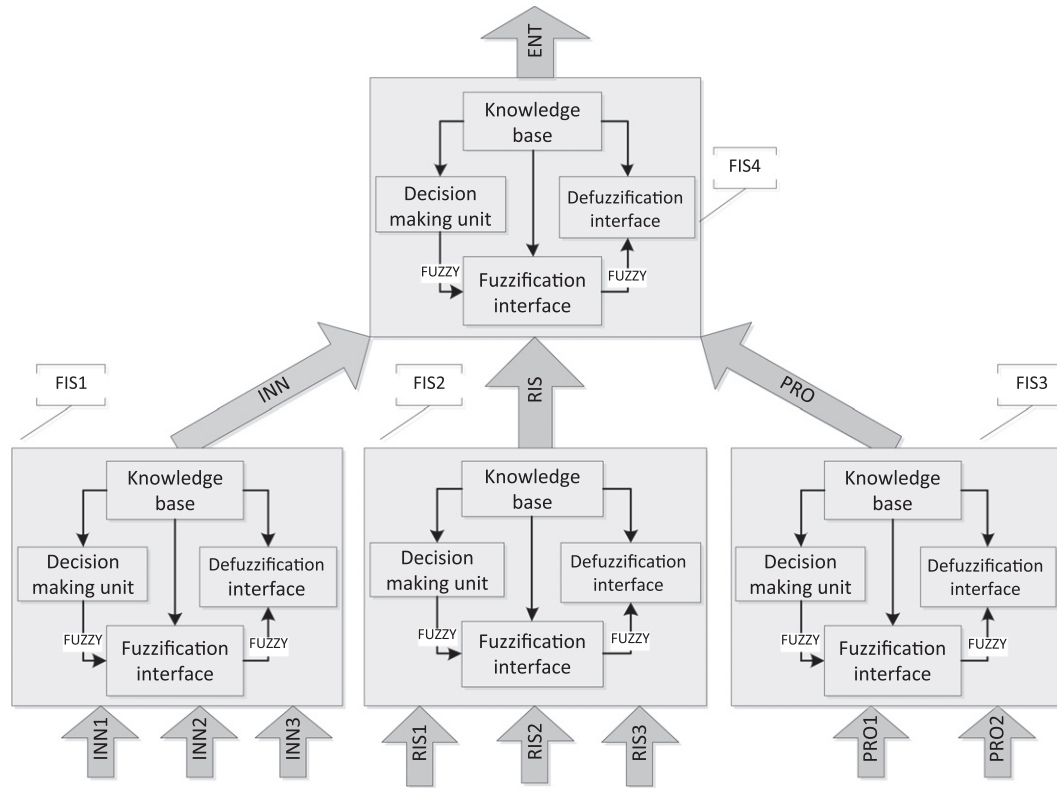


Fig. 2. The proposed two-level fuzzy inference system.

industry represents a dynamic sector that preserves the variation in the degree of entrepreneurial behavior among the entrepreneurs. In addition, by electing a single industry, we were able to draw among the start-ups.

Furthermore, it is important for a participant to have existed for at least three years, which means it has survived the start-up phase, which can be considered the most critical phase for small firms: once firms have survived for three years they can be said to have passed through the “valley of death” (Gibb & Davies, 1990; Littunen, 2000). After the first three years, strategic choices become an import factor in determining where a firm will go in the future. Also, their business practices presumably approximate those of established firms rather than new ventures. Therefore, we selected firms that were founded between 2002 and 2004. According to the third condition, all these firms have a maximum of 65 full-time employees. As such, they can all be classified as small firms. Finally, all firms must have a management team consisting of two or more members, which is necessary for the data regarding the composition of the team. In this research, management team members of small firms are defined as managers are responsible for strategic formulation and decision-making, policy-setting and championing the status quo of the firms. The REACH database and the Dutch Chambers of Commerce were used to locate the firms for our sample.

The empirical information was obtained by Internet questionnaires. Questionnaires have the advantage of obtaining data more efficiently in terms of researcher time, energy and costs. Also, questionnaires are an efficient data collection mechanism in cases where researchers know exactly what is required and how to measure the relevant variables (Sekaran, 2003). Internet questionnaires have the same properties as mail questionnaires, with several important advantages. For example, the flexibility of data collection and the diversity of questions in Internet surveys are moderate to high compared to low for traditional mail questionnaires. Most importantly, however, the sample control is slightly better

and the speed with which data can be gathered is much higher than it is in the case of mail questionnaires (Malhotra & Birks, 2000). The Internet questionnaire was designed using a questionnaire generator (www.thesistools.com). The questionnaire was divided into different sections, each relating to a particular variable (Dillman, 1978), thus minimizing negative effects related to this structural format.

The variables used in this research have already been studied in previous studies and are based on the entrepreneurial orientation (EO) scale developed by Miller (1983), and Covin and Slevin (1986, 1988, 1989). The existing scales were translated into Dutch as accurately as possible, making it easier for the respondents to complete the questionnaire.

4.2. Naïve methodology

Using this methodology, we simply calculate the mean of eight items with the equal weights (for items under each dimension) as follows:

$$N = \frac{1}{3} \left(\frac{INN1 + INN2 + INN3}{3} + \frac{RIS1 + RIS2 + RIS3}{3} + \frac{PRO1 + PRO2}{2} \right).$$

4.3. Statistical methodology

Using the procedure discussed in Section 3.2, the following weights are obtained for different items as follows:

Innovation items weight: W_{INN1} : 0.816; W_{INN2} : 0.863; W_{INN3} : 0.704.
 Risk taking items weight: W_{RIS1} : 0.775; W_{RIS2} : 0.778; W_{RIS3} : 0.775.
 Proactiveness items weight: W_{PRO1} : 0.799; W_{PRO2} : 0.892.

