Paper:
Beynon, M., Jones, P., Pickernell, D. & Packham, G. A NCaRBS analysis of SME intended innovation: Learning about the Don't Knows. *Omega, 59*, 97-112.
http://dx.doi.org/10.1016/j.omega.2015.04.018

Elsevier Editorial System(tm) for Omega, The International Journal of Management Science
Manuscript Draft

Manuscript Number: OMEGA-D-14-00710R2

Title: A NCaRBS Analysis of SME Intended Innovation: Learning about the Don't Knows.

Article Type: SI: Business Analytics

Keywords: NCaRBS; innovation, SME, Don't Knows

Corresponding Author: Dr. Paul Jones, Ph.D

Corresponding Author's Institution: Plymouth University

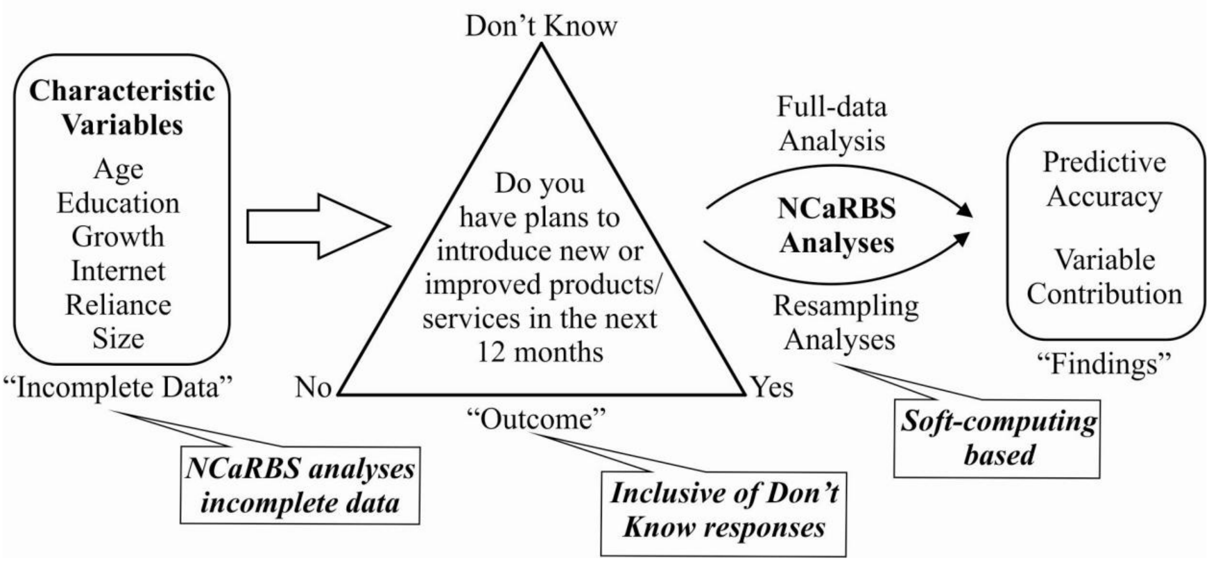
First Author: Malcolm J Beynon, PhD

Order of Authors: Malcolm J Beynon, PhD; Paul Jones, Ph.D; David Pickernell, PhD; Gary Packham, PhD

Manuscript Region of Origin: UNITED KINGDOM

Abstract: This study demonstrates a novel form of business analytics, respecting the quality of the data available (allowing incompleteness in the data set), as well as engaging with the uncertainty in the considered outcome variable (inclusive of Don't Know (DK) responses). The analysis employs the NCaRBS technique, based on the Dempster-Shafer theory of evidence, to investigate the relationship between Small and Medium-sized Enterprise (SME) characteristics and whether they intended to undertake future innovation. The allowed outcome response for intended innovation was either, Yes, No and DK, all of which are considered pertinent responses in this analysis. An additional consequence of the use of the NCaRBS technique is the ability to analyse an incomplete data set, with missing values in the characteristic variables considered, without the need to manage their presence. From a soft computing perspective, this study demonstrates just how exciting the business analytics field of study can be in terms of pushing the bounds of the ability to handle real 'incomplete' business data which has real, and sometimes uncertain, outcomes. Further, the findings also inform how different notions of ignorance in evidence are accounted for in such analysis.

A NCaRBS Analysis of SME Intended Innovation: Learning about the Don't Knows (Graphical Abstract)



Highlights

- This study demonstrates a novel form of business analytics as well as engaging with the uncertainty in the considered outcome variable.
- The analysis employs the NCaRBS technique to investigate the relationship between Small and Medium-sized Enterprise (SME) characteristics and whether they intended to undertake future innovation.
- The NCaRBS technique allows the ability to analyse an incomplete data set, with missing values in the characteristic variables considered, without the need to manage their presence.
- This study demonstrates how to handle real 'incomplete' business data which has real, and sometimes uncertain, outcomes.
- The findings also inform how different notions of ignorance in evidence are accounted for in such analysis.

Dear Professor Doumpos

Please find attached our revised submission entitled “A NCaRBS Analysis of SME Intended Innovation: Learning about the Don’t Knows” for your special issue on Business Analytics. This study investigates small and medium sized enterprises intended innovation employing a large dataset (n=7500+) from the Federation of Small Business survey. The paper has been significantly revised in line with the reviewer and editors comments. It now presents a more technical as opposed to applied study.

Employing the novel NCaRBS analysis business analytics technique, the study considers the relationship between SME characteristics and a response to whether they intended to undertake future innovation. The study contributes to knowledge from two perspectives. Firstly, it highlights a novel form of business analytics, in NCaRBS which respects the quality of the data available (allowing incompleteness in the data set), as well as allowing uncertainty in the considered outcome variable (inclusive of a Don’t Know response option).

We hope you find the study of interest and relevant to your special issue. We are fully prepared to further develop this study in line with the requirements of your special issue if required. If you require anything further please do not hesitate to contact us.

Kind Regards

Professor Malcolm Beynon (Cardiff University)
Dr Paul Jones (Plymouth University)
Professor David Pickernell (University of South Wales)
Professor Gary Packham (Anglia Ruskin University)

Omega paper revision Response to Reviewer comments for paper entitled: A NCaRBS Analysis of SME Intended Innovation: Learning about the Don't Knows.

1. In response to the Editor's request we have added seven additional references from the Omega journal to the manuscript. We hope this is sufficient to gain acceptance.

Our thanks to the Reviewers, Guest Editors and Editor in Chief for the positive comments we have received on the revised paper.

A NCaRBS Analysis of SME Intended Innovation: Learning about the Don't Knows.

Abstract

This study demonstrates a novel form of business analytics, respecting the quality of the data available (allowing incompleteness in the data set), as well as engaging with the uncertainty in the considered outcome variable (inclusive of Don't Know (DK) responses). The analysis employs the NCaRBS technique, based on the Dempster-Shafer theory of evidence, to investigate the relationship between Small and Medium-sized Enterprise (SME) characteristics and whether they intended to undertake future innovation. The allowed outcome response for intended innovation was either, Yes, No and DK, all of which are considered pertinent responses in this analysis. An additional consequence of the use of the NCaRBS technique is the ability to analyse an incomplete data set, with missing values in the characteristic variables considered, without the need to manage their presence. From a soft computing perspective, this study demonstrates just how exciting the business analytics field of study can be in terms of pushing the bounds of the ability to handle real 'incomplete' business data which has real, and sometimes uncertain, outcomes. Further, the findings also inform how different notions of ignorance in evidence are accounted for in such analysis.

1 Introduction

Individual Small and Medium-sized Enterprises (SMEs) have their own strategies for their survival and contribution to the associated economy (Westhead *et al.*, Van Looy *et al*., 2003; Hadjimanolis, 2006, Theodorou and Florou, 2008), including in respect to innovation. Innovation, put simply finding a more effective way of doing something (or the application of enhanced solutions that meet new requirements), can therefore be seen to play a critical role in enabling these firms' business growth and improving performance (Harris *et al*., 2013). Whilst this highlights an important applied business research area, there is an associated research problem, specifically the uncertainty of this potential future activity for the firms themselves (Sawyer *et al*., 2003). Within a business analytics context, this study asks the question whether it is possible, and indeed relevant, to gain knowledge of firms expressing uncertain innovation plans, such as by answering 'Don't Know' (DK) to related questions. For example, if an SME gives a DK response to an intended innovation question, is there an underlying indication that the firm is more inclined to actually mean 'No' or 'Yes' to such intended innovation.

In terms of analysing such uncertainty, Francis and Busch (1975) suggest, generally, which respondents with non-substantive responses, such as DK, should not be excluded from analysis, arguing such responses are not random and so exclusion would introduce bias in any undertaken analysis. The general limited investigation of the DK response problem, considered a vexing problem to researchers (Feick, 1989), with the slight exception of within the area of political opinion (Feick, 1989; Gilljam and Granberg, 1993; Lee and Kanazawa, 2000; Luskin and Bullock, 2011), may be due to the lack of technical approaches able to pertinently investigate this problem. Business analytics can assist in such analysis, as an area of research, it has manifested itself to cover the more general data mining and knowledge discovery terms often used (see Piatetsky-Shapiro, 2007), and has been welcoming of the development of new approaches to analyse data.

This paper, demonstrates the exciting potential of business analytics, using a nascent soft computing based methodology (see later), in a multi-direction investigation of SME intended innovation in the UK. Beyond the prior mentioned intention to be inclusive of the non-substantive DK response and how other variables may relate to them, a further direction of this study is to consider the pertinent ability to analyse incomplete data, here meaning without the need to manage in any way prevalent missing values, without needing to transform the data in any way. This approach is in contrast to the perceived inevitable problem of how to deal with the missing values, indeed Svolba (2014) states this very point, going onto highlight the business point of view on the handling of missing values.

Whether it is concerned with small, medium or big data, the issue of analysing incomplete data usually means some form of data management is required (Allison, 2000; Schafer and Graham, 2002; Svolba, 2014). For example, dummies representing missing values in predictors can be incorporated into regression analysis, an example of how more traditional techniques might accommodate such incompleteness (see Graham, 2009, for recent survey of literature on missing values). The level of impact of the missing value issue is succinctly described by Koslowsky (2002, p. 312), who stated;

> "*One of the most critical issues in model formulation and marketing analytics is how to handle missing data. If not handled correctly, even the best analysis efforts can fail, and even worse, an entire database marketing strategy can be seriously damaged*."

The ability to analyse incomplete data, without having to manage the missing values in some way, therefore, introduces an important dimension of intelligence to the business analytics area of research. Specifically, this identifies an interesting point, namely that intelligence here may not just be about producing a more pertinent answer, but also about more pertinently using the data available. Indeed, what is more intelligent, using an 'intelligent' method to transform the incomplete data into complete data (see for example, Huang and Zhu, 2002), or using an intelligent method that allows the use of the original incomplete data without any transformation (as in this study)? A consequence of this study includes the elucidation of two notions of ignorance in the evidence in the classification problem (ignorance due to missing values and ignorance from variable value contribution).

Such an intelligent method, however, in addition to being able to handle these two issues, of uncertain DK responses and incomplete (missing) data, would also need to still be able to analyse the important applied problem which the data has been identified as being able to help address, here SME intended innovation, producing results that are clearly interpretable. One specific feature of the unfolding popularity of business analytics is its association to producing results that can be then used in policy decisions, and for example, the ability to offer competitive advantage amongst organisations (see for example, Kohavi *et al*., 2002; Sharma *et al*., 2010). Here, the competitive advantage in the considered applied problem may be more at the policy maker level, being able to use the presented results to develop policies that inspire higher SME performance (here innovation).

The technique employed throughout this study is the N-State Classification and Ranking Belief Simplex (NCaRBS), introduced in Beynon and Kitchener (2006) and Beynon *et al*. (2014), a development from the original CaRBS (Beynon, 2005a, 2005b). With its methodology based on the Dempster-Shafer theory of evidence (Dempster, 1967; Shafer, 1976), also called theory of belief functions, the technique has a close association to soft computing (see for example, Jiroušek, 2010). In this study, the use of NCaRBS will demonstrate the ability to pertinently work throughout the three research directions outlined previously. Results presented will include consideration of the level of classification fit of the analysis undertaken, contribution (predictive power) of the characteristic variables considered, the ability to interpret analysis of individual objects and validation of results through re-sampling based analysis.

The structure of the rest of the paper is as follows: In section 2, brief descriptions of soft computing, the NCaRBS analysis technique and incomplete data handling are presented. In section 3, the incomplete FSB-innovation data set is described and research problem presented. In section 4, an initial analysis using NCaRBS is presented, including exposition of the level of classification fit, contribution of characteristic variables and elucidation of individual objects' classification details. In section 5, validation of the results is given with respect to a re-sampling based analysis of the data set, using in-sample and out-sample partitioned data sets. In section 6, inferences in respect to SME innovation and business analytics are given. In section 7, conclusions are given as well as direction for future research.

2 Soft computing, NCaRBS technique and incomplete data handling

This section is broken down into three subsections, briefly describing the issues of, soft computing, NCaRBS technique and incomplete data handling.

Soft computing

One direction contributing to the nascence of business analytics has been technical development in the area of soft computing. The understood tolerance of imprecision, uncertainty and approximation, underpinning the inspiration of soft computing in respect to modelling a wide variety of human rational decisions (Seising and Sanz, 2011), has brought a number of non-traditional analysis techniques into the domain of business analytics.

Pertinent to this study, Azvine *et al*. (2003) focuses on soft computing as an emerging technology suitable for incorporation into business analytics applications, highlighting the often significant degree of manual intervention in preparing, presenting and analysing business data. The analysis presented in this study, will remove some of the often awkward impact of managing missing values within incomplete data, as referred to previously, with here the ability to analyse incomplete data without such management (see later).

