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Doctoral thesis

The Level of Adoption of Analytical Tools

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To my parents.

To my son.

Acknowledgements

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Abstract

This PhD thesis is focused on disclosing the key drivers that might cause the increase in the use of analytical tools for better decision making. The theoretical part of this research is developed in two phases. At first, an exhaustive literature review was conducted with the purpose of identifying the main features in companies that impact positively the adoption of new analytical tools. This review brought our attention in four key drivers which were the foundation of the theoretical model: management support on data analysis, data based competitive advantage, systemic thinking and communication outside the company. Secondly, a scale was proposed with the purpose of classifying companies according with how its analytical capabilities are developed.

The theoretical model and scale required to be validated with data from the real-world. Four constructs derived from the model were operationalized in 17 items. The output was a draft of questionnaire ready to be validated. An exhaustive statistical research related with the agreement, convergence, test-retest reliability and factor structure of the dimensions was conducted. This research allowed us to ascertain that our instrument is reliable and valid. At this point the questionnaire was ready to be sent to the companies.

The central part of the research is focused on analyzing data obtained from the companies. At first, the statistical engineering, which can be conceived as the link between the statistical thinking (*or the strategic management*) and the statistical methods (*or the day-to-day operations*), was adapted as guideline. A set of seven statistical tools were wisely assembled in a sequential order for obtaining relevant conclusions. At this point it was necessary to validate our preliminary conclusions with additional research and make them more robust. A second approach was utilized with this purpose. The evidential reasoning, which is a generic type of multi criteria decision analysis, was implemented. It is highlighted that two different approaches lead us to similar results.

At this phase of the thesis unstructured and soft features about the analytical practices were still missing. A complementary approach was needed to include aspects as values, beliefs and motivations and identify how they influence the analytical practices in companies. The laddering methodology was utilized for these purposes. Basically it is defined as a type of in-depth interview that is applied to understand how individuals transform attributes of any given concept into meaningful associations with respect to themselves. Consider this

analogy; the data from questionnaires gave us "*the picture of forest*", then in-depth interviews yielded "*the picture of the three*".

The last part of the thesis is reserved to provide guidelines to companies interested on increasing their analytical capabilities. Here it is offered a road map composed of five stages. This is intended to work in this way: a company receive its diagnostic and is allocated to a stage in the road map, later practical suggestions and guidelines are provided to move the company upwards into the scale. The sequence of *diagnostic-guidelines-diagnostic* should be repeated until the company reach the highest level in the scale: analytics as competitive advantage.

At the end of the thesis are presented two sets of values and attributes which were found decisive for increasing the adoption of analytical tools. In the first set, three values: honesty, serving the society and leadership are influencing the statistical thinking (the strategic level) in the company, whereas three attributes: the goal setting, creativity and information from outside are acting on the statistical methods (the operational level). The statistical engineering (the tactical level) is establishing the link between strategic and operational levels.

All the tools and methods developed in this thesis, including the questionnaire, the scale for ranking the companies, the script for in-depth interviews, the road map for moving upward to higher levels in the scale and its related guidelines, represent an original and helpful toolkit for improving the analytical capabilities in companies.

Contents

List of figures.

List of Tables.

1. Introduction

This chapter describes the main motivation for studying the how and why analytical tools are adopted in companies. The general objectives and the thesis structure are also presented.

1.1. Motivation.

The business environment has changed importantly in the last 30 years. The emergence of the internet, and other electronic technologies such as wireless and mobile devices changed radically the way companies interact with customer, employees, suppliers and society. For instance, according with Burby & Atchison (2007) better informed customers make more sophisticated purchase decisions and thus, companies are required to provide better information about its product and services. In addition, the geographical borders, which in the past used to provide protection to companies by preserving captive customers, are not available any more. In contrast, the geographical and economical borders are gradually disappearing due to the global economy. This new scenario means that any company located at anywhere in the world could be considered a competitor. Additionally, the life cycle in products and services is becoming shorter. For example, in the 70`s, car manufacturing companies used to design their cars to guarantee a lifetime for at least of 15 years to the customer. In present days, it is almost impossible to expect one car will be working in optimal conditions for more than 4 years. It is more likely that the customer might be willing to change it for another newer in the first or second year; rather than a malfunction might show up. In the same way, Davenport & Harris (2007) affirm that shorter life cycles and more demanding and better informed consumers have forced companies to strengthen its innovations and R&D (research and development) areas. In modern business environment, efficiency and innovation are playing a key role to successfully compete in a global market.

Another remarkable change is direct consequence of the introduction of new electronic devices. The emergence of PC's, smart phones, tablets and other electronic devices is producing more data than any moment in the history of humankind. This new digitalized world brings up new possibilities and opportunities to companies who are pursuing innovation, efficiency and competitive advantages. At every industry, in every part of the world, managers should be wondering how they can increase the value of their companies from analyzing the massive amounts of accumulated data. In Kaushilk (2011) it is stated that companies than reach competitive advantages and perform innovations by applying the proper technologies on its data. Modern companies are in need of finding responses to questions such as: what is happening outside? What is likely to happen next? And, what decisions should be made to maximize the benefits? By collecting, processing and analyzing the proper data in the three levels of the company: operational, tactical and strategic, it is possible to answer this sort of questions.

Considering how is the new scenario in business environment, the present thesis is about to propose a scale to measure the degree of analytical capabilities in companies, and then, based in that diagnostic to provide general guidelines for improving the value of data analysis. For instance, a company could adopt several actions based on data analysis and then, make decisions about hiring or retention of staff, buying, selling, marketing, promotions and future investments, among others. Additionally by making more accurate decisions, companies can create competitive advantages and gain a leadership in the market. Considering the above, this thesis is focused on creating competitive advantages from improving data analysis, but before going directly to present the scope and objectives of this research, it is necessary to provide a formal definition of business analytics, which according with Stubbs (2011) it refers to the adoption of analytical tools derived from applied mathematics, applied probability and applied statistics which are combined with computer science and focused to analyze data in order to obtain better knowledge of the company's performance. Based on the quantitative findings, managers can make better informed decisions. Common examples of business analytics are the decision support systems, such as Enterprise Resource Planning (ERP), Manufacturing Resource Planning (MRP), Customer Relationships Manager (CRM), which aid executives and other leaders in the company to make more accurate decisions.

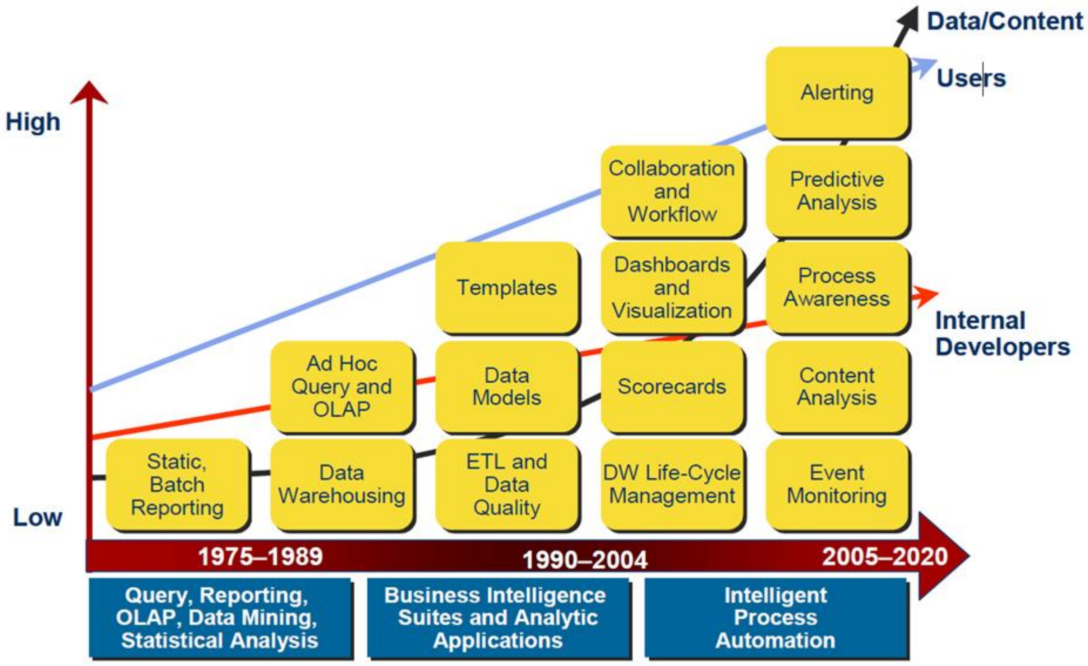

Figure 1.1. The evolution of the business analytics in the last 35 years. Adapted from McDonough (2009)

McDonough (2009) states that business analytics has changed in the last 30 years, from being focused on performing static reporting to predictive analysis and event monitoring. It can be said that the beginning of business analytics consisted on doing basic statistical analysis and reporting historical data. This scenario changed radically and business analytics has moved from understanding past performance to predict trends and behaviors, and based on those predictions to issue alerts. Although progress in the field of business analytics has been important during the last 30 years; there is still a lot of room for improvement. For example, according with Hass (2011) only the 5% of the organizations in USA manage their data effectively and the main reason for the above is that senior managers and leaders consider that analyzing data might either consume too much time or be extremely expensive. Today, there is more powerful software specialized in analytics, capable to carry out calculations by using complex mathematical and statistical models, which turns out to be cheaper and more affordable to all kind of companies.

1.2. The objectives for this thesis.

As it was stated before, the emergence of new technologies allowed companies to accumulate massive amounts of data, and more powerful specialized software is now more accessible and affordable to companies. These are opportunities which managers and decision makers should consider as options to successfully compete in a complex and globalized market. With the purpose of assisting managers to create competitive advantages from of those opportunities, the present thesis will accomplish the following objectives:

1. Propose a theoretical scale to measure the level of adoption of analytical tools in companies.
2. Design a reliable and valid instrument to collect data from a sample of companies located in Barcelona, Spain.
3. Analyze data collected from the surveyed companies, in order to draw conclusions about the level of adoption of analytical tools in Barcelona by applying the ***Statistical Engineering*** approach.
4. Rank the sampled companies in the scale by applying the ***Evidential Reasoning*** approach.
5. Conduct in-depth interviews with managers, consultants and academics with the purpose of finding out soft and unstructured aspects about the level of adoption of analytical tools in Barcelona by applying the ***Laddering Methodology***.
6. Based on results generated, provide practical guidelines to stakeholders who are interested in expanding the use of analytical tools in companies and creating competitive advantages from this.

1.3. Thesis structure and chapters.

In the following lines is presented a brief executive summary for each chapter. The main point is to provide an overall view of the structure of the thesis.

1.3.1. Chapter 2. A theoretical perspective of the use of analytical tools.

The second chapter consists of a literature review on which some important changes which took place in the business environment over the last 30 years are discussed. Moreover, two definitions are provided in this chapter: The Adoption of Analytical Tools (AAT) is understood as the extensive use of data, statistical and quantitative methods which combined with information technology, allows us to explain trends and predict behaviours. The second is Applied Statistics on Business Management (ASBM) which is defined as the wide use of data, information technology and statistical models to make predictions understand past performance and make better business decisions. This chapter introduces four factors or key drivers which are indispensable for expanding and increasing the level of adoption of analytical tools: the first is the data based competitive advantages, the second is related with systemic vision in the company, the third is about communication outside the company, and finally management support on data analysis. The four of them are deeply discussed throughout this chapter. In the last section of this chapter a five-level scale to measure the level of adoption of analytical tools is introduced.

1.3.2. Chapter 3. Compilation of analytical applications in different areas of the company.

This chapter consists on a compilation of cases in which several analytical and statistical tools are applied in different areas of the company. In the first part of the chapter, examples of analytical applications in human resources, finances, Research and Development (R&D), manufacturing and marketing are presented. The second part discusses applications in which data from customers and suppliers is analyzed.

The main objective in this chapter is to provide a wider perspective of the adoption of analytical tools in business, and illustrate how much it has changed in the last two decades. In the same way, this chapter is aimed to give some real examples of novel analytical applications in order to reach expectations from managers and businessmen. That is to say, by discussing real and successful cases of analytical applications, company's stakeholders might be inspired to start their own analytical projects at their own companies.

1.3.3. Chapter 4. A questionnaire design

In this chapter an instrument to measure the level of adoption of analytical tools is designed. The four key drivers previously introduced in the second chapter are operationalized into the same number of dimensions by applying a two-stage methodology proposed by Menor & Roth (2007). In the first stage the theoretical domain and the items are defined, a pilot test is carried out and quantitative measures for validity and reliability are calculated. In the second stage, the final questionnaire is obtained and sent to sampled companies. A confirmatory analysis is conducted in order to guarantee the validity of the scale. Basically this chapter is proposing a scale to measure the level of adoption of analytical tools, which is reliable and valid, and it is ready to use by managers and consultants who are interested in assessing the analytical performance on their companies.

1.3.4. Chapter 5. A Statistical Engineering case of study.

Here, the reader will find a sequential integration of statistical methods, concepts and tools, which combined with information technology were applied on our dataset in order to obtain relevant conclusions from companies. Based on the Statistical Engineering approach proposed by Hoerl & Snee (2010), total of 7 different statistical tools were assembled and integrated. Relevant and novel conclusions about the adoption of analytical tools are provided and discussed in the last section of the chapter.

1.3.5. Chapter 6. An evidential reasoning case of study.

In this chapter the five-level scale (previously introduced in chapter 2) is applied to surveyed companies. The Evidential Reasoning approach proposed by Yang & Sen (1994) and the Intelligent Decision Systems (IDS) software introduced by Yang (2001), Yang & Xu (2000) and Xu & Yang (2001) are utilized to rank the companies in the scale. In order to get a clearer perspective of the level of adoption of analytical tools, surveyed companies are clustered according with the key-drivers (or parent attributes) and results are presented given that classification. The distributed assessment for each key-driver is calculated and the differences in analytical capabilities, given the company's size are disused. Guidelines to managers with the purpose of building competitive advantages by expanding the use of analytical tools are provided in the last section of this chapter.

1.3.6. Chapter 7. The laddering method in practice. A study case.

In order to complement the information acquired by the questionnaire, in-depth interviews to managers, consultants and academics were carried out. These in-depth interviews were looking for soft and unstructured aspects of the level of adoption of analytical tools and statistical methods, which cannot be identified by analyzing the information obtained from only the questionnaire. Taking into account that the main objective was to find soft and unstructured aspects, the Laddering Methodology proposed by Reynolds & Gutman (1998) was selected to design and carry out the interviews. More precisely, the laddering is applied in this research to uncover attributes, consequences and values about the analytical practices in companies. In addition, it is attempted to disclose personal values from managers, practitioners and academics which are also significant on improving analytical practices.

1.3.7. Chapter 8. Practical guidelines to stakeholders interested in increasing the adoption of analytical tools in companies.

Consider this analogy: with the questionnaire "*the picture of the forest*" is drawn, and thus quantitative and structured aspects of the analytical and statistical practices are identified. On the other hand the in-depth interviews provided "*the picture of the tree*" and unstructured, soft and qualitative aspects of these practices are investigated. Both approaches are complementary and together present to us a better understanding of studied phenomenon.

At first the results obtained in questionnaires are analyzed and discussed. Based on these results practical guidelines for upgrading in the scale are provided. More specifically, a five-stage roadmap is introduced in order to present a clearer explanation of the actions which should be taken to expand the use of analytical tools, given a particular level in the scale. For instance, companies in level one are required totally different actions in comparison with companies in level five.

In addition, results obtained through the in-depth interviews and the laddering methodology, are discussed in this chapter. At first three basic attributes, which have the biggest influence in the operational part of the level of adoption of analytical tools, were identified. Secondly, a set of three values, which are significant to the strategic part of the expansion of the adoption of analytical tools, was found. These attributes and values are complementary and together constitute a holistic approach of the adoption of analytical tools on companies.

1.3.9. Chapter 9. Future lines of research.

The last part of this thesis of reserved to discuss a research proposal. Taking as input the results obtained from questionnaires and in-depth interviews, a common framework for aggregating the scales of both instruments is investigated. Most of this proposal is based on the research conducted by Yang et al (2011) on which several transformation methods are illustrated in detail.

The chapter is composed of three sections. In the first an introduction is provided in order to offer a general perspective of how data have been growing in recent years. Some of the most important implications derived from this phenomenon are also discussed. In the second section, the methodology, on which transformation methods for questionnaires and in-depth interviews are proposed, is explained in detail. Subsequently a common framework for aggregating both scales is introduced. In last subsection the rules to be applied for carrying out this aggregation are described. At the end of the chapter is introduced a process six-stage which will be followed for the implementation of the methodology in our data.

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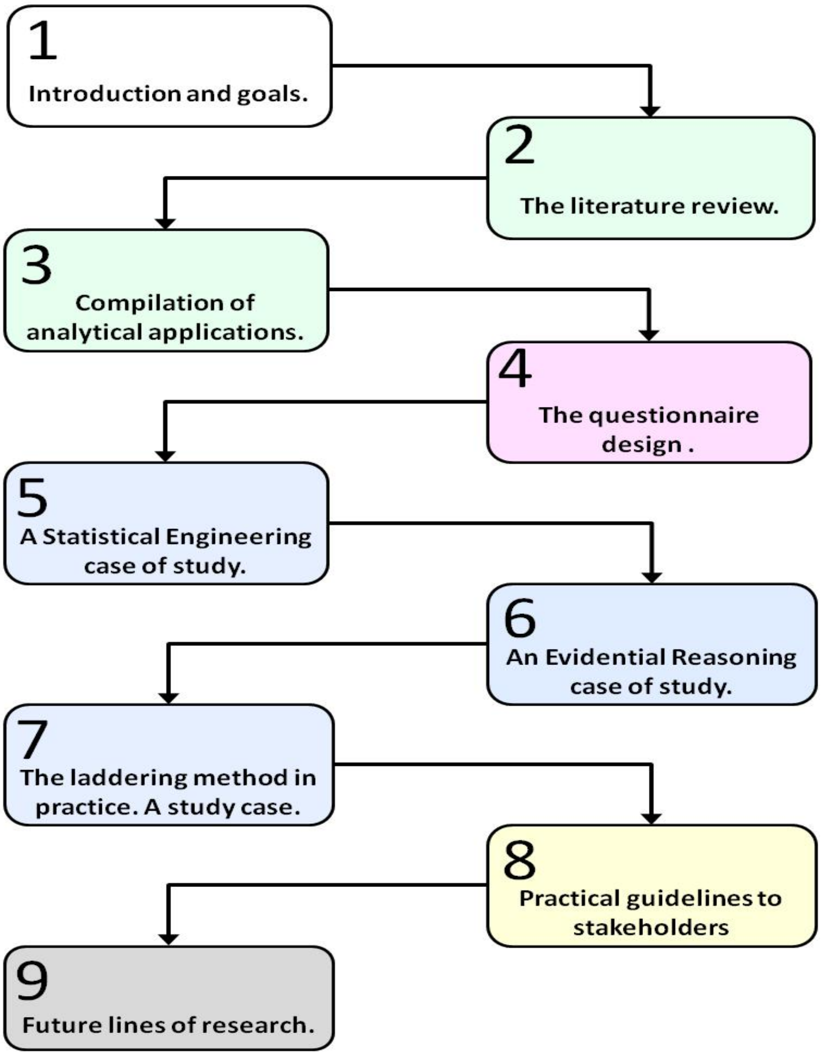

Figure 1.2. The structure of the thesis.

2. The level of adoption of analytical tools: A theoretical perspective.

This chapter provides formal definitions for Applied Statistics on Business Management and for the Adoption of Analytical Tools on Companies. It also introduces the theoretical 5-level scale to measure the level of adoption of analytical tools.

2.1. Introduction.

Contemporary companies are saturated with data, but short on methods, procedures and tools to create value from that data. Most of the areas on companies generate data everyday about customers, processes, suppliers and human resources. However, such data are not analyzed or in the best of the cases, it is underutilized. Under this context, new business opportunities remain hidden, or situations related with lack of productivity or inefficiency are unseen. Nevertheless, a small group of companies have started to make decisions differently. By taking advantage of the technological breakthroughs, these organizations are analysing the available data and making smarter decisions. They don't limit themselves to store data and create reports. The emergence of the Internet and more powerful computers, capable of processing larger amounts of data in less time, revolutionized the way businessmen and managers make decisions in companies. The majority of the big companies on the actual business environment are led for the first generation of managers who were born and grown by full access to Internet. More frequently the decisions on companies are made by using different quantitative approaches based on data analysis. Every day we can see that Internet, statistics and other analytics tools are more widely used at different functional areas of the company, such as human resources, marketing, operations, manufacturing and finances.

This tendency began three decades ago and the first attempts to successfully use statistics with computers became more common in the early 70´s, when the first spreadsheet and specialized statistical software were more accessible to researchers, practitioners and managers Webster (2000). Nowadays the tendency is that data analysis by using specialized software will continue to increase. This trend represents a unique opportunity for practitioners, academics and experts in statistics, taking into account the actual business environment, which is richer in data and bigger on technological sophistication. Moreover, during the last three decades most of the industries have been globalized and standardized. The tendency is that companies more frequently will offer similar products and use comparable technology. Today there are fewer points of differentiation and many of the traditional ways of competing in any given industry are not longer applicable. For example, the advantage of a unique geographical location that a company may have had in the past is now decreasing due to global market. Patents and protected technology are rapidly imitated and reproduced. Products and services have increasingly shorter life cycles. In this complex business environment, there is still one thing valid, as it was also valid 100 years ago: to execute the business with maximum efficiency and effectiveness and make the smartest business decisions with the fewest possible resources. At this point statistics and analytical tools can contribute significantly to the business. The point is to select one distinctive capability on which the company's strategy is based, and then apply extensive statistical and quantitative analysis in order to improve the overall performance on the company.

As it was introduced before, the adoption of analytical tools is understood as the extensive use of data, statistical and quantitative methods which combined with information technologies, allows the explanation and the prediction of trends and behaviours, with the purpose of making better informed business decisions. According with Hoerl & Snee (2010) it is important to clarify that the adoption of analytical tools and applied statistics on business management (ASBM) are not a strategy by themselves. They constitute, together, a toolkit which props up the strategy by supporting managers to make better informed decisions. In addition Davenport & Harris (2007) suggest that whatever the distinctive capabilities and the strategy are on the company, the ASBM can propel them to higher levels of performance. On other hand, Webster (2000) defines the applied statistics on business management as the extensive use of data, information technology and statistics methods to predict trends and behaviours in order to make better business decisions based on quantitative evidence. Considering this definition, it is clear that ASBM should be an input to make better decisions. In addition, the ASBM can be also considered a support to automate all decisions taken by managers and stakeholders. It can be said that the ASBM is an intangible asset for the company and complementary element its business intelligence. The more systemic and supported by senior management the ASBM is, the better the business intelligence is. If the business intelligence is better, it has bigger impact on competitive advantages.

From a generic perspective, Yule & Kendall (1950) define statistics as a common language with standardized symbols and procedures, which are intended to draw conclusions from imperfectly known information. Considering that statistics is a standardized and generic science, it is able to break through along all other sciences and disciplines, from natural to social, and from politics to management. Mathematics is another science capable to break through different sciences, and it uses symbols and methods that are universally known as well. This is one of the reasons why it is important to make a distinction between *statistics* and *mathematics*. According to Yule & Kendall (1950), mathematics is more related with the certainty than statistics. This means that statistics is more focused on treating problems that involve uncertainty, whereas mathematics is pursuing the opposite: try to define with the highest degree of certainty any observed phenomenon.

A second important distinction to be mentioned is the difference between statistics as pure science and applied statistics on business management (ASBM). This distinction has been discussed in literature by, for example, Deming (2000), Roberts (1990), and Banks (1993). These two branches of statistics use the same symbols and methods, but ASBM makes more emphasis on solving real world problems, while *statistics* as pure science is focused on producing new knowledge by proposing new theories and methods. According with the audiences which are directed to, ASBM is mainly applied in companies by decision makers that are concerned with decreasing variability, increasing process efficiency and reducing costs. In many cases decision makers in companies may have limited knowledge about statistics methods or theory. Nonetheless, the relationship between scientific statistics and ASBM has been frequently discussed in literature, and it is evident that a closer integration between these two branches can produce more benefits to academics, practitioners and decisions makers, according to Roberts (1990) and Hoerl & Snee (2010). For example, the progress in scientific statistics brings more methods and procedures which later are available for companies and businessmen. Decision makers in companies will have access to more powerful tools for dealing with problems, while academics will have an opportunity to test the new methods in real world problems. In short, a closer relationship between academy and industry produces significant benefits for all stakeholders involved. Now, the question is: how these two faces of statistics can work closer in order to get improved results? What can be done to increase the use of statistics at companies?

There are several recommendations to improve the collaboration between Scientific Statistics and ASBM. According to Hoerl & Snee (2010), Banks (1993), and Tort-Martorell et al (2011) it is required that all the statistics programs taught at universities, with special focus on the postgraduate level, should include periods of exposure to real consulting problems to their students. By this exposure, students will be able to learn required skills for professional successes which are not taught in any text book. Davenport & Harris (2007) affirm that several applications of analytical tools in business management for the purpose of making better informed have importantly increased in the last 30 years; nevertheless there is still too much room for improvement. For example, there is a wrong paradigm on the majority of the contemporary companies, which belief that analytical tools and statistical methods should be used to deal only with local problems and they have small impact on the strategy and also marginal contribution for competitive advantages. Indeed, the ideal scenario should be exactly the opposed: companies must ensure that data collection, exploitation and analysis are applied to make business decisions, which have impact in the three levels: operational, tactical and strategic. According with Davenport, Harris & Morrison (2010) the frontier of decisions made by analytical approaches is moving forward in the contemporary companies. Traditional non quantitative areas, such as human resources and marketing, are accumulating massive amounts of data and intuition on supporting decision making is becoming suboptimal. Now the challenge is how companies control, store and analyse their data in order to make sure that stakeholders make decisions based on the correct data, information and assumptions.

On the other hand, Davenport & Harris (2007) affirm that there are four common characteristics which all sophisticated and successful analytical companies should exhibit:

1) Analytics must prop up the competitive advantage,
2) Analytical approaches must be implemented at enterprise-wide level.

3) There must exist support and commitment from the senior management, and
4) The company must make a significant bet for the analytical approaches.

In addition Hoerl & Snee (2010) suggest that data analysis through statistical methods should be one strategic support for competitive advantages. Indeed, several authors such as Hoerl & Snee (2010), Davenport & Harris (2007), Deming, (2000) and Banks (1993) among others have emphasized the importance of the senior management support for a successful implementation of analytical projects. Besides, data analysis and exploitation should be complemented with a systemic vision. Deming (1993) defines a system as a complex entity made up of interrelated components of people and processes with a clearly defined destination or goal. Moreover Hahn et al (2000) emphasize the importance of the systemic vision for a successful implementation of six sigma projects and Yeo (1993) proposes complete definition of systemic vision applied to business management.

It is discussed on literature, outstanding relationships with clients and suppliers are a key source of competitive advantages. At the same time high performance relationships outside the company are achieved by improving the communication. For instance Langfield-Smith & Greenwood (1998) found that communication is a strategic factor to develop solid and productive relationships with buyer and suppliers. Moreover, it has been demonstrated that solid relationships with buyers and suppliers are important source of competitive advantages. Given this, efficient and effective communication outside, especially with clients and suppliers, is another feature which highly analytical companies must improve. Deming (2000) introduced a philosophy of business management named "*system of profound knowledge*", which is composed for 4 inter-dependent factors. Together these factors describe how organisations should be managed to achieve successful results. The necessity of thinking systematically, understanding the variation (through the use of quantitative methods), knowledge of psychology and the knowledge of the business, addressed the importance of analysing data. (The reader might have listened before the famous Deming's expression "*Show me the data!*"). In Tort-Martorell et al (2011) it is highlighted the importance of making decisions based on facts. The management should use the best knowledge available to make decisions. More specifically, a *well-decision* is defined as the ability to identify the information needed to make and formulate the suitable questions. The answered questions will lead us to make the most accurate decisions. In any time, assumptions or intuitive feeling should be avoided while the needed information is gathered. Davenport, Harris & Morrison (2010) describe five critical factors which an organization must observe to succeed by “*doing analytics*”, and were grouped using the acronym DELTA. Where “**D**” makes reference to the data and its desired features, “**E**” is related with the enterprise orientation, “**L**” for the analytical leadership, “**T**” for targets and, “**A**” for the required analytical talent. These factors should be considered as critical if the company expect to success by improving its analytical capabilities. On the other hand Hoerl & Snee (2010) emphasize the importance of the strong link among statistical methods and overall problem-solving methodology. The stronger this link is, the broader the impact of the statistics on decision making at the three levels of the company’s structure: operational, tactical and strategic.