The final average score of entrepreneurship of each firm is then calculated as follows:

$$ENT_{avg} = (INN_{avg} + RIS_{avg} + PRO_{avg})/3,$$

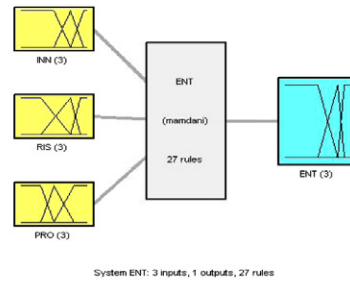
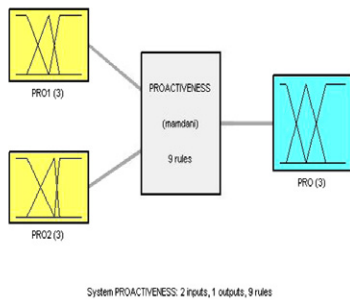
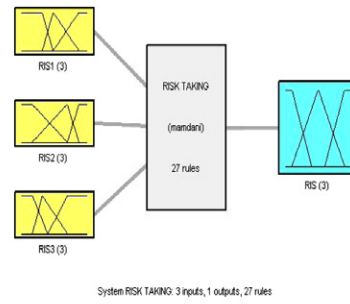
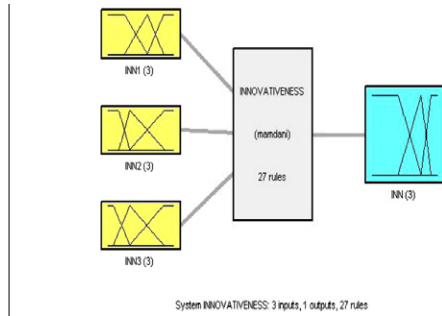


Fig. 3. Intended fuzzy inference systems (FIS1, FIS2, FIS3 and FIS4).

$$\begin{aligned}
 INN_{avg} &= (INN1 * W_{INN1}) + (INN2 * W_{INN2}) + (INN3 * W_{INN3}) \\
 RIS_{avg} &= (RIS1 * W_{RIS1}) + (RIS2 * W_{RIS2}) + (RIS3 * W_{RIS3}) \\
 PRO_{avg} &= (PRO1 * W_{PRO1}) + (PRO2 * W_{PRO2})
 \end{aligned}$$

In fact, this methodology is a hybrid methodology (statistical and naïve) in which a statistical methodology is used to combine item scores in dimensions, whereas the dimensions are simply combined into EO in a naïve way by adding their values.

4.4. Intended fuzzy inference system

Based on the model proposed in Fig. 1, the designed methodology contains two levels. We first have to measure the three dimensions of innovativeness, risk-taking and proactiveness, based on their sub-components (level 2), after which the measures are aggregated to obtain the overall degree of entrepreneurship of a firm (level 1). Consequently, we have to design four fuzzy inference systems, three to measure the dimensions and one to aggregate the dimensions measures. Fig. 2 shows the proposed two-level fuzzy inference system.

4.4.1. Fuzzification interface

Fig. 2 illustrates the intended FISs. In FIS1 (innovativeness), we define three linguistic input variables for each firm. They are ‘the number of new lines of products and services’ (INN1), ‘change intensity in product or service lines’ (INN2), and ‘managers’ emphasis on tried and true products and services vs. on R&D, technological leadership and innovation’ (INN3). In FIS2 (risk-taking), we define three linguistic input variables for each firm: ‘proclivity for risk taking in projects’ (RIS1), ‘owning to the nature of environment’ (RIS2), and ‘dealing with uncertainty’ (RIS3). In FIS3 (proactiveness), we define two linguistic input variables: ‘initiating actions vs. responding to competitors actions’ (PRO1), and ‘avoiding vs. adopting competitive posture’ (PRO2).

Table 1
Fuzzy rule base for innovativeness (level 2).

Rule No.	Fuzzy rule base input			Fuzzy rulebase output
	INN1	INN2	INN3	
1	L	L	L	L
⋮	⋮	⋮	⋮	⋮
13	M	M	L	M
14	M	M	M	M
⋮	⋮	⋮	⋮	⋮
27	H	H	H	H

The fuzzification of the output variables INN (degree of innovativeness), RIS (degree of risk-taking), PRO (degree of proactiveness), and ENT (degree of entrepreneurship) are presented. To develop these membership functions, we used the knowledge of three academic experts. To fuzzify the input and output variables, the following fuzzy subsets (linguistic values) are used: Low (L), Medium (M), and High (H). We also use triangular and trapezoidal membership functions. The various INN1, INN2, INN3, INN, RIS1, RIS2, RIS3, RIS, PRO1, PRO2, PRO, and ENT values, which are denoted by $inn1 \in INN1, inn2 \in INN2, inn3 \in INN3, inn \in INN, ris1 \in RIS1, ris2 \in RIS2, ris3 \in RIS3, ris \in RIS, pro1 \in PRO1, pro2 \in PRO2, pro \in PRO,$ and $ent \in ENT,$ respectively. These construct the base variable values within a context that is defined as $x \in X.$

4.4.2. Knowledge base

The membership functions of inputs and outputs (Fig 3) were designed by three academic experts based on their knowledge of the system and their experience. However, the main purpose of the knowledge base is to provide a fuzzy rule base needed for the fuzzy processor.