Underlying the technique employed in this study (NCaRBS - see next subsection), and associated with soft computing, is Dempster-Shafer theory (DST - Dempster, 1967; Shafer, 1976), otherwise known as the theory of belief functions (see for example, Denœux and Masson, 2012). Liu (2003) states where DST fits with other, more common, methodologies (p. 1):

> "*The Dempster-Shafer theory of belief functions has become a primary tool for knowledge representation that bridges fuzzy logic and probabilistic reasoning*."

Further, DST is closely associated with uncertain reasoning (understanding uncertain knowledge and how to represent it). Canfora and Pedrycz (2008, p. 1), confirm the association of uncertain reasoning and soft computing:

> "*Soft computing technologies have provided us with a unique opportunity to establish a coherent software engineering environment in which uncertainty and partial data and knowledge are systematically handled*."

The technique next described and employed in this study is based on DST, and is able to demonstrate much of the qualities of uncertain reasoning/soft computing based business analytics. Throughout the analysis part of this study, the reader should be conscious of the data able to be analysed, and how the approach can be used in other areas closely associated with business analytics.

Technical description of NCaRBS

NCaRBS (N-state Classification and Ranking Belief Simplex, Beynon *et al*., 2014), models the classification of n_{O} objects (o_1, o_2, ..), to n_{D} decision outcomes (d_1, d_2, ..), based on their description by n_{C} characteristics (c_1, c_2, ..). The characteristics' evidence is expressed through the initial construction of *constituent* BOEs (bodies of evidence – see Dempster, 1967; Shafer, 1976), from characteristic values $v_{i,j}$ (i^{th} object, j^{th} characteristic), to discern between an object's association to (focal elements) a decision outcome (say $\{d_h\}$), its complement ($\{\neg d_h\}$) and a level of concomitant ignorance ($\{d_h, \neg d_h\}$).

The construction of a constituent BOE, defined $m_{i,j,h}(\cdot)$ (i^{th} object, j^{th} characteristic, h^{th} outcome), discerning between $\{d_h\}$ and $\{\neg d_h\}$, is described Figure 1 (adapted from Beynon, 2005a; Beynon *et al*., 2014).

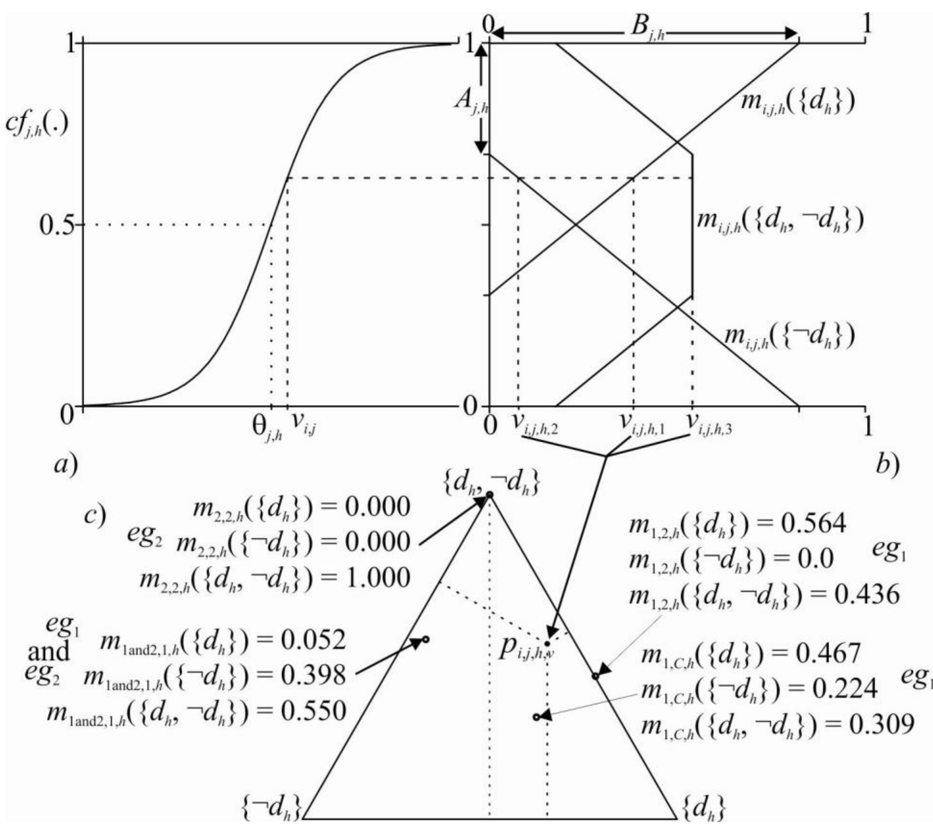


Figure 1. Stages within the NCaRBS technique (adapted from Beynon, 2005a; Beynon *et al*., 2014), including exposition of the representation of a missing value

In Figure 1, stage *a*) shows the transformation of a characteristic value $v_{i,j}$ into a confidence value $cf_{j,h}(v_{i,j})$, using $cf_{j,h}(v_{i,j}) = 1/(1 + \exp(-k_{j,h}(v_{i,j} - \theta_{j,h})))$, with control parameters $k_{j,h}$ and $\theta_{j,h}$ (a process to standardize the domains of each characteristic variable considered). Stage *b*) transforms a $cf_{j,h}(v_{i,j})$ into a constituent BOE $m_{i,j,h}(\cdot)$, made up of the three mass values (see Safranek *et al*., 1990);

$$m_{i,j,h}(\{d_h\}) = \max\left(0, \frac{B_{j,h}}{1-A_{j,h}} cf_{j,h}(v_{i,j}) - \frac{A_{j,h}B_{j,h}}{1-A_{j,h}}\right),$$

$$m_{i,j,h}(\{\neg d_h\}) = \max\left(0, \frac{-B_{j,h}}{1-A_{j,h}} cf_{j,h}(v_{i,j}) + B_{j,h}\right),$$

and $m_{i,j,h}(\{d_h, \neg d_h\}) = 1 - m_{i,j,h}(\{d_h\}) - m_{i,j,h}(\{\neg d_h\})$,

where $A_{j,h}$ and $B_{j,h}$ are two further control parameters. Stage *c*) shows a BOE $m_{i,j,h}(\cdot)$; $m_{i,j,h}(\{d_h\}) = v_{i,j,h,1}$, $m_{i,j,h}(\{\neg d_h\}) = v_{i,j,h,2}$ and $m_{i,j,h}(\{d_h, \neg d_h\}) = v_{i,j,h,3}$, can be represented as a simplex coordinate ($p_{i,j,h,v}$) in a simplex plot (equilateral triangle), with example BOEs shown (discussed in next subsection).

Dempster's rule of combination is used to combine these BOEs (see Dempster, 1967; Shafer, 1976; Beynon *et al*., 2005a, 2005b). To illustrate, the combination of two constituent BOEs, $m_{i,j_1,h}(\cdot)$ and $m_{i,j_2,h}(\cdot)$, for the same object (o_i) and single outcome (d_h), defined $(m_{i,j_1,h} \oplus m_{i,j_2,h})(\cdot)$, results in a combined BOE with mass values (and focal elements) given by:

$$(m_{i,j_1,h} \oplus m_{i,j_2,h})(\{d_h\}) = \frac{\begin{array}{r} m_{i,j_1,h}(\{d_h\})m_{i,j_2,h}(\{d_h\}) + m_{i,j_2,h}(\{d_h\})m_{i,j_1,h}(\{d_h,\neg d_h\}) \\ + m_{i,j_1,h}(\{d_h\})m_{i,j_2,h}(\{d_h,\neg d_h\}) \end{array}}{1-(m_{i,j_1,h}(\{\neg d_h\})m_{i,j_2,h}(\{d_h\}) + m_{i,j_1,h}(\{d_h\})m_{i,j_2,h}(\{\neg d_h\}))}$$

$$(m_{i,j_1,h} \oplus m_{i,j_2,h})(\{\neg d_h\}) = \frac{\begin{array}{r} m_{i,j_1,h}(\{\neg d_h\})m_{i,j_2,h}(\{\neg d_h\}) \\ + m_{i,j_2,h}(\{d_h,\neg d_h\})m_{i,j_1,h}(\{\neg d_h\}) \\ + m_{i,j_2,h}(\{\neg d_h\})m_{i,j_1,h}(\{d_h,\neg d_h\}) \end{array}}{1-(m_{i,j_1,h}(\{\neg d_h\})m_{i,j_2,h}(\{d_h\}) + m_{i,j_1,h}(\{d_h\})m_{i,j_2,h}(\{\neg d_h\}))}$$

$$(m_{i,j_1,h} \oplus m_{i,j_2,h})(\{d_h,\neg d_h\}) = 1-(m_{i,j_1,h} \oplus m_{i,j_2,h})(\{d_h\}) - (m_{i,j_1,h} \oplus m_{i,j_2,h})(\{\neg d_h\}).$$

The combination process can be performed iteratively to combine the characteristic based evidence, constituent BOEs $m_{i,j,h}(\cdot)$ $j = 1, .., n_C$, for an object o_i to a single outcome d_h, producing an *outcome* BOE, defined $m_{i,-,h}(\cdot)$ (other ways of combining the evidence can be considered - see later). The outcome BOEs can also be combined to bring together the evidence contained in them, the result termed an *object* BOE, for object o_i is defined $m_{i,-,-}(\cdot)$ (reduced to $m_i(\cdot)$), contains the evidence on the associations of the object to the n_{D} decision outcomes.

The object BOEs are made up of mass values associated with focal elements that are the power set of $\{d_1, d_2, ..\}$ (minus the empty set). To enable the assignment of values to individual outcomes, the pignistic probability function $BetP_i(d_h) = \sum_{\substack{s_j \subseteq \{d_1, d_2, ..\} \\ s_j \cap \{d_h\} \neq \emptyset}} m_i(s_j) / |s_j|$ for object o_i represents the level of pignistic probability associated with the outcome d_h from the object BOE $m_i(\cdot)$. The series of pignistic probability values $BetP_i(d_h)$ $h = 1, .., n_{\mathrm{D}}$ (see Denœux and Zouhal, 2001), dictates the levels of association of the object o_i to each of the outcomes d_h $h = 1, .., n_{\mathrm{D}}$.

The effectiveness of the NCaRBS technique, is governed by the values assigned to the incumbent control parameters $k_{j,h}$, $\theta_{j,h}$, $A_{j,h}$ and $B_{j,h}$, $j = 1, .., n_{\mathrm{C}}$ and $h = 1, .., n_{\mathrm{D}}$. This necessary configuration is considered as a constrained optimization problem, solved here using trigonometric differential evolution (TDE), see Fan and Lampinen (2003). The configured NCaRBS system can be measured by a defined objective function ($\mathrm{OB}^{\mathrm{NCaRBS},w}$). In this study, the original $\mathrm{OB}^{\mathrm{NCaRBS}}$ presented in Beynon *et al*. (2014) is developed to fairly take account of the imbalance in the number of objects with known classification to each of the known n_{D} discrete decision outcomes, so termed $\mathrm{OB}^{\mathrm{NCaRBS},w}$.

This class imbalance problem is well known (see Japkowicz and Stephen, 2002), and is here resolved by weighting the error between each actual and predicted classification of an object by the number of objects with the same decision outcome as the object in question (the weighting term is defined w_i signifying the proportion of objects associated with the same decision outcome as that for object o_i – with condition the sum of w_is equals n_D). The $\mathrm{OB}^{\mathrm{NCaRBS},w}$ is then defined as:

$$\mathrm{OB}^{\mathrm{NCaRBS},w} = \frac{1}{3n_O} \sum_{i=1}^{n_O} \sqrt{\frac{\sum_{h=1}^{n_{\mathrm{D}}} \left(BetP_i(d_h) - v_{d_h,i}\right)^2}{w_i}},$$

where, in the limit, $0 \leq \mathrm{OB}^{\mathrm{NCaRBS},w} \leq 1$.

Incomplete data handling

An age old problem in itself, what to do with missing values in incomplete data is an issue that appears across a wide range of business related research (Schafer and Graham, 2002). In the case of survey data this is certainly an ever present problem (Brick and Kalton, 1996), with regular suggestions given on how to pertinently manage the presence of missing values, including deleting the objects which have missing values amongst the variable values describing them and imputing the missing values present (Little and Rubin, 1998). These traditional approaches, and others, transform the original data in some way, and so will negatively impact on the ability to achieve analysis results that fairly reflect the information in the original data. It is noticeable in the literature how standard, and acceptable, it is to have to transform incomplete data (see for example Svolba, 2014), something challenged in this study.

Using the NCaRBS technique, however, there is no need to transform the incomplete data in anyway, meaning the missing values present are retained in the analysis. Moreover, with DST forming the rudiments of the NCaRBS technique, the missing values are considered ignorant pieces of evidence (see Beynon, 2005b). For a missing value $v_{i,j}$ (i^{th} object, j^{th} characteristic), its 'missingness' is interpreted as offering only ignorant evidence (the term ignorance here should not be viewed with negative reverence instead highlighting that it offers no specific evidence that would lead to a correlative or causal relationship with other variables), and modelled to this effect in the associated constituent BOE. That is, within NCaRBS, the constituent BOE $m_{i,j,h}(\cdot)$, which contains the evidence from a variable value, is able to model this ignorance, by assigning full belief (mass value) to ignorance, namely by defining such a BOE $m_{i,j,h}(\cdot)$ as:

$$m_{i,j,h}(\{d_h\}) = 0.000,\ m_{i,j,h}(\{\neg d_h\}) = 0.000 \text{ and } m_{i,j,h}(\{d_h, \neg d_h\}) = 1.000,$$

for any value $v_{i,j}$ known to be missing. This constituent BOE is fixed, and does not change depending on the identified control parameters ($k_{j,h}$, $\theta_{j,h}$, $A_{j,h}$ and $B_{j,h}$), found when configuring NCaRBS (see discussion around Figure 1). That is, the configuration process is not effected by missing values, and configuration is based on the variable values that are present in the data.