In next paragraphs a more detailed explanation of these concepts is provided. For a better comprehension we classified the further literature review in four groups. The first is the data based competitive advantage, the second is related with the systemic vision in the company, the third is about communication outside the company as source of competitive advantages, and finally the management support on data analysis. (See Figure 2.1)

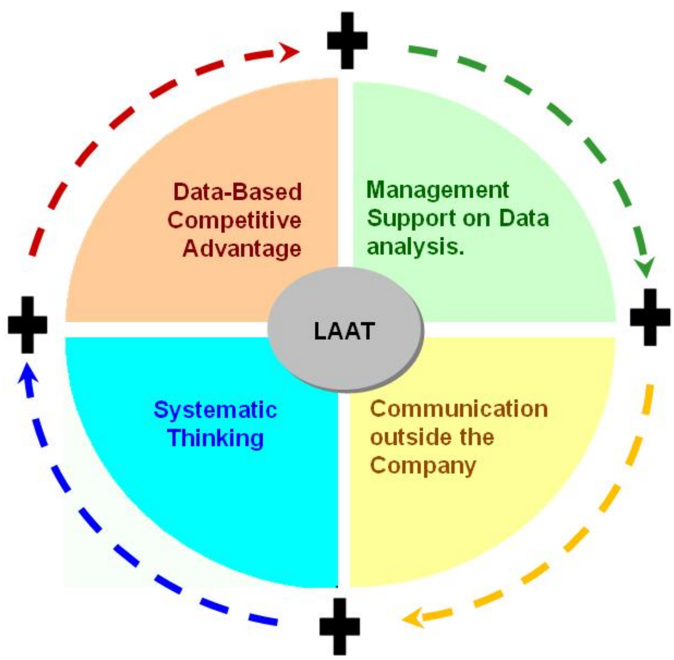

Figure 2.1. Characteristics or key drivers, which any analytical company should observe.

2.2. Data Based Competitive Advantage.

Considering the main purpose for this research, which is related in providing guidelines to companies who are interested in reaching competitive advantages from data analysis, in this subsection a definition of competitive advantages is widely discussed. According with Porter (1990) competitive advantages are defined as one or more attributes and characteristics on products, services or procedures, which give a company a superior position over other actors on the same industry. For example, competitive advantages can be a prestigious brand or image, a successful specialization on one specific market niche, a privileged geographical location, or confidential procedures which give to the company lower costs and, therefore, lower sale prices.

Porter (2008) states that the most effective way of identifying competitive advantages is by carrying out a detailed inventory of all performed activities, from the very beginning until the product or service is put in the customer's hands. Once all the activities are identified and put on logical order, the next step is to find out interactions among them. With this we recognize those activities, which were identified as strategic, but at the same time, are performed at lower cost or shorter time than the competitors. In other words, one company develops competitive advantages by performing strategic activities but faster or at lower cost than other actors in the same market. Additionally, competitive advantages can be a feature, a privileged location, a prestigious image, a strategy for focusing on data analysis, or any other features which distinguishes the company from other actors of the same market. The competitive advantages allow the holder to receive greater benefits than the rest of actors on the industry. Porter (2008) proposes four generic business strategies which could be adopted in order to develop competitive advantages. The name *generic* is due to the fact that they can be adopted by any company, on any market or industry, regardless of activity, size or location. As it is shown in figure 2.2, the scope of competitive advantages and business strategy can be either narrow or broad. This concept refers to the extent a company seeks differentiation on its products.

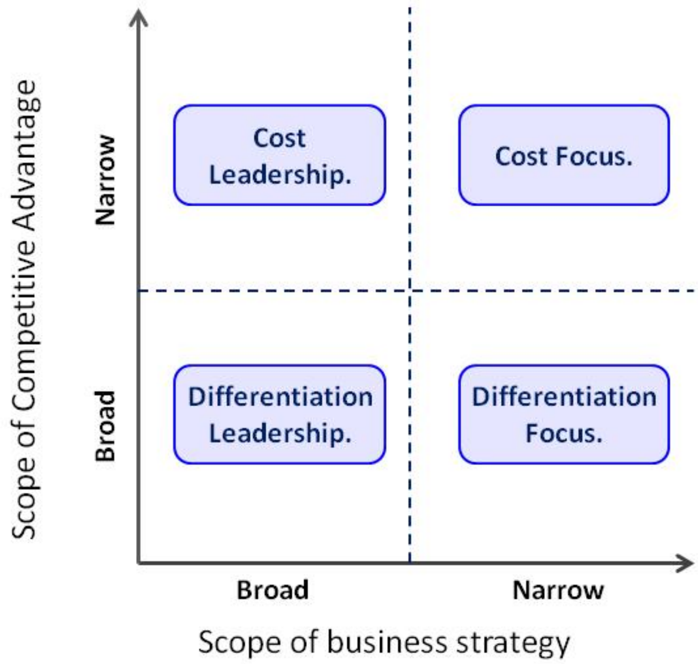

Figure 2.2. The generic strategies for gaining competitive advantage. Adapted from Porter (2008)

The strategies related with differentiation and cost leadership are aimed to reach competitive advantages by focusing on a broader range of market's segments. On the other hand, differentiation and cost-focus strategies are implemented in narrower markets or segments.

Cost leadership: Under this strategy the main objective is to reach the lowest production-cost in the market by improving efficiency on the process. Deming (1993), Takeuchi (1981) and Davenport, Harris & Morrison (2010) have documented cases on which different analytical tools have been used in order to successfully implement a cost leadership strategy, among them statistical control process, six sigma, histograms, Pareto`s charts, cause-effect diagrams (Ishikawa) and design of experiments. Basically, by analyzing data through analytical tools, companies seek to produce goods or services on a larger scale while minimizing the associated cost and reaching economies of scale. The cost leadership is an important strategy because the majority of the markets or industries are supplied with the emphasis on the minimum cost. Besides whether the selling price is equal or lower to the market average, the owner of the lowest-cost will receive greater benefits. This type of strategy is frequently implemented in large scale markets, which offer "*commodities*" or "*standardized*" products with few differentiations. Taking into account that all competitors have similar products (or, at least, with similar features), the price might has the highest weight when the customer makes the purchase decision. Frequently, in this kind of industries, the low-cost leader will discount its product to maximise sales, particularly if it has a significant cost advantage over other competitors and, by doing this, it can further increase its market share.

Cost focus: In contrast with the cost leadership strategy, by following a cost focus strategy a company aims to achieve a lower-cost advantage, but only on a smaller number of market segments. Usually companies competing under this type of strategy offer products or services, which are in essence, similar to the higher-priced and featured products and with lower but acceptable quality to a smaller group of consumers. A good example of this strategy are all products known as "*me too's*". On which the company attempts to avoid losing market share to a competitor by offering a product that is a copy (or extremely similar) of the competitor innovation. ("Me too's products", 2013). For example, many companies in the smart-phone industry who neither get first in the market nor domain the market share, should implement this strategy by offering almost equal products to the leader (*iPhone* for example). Therefore they will offer their own version of smart-phone but at lower cost and reduced features.

Differentiation focus: On this type of strategy, companies aim to differentiate from competitors but within just one or small number of target-market segments. In other words, special customers look for products which are clearly different from others. An important concept behind this strategy is the fact that the company must realize that customers have different needs, and a smaller group is always willing to pay a higher price for products which satisfy their expectations of status, recognition or prestige. The differentiation focus strategy is also known as the classic niche-market strategy. The majority of smalls and local business are implementing this type of strategy by providing more personalized attention to their customers, in comparison with an un-differentiated service usually offered on large shopping centres.

Differentiation leadership: A company following a differentiation leadership strategy aims to achieve competitive advantage across the whole industry by targeting larger markets than those targeted by the differentiation focus strategy. Frequently this strategy implies to charge a premium price for the product in order to reflect extra added-value and additional features which are not present on the rest of the products of the same market. There are several ways in which a company can implement this strategy, even though it’s not simple and it requires important investments in marketing and promotion. Some of the methods suggested by Porter (2008) are:

- Superior quality (features, benefits, benefits, reliability, security, etc)
- Branding (strong customer recognition and desire, brand loyalty)
- Industry-wide distribution across all major channels. (i.e. the product or brand is an essential item to be stocked by retailers)
- Consistent promotional support – often dominated by advertising or sponsorship etc.

It is possible to mention Nike® and Rolex® as remarkable examples of differentiation leadership at global level. These brands are built on persuading customers to become loyal and receive extra added-value by paying a premium price.

Until here the generic type of competitive advantages were discussed, now it is necessary to consider a possible scenario on which a company decides to increase the adoption of analytical tools and statistical methods, in order to increase with this the competitive advantages. Under this scenario, the company must master the use of data and analytical tools with the purpose of obtaining the market leadership. It is clear that high quality on data is mandatory requirement to develop a data based competitive advantage. For instance, the accessibility, interpretability and accuracy on data are critical attributes. In addition, security and relevancy should be included for a complete definition of data with high quality. According with Wang & Strong (1996) data must observe some characteristics in order to be considered of high quality. Theses authors have clustered 15 attributes in four groups: intrinsic, contextual, accessibility and representational. It is not the main purpose of this research to discuss deeply this classification but a detailed explanation of the features for high quality on data can be found in Bhatt & Grover (2005) and Poon &Wagner (2001).

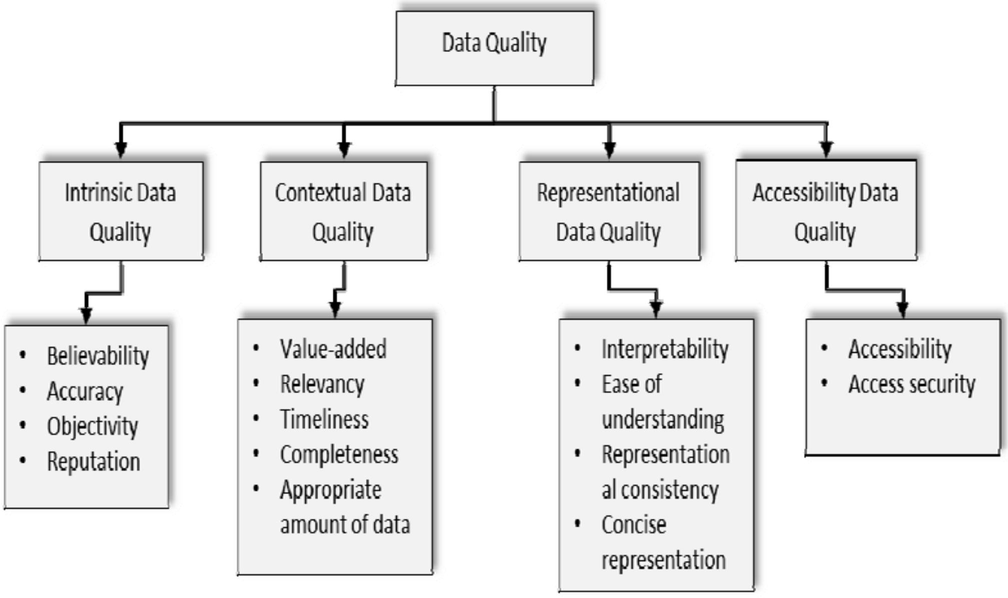

Figure 2.3. Attributes for data quality. Adapted from Wang, R.Y and Strong, D. M. 1996**.**

In short, this definition proposes that data of high quality is a factor which must be compulsory developed by companies, if they pursuit to create a data-based competitive advantages. In other words, the set of attributes which conforms the definition for high quality in data are the foundation of competitive advantages based on data analysis.

2.3. Management support on data analysis.

In order to create competitive advantages based on the use of analytical tools, some changes in culture, procedures, and employee´s skills are required. The success on this enterprise will be achieved only by having the top management support. The head of the company and other leaders might act as the main promoters of the change by demonstrating commitment and passion for data analysis and decision making based on quantitative evidence.

In the literature, there is plenty of research that demonstrates the importance of management support into achieving the settled goals on projects of different fields. Regardless of the scope, activity, size or location of the analytical enterprises, the management support has been one indispensable factor for achieving the planned results. Several projects related with continuous improvement, process optimization, introduction of new products and six sigma have been documented on literature by

Davenport & Harris (2007), Deming, (2000), Deming, (1993) and Hoerl & Snee (2010) . All these projects have one important element in common: the management support was essential to obtain the desired results.

For example, according with Flynn et al (1994), the strong commitment from top management in total quality management is vital to obtain high performance. Moreover, the employees behave as they perceive they are expected to do, and those expectations are at first given by the higher levels of management. In addition, Garvin (1986) affirms that high levels of quality performance are always accompanied by an organizational commitment to that goal, in the same way; high quality on services and products does not exist without strong top management commitment. On the empirical study carried out by Takeuchi (1981) it was found that 89% of the surveyed companies with high quality performance were the same on which theirs presidents attended company-wide quality events, continuous improvement circles, visited floors in manufacturing plants, took part of training programs and applied analytical tools to make decisions. Garvin (1986) and Takeuchi (1981) have documented cases on which the top management has established a suitable environment in order to reward all actions conducted to maintain high quality performance. These cases should be taken as guidelines to generate an appropriate environment for the adoption of analytical tools on business decisions. In short, it is required that top management establishes an environment on which the knowledge and the use of analytical tools are rewarded; as well as an environment on which the staff is recompensed in function of the use of analytical.

Sila & Ebrahimpour (2003) conducted a research on which it was demonstrated that the way the performance is rewarded and measured, is the key to achieve high quality levels in Japanese manufacturing plants. In addition, Garvin (1984) found a relationship between quality levels and the way companies used to reward their workers. The pattern was that companies with the lowest levels of quality used to reward their workers at the end of the process, and based on the total output (the percentage of defects). In contrast, plants that implemented policies focused on rewarding actions for preventing defects and errors, shown higher levels of quality performance. Moreover, the compensation schemes for groups have been found to lead higher performance levels, in contrast with the rewards based only on individual performance. According with Lawler & Ledford (1985) the skill-based-pay approach, which compensates employees based on the number of tasks that they are qualified to perform, is a system that leads to high quality performance. Hoerl & Snee (2010) affirm that there are typical manifestations of the existence of the management support in making decisions based on quantitative evidence, for instance: assist to remove obstacles, provide financial and technical resources, encourage all staff involved in the analytical project and share the vision of success with all staff on the company. According with Deming (2000) some of the most typical manifestations of the existence of the management support on improvement projects are:

1) There is plenty access to technical, financial and humans resources,

2) There plenty of assistance on finding solutions to problems

3) The leadership is giving by the example and demonstrating passion for decision making based on analytical approaches and

4) The motivation and encouragement to all staff is provided by pushing forward all the analytical initiatives on the company.

Ang, Sum & Yeo (2002) conducted a study to develop multi-dimensional indicators able to measure the degree of success in materials requirements planners (MRPs) implementations. The study collected information about MRPs implementations in 10 manufacturing companies. It was designed in a two-phase data collection approach, starting with questionnaires and followed by personal interviews. These authors identified seven critical factors of success for a MRPs successful implementation. These features, conditions and variables were identified to have direct impact on the effectiveness and efficiency of the project.

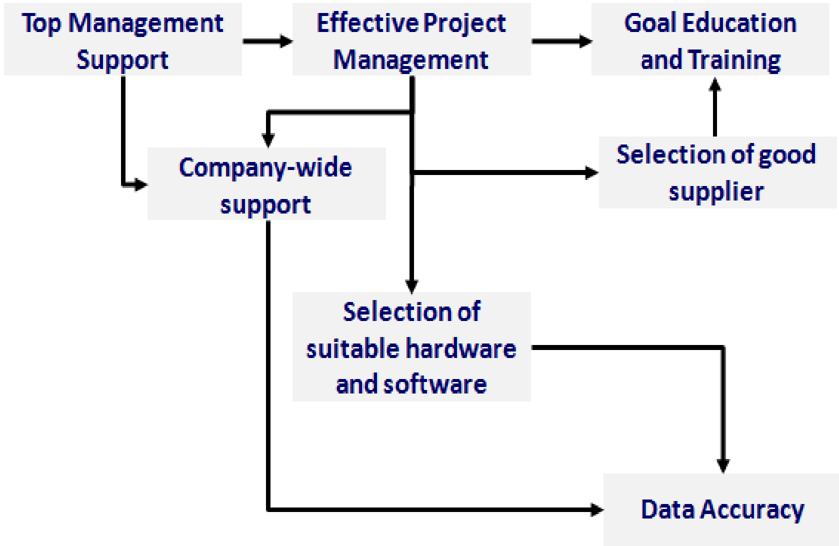

Figure 2.4. The importance of the management support on MRPs implementation. (Adapted from Ang, Sum & Yeo 2002).

The model shown in figure 2.4 essentially represents the hierarchical and causal relationships among the seven critical factors for success. At first, the top management performs an effective project administration by ensuring that adequate training is provided and ensuring that support exists at company-wide level. Moreover, the support is reinforced by an effective project management. The employees involved on the project are equipped with adequate training and finally they will be able to produce data with high quality. It is important to mention that the absence of any of the critical factors of success would affect the whole interactions and result on unsuccessful project implementation. Therefore, the factors are equally important on implementing successfully the project. The top management support has relevant importance and it would be consider the "*trigger*" for the whole project. On the other hand, data accuracy is at the end of the "*chain-reaction*", and this means that data of high quality should be one of the outputs to be accomplished. This study provides empirical evidence in order to demonstrate the importance and relevance of the top management support in projects related with high quality on data, and, therefore, on the adoption of analytical tools.

2.4. Systemic thinking and data analysis.

The first antecedents of systemic thinking took place in the early 50´s, when two new tools were introduced: the system analysis and the engineering systems. At the very beginning, these concepts emerged to solve problems basically for the military industry. According with Yeo (1993), under the engineering systems philosophy, some analytical tools emerged as solutions to problems in the industry, among them the analysis of variance, several methods to calculate the added-value on procedures, multivariate analysis to solve basic optimization problems and decision matrix to determine the value for intangible assets. On the other hand, Deming (1993) states that the company should be understood as a system and, thus suppliers, customers and society should be involved.

Checkland (1999) defines a system as any entity with a common and defined purpose; it is composed by two or more elements and there are interactions among those elements. This author proposes four generic properties which can be found in any system: the emergence, hierarchy, communication and control. The *emergency* means that each system exhibits special characteristics, only when it is analysed as a whole, in contrast to the result that would be obtained if it is analysed by observing its parts individually. In other words, the *emergency* in the systems means that the properties of the system itself could change whether it is observed as a whole or by separating its elements. The second property makes reference to the *hierarchy*: the lower the level of hierarchy for one element in the system, the greater the *emergency* for this particular element. This means that e*mergency* and *hierarchy* are inverse properties according with the systems theory. The third property is related with the *control* of the system. In words of Checkland (1999) pag. 313 it represents:

> *….. The means by which a whole entity retains its identity and/or performance under changing circumstances …..*

That is to say, the system is able to reach its goals by taking control of its components once a deviation on the settled parameters is detected. For example, the temperature inside a fridge is controlled by either increasing or reducing the cold put into the system, once a variance on the current temperature is detected. If the control does not exist, changes in the environment could cause the collapse of the system itself. Finally the last property is related with the *communication* of the system. It is clear that if a system functions as a whole, its components must communicate among themselves. More specifically, in order to achieve the ultimate goal for whole system, each subsystem should receive information that regulates its behaviour. The *communication* between subsystems could be given in different ways and formats, for instance electrical signals, verbal messages, specific types of sounds, light signals, etc.

Considering the four properties all together, the introduction of a new product that generates important benefits for the company is an emergent property of several elements in the system. At first marketing, where a sales forecast was calculated and the voice of the customer was identified; the research and development where a prototype was build in terms of the customer expectations; the human resources where all the required staff was hired and trained and production where a master plan was designed to satisfy the forecasted demand by marketing while minimizing the associated production costs. It is important to remark that in the context of business environment, the properties of communication and controls play a strategic importance. The overall performance of the system or even its survival, depend on an efficient and effective communication between all the elements. In addition the control and timely feedback are also quite important in order to ensure the success of the project.

2.5. Communication with customers and suppliers.

Contemporary successful companies fully understand the benefits of strong relationships with customers, suppliers and other actors outside the organization. In today's business environment, long term collaborations with actors outside the company are strategic issue in order to reach competitive advantages.

In terms of information technology, systems as customer relationship management (CRM) and supply chain management (SCM) traditionally have been operated isolated one from another. The CRM is an integrated information system that is expected to plan, schedule and control presales and post-sales activities in a company. In addition, the CRM embraces all aspects of dealing with prospects and customers, including call centres, sales force, marketing campaigns and technological support. ("CRM", 2013) The sales force automation, which at first was available for companies in the late 80`s was also considered the first element of CRM. Later, during the 00's, other technological recourses as the Internet were incorporated in order to improve the profitability on the company through better understanding of the consumer behaviour. On the other hand the SCM is referred to the planning, scheduling and control of the supply chain, which usually includes activities like store, make, manufacturing and assemble materials from one supplier to another and ending in the warehouse ("SCM", 2013). One of the most important purposes of this system is to minimize the levels of inventory. According with Blanchard (2010) the supply chain management is all about having the right product in the right place, at the right price, at the right time and in the right condition.

Traditionally CRM has been used mainly to manage sales and marketing campaigns. On the other hand, SCM has been focused on monitoring inventory levels and sending purchase orders to suppliers. In many cases these two information systems used to work in isolation and limited to its functional area. Davenport & Harris (2007) affirm that in the 90's the majority of American companies had underutilized and partially wasted those systems. In the 00's that scenario changed, and in today´s business environment more companies are overcoming this fragmented approach. The goal is to transform the scenario in which the isolated and underutilized systems are merged into a systemic vision in which all functional areas contribute with the analytics performance. According with Davenport & Harris (2010), the tendency is to see that more companies are aligning their systems in both addresses: the customer needs (CRM) and the supply chain management (SCM). It is clear that the new integrated approach is generating more complex data in comparison with the isolated perspective. Now the challenge for experts in analytics and statistics is to facilitate the decision making process to stakeholders by exploiting integral data coming from all functional areas.

The creation of competitive advantages requires efficient teamwork and constant communication with customers and suppliers. It is evident that high levels of trust are indispensable for successful associations. In order to share data, information and knowledge with business partners in an efficient and effective way, companies should start by improving their means of communication. In order words, the communication is a basic requirement for successful relationships with actors outside the company. In the contemporary business environment there are plenty of tools which can be used in order to improve communication with customers and suppliers. For instance, the emergence of wireless media devices, such as smart phones, tablets and laptops have made easier to share data and information. The emergence of such devices has changed radically the modern business environment and the way companies communicate with their stakeholders. Companies now can share data, information and communicate with buyers, suppliers or other actors by web-base, video conferencing, e-mail, electronic reports, presentations, telephone meetings, forum boards, or face-to-face meetings.

One consequence of the emergence of all these new wireless devices is that they are generating massive amounts of data. In the past, it was easy and clear to distinguish if the data was generated either inside or outside the company. However, now, with the huge amounts of data generated by these new technologies, it is more difficult to find out that difference. If the top management has been doing important efforts to work and improve relationships with customers and suppliers and, because of that, there are high levels of communication and trust among them, then the required scenario which contributes to reach competitive advantages based on the adoption of analytical tools is achieved. According with Davenport & Harris (2007), some of the practical tasks which top management should perform in order to increase communication with customers are: to align systems as CRM and SCM to the company's strategy, and to apply predictive analytical tools in order to identify the most profitable customers or those with the highest probabilities of becoming big customers. Even better, it is also feasible to create statistical models to predict which customers are in risk of moving to the competence, leaving or dropping the company's products. For example, according with Kotler et al (2009), the marketing campaign is an important part of the total cost for the product or service. Depending of the type of industry, the cost of a marketing campaign can be in a range from 10% to 50%. Taking this important cost into account, there is no room for mistakes, the marketing campaign is expensive and managers must be sure that everything is working according with the settled objectives.

Considering mentioned scenario, managers can perform sophisticated experiments to measure the overall impact of marketing campaigns. Moreover, taking into account that an important part of the total sales is performed online, these experiments produce practical and immediate results. There is no need to wait for days or even weeks to measure the performance, as it used to be in the past with marketing campaigns on radio or TV, in which the first results were known two or three weeks after started. Maybe two or three weeks of losses could cause the company bankruptcy. Now, with the use of analytical tools, managers don't have to wait a long time in order to know the measures of performance in a marketing campaign and to make more accurate decisions.

2.6. The theoretical scale

We introduce a scale to measure the level of adoption of statistical tools in companies. The higher in the scale, the better a company is in the utilization of analytical tools. At first it was necessary to define the number of levels in which, the scale should be integrated. With the purpose of doing benchmarking, several previously developed scales were investigated. In Davenport &Harris (2007) it was proposed a five-level scale to measure the analytical performance in companies, Tallon, Kraemer & Gurbaxani (2000) introduced a seven-level scale to measure the value of the business in a sample of 304 executives worldwide, and Powell & Dent-Micallef (1997) propose a five-level to measure the degree of contribution of information technology to the competitive advantages. Six more scales (which are not mentioned as were found less related with the topic of this thesis) were reviewed and all of them incorporated levels between 5 and 7. In addition, the scale proposed by Davenport & Harris (2007) neither provides the operationalization of the variables nor quantitative metrics which can be used in real cases. Based on the above, we concluded that by adapting the scales proposed by these authors in our research and further carry out the operational definition of variables represents an original contribution in the field of the business analytics. Later, each level of the scale was given a name according to the analytical practices documented in literature by Davenport, Harris & Morrison (2010), Deming (2000), Harris et al (2009), Checkland (1999) and Poon &Wagner (2001) among others. In next paragraphs it is explained each of its levels.

Level 1. Analytical ignorance: Companies in level 1 may have some interest in improving their analytical and statistical skills, but they are far from transforming data analysis into a distinctive competence. They may have human, financial or technological obstacles to data analysis, such as the lack of interest from senior management or deficiencies in technical infrastructure. Additionally, these companies may have serious problems with datasets of poor quality, due to inadequate practices in collection, debugging and storage of data. There could be a small group of experts in statistics that work in isolation and produce basic reports which have limited impact on the decision making processes. Usually in this type of companies it doesn´t exist the management support, communications with actors outside the company is unstructured, irregular and in many cases inefficient.

Level 2. Local focus: Companies in level 2 may have strong initiatives related to data analysis with statistical methods in one or more functional areas. They may apply sophisticated and complex statistical techniques, but usually this work only has an impact at a local or departmental level. For the majority of level 2 companies, the biggest concern is how to use the data to make reports that attempt to analyze and explain past performance. These companies neither appreciate nor understand that data analysis can produce competitive advantages. There is data exploitation through statistical methods, but there is no vision to transform these analytical capabilities into a distinctive competence. Therefore, it can be said that the lack of commitment with an analytical vision is the most important deficiency for these companies. They may have powerful enterprises resources planning (ERP) or other business intelligent systems and eventually data with high quality, but in many cases, these systems are not used to their full potential.

Level 3. Analytical aspirations: Companies in level 3 understand and comprehend the benefits of data analysis through statistical techniques. Companies at this level are pushing up the first broad and large scale analytical project. The biggest strength in companies at this level is that they are defined analytics mission and vision statements, and the senior management is seeking that all staff in the company know and share those statements. In addition, companies at this level may be struggling with problems such as the lack of extra support from senior management, absence of statistical experts in workgroups or limited technological infrastructure. At this level, companies may have started to transform data analysis into a distinctive competence, and thus they are developing their analytical capabilities.