4.4.3. Fuzzy rule base

The rule base of our study contains 90 rules $3^3 = 27$ rules for innovativeness, $3^3 = 27$ rules for risk-taking, $3^2 = 9$ rules for proactiveness and $3^3 = 27$ rules for entrepreneurship), which include all variations of the linguistic values. The rules were constructed on the basis of the knowledge of three academic experts, and have the following form:

<i>Level 2 (innovativeness)</i>			
IF	the number of new lines...	is	$inn1 \in INN1$
	AND change intensity in product...	is	$inn2 \in INN2$
	AND managers' emphasis on tried...	is	$inn3 \in INN3$
THEN	innovativeness	is	$inn \in INN$
<i>Level 2 (risk-taking)</i>			
IF	proclivity for risk taking in projects	is	$ris1 \in RIS1$
	AND owning to the nature of environment	is	$ris2 \in RIS2$
	AND dealing with uncertainty risk-taking	is	$ris3 \in RIS3$
THEN	risk-taking	is	$ris \in RIS$
<i>Level 2 (proactiveness)</i>			
IF	initiating actions vs. responding	is	$pro1 \in PRO1$
	AND avoiding vs. adopting competitive	is	$pro2 \in PRO2$
THEN	proactiveness	is	$pro \in PRO$
<i>Level 1 (entrepreneurship)</i>			
IF	innovativeness	is	$inn \in INN$
	AND risk-taking	is	$ris \in RIS$
	AND proactiveness	is	$pro \in PRO$
THEN	entrepreneurship	is	$ent \in ENT$

Table 1 shows an example of the rule base for innovativeness (dimension 1, level 2).

4.4.4. Decision making unit

In this paper, the inference engine developed by Mamdani and Assilian (1975) was used by employing a compositional minimum operator. In the case of minimum inferencing, the entire strength of the rule is seen as the minimum membership value of the input variables' membership values:

$$\mu_{output} = \min \{ \mu_{input1}, \mu_{input2}, \dots, \mu_{inputN} \}. \tag{3}$$

4.4.5. The defuzzification interface

In this paper, we apply the most commonly used Center of Gravity (COG) defuzzification, which calculates the center of the area of the combined membership function as:

$$y_0 = \frac{\int \mu_F(y_i) y_i dy_i}{\int \mu_F(y_i) dy_i}$$

where y_i is the representative value of the fuzzy subset member i of the output, and $\mu_F(y_i)$ is the confidence in that member (membership value) and y_0 is the crisp value of the output.

4.5. DEA-like methodology

Considering $INN1$, $INN2$, $INN3$, $RIS1$, $RIS2$, $RIS3$, $PRO1$ and $PRO2$ as eight inputs and ENT as the-indigenous-output, we apply model (1) for 59 firms to obtain their relevant level of entrepreneurship.

Because the relevant level of entrepreneurship of 11 firms is 1, we used model (2). The results are shown in Table 2.

5. Comparison

In this section, we compare the results of the afore-mentioned methodologies and discuss the similarities and differences. Based on their advantages and disadvantages, we can assess the situations where a particular methodology is most appropriate. As a first step in comparing the four methodologies, we look at the correlations between their final scores (see Table 4).

As it can be seen, there are significant correlations between all four methodologies. While naïve and statistical methodologies show the highest degree of correlation (1.00), DEA-like and fuzzy logic methodologies have the lowest correlation compare to the other methodologies (0.797). There are some important differences between the methodologies with regard to how they rank the firms (Section 5.1), the classification (Section 5.2), the vulnerability of the results (Section 5.3) and the data-set limitations (Section 5.4).

5.1. Ranking the firms

As mentioned before, naïve and statistical methodologies obtain the final score in the same way: both use a weighted-sum of item scores. However, while a statistical methodology applies the loadings as the weights, a naïve methodology applies equal weights to all items. Statistical and DEA-like methodologies are also relatively similar. Because of the similarities, we focus on the comparison between FIS, statistical and DEA-like methodologies.

5.1.1. FIS vs. statistical

As it can be seen from Table 3, there are some differences in the ranking of firms, for instance if we compare firms 45 and 59. When using fuzzy logic, firm 59 comes in first place and firm 45 in seventh. By contrast, a statistical methodology places firm 59 in seventh place and puts firm 45 first. Here, we discuss some of the reasons with regard to this difference. As mentioned before, the statistical methodology applies a linear function to obtain the final average score of a firm, which implies that, using statistical methodology, a linear trade-off between the item or dimension measures is assumed, and a given firm can compensate its lack of a specific item or dimension by attaining a higher value with regard to another item. For example, a firm can compensate one unit shortage of its 'INN1' measure by having extra $0.94 \left(\frac{W_{INN1}}{W_{INN2}} \right)$ unit of $INN2$ or $1.16 \left(\frac{W_{INN1}}{W_{INN3}} \right)$ unit of $INN3$ or even by having some extra units of other items (risk-taking and proactiveness).