This concept of managing the missing values is next illustrated. In Table 1, a hypothetical example of two objects (eg_1 and eg_2) is given, with two variables each potentially describing them (for reference the positions of all the next described BOEs in this example are given in Figure 1*c*). From Table 1, object eg_1 has two numerical values present ($v_{1,1}$ and $v_{1,2}$), hence there are two BOEs associated with them that contain the evidence from each variable value (here using the same control parameters for the BOEs' construction, namely, $k_{j,h}$ = 0.5, $\theta_{j,h}$ = 4.0, $A_{j,h}$ = 0.333, $B_{j,h}$ = 0.9), whereas for eg$_2$ one of its variable values ($v_{2,2}$) is missing (denoted by -), and actually has the same other variable value as eg$_1$, that is, $v_{2,1} = v_{1,1}$.

Example	$v_{i,j}$		$m_{i,j,h}(\{d_h\})$	$m_{i,j,h}(\{\neg d_h\})$	$m_{i,j,h}(\{d_h, \neg d_h\})$
eg$_1$ | $v_{1,1}$	2.950		0.052	0.398	0.550
eg$_1$ | $v_{1,2}$	6.210		0.564	0.000	0.436
eg$_2$ | $v_{2,1}$	2.950		0.052	0.398	0.550
eg$_2$ | $v_{2,2}$	-		0.000	0.000	1.000

Table 1. Example BOEs including representation of missing value

In Table 1, the BOE mass values can be found using the $m_{i,j,h}(\{d_h\})$, $m_{i,j,h}(\{\neg d_h\})$ and $m_{i,j,h}(\{d_h, \neg d_h\})$ expressions given in the previous subsection. For the case of value $v_{2,2}$ for object eg$_2$ since it is a missing value the BOE is assigned to it as previously described (including $m_{2,2,h}(\{d_h, \neg d_h\}) = 1$).

Moving onto the combination of the evidence in the pairs of BOEs for each example object, eg$_1$ and eg$_2$, their combination is next shown, using the $(m_{i,j_1,h} \oplus m_{i,j_2,h})(\cdot)$ based combination rule shown in the previous subsection.

For eg$_1$:

$$(m_{1,1,h} \oplus m_{1,2,h})(\{d_h\}) = \frac{0.052 \times 0.564 + 0.564 \times 0.550 + 0.052 \times 0.436}{1-(0.398 \times 0.564 + 0.052 \times 0.000)} = 0.467\,,$$

$$(m_{1,1,h} \oplus m_{1,2,h})(\{\neg d_h\}) = \frac{0.398 \times 0.000 + 0.436 \times 0.398 + 0.000 \times 0.550}{1-(0.398 \times 0.564 + 0.052 \times 0.000)} = 0.224\,,$$

$$(m_{1,1,h} \oplus m_{1,2,h})(\{d_h, \neg d_h\}) = 1 - 0.467 - 0.224 = 0.309\,,$$

as shown in Figure 1*c* where it is termed $m_{1,\mathrm{C},h}(\cdot)$ (showing the graphical form of the combination of two pieces of evidence – two BOEs).

For eg$_2$:

$$(m_{2,1,h} \oplus m_{2,2,h})(\{d_h\}) = \frac{0.052 \times 0.000 + 0.000 \times 0.550 + 0.052 \times 1.000}{1-(0.398 \times 0.000 + 0.052 \times 0.000)} = 0.052\,,$$

$$(m_{2,1,h} \oplus m_{2,2,h})(\{\neg d_h\}) = \frac{0.398 \times 0.000 + 1.000 \times 0.398 + 0.000 \times 0.550}{1-(0.398 \times 0.000 + 0.052 \times 0.000)} = 0.398\,,$$

$$(m_{2,1,h} \oplus m_{2,2,h})(\{d_h, \neg d_h\}) = 1 - 0.052 - 0.398 = 0.550\,,$$

the resulting piece of evidence is the same as from the variable $v_{2,1}$ ($m_{2,1,h}(\cdot)$ BOE). This is because the ignorance associated with the missing value from $v_{2,2}$, has not impacted on the available evidence for this object, the associated $m_{2,2,h}(\cdot)$ BOE does not impact during the combination process (hence the whole NCaRBS configuration process).

3 FSB data and SME innovation

Background

The Federation of Small Businesses is the UK's largest campaigning pressure group promoting the interests of the self-employed and owner/managers of SMEs with over 200,000 members across 33 regions (FSB, 2014). The FSB survey is a significant biannual study of UK private sector organisations behaviour and attitudes, and is the largest representative survey of UK firms available for academic research purposes.

Data Set

The FSB 2010 survey instrument itself was a reiteration and evolution of prior FSB surveys and was developed in consultation with FSB members to ensure the instrument design was logical and transparent. The paper authors were granted access to use the data for academic research purposes after representation to the FSB.

Individual enterprises were considered the unit of analysis, with Owner/Managers being asked to complete the questionnaire. The 2010 survey was sent out to the FSB's entire UK membership of approximately 200,000 firms. This enabled access to a large dataset, with a notable number of usable (in raw or adjusted form) variables. Overall 11,367 enterprises responded, providing 7,880 responses that were usable for the research discussed in this paper (for reasons discussed further below, usable respondents had to contain a response to the outcome variable and at least one of the considered characteristic variables).

Coding

While the presence of missing values was not considered a problem here, with no action needing to be taken on their presence, allowing them to be retained in the analysis (as described in section 2), the coding of the considered variables in terms of their meaning is next given. Six characteristic variables, found in the literature to be potentially linked to intended SME innovation are used to describe each SME, namely, Age, Education, Growth, Internet, Reliance and Size (but where the literature is currently inconclusive as to the precise nature of that relationship, particularly with regard to the issue of non-substantive "Don't

Know" responses). These are described below, following a discussion of the outcome variable, Innovation intention.

Outcome

Innovation intention:

Innovation is one of the main determinants of competitiveness (Orfila-Sintes and Mattsson, 2009) however there is a limited literature considering its adoption characteristics (Utterback and Abernathy, 1975; King and Kugler, 2000). Edwards *et al*. (2005) suggests SMEs flexibility and specificity can be advantageous in accelerating innovation. Russell and Russell (1992) also argue that entrepreneurship and innovation are closely intertwined processes, and that both have high degrees of uncertainty associated with them in terms of both processes and outcomes. In terms of related work which has considered the non-substantive DK response, Reynolds *et al*. (2005) used DK as an answer option, for potential entrepreneurial activities. Schultze and Stabell (2004) also argue that the management of knowledge requires research into the management of ignorance, partly because it raises issues over the use of "ignore" strategies in management, highlighting the importance of what a DK response actually means.

The FSB survey question asked was "Do you have plans to introduce new or improved products/services in the next 12 months?", with response of either, Yes, No or Don't Know (DK), see Figure 2*a*. In Figure 2*b*, the response representation at the vertices of a simplex plot is shown, this is the domain later used in the classification analysis undertaken (using NCaRBS).

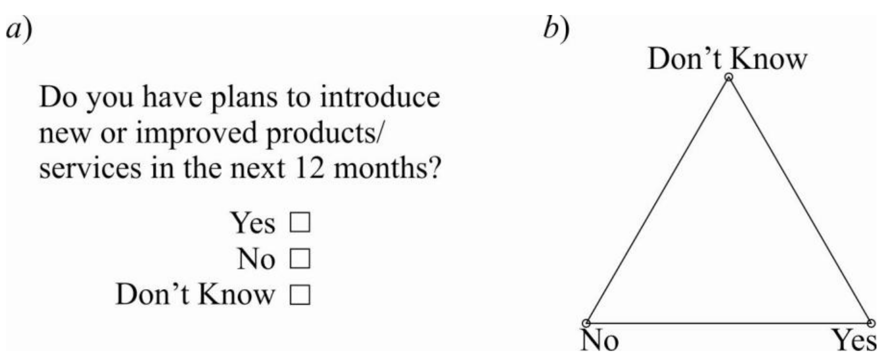


Figure 2. Intended innovation question with response options (*a*) and response representation in simplex plot domain (*b*)

The representation of the three responses No, Yes and DK, shown in Figure 2*b*, offers a consistent domain to view them. The quantification of the outcome variable in this study, is in a three value vector, where [1, 0, 0], [0, 1, 0] and [0, 0, 1] represent the outcome responses No, Yes and DK, respectively (and are the points at the vertices of the presented simplex plot in Figure 2*b*).

Characteristic variables

Firm Age:

Salavou *et al*. (2004) recognise the contrasting extant research between firm age and innovation, suggesting that younger firms are more innovative (see also Patel, 2005). By contrast, research including Sorensen and Stuart (2000) and Camison-Zornoza *et al*. (2004) identify that older more established SMEs have the capability to acquire innovative knowledge and engage in a greater level of innovative activity which enhances organisation performance.

The FSB survey question asked was "How many years have you owned or co-owned your main business?" with response given as number of years. So increasing value of Age indicates increasing age of the business.

Education:

Pickernell *et al*. (2011) suggest that graduates possess skills, abilities, and resources that will produce more beneficial outcomes than non-graduates for a firm (see also for example, Galloway *et al*., 2005). The research highlighted here considers higher education level with more employment in innovation oriented SMEs.

The FSB survey question asked was "Which of the following is the highest level of education that you have attained so far?" with response modelled in a binary variable 0 – less than Bachelor Degree or equivalent and 1 - Bachelor Degree or equivalent or above. So increasing value of education indicates increasing level of education of SME Owner/Managers.

Growth aspiration:

Prior studies suggest that rapid growth can occur in labour and knowledge intensive industries in both manufacturing and service industries (Davidsson and Delmar, 1997), and in firms of all ages (Smallbone *et al*., 2002). Related to this, several factors have been identified as potential signs of high growth competency, including higher levels of innovativeness (Allen and Stearns, 2004).

The FSB survey question asked was “What has been the main business objective for the next 12 months?” four ordinal categories went from 1 - to downsize/consolidate the business, upto 4 - to grow rapidly in terms of turnover/sales were considered. Businesses were removed from the analysis which indicated they would be discontinuing the business namely, closing the business or handing on the business. Therefore, increasing value of Growth indicates the future intention to grow the business.

Internet:

Teoa *et al.* (1999) and Lesjak and Vehovar (2005) recognised that Internet use contributed to the creation of current and future economic benefits and usefulness, which was reflected in increased market value. It has also been recognised that Internet utilisation and adoption in SMEs remains an under researched topic, especially with regard to recognising the antecedents to successful deployment (Fink and Disterer, 2006).

The FSB survey question asked was “Which of the following, if any, do you use the internet for whilst running your business”. Fourteen categories were shown as well as “do not use the internet” (see Figure 3).

☐ Emailing
☐ Maintaining a business website
☐ Paying bills/tax returns
☐ Finding advice, guidance and information
☐ Searching for staff/recruitment
☐ Placing adverts/marketing
☐ Online trading
☐ Downloading information/documents
☐ Web conferencing/Voice over IP
☐ Visiting Government website to comply with legislation
☐ Searching for tender opportunities/submitting tender documentation
☐ Obtaining advice on running/starting business (e.g. Business Support Business Link)
☐ Using shared resources/software or file storage (i.e. cloud computing)
☐ Other (please specify below)
☐ Do not use the internet

Figure 3. Categories of internet use by SME

Measured here as a view of internet intensity, the sum of the fourteen categories ticked was used, along with a 0 when the ‘Do not use the internet’ term was highlighted. So increasing value of Internet indicates increased level of internet intensity.

Reliance:

Keskin (2006) and Demirbag *et al*. (2010) suggests that SMEs following a proactive business strategy foster innovativeness as a central part of their organisational culture. High-tech SMEs, including electronics, software, and biotechnology can demonstrate improved performance by continuously generating new markets and industries due to their innovativeness (Romijn and Albaladejo, 2002). The positive role of firm innovativeness on organisation performance has been supported by several studies (Calantone *et al*., 2002).

The FSB survey question asked was "What percentage of your revenue comes from new products or services that have been introduced in the past two years?", with eight categories ranging from zero% (0) to more than 60% employed (7) as well as a DK option. So increasing value of the Reliance characteristic indicates increased level of reliance on new products or services.

Firm Size:

Schumpeter (1942) claimed that large firms had an advantage with regards to innovation over SMEs as their financial capabilities enabled them to be the most effective innovators (see also Laforet, 2008). In contrast, Cohen and Klepper (1996), who suggested that larger firms suffered from excessive bureaucracy that impedes creativity and flexibility in contrast to the SME sector (see also Rothwell and Zegveld, 1986; Bertschek and Entorf, 1996).

In the survey, the question asked was "Including yourself how many of each of the following types of employee work in your business". Here the number of full time staff is therefore a term to describe size. So increasing value of Size indicates increased size of the business.

The Potential Relationships between the Characteristics Variables and DK for Innovation

In terms of the characteristic variables, in addition to their inferred linkages with innovation, discussed above, they may also be specifically related to the DK response for innovation. Birkinshaw *et al*. (2008), focus their research on innovations which have a high degree of uncertainty of outcome (a common issue for innovation more generally), seeing this as a particular issue in organisations that lack expertise (which may be linked to firm size and age, and also the educational level of the owner), and where understanding of the innovation may be difficult or negative consequences may be possible (which may be linked to a lack of growth intention as innovations that reduce costs or increase efficiency in non or low growth organisations will inevitably lead to reductions in resources).