Level 4. Analytical engineering: Companies in level 4 have successfully developed data of high quality, the management support is strong and communication outside the company is efficient. However, these companies could face problems such as lack of additional commitment from senior management to data analysis, even though there is support for making decisions based on quantitative approaches. Similarly, data analysis is held in all functional areas, but there may be problems sharing and transferring the knowledge throughout the company. The main challenge is to deploy the analytical vision throughout the company and strengthen efforts in order to create a unique distinctive competence, which is based on data exploitation and analysis.

Level 5. Analytics as competitive advantages: Companies in level 5 have reached the highest level in relation to data quality, management support, systemic thinking and outside communication. These attributes give them a strong competitive advantage within the market. One important characteristic of this type of company is that they are always testing new ways of collecting, debugging, exploitation and analysis of data, focusing those efforts on creating the strongest competitive advantage. These companies are led by executives and managers with big passion for making decisions based on quantitative evidence. Tasks such as exchange transfer and flow of statistical knowledge between divisions and departments is quick and simple. Most of the employees have basic training on the use of statistical techniques and there could be one or more expert in each functional area. An important fact is that these companies have a strategic plan in order to allocate all the necessary resources (financial, human and technical) to maintain and enhance their analytical competences. Usually companies at this level are the leaders on their sector and the use of analytical tools has become a source of competitive advantages.

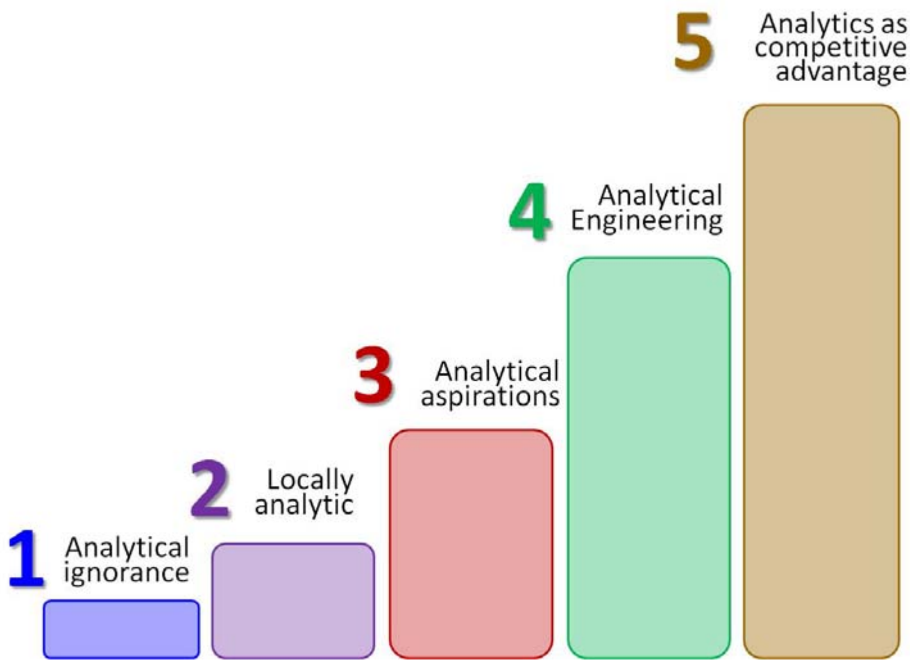

Figure 2.5. The 5-level proposed scale to measure the level of adoption of analytical tools**.**

3. Compilation of analytical applications on different areas of the company.

This chapter presents a compilation of analytical tools applied on different areas of the company. It is described and exemplified how traditionally non-analytical areas have recently started to adopt quantitative approaches.

3.1. Introduction

In this chapter is reviewed the use of analytical tools in different areas of the company. The main objective of this compilation of cases is to provide a general perspective of different applications of analytical tools in modern business. We identified features on successful analytical companies which are constantly present regardless of industry, size or location. That is to say, some of the common factors observed on highly analytical oriented companies are:

- Sophisticated methods and technology for collection, debugging and analyzing data are present in all company. Data is adding big value to the decision making process.
- High levels of understanding on customers, their motivations and behaviours, have reached through the use of analytical tools. The company is profitable as consequence of this understanding.
- The use of analytical tools is not limited to create reports. Several quantitative models are built to anticipate changes, predict events or prevent undesired results.
- Rather than swamping to the top management with reports of any kind or activity, the information is shared in all company at the three levels: operative, tactical and strategic.

We have carried out this compilation in two phases. At first, it is discussed the internal perspective, on which the cases of finances, manufacturing, research and development and human resources are described. In the second perspective, the cases related to customers and suppliers are presented. Only cases for the typical areas of the company are discussed, while other areas might be missed, especially if the company is large. (See figure 3.1 for the typical areas of the company). This compilation is only illustrative, and there is plenty of literature on this topic, for example, Burby & Shane (2007), Hahn, Doganaksoy & Hoerl (2000) and Kaushik (2011) among others, which demonstrate that these tendencies are valid for more areas than those discussed here (See figure 3.1).

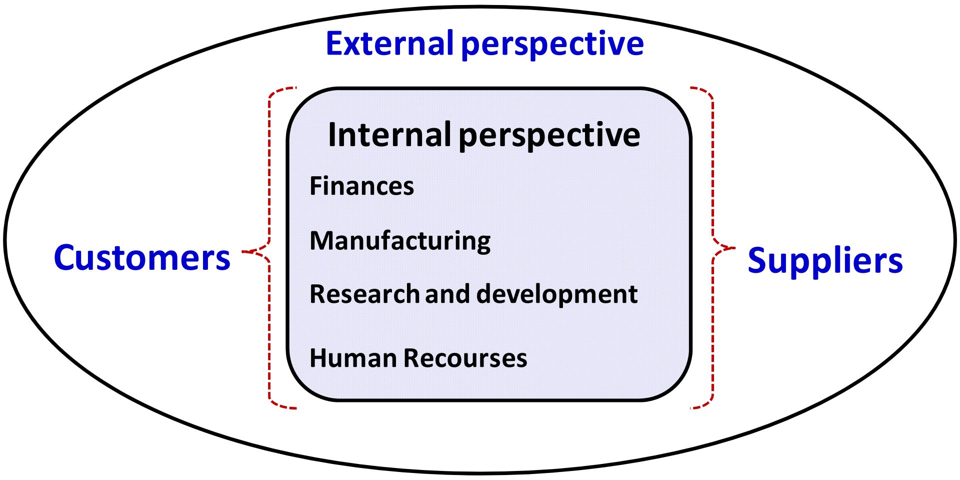

Figure 3.1. Classification applied to the study of the adoption of analytical tools**.**

3.2. The analytical tools in finances and accounting.

It is evident that on the contemporary business environment most of the companies, regardless of its size or activity, use different analytical tools in order to make better informed business decisions and therefore improve their financial performance. According with a survey carried out by Janis (2008), the most common applications of analytical tools in finances are focusing on making decisions related with further investments and values of stocks. In the following lines two cases documented on literature are provided.

The first discussed example is the utilization of the evidential reasoning for improving the decision making. According with Yang & Singh (1994) the evidential reasoning approach is a powerful analytic tool for analyzing multiple criteria decision problems under various types of uncertainty. The Multi Criteria Decision Making (MCDM) problems can be modelled using decision matrices on which each element represents the outcome of an alternative course of action (or simply an alternative or a decision) measured against a criterion. This analytical tool has been successfully used on solving several MCDM problems, as a portfolio investment. For instance, it may be considered that there are 10 different possible options for to invest a fixed amount of money. Each of these investment options has different criteria as interest rate, duration, terms and conditions. The point is to find out which investment option will bring the higher benefit given some attributes and characteristics. In Xu (2012) it is shown that the evidential reasoning approach allows researchers to make more accurate decisions in financial problems while dealing with different levels of uncertainty, ignorance or random variables.

A second example of analytical tools applied to improve financial performance is the prediction of profits by analyzing non-financial variables, for example, answering questions of this sort: How can be ensured that the business strategy is effectively translated into financial benefits? Are the mission and vision statements aligned with the financial performance? According with Davenport & Harris (2007), it is possible to find quantitative relationship between these two sets of variables, by performing a principal component analysis. This statistical method allows us to establish quantitative relationships between variables as training, work environment and employees morale, on one hand, and financial results on the other. In addition, a survey conducted by Morris et al. (2002) demonstrated that the use of analytical tool in companies has significant impact on business performance. More specifically, the main objective for this survey was to find out the experience of 43 companies, all of them located in the USA, which had implemented a strategy based on data analysis. The results show that 54% of the surveyed companies had an average of 112% per year on the return over investment for the five years after the implementation of any type of business intelligence systems in conjunction with statistical methods and other analytical tools. About the reasons why the companies decided to develop their analytic skills are to increase visibility on data produced, to improve data exploitation across different functional areas and increase company´s competitive advantages.

3.3. The analytical tools in manufacturing.

It is a fact that analytical tools and statistics methods were originally introduced in the production and manufacturing areas and, thereafter, expanded to other departments of the company. According with Hoerl et al (1993), methodologies such as Six Sigma and Statistical Process Control were originally conceived as solutions to specific problems at manufacturing and production and, subsequently they were adapted in other areas such as marketing, finances or human resources.

One important contribution on the utilization of the analytical tools for solving problems in production and manufacturing was the introduction of the seven statistical tools by Ishikawa (1988). The seven statistical tools rapidly gained popularity on the business environment because they are relatively easy to implement and understand. It is possible to affirm that on the present business environment these statistical tools are widely known and accepted, not only for solving production and manufacturing problems. There are plenty of documented cases on which they have been applied in areas such finances or marketing as well. The names given to them were: *control sheet, histogram, Pareto chart, cause-effect diagram, stratification-chart, scatter diagram and control chart*. It can be said that the seven statistical tools are a simple and standardized data encoding and its use has become a ritual during the past 45 years on several industries, in particular on the Japanese industry. Additionally, Futami (1986) states that the use of the seven statistical tools should be carried out with precaution in order to avoid their misuse and the real scenario is that in most of the cases, they are applied only to solve local problems which have impact only at local or departmental level without taking into account the company’s strategy, and finally ignoring their impact on developing competitive advantages.

According with Futami (1986), in 1976 the Japanese Union of Scientists and Engineers (JUSE) considered the necessity of new quantitative tools for sharing and promoting information about projects among stakeholders and staff involved. In response of this necessity, they introduced a new set of seven quality control tools which later were better known as *the seven management and planning tools* (or simply the seven management tools). Such set of tools was rapidly incorporated on the industry and business environment. They were named: *affinity diagram, tree diagram, relationship diagram, matrix diagram, matrix data-analysis and graphical programming decisions.* In addition to the previously mentioned 14 analytic tools, companies have introduced the Total Quality Management (TQM) principles over the past 45 years in order to improve their performance at manufacturing and production. In Deming (2000) it is documented that the TQM principles put greater emphasis on the voice of the customer, the strategic importance of producing goods and services with high quality and added value, the meaning of watching over the movements of competitors, and the sense of teamwork in order to achieve the established goals.

3.4. The analytical tools in research and development.

It is evident that in the area of research & development (R&D) is where analytical tools and statistical methods are more frequently used. According with Davenport, Harris & Morison (2010) if the R&D area is properly running, new experiments are conducted on daily basis, hypothesis are tested routinely, different controls groups are defined and new prototypes are introduced.

There are several industries such as oil extraction and pharmaceutical, on which according with the law and government regulations, it is mandatory that the company runs a R&D area. The pharmaceutical industry is a remarkable example of industry with a quite developed R&D area. In this particular industry, the introduction of a new drug implies important research, in order to guarantee that drugs are safe for the customers and patients. In addition, the severity of the legal requirements for the introduction of new drugs to the market has caused that laboratories and pharmaceutical companies apply sophisticated and complex analytical methods such as clinical trials and survival analysis. It is important to remark that clinical trials are a well established discipline, which have quite standardized methods and procedures combined with cutting edge analytical tools and specialized software. According with National Health System of United Kingdom, a clinical trial is a particular type of research applied to medicine and human health which compares one treatment with another. A clinical trial may involve patients, healthy people, or both. Small studies produce less reliable results than large ones, so studies often have to be carried out on large samples before the results can be considered reliable ("NHS", 2013). Basically the clinical trials help to determine whether: drugs are safe, treatments have collateral effects on patients or new treatments which could be better than currently available treatments.

The chemical industry is another example of industry where analytical tools and statistical methods are widely applied in similar way that a R&D area. There are plenty of documented cases, on which sophisticated analytical tools are applied on this industry, for example the petroleum and plastic industries. More specifically, in Liu et al (2008) it is documented the use of multi criteria decision making methods in order to assess different projects. Usually, starting a new R&D project implies important amounts of economic recourses. Consequently, the use of a reliable and rational evaluation system to assess the projects is very important to enhance the effectiveness and the capacity of improving competitive advantages. In order to evaluate several projects, various types of attributes need to be taken into account, which may be quantitative, measured by numerical values or qualitative and assessed using subjective judgments with uncertainties. The quantitative assessment is obtained directly by measuring the attributes on each R&D project. On the other hand, the subjective judgments are often provided by a group of assessors because an individual sometimes may be incapable of providing reliable judgments due to the lack of information or experience. The evidential reasoning is a well-suited tool for addressing uncertain multi criteria decision analysis problems with qualitative attributes on strategic R&D projects assessment. In addition, this analytical tool includes its ability to represent incomplete and vague subjective judgments.

3.5. The analytical tools in human resources.

In terms of King (2009), human resources management is defined as the planning, organizing, directing and controlling the development, compensation, integration and maintenance of the human resources on the company, in order to accomplish the stakeholder's expectations. For many years, it has been managed in terms of supply and demand. For instance, the company has some vacancies to hire and the human resource area was supposed to bring as many candidates as possible. This traditional way of managing the human resources put emphasis on bringing people from outside rather than facilitate the necessary resources to let the current staff to grow professionally.

Moreover, the traditional approach should consider this resource as a cost for the company rather than an investment, and thus it should be minimized at each opportunity.

But the traditional approach for the human resource management has been changing in recent years and today there is a tendency to conceive the human resources as a real intangible asset at the company; as other tangible assets in the company, Humans resources can be quantified, measured and included in the balance sheet. For example, according with Harris, Craig & Egan (2009), the majority of the USA large corporations have implemented a human resource information system over the last 10 years. These information systems are able to generate massive amounts of valuable data about the company's staff. For example, promotions per employee, trained provided in the last year, performance indices and salary level, among others. Having all this data available, it is possible to go one step further and calculate a quantitative measure of the impact that human resources have in company's competitive advantages. For instance, it would be possible to achieve this calculation by correlating human resources investments against financial performance. Another possibility is to calculate the correlation between money invested in training versus financial performance.

In Davenport & Harris (2007) it is provided one example which shows the level of quantitative expertise and accuracy that can be achieved in the human resources area. The professional sports in USA and the National League Football (NFL) is a remarkable case. Specifically, some NLF teams have produced quite detailed records about their player's performance. Using all this data, the managers make predictions for player´s performance based in sophisticated analytical models. For instance, the New England Patriots have developed a complex measurement system and indicators about the index of selfishness, teamwork willingness or emotional intelligence. By the combination of powerful computers, experts on statistics methods and massive amounts of data, the managers are able to answer questions like: What is the highest salary that we can offer to each player to renew contract for the next season? The New England Patriots, leading on introducing analytical tools for making decisions about human resources management in the NFL, have played 4 of the last 10 super bowls and have won 3.

Maybe the best known case of analytical tools applied in sports is found in the book "*Moneyball: The Art of Winning an Unfair Game*" which later led to the movie with similar name. According with Lewis (2003) the main idea behind *Moneyball* is that reaching wisdom in baseball (about human resources: players, managers, coaches and scouts) by using intuition and personal expertise is risky and flawed. The approach with highest accuracy which leads to the best decisions is to analyze statistics such as *stolen bases, runs batted in, batting average, among others*. In addition, this book widely describes how the Oakland A's' general manager is adopting several analytical approaches to make decisions about players with the goal of competing successfully against the richer competitors in Major League Baseball (MLB). By implementing rigorous statistical analysis the Athletics were able to create new metrics (e.g. *on-base percentage and slugging percentage*) and later demonstrated that those metrics leads to better results. These new metrics and the new approach for making decisions changed the conventional baseball wisdom and beliefs in executives, managers and coaches of the entire MLB.

On the other hand, Armstrong (2012) discusses another challenges related with creating an analytical organization. For instance differences between "*traditionalists*" vs "*saber-metrics*" (*traditionalist* tend to make decisions based on intuition while the *saber-metrics*[1] do exactly the opposite), the democratization of the information which collapses the hierarchies in the organization and thereafter a flatter structure is more efficient. In Lewis (2003) it is described this change as:

> *….. the journey of Oakland Athletics to the ruthless drive for efficiency that capitalism demands…..*

3.6. The use of analytical tools in marketing

As it was mentioned above, the first applications of analytical tools and statistics took place in production and operations areas. At the second half of the 19th century with the advent of the mass production, it was necessary to increase the process control and the analytical tools were a powerful outfit that helped managers to reduce the sources of variation. According with Deming (2002) the adoption of analytical tools allowed coping with the variation caused by the introduction of the new production methods in

[1] *Sabermetrics* is the specialized analysis of baseball through objective evidence, especially baseball statistics that measure in-game activity. The term is derived from the acronym SABR, which stands for the Society for American Baseball Research.

the last century. Although the earliest adoptions of analytical tools occurred in manufacturing and production areas, at our present time this scenario has changed. Since the last ten years we have seen and important grow of analytical applications in areas such as sales or marketing. We are discussing some examples in following pages.

The use of data analysis for making better business decisions is a practice as old as the trade itself. Since ancient times, companies have used the available data to know the reasons why their customers buy products and services. The customer behaviour has been always an issue that grasped the manager's attention since the beginning of trading. During the last century, in the fields of marketing, advertising and sales, art has dominated over quantitative sciences. For example, talking about marketing and promotion, the perception used to be more important than data analysis at the moment of making business decisions. At our present time, there may be companies that consider this approach could lead them to success, but they are not taking into account that now the customer has control over the Internet in contrast with television, radio or written media. The media has changed in the last 20 years and with them the way the companies interact with the customer. Now, it is impossible for marketing specialists at companies to design a campaign based only on perceptions, emotions or other subjective approaches without reaching unsatisfactory results.

According with Burby & Atchison (2007), marketing specialists should design and create quantitative measures, analyze the available online data and combine all these information with other qualitative measures as emotions and perceptions. In other words, given the increase in complexity of the new business environment over the last years, managers need to create a hybrid approach, which is composed of quantitative and qualitative data in order to reach satisfactory results in marketing campaigns. This scenario makes clear that the emergence of the Internet has radically changed the way companies do marketing and interact with their customers. One of the most important consequences of the emergence of the Internet is the massive amount of data that it has generated. This big data is now available to be analyzed with several analytical tools and statistics methods. Some examples of this massive amount of data include records of bank transactions, responses to promotional emails, clicks on banners ads, personal data captured in profiles and social networks, just for mention the most relevant. In deed all these changes resulted in a new discipline called Web Analytics.

The first analysis of data from the web dates back to the early 1990s, but according with Kaushik (2009) the web analytics was established as discipline in 2000, when there were calculated some basic metrics such as number of visits and web page views. Some years later, with the evolution of the Internet, there were incorporated another more complex analytical tools as design of experiments, bayesian inference and multivariate methods. On the other hand, the empowerment given to the customer by the internet has been an important reason why contemporary companies are adopting customer-centred approaches. Now in order to develop competitive advantages, companies must understand how customers interact with the web site and, based on those findings, create a strategy based on customer's behaviour rather than only considering the organization goals. The use of web analytics combined with statistical methods and specialized software allows the company to optimize the web site and gain customer loyalty.

In order to develop and implement a successful strategy of web-analytics, the company may require a considerable amount of resources as technology, human staff and knowledge. At first, the company must develop a culture of decision making based on data analysis and quantitative evidence, and incorporate the use of several analytical tools and statistic methods. This new way of making decisions must gradually replace the old methods based on perceptions and subjective judgements. Even though the analytical tools are more widely used in areas as finances, manufacturing or production, the tendency is to incorporate them in greater scale on all areas of the company for the purpose of making better decisions with data coming from the Internet. In order to illustrate the important growing on the use of analytical tools for data coming from the Internet, there is a survey conducted by Janis (2008). This study included 345 companies located in United States. Companies were asked about the use of data from Internet for making strategic decisions. The 40% of the surveyed companies answered that data online was a tactical input on their decision making process. Moreover, 76% of the companies use data from Internet only to create several types of reports. This means that the majority of the companies were using data online to elaborate reports. The most frequently mentioned reports were: number of visits to a web page or the time spent on the web page before leaving.

According with Davenport, Harris & Morison (2010), reporting is just the beginning of the exploitation of data and there is a disadvantage in this. The reports relate only to historical behaviour and past performance, they narrate events occurred in the past. Instead of creating reports it is possible to go further. With online information and the application of several analytical tools, it is feasible to predict trends, behaviours or to establish quantitative relationships between variables. It is also possible to conduct experiments with online data in order to predict trends or apply forecasting methods to know the probability of occurrence of a certain event. With the purpose of creating competitive advantages by the use of Internet data, it is necessary to coordinate staff, processes and technology available and exploit online data in order to perform analysis such as regression models, forecasting, predictive analysis, optimization models and inferences. Any of these analytical tools adds greater value to the company than just reporting.

3.7. The use of analytical tools with suppliers.

All companies need to work with different types of suppliers. A relationship based on synergy with suppliers is an important factor for improving the competitive advantages. In addition, the decision about choosing the best suppliers is another strategic factor that companies must consider. In order to select a new supplier, companies have to gather information such as external recommendations, industry directories, added value and guarantees offered, among others. According with Petroni & Braglia (2000) the methodology named supply chain management (SCM) emerged in the 90´s as a helpful tool for managing the relationships with suppliers. In recent years the SCM has received more attention on literature related with business analytics and applied statistics. The trend is that purchasing managers and decisions makers on companies are using more frequently different analytical tools to evaluate and select their suppliers. Furthermore, movements such as Total Quality Management (TQM) and Just in Time (JIT) promoted and intensified the analysis of data and it resulted that in modern business environment, decisions driven by quantitative approaches have greater weight. This is also valid for managing the relationship with suppliers.

When it is discussed about relation with suppliers, activities such as collection, using and analysing data from outside of the company should be also considered. In the majority of the companies, the big challenge is to transform the external data into information and valuable knowledge which adds value to company´s competitive advantages. Now it is clear that the sources of competitive advantages are not found in the research laboratory in isolation, as it used to be in the past. In the modern business environment, the innovation and the drivers for competitive advantages are found by working closely with all the actors of the supply chain. In other words, the tendency is to involve suppliers and clients on the strategic decisions of the company.

On the other hand, there are several cases reviewed in the literature on which several analytical tools and statistics methods have been applied in order to make decisions about suppliers. For instance, Verma & Pullman (1998) suggest the use a multiple attribute approach, which is based in the principal components analysis (PCA) and focused on assisting purchasing managers to formulate viable strategies for assigning suppliers. The PCA proved to be capable of handling multiple conflicting attributes which are a typical situation in this kind of problems. Other case is provided in Nydick & Hill (1992), on which it was applied the analytics hierarchy process (AHP) to select the best suppliers based several quantitative criteria. Additionally in Verma & Pullman (1998) the design of experiments (DOE) methodology is applied for the purpose of using data from suppliers in order to make more accurate business decisions.

The last case discussed in this section is provided by Ghemawat, Mark & Bradley (2004) and it is related to Wal-Mart, the biggest worldwide retail store. This case shows that the company had stored in 2004 approximately 584 terabytes of information about purchases, inventories levels and suppliers details. All this information was being stored and managed in a unique system which it could be accessed by managers, customers, supervisors and suppliers. Moreover, this massive information system allows managers to constantly monitor the key points of the Supply Chain Management. Managers use the system to make decisions about purchasing or sales forecasting. Walt-Mart buys approximately 17,400 different products from suppliers in eighty different countries, and each store uses the same information system to track the movement of their products. Also, with a username and password, suppliers have access to the system and they can see inventory levels, sales of products, customer segments, invoices and payments. In 2004 Wal-Mart introduced consumer behaviour information on its technology platform which shares with its suppliers. Wal-Mart is the largest private organization that collects information about consumer habits worldwide, in order to ensure that consumers have the products they want, when they need it, in the place and at the price requested. For example, Wal-Mart has learned that after a hurricane, consumers need to stock up on products which do not require refrigeration. Thus, using statistical tools and including variables on the weather forecast, the company takes actions before, during and after the hurricane.

4. A construct development and measurement validation.

This chapter widely describes the methodology which was followed to design a valid and reliable instrument to collect the data. This instrument allowed us to validate the theoretical scale by using data from the real world

4.1. Introduction

As we commented in previous chapters, if the level of adoption of analytical tools is gaining importance on the contemporary business management, now it seems necessary to measure it. Considering this, the main objective of this chapter is to propose a reliable and valid instrument, which can be used to measure it. It has been decided to use the questionnaire as means to collect the data because it offers several advantages. At first, the increasing emphasis on making decisions based on facts, as is stated by Tort-Martorell et al (2011), has brought the need of generating quantitative information of high quality. In the same way, the use of questionnaires allows for the collection of data through a standardized manner. Its use in conjunction with the techniques of the random sampling makes possible the extraction of data that are representative of the population. This is valuable for researchers because it allows the inference of the results to the population. Other important advantage in the use of questionnaires is the capacity for collecting structured data. For example, the reader could get an idea of how difficult would be to analyse information obtained from 255 companies if questions weren't structured from the very beginning. In this way, data collected can be compared among responders and several statistical methods can be applied to obtain deeper insights.

According with Menor & Roth (2007), several aspects should be considered while the questionnaire is designed. At first, it is necessary to carry out and extensive literature review, with the purpose of defining the subject of the study. The variables and its operative definitions should be included as well as quantitative measures for validity, reliability. It is clear that, during the design process, the target responders should be kept in mind by considering their education level and background. This and other aspects which characterize valid and reliable questionnaire are deeply explained in further paragraphs.

4.2. Scale development.

The scale development is a multifaceted process. According with Hinkin (1998), an accurate scale development is composed by an appropriate operational definition of constructs and quantitative tests with the purpose of demonstrating its validity, reliability and internal consistency. Together, all these integrated phases provide solid evidence to demonstrate that the scale is accurate and supports the research objectives. In addition, there are three important aspects that researches should consider in developing an accurate scale. At first, the researcher should specify the domain of the construct, secondly the extent to which items measure the empirical domain should be determined, and finally examine the extent to which the scale produces stable, reliable and valid results. Bhatt & Grover (2005) affirm that construct validity is the link between theory and the observed phenomena. Menor & Roth (2007) state that multi item measurement and scale development must be preceded by solid constructs which are to be defined after an exhaustive literature review. Specifically in this case, we are adopting a methodology that is composed of 2 stages and 7 steps (See figure 4.2). In the following paragraphs each step is described.