The linear compensation between dimensions is not consistent with the theoretical foundations of entrepreneurship. For example, as mentioned by Lumpkin and Dess (1996) and Shane and Venkataraman (2000), innovation is the essence of entrepreneurship. Theoretically speaking, therefore, we may conclude that there is no linear substitution between items, and especially between dimensions. Fuzzy logic is able to look at this crucial issue in a different way. This shows itself in the rule-making phase. For example, in the rule list of the first-level system, regardless the linguistic values of risk taking (RIS) and proactiveness (PRO), whenever the innovativeness (INN) is 'low' the consequence (level of entrepreneurship of the firm) is not 'high'. This implies that experts implicitly consider this a necessary condition. This is the main reason for the differences in ranking. To examine this case in greater detail, see Table 5.

As it can be seen, firm 59 has a higher ranking than firm 45 in terms of its innovativeness (INN) and risk-taking behavior (RIS) in both methodologies, and what gives firm 45 its higher ranking in the case of the statistical methodology is merely only its

Table 2
the results obtained by the methodologies.

Firm #	Item measures								Final entrepreneurial degree of firms using the four methodologies			
	INN1	INN2	INN3	RIS1	RIS2	RIS3	PRO1	PRO2	NAIVE	FUZZ	STAT	DEA
1	5	5	4	4	4.5	4.5	5	5.5	4.750	0.578	3.850	0.8843
2	4.5	5	5	5.5	5.5	5.5	4.5	4	4.861	0.722	3.895	0.9109
3	4.5	3.5	5.5	5.5	3.5	5	3.5	4	4.306	0.554	3.441	0.8689
4	5	4.5	5	5	4.5	5	6	5.5	5.139	0.658	4.143	0.9033
5	5.5	5.5	6	4.5	5	5	4.5	4.5	5.000	0.749	4.014	0.9496
6	6	6	5.5	3.5	4.5	4	4.5	5	4.861	0.816	3.927	0.9231
7	4	3.5	4	4.5	4.5	5	5.5	5	4.583	0.444	3.694	0.8526
8	5	4.5	4.5	5	4.5	4	5	3.5	4.472	0.613	3.587	0.8336
9	5	4.5	5.5	4.5	5	5.5	5	5.5	5.083	0.648	4.092	0.9200
10	5	5.5	5	5	5.5	5.5	4.5	4.5	5.000	0.724	4.019	0.9402
11	6.5	5.5	6	6	6.5	6	5.5	5.5	5.889	0.873	4.731	1.1138
12	5.5	5	5	5.5	5	4.5	6.5	6.5	5.556	0.739	4.494	1.0426
13	5	5.5	5	6	5.5	5	4.5	3.5	4.889	0.736	3.914	0.9706
14	4	3.5	4	4.5	4.5	4.5	4.5	4	4.194	0.390	3.369	0.7633
15	5	4.5	5.5	4	3.5	3.5	5	4.5	4.472	0.640	3.598	0.8378
16	5	4	5	4	4.5	5	3	3.5	4.139	0.427	3.311	0.8082
17	4.5	3	4.5	5	5.5	6	4	4.5	4.583	0.483	3.672	0.9726
18	5.5	5	5.5	5.5	4	5.5	6.5	6.5	5.611	0.740	4.533	1.0000
19	5	6	5.5	4.5	5	5	6.5	6	5.528	0.746	4.467	0.9945
20	5	4	4	4.5	5	4.5	5.5	3.5	4.500	0.570	3.609	0.8750
21	3.5	4	3	3.5	4	3	2.5	3	3.250	0.352	2.620	0.6780
22	4.5	5	4.5	3.5	4	3.5	5	6	4.611	0.616	3.746	0.9259
23	5	4	5.5	4.5	3.5	3.5	4.5	5	4.472	0.591	3.601	0.8130
24	3.5	2	4	4.5	4	5.5	6.5	5.5	4.611	0.441	3.712	0.9294
25	4.5	5.5	5	5.5	6	5.5	4.5	3.5	4.889	0.738	3.912	0.9661
26	6.5	4.5	6.5	5.5	4.5	5.5	7	6	5.833	0.825	4.689	1.0390
27	6	4.5	7	5.5	5.5	5.5	6.5	6	5.861	0.789	4.703	1.0556
28	3.5	4	4	4.5	4	4.5	4.5	5	4.306	0.399	3.477	0.8000
29	5	3.5	5.5	4.5	4	4.5	4.5	6.5	4.833	0.588	3.905	1.0000
30	2.5	3	2.5	4	3.5	4.5	4	3.5	3.472	0.364	2.797	0.7123
31	6.5	4.5	7	5.5	5	5.5	6	6	5.778	0.825	4.639	1.0385
32	4.33	4	3.67	3.33	3	3.33	3.67	4.33	3.740	0.413	3.028	0.6928
33	3.67	2.67	4.33	4.33	4.67	3.67	5.33	5.67	4.427	0.432	3.573	0.8932
34	2.67	3.33	3.67	5.33	4.67	4.67	3.67	4.33	4.038	0.366	3.245	0.8613
35	6.33	5.33	5.67	4.67	5.67	5.67	5.67	5.33	5.538	0.827	4.456	0.9738
36	5.5	5.5	5	6	6	5.5	5.5	4.5	5.389	0.774	4.327	0.9853
37	5.67	4.67	5.33	4.67	5.67	4.33	4.67	5.33	5.038	0.725	4.058	0.9265
38	4.5	5.5	5.5	4.5	5	4.5	5	5	4.944	0.741	3.982	0.9076
39	5.67	5.33	5.33	5.33	4.67	3.67	4.67	5.67	5.057	0.754	4.085	0.9380
40	4.33	4.67	4.33	4.67	4.33	4.33	5	4.67	4.574	0.518	3.688	0.8096
41	4.5	5	4	5	4.5	4.5	5.5	4.5	4.722	0.598	3.809	0.8718
42	5.67	4.67	5.67	4.67	4.67	5.33	4.67	5.67	5.132	0.725	4.135	0.9240
43	6.5	6.5	6	5.5	5	5.5	6.5	6	5.972	0.842	4.819	1.1157
44	4	3.5	3.5	5	4.5	4	4.5	4	4.139	0.386	3.330	0.8050
45	6	5.5	6.5	5.5	4	6.5	7	6.5	6.028	0.819	4.857	1.1286
46	4.5	6.5	5.5	5.5	4.5	4	4.5	6	5.139	0.751	4.159	1.0000
47	4.67	6.33	5.67	5.33	4.67	4.67	5.67	5.67	5.372	0.766	4.336	0.9738
48	5.67	4.67	6.67	4.33	4.67	4.33	4.33	3.67	4.704	0.636	3.755	0.9735
49	3.33	2.67	4.33	3.67	4.33	5.33	4.67	5.33	4.296	0.421	3.460	0.8680
50	4.33	4.67	3.67	4.33	4.33	4.33	3.67	4.33	4.184	0.439	3.380	0.7685
51	4.67	5.67	5.33	4.67	3.67	5.67	3.67	5.33	4.798	0.476	3.873	0.9450
52	3.33	2.67	2.67	5.33	3.33	4.67	3.33	4.33	3.721	0.359	3.003	0.8613
53	4.67	3.33	5.33	4.33	3.67	4.33	4.67	5.67	4.574	0.561	3.687	0.8723
54	3.67	4.33	3.33	5.33	3.67	4.33	4.33	4.67	4.240	0.354	3.428	0.8779
55	3.33	2.33	3.67	4.33	4.67	3.67	5.33	3.67	3.944	0.435	3.160	0.8333
56	4.5	4.75	3.25	4.25	4.5	4.75	3	3.75	4.014	0.435	3.238	0.8077
57	5	5.5	5.25	5.25	4.75	4.5	5.25	4.75	5.028	0.736	4.047	0.9000
58	4.8	4.2	5.2	3.6	4.2	4.4	4.2	3.8	4.267	0.511	3.421	0.7902
59	6.33	5.67	6.33	6.33	5.33	6	5.67	4.67	5.722	0.874	4.584	1.0550