They also argue that these uncertainties are also likely to be greater where there is a lack of precedence for the innovation (suggesting that previous innovation experience should reduce the uncertainty). Adner (2006) also notes that, with innovation, the greater the number of intermediaries involved, the greater the degree of uncertainty (which may suggest that where internet use brings the company closer to the customer such uncertainty may be reduced). Not generally explicitly considered in the extant literature, however, is what impact these variables might have on an SME knowing their future innovation intention, with emphasis here in actually knowing, Yes or No, compared to not knowing (DK).

Incomplete FSB-Innovation Data Set

Based on the described characteristic and outcome variables, from the FSB survey, a total of 7,880 SMEs (responses) were able to be used (from an original 11,367 responses). Two reasons for the reduction in used SMEs are, *i*) at least one characteristic variable value has to be present to describe each SME, and *ii*) the outcome variable was not allowed to be missing. In the case of the outcome variable Innovation-intention, the breakdown of SMEs to the three response outcomes, No, Yes and DK was 1,795, 5,061 and 1,032, respectively. With 13.083% (1,032 out of 7,888) giving the non-substantive response of DK to the outcome survey intended innovation question (see Figure 3*a*), this is above the largely academic level of less than 5% suggested by Gilljam and Granberg (1993) but below the uncommon sight of between 20-30% (*ibid*.).

It is worth noting, Gilljam and Granberg (1993) use the term ‘easy out’ provision when a DK response option is given to a respondent. While here we include the DK outcome response, other papers have taken the decision to recode such a response as No, in job practises for example (see Wright *et al*., 2003). Groothuis and Whitehead (2002), also asked whether a don't know response actually meant no, they generated findings that suggested circumstances existed where DK could mean No, Yes or indicating uncertainty or ambivalence. Perhaps pertinent to this study of SME intended innovation, Turner and Michael (1996), argue that DK is not always a sign of knowledge deficit (i.e. uncertainty or ambivalence), but can also be a “political” statement, and thus the social context must also be considered (in our analysis whether an SME manager would want to admit to saying No to intended innovation – preferring instead to say DK in their response).

Clearly, in terms of the analysis to be undertaken in this paper, if these were not included in the analysis (listwise delete SMEs with DK as outcome response), there would be a noticeable decrease in the size of the considered data set, down to 6,856 (analysis of which is not undertaken here). A brief empirical description of the considered characteristic variables within the incomplete FSB-innovation data set is given in Table 2.

Variable	Min	Mean	Max	Std Dev	Missing
Age	0	12.567	262	11.096	55
Education	0	0.381	1	0.486	121
Growth	1	2.775	4	0.789	347
Internet	0	6.610	14	2.507	0
Reliance	1	3.466	8	1.937	3,625
Size	0	4.803	150	8.773	743

Table 2. Descriptive statistics of characteristic variables

While the descriptive statistics given in Table 2 offer some elucidation to the variations in data being considered, the missing column quantifies the number of missing response values to each of the characteristic variables considered. That is, the least and largest numbers of missing responses is with respect to Internet (0 out of 7,888 missing) and Reliance (3,625 out of 7,888), respectively. In the case of the Internet characteristic, the respondent had the option to tick against a number of different Internet uses as part of their business, but importantly also able to respondent with 'Do not use the Internet' (see Figure 3), hence no missing responses in this case. For Reliance, this survey question may have required the SME's Owner/Managers own investigation into actual level of innovation reliance (Reliance) their SME has, hence for many (near 45.956% of SMEs) their non-response may indicate their unwillingness of the Owner/Managers to give time to the answering of this question (the time to find the answer).

An example of the types of SME data considered in this analysis is given in Table 3, to aid in the understanding of the impact of having missing responses (values) amongst the considered SMEs in the FSB-innovation data set.

SME	Age	Education	Growth	Internet	Reliance	Size	No	Yes	Don't Know
o_{3728}	-	0	-	4	-	-	0	0	1
o_{3835}	28	-	-	10	-	-	0	1	0
o_{3910}	6	0	3	7	-	-	0	1	0

o_{4865}	-	1	2	4	-	15	1	0	0
o_{6624}	25	1	3	7	2	7	0	0	1
o_{7612}	25	1	2	7	4	2	1	0	0

Table 3. Example SMEs from incomplete FSB data set

Within Table 3, different SMEs have different numbers of the characteristic variables' values present (or missing if you see it like that). In this paper all these SMEs, and those like them, are included in the analysis, with the missing values kept as missing. A breakdown of the number of SMEs and number of missing values associated with them showed, 0 missing - 3,722, 1 - 3,525, 2 - 561, 3 - 76, 4 - 4. For example, there are 76 SMEs with half of their characteristic values missing (76 + 4 = 80). Moreover, from this breakdown, if only complete data was to be considered, employing listwise deletion approach to missing value management, only 3,722 (47.186%) SMEs would be considered in a completed data set based analysis.

With 4,891 (10.334%) of characteristic variable values missing, any imputation based completion of the data set would dramatically change the content of the data. It is clear from the description of the data set that the ability to analysis incomplete data allows this analysis to pertinently take place, a noticeable intelligent dimension to business analytics based analysis.

4 Results from NCaRBS analysis

This section reports an NCaRBS analysis of the incomplete FSB-innovation data set, through the configuration of a NCaRBS model (see Beynon *et al.*, 2014, for example of its previous analysis).

As described in the description of the NCaRBS technique, the configuration process involves the assignment of values to the control parameters, $k_{j,h}$, $\theta_{j,h}$, $A_{j,h}$ and $B_{j,h}$, $j = 1, .., n_{\mathrm{C}}$ and $h = 1, .., n_{\mathrm{D}}$, from which the evidence is constructed in constituent BOEs then combined to give the predicted classifications of objects (here SMEs). Bounds on these control parameters we employed (following Beynon *et al.*, 2014), were; $-6.000 \leq k_{j,h} \leq 6.000$, $-3.000 \leq \theta_{j,h} \leq 3.000$, $0.000 \leq A_{j,h} \leq 1.000$ and $0.000 \leq B_{j,h} \leq 0.600$. The specific bound on the $B_{j,h}$ control parameters, is a technical issue, and incorporates the existence of some level of ignorance in each constructed constituent BOE, necessary for the combination of constituent BOEs, see Beynon *et al.*, 2005b). Moreover, this is to mitigate the impact of contradictions in evidence from different sources (in constituent BOEs), a feature of the issue regarding the independence of evidence when combining BOEs (see for example, Altınçay, 2006; Smets, 2007; Cattaneo, 2011), where independence is, in qualitative terms here, viewed in terms of the distinctness of each characteristic variable (see Smets, 2007).

The results presented in this analysis are in three forms, *i*) a description of the classification fit of the findings, *ii*) the contribution of the individual characteristic variables in the analysis, and *iii*) an example elucidation of one respondents classification details. Further validation of the results are presented in section 5, where re-sampling based analyses are described.

Classification fit

With the outcome measure here being a vector of three values (see discussion around Figure 2*b*), identifying which of the three responses an SME is associated with, in terms of intended innovation, No (vector [1, 0, 0]), Yes (Ys) ([0, 1, 0]) and Don't Know (DK) ([0, 0, 1]). The NCaRBS analysis was undertaken, with 10 runs of the configuration process performed (each time using TDE to minimise the $OB^{NCaRBS,w}$ objective function described in Section 2). The best classification fit was found to be $OB^{NCaRBS,w} = 0.688$.

Since each of these 'predicted outcome' vectors sums to one, they can all be represented in a simplex plot (see Figure 2*b*). The NCaRBS is concerned with ambiguous classification, the predicted classification results may indicate part association to more than one possible response, and in terms of the simplex plot, illustrated in Figure 2*b*, this means a point inside the presented simplex plot (see Beynon, 2005a). In the analysis of the 7,888 SMEs, Figure 4 shows the predicted outcome classifications of the individual SMEs, to the three outcome responses, No, Yes and DK (shown separately).

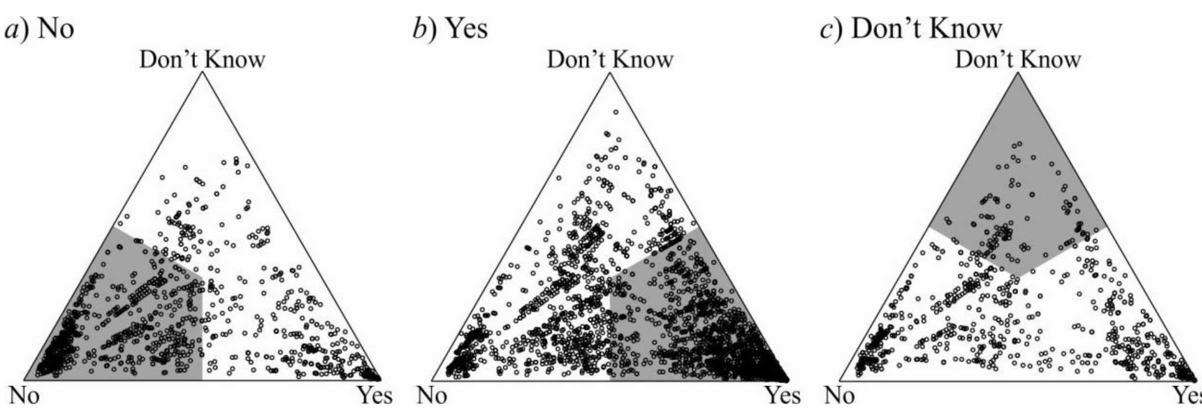


Figure 4. Simplex plot based representation of predicted outcome variable

In Figure 4, the three simplex plots shown, describe separately the predicted outcomes of those SMEs originally known to be associated with the outcome response, 1,795 No (4*a*), 5,061 Yes (4*b*) and 1,032 Don't Know (4*c*). From the description of the NCaRBS analysis, the variation in the numbers of SMEs associated with each outcome was taken into account, allowing each group of SMEs equal weighting in achieving their correct classification (see description around description of $\mathrm{OB}^{\mathrm{NCARBS},w}$ objective function).

In each simplex plot shown in Figure 4, the shaded region shows the area within the simplex where there is correct classification (based on majority association) of an SME predicted outcome to their actual outcome response. A numerical breakdown of the correct/incorrect classification of SMEs is given in Table 4.

Actual / Predicted	No	Yes	Don't Know	Ambiguous	Total
No	1,328 (0.740)[1]	334 (0.186)	119 (0.066)	14 (0.008)	1,795 (0.228)
Yes	1,205 (0.238)	3,436 (0.679)	404 (0.080)	16 (0.003)	5,061 (0.642)
Don't Know	564 (0.523)	326 (0.316)	139 (0.135)	3 (0.003)	1,032 (0.131)
Total	3,097 (0.393)	4,096 (0.519)	662 (0.079)	33 (0.004)	7,888

[1] Numbers in brackets are the proportions of the values originally associated with each row's actual classification (these are presented for comparison purposes with the re-sampling results presented later which was unstratified in nature) - with exception of Total row and column.

Table 4. Confusion matrix of classification results

In Table 4, the actual and predicted classifications of the 7,888 SMEs is provided, for each group of SMEs the spread of these across the three possible outcome responses is given. For the case of the 1,795 No SMEs, then 1,328, 334 and 119, were classified as being No, Yes and DK response SMEs, respectively (the latter two numbers indicating the number of incorrect classifications). From this table, the overall level of correct classification is found to be 4,903 out of 7,888 (62.158%) SMEs. The ambiguous column in Table 4 is to acknowledge that for small numbers of SMEs (33 - 0.4%), their predicted classifications were ambiguous, meaning two (or more) of their $BetP_i(d_h)$ values were equal to each other (often associated with SMEs with missing values, so classification evidence limited to one or two pieces of evidence – such as with cases o_{3728} and o_{3825} shown in Table 3).

The bracketed values, showing proportions of respondents, enable comparisons across the different actual classifications groups of SMEs, it is noticeable that in terms of correct predicted classifications, the No SMEs are most correctly classified (0.740), followed by the Yes respondents (0.679), but lastly DK (0.135) showing a particular lack of ability to correctly classify DK respondents away from other respondents. Beyond that, over half of the DK respondents were miss-classified as No respondents. So taking the nature of the question, in terms of intended innovation, into account, this may suggest that respondents who, based on their characteristic variables, would have given "No" responses, may have given a DK response. This result, again acknowledging this is based on the predictive quality of the considered characteristic variables, supports the view in Groothuis and Whitehead (2002) that a predominance of DK response SMEs are more similar to the No response SMEs.

For specific variables, however, a variety of relationships between No, Yes and Don't Know were found to exist. These are discussed below.

Characteristic contribution

Beyond the classification fit of the undertaken analysis, this subsection considers the contribution of the individual characteristics, an important facet of business analytics based analysis. The form of this elucidation of characteristic variable contribution is graphical, and is based on the general forms of the relevant constituent BOEs. Moreover, for a specific variable, a *variable* BOE can be constructed, through the combining of the evidence in the constituent BOEs, $m_{i,j,h}(\cdot)$ $h = 1, .., n_{\mathrm{D}}$, termed a variable BOE, defined $m_{i,j,-}(\cdot)$. The resultant variable BOE $m_{i,j,-}(\cdot)$, for each characteristic variable, found from the configured NCaRBS model can be presented graphically, based on their pignistic probability form (see Beynon *et al.*, 2014), see Figure 5.