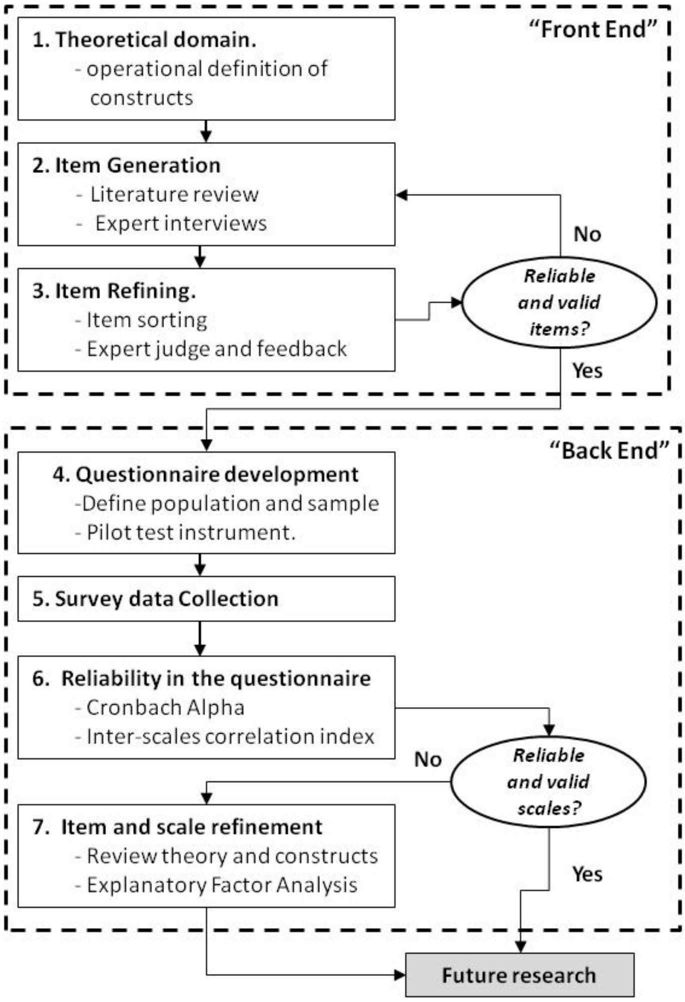

Figure 4.1. Two stage approach for new scale development. Adapted from Menor & Roth 2007

4.2.1 Theoretical domain.

A theoretical domain consists of units of analysis, environments or subjects on which the theory is assumed to be embraced. Hinking (1998) defines a theoretical domain, as a group of related theoretical constructs. Similarly, Michie et al (2005) state that a theoretical domain is composited by a group of interrelated theoretical constructs, where the last are concepts specially devised to be part of a theory. More specifically, the theoretical constructs must be a reflection of the theoretical domain. Fleishman & Benson (1987) suggest that the theoretical domain could be similar to an "*umbrella*" under which related constructs are grouped. For instance, constructs for social identity, group norms, professional role and cultural background could be grouped in the domain "*social influences*". In this research, the domain is composed by four theoretical constructs which were discussed in chapters 2 and 3. Besides, according with Bryman

(2012), the constructs are abstractions used by researchers to describe their theories. The level of narrowness on which each construct is defined, is in inverse relationship with its level of abstraction. The more abstracted a construct is, the less narrowed its definition is.

Considering this an empirical research, each construct is assumed to have its own empirical domain (E) which include all the potential observables (items, indicators, measures, etc). The empirical domain includes all possible ways to measure the constructs. Moreover these constructs (C) are thought to represent the domain. In other words the theoretical domain comprises all the possible ways to measure the constructs. The specific measure (M) represents the operational definition of the theoretical construct, through describing the observed variables for the construct (See figure 4.1).

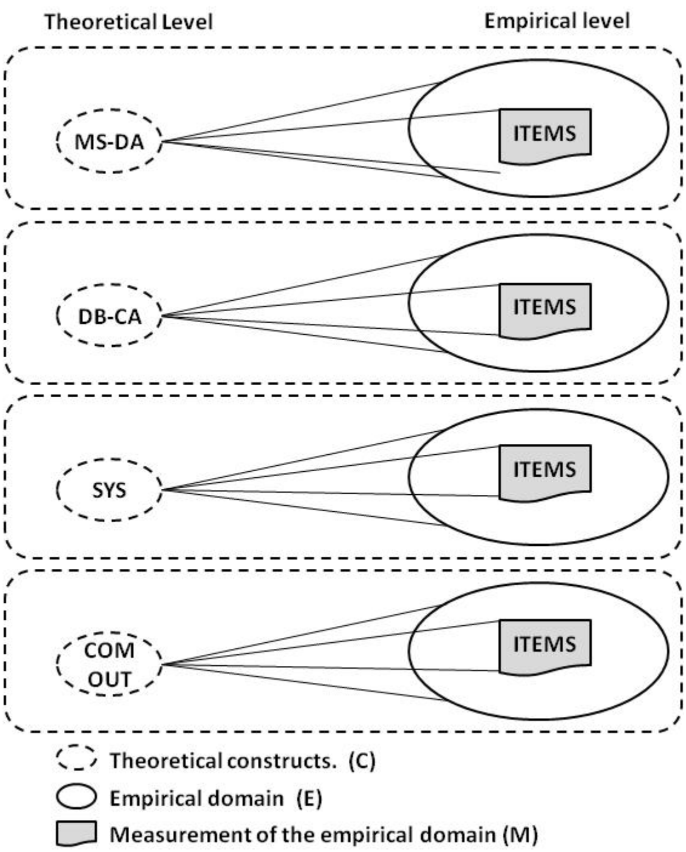

Figure 4.2. Theoretical constructs empirical domain and measurements for scale development.

According with Bryman (2012), the operationalization is the process of strictly finding a measurable variable for the theoretical construct. In addition, the operaationalization moves the researcher from the abstract level of the empirical domain to the construct level, where the focus is in variables rather than concepts. Menor & Roth (2007), affirm that a good operationalization of variables should include operations and procedures needed to measure the constructs. In this case of study, we are operationalizing four constructs, which are the four key drivers explained in chapter 2. (See appendix C for the operational definition of the variables)

4.2.2 Item generation.

A total of four constructs were operationalized in 17 items. All the questions were designed in a Likert scale from 1 to 5, where 1 refers to the lowest score in the measurement system, while 5 the highest. We simplified the written structure in each question, avoiding double barrelled and ambiguous questions. Considering that our target was to obtain responses from senior managers, quality or information technology managers all questions were specific enough to reduce the variability in the answers.

While the items were been generating generated, we conducted 8 interviews with academics, senior managers, and practitioners. The resource based method (RBV) proposed by Ray, Barney & Muhanna (2004) was adapted as guidelines to carry out the script for our interviews. Each responded was asked to read all questions and provide feedback about the level of understanding and comprehension by giving a grade between 1 and 5, where 1 meant that it was impossible to understand whereas 5 meant it was completely understandable (See table 4.1). Later, these grades were employed to calculate a measure of agreement for our scale.

Table 4.1. Grades given by experts to the degree of agreement in the items.

ITEM	Judge1	Judge2	Judge3	Judge4	Judge5	Judge6	Judge7	Judge8
DB-CA1	4	4	4	4	4	4	4	4
DB-CA2	4	4	4	4	4	4	4	4
DB-CA3	4	5	4	5	4	5	4	5
DB-CA4	5	5	4	4	4	4	4	4
DB-CA5	4	4	4	4	4	4	4	4
MS-DA1	4	4	4	4	4	4	4	4
MS-DA2	4	4	4	4	4	4	4	4
MS-DA3	4	4	4	5	4	5	4	4
MS-DA4	4	4	4	4	4	4	4	4
MS-DA5	4	4	4	4	4	4	4	4
MS-DA6	5	5	5	5	5	5	5	5
SYS1	5	5	5	5	5	5	5	5
SYS2	5	5	5	5	5	5	5	5
SYS3	4	5	5	5	5	5	4	5
SYS4	5	5	5	5	5	5	5	5
SYS5	5	5	5	5	5	5	5	5
COMOUT	5	5	5	5	5	5	5	5

For the purpose to adequately define our response variable, we examined in literature several scales to measure analytical performance in Davenport & Harris (2007), company value in Talion, Kraemer & Gurbaxani (2000), and impact of the information systems in competitive advantages in Powell & Dent-Micallef (1997). The scale proposed by Davenport & Harris (2007) does not provide variables or indicators to measure the level of adoption of analytical tools. With this, we identified an opportunity to make a research contribution by proposing quantitative measures to this scale. On the other hand, on the empirical study to measure the role of information technology in competitive advantages conducted by Bhatt & Grover (2005), the depended variable was defined in terms of percentage with a closed range. Considering this, we defined our response variable in a closed range from 1 to 5, where 1 represented the lowest level of adoption of analytical tools while 5 the highest. The name of each level and its features are widely discussed in chapter 2. In figure 4.3 the constructs (or key-drivers) which were operationalized and its related numbers of items.

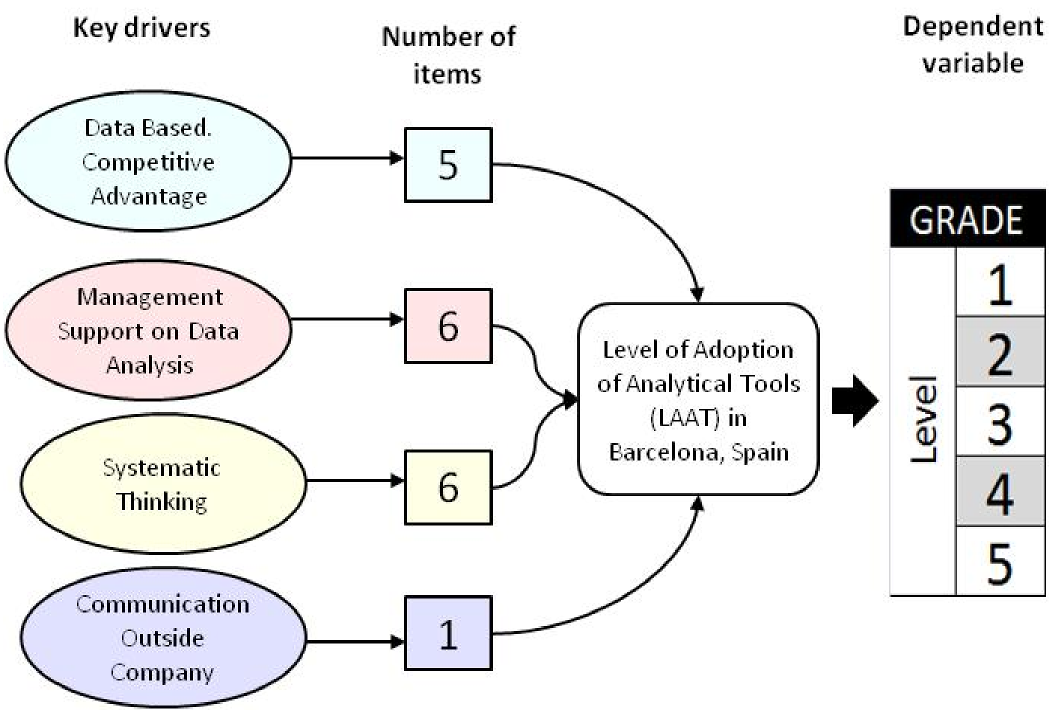

Figure 4.3. The dependent variable with its key drivers for the level of adoption of analytical tools.

4.2.3 Item refining

The coefficient of agreement for nominal scales or kappa index was proposed by Cohen (1960) in the context of psychology diagnosis. Basically, what the Kappa index is intended to answer is whether two classifications of the same group of subjects agree or not. Considering that Kappa index was developed in the medicine field, its first applications were addressed to know whether professionals performing a diagnostic agree in general. If there was not agreement, it was implied that something was wrong either with the evaluation method or with the examiners. In short, the Kappa index was created as a quantitative tool to measure the degree of agreement.

There are plenty of documented cases of applications kappa index in literature. Authors such as Landis & Koch (1977), Conger (1980) and Donner & Klar (1996) among others provide examples of Kappa index applications for categorical data, for multiple ratters and multiple samples respectively. In this research we are using the kappa index for multiple ratters to provide a quantitative measure of the degree of agreement in our scale. Furthermore, in social research it is frequent that a researcher needs to assess the agreement of a nominal scale, which is intended to be used as a measurement system. This agreement can only be obtained in situations on which two or more different ratters have used the same measurement system. For example, two or more different experts read a particular item and provide an assessment according with their degree of understanding. Only in this way it is possible to calculate a measure of agreement. One way to estimate the agreement is by either calculating the overall percentage of agreement (that is, overall paired ratings) or the effective percentage of agreement (that is, over those paired ratings where at least one expert rated a higher grade). Even though these percentages provide a measurement of agreement, neither considers the agreement that is expected by purely chance. For example, if experts agree just by chance, indeed they are not really agreeing. Thus, the Kappa index can be considered a type of "*true*" agreement because it is able to indicate the agreement higher than expected by chance. (The agreement by chance is given the joint probability of the marginal proportions). The agreement achieved beyond (or higher) than chance, is defined by

$$k = \frac{P_o - P_c}{1 - P_c} \tag{4.1}$$

where P_o is the proportion of observed agreement and P_c is the proportion of agreement expected by chance. The simplest expression of Kappa index (for the case in which 2 judges each give a single rating for the same observed topic) was first proposed by Cohen (1960). Some improvements were incorporated later by other authors including Cohen (1968) who proposed a new index for nominal scales; Fleiss (1971) introduced a procedure for three or more ratters; and Barlow et al (1991) brought in a special kappa on which subjects are grouped into strata, well known as "*stratified kappa*". Considering that the main purpose is to evaluate whether or not our scale is understandable (by providing a quantitative measure of agreement), the methodology proposed by Fleiss (1971) is implemented through this chapter.

According with Fleiss (1971), if a judge rates one particular item, the assessment given does not have to be the same for rating other different. This means that one judge assess items differently. Given this, we can consider a dataset of ($n=17$) items, which were rated independently by ($M=8$) different judges and they used a scale with ($k=5$) different values (See table 4.1). Now let m be a constant value, which represents the number of ratings per item and x_{ij} is the number of ratings on the *item* $i(i=1,\ldots,n)$ into *scale* $j(j=1,\ldots,k)$, where m is given by $m = \sum_{j=1}^{k} x_{ij}$. Similarly, the *mean-number* of ratings per item, (denoted by $\bar{m}$) is defined as $\bar{m} = \frac{\sum_{i=1}^{n} m_i}{n}$. In addition, $\bar{p_J}$ denotes the overall observed agreement in the *scale* $j(j=1,\ldots,k)$**.** Note that if we have 5 different levels in our scale, then the same number of *observed-agreements* will be obtained. Considering that $\bar{p_J}$ is defined as $\bar{p_J} = \frac{\sum_{i=1}^{n} x_i}{n\bar{m}}$, the values of $\bar{p_J}$ and m can be taken as inputs for calculating the kappa index $\widehat{k_J}$ $j(j=1,\ldots,k)$ based on the following expression.

$$\widehat{k_J} = 1 - \frac{\sum_{i=1}^{n} x_{ij}(m - x_{ij})}{nm(m-1)\bar{p_J}\,\bar{q_J}} \tag{4.2}$$

Thereby, $\widehat{k_J}$ is considered a measure of inter-ratter per category, where $\bar{q_J} = 1 - \bar{p_J}$. As it was mention before, we are considering $k(k=1,\ldots,5)$ different levels in the scale and each one represent the *inter-agreement* for the judges.

Regarding with the interpretation of the kappa value, Cohen (1960) and Fleiss et al (2003), affirm that values close to 0.80 should be interpreted as substantial agreement and thus a good level of understanding on the proposed scale. As it was mentioned before, an estimated value of Kappa itself could be due to chance. Considering this it is required to perform a hypothesis test. We are using a Z distribution to test H_o: the value of kappa is due to chance versus, H_1: it is not. In this specific case, we reject H_o and there is not statistical evidence to ascertain that kappa index is due to chance (See table 4.2).

Table 4.2. Values for kappa index of agreement.

Grade	Kappa	Standard Error	z	Prob>Z
4	0.77980	0.045835	170132	<.0001
5	0.77980	0.045835	170132	<.0001
Overall	0.77980	0.045835	170132	<.0001

According with Siegel & Castellan (1988), the Kendall´s coefficient of concordance is a measure of the agreement among ($n=17$) items that are assessed by ($M=8$) judges. In this particular case, the Kendall coefficient is 0.8315, which allows us to confirm that the proposed scale is understood by the judges (See table 4.3).

Table 4.3. Values for Kendall coefficient of concordance.

Coeff of Concordance	F	Num DF	Denom DF	Prob>F
0.82092	32.09	15.75	110.25	<.0001

In this subsection we focused on the item generation. At first we defined our theoretical domain and constructs. Later through an operational definition of variables items were generated. At this point it was required to ensure that our items were well redacted and are understandable prior the questionnaire redaction. A quantitative measure for agreement was calculated in order to provide quantitative evidence which allow us to ascertain that our items are understandable by responders.

4.2.4. Questionnaire development and pilot test.

A total of 17 items were grouped into four constructs (or key drivers). In addition three categorical questions were included and related with number of employees, economic activity and type of generic competitive advantage according with Porter (2008). This means that the final draft had five sections and 20 items. In table 4.4 the questionnaire structure.

Table 4.4. The structure of the first questionnaire draft

Section	Number of items
Categorical questions	3
Data Based Competitive Advantage	5
Management Support Data Analysis	6
Systemic Thinking	5
Communication outside the company	1
Total	**20**

Once the draft of the questionnaire was obtained, we carried out a pilot test in order to try out the tools related with sending, processing and storing received responses and calculating basic descriptive statistics. This pilot test was composed for two steps; at first we share our questionnaire in social networks as LinkedIn® and XING®. Secondly, we sent it by email to 300 companies, which are members of the Association of Friends of the Technical University of Catalonia (AAUPC for its acronym in Catalan). From this pilot test we received 31 responses and we used them to improve features as the logical order of the questions, the questionnaire`s layout and contents of the cover letter. (See appendix A for the questionnaire, which include the cover letter, instructions for responders and the questions)

4.2.5. Survey data collection

We defined the population subject to study as all companies with offices in the Barcelona area. According with the Institute of Statistics of Catalunya (IDESCAT for its acronym in Catalan) there are registered 602,161 companies in Barcelona ("IDESCAT", 2013). On the other hand, the sampling frame is composed by 6,064 companies, which were invited to participate in the study by sending to them our questionnaire electronically. In order to maximize the number of responses, we offered to any interested company a free diagnostic about its analytic capabilities. In the same way, we stated in the cover letter our open intention to share the final results and conclusions with anyone interested.

During a 24 weeks period we sent three extra reminders to the same sample frame. After 36 weeks we accumulated 255 responses, which represent a response rate of 4.2%. Nevertheless, five questionnaires with non-random missing responses were deleted from our dataset. The non-response bias was assessed through comparisons of early and late responses. We carried out statistical tests for comparison of means and no statistically significant differences were detected between early and late responses. In addition, we made phone calls to randomly selected companies in order to obtain feedback about the persons who already answered, identify possible problems in the questionnaire and receive suggestions for improvement.

4.2.6. The reliability in the questionnaire.

In order to ensure that our questionnaire is reliable, it was necessary to provide an internal measure of consistency. According with Cortina (1993), the internal consistency is a measure given for the correlations between items of the same questionnaire (or the same subsection). It can be interpreted as an indicator of the capacity of several items to measure a common construct and produce similar results. For example, if a respondent answers "*completely agree*" to the item "*We apply analytical tools in all decisions we make*", at the same time answers "*strongly agree*" to the item "*We exploited and analyzed plenty of data during the last year*" and "*completely disagree*" in "*The use of statistics is useless to build competitive advantages in our company*". These three items would indicate a good internal consistency in the test. (In appendix "A" the questionnaire is shown)

A quantitative measure of reliability is given by the Cronbach's Alpha. It was introduced by Cronbach (1951) as an index with values between 0 to 1. Later, several authors such as Streiner (2003) documented cases on which the Cronbach's Alpha was applied as a measure of reliability in questionnaires. According with this author, the reliability of one questionnaire is understood as the capacity to measure what it is supposed to measure. In other words, reliability is equivalent to stability and predictability. The mathematical formulation of the Cronbach's Alpha is defined as.

$$\alpha = \left[\frac{k}{k-1}\right]\left[1 - \frac{\sum_{i=1}^{k} S_i^2}{S_t^2}\right] \tag{4.3}$$

Where k is the number of items in the questionnaire (or subsection), S_i^2 is the variance for the single item and S_t^2 is the total variance for the subsection. Bryant, Yarnold, & Michelson (1999) suggest that 30 are the minimum required responses for calculating an accurate alpha, if the researcher wants to obtain accurate results. Considering that we obtained 255 responses from our survey data collection and having discussed the concept of reliability, we proceeded to calculate and interpret the Alphas for our questionnaire.

According with Cortina (1993), values higher than 0.65 in the Alpha show an acceptable consistency. For the four sections which compose our questionnaire, we obtained values higher than 0.700. The lowest Alpha was for the systemic thinking section equals to 0.776, while the highest was for the data based competitive advantage equals to 0.8884. The section communication outside the company is a one-item section, for this reason it was obtained an Alpha equal to 1.0. Having these calculations, there is statistical evidence to ascertain that our questionnaire is consistent (See table 4.5).

Table 4.5. The Cronbach's Alpha values for each subsection.

Subsection	Alpha
Data Based Competitive Advantage. (DB-CA)	0.8884
Management Support in Data Analysis. (MS-DA)	0.8025
Systemic Thinking (SYS)	0.7761
Communication Outside the Company (COM-OUT)	1.0000

On the other hand, an inadequate use and interpretation of the Alpha could lead to false or worthless conclusions. In order to prevent a misuse of the Alpha coefficient, it is important to make a distinction between internal consistency and homogeneity. As we explained before, according with Tavakol & Dennick (2011) the internal consistency is related with the interrelatedness of the items, whereas homogeneity refers to whether the items measure a single latent or construct. In other words, a substantial consistency in the items is important (alpha higher than 0.70), but it's not sufficient to ensure the reliability and validity for the questionnaire. It is clear that it is necessary to provide a measure for the homogeneity in order to complement our analysis. In next lines the concept of interclass correlation coefficient is introduced.

The Interclass Class Correlation Coefficient (ICC) is defined by Shrout & Fleiss (1979) as a measure of the level of association among entities or groups. Since its proposal in 1979, the ICC has been used in different areas and fields. For instance, in Goodman et al (1990) it was applied to measure the degree of agreement between different epidemiological studies. In Weir (2005) it was used to assess the reproducibility of the questionnaire and its grades. In the field of biostatistics, several cases are documented where the ICC was applied to measure the degree of relationship between biological variables such as blood pressure in Donner (1985), cholesterol level in Tian (2005) and lung capacity in Mian & Shoukri (1997). A common characteristic in all these implementations is that they are looking for a quantitative measure of the degree of homogeneity between groups, clusters, variables, studies, etc.

In this particular research, we are interested in calculating the ICC to obtain a quantitative measure of the questionnaire`s homogeneity. Specifically we are calculating the ICC for (*j=17*) items for a sample of ($i = 255$) companies who responded our questionnaire. Let n_{ij} be the number of items of the *j*th section and the variable *Y* the observed value by considering n_{ij} items. Then the model for calculating the ICC with respect of *Y* is given by the following expression.

$$Y_{ijk} = \mu + a_i + \beta_j + \varepsilon_{ijk} \tag{4.4}$$

where *i*(*i=1,...,* 255) is the number of companies, *j*(*j=1,...,17*) is the number of items, and μ represents the mean computed for each responder. In addition a_i is interpreted as the responder effect (company or between effect), whereas β_j is item effect (or within effect). The random-error component is the sum of the inseparable effects and given by ε_{ijk} . We are considering that a_i , β_j and ε_{ijk} are mutually independent and normally distributed *N*(0, $\sigma^2_{a,i}$), *N*(0, $\sigma^2_{\beta,j}$) and *N*(0, $\sigma^2_{\varepsilon,k}$) respectively. Moreover, the total variance of the questionnaire is given by the sum of the variances of each component and the random-error component. Now let $\sigma^2_T = \sigma^2_{a,i} + \sigma^2_{\beta,j} + \sigma^2_{\varepsilon,k}$ be the total variance, then the ICC is given by

$$ICC = \frac{\sigma^2_{T,}}{\sigma^2_T + \sigma^2_{a,i} + \sigma^2_{\beta,j} + \sigma^2_{\varepsilon,ijk}} \tag{4.5}$$

According with Tian (2005) and considering the equation (4.9), the ICC is understood as the ratio of between groups to the total variance. In other words, we are separating the total variance in three components; the first is related with the "*between companies variance*", the second is the "*within items variance*". Finally the inseparable observed variance of the random-error. With these three variance components, we calculate the ratio in order to know the proportion of the total variance σ_T^2 which is attributable to the companies ("*between*") and items ("*within*") effects.

Besides, the dataset was prepared for the ICC calculations; we set the first column (from the right to the left) as the company's ID. Each following column represented one item and each cell a company's evaluation on that particular item in five-level Likert scale. According with the methodology proposed by Shrout & Fleiss (1979) it was used a two way mixed ANOVA for calculating the ICC. It was also considered the company as random effect while items a fixed effect. In figure 4.4 it is presented a fraction of the dataset.

Company	SYS5	MS_DA6	DB_CA2	DB_CA3	DB_CA4	DB_CA5	MS_DA1	MS_DA2	MS_DA3	DB_CA1	MS_DA4	MS_DA5	SYS1	SYS2	SYS3
1	2	4	4	4	5	4	4	4	4	4	3	3	4	5	4
2	4	4	2	3	3	4	1	2	2	4	1	2	4	5	5
3	1	4	5	4	5	5	4	4	4	5	4	5	5	5	5
4			4	1	3	3	5	4	5						
5	3	4	2	2	3	2	2	2	1	4	1	4	2	4	2
6	3	5	4	4	5	4	4	4	3	4	3	3	3	4	4
7	4	3	4	3	4	2	2	2	2	3	2	2	2	2	3
8	4	2	2	2	2	1	1	2	2	2	2	2	2	2	2
9	2	3	2	4	2	2	1	2	2	4	1	4	2	3	3
10	5	5	1	1	1	1	1	1	1	1	1	2	1	5	2
11	2	4	3	4	4	4	2	4	4	5	1	2	4	3	4
12	4	4	2	2	2	2	2	2	2	2	2	2	2	5	2
13	2	4	4	4	4	3	4	4	4	5	1	4	4		
14	4	4	2	2	2	2	2	2	2	2	1	2	2	1	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
237	2	5	4	4	4	4	2	5	5	5	2	3	4	5	5
238			5	5	5	5	3	4	5						
239	4	3	2	3	4	2	1	1	1	2	1	1	1	5	2
240			4	4	5	4	3	4	4						
241	2	5	4	4	4	4	1	2	5	3	1	4	1	3	4
242															
243	4	3	3	3	4	3	1	1	1	1	1	1	1	4	2
244															
245	3	3	2	5	4	2	1	2	2	3	1	2	2	4	2
246	3	4	2	2	3	2	2	2	2	2	1	2	2	3	2

Figure 4.4. Fragment of the dataset applied for calculating the ICC.

In table 4.6 it is presented the ANOVA table which was used to calculate the ICC. As it was mentioned before, this is a mixed effect on which companies rated the items but the sequence by each company answers each question is a random effect. On the other hand there are 17 items, which is considered a fixed effect. The "*between companies*" is the row effect whereas the "*within items*" is the column effect.

Table 4.6. ANOVA table for values in the Interclass Class Correlation Coefficient .

Source of variation		Sum of Sq	D.F	Mean of Sq	F-Value	Pr(>F)
Between Companies		1734.138	153	11.334		
Within Companies (item-effect)	Between Companies	817.168	15	54.478	55.768	.000
	Residuals	2241.894	2295	.977		
	Total	3059.063	2310	1.324		

As it was mention before, the ICC is a measure of homogeneity. When the ICC takes values closer to 1.0 can be interpreted as any given row tends to have the same value for all columns. In our specific case the row is given by the *company-effect* while the column is the *item-effect*. In order to illustrate this relationship, Lin (1989) discuses a dataset obtained from a Census, on which columns represent the items while the rows are responders. In addition, an attribute assigned with either 1 to male and 0 to female respondent. For this particular example, if items are homogenous by gender, any given row will then to have mostly 0`s or 1's and therefore the ICC will have values closer to 1.0. That is to say, according with Shrout & Fleiss (1979) the ICC is closer to 0.00 when *within-groups* variance almost equals to *between-groups* variance. This is an indicative that the grouping variable does not have any effect.