superior performance with regard to proactiveness (PRO). In fact, the superior performance of firm 45 in two item measures of proactiveness compensates for its inferior performance with regard to the other two dimensions. Therefore, because of the linear relationship in the statistical methodology, in the final ranking, firm 45 wins. By contrast, the FIS does not allow firm 45 to take advantage of this superiority. In the proposed FIS, which is based on the rules made by experts, not having some necessary and more important items and/or dimensions cannot be compensated in this

way. For instance, as it in the present case, having a level of proactiveness (PRO) that is equal to or higher than 0.8 is enough for a firm to be considered 'high' (with membership degree of 1) in PRO, which means that an additional amount of PRO higher than 0.8 cannot compensate for the lack of other dimensions related to INN and/or RIS. Fig. 4 shows the activated rules that determine the level of entrepreneurship of these two firms.

In fact, as mentioned before, scoring higher in terms of proactiveness (PRO) does not guarantee the superiority of firm 45 in

Table 3
The ranking results of the methodologies.

Rank	Firm #	NAIVE	Firm #	FUZZ	Firm #	STAT	Firm #	DEA
1	45	6.028	59	0.874	45	4.857	45	1.1286
2	43	5.972	11	0.873	43	4.819	43	1.1157
3	11	5.889	43	0.842	11	4.731	11	1.1138
4	27	5.861	35	0.827	27	4.703	27	1.0556
5	26	5.833	31	0.825	26	4.689	59	1.0550
6	31	5.778	26	0.825	31	4.639	12	1.0426
7	59	5.722	45	0.819	59	4.584	26	1.0390
8	18	5.611	6	0.816	18	4.533	31	1.0385
9	12	5.556	27	0.789	12	4.494	18	1.0000
10	35	5.538	36	0.774	19	4.467	29	1.0000
11	19	5.528	47	0.766	35	4.456	46	1.0000
12	36	5.389	39	0.754	47	4.336	19	0.9945
13	47	5.372	46	0.751	36	4.327	36	0.9853
14	46	5.139	5	0.749	46	4.159	35	0.9738
15	4	5.139	19	0.746	4	4.143	47	0.9738
16	42	5.132	38	0.741	42	4.135	48	0.9735
17	9	5.083	18	0.740	9	4.092	17	0.9726
18	39	5.057	12	0.739	39	4.085	13	0.9706
19	37	5.038	25	0.738	37	4.058	25	0.9661
20	57	5.028	13	0.736	57	4.047	5	0.9496
21	5	5.000	57	0.736	10	4.019	51	0.9450
22	10	5.000	37	0.725	5	4.014	10	0.9402
23	38	4.944	42	0.725	38	3.982	39	0.9380
24	13	4.889	10	0.724	6	3.927	24	0.9294
25	25	4.889	2	0.722	13	3.914	37	0.9265
26	2	4.861	4	0.658	25	3.912	22	0.9259
27	6	4.861	9	0.648	29	3.905	42	0.9240
28	29	4.833	15	0.640	2	3.895	6	0.9231
29	51	4.798	48	0.636	51	3.873	9	0.9200
30	1	4.750	22	0.616	1	3.850	2	0.9109
31	41	4.722	8	0.613	41	3.809	38	0.9076
32	48	4.704	41	0.598	48	3.755	4	0.9033
33	22	4.611	23	0.591	22	3.746	57	0.9000
34	24	4.611	29	0.588	24	3.712	33	0.8932
35	7	4.583	1	0.578	7	3.694	1	0.8843
36	17	4.583	20	0.570	40	3.688	54	0.8779
37	53	4.574	53	0.561	53	3.687	20	0.8750
38	40	4.574	3	0.554	17	3.672	53	0.8723
39	20	4.500	40	0.518	20	3.609	41	0.8718
40	8	4.472	58	0.511	23	3.601	3	0.8689
41	15	4.472	17	0.483	15	3.598	49	0.8680
42	23	4.472	51	0.476	8	3.587	34	0.8613
43	33	4.427	7	0.444	33	3.573	52	0.8613
44	3	4.306	24	0.441	28	3.477	7	0.8526
45	28	4.306	50	0.439	49	3.460	15	0.8378
46	49	4.296	55	0.435	3	3.441	8	0.8336
47	58	4.267	56	0.435	54	3.428	55	0.8333
48	54	4.240	33	0.432	58	3.421	23	0.8130
49	14	4.194	16	0.427	50	3.380	40	0.8096
50	50	4.184	49	0.421	14	3.369	16	0.8082
51	16	4.139	32	0.413	44	3.330	56	0.8077
52	44	4.139	28	0.399	16	3.311	44	0.8050
53	34	4.038	14	0.390	34	3.245	28	0.8000
54	56	4.014	44	0.386	56	3.238	58	0.7902
55	55	3.944	34	0.366	55	3.160	50	0.7685
56	32	3.740	30	0.364	32	3.028	14	0.7633
57	52	3.721	52	0.359	52	3.003	30	0.7123
58	30	3.472	54	0.354	30	2.797	32	0.6928