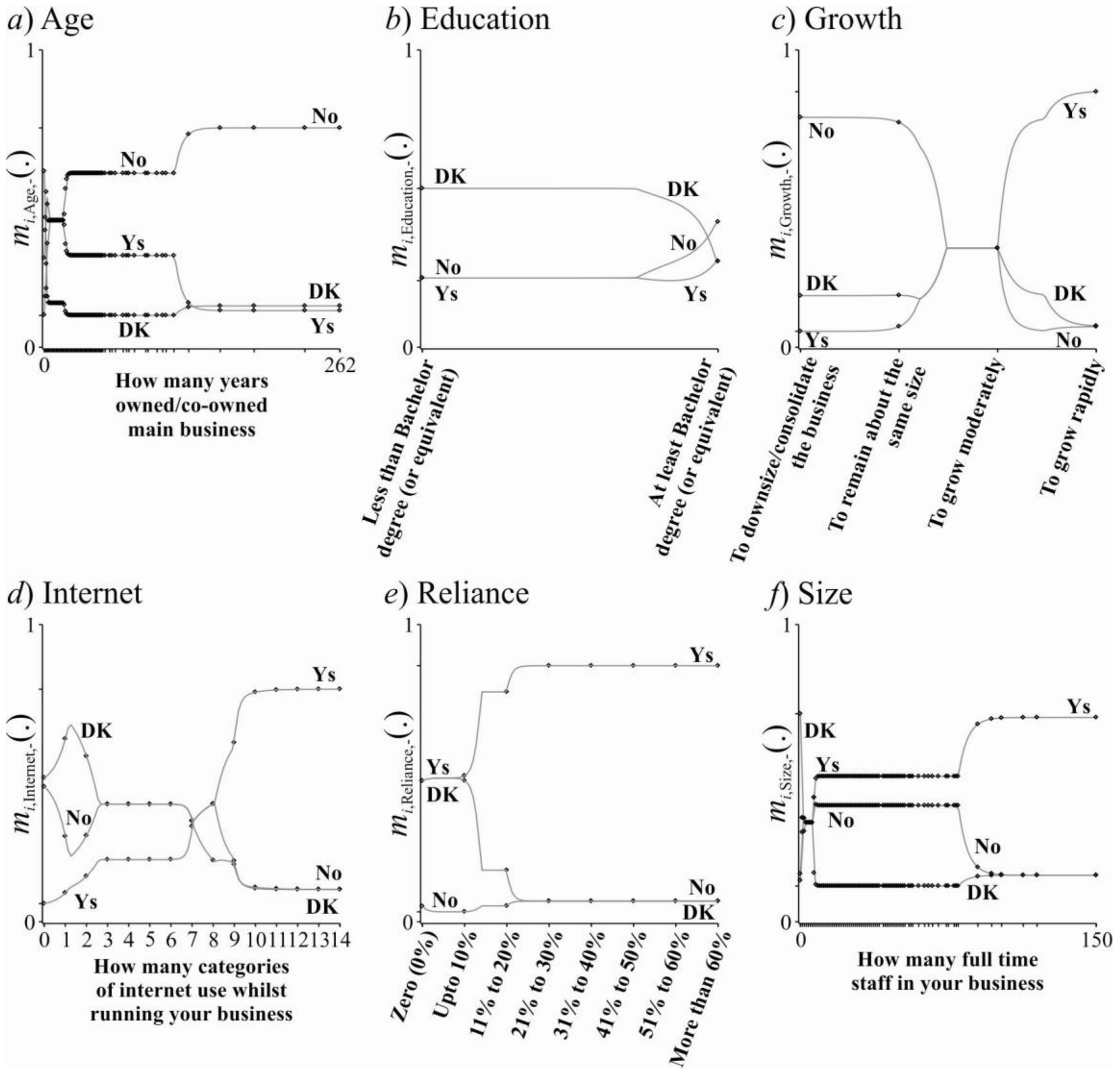


Figure 5. Graphical elucidation of characteristic variables - showing pignistic probability forms (sets of points) of variable BOEs (lines connecting points are to signify the internal structure of going from one possible set of pignistic probability values to another)

In Figure 5, each graph gives a graphical elucidation of the variable BOEs associated with the six characteristic variables considered in this analysis. It should be noted, the points on each line illustrate where actual values of the characteristic variable existed, and so actual variable BOEs would be constructed, the lines between these points show the underlying structure of the variable BOEs for each characteristic variable. For example, in the case of the Education characteristic, only two values 0 (Less than Bachelor degree) and 1 (At least Bachelor degree) exist, but the lines between these two points show the structure of the variable BOEs getting from 0 to 1 (in this case). This is helpful since it elucidates the non-linear contribution possible from a characteristic variable in the configured NCaRBS model.

Each of the contribution graphs in Figure 5 are next explained (further elucidation will be given in a later section).

Age (5a)

Beyond the very recently started SMEs there is continued increase of evidence towards No to intended innovation as the age of the SME increases. In contrast, as the age of the SME increases there is a similar decrease in the evidence towards Yes and DK (Don't Know) intended innovation. This result tends to favour the research of Salavou *et al*. (2004) that firms must exhibit innovation behaviour as young entities and it is more difficult to acquire such behaviour as the firm ages (see also Wang *et al*., 2007).

Education (5b)

As a binary variable the only details to be concerned with are the left and right hand sides of the graph. On the left side, with Owner/Manager education level less than Bachelor degree there is noticeable discernment between the greater evidence suggesting DK as outcome response against the more substantive responses of No and Yes. In contrast, with those Owner/Managers with at least a Bachelor degree there is discernment in the evidence towards the substantive responses, noticeably the association to DK is reduced, with most increase to No and minimal change to Yes. This result suggests that SME Owner/Managers acquire informed decision capabilities towards innovation deployment by the completion of a Bachelor degree. One issue of relevance here is the date of the survey. It was conducted in the middle of the severe UK and global recession, hence this may be contributory factor for the negative outlook on intended innovation

More importantly, this result supports the view that the education of the individual does impact on the use of the non-substantive response DK, following Ferber (1966), contrasting slightly with Francis and Busch (1975). That is, with more education (higher education attainment), there is more focus on a substantive response.

Growth (5c)

The growth characteristic (taking one of four values), shows variation in the evidence it offers towards the outcome responses No, Yes and DK. As growth belief increases there is understandable increase and decrease in the evidence towards Yes and No to intended innovation, respectively, suggesting a positive relationship between growth and intended innovation. The case of the DK is interesting, in that as growth belief increases, there is initial increase in DK but then decrease. That is, at the extremes of knowledge of the growth of the SME there is the least evidence to DK, in the middle where the growth believe is muted (qualitative terms shown in Figure 5*c*), so there is more evidence towards the DK outcome response. This result potentially indicates the uncertainty and lack of evaluation within SMEs to fully understand the association between innovation and attaining growth (Hudson *et al.*, 2001).

Internet (5d)

The description of the Internet characteristic is that the higher the value the more intense the use of internet. From the variable BOE graph in Figure 5*d*, for no or little use of the internet, there is more evidence suggesting No intended innovation or DK, with little evidence towards Yes. As internet use increases so there is increased evidence towards Yes to intended innovation, with consequential decrease in evidence towards No or DK (relatively close similarity in evidence towards No and DK across this characteristic). This result suggested that SMEs that are adopting technologies like the internet are typically more innovative. This is a logical finding in that the SMEs concerned are using technological solutions as a potential enabler towards more innovative behaviour (Loebbecke and Schäfer, 2001).

Reliance (5e)

For this characteristic the variable BOE graph shows as the reliance of the SME on innovation increases so there is understandable increase in the intention for more innovation in the next 12 months. This increase in Yes is balanced by a decrease in the DK outcome, with little movement of the evidence towards No. This seems a logical finding in that the desire for the firm to be innovative is self-perpetuating and increased reliance is based on this behaviour as proposed by Keskin (2006).

Size (5g)

The Size characteristic, demonstrates for small SMEs a marked difference to when there is a slight increase in its size. As the size of the SME increases so there is increasing evidence towards Yes to intended innovation. In contrast, there is different levels of decrease in the evidence towards No and DK when SME size goes up (more dramatic for DK when SME size increase from near small). These results tend to support the findings of Laforet (2008) who argue that larger firms are more likely to be innovative. This finding supports the belief that larger firms have greater capacity (e.g. finance, staff etc.) to invest in and support entrepreneurial activity.

Example of individual SME's classification details

To offer further elucidation of the processes by which the evidence from a SME's survey responses contributes to their final predicted classification to their outcome response, a single SME case is considered, namely for o_{199}. In Table 5, for SME o_{199}, the majority of the numerical details are given, in terms of constituent BOEs and outcome BOEs, representing its evidence in the NCaRBS analysis.

Outcome	Variable	Age	Education	Growth	Internet	Reliance	Size	Outcome BOEs
	Value (Stdz)	–1.042	1.275	0.286	–0.243	-	-	
No	No	0.000	0.121	0.000	0.000	0.000	0.000	0.108
	Ys, DK	0.120	0.000	0.000	0.000	0.000	0.000	0.107
	No, Ys, DK	0.880	0.879	1.000	1.000	1.000	1.000	0.785
Yes	Ys	0.193	0.000	0.000	0.000	0.000	0.000	0.132
	No, DK	0.000	0.000	0.000	0.363	0.000	0.000	0.315
	No, Ys, DK	0.807	1.000	1.000	0.637	1.000	1.000	0.553
DK	DK	0.296	0.000	0.000	0.000	0.000	0.000	0.296
	No, Ys	0.119	0.000	0.000	0.000	0.000	0.000	0.119
	No, Ys, DK	0.585	1.000	1.000	1.000	1.000	1.000	0.585

Table 5. Constituent and outcome BOEs for SME o_{199}

In Table 5, the standardized values of the SME question's responses are given (those used in the NCaRBS analysis), with a '-' showing where the SME did not give a response to a variable question (the characteristic variables Reliance and Size in this case). In the next three table subsections (sets of three rows) the constituent BOEs ($m_{199,i,h}(\cdot)$) are given across the different characteristic variables, and when each of the outcome responses are considered (No, Ys and DK) against their complement and ignorance. The last column of the table shows the aggregated evidence from the combination of groups of constituent BOEs, using Dempster's combination rule, with respect to a specific outcome, in this case producing the outcome BOEs ($m_{199,\text{-},\text{No}}(\cdot)$, $m_{199,\text{-},\text{Ys}}(\cdot)$ and $m_{199,\text{-},\text{DK}}(\cdot)$).

The combination of the three outcome BOEs, following the same combination process, results in the final object BOE ($m_{199,\text{-},\text{-}}(\cdot) \equiv m_{199}(\cdot)$), for SME o_{199}, is found to be:

$m_{199}(\{\text{No}\}) = 0.104$, $m_{199}(\{\text{Ys}\}) = 0.099$, $m_{199}(\{\text{DK}\}) = 0.270$, $m_{199}(\{\text{Ys, DK}\}) = 0.038$,

$m_{199}(\{\text{No, DK}\}) = 0.157$, $m_{199}(\{\text{No, Ys}\}) = 0.056$ and $m_{199}(\{\text{No, Ys, DK}\}) = 0.276$.

In the outcome BOE $m_{199}(\cdot)$ the focal elements are from the power set of the frame of discernment {No, Ys, DK} (minus empty set {}). In terms of final predicted classification to the individual outcomes, as described previously, the $BetP_{199}()$ values (for No, Ys and DK), based on the object BOE $m_{199}(\cdot)$, is found to be:

$$BetP_{199}(\text{No}) = 0.303,\ BetP_{199}(\text{Ys}) = 0.237,\ BetP_{199}(\text{DK}) = 0.460.$$

In this case the largest of these values is associated with the DK outcome response ($BetP_{199}(\text{DK}) = 0.460$), the correct classification in this case (based on majority association).

This process of evidence representation, evidence combination and final predicted classification specification for this SME is next visually reported, see Figure 6.

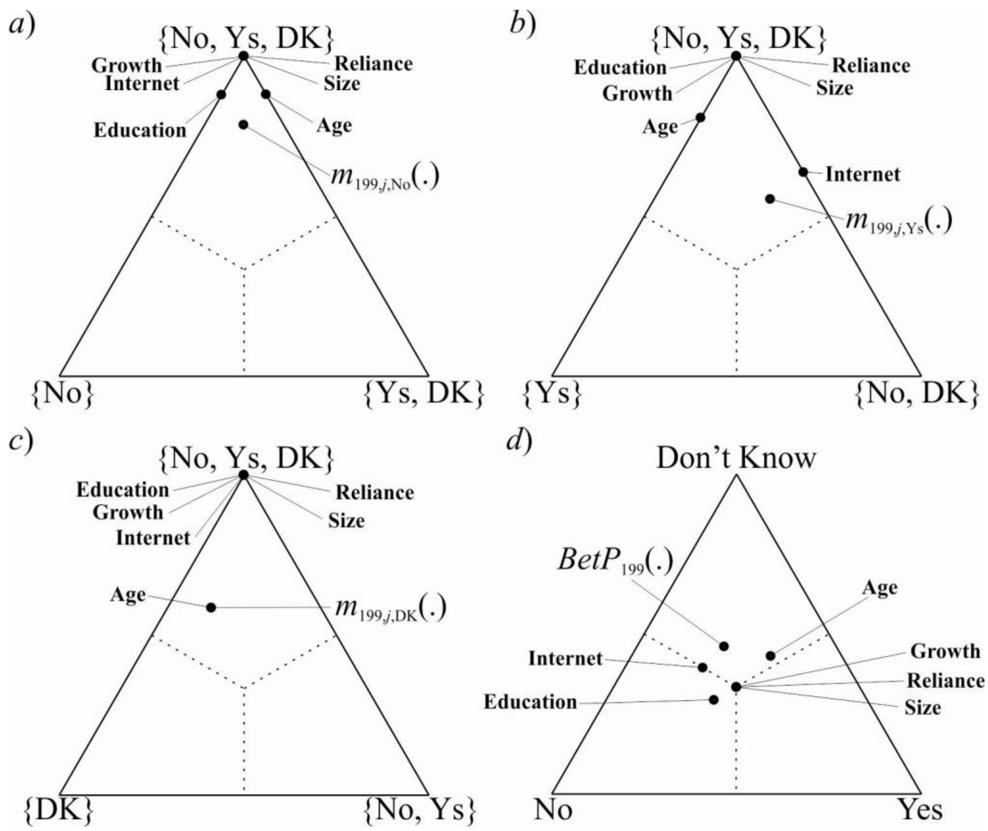


Figure 6. Simplex plot based representation of evidence associated with SME o_{199}.