For our questionnaire, the obtained ICC was equal to 0.887. With this value we can affirm that the amount of variance in the "*within the companies*" effect is acceptable and therefore the questionnaire can be considered homogenous.(See table 4.7).

Table 4.7. The ICC as a measure of homogeneity in the questionnaire.

Intra- class Correlation Coefficient (ICC)			
Two-way Random Effect Model	ICC	95.00% C.I	
		Lower	Upper
Average Measure (Within effect)	.887	.851	.915

4.2.7. Item and scale refinement.

Until here we carried out several analyses in our questionnaire with the purpose of measuring agreement, validity, reliability, and homogeneity. In this last section a confirmatory analysis is performed in order to provide a quantitative foundation to our conceptual model. According with Harvey et al (1985), principal component analysis

(PCA) is a widely used statistical method to further refine new scales. The PCA allows the reduction of a set of observed items into a smaller one without losing consistency and reliability in the scale. In the same way, other authors as Kim & Mueller (1978) suggest that prior to conduction a factor analysis the researcher should examine the correlations between variables and then remove any variable that correlates with less than 0.4 with other variables. The main reason for this is that low correlations indicate that items are producing only noise, error and unreliability. Basically, by applying the PCA we are refining our scale and keeping the minimal number of factors which explain the maximum amount of variance. The researcher should have a strong theoretical justification for determining the number of factors that are retained. Moreover the item loadings on latent factors should provide a confirmation for the operational definition of variables done at the beginning of the scale development.

According with Long (1983) it will be a decision made by the researcher deciding the number of factors to retain. If items were carefully developed, the number of factors that emerge should be the same as the number of constructs.

Prior to the conduction of the confirmatory analysis, a couple of statistical test were performed, the Kaiser-Mayer-Olkin (KMO) and Bartlett's tests. The KMO is a measure of adequacy to the exploratory analysis and it is given in an index between 0 and 1. Krzanowski (2000) suggests that values near to 1.0 indicate the absence of significant variance among the retained factors while values lower than 0.5 show an important amount of shared variance which is interpreted as indicative of underlying of latent common factors. On the other hand, the Bartlett's test is applied to evaluate if the correlation matrix $R = (r_{ij})_{pxp}$ diverges significantly from the identity matrix. In short, the exploratory analysis is able to achieve a compression of the data only if the null hypothesis is rejected, which follows χ^2 distribution with a [p (p-1) / 2] degrees of freedom.

Moreover, the implementation of this method was performed with the SPSS software. We decided to use the Varimax rotation proposed by Kaiser (1958) because it presents some advantages. For instance, this method seeks that each factor has a small number of big loadings and large number of small (or even zero) loadings. This feature makes easier the interpretation for the researcher, especially in the field of questionnaire design, on which it is necessary grouping the items into the factors. In the appendix E are shown the outputs obtained with the SPSS software. As the reader will notice in figure E1 three items with similar loadings in two or more different factors were identified. Considering this a conflictive situation, it was necessary to make a decision about the factor on which these items should be grouped. As it was suggested by Kim & Mueller (1978) the criterion of the researcher, based on an exhaustive literature review and an operative definition of variables, should be applied as complementary tool to the exploratory analysis. In this way, the three conflictive items are grouped by applying the criterion of the researcher. Figure E5 shows the final arrangement.

4.3 Conclusions.

As the famous quote "*if you cannot measure it you cannot improve it*" by Lord Kelvin well known for his work in thermodynamics, if we are willing to improve analytical capabilities in companies, at first it is necessary to measure them. Addressing this challenge requires of valid and reliable scale measures. The literature review presented in chapters 2 and 3 allowed us to formulate a conceptual model, which later in this chapter became the constructs of the questionnaire. While we developed these measures, we did not know evidence of similar operationalization of the adoption of analytical tools on the field of business analytics literature.

In this chapter is documented the process development and validation of a new-item measurement scales. The level of adoption of analytical tools is conceptualized as multidimensional construct composed by four dimensions: management support on data analysis, systemic thinking, data-based competitive advantage and communication outside the company. The two-stage approach for scale developing proposed by Menor & Roth (2007) was adapted. In the first stage, we calculated the judgment-based nominal scales, through the item-sorting process in order to assess the degree of understanding by calculating the coefficient of agreement. In the second stage, measurement-model was validated by performing a confirmatory factor analysis. All calculations performed in this chapter allowed us to verify the agreement, validity, reliability and homogeneity in our questionnaire. The scale applies to companies interested on improving their analytical capabilities. Managers can apply this scale, either as a diagnostic tool to assess their company's analytical performance or for a profitably competitive benchmarking.

5. A Statistical Engineering case of study.

Based on the Statistical Engineering approach and using the data previously collected, this chapter illustrates how a set of seven statistical tools were assembled in order to perform an analysis and obtain relevant conclusions.

5.1. Introduction

As it was defined in previous chapters, the applied statistics on business management (ASBM) is the extensive use of data, information technology and statistical methods to predict tendencies, behaviours and reduce variation for making better decisions based on quantitative evidence. The ASBM is an intangible asset for the company and it complements the business intelligence strategy. In addition, the ASBM inputs and outputs are important to stakeholders. A stakeholder is a person who is affected by a decision carried out using ASBM, or someone who has a "*stake*" in outcomes shaped by the ASBM. For the purpose of this research, those defined as stakeholders include shareholders, directors, managers, employees, customers, suppliers, government and the community.

It is clear that stakeholders of the ASBM should take advantages of the possibilities derived from this new scenario. In Steinberg et al (2008) the authors stated that the environment of the statistics profession has moved its traditional application, and has grown from industry to other areas such as marketing and computer science. Considering these changes, businessmen, practitioners and academics must respond appropriately. According with Hoerl & Snee (2010) the following actions and strategies can be followed by ASBM's stakeholders in order to respond suitably to changes in the contemporary business environment.

- Use statistical thinking and methods to drive improvement in leadership.
- Determine how the existing body of statistical science can be used most effectively for the competitive advantage of the organization.

- Contribute to improve the business results of the organization, beyond the scope of statistics.
- Understand that statistics is both an engineering discipline as well as a pure science.

If applied statistics on business management is understood from an engineering approach, it can be used in relation to leadership, competitive advantages and business results. A generic definition of engineering is the practical application of scientific ideas and concepts, or the application of scientific and mathematical principles to practical ends for the benefit of the human kind ("Engineering", 2013). Then, according with Anderson-Cook et al (2012), Statistical Engineering is defined as how to best utilize the principles and techniques of the statistical science for the benefit of the human kind. From the operational perspective, it is the study of how to best integrate statistical concepts, methods and tools with information technology and other relevant sciences, in order to generate improved results.

This case of study does not focus on the advancement of fundamental statistical science, but rather how well-known statistical methods may provide practical benefits real world problems. This research is centred in studying the level of adoption and implementation of statistics tools by companies located at Barcelona, and to use those findings to assist them to improve their statistical capabilities. Two specifics objectives were defined for this present chapter:

- Assemble a set of 7 statistical tools, based on the Statistical Engineering approach for extracting relevant conclusions of data.
- Provide a documented case of study, which illustrates the relation between statistical thinking and statistical methods.

Now it is important to make clear the differences between statistical engineering and applied statistics. The definition of statistical engineering provided here represents a new way of approaching the statistical thinking and methods. According with Hoerl & Snee (2010), the main contribution of statistical engineering is the integration of theory and practice for the purpose of generating improved results. It needs to be based on solids theoretical foundations but at the same time, the obtained outputs must be meaningful through creating value to society. On the other hand, applied statistics is defined by Hoerl & Snee 2012 as the application of formal statistical methods to real problems. It is evident that the definition for applied statistics is narrower because it does not include the use of statistical thinking at strategic level, but is focused on the best utilization of the methods available.

Typically, applied statistics embraces the use of individual tools (e.g. histogram, regression, charts, etc) to solve *well-defined* technical problems. According with Hoerl & Snee (2010), the main challenge for applied statistics is to determine the most appropriate methods for a particular problem and data given, and then apply it. It is a fact that many of the real problems which managers face in the industry are more complex and don't fit well this structure (indeed, many of them are unstructured). In contrast, statistical engineering addresses complex problems, which could include political, social and technical challenges. There is not a single statistical method able to address the totality of the problem and therefore, a novel approach is to find a solution by "*doing engineering*", and using various statistical methods simultaneously. The assembling of methods to address complex problems is not limited to statistical tools, and methods from other disciplines should be integrated, when necessary. With the real case presented in further paragraphs the reader will obtain a deeper understanding behind statistical engineering core philosophy.

5.2. A case of study. Statistical Engineering applied to survey research.

5.2.1 General overview

We invited to 6,064 companies to participate in the study by sending to them a questionnaire composed of 21 items, of which 4 were categorical related with size, years in operation, activity and generic type of competitive advantages proposed by Porter (2008). The last 17 items were designed in a 5-level Likert scale and related about characteristics and practices on data analysis by using statistical methods. All the invited companies are located in Barcelona, Spain and the questionnaire was sent electronically.

5.2.2. Defining the scope for this Case of Study.

A flowchart was outlined in order to follow a logical order, which facilitate us the analysis under the statistical engineering approach. This case of study is composed by 5 steps and 7 statistical tools were applied (See figure 5.1).

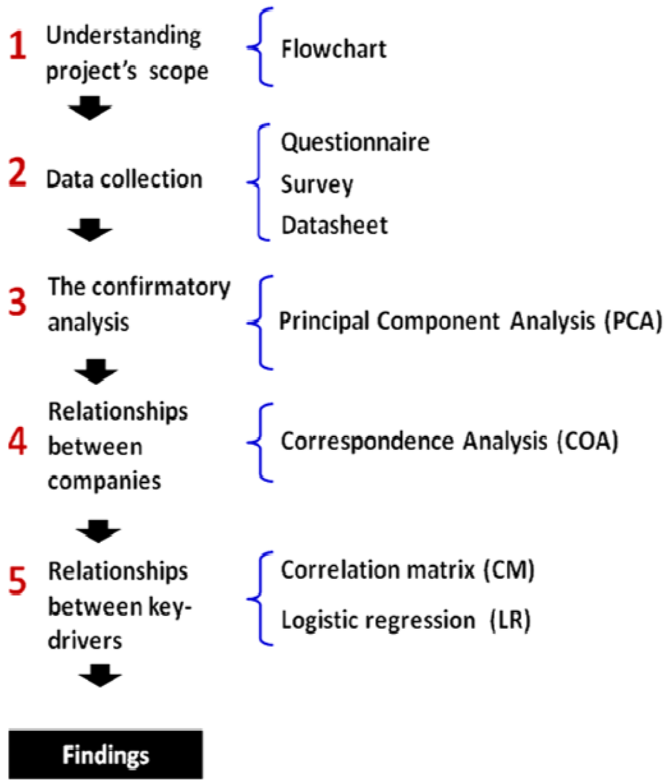

Figure 5.1. Logical progression for this statistical engineering case of study.

5.2.3. Data collection.

The questionnaire was addressed to the managing directors, quality managers or IT managers. We asked for it to be forwarded to the appropriate person, should it be required. We sent the questionnaire by email to 6,064 companies and we received 255 responses, which is a response rate of 4.2%. A total of 17 items were grouped in the four key drivers: data-based competitive advantage (DB-CA), management support for data analysis (MS-DA), systemic thinking (SYS) and communication outside the Company (COM-OUT). In addition Companies were asked for four features: size with four levels, years in operation with 12 levels, activity as dichotomous either "*products*" or "*services*", and generic type of competitive advantage with four values. In the appendix A the final questionnaire can be found. Its structure is shown in table 5.1.

Table 5.1. The structure of the questionnaire.

Section	Items
Company size.	1
Activity.	1
Age of the company.	1
Type of Competitive Advantage	1
Management support in data analysis (MS-DA).	6
Data Based Competitive advantage. (DB-CA).	5
Systemic Thinking (SYS).	5
Communication Outside the company (COM-OUT).	1

The structure in the questionnaire and responses provided by companies allowed us to create a dataset of order *Q*=255 x *J*=22, where *Q* is the number of rows while *J* are the columns (See figure 5.2).

	Date	Size	sector	Advantage VC1	Reinforcement on data usage SYS5	Competitor's Investigation MS_DA6	Product Improvement DB_CA2	Statistics Support DB_CA3	Statistics Importance DB_CA4	Statistics Encouragement DB_CA5	Statics Trainin MS_D
1	03/08/2011	4 Big(201 or more)	services	2 Better or different	2	4	4	4	5	4	4
2	03/07/2011	1 Micro(1 to 10)	services	2 Better or different	4	4	2	3	3	4	1
3	03/04/2011	3 Middle(51 to 200)	services	3 Market niche	1	4	5	4	5	5	4
4	03/04/2011	2 Small(11 to 50)	services	2 Better or different	.	.	4	1	3	3	5
5	03/04/2011	4 Big(201 or more)	services	3 Market niche	3	4	2	2	3	2	2
6	03/04/2011	2 Small(11 to 50)	services	3 Market niche	3	5	4	4	5	4	4
7	03/03/2011	1 Micro(1 to 10)	products	3 Market niche	4	3	4	3	4	2	2
8	03/03/2011	2 Small(11 to 50)	services	5 None	4	2	2	2	2	1	1
9	03/03/2011	2 Small(11 to 50)	services	3 Market niche	2	3	2	4	2	2	1
10	03/03/2011	2 Small(11 to 50)	products	2 Better or different	5	5	1	1	1	1	1
11	03/03/2011	1 Micro(1 to 10)	products	2 Better or different	2	4	3	4	4	4	2
12	03/03/2011	4 Big(201 or more)	services	2 Better or different	4	4	2	2	2	2	2
13	03/03/2011	3 Middle(51 to 200)	services	5 None	2	.	4	4	4	3	4
14	03/03/2011	3 Middle(51 to 200)	products	2 Better or different	4	4	2	2	2	2	2
15	03/03/2011	2 Small(11 to 50)	services	2 Better or different	.	.	2	1	2	2	2
⋮		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	
242	04/30/2011	4 Big(201 or more)	services	5 None	.	.	.	.	.	.	.
243	04/30/2011	3 Middle(51 to 200)	services	2 Better or different	4	3	3	3	4	3	1
244	04/29/2011	4 Big(201 or more)	services	5 None	.	.	.	.	.	.	.
245	04/29/2011	4 Big(201 or more)	services	4 privileged location	3	3	2	5	4	2	1
246	04/28/2011	3 Middle(51 to 200)	services	3 Market niche	3	4	2	2	3	2	2
247	04/28/2011	1 Micro(1 to 10)	services	5 None	.	.	.	.	.	.	.
248	04/28/2011	3 Middle(51 to 200)	services	2 Better or different	1	5	5	5	5	5	5
249	04/27/2011	1 Micro(1 to 10)	services	2 Better or different	2	4	4	4	5	4	5
250	04/18/2011	2 Small(11 to 50)	services	5 None	1	2	3	2	5	2	5
251	04/17/2011	4 Big(201 or more)	services	5 None	.	.	.	.	.	.	.
252	04/06/2011	1 Micro(1 to 10)	services	5 None	4	.	3	3	4	3	3
253	05/31/2011	1 Micro(1 to 10)	services	1 Lower cost	4	2	2	3	3	3	2
254	04/27/2011	4 Big(201 or more)	services	5 None	.	.	.	.	.	.	.
255	07/08/2011	2 Small(11 to 50)	services	2 Better or different	3	2	5	5	4	4	4

Figure 5.2 A fragment of the dataset**.**

5.2.4. The confirmatory analysis.

As the reader will notice, in subsection 4.3.7 were discussed some of the most relevant purposes for carrying out a confirmatory analysis. The principal component analysis, which is the statistical technique used to perform this kind of analysis, was introduced in conjunction with its related statistical tests. Moreover, considering this a statistical engineering case of study, this section is more focused on the practical aspects of the statistics rather than its definitions. In this way, the results (obtained with the statistical techniques introduced in the last chapter) are presented and interpreted along this section.

The Kaiser-Myer-Olkin (KMO) index and Bartlett's Test of Sphericity were calculated prior the principal components analysis. The purpose was to assess the suitability of our dataset to this analysis. According with Hair, et al (2006), a KMO bellow 0.50 is unacceptable and the overall KMO should be greater than 0.80 in order to ascertain its suitability. The overall KMO was equal to 0.926 which indicates that our data is appropriate for the PCA. Besides, the Bartlett´s test of Sphericity uses a Chi-Square distribution to test the Prob>X^2 for H_0: There are not common factors in the sample and four factors are sufficient to explain the correlations. The Bartlett's Test of Sphericity had a p-value lower than 0.001, which indicates the absence of common factors, and four factors are sufficient to explain its correlations. The variance explained for the first 4 factors was equal to 0.709. According with Krzanowski (2000) this value is acceptable to perform the PCA while retaining four factors.

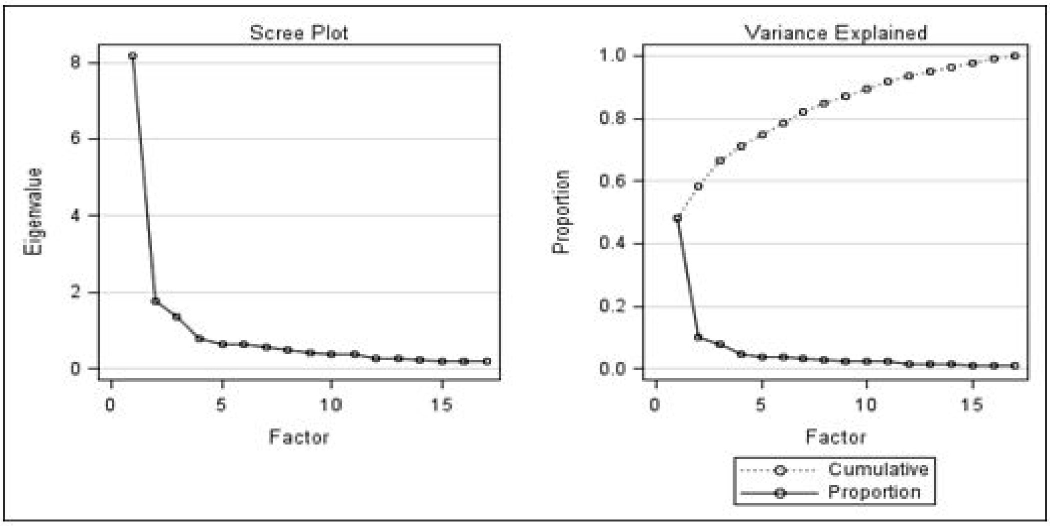

Figure 5.3. The Eigenvalues and variance explained in each factor**.**

We grouped our 17 items in the four retained factors by using the observed loading of each item in the factors. The criterion applied was: The bigger the loading of one item, the better it fits with that particular factor. The first factor grouped five items related with the data-base competitive advantage (DB-CA). In the second cluster, six items were related with the management support on data a analysis (MS-DA). In Factor 3, five items associated with systemic thinking (SYS) were grouped, while in Factor 4 a unique item was clustered with communication outside the company (COM- OUT) (See table 5.2).

The clustering of the 17 items into the four factors, by using the loadings values as classification criteria confirms the theoretical model which was widely discussed in chapters 2 and 3. This analysis demonstrates that PCA is a helpful statistical tool to establish quantitative link between the theoretical model of the research and the data collected from the real world. The PCA described in this subsection represents the step three of the flowchart shown in figure 5.3. In further paragraphs are discussed the application of three additional statistical tools.

Table 5.2. Rotated Factor Pattern for the Questionnaire items.

Questionnaire ITEM	Factor1	Factor2	Factor3	Factor4
Understanding benetifs DB_CA1	0.757			
Product Improvement DB_CA2	0.756			
Statistics Support DB_CA3	0.831			
Statistics Importance DB_CA4	0.806			
Statistics Encouragement DB_CA5	0.659			
Staticstics Training MS_DA1		0.826		
New knowledge implementation MS_DA2		0.723		
Data collection process MS_DA3		0.527		
Budget for projects MS_DA4		0.837		
Technological resources MS_DA5		0.622		
Competitor's Investigation MS_DA6		0.561		
Efforts recognition SYS1			0.595	
Mission understanding SYS2			0.693	
Communication openness SYS3			0.571	
Teamwork culture SYS4			0.764	
Reinforcement on data usage SYS5			0.534	
Communication suppliers/customers COM_OUT				0.852

5.2.5. Relationship between companies

In this section, the correspondence analysis is applied to our data in order to find similarities and differences between companies. According with Greenacre & Hastie (1987) an important feature of this statistical method is its capacity of picturing the generated contingency tables in order to find "*visual*" associations between variables. The main idea is taking advantages of these graphical features of the COA to reach novel conclusions about the level of adoption of statistical tools.

At first, the categorical variables were coded into a matrix, which allowed us to handle them easily. If we have Q categorical variables, our dataset is of the form $Z(I \ x \ J)=[Z_1 \ldots Z_Q]$. The qth variable has J_q categories and, therefore, Z_Q is also $I \ x \ J_q$ and $J = \sum_{q=1}^{Q} J_q$ is the total number of categories. With this number of categories, there are $J_1 \times \ldots \times J_q$ types of combinations possible.

The 255 companies were classified according to size, sector, type of competitive advantage and level in the scale, which means Q=4 the number of categorical variables and J=15 the total number of categories. The matrix is of order 255 x 15. For any configuration of column points representing the 15 categories, each company (row) point lies at the average position of its respective category points which characterize its response vector. The figure 5.4 is the representation for the correspondence analysis. The axes were formed by selecting the factors with the highest contribution to the inertia: F1=45.49% and F2=10.78% .Each little blue dot represents one surveyed company, the red rhombus represent the company size, the activity is a dichotomy variable represented with purple circles, the type of competitive advantage is represented with blue squares and finally the level of adoption in statistical tools is symbolized with green triangles.

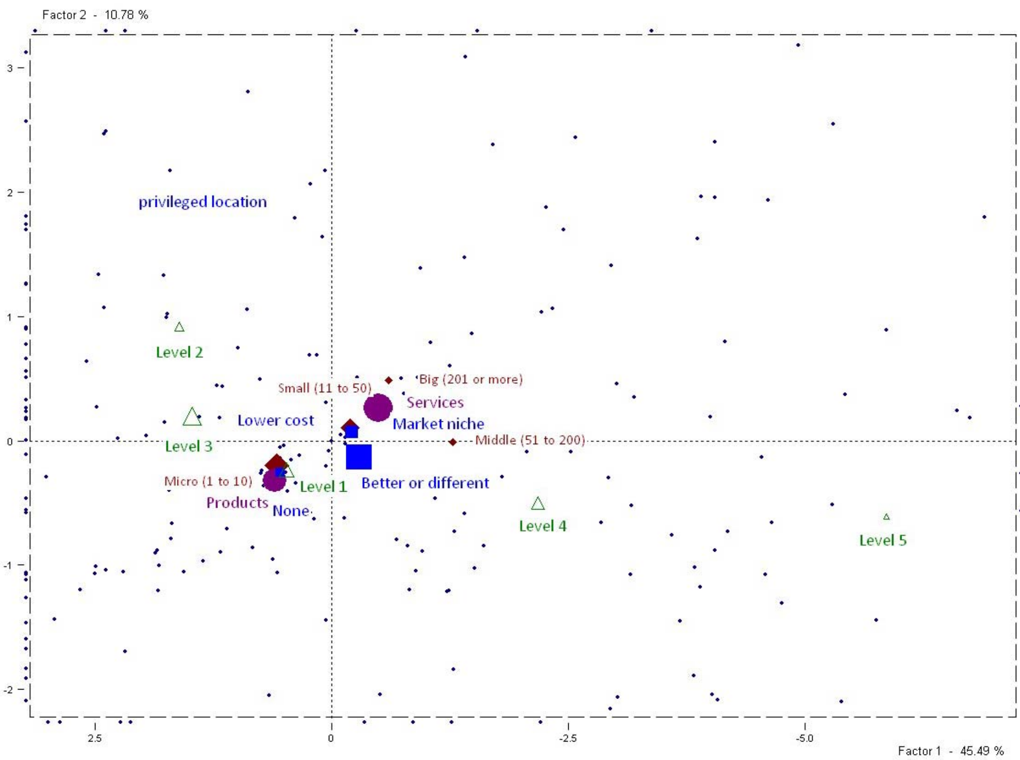

Figure 5.4. The correspondence analysis for the categorical variables: company size, activity, level in the scale and type of competitive advantage.

This correspondence analysis reveals a relationship between four categories: companies at level 1 in the scale tent to be also micro size, they offer products and they don't have any competitive advantage. In other words, it seems to be a relationship of the lowest level of the scale and not having any competitive advantage identified. In the same way, micro-size companies are apparently at lowest levels of adoption of statistical tools. This is also valid for all production-companies. Besides, medium sized companies were closer to the highest levels at the scale. In fact, these companies were closest to levels 4 and 5, the highest on the scale. This reveals that medium sized companies are the most analytical oriented. In addition, some features for the medium sized companies are: they are more oriented towards services than products; they have the "*better or different*" and "*market niche*" strategies as the most related types of competitive advantages.

Another correspondence was identified between level 3 of the scale, small-size companies and "*lower cost*" strategy. This means that small companies have statistical aspirations and are willing to develop their analytical capabilities, this type of companies also adopt "*lower cost*" strategy to reach competitive advantages. Moreover, the strategy of "*privileged location*" was closer with level 2 at the scale and small companies were identified closer to this level.

In short, the correspondence analysis allowed us to identify relationships between categorical variables, which at first instance would be more difficult to reveal by only using descriptive statistics. We call the graph obtained with this analysis the "*picture of the forest*" because it gives us the big picture of analytical context. The figure 5.4 shows this *big-picture* of the analytical practice in Barcelona.

5.2.6. Relationship between Key Drivers

In the last section we introduced the *big-picture* of our data ("*the picture of the forest*") by performing a correspondence analysis. Now it is necessary to take "*the picture of the tree*" which allow to us to get better understanding of the key drivers. Namely, the purpose in this section is to understand how the adoption of statistical tools takes place inside the company by studying deeper our four key drivers. This means that both perspectives (pictures of forest and tree) are complementary. Two additional statistical tools are introduced in this section: correlation matrix and logistic regression.

Pearson Correlation Coefficients				
	DBCA	MSDA	SYS	COMOUT
DBCA. Data Based Competitive Advantage	1.000	**0.70243**	0.69484	0.05246
MSDA. Management support data analysis		1.000	**0.64852**	-0.03397
SYS. Systematic Thinking			1.000	**0.30036**
COMOUT. Communication Outside Company				1.000

Figure 5.5. The Pearson Correlation Coefficients of the key drivers**.**

Figure 5.5 displays the Pearson correlations coefficients (PCC) for the four key drivers. Note that these correlations were calculated as groups of averages of the 17 items of the questionnaire. Regarding with the results, it was found the strongest correlation between DB-CA and MS-DA, with r equal to 0.702. Similarly, the second strongest correlation was between DB-CA and SYS, r=0.695. Note that SYS is correlated simultaneously with two key drivers and these two correlations have almost the same value. The third most important correlation was found between MS-DA and SYS, r=0.648. The correlation between SYS and COM-OUT had a lower value, r=0.300. The COM-OUT is slightly correlated with DB-CA and MS-DA, with r=0.0526 and r=-0.0339 and they are the lowest correlations identified. (See figure 5.6)

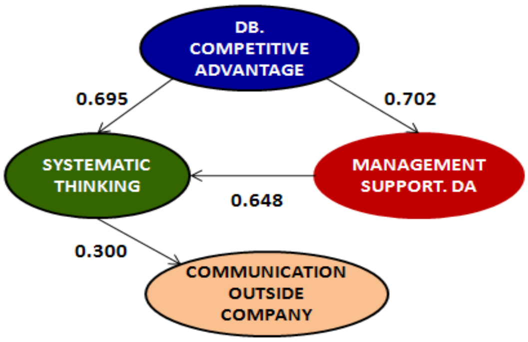

Figure 5.6. Visual output for the indentified correlation in the four key drivers**.**

In further lines results obtained with the logistic regression are described. The logistic regression is the last statistical tool used in this statistical engineering case of study. According Philip and Teachman (1998), the logistic regression extends the technique of multiple regression analysis to situations in which it is necessary to analyse categorical variables. This is suitable for our objective because we pretend to identify how the key drivers impact on the expansion of the adoption of analytical tools. Moreover, the logistic regression can be performed in different ways. For example, if all the variables are categorical the weighted-last-squares or maximum-likelihood, algorithms should be applied. In contrast, when the data contain continuous-level predictor variables, the maximum-likelihood procedure must be used. Specifically for this analysis, four ordinal variables were defined as predictors; all of them based on a Likert scale value with a range between 1 and 5, given this the maximum-likelihood algorithm, properly described in Philip and Teachman (1998) it was found suitable for this model. (See formula 5.1 for the logistic regression model)

$$Ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_i G_1 + \beta_j G_2 + \beta_k G_3 + \beta_l G_4 + \varepsilon_{ijkl} \qquad (5.1)$$

The first variable referred to whether managers and decision makers at companies were able to understand the benefits of data analysis and exploitation through statistical methods (coded as DB-CA1). The second predictor considered whether the managers at companies consider that ASBM helps to build competitive advantages (DB-CA3). The third one referred to whether there is a mission statement at the company and if so, was it known by the staff (SYS2) The last predictor is whether or not communication outside the company was considered a strategic issue (COM-OUT). We wanted to know whether companies in the Barcelona area have analytical aspirations. A definition for a company having analytical aspirations is the fact that it is ranked at levels 4 or 5 in our scale. In contrast, if a company does not have analytical aspirations, it is ranked at level 1, 2 or 3 (See table 5.3).