59	21	3.250	21	0.352	21	2.620	21	0.6780

the final ranking. Instead, what makes firm 59 superior in the final ranking based on the FIS methodology is its superior score on

Table 5
the detail data of two selected cases for comparison purpose (firms 45 and 59)*.

Firm	INN			RIS			PRO			ENT	
	Measures	S-rank	F-rank	Measures	S-rank	F-rank	Measures	S-rank	F-rank	S-rank	F-rank
45	(6,5,5,6,5)	4	8	(5,5,4,6,5)	13	12	(7,6,5)	1	1	1	7
59	(6,3,5,6,7,6,33)	2	2	(6,33,5,33,6)	2	2	(5,6,7,4,6,7)	24	2	7	1

* S-Rank = ranked by statistical methodology; F-rank = ranked by fuzzy logic methodology.

Table 4
The correlation between the results of the four methodologies.

	1	2	3	Average
1. Naive methodology				0.936
2. Fuzzy logic methodology	0.898**			0.863
3. Statistical methodology	1.000**	0.896**		0.935
4. DEA methodology	0.912**	0.797**	0.910**	0.873

N = 59.
** p < 0.01.

innovativeness, which activates some of the most powerful rules, such as rules 26 and 27.

5.1.2. Statistical vs. DEA-like

The proposed DEA-like methodology proposed in this paper is similar to the statistical methodology, as both use linear functions to calculate the level of entrepreneurship of a firm. However, the difference between the two methodologies is that, while the statistical methodology uses the same items' weights for all firms, the DEA-like methodology uses different item' weights. In other words, the statistical methodology applies a single linear function, while the DEA-like methodology applies a different linear function measuring a firm's level of entrepreneurship. This means that the DEA-like methodology uses the best weights in favor of each firm. As a result, having high score(s) on one or more items guarantees a high ranking when using a DEA-like methodology. For example, firm 29 has an efficiency score of 1 and is ranked in the 10th place because its PRO2 score is 6.5, which is the highest score among all the firms. Meanwhile, this firm is ranked 27th in the statistical methodology.

5.2. Classification

Another difference between the methodologies lies in their classification potential. Making the membership functions for the dimensions and aggregated entrepreneurship in FIS provides us with a logical framework to classify the firms, while no such framework is available in the case of the naïve and statistical methodologies. DEA-like methodology also has a robust framework to classify firms as either being efficient or inefficient. However, fuzzy logic is better than DEA-like methodology in classifying the firms, because it can classify them into three groups and, even if we have more than three sub-functions for entrepreneurship (here there are three), there may be more classes for the firms.

Although one may argue that we can determine some cut-off points to classify firms in naïve and statistical methodologies, determining these cut-off points poses a challenge. If one believes that it is possible to classify firms based on the cut-off points, one also assumes that we can actually determine these cut-off points for other dimensions as well. This kind of thinking would result in the application of fuzzy logic.

Considering the results obtained from FIS, based on the membership function built for entrepreneurship (refer to Fig. 3(d)), we can classify firms whose final score is less than 0.5 as 'firms with a low level of entrepreneurship'. Firms with a final score between 0.5 and 0.8 can be classified as 'firms with a medium level of

Table 6
Classification of the firms based on the final degree of their entrepreneurship.