In Figure 6, a simplex plot based representation of the evidence previously described in respect of SME o_{199} is given, over a number of different simplex plots. In Figures 6*a*, 6*b* and 6*c* the constituent BOEs ($m_{199,i,h}(\cdot)$) are shown (relating directly to their respective variable values in Table 5), along with their respective outcome BOEs (numerical values also shown in Table 5). The fourth simplex plot shows the final object BOE based $BetP_{199}(.)$ for the SME o_{199}, and also respective variable BOE based $BetP_{199,j}(\cdot)$s. A number of points are exhibited from these results (demonstrating the interpretive power of NCaRBS at the individual object level), in terms of associated notions of ignorance with the characteristic variables.

i) *Missing characteristic variable values* – For the SME o_{199} there are two missing response values, for Reliance and Size, hence throughout the analysis, the evidence from these two variables is only ignorance ($m_{199,j,h}$({No, Ys, DK}) = 1.000 etc.). Hence for these two variables their points in the simplex plots in Figures 6*a*, 6*b* and 6*c* are at the respective top vertex (labelled {No, Ys, DK}). In Figure 6*d* the associated variable BOE based $BetP_{199,j}(\cdot)$s are at the centre of the simplex plot, since the ignorance only evidence associated with them is simply split equally amongst the three outcomes No, Ys and DK (hence each $BetP_{199,j}(d_h)$ = 0.333).

ii) *Ignorance only variable contribution* – For the variable Growth, while its response value is present, the results in the simplex plots in Figure 6*a*, 6*b* and 6*c*, as in point i), shows only ignorant evidence towards innovation. That is, from the NCaRBS analysis undertaken, this response value for Growth characteristic variable, offers only ignorant evidence (for any SME with this outcome), meaning that it is not related in any relational way with the innovation outcome variable (that is zero predictive power). This is confirmed with inspection of Figure 5*c*, where for the 'To grow moderately' response to the Growth question there is an equal level of evidence to each outcome (0.333 values).

5 Re-sampling based validation

The results presented in Section 4 are from a one-off analysis using all the available data (7,888 SMEs). To add confidence in the validity of the results from this analysis, a re-sampling procedure is undertaken and further NCaRBS models configured (see for example Twomey and Smith, 1998).

The re-sampling undertaken here was based on performing multiple runs of the NCaRBS technique using identified in-samples and out-samples of SMEs. Here, 40 runs were performed over a number of different partitions of the data. The initial partition of the FSB-innovation data set was based on 90% of SMEs (7,099) were used as the in-sample on which the NCaRBS was run to configure a model, and 10% of SMEs (789) were used as an out- sample. Later, summary results are also given for the further partitions of *i*) 80% (6,310) and 20% (1,578), *ii*) 70% (5,522) and 30% (2,366) and *iii*) 60% (4,733) and 40% (3,155).

For the 90%/10% partition of the data and each pair of in-sample and out-sample sets of SMEs, levels of classification fit can be found based on the objective function ($OB^{NCaRBS,w}$), see Figure 7.

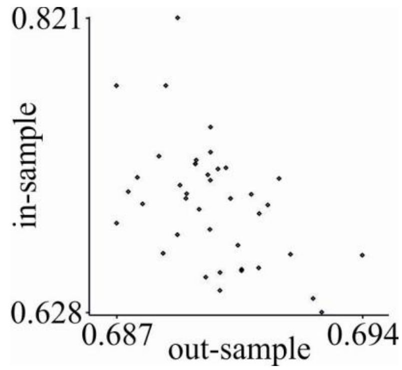


Figure 7. Scatter-plot of in-sample and out-sample classification fit values over 40 runs (based on $OB^{NCaRBS,w}$ and FSB-innovation data set)

In Figure 7, the two axes depict the $OB^{NCaRBS,w}$ fit values for in-sample (horizontal) and out-sample (vertical) sets of data. Clearly, there is a limited inverse relationship between the pairs of fit values, namely as the level of in-sample fit increases so the level of out-sample fit decreases. Beyond this relationship, whether there is significant difference between the in-sample and out-sample fit values are considered using a paired-sample t-test (see for example Kula and Tatoglu, 2003). From the test there was not a significant difference between the fit values for in-sample (M = 0.690, SD = 0.00145) and out-sample (M = 0.700, SD = 0.040) sets of data; $t(39) = 1.580$, $p = 0.122$.

Following the classification/prediction results for the one-off analysis shown in Table 4, comparisons with these in terms the 90%/10% re-sampling are first shown in Table 6 (SMEs with ambiguous prediction results not included here – limited to near 0.4% of cases).

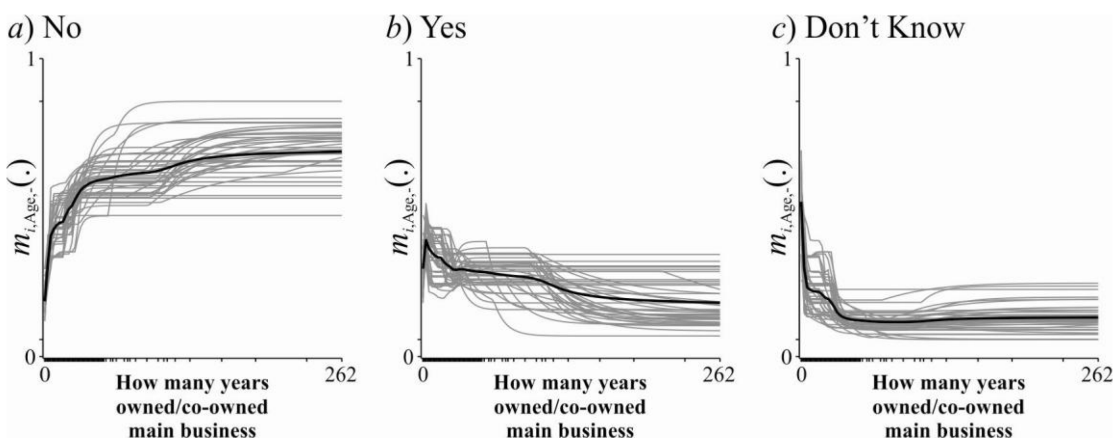
Actual / Predicted (90% in-sample)	No	Yes	Don't Know	Total
No	0.736 (0.025)	0.194 (0.011)	0.070 (0.020)	0.227 (0.002)
Yes	0.241 (0.015)	0.690 (0.009)	0.068 (0.017)	0.642 (0.002)
Don't Know	0.535 (0.031)	0.337 (0.015)	0.127 (0.030)	0.131 (0.001)
Total	0.392 (0.018)	0.531 (0.009)	0.077 (0.019)	7099

Actual / Predicted (10% out-sample)	No	Yes	Don't Know	Total
No	0.715 (0.045)	0.210 (0.028)	0.075 (0.031)	0.229 (0.014)
Yes	0.243 (0.022)	0.686 (0.019)	0.071 (0.019)	0.642 (0.017)
Don't Know	0.570 (0.045)	0.335 (0.045)	0.096 (0.030)	0.129 (0.013)
Total	0.394 (0.026)	0.531 (0.016)	0.075 (0.020)	789

Table 6. Confusion matrices of classification/prediction results from 90%/10% in-sample/out-sample re-sampling analysis

In terms of classification prediction accuracy, the results from the 90% in-sample and 10% out-sample data sets show (mean (standard deviation)), 0.627 (0.005) and 0.617 (0.018). These results, with respect to each other, show an understandable slight dip in predictive accuracy when going from in-sample to out-sample results, while a further understandable increase in the respective variations (seen through standard deviation values) in these results. When compared with the full analysis (see Table 4), the in-sample accuracy here of 0.627 is slightly above the previously found 0.621, due to the less objects being considered in the 90%/10% in-sample data.

The contribution of the individual characteristic variables to SME intended innovation, following the re-sampling procedure, can be illustrated graphically as for the one-off analysis using all of the data (see Figure 5), here shown for the two characteristic variables, Age (8*a*, 8*b* and 8*c*) and Internet (8*d*, 8*e* and 8*f*).



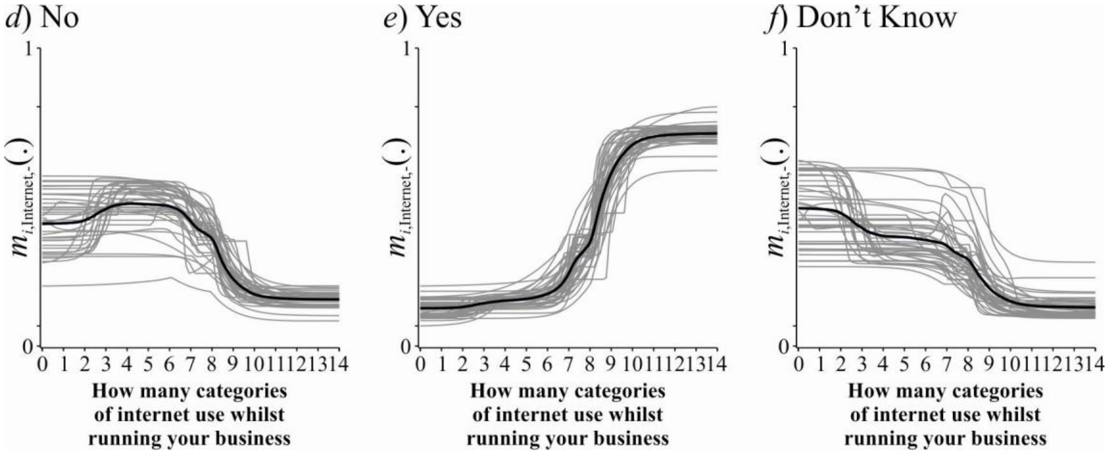


Figure 8. Age (*a*, *b* and *c*) and Internet (*d*, *e* and *f*) characteristic variable contribution lines in 40 runs (with 90%/10% partition)

In each graph in Figure 8, the contribution lines (in grey) from each of the 40 runs are presented for each of the possible outcome responses, No, Yes and Don't Know, for the two characteristic variables Age and Internet (separate graphs for No, Yes and Don't Know are given to enable their clear elucidation). As before, these lines show the internal connections between the actual values which exist for each characteristic variable. Also shown in each graph, is a thicker solid black line representing the average contribution line (from the 40 runs undertaken).

Similar average contribution lines are shown for all the characteristic variables considered in this analysis, see Figure 9.

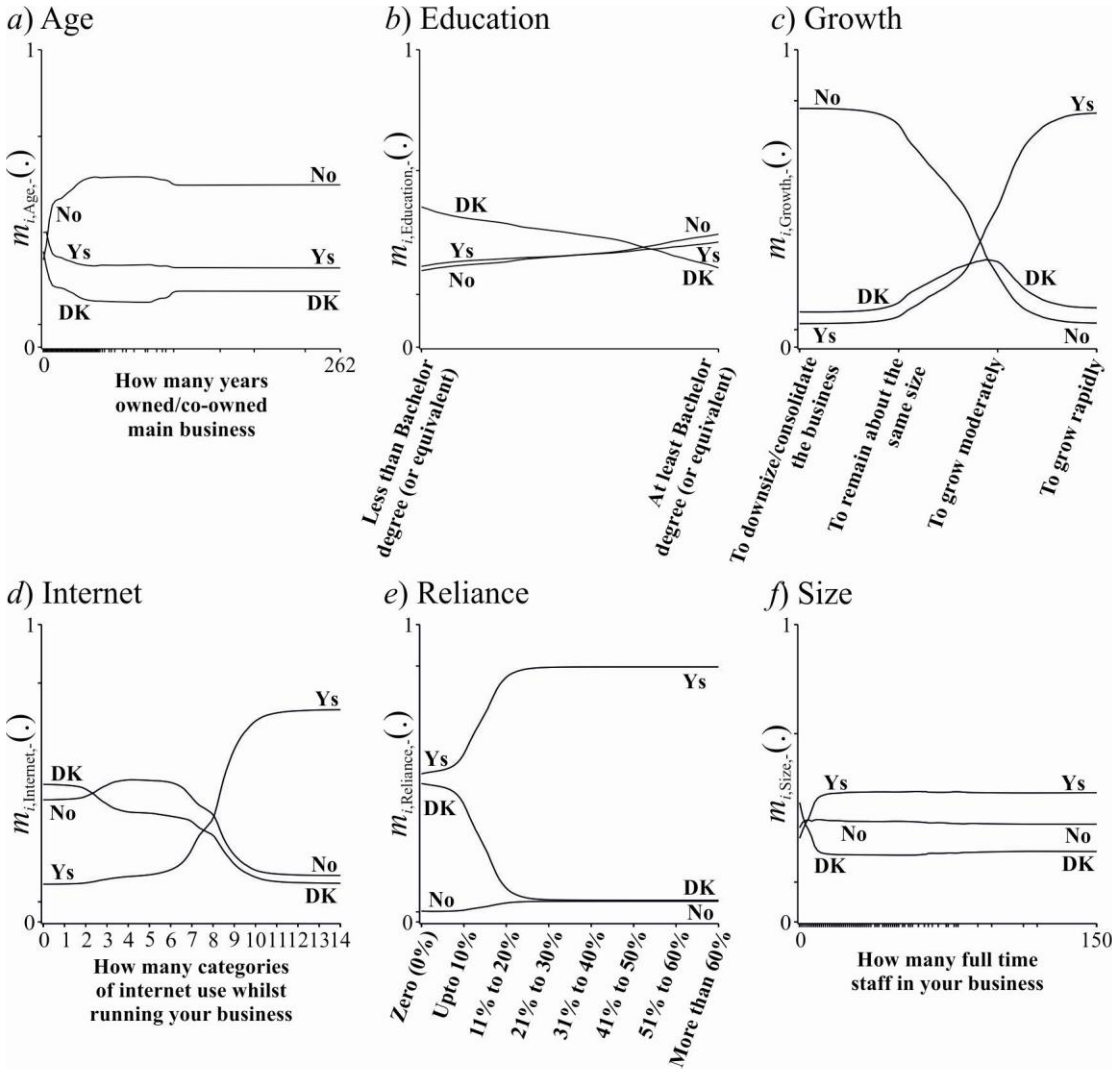


Figure 9. Average characteristic variable contribution lines in 40 runs (with 90%/10% partition)

The results in Figure 9, for each characteristic are comparable with the results from the one-off analysis shown in Figure 5. As the contribution lines are the average of the respective lines from the 40 runs, they are smoother than those evident in Figure 5. Across the board, with a 90%/10% partition of the data, the inference is very similar to the analysis of all the data (see Figure 5), with one exception being with the Size characteristic.