Table 5.3. Definitions for the Logistic Regression Analysis

Response variable definition.	Outcom e.	Number of companies	%
No analytical aspirations. (Level 1, 2 and 3 of the scale)	Y=0	186	73%
Analytical Aspirations (Level 4 and 5)	Y=0	69	27%
Total surveyed companies		255	100%

According with definitions shown in table 5.3, if a company has analytical aspirations the response variable is equals to 1 (Levels 4 and 5 of the scale). Otherwise, it is equal to 0 (for levels 1, 2 and 3 of the scale).

The logistic regression analysis was performed simultaneously with a *goodness-of-fit* in order to verify that our model fits adequately our data. The methodology proposed by Philip and Teachman (1998) was followed with a Chi-Square hypothesis to test H_o: The model fits well to the data versus H_1: The model does not fit adequately. We fail to reject with a p-value of 0.730, and there is not enough evidence to ascertain that the model does not fit our data adequately (See table 5.4).

Table 5.4. The goodness-of-fit test results for logistic regression**.**

```
Goodness-of-Fit Tests
Method     Chi-Square  DF      P
Pearson       6.95295  10  0.730
Deviance      7.88622  10  0.640
```

On the other hand, in table 5.5 are shown the coefficients of the logistic model. The four predictors previously defined in equation 5.1 are considered significant. Given this, four features have strategic importance in building analytical aspirations at companies: first, when managers understand the benefits of data analysis and exploitation, second the support and promotion given by the top management to all initiatives is focused on improving decision making based on data analysis, third when there is a mission statement well known by all the staff and fourth when the company is in constant communication with actors outside. The positive coefficients in the logistic regression model make clear this effect, these factors are significant for the expanding the analytic skills in companies of Barcelona. This fact was verified with results of obtained in subsection 5.2.4. Note that predictors DB-CA2, SYS2 and COM-OUT of the table 5.5 appear in different factors (or axes) on the PCA of table 5.2. This allows us to ascertain that there is not multicollinearity among them.

Table 5.5. The Logistic Regression Table

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-17.8045	3.13596	-5.68	0.000			
DB_CA1	1.65439	0.313537	5.28	0.000	5.23	2.83	9.67
DB_CA3	0.723906	0.271505	2.67	0.008	2.06	1.21	3.51
SYS2	1.12321	0.273354	4.11	0.000	3.07	1.80	5.25
COM_OUT	1.54055	0.382019	4.03	0.000	4.67	2.21	9.87

Log-Likelihood = -40.857

5.3. Conclusions.

As it is shown in this case of study, there are situations in which applied statistics it not sufficient to address complex and unstructured problems. It is clear that more systemic approaches, based on both: statistical thinking and methods, are required in order to reach improved results. Indeed, the majority of the problems in the industry don't fit well a single statistical method due to the complexity and therefore a set of methods should be integrated. The core philosophy behind statistical engineering is to establish a link between statistical thinking and methods. The first contributes to draft an integral approach (while assembling several methods and tools) while the second is focused to properly apply the available statistical methods and tools. Moreover, statistical engineering is not limited to the use of statistical tools, its scope include the integration of different tools (either statistical or not) into a system in order to achieve solutions which add value to the stakeholders. For instance, in this case of study the logistic regression allowed us to know the importance of a strong communication of actors outside of the company as source of competitive advantage based on data analysis. Later this fact was ascertained with results obtained in the correspondence analysis and the correlation matrix. This integration of methods around common objectives is the statistical engineering. Basically this set of several statistical methods creates a system that is more than the sum of the parts. Finally this system must add value to the stakeholders.

There are cases of application of the statistical engineering in meteorology, automobile industry, manufacturing and quality improvement, among others. All these cases (included the one discussed in this chapter) are transactional and focused into a unique objective through of the integration of several method and tools. Recently, the work of Roger Hoerl and Ron Snee has attracted the attention from practitioners, managers and academics. Now, it seems that the topic is beginning to move to a successful transition between statistical thinking and the use of statistical methods. A dynamic and strong interaction between statistical thinking and statistical methods and tools is the main idea of statistical engineering.

6. An Evidential Reasoning case of study.

This chapter illustrates how the Evidential Reasoning approach is applied to rank companies in the five-level scale. Based on the performed calculations, at the end of this chapter relevant conclusions about the key drivers for the adoption of analytical tools in companies are provided

6.1. Introduction

In this chapter the data provided by companies is analysed by the Evidential Reasoning (ER) approach in order to obtain relevant information about key drivers for expanding analytical capabilities. The application of this scale in combination with the use of the ER approach to measure analytical capabilities represent an original contribution in the field of business analytics.

Before continuing, it is necessary to review a definition of analytical tool. An Analytical Tool is defined as any mathematical, statistical or quantitative method combined with information technology, which is applied to extract relevant information from data in order to make decisions based on quantitative evidence. The purpose of using analytic tools in business management is to assist stakeholders to make better informed decisions, or to automate and optimize the process. According with Davenport& Harris (2010), there are 19 analytical tools which are most widely used in business management (See table 6.1).

Table 6.1. The most commonly used analytical tools in business**.**

1	Data collection	11	Future value analysis.
2	Stratified Analysis	12	Six Sigma
3	Histograms	13	Constraints analysis
4	Pareto´s charts	14	Price optimization
5	Cause and effect diagram (Ishikawa)	15	Monte Carlo simulation
6	Dispersion chart	16	Textual analysis strategies
7	Regression analysis	17	Reliability and survival analysis
8	Statistical Process Control	18	Principal Components Analysis
9	Design of Experiments	19	Bayesian methods
10	Time series analysis		

Although most large organizations have some sort of analytical applications in place and several business intelligence systems running, it is clear that each company adopts different analytical tools according to its size and requirements. This means that the level of adoption of analytic tools (LAAT) may vary according to size or activity. LAAT is important to improve the decision making process and therefore competitive advantages. The higher the LAAT is, the more accurate the decision making can be.

Given the above background, the main purpose in this chapter is to identify the factors and features which have positive impact on increasing the adoption of analytical tools for decision making. Three specific objectives were defined:

- Introduce a five level scale to measure LAAT in a sample of 255 companies located in Barcelona, Spain.
- Apply the Evidential Reasoning algorithm to extract relevant conclusions about which attributes clearly contribute to the expansion of LAAT and therefore to reach competitive advantages.
- Rank companies in the previously introduced scale and identify key features that have positive impact on the level of adoption of analytical tools in companies.

In the next section the Evidential Reasoning (ER) approach is briefly discussed. In section 2 the methodology applied for this case of study is presented. The results are discussed in section 3 and finally the conclusions are provided in last section.

6.2. The Evidential Reasoning approach.

The evidential reasoning approach is a generic "*evidence-based*" type of multi criteria decision analysis (MCDA). Basically it is used for dealing with problems which are composed of both quantitative and qualitative information. It is applied to support several decision making problems, assess and evaluate alternatives such as business activities, environmental impact, quality models, among others.

Considering that the evidential reasoning is of part of the MCDA family Xu & Yang (2001) state that in the last 30 years other types of these methods have emerged, as the Multi Attribute Utility Theory (MAUT) and the Analytical Hierarchy Process (AHP) proposed by Saaty (1986). Traditional MCDA problems are modelled using a decision matrix, in which each alternative is measured by a single value on an attribute. In contrast to traditional methods, the evidential reasoning approach describes a MCDA problem by using a belief decision matrix. Moreover in Yang & Singh (1994) is stated that the evidential reasoning approach is different from conventional MCDA methods in that it uses *evidence-based* reasoning process to reach a decision. One of the most important contributions of this method is its capacity to describe a scenario by using a belief structure or a belief decision matrix, on where each alternative is assessed by a vector of paired elements. The paired elements are attribute values (for example, values for 17 attributes in the LAAT expansion) and their associated degree of belief. Moreover the belief matrix allows us to generate a more informed model, and decision makers are no obliged to aggregate their decision information into a unique value.

The Dempster-Shafer theory proposed by Dempster (1967) & Shafer (1976) is a generalization of the Bayesian theory of subjective probability. What it was a contribution in Dempster-Shafer theory is the inclusion of belief functions. Whereas the Bayesian theory requires probabilities for each question of interest, belief functions allow us to base degrees of belief for one question. These degrees of belief might or might not have the mathematical properties of probabilities.

Besides Dempster-Shafer theory is based in two main concepts: the idea of obtaining degrees of belief for one question from subjective probabilities for a related question, and Dempster's rule for combining such degrees of belief when they are based on independent items of evidence. According with Xu & Yang (2002) these facts are relevant because its inclusion into the ER framework allows the distributive information contained in a belief decision matrix to be aggregated to produce consistent and rational results. Yang & Singh (1994) and Yang & Sen (1994) also state that the Dempster-Shafer theory is a suitable tool to cope with belief decisions matrix because it has demonstrated to provide a powerful evidence combination rule and reasonable requirements to apply rule. Moreover, Yang (2001) proposes a rule and utility based information techniques which allow for the transformation of various sets of evaluations into a unique set, and consequently both types of criteria, quantitative and qualitative, can be assessed in a consistent and compatible way by the incorporation of these techniques to the ER framework. In Yang & Xu (2002) it is discussed an important feature of the ER related with its non-linearity. Basically the ER approach uses a non-linear process to aggregate attributes. The non linearity is given by the weights of criteria, and the mode each criterion is assessed. This is an ER´s characteristic that is not available in traditional MCDA methods.

Based on what was stated in Yang & Singh (1994), the ER has proved to be a consistent and reliable MCDA method, because it is able to deal with problems which are not possible to be solved by using the traditional methods. Consider the following situations.

- Large number of attributes in a hierarchy.
- Large number of alternatives
- Uncertainties.
- Mixture of Quantitative and Qualitative information.
- Incomplete or missing information.

In order to provide a deeper explanation of how the ER approach works, consider the following case. We want to evaluate the level of adoption of analytical tools by companies in Barcelona, Spain, and H=5 grades are defined as follows:

$$H = \{ H_1 , H_2 , H_3 , H_4 , H_5 \}.$$

$$= \{ \text{Worst, Poor, Average, Good, Best} \}.$$

In addition, there are K alternatives defined, O_j $(j=1,\ldots,K)$ and then let M be the number of attributes, A_i $(j=1,\ldots,M)$. If we use 5 evaluation grades, the assessment of an attribute A_1 on the alternative O_1 is denoted by $S(A_1(O_1))$. The belief structure has the following expression. In the next section is provided a numerical example.

$$S(A_1(O_1)) = \{(\beta_{1,1}, H_1), (\beta_{2,1}, H_2), (\beta_{3,1}, H_3), (\beta_{4,1}, H_4), (\beta_{5,1}, H_5)\} \qquad (6.1)$$

where $0 \leq \beta_{n,1} \leq 1$ (n=1,...,5) denotes the degree of belief that the attribute A_1 is assessed to the evaluation grade H_n. $S(A_1(O_1))$ reads that the attribute A_1 is assessed to the grade H_n to a degree of $\beta_{n,1}\times100\%$ (n=1,...,5) for the alternative O_1

It is inaccurate to have $\sum_{n=1}^{5}\beta_{n,1} > 1$. Moreover, $S(A_1(O_1))$ is considered as a complete distributed assessment if $\sum_{n=1}^{5}\beta_{n,1} = 1$ and incomplete if $\sum_{n=1}^{5}\beta_{n,1} < 1$. According with Yang (2001) in the ER framework both complete and incomplete assessments can be processed.

As it was discussed in the last section, instead of aggregating average scores the ER approach applies the utility based theory and Dempster-Shafer theory to aggregate belief degrees. This means that instead of aggregating a single average value for each attribute, the ER approach allows us to aggregate belief structures, which produce more informative results. This feature was relevant when we analyzed the averages of each 17 attributes for the LAAT expansion.

In order to illustrate how the ER approach aggregates assessments, consider ω_i as the relative weight of the attribute A_i and it is normalized, so that $0 \leq \omega_i \leq 1$ and $\sum_{i=1}^{L}\omega_1 = 1$ if weights information is complete or $\sum_{i=1}^{L}\omega_1 < 1$ for incomplete information. In addition L is the total number of attributes.

Suppose the first assessment is given in the equation (6.1) and the second assessment is given by the following expression.

$$S(A_2(O_1)) = \{(\beta_{1,2}, H_1), (\beta_{2,2}, H_2), (\beta_{3,2}, H_3), (\beta_{4,2}, H_4), (\beta_{5,2}, H_5)\} \tag{6.2}$$

The challenge is to aggregate these two assessments $S(A_1(O_1))$ and $S(A_2(O_1))$. The output is a combined assessment $S(A_1(O_1)) \oplus S(A_2(O_1))$. We consider that $S(A_1(O_1))$ and $S(A_2(O_1))$ are both complete. This means that there is not missing data in the assessments given by the experts. On the other hand the mass probability is given by the product of the belief of degree (β) and its weight (ω). It is denoted for $m_{n,j}$ and defined in the following expression.

$$m_{n,1} = \omega_1\beta_{n,1} \quad (n=1,...,5) \qquad \text{and} \qquad m_{H,1} = 1 - \omega_1\sum_{n=1}^{5}\beta_{n,1} = 1 - \omega_1$$

$$m_{n,2} = \omega_2\beta_{n,2} \quad (n=1,...,5) \qquad \text{and} \qquad m_{H,2} = 1 - \omega_2\sum_{n=1}^{5}\beta_{n,2} = 1 - \omega_2$$

where each $m_{n,j}$ (j=1,2) is referred to as the basic probability mass and each $m_{H,j}$ (j=1,2) is the remaining belief for attribute j unassigned to any H_n (n=1,...,5). By applying the ER algorithm, the basic probability masses are aggregated in order to generate a combined probability masses, as defined in the following expressions:

$$m_n = k\left(m_{n,1}m_{n,2} + m_{H,1}m_{n,2} + m_{n,1}m_{h,2}\right), \quad (n=1,...,5)$$

$$m_H = k\left(m_{H,1}m_{H,2}\right),$$

where

$$k = \left[1 - \sum_{t=1}^{5}\sum_{n=1}^{5} m_{t,1}\, m_{n,2}\right]^{-1} \tag{6.3}$$

Altough this explanation covers the case for only two asssesments, the algorithm can be repeated in the same manner until three or more assessments are aggregated. The obtained β_n (n=1,...,5), which represents the combined degree of belief, is given by the following expression.

$$\beta_n = \frac{m_n}{1-m_H} \qquad (\mathrm{n} = 1,\ldots,5) \tag{6.4}$$

These final combined probability masses are independent of the order in which individual assessments are aggregated. On the other hand, the combined assesment for the alternative O_1 is given by the following expresion.

$$S\left((O_1)\right) = \{(\beta_1, H_1), (\beta_2, H_2), (\beta_3, H_3), (\beta_4, H_4), (\beta_5, H_5)\} \tag{6.5}$$

The last measurement that we introduce in this section is denoted by $u(O_1)$ and it is an average score for O_1. This average can represent the weighted average of the scores (or utilities) of the evaluation grades with the belief degrees as weights.

$$u(O_1) = \sum_{i=1}^{n} u(H_i)\beta_i \tag{6.6}$$

where $u(H_i)$ is the utility for the i-th evaluation grade H_i. In this particular case, if we assume an equal distance between each evaluation grade, and therefore equidistantly distributed in the utily space, our evaluations grades are given by:

$u(H_1)$:= u (*Analytic ignorance*) =0.00
$u(H_2)$:= u (*Local applications*) = 0.25
$u(H_3)$:= u (*Analytical aspirations*) =0.50
$u(H_4)$:= u (*Analytics as a systems*) = 0.75
$u(H_3)$:= u (*Analytics as competitive advantage*) = 1.00

Until here the ER approach for two assessments has been illustrated. The complexity in calculation increases when we add criteria or alternatives. In order to deal with this, Xu & Yang (2003) introduce the Intelligent Decision Software (IDS), which is a software tool based on the ER approach. It it is documented in Xu, Grace & Yang (2006) that IDS sofware has been applied to quality management, product selection, supplier assessments and policy consultation among others. (See http://www.e-ids.co.uk). The next section explains how the IDS based on ER approach is applied to our data analysis.

6.3. Methodology.

The methodology is described in the following subsections, from the data collection to the assignment of belief degrees.

6.3.1. Data collection.

A questionnaire was sent to 6,064 companies located in Barcelona, Spain and it was addressed to Senior Managers, Quality Managers or Information Technology Managers. We asked the questionnaire to be forward to a right person if necessary. The questionnaire was composed of 17 items in Likert scale plus 1 categorical variable related to the size of a company with 4 levels. The concepts proposed by Deming (2000), Harris, Craig & (2009), Jackson (1992), Poon & Wagner (2001) and in-depth interviews with managers, academic and consultants allowed us to cluster the 17 items into four groups: management support in data analysis (MS-DA), data based competitive advantage (DB-CA), systemic thinking (SYS) and communication outside the company (COM-OUT). In addition, with the purpose of making this classification more robust, in Barahona & Riba (2012) it was performed a confirmatory analysis.

A total of 255 companies provided us information about their use of analytical tools; it represents a response rate of 4.2%. The respondents rated each attribute (or item) in 5 different values {*Worst, Poor, Average, Good, Best*}, and there were four types of companies who participated {*micro, small, middle and big*}. We used this data to shape our model, which is defined in the next subsection. (In figure 6.2 it is shown a graphical representation of the model)

6.3.2. Model definition.

In order to be consistent with ER literature, we carried out changes in terminology. The questionnaire items were named *bottom attributes*, the questionnaire sections resulted in *parent attributes* and the categorical questions became the four *alternatives* to be assessed. Practically, the structure remains the same and it still has three hierarchical levels. The highest level represents the level of adoption of analytical tools, the middle levels are the parent attributes (or key drivers) and the bottom attributes (or items) are the lowest level. (See figure 6.1)

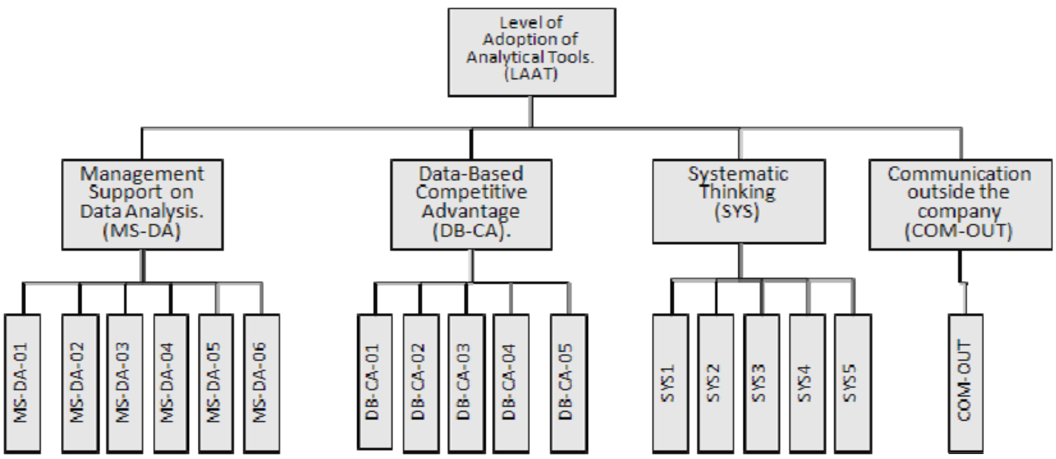

Figure 6.1. Attribute Hierarchy for the Level of Adoption of Analytical Tools

6.3.3 Relate father and bottom attributes.

Yang (2001) states that it is required to establish a quantitative relationship between parent and bottom attributes. In other words, define how the grades of the attributes are converted to the ones of their parents. In our case study, the overall performance for LAAT is given by its four attributes and assessed by 5 grades. For example the MS-DA is assessed by 5 values *{0, 0.25, 0.50, 0.75, 1.00},* the challenge is to relate the MS-DA with the overall performance of LAAT.

There are two ways to convert grades to its father ones. The first is based on rules and the other one on utilities. In this chapter, we are applying the rule based approach proposed in Yang (2001). An example is further shown in order to illustrate how the rules were built, but note that the rules for the 17 attributes were built similarly.

Table 6.2. Example of how to relate the MS-DA to its father attribute

If MSDA is ***worst =0.00***	Then Overall Performance is ***Analytical Ignorance=100%***
If MSDA is ***poor=0.25***	Then Overall Performance is ***Local Aspirations=100%***
If MSDA is ***average=0.50***	Then Overall Performance is ***Analytical aspirations=100%***
If MSDA is ***good=0.75***	Then Overall Performance is ***Analytics as System=100%***
If MSDA is ***excellent=1.00***	Then Overall Performance is ***Analytics as Comp. Advantage=100%***

Once the attributes are related by defining rules, the next task was to assign weight to each attribute.

6.3.4. Assigning weights

The weight of an attribute is its relative importance with respect to the rest of attributes. Thus, different features may have different importance. For example, the management support might be more important on data analysis than the technological infrastructure, and thereby the management support should have a larger weight in the model.

We adapted the methodology proposed by Xu, Grace & Yang (2006) for assigning the weights to the attributes (or items) of our model. At first we calculated the mean for each attribute by including all the responses from the questionnaire. As such, the higher the mean of an attribute was in the questionnaire, the larger weight this attribute was given in the model. A total of 17 means were obtained and the relative weight for each of them was calculated by using a normalized scale.

For the parent attribute *data based competitive advantage* the criterion DB-CA1 was the most important, which refers to whether managers understand the benefits of the analytic tools for extracting valuable information from data. For *management support on data analysis* the criterion MS-DA6 was the most important, which refers to whether the top management promotes the use of data to evaluate how the competitors are evolving. For *systemic thinking* the most important criterion was SYS4, which refers to whether there is a teamwork culture in the company. The *communication outside the company* is a unique criterion. The figures 6.2A to D show the standardized weight of each attribute.

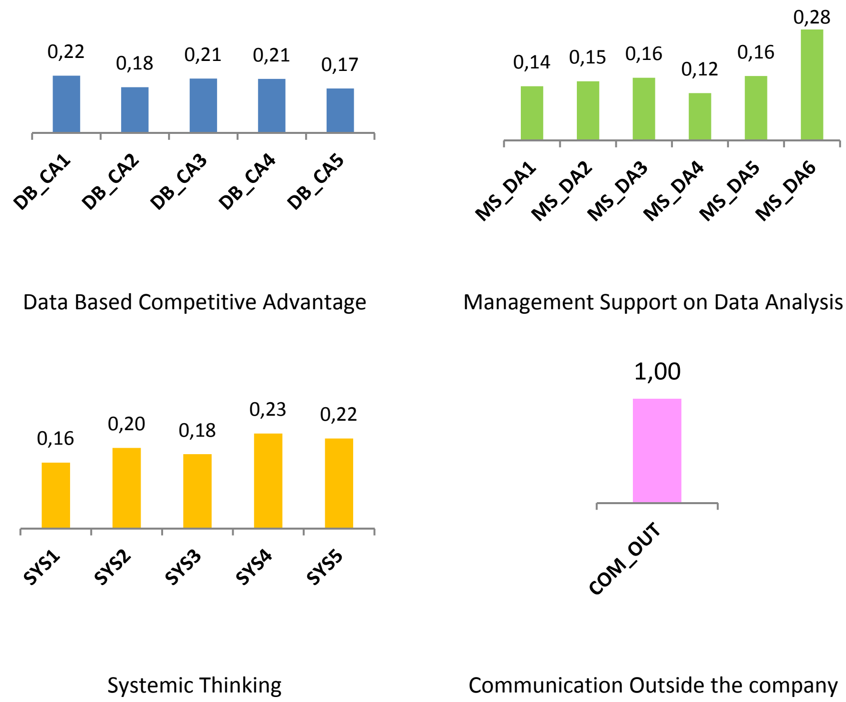

Figure 6.2A to D. Normalized weight for the bottom attributes (or items in the questionnaire)

6.3.5. Assigning belief degree.

According with Yang (2001) and Xu & Yang (2003) the degree of belief represents the extent to which an answer is believed to be true. In addition, the use of beliefs degrees allows for the freedom of assigning two or more different values to a single grade. Indeed, the IDS software preserves the belief information when the ER approach aggregates the entered data from lower questions to higher levels in a hierarchy. We defined the function $g: [1,5] \subset \mathbb{R} \rightarrow A \subset [0,1]^5$, which transforms the mean of each attribute into a vector of five components.

Given any $\bar{x} \in [1,5]$ the *th-i* component of g($\bar{x}$) is defined in the following way.

$$g(\bar{x})_i = \begin{cases} 0 & \text{if} \quad \lceil \bar{x} \rceil > i > \lfloor \bar{x} \rfloor \\ \bar{x} - \lfloor \bar{x} \rfloor & \text{if} \quad i = \lceil \bar{x} \rceil \\ \lceil \bar{x} \rceil - \bar{x} & \text{if} \quad i = \lfloor \bar{x} \rfloor \end{cases} \qquad (i=1\ldots5) \qquad (6.7)$$

For example, according with equation 6.7, a mean equal to $\bar{x}$=3.80 for the attribute SYS4, is assigned the following belief structure {("*Worst"* with 0.00 of belief degree), ("*Poor"* with 0.00 of belief degree), ("*Average"* with 0.20 of belief degree), ("*Good"* with 0.80 of belief degree), ("*Best*" with 0.00 of belief degree)}. In similar ways, belief degrees were assigned for the 16 remaining attributes.

By having the model defined, bottom and parent attributes related, the weights assigned (figure 6.2A to D) and the belief structure allocated (table 6.2), the model was ready to be used for simulation and the obtained results are discussed in the next section.

6.4. Results.

The results are presented in three parts. At first the overall performance for the four types of companies is analyzed. Secondly, the distributed assessment for each type of company is discussed; the last part of this section explains similarities and differences between attributes.

6.4.1 The overall performance

The four sizes of companies were assessed according to their level of adoption of analytical tools. Middle size companies happen to be more analytical than big ones although the difference among them is small. On the other hand, the less analytical oriented companies were the micro size ones. Small companies are in the third position (See Figure 6.3).