Low level firms (total = 19)	Medium level firms (total = 32)	High level firms (total = 8)
<i>FIS methodology classes</i> 17; 51; 7; 24; 50; 55; 56; 33; 16; 49; 32; 28; 14; 44; 34; 30; 52; 5421	27; 36; 47; 39; 46; 5; 19; 38; 18; 12; 25; 13; 57; 37; 42; 10; 2; 4; 9; 15; 48; 22; 8; 41; 23; 29; 1; 20; 53; 3; 40; 58	59;11;43;35;31;26;45;6
Entrepreneurial	Non-entrepreneurial	
<i>DEA-like classes</i> 45; 43; 11; 27; 59; 12; 26; 31; 18; 29; 46	1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 13; 14; 15; 16; 17; 19; 20; 21; 22; 23; 24; 25; 27; 28; 30; 32; 33; 34; 35; 36; 37; 38; 39; 40; 41; 42; 44; 47; 48; 49; 50; 51; 52; 53; 54; 55; 56; 57; 58; 59	

Table 7
Characteristics of the methodologies.

Characteristic ^a	Methodology			
	Naïve	Fuzzy logic	Statistical	DEA-like
Compensation between items/dimensions (–)	Yes	No	Yes	Yes
Having a framework to classification (+)	No	No	No	Yes
Vulnerable to add or remove some firms (–)	No	No	Yes	Yes
Requires experts' knowledge (–)	No	Yes	No	No
Data-set limitation (–)	No	No	Yes ^b	Yes ^c
Ability to consider the effect of one or more variables in presence of the others (+)	No	Yes	No	No
Dimensions/items' weights are independent from the data (+)	Yes	Yes	No	No
Ability to consider subjective items that cannot converted to objective measures (+)	No	Yes	No	No

^a Characteristics considered as advantage are marked by (+) and as disadvantage by (–).

^b A minimum number of subjects and items/variables are needed.

^c A minimum number of 3 times of the number of inputs and outputs.

entrepreneurship' and, finally, firms with a final score higher than 0.8 as 'firms with a high level of entrepreneurship'.

According to the final results obtained from DEA-like methodology, we can divide the firms into two groups: efficient (entrepreneurial) (those with final score equal or more than 1) and inefficient (non-entrepreneurial) (those with final score less than 1).

Table 6 shows the classification based on two methodologies (FIS and DEA-like).

This procedure can be also applied at the level of dimensions and can help incubators, venture capitalists, corporate venturing units, angel investors, investment banks and governments select the best firms in terms of investment opportunities.

5.3. Post analysis (vulnerability)

Undoubtedly, one of the most important features of a methodology is the stability of its results. As mentioned before, the statistical methodology calculates the final average score of each firm using a linear function, in which the weight of each item is its loading in factor analysis. Therefore, the final average score depends on the data set, which means that, if we add the data of another firm to the data set, new loadings (weights) will result, which in turn affect the final score for the individual firms. Therefore, there is a chance that firms will end up being re-ranked differently each time a new firm is added. If two data-sets are applied, one to assess the model (weights) and another for which the degree of EO has to be assessed, this problem can be circumvented. However, such a methodology requires a lot of data.

A DEA-like methodology has the same weakness in this respect. While using fuzzy logic, which does not depend on the data set, adding new firms does not change the previous ranking of firms. For example, suppose new firm with the following measures – INN1:6; INN2:6; INN3:6; RIS1:5; RIS2:5; RIS3:5; PRO1:4; PRO2: 4 – is added to the data set as the 60th firm. Using the statistical methodology, we should obtain the loadings (weights) via a new

factor analysis and calculate the final average score of the firms and rank them. If we do this, the new ranking result is, to some extent, different from the previous one. The new firm is ranked 23rd and the position of 15% of all the firms changes (firms 13, 25, 29, 7, 40, 53, 20, 23, 15). On the other hand, fuzzy logic does not encounter this problem because it is not sensitive to the data set. Using the proposed methodology, the new firm is ranked 26th, while the position of the other firms remains as it was before.

With the naïve methodology, we apply equal weights for all items, which means that adding one or more firms does not affect the weights and consequently the final scores and rankings of the other firms.

On the other hand, the fuzzy logic methodology relies on expert knowledge, which means the experts may influence the rules, which will consequently affect the rankings. The other methodologies do not encounter this problem. We may, however, consider this characteristic of fuzzy logic as an advantage, as we can adjust the rules in certain real-world situations.

5.4. Data-set limitation

The statistical methodology requires a large data set to calculate the loadings (weights). The DEA-like methodology also has this limitation. As an experimental limitation which comes from DEA literature, we should have at least the following number of DMUs (firms), to calculate the efficiency (entrepreneurial) score of the DMUs (firms):

$$\text{Minimum number of (DMUs) firms} \\ = 3(\text{the number of inputs and outputs}).$$

In this paper, for instance, we should have at least 29 firms in order to apply DEA-like methodology with accuracy. By contrast, fuzzy logic and naïve methodologies can be applied even to a population with only two firms.