Beyond just the 90%/10% partition of the data, other partitions were also considered, namely 80%/20%, 70%/30% and 60%/40%. The statistical results in terms of t-tests between the in-sample and out-sample fits were found to be, for 80%/20%, in-sample (M = 0.689, SD = 0.00217) and out-sample (M = 0.698, SD = 0.028) sets of data; t(39) = 2.150, p = 0.038, 70%/30%, in-sample (M = 0.688, SD = 0.00301) and out-sample (M = 0.699, SD = 0.026) sets of data; t(39) = 2.491, p = 0.017 and 80%/20%, in-sample (M = 0.687, SD = 0.00310) and out-sample (M = 0.699, SD = 0.020) sets of data; $t(39) = 3.608$, $p = 0.001$. It can be seen from these results there is increasing significant difference between the classification fit levels of the in-sample and out-sample partitions of the data.

In regards to characteristic contribution, Figure 10 reports contribution graphs, showing average contribution lines, for the Age and Internet characteristics, over the 80%/20%, 70%/30% and 60%/40% partitions of the data.

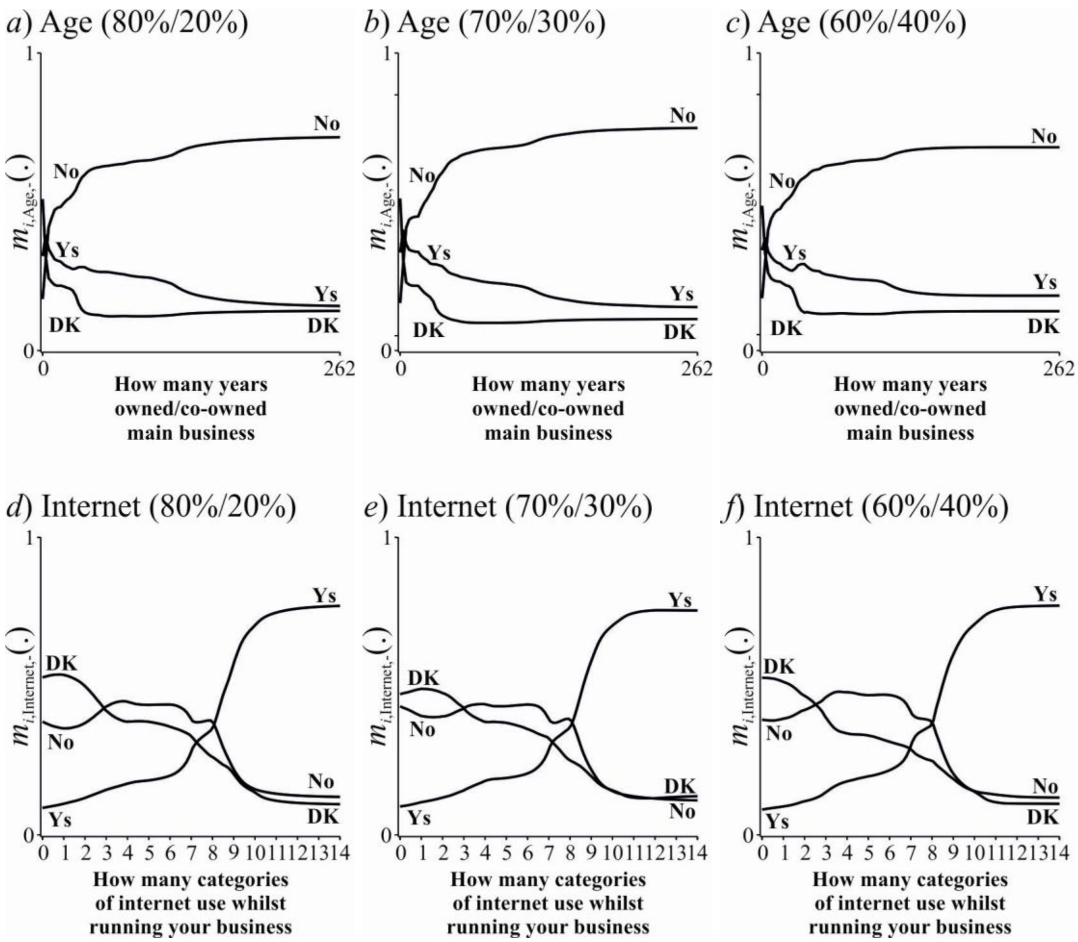


Figure 10. Average characteristic variable contribution lines for Age and Internet over the resample partitions of, 80%/20% (*a* and *d*), 70%/30% (*b* and *e*) and 60%/40% (*c* and *f*), using 40 runs in each case.

In terms of the contribution of the variables, Figure 10 shows the average contribution lines for the characteristic variables Age and Internet, over these three sets of partitions of the data. The results are similar over the different sets of partitions, with only slight changes identifiable. These results give support to the contribution results found in the on-off analysis given in Figure 5, and 90%/10% partition analysis given in Figures 8 and 9.

In terms of classification prediction accuracy, the results from the different in-sample and out-sample results are (each set of values is mean (standard deviation)): 80%/20% - 0.626 (0.007) and 0.619 (0.010); 70%/30% - 0.626 (0.007) and 0.618 (0.015); and 60%/40% - 0.628 (0.009) and 0.617 (0.013). As before (see discussion around Table 6), these results show, with respect to each other, an understandable slight dip in predictive accuracy when going from in-sample to out-sample results, while a general no change across the in-sample results.

6 Inference on Innovation, Don't Know and NCaRBS

The inference discussed in this section is broken down into three sub-sections, namely that regarding the innovation problem considered, contribution to the issue of how to handle the non-substantive response Don't Know or what inference to specifically associate with it, and the role of NCaRBS in business analytics based research.

Innovation

This subsection summarizes the inference evident on the understanding of intended innovation in SMEs and a sample of the characteristics considered.

The case of the Education characteristic variable is interesting in its own way, there is clearly discernment in the level of education of the Owner/Manager and their association to the No and Yes responses to that of the DK response. Moreover, the strength of evidence towards a substantive response of either No or Yes increases as the level of education is higher, with a respective decrease in the evidence towards Don't Know. It would be interesting to see if this increase in substantive response is because the higher education characteristic enables a more informed/educated opinion, or simply that the higher education has given the respondent more confidence to provide such a substantive response.

Worth separately mentioning is the Growth characteristic variable, where for the two more muted responses of 'To downsize/consolidate the business' and 'To remain about the same size' there is more association to No in terms of innovation intention than to either Yes or DK (the level of evidence being similar may be due to the similarity in the statement terms – consolidate and remain about the same), there is then continued increase in evidence towards a Yes response to innovation intention, unlike for the evidence towards DK where initial increase then becomes a decrease (noting the subtle difference in growth being moderate or rapid – almost the difference between a rash or cautious general).

The size characteristic suggests that larger SMEs are more likely to embrace innovation due to their internal capabilities and finances. Similarly, SMEs which adopted Internet technologies had a more innovative mindset. However, by contrast innovative behaviour is more prevalent within younger firms than older entities. This suggests the importance of new start-ups adopting an appropriate mind-set towards innovation as a means of achieving competitive advantage and growth. This is further support by the Reliance characteristic whereby the desire for the firm to be innovative is self-perpetuating and increased reliance is based on ongoing innovation as a core business focus. Thus, these results suggest that innovative SMEs require several inter-related characteristics to enable effective innovative behaviour.

Learning about Don't Know

A consequential beneficial impact of allowing the non-substantive response Don't Know to be one dimension of the outcome response is that it allows us to consider how its presence has impacted on the results (rather than having to make assumptions about this and thus losing the value of this data). In section 4, and Table 4, there was supportive evidence that the predictability of the responses of SMEs, to whether they were No, Yes or DK to SME intended innovation was possible, based on the considered characteristic variables. Further, there was a suggested predominance of a majority of DK responses being predicted more to a No response. This is supported by the research literature that has connected the making of the DK response more with the No response that with the Yes response (see Groothuis and Whitehead, 2002).

With respect to the intended innovation outcome considered there could also be a level of social bias contributing to the DK response being more associated with the No response. That is, for many SMEs, there is an internal desire to be innovative, hence when asked about future innovation intention, there may be a reluctance to say No, instead responding DK as the 'easy out' option, as termed by Gilljam and Granberg (1993). It may be that in future FSB surveys, further gradations of response may be included that will offer more pertinent responses between No and Yes, rather than just DK, for example, allowing a gradation between 0% and 100% certainty of undertaking innovation.

The relationships between the three dimensions of outcome response, No, Yes and DK, and the individual characteristic variables also, however, needs to be considered. From inspection of Figures, 5, 8, 9 and 10, there is a predominance for more association of the evidences over the domains of the characteristic variables to show similarities between the

No and DK outcome responses, at least in terms of when the levels of belief based evidence are near same (such as in the case of the Reliance characteristic variable in Figure 5 – for 21% or above), but with the exceptions of the Age and Education characteristics.

These findings will contribute to the issue of how to handle, and whether to include non-substantive responses, like DK, in survey questionnaires generally, and here specifically in surveys associated with SMEs. Moreover, there may be policy inference that may be taken forward from such non-substantive responses, which will differ depending on the relationships between Yes, No and DK for different sets of variable relationships.

NCaRBS

From the previous two subsections of this section, the findings of the NCaRBS analyses have enabled important discussions on innovation intention in SMEs and survey design to be given. Beyond this, the NCaRBS has allowed perhaps the most intelligent approach to handling missing values in an incomplete data set, namely through their retention and the removal of any need to manage their presence in any way. The ability of a constituent BOE to represent a missing value is an important contribution of the soft computing based analysis using NCaRBS. This can only be a positive for the development of pertinent business analytic based analyses of data, whether small, medium or big data.

7 Conclusions

This study has given a novel demonstration on a future direction of business analytics. The NCaRBS analysis technique employed, through its rudimentary association to soft computing, *i*) enabled the analysis of real incomplete data without any transformation/manipulation of the data, *ii*) offered novel insights in terms of the role of non-substantive outcome responses, and *iii*) offered insights into the issue of SME innovation intention. Overall, in most of the characteristics a DK response was more associated with a no response, although there was at least one characteristic where DK seemed more associated with yes, and at times at least for some variables DK really meant DK. This greater discernment capability is another important advantage of this technique as it clearly shows that one cannot assume a static relationship between No and DK for all relationships. At the very least, this indicates that the processes described in this paper may assist in more accurately reclassifying DKs for more traditional regression-based techniques (if required – subject to some form of pre-processing of the data to handle the incompleteness of the data).

The study contributes increased knowledge regarding SME characteristics and their impact on innovative behaviour/non-behaviour and uncertain behaviour within the firm, more accurately meeting the call for more research into the impact of innovation upon the SME and its key influences (McAdam *et al*., 2004), a call that is an example of business analytics. This assists SME Owner/Managers to understand how to embrace innovation effectively within their processes and practices, but also provides evidence of assistance for policy makes and enterprise decision makers. The differing influence of a range of SME characteristics upon innovation intention is also apparent. Such data will be of relevance to policy makers and SME support agencies in their encouragement of innovation within the SME sector. The ability to recognise SMEs capable of more entrepreneurial behaviour could also be enabled by business analytics techniques like NCaRBS.

A limitation of this paper, is the lack of comparison between NCARBS and alternative, more traditional methods of handling such data. The management of missing values (as well as DK responses), and approaches used to manage these issues, are many and diverse. Since any findings on a managed data set would, by their definition, be on a new (transformed data set), they would only be partially comparable to the NCaRBS results presented here and within the context of business analytics, the use of soft computing has already found its stand-alone status, hence there may be less need to compare results with other techniques.

However, such comparison could also have its place and offers an interesting area of future research. Comparing techniques such as NCaRBS, against other more traditional techniques, where some can analyse incomplete data and some cannot, would allow more in-depth examination of the issues surrounding different pre-processing requirements before analysis is undertaken. By NCaRBS having the ability to analyse incomplete data, it would therefore allow for a whole new direction of research to be undertaken comparing the results of using different missing value management processes, against a benchmarked set of results from the original incomplete data using NCaRBS. This is an interesting, and exciting possibility, in particular offering a very important future research direction section.

Clearly, the fast growing interest in the role, or use, of business analytics, is in its ability to pertinently analyse data (small, medium or big data). As important, however, is the ability to analyse the data available, as exemplified in this study. The direction, or many directions, business analytics may go is an exciting question, probably with no one analysis approach (or technique) being able to do everything. The study here has shown that techniques do exist to undertake business analytics, in ways even recently not thought possible (such as analysing incomplete data for example). It is fair to say that the term business analytics is fitting since it contributes to the interest (excitement) such analysis is achieving.