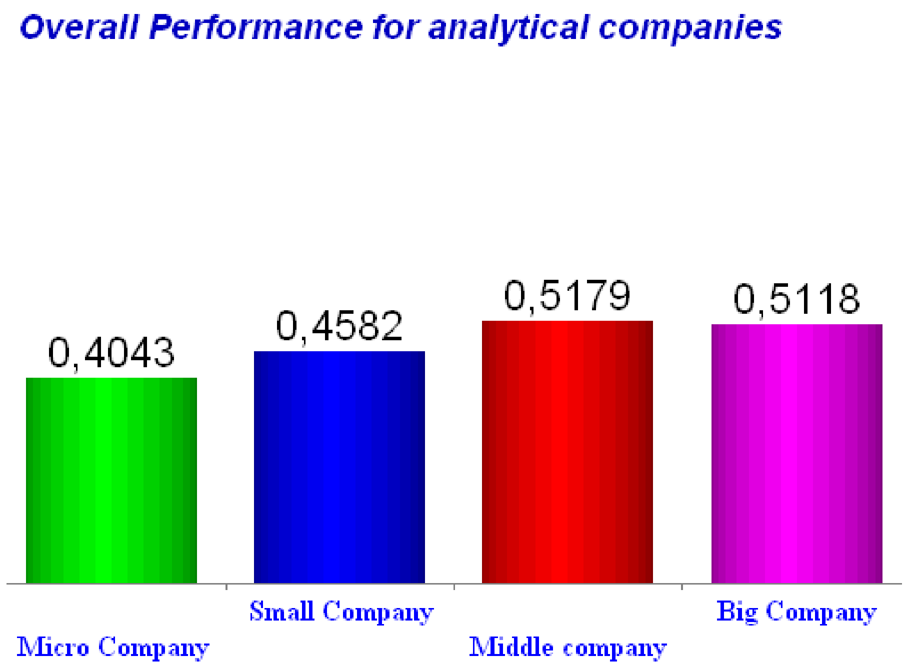

Figure 6.3. Overall assessment for the level of adoption of analytical tools by company size

6.4.2. Distributed assessments for alternatives.

The distributed assessment allows for the comparison among the studied alternatives. The comparison generates more insightful information about how the attributes impact on the alternatives. In figures 6.4A to 6.4D the distributed assessments for each size of company are presented.

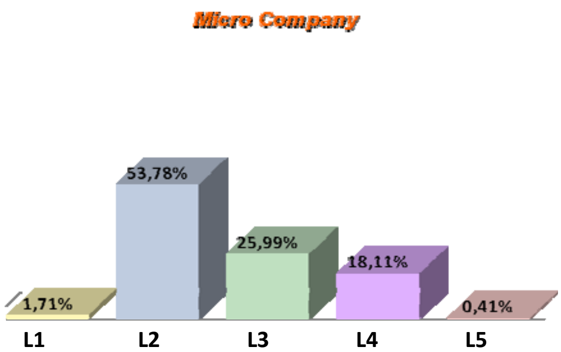

Figure 6.4A. Distributed assessment for micro

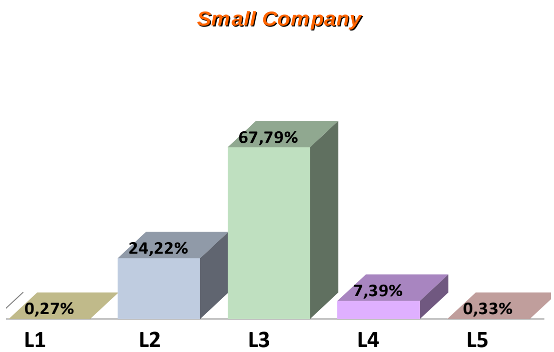

Figure 6.4B. Distributed assessment for small

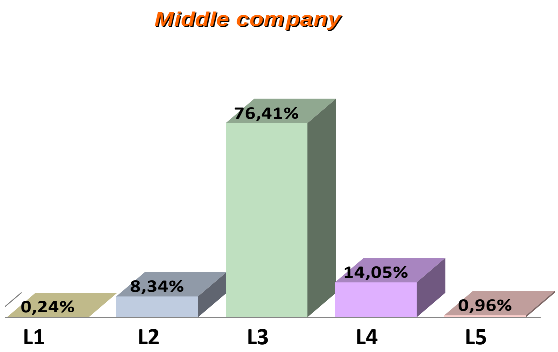

Figure 6.4C. Distributed assessment middle

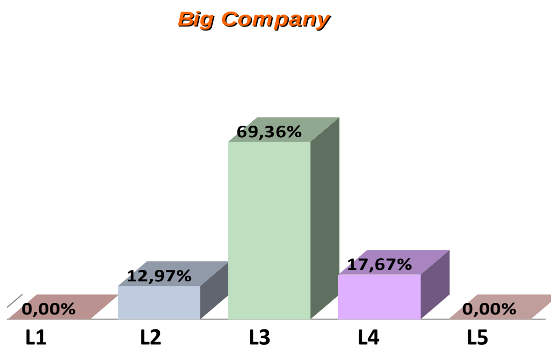

Figure 6.4D. Distributed assessment for big

The middle companies obtained the highest assessment on Level 5, "*Analytical tools as competitive advantage*". Similarly, this group has the largest number of companies in Level 3, "*Analytical aspirations*" (See figure 6.4C). Given this, we might consider the middle size companies in Barcelona area the most analytically oriented.

On the other hand, micro size companies are the less analytically oriented companies. That is due to two reasons. The biggest group on Level 1 "*Analytical Ignorance*" belongs to micro size companies (1.71%). In addition, the micro size group has also the biggest number of companies in Level 2 *"Local focus"* (See figures 6.4).

The majority of companies ranked on Level 1, "*Analytical Ignorance*" were micro size (1.71%). In addition, this group has the biggest number of companies in Level 2, "*Local focus*" (See figures 6.4).

6.4.3. Similarities and differences among attributes

At first, we found that micro companies are evaluated as "*poor*"=91% on its communication outside. On the other hand, big companies are evaluated as "*average*"=61.2% and "*good*"=38.8%. Given this, it might be a direct relationship between company size and communication with actors outside. The bigger a company is; the better the communication outside (See figures 6.5A to 6.5D).

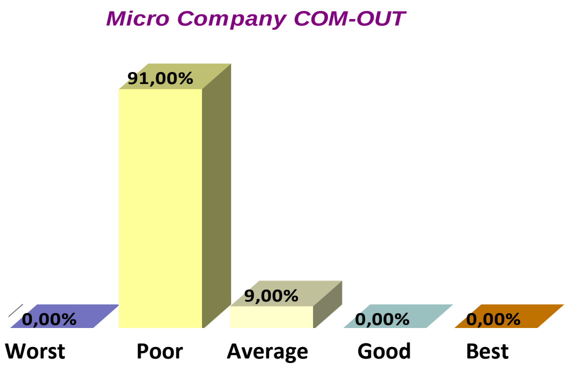

Figure 6.5A. COM-OUT assessment for micro

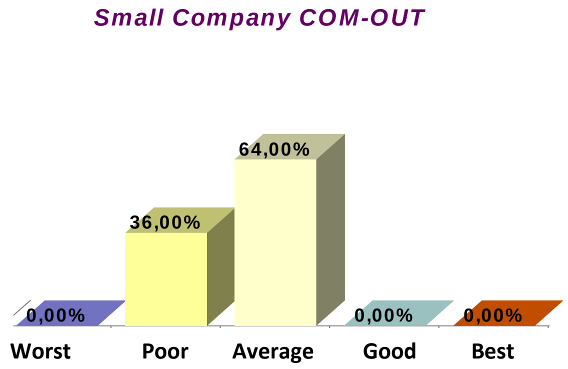

Figure 6.5B. COM-OUT assessment for small

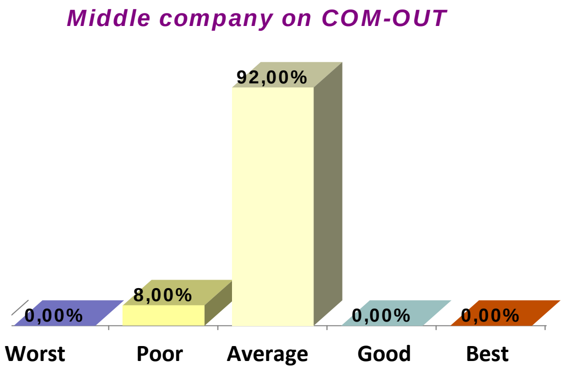

Figure 6.5C. COM-OUT assessment for middle

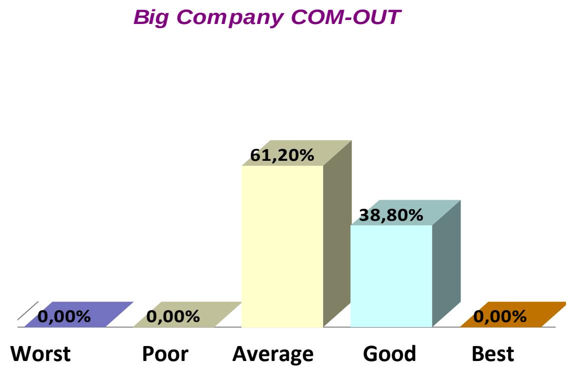

Figure 6.5D. COM-OUT assessment for big

Micro size companies are evaluated as "*poor*"=40.6% and "*average*"=43.9% on features related with the competitive advantages based on data analysis. In contrast, middle companies are evaluated as "*average*"=81.25% and "*good*"=17.4% on this attribute. Indeed middle companies got the highest assessment on this attribute, and considering this, we might think that middle companies have best practices related with high quality in data. (See figures 6.6A and 6.6D)

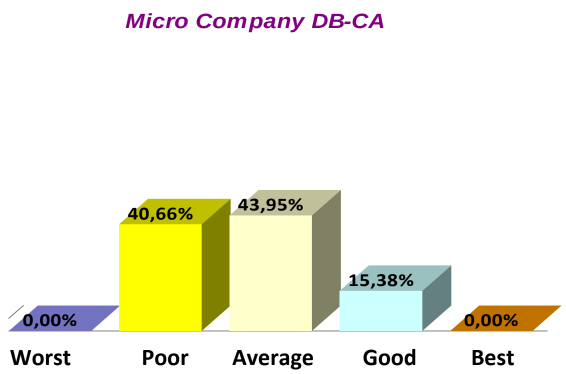

Figure 6.6A. DB-CA assessment for micro

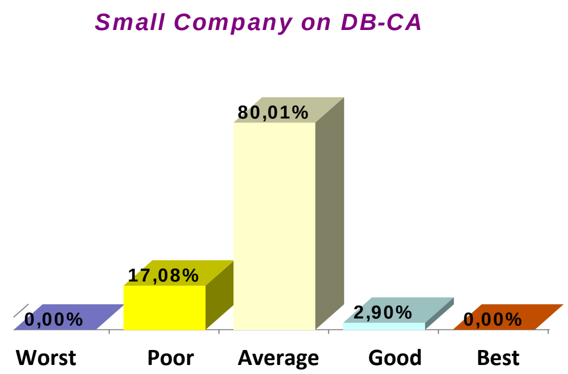

Figure 6.6B. DB-CA assessment for small

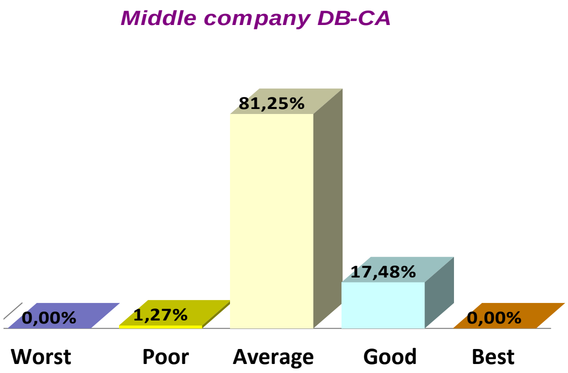

Figure 6.6C. DB-CA assessment for middle

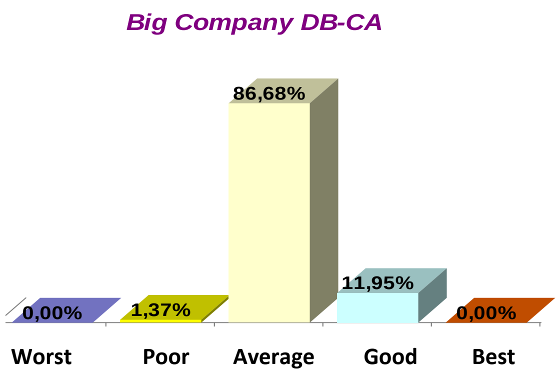

Figure 6.6D. DB-CA assessment for big

Middle companies are the most highly evaluated in systemic thinking, with the values of "*average*"=70.50% and "*good*"=25.2%. On the other hand, micro size companies are assessed as "*poor*"=18.5 % and "*average*"=46.4% on systemic thinking. Given this, the middle companies might be considered as the most systemic thinkers. (See 6.7A and 6.7D)

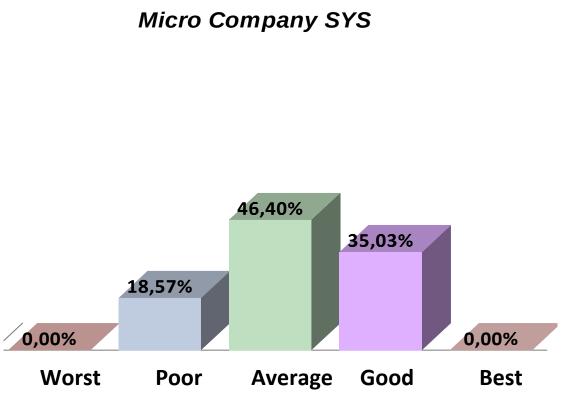

Figure 6.7A. SYS assessment for micro

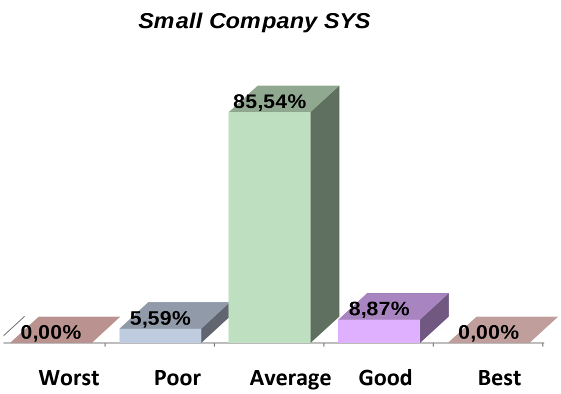

Figure 6.7B. SYS assessment for small

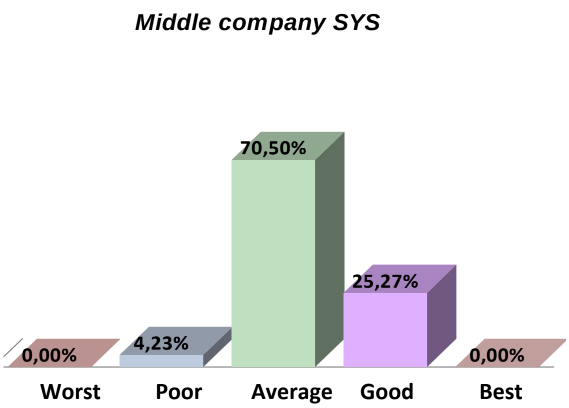

Figure 6.7C. SYS assessment for middle

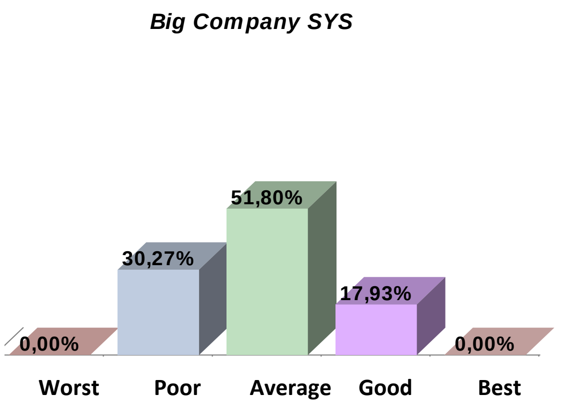

Figure 6.7D. SYS assessment for big

Micro companies are given the lowest evaluation on the management support on data analysis with "*worst*"=9.1% and "*poor*"= 62%. In contrast, big companies obtained the highest evaluation on this feature with "*poor*"=28.3%, "*average*"=57.5% and "*good*"=14.10%. It might be because big companies have the strongest management support on data analysis. (See figures 6.8A to 6.8D)

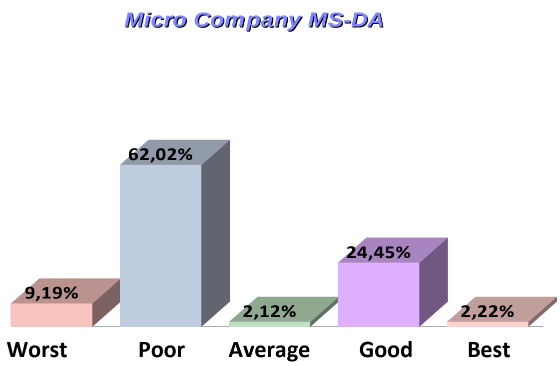

Figure 6.8A. MS-DA assessment for micro

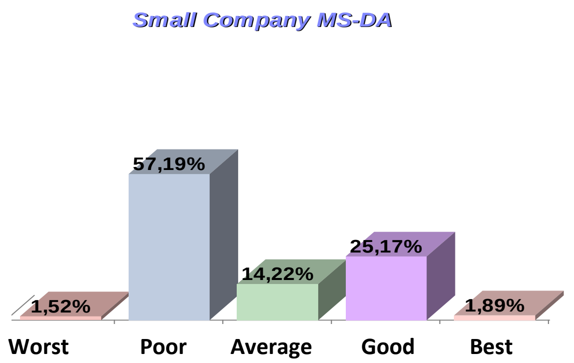

Figure 6.8B. MS-DA assessment for small

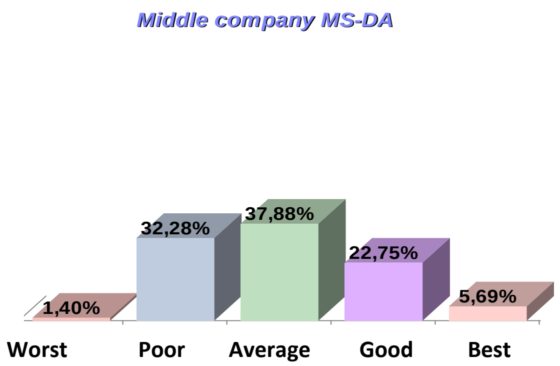

Figure 6.8C. MS-DA assessment for middle

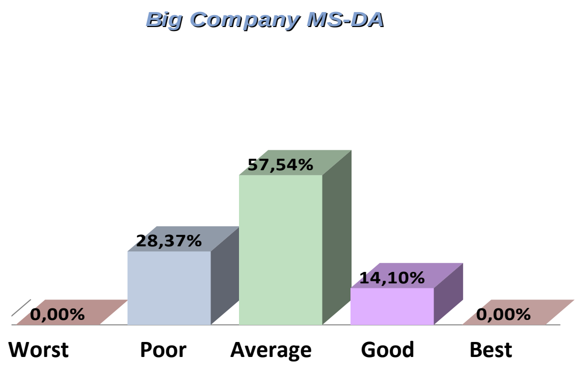

Figure 6.8D. MS-DA assessment for big

The results indicate a direct relationship between company size and the level of use of analytical tools: the bigger a company is, the better in its analytical capabilities. Although it is clear that the relationship is not linear because middle companies are the most analytically oriented. It will be necessary to confirm these results with further research given the slight difference between ranks obtained for middle and big companies (See figure 6.3). Additionally middle companies have the highest evaluation in level 3 "*analytical aspirations*" and level 5 "*analytics as competitive advantage*" (See figures 6.4A to 6.4D). Besides micro companies were ranked in level 2 "*locally focused*" and level 3 "*analytical aspirations*"

For managers running micro companies, a priority should be to move organizations from level 2 to level 3. In other words, actions need to be taken in order to break the analytic isolation and to promote and facilitate the use of analytical tools in all departments. For small and middle companies the challenge is to move from level 3 to level 4. Senior management must provide the new philosophy in order to consolidate a strong systemic vision. In addition small and middle companies must maximize benefits from systems such as balanced score cars, enterprise resource planning or other business intelligence platforms. This is also valid for big companies. It is positive to see that only the 1.7% of micro companies was ranked in Level 1 or "*analytical ignorance*". This demonstrates that companies in Barcelona, at least, applied the basic analytical tools to make better decisions. Additionally, the majority of companies belong to Level 3, which indicates that there is still a lot of room for improvement. It is clear that companies need to improve their systemic vision and management support, and learn how to apply more powerful analytical tools.

6.4.4. The sensitivity tests.

In this subsection a sensitivity analysis is performed to investigate how changes in weights of the attributes impact the overall performance. Assume that all the four attributes are normalized so that their sum is equal to one. Suppose that the weight for systemic thinking (w_3) changes from cero to one while the other three attributes remain equal, so that, $w_1 = w_2 = w_4 = (1-w_3)/3$. Then four average scores can be drawn for the same number of alternatives. (micro, small, middle and big companies). The IDS software is used to perform these calculations and the Figure 6.9 is obtained.

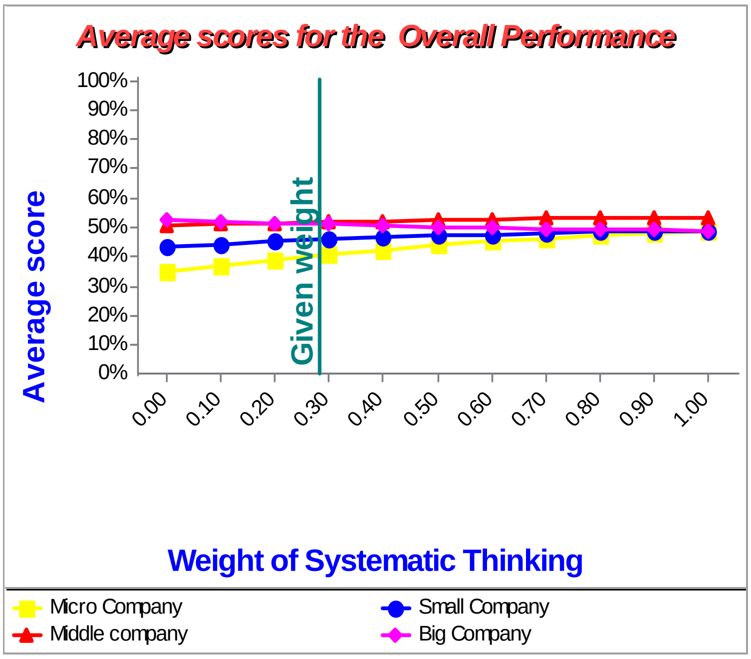

Figure 6.9. The sensitivity test for systematic thinking.

According with figure 6.9, a change in weight of systemic thinking will have the biggest impact in micro companies. In other words, micro companies are the most sensitive to changes in systemic thinking. On the other hand, middle companies are the less sensitive. Note that the red line is almost horizontal and maintains the average score while the weight of systematic thinking is changing. In addition, when w_3 is small (0.10) the differences between average scores are bigger. These differences become smaller as the w_3 increases. In the opposite case, with big values of w_3 the average score for the four types of companies tend to be equal.

A second analysis of sensitivity is provided in order to investigate the communication outside the company. In similar way to the previous analysis, we are supposing the weight for this attribute changes from cero to one with the other three being equal, that is $w_1= w_2= w_3=(1-w_4)/3$. Figure 6.10 shows the chart obtained with the IDS software.

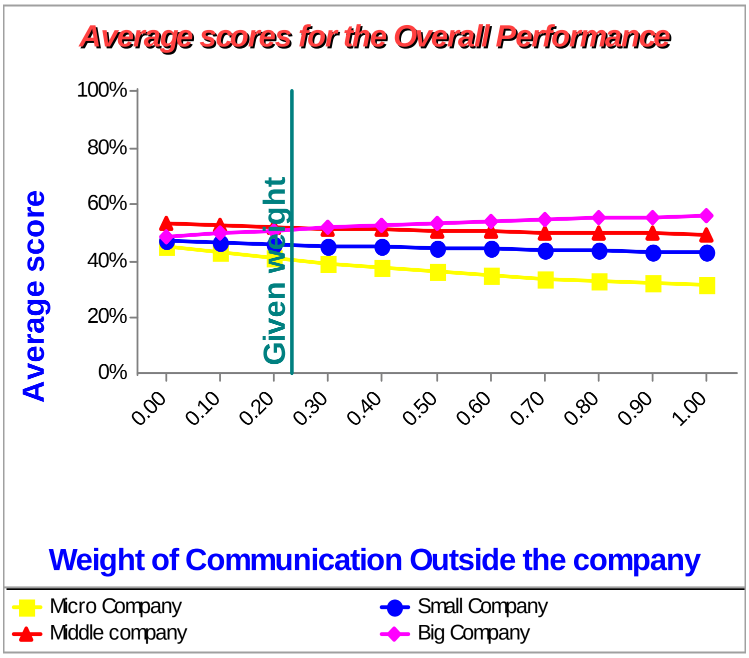

Figure 6.10. The sensitivity test for communication outside the company.

Similarly with it was found on the previous analysis, it seems that micro company has the biggest sensitivity to changes in the communication outside. In the opposite case, it seems that small companies are the less sensitive to changes in this attribute. The blue line, that is almost horizontal, makes clear this pattern. In addition, it is interesting that for small values of w_4 the four types of companies have the same average score. The differences in average scores tend to be bigger while w_4 increases. This is an inverse pattern compared with the systematic thinking.

Until here two analysis of sensitivity were performed. It remarkable the two analysed attributes have the opposite effect, for systemic thinking an increase in its weight will result in lower the differences among alternatives. For communication outside the company the opposite effect is identified, an increase in its weight will result in bigger differences. There are omitted two additional analyses for management support on data analysis and data base competitive advantages, which were also performed but no relevant sensitivity was found.

6.5. Conclusions.

In this chapter, the evidential reasoning approach was proposed for raking a sample of companies according its analytical capabilities. The evidential reasoning is a methodology composed of an innovative *evidence-driven* decision modelling framework. At first it was necessary to transform the data from the survey by applying pragmatic rule-based functions. Later the evidential reasoning approach was used to aggregate the data according to the previously defined rules, and finally the overall assessment for each alternative was obtained. The case of study illustrates the application of the decision modelling framework and decision support process for ranking of companies according its analytical capabilities. Additionally it was shown the flexibility of the methodology which is able to be adapted successfully in different problems, context and situations.

With the purpose of simplifying calculations during the implementation of the methodology, the IDS software was incorporated. Besides of the inclusion of the mathematical formulation in which the evidential reasoning is based, the IDS software is able to record the assessment information, including evidence and comments in organized structures and provides a systemic support at every stage of the implementation process.

There are several applications of these tools in management and engineering, including product and process design, risk and safety analysis, research and development projects, quality management models and marketing strategy analysis among others. The case of study about the level of adoption of analytical tools represents innovative and original application of this methodology.

7. The laddering methodology in practice.

In this chapter the data collected through the in-depth interviews is processed and analyzed by applying the laddering methodology. This analysis leads us to relevant conclusions about soft and unstructured features of the level of adoption of analytical tools, which were undetectable by only analysing data from the questionnaire

7.1 Introduction.

There is plenty of research about the influence of personal values in decision making. For example, Johnson, Melin & Whittington (2003) investigated how day-to-day activities and values affect the strategic planning in companies. In Von Krogh, Ichijo, & Nonaka (2000) is described the relationship between values and the knowledge creation process and Tort-Martorell et al (2011) emphasize the use of quantitative evidence for making more accurate decisions in business. For instance an important factor on whether a manager decides to use any given analytical or not, is directly connected with her or his perception about the degree of usefulness of such tool. According with Hoerl & Snee (2010), with the purpose of increasing analytical capabilities in companies it is almost mandatory that managers perceive those statistical tools as useful as possible in supporting accurate business decisions, not only for dealing with local decisions, but also considering the three organizational levels: operational, tactical and strategic. The more managers are able to perceive this usefulness the higher the level adoption of analytical tools.

Moreover, taking into account that the perception is directly related with personal values, the question is: what kind of personal values have a positive impact on manager`s perception to increase the use of analytical tools? To understand the role of personal values and its impact on the level of adoption of analytical tools, it is required to employ qualitative research methods which uncover the way managers' values functions and influences their decision making. In addition, it is highly probable that acquiring information about values from senior executives, consultants or academics could be a challenging task due to privacy and sensitive issues. Given this, it is necessary to use a suitable methodology which is able to effectively elicit personal values in an ordered and structured way. The laddering methodology, which was proposed by Reynolds & Gutman (1988), has proved to be a powerful tool to elicit personal values in different areas such as marketing, management and survey research. In addition, the laddering provides several benefits, for instance it is possible to analyze relationships between two or more individuals' values and other variable of interest (for example, the level of adoption of analytical tools). This chapter pursuits three specific objectives:

- Carry out 10 in-depth interviews to managers, consultants and academics in order to pick up information about personal values and the adoption of analytical tools in Barcelona, Spain.
- Apply the Laddering methodology with the purpose of extracting valuable information from interviews.
- Provide guidelines related with personal values to businessmen interested on expanding the adoption of analytical tools in their companies.

This chapter is composed by 5 sections. In the next section an explanation of the laddering methodology is provided. How the script for the interview was designed and general guidelines which should be considered while carrying out the interview are discussed in section 3. In section 4 is discussed how the data was analyzed. The section 5 is reserved for discussing the findings and results.

7.2 The Laddering theory.

According with Herrmann et al (2000), the laddering technique was developed with psychological purposes in the 1960s as a tool to investigate patients' values or core beliefs. From the very start, the laddering was believed to be a simple and practical way to investigate individual's core set of constricts on how they perceive the world. Because its advantages and benefits with respect other interviewing techniques, as for example relatively simple to implement, understand and able to provide practical results, the laddering technique was rapidly adapted to other fields such as management, marketing research and survey research among others.

In accordance with Reynolds & Gutman (1984), in the field of marketing research the laddering was first adapted in the 1980s. During this adaptation process the Means-End theory, which describes the linkages between personal values and behavior, was incorporated. In addition, Reynolds & Gutman (1988) state that in the context of survey research, the term laddering refers to an *in-depth, one-to-one interviewing technique, which is applied to understand how customers transform attributes of any given product or service into meaningful associations with respect to self by following the Means-End theory.* That is to say, given information about products or services one person forms a conception for the degree of suitability (*means*) which it is able to fill out a specific need (*end*). The first special adaptation of the Means-Ends theory in the field of customer research was proposed by Gutman (1982). In essence, this model describes how consumers give consequences and assign importance to one given product or service. The importance given is affected by the context of situation, which force the consumer to review the consequences given a particular situation (for example, in times of economic crisis, if consumers had their incomes reduced, they might consider avoiding buying luxury goods or going to clubs and casinos). In figure 7.1 is represented the core concept of the Means-Ends theory.

Over the time, consumers learn to distinguish between satisfiers which they wouldn't use from those used only in some particular situations. For example, consider the situation where a manager is thinking about either to adopt or not a new analytical tool for making decisions. What consequences are produced by the adoptions of such new analytical tool and how do these consequences relate to his/her values? At first instance, there are many potential consequences which are given by different personal beliefs, for instance: academic background, past experiences with mathematics and statistics, degree of usefulness, usability and affordability.

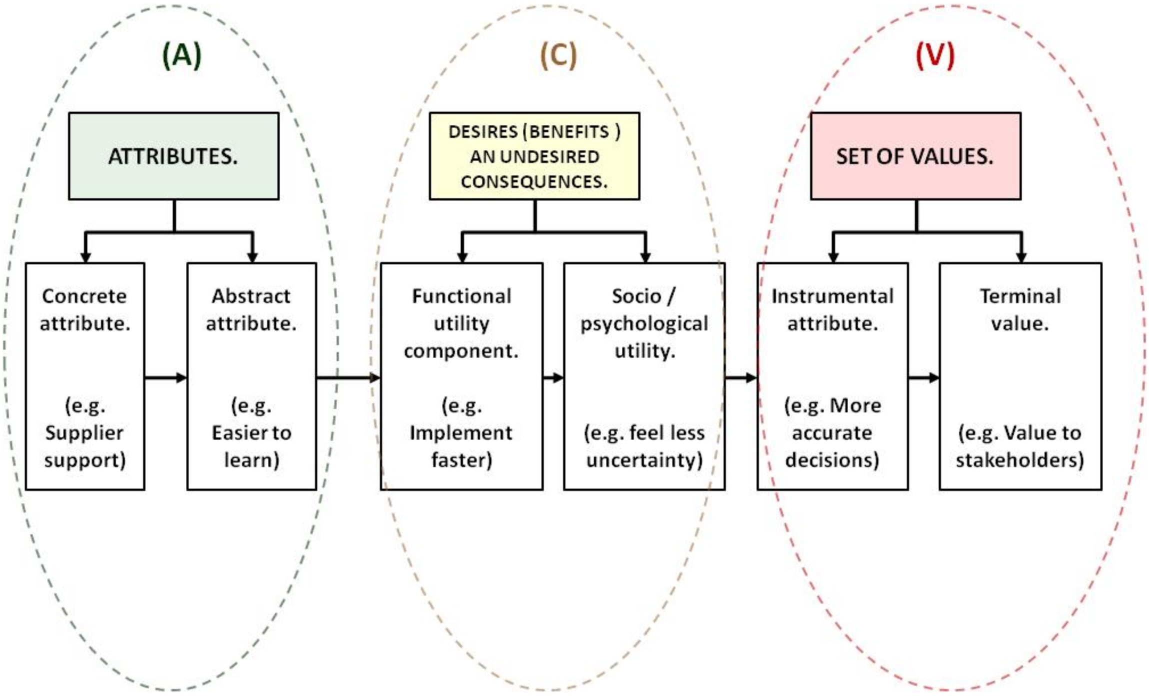

Figure 7.1. The Means-End model. Adapted from Herrmann et al (2000)

According with Gutman (1982), values related with enjoyment, living a comfortable life, religion and good health, among others, play a decisive role in attaching importance to its respective consequences. For example the value "*social recognition*" is related with good health and thus it will have attached a consequence rated as important. But how can these types of values be uncovered and disclosed? A novel feature in this research is the application of the laddering technique to find out values which are relevant in adopting new analytical tools in companies. According with Reynolds & Gutman (1988) the laddering technique involves a format that uses, basically, a series of directed questions such as "*Why is that important to you?*", on which the final objective is to uncover the linkages between the key perceptual elements of attributes (A), consequences (C) and values (V) . At this point a ladder is defined *as the output obtained through several interactions of the questions, in order to create different levels of abstraction which follow the order (A)-(C)-(V).*

Moreover distinctions at different levels of abstraction, represented by the constructed ladders (With the form A-C-V), provide a deeper understanding of how the managers' perception about the Level of Adoption of Analytical Tools is processed from what could be called a motivational perspective. The ultimate purpose is to find out reasons why an attribute or a consequence is important. In figure 7.2 it is presented a ladder in which the basic distinctions between features in the use to analytical tools are illustrated. It represents a fraction of data collected in the in-depth interviews which were carried out during this research.

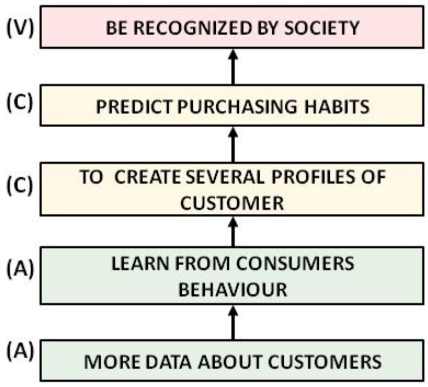

Figure7.2. Example of ladder constructed with data collected in the interviews.

This is the logic behind the laddering technique: starting from attributes (A) the elements were sequentially elicited by the respondent from the bottom to the top. One important aspect in the laddering technique is the ability to cause the responder to think critically about his or her personal motivations. Later, the analysis of data from multiple responders can be summarized and the key elements can be extracted from it by applying the standard content-analysis technique proposed by Kassarjian (1977), which emphasize that the levels of abstraction (Three levels for this case: A-C-V) must be taken in mind while the data is processed (or "*laddered*").

Once the raw data is summarized, the final output is a table which contains all dominant connections. In the last step, one graphical representation of those dominant connections is made. In accordance with Reynolds & Gutman (1988) this graphical representation is named Hierarchical Value Map (HVM) and it is a sort of cognitive map which, unlike other well-known traditional multidimensional methods as factor analysis or correspondence analysis, it is capable to represent the linkages or associations across the levels of abstraction in a very didactic way.

The interpretation of the HVM permits to understand the personal values of managers, consultants or academics from which they might decide to adopt a new analytical tool. Each unique relationship from one attribute to value represents a perceptual orientation.

Basically, one of the most important contributions of the laddering technique and the HVM is the possibility of differentiate the adoption of analytical tools, not only by its attributes, but rather by communicating how the adoption of analytical tools itself delivers higher consequences and ultimately how it is relevant in terms of values. Normally this understanding serves as the foundation for the development of new strategies for the adoption of new analytical tools

We provided definitions for the Means-end theory and laddering technique. An example of ladder and its definition was also provided. Considering these theoretical concepts, it might be easier to understand them if a numerical example is shown. In section 7.4 the reader will find a detailed explanation of how these concepts were implemented. The next section is reserved to illustrate how the interview should be performed in order to achieve useful ladders.

7.3 General considerations for the in-depth interviews

In Reynolds & Gutman (1988) it is stated that some environment conditions in which the interview should take place are indispensable for obtained valuable data. At first, a friendly atmosphere must be created in order to make the respondent feel confident and willing to be introspective, look inside and seek feelings and motivations. It is advisable that the interviewer provides some introductory comments in which it is stated that there are not right or wrong answers, with the purpose of making the responder feel relaxed. The interviewer should insist that the main purpose of the interview is to talk about perceptions, feelings and notions and there is nothing to be evaluated. In addition, the responder should be put as an expert on the topic under discussion. The interviewer should always keep in mind that the ultimate objective of the interview is to understand the way in which the responder, based on feeling and motivations, perceives the world.

It is also extremely important that the interviewer acts merely as facilitator of this self-discovery process, and with it all personal opinions and judgments must be avoided. A strategy suggested by Reynolds & Gutman (1988) is starting with the questions which may seem obvious, very simply or even stupid. The above shall make feel the respondent more confident and more willing to talk. Even though the respondent speaks most of the time and the interview remains in silent, it is completely necessary that for interviewer to never mislay the control during the interview process. Reynolds &

Gutman (1988) state that when there are signals which indicate that the control of the interview is being mislaid, the interviewer should ask as direct as possible questions, always followed by the sort of question "*Why that is important to you"?* In short, by constantly asking this question, the interviewer is able to keep the control of the interview along the process and reinforces the perception of being completely interested on what the respondent is saying and expressing.

The main idea behind the laddering methodology is to move the respondent to make distinctions about meaningful differences between brands, product, concepts, or for instance, the level of adoption of analytical tools in decision making. According with Gutman (1982) those distinctions should be bipolar, that is to say, it is supposed that the interviewer presents two possible options, where at the end the respondent is persuaded to select just one pole (See appendix B for the script designed). Once the respondent has selected one pole, it operates as basement to ask some sort of question: "*Why is important to you*?" Based on this structure, Reynolds & Gutman (1988) propose six general methods by which the interviewer might elicit preferences from the responder (See table 7.1).

It is clear that the six methods for eliciting responder's motivation and feelings are very similar and maybe it would be difficult to distinguish one from another. According Herrmann et al (2000), an effective laddering interview should include a combination of all of them. Plenty of experience and knowledge from the interviewer is required, in order to smartly apply any given method to any situation during the interview process. According with Reynolds & Gutman (1988) the key idea is: the more familiar the interviewer becomes with the methods presented in Table 7.1, the better the interviewer will be able to manage, combine and integrate them and finally to reach feelings, motivations and values from the responder. The main topic along the whole interview must always be the person (not the service, the idea, the concept or the product). By using all the interviewee's expertise and knowledge, the interviewer should keep the focus on the main target of the laddering method: the person.

Table 7.1. The most commonly interview techniques used in the laddering method.

Laddering method	**Description**	**Example questions**
1. Evoking any given situational context.	It is feasible to reach a ladder when the respondent thinks about one past moment in which he/she interacted with the service, product or concept.	When was the last time you applied an analytical tool? Why it was important to you?
2. Supposing the absence.	Another method to reach a ladder is by asking for feelings and sensations, but given the hypothetical situation when there is a lack of the service, product or concept.	How do you make a decision if you cannot access to computers and analytical tools? Why this (absence or presence) is important to you?
3. Negative – Inverse Laddering	Sometimes the responder is unable to articulate his/her feelings. If this is the case, a negative question may help to clarify responder's mind	Given that situation. What would happen if you don't use an analytical tool?
4. Back in time.	Invite responder to backward in time is another method to elicit feelings and motivations.	Do you know how your grandpa used to apply analytical tools to reach a decision? Or your father? Can briefly explain?
5. Third person experience.	Sometimes the responders will find difficult to talk about her/his experience. In this case, evoking a third person will stimulate the responder to speak about his/her own experience.	What problems are your colleagues struggling with due to the lack of use in analytical tools? Why do you think that is important for your colleague?
6. Redirecting methods: silence, rapport and check	Silence in one part of the interview will be helpful to maintain the responder thinking about feelings and motivations. Likewise all the types of interviews the checking and rapport are important.	Rapport in the interviews occurs when both (respondent and interviewer) feel they are in sync and relate each other. Interview rapport should include mutual attention, positivity and coordination.

According with Reynolds & Gutman (1988), the typical standard interview should last between 60 to 75 minutes, and around 4 ladders can be obtained from it. In this particular research, a total of 10 in-deep interviews were carried out and 84 different ladders were constructed. Consider this a qualitative research and is almost impossible to obtain the same number of ladders from each responder. The number of ladders obtained will be obtained in function of the willingness of the responder to collaborate and participate in the interview.

7.4 Results.

A total of 10 interviews were performed with academics, businessmen and consultants. All persons interviewed were asked if it could be possible to record the entire interview and all of them agreed, so that, there are available the digital records of such interviews on mp3 format to those who request them. Working in our records, the first step consisted on classifying the content of each interview in groups according with the closest in meaning. For example, the concept "*data should support more accurate decision making*" is close in meaning with "*data accessibility supports better decision making*" and they were classified in the same group. Moreover "*data online facilitates the communication*" was found similar with "*sharing information is easier when data is online*" and then they were classified in a group named "*data online*". By listening our digital records six times each, a total of 35 groups were created and utilized to codify data from interviews. The next step was to classify them into the three basics A-C-V (Attributes / Consequences / Values). In figure 7.3 are shown the 35 created groups and their classification.

	Attributes	Count
1	Data is accessible and supports decisions	17
2	Data online	12
3	Goal setting	11
4	Standardized procedures	10
5	High skilled staff	7
6	Enough support	6
7	High tech	6
8	Communication with customers and suppliers	5
9	Creativity to propose new ideas	5
10	Information outside the organization	5
11	Market research	5
12	The most efficient structure	5
13	Flexibility on management	4
14	Respond more quickly	4
15	Innovate products and services	2

	Consequences	Count
16	Analyse data from market	5
17	Continuous learning	3
18	Distinctive competence	6
19	Exceeding the customer expectations	7
20	Good image of the organization	6
21	Improve data analysis	18
22	Improving process	7
23	Improving results	14
24	Knowledge of data	7
25	Long term relationships with actors	7
26	Lower cost	5
27	More money	13
28	Staff efficiency and motivation	11
29	Monitor the costs (lower cots)	2

	Values	Count
30	Add value to stake holders	13
31	Being a leader	9
32	Communication and trust	9
33	Honesty and credibility	5
34	Passion, Quality and Excellence	11
35	Serving the society	12

Figure7.3. Summary content for the in-depth interviews related with the level of adoption of analytical tools in Barcelona, Spain.

While the data from in-depth interviews was processed and analyzed, the main objective of the study was always kept in mind: to understand the relationships between elements or concepts. That is to say, the relationships among A-C-V are the main subject of study and not the concepts themselves. Grunert & Grunert (1995) state that a distinctive feature which separates the laddering methodology from others in-deep interview techniques, is its capacity of "*crossing over*" from the qualitative nature of the interviews to the quantitative and structured data. That is to say, by creating a score matrix from the ladders it is possible to identify, in a quantitative way, dominant pathways or connections between key elements. Explained in a simpler way, the score matrix (or better called implication matrix) displays the number of times one concept leads to another. Such matrix is a square matrix with size reflecting the number of concepts that we are trying to represent. According with Reynolds & Gutman (1988) two types of relations may be included in the implication matrix: direct and indirect relations. Direct relations refer to relations among adjacent elements. Consider the following example of direct relations.

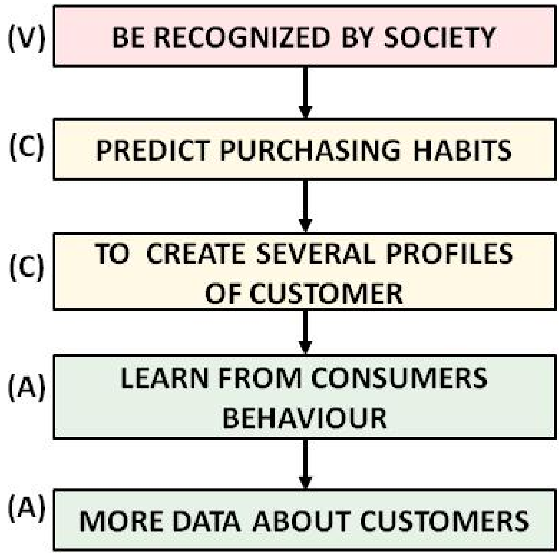

Figure7.4. Example of direct relations in a typical ladder.

In figure 7.4 is shown that the relation A→B (*autonomy for using data* **leads to→** *stimulate creativity*) is a direct relation. In the same way, B→C (*autonomy for using data* **leads to** → *use more data for decision making*). C→D (*use more data for decision making* **leads to** → *achieve goals and objectives*) and D→E (*use more data for decision making* **leads to** → *be recognized for society*) are all direct relations. This example illustrates how direct relations are constructed. In addition Gutman (1982) suggests that studying indirect relations is helpful to get a deeper understanding. Continue following the example of figure 7.4 we identify that A→C, A→E or C→E are indirect relations.

According with Reynolds & Gutman (1988), in the implication matrix for each *row-column* is presented the frequency which indicates the number of times, directly and indirectly, a *row-element* leads to a *column-element* (See table 7.2 for better understanding). The reader will notice that numbers are separated by '-' symbol, which is applied to differentiate direct from indirect relations: numbers at the left of the '-' represent the direct relations while those at the right side are the indirect relations. For instance, the first attribute "*data is accessible and support decisions*" (row 1) leads to "*improve data analysis*" (row 21) seventeen times directly and only one indirectly. In the same way "*staff efficiency and motivation*" (row 28) leads to "*communication and trust*" (row 31) eleven times directly and cero indirectly.

Table7.2. Implication matrix for the Level of Adoption of Analytical Tools in Barcelona.

		Element	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
A	1	Data is accessible and supports decisions					8-00	17-01	4-00	4-00	4-00	0-03	0-05	0-09	0-08	0-13	0-09	0-09	0-08	0-11	0-04
A	2	Data online	3-00		3-03			7-03	4-00	4-00	5-00		0-06			0-06					0-04
A	3	Goal setting	3-00	3-00	2-00	4-00	2-00	5-00	2-00	2-04	13-00		5-05		4-00	0-06	0-06	0-05	0-10	0-11	0-12
A	4	standardized procedures	2-00	1-00	1-00	3-00		6-00	3-00	0-03			0-06	0-03	11-06	0-05	0-10	0-10	0-05		
A	5	High skilled staff	3-00		3-00	1-00		5-00	2-00		0-03			0-04	4-00			0-10	0-08	0-10	0-06
A	6	Enough support			0-03			6-00	3-00			0-06			4-00	0-03	0-08	0-09	0-05	0-09	0-06
A	7	High tech	0-02	0-03		0-04		3-00			0-03		0-07	0-03			0-10				
A	8	communication with customers and suppliers	5-03	4-00	3-00	2-00			4-00	0-08	0-02				0-05	0-05		0-08	0-10	0-02	0-05
A	9	Creativity to propose new ideas		4-00	5-00	5-08			4-00	0-08	8-04		0-06	1-08	5-00	0-06		0-08	0-10	0-07	0-08
A	10	information outside the organization	7-04		2-00	1-00	3-00					0-05					0-06				0-08
A	11	Market research	4-00	2-00	0-04	0-04				0-02	0-06	0-04					0-04				
A	12	the most efficient structure											5-00	3-00	6-05	0-06	0-06	0-06	0-04	0-02	
A	13	Flexibility on management		2-00	4-00	5-00	0-05	2-02						0-04		0-01		0-06			0-06
A	14	respond more quickly		2-00	3-00	3-07			3-00	0-03	6-00	0-02	0-05	0-04	3-00		0-05	0-08		0-04	0-05
A	15	to innovate products and services			4-00	3-00		0-10			3-00	0-02	0-02	0-05	4-00	2-00		0-02		0-04	0-05
C	16	Analyse data from market		10-00	0-05	3-00			0-03	0-05	6-00			0-06		0-05					
C	17	Continuous learning			4-00			5-00	0-03			0-02			0-06	0-04		0-04	0-03	0-06	0-06
C	18	distinctive competence				3-00							6-00	0-08		0-06				0-06	0-06
C	19	Exceeding the customer expectations		4-00			0-04			3-00					2-00						
C	20	good image of the organization						0-02				8-00			0-02				0-06	0-04	0-05
C	21	improve data analysis							6-00	5-00			0-06	0-05		18-00	10-00			14-00	
C	22	improving process		11-00								0-06	4-00	0-04	0-05	7-00	2-10	0-05	0-05	0-10	0-07
C	23	Improving results		14-00																0-10	0.07
C	24	knowledge of data							4-00	7-00											
C	25	long term relationships with actors															7-00				0-08
C	26	lower cost												5-00							
C	27	More money														13-00	12-00				
C	28	staff efficiency and motivation														12-00		11-00		8-00	
V	29	add value to stake holders																	6-00		
V	30	Being a leader																	6-00		
V	31	Communication and trust																			7-00
V	32	honesty and credibility																			14-00
V	33	Passion, Quality and Excellence																	9-00		
V	34	serving the society																			

As the reader will notice, the first column in the implication matrix the classification of each element is found (A-C-V). It is followed for the element itself. In the rest of the columns are shown one-by-one the consequences and the attributes. Note that attributes don't figure in the columns because is impossible they related with themselves. Later it was necessary to compute all the direct and indirect relationships and represent them in paired elements in order to build the implication matrix. This is relevant because the implication matrix allowed us to identify dominant and relevant connections. For instance, the consequence "*improve data analysis*" (row 21) has the biggest number of direct connections with "*add value to stake holders*" row (29) equals to19 direct relations. Following this pattern it was possible to identify the dominant connections and represent them in a form visual diagram. Now another important tool applied to analyze our information is introduced. According with Reynolds & Gutman (1988) the *HVM is a way to graphically represent the most dominant connections. It is a representation of the linkages across levels of abstraction, starting with attributes and finishing with values*. Based in the research conducted by Henneberg et al (2009) and Gruber et al (2009), the most common approach is to include in the HVM all the connections which are composed by at least 4 or more direct relations. Specifically in this case a total of 84 ladders which have this characteristics, are being considered for building our HVM.

Additionally Gengler, Klenosky, & Mulvey (1995) suggest that the main objective in constructing the HVM is to highlight meaningful connections between attributes-consequences-values (A-C-V). The obtained result can be represented in one chart which includes all relevant and most important relations in a graphical form, which is usually easier to understand.

The goal to achieve when mapping these hierarchical relations is to relate all the meaningful chains in a single map, in which it is possible to draw the most frequent relations and analyze their interactions. In figure 7.5 is presented the HVM, the elements (A-C-V) are ordered starting with the attributes at the bottom and ending with the values at the top. Besides there are black arrows connecting the elements and indicating the direction of the relation. The red numbers also indicate the number of existing connections between elements. A numerical explanation, based in data presented in figure 7.5 is now provided.

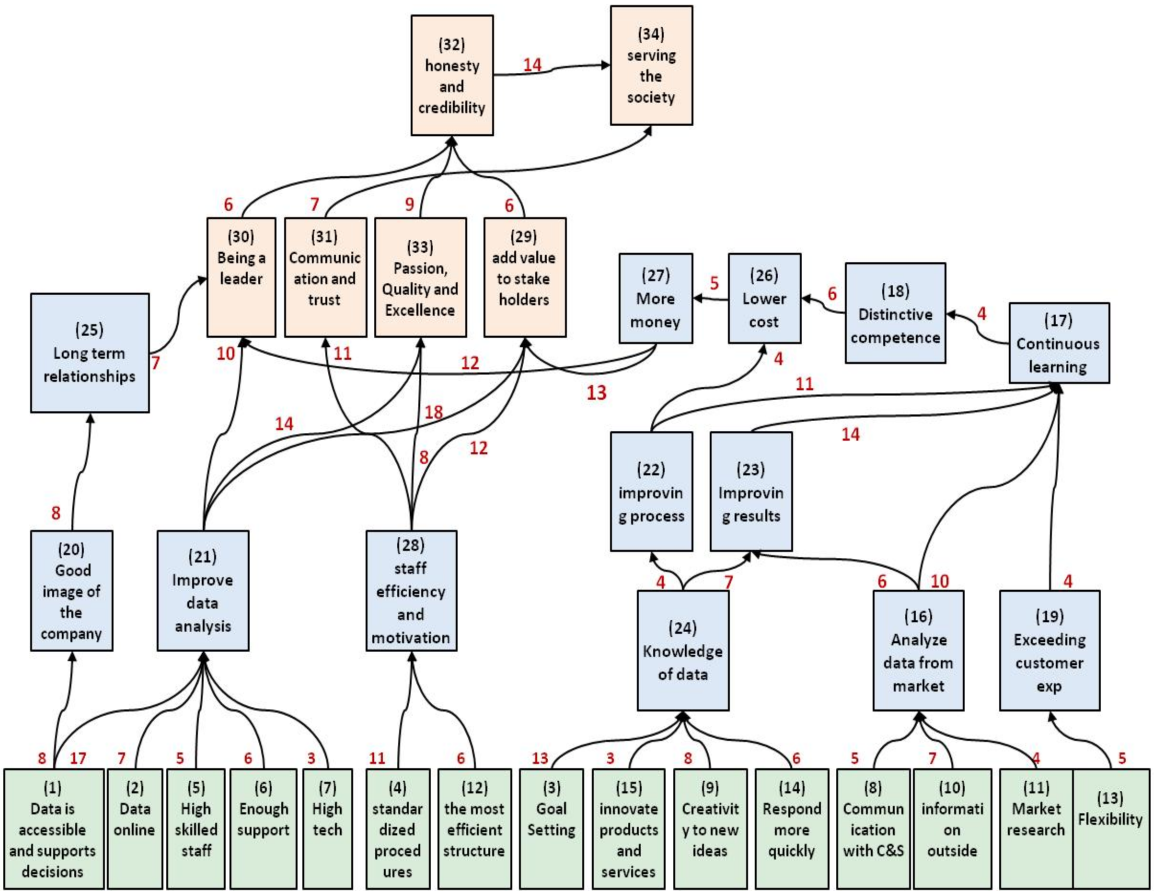

Figure7.5. Hierarchical Value Map for the Level of Adoption of Analytical Tools in Barcelona.

For instance, the attribute "*data is accessible and supports decisions*" **(1)** leads 17 times to the consequence "*improve data analysis*" **(21)**, likewise it leads 18 times to the value "*add value to stakeholders*" **(