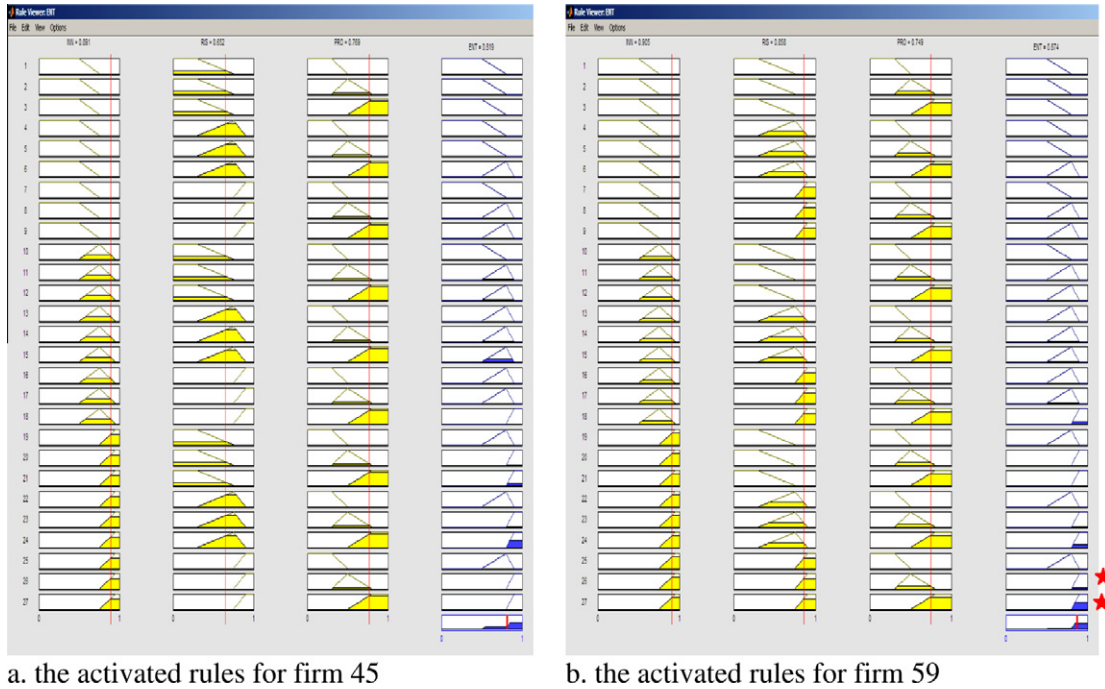


Fig. 4. Rules output for two firms 45 and 59.

6. Conclusions, implications and future research

6.1. Conclusion

The construct entrepreneurial orientation for measuring the level of entrepreneurial behavior at firm level has received a great deal of interest and has been applied in numerous studies over the ten years (Rauch et al., 2009). Despite its popularity, various scholars (George, 2006; Zahra, 1993) have raised concerns with regard to the measurement and algorithm used to analyze the construct, which in turn affects the conclusions drawn with regard to a firm's entrepreneurial orientation. In this article, we assess the extent to which different algorithms affect the calculation of the overall entrepreneurial behavior of a firm, focusing on two types of criticism: the redundancy in the items (Zahra, 1993) and the question whether a construct is of a reflective or formative nature (George, 2006; Stetz et al., 2000). Our approach uses three steps to assess the level of entrepreneurship of firms. Firstly, the meaning of entrepreneurial character has to be defined and different dimensions of the construct have to be identified. Secondly, the measurement of the construct has to be described. And thirdly, the algorithm used to assess the overall entrepreneurial character of a firm has to be selected. This article focuses on the third step, the algorithm used to assess the overall entrepreneurial character of a firm. We have compared the results for four different algorithms: the traditional statistical methodology, a fuzzy-logic methodology, a DEA-like methodology and finally a naïve methodology. Below, we summarize the characteristics of these methodologies (Table 7).

As it can be seen from Table 7, the fuzzy logic and statistical methodology have the most and least advantages respectively.

6.2. Managerial implications of the findings

It is important for managers to be able to assess explicitly the level of entrepreneurship of their firm. Incubators, corporate venturing units and investment banks need more solid measures than expert intuition to assess the entrepreneurial nature of firms and their founders before they invest in these firms. Our

comparative study has revealed significant differences between four methodologies that can be used to assess the level of entrepreneurship of firms. These differences originate, for example, from different ways to weight the effect of items on specific dimensions (and in turn of the dimensions on the overall score) and from the fact that some methodologies allow for a linear compensation of values, while other methodologies do not.

It is relevant to know when (in what circumstances) a particular methodology can be used:

When an expert committee is evaluating a limited number of firms, a simple naïve methodology (adding up scores) is the most appropriate. The results of this lie in between that the other methodologies and it can be used in case of small populations. The disadvantage of this methodology has to do with the linear compensation it allows, which can tilt the conclusions.

When a committee is heterogeneous in nature and wants to assess a model before assessing companies and see whether multiple interdependencies and contingencies are apparent in the criteria used to assess entrepreneurial orientation (EO), although a limited number of cases are available, fuzzy logic would appear to be the best option.

When much data is available and/or a separate data-set was used to design a model, a statistical methodology is the most appropriate. A disadvantage of this methodology is the linear compensation it allows.

When it is impossible to determine the same item/dimension weight for different firm, the best methodology would be a DEA-like one. However, again, a disadvantage of this methodology is the linear compensation it allows.

6.3. Future research

Firstly, the methodologies discussed in this paper have to be applied to other different industries to draw a comparison and to determine the most suitable methodology in different situations. Secondly, in this paper we propose and compare different methodologies to determine the level of entrepreneurship of a firm. Future research should apply these methodologies to assess the

relationship between the level of entrepreneurship and other variables, such as performance, growth, etc. Thirdly, we can also use these methodologies in real-world situations where firms need to be ranked according to their level of entrepreneurship. Finally, we adopted a specific model of EO, while, in future studies, we could consider different theoretical models and compare the results when applying the proposed methodologies.

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