References

1. Adner, R. Match Your Innovation Strategy to Your Innovation Ecosystem. Harvard Business Review 2006 April, 1-11.
2. Allen K, Stearns T. Technology entrepreneurs. In: Gartner WB, Shaver KG, Carter NM, Reynolds PD. (Eds.), Handbook of Entrepreneurial Dynamics: The Process of Business Creation, Sage Publications, Thousand Oaks, CA 2004.
3. Allison PD. Missing Data. Quantitative Applications in the Social Sciences, 136. Sage University Paper Series 2000.
4. Altınçay H. On the independence requirement in Dempster-Shafer theory for combining classifiers providing statistical evidence. Applied Intelligence 2006;25(1):73-90.
5. Azvine B, Nauck D, Ho C. Intelligent Business Analytics – A Tool to Build Decision-Support Systems for ebusinesses. BT Technology Journal 2003;21(4):65-71.
6. Bertschek I, Entorf H. On Nonparametric Estimation of the Schumpeterian Link between Innovation and Firm Size. Empirical Economics 1996;21(3):401-26.
7. Beynon MJ. A Novel Technique of Object Ranking and Classification under Ignorance: An Application to the Corporate Failure Risk Problem. European Journal of Operational Research 2005a;167:493–517.
8. Beynon MJ. Optimizing object classification under ambiguity/ignorance: application to the credit rating problem. International Journal of Intelligent Systems in Accounting, Finance and Management 2005b;13:113–30.
9. Beynon MJ, Andrews RA, Boyne, G. Evidence-based modelling of hybrid organizational strategies. Computational and Mathematical Organization Theory 2014; forthcoming.
10. Beynon MJ, Kitchener M. Analyzing Strategic Stance in Public Services Management: An Exposition of NCaRBS in a Study of U.S. States' Long-Term Care Systems, Business Applications and Computational Intelligence, editors: Voges, K. E. and Pope, N. K. Ll., IDEA Group Inc., PA, USA. ISBN 1-59140-702-8. 2006; Chapter 17, pp. 344–59.

11. Birkinshaw J, Hamel G, Mol M. Management Innovation. Academy of Management Review 2008;33(4);825-45.
12. Brick JM, Kalton G. Handling missing data in survey research. Statistical Methods in Medical Research 1996;5(3):215-38.
13. Calantone RJ, Cavusgil ST, Zhao Y. Learning orientation, firm innovation capability and firm performance. Industrial Marketing Management 2002;31:515-24.
14. Camison-Zornoza C, Lapiedra-Alcami R, Segarra Cipres M and Boronat-Navarro M. A meta-analysis of innovation and organizational size. Organization Studies 2004;25(3): 331–61.
15. Canfora G, Pedrycz W. Special issue on Software Engineering and Soft Computing. Soft Computing 2008;12(1):1-2.
16. Cattaneo MEGV. Belief functions combination without the assumption of independence of the information sources. International Journal of Approximate Reasoning 2011;52(3): 299-315.
17. Cohen WM, Klepper S. Firm size and the nature of innovation within industries: the case of process and product R&D. The Review of Economics and Statistics 1996;78(2):232–43.
18. Davidsson P, Delmar F. High-growth firms and their contribution to employment: the case of Sweden 1987-96. OECD Working Party on SMEs, Organisation for Economic Co-operation and Development, Paris 1997.
19. Demirbag M, Tatoglu E, Glaister KW, Zaim S. Measuring strategic decision making efficiency in different country contexts: A comparison of British and Turkish firms. Omega 2010; 38(1-2); 95-104.
20. Dempster AP. Upper and lower probabilities induced by a multiple valued mapping. Ann. Math. Statistics 1967;38:325-39.
21. Denœux T, Masson M-H. (Eds) Belief Functions: Theory and Application, Proceedings of the 2nd International Conference on Belief Functions, France. Springer-Verlag, Heidelberg. 2012.
22. Denœux T, Zouhal M. Handling possibilistic labels in pattern classification using evidential reasoning. Fuzzy Sets and Systems 2001;122:409-424.
23. Edwards T, Delbridge R, Munday M. Understanding innovation in small and medium-sized enterprises: a process manifest. Technovation 2005;25:1119–20.
24. Fan H-Y. Lampinen J. A Trigonometric Mutation Operation to Differential Evolution. Journal of Global Optimization 2003;27(1):105-29.

25. Federation of Small Business (FSB), About the FSB, Available online: http://www.fsb.org.uk/about. Accessed 28th August 2014.
26. Feick, F. Latent Class Analysis of Survey Questions that Include Don't Know Responses. Public Opinion Quarterly 1989;53:525-47.
27. Ferber R. Item Non-response in a Consumer Survey. Public Opinion Quarterly 1966;30, 399-415.
28. Fink D, Disterer G. International case studies – to what extent is ICT infused into the operations of SMEs? Journal of Enterprise Information Management 2006;19:608-24.
29. Francis JD, Busch L. What We Now Know About "I Don't Knows". The Public Opinion Quarterly 1975;39:207-18.
30. Galloway L, Anderson M, Brown M, Whittam G, The Impact of Entrepreneurship Education in HE, Report, (2005), Business Education Support Team, Oxford, May.
31. Gilljam M, Granberg D. Should we take Don't Know for an Answer. The Public Opinion Quarterly 1993;57(3):348-57.
32. Graham JW Missing Data Analysis: making It Work in the Real World. Annual Review of Psychology 2009; 60: 549-76.
33. Groothuis PA, Whitehead JC. Does don't know mean no? Analysis of 'don't know' responses in dichotomous choice contingent valuation questions. Applied Economics 2002;34(15):1935-1940.
34. Hadjimanolis A. A case study of SME–university research collaboration in the context of a small peripheral country (Cyprus). International Journal of Innovation Management 2006;10:65–88.
35. Harris R, McAdam R, McCausland I, Reid R. Levels of innovation within SMEs in peripheral regions: the role of business improvement initiatives. Journal of Small Business and Enterprise Development 2013;20(1):102–24.
36. Huang X, Zhu Q. A pseudo-nearest-neighbour approach for missing data on Gaussian random data sets. Pattern Recognition Letters 2002;23:1613-622.
37. Hudson M, Smart A, Bourne M. Theory and practice in SME performance measurement systems. International Journal of Operations and Production Management 2001;21:1096–115.
38. Japkowicz N, Stephen S. The class imbalance problem: A systematic study. Intelligent Data Analysis 2002;6(5):429-49.
39. Jiroušek, R. An Attempt to Define Graphical Models in Dempster-Shafer Theory of Evidence, In: Borgel et al. (Eds.) Combining Soft Computing and Statistical Methods

in data Analysis (Advances in Intelligent and Soft Computing 77), Springer-Verlag, Berlin Heidelberg, 2010; p. 361-368.

40. Keskin H. Market orientation, learning orientation, and innovation capabilities in SMEs: An extended model. European Journal of Innovation Management 2006;9:396-417.
41. King WR, Kugler JL. The impact of rhetorical strategies on innovation decisions: an experimental study. Omega 2000; 28(5):485-99.
42. Kohavi R, Rothleder NJ, Simoudis E. Emerging Trends in Business Analytics. Communications of the ACM 2002; 45(8):45-8.
43. Koslowsky S. The case of missing data. Journal of Database Marketing 2002;9(4):312-18.
44. Kula V, Tatoglu E. An exploratory study of internet adoption by SMEs in an emerging market economy. European Business Review 2003;15(5):324-33.
45. Laforet, S. Size, strategic, and market orientation effects on innovation. Journal of Business Research 2008;61:753–64.
46. Lee S-G, Kanazawa Y. Handling "Don't Know" Survey Responses: The Case of Japanese Voters on Party Support, Behaviormetrika 2000;27:181-200.
47. Lesjak D, Vehovar V. Factors affecting evaluation of e-business projects. Industrial Management & Data Systems 2005;105:409-28.
48. Liu L. Special Issue on the Dempster-Shafer Theory of Evidence: An Introduction. International Journal of Intelligent Systems 2003;18:1-4.
49. Little RJA, Rubin DB. The Analysis of Social Science Data with Missing Values. Sociological Methods Research 1998;18(2-3):292-326.
50. Loebbecke C, Schäfer S. Web portfolio based electronic commerce: the case of transtec AG. Logistics Information Management 2001;14:54-67.
51. Luskin, RC, Bullock, JG. "Don’t Know" Means "Don’t Know": DK Responses and the Public’s Level of Political Knowledge. The Journal of Politics 2011;73:547-57.
52. McAdam R, Reid R, Gibson D. Innovation and Organisational size in Irish: an empirical study. Intentional Journal of Innovation Management 2004; 8:147-65.
53. Orfila-Sintes F, Mattsson J. Innovation behavior in the hotel industry. Omega 2009;37:380-394.
54. Patel SH. Business age and characteristic of SME performance. Working paper series no. 14, Kingston. Business School, 2005 Kingston University, London, UK.

55. Piatetsky-Shapiro, G. Data Mining and Knowledge Discovery 1996-2005: Overcoming the Hype and Moving from "University" to "Business" and "Analytics". Data Mining and Knowledge Discovery 2007;15:99-105.
56. Pickernell D, Packham G, Jones P, Miller C, Thomas B. Graduate entrepreneurs are different: they have more knowledge? International Journal of Entrepreneurial Behaviour and Research 2011;17:183-202.
57. Reynolds P, Bosma N, Autio E, Hunt S, De Bono N, Servais I, Lopez-Garcia P, Chin N. Global Entrepreneurship Monitor: Data Collection Design and Implementation 1998–2003, Small Business Economics 2005;24:205-31.
58. Romijn H, Albaladejo M. Determinants of innovation capabilities in small electronics and software firms in southeast England. Research Policy 2002;31;1053-1067.
59. Rothwell R, Zegveld W. Innovation and the small and medium sized firm. London: Francis Pinter; 1986.
60. Russell R, Russell C. An examination of the effects of organisational norms, organisational structure, and Environmental uncertainty on Entrepreneurial Strategy. Journal of Management 1992;18(4):639-56.
61. Safranek RJ, Gottschlich S, Kak AC. Evidence accumulation using binary frames of discernment for verification vision. IEEE Transactions on Robotics and Automation 1990;6:405-17.
62. Salavou H, Baltas G, Lioukas S. Organisational innovation in SMEs: The importance of strategic orientation and competitive structure. European Journal of Marketing 2004;38: 1091-112.
63. Sawyer O, McGee J, Peterson M. Perceived Uncertainty and Firm Performance in SMEs: The Role of Personal Networking Activities. International Small Business Journal 2003; 21(3):269-90.
64. Schafer JL, Graham JW. Missing Data: Our View of the State of the Art. Psychological Methods 2002;7(2):147-77.
65. Schultze U, Stabell C, Knowing What You Don't Know? Discourses and Contradictions in Knowledge Management Research. Journal of Management Studies 2004;41(4):549-73.
66. Schumpeter J. Capitalism, Socialism and Democracy. New York: Harper; 1942.
67. Seising R, Sanz V. From Hard Science and Computing to Soft Science and Computing – An Introductory Survey. In Seising R, Sanz V. (Eds.) Soft Computing in

Humanities and Social Sciences (Studies in Fuzziness and Soft Computing), Springer 2011; p. 3-35.

68. Shafer GA. Mathematical theory of evidence. Princeton, Princeton University Press 1976.
69. Sharma R, Reynolds P, Scheepers R, Seddon PB, Shanks G. Business Analytics and Competitive Advantage: A Review and a Research Agenda, in Respicio et al. (eds.) Bridging the Socio-technical Gap in Decision Support Systems, IOS Press, 2010; p. 187-198.
70. Smallbone D, Baldock R, Burgess S. Targeted support for high-growth start-ups: some policy issues. Environment and Planning C: Government and Policy 2002;20:195-209.
71. Smets P. Analyzing the combination of conflicting belief functions. Information Fusion 2007;8:387-412.
72. Sorensen JB, Stuart TE. Aging, obsolescence, and organizational innovation. Administrative Science Quarterly 2000;45:81-112.Svolba G. Missing Values: The origin, detection, treatment and consequences of missing values in analytics. Analytics: Driving Better Business Decisions 2014, Jan/Feb:58-65.
73. Teoa, TSH, Limb VKG, Laia RYC. Intrinsic and extrinsic motivation in Internet usage. Omega 1999;27(1):25-37.
74. Theodorou P, Florou G. Manufacturing strategies and financial performance - The effect of advanced information technology: CAD/CAM systems. Omega 2008; 36(1):107-121.
75. Twomey JM, Smith AE. Bias and Variance of Validation Methods for Function Approximation Neural Networks under Conditions of Sparse Data. IEEE Transaction on Systems, Man and Cybernetics – Part C: Applications and Reviews 1998;28:417-430.
76. Turner J, Michael M. What do we know about “don't knows”? Or, contexts of “ignorance”. Social Science Information 1996;35(1):15-37.
77. Utterback JM, Abernathy, WJ. A dynamic model of process and product innovation. Omega 1975;3(6):639-656.
78. Van Looy B, Debackere K, Andries P. Policies to stimulate regional innovation capabilities via university–industry collaboration: an analysis and an assessment. R&D Management 2003;33(2):209–29.

79. Wang C, Walker EA, Redmond J. Explaining the lack of strategic planning in SMEs: the importance of owner motivation. International Journal of Organisational Behaviour 2007; 12(1):1-16.

80. Westhead P, Wright M, Ucbasaran, D. International market selection strategies selected by ‘micro’ and ‘small’ firms. Omega 2002;30(1):51-68.

81. White M. 1988, Small Firm's Innovation: Why Regions Differ, Policy Studies Institute, London.

82. Wright PW, Gardner TM, Moynihan LM. The impact of HR practices on the performance of business units. Human Resource Management Journal 2003; 13(3):21-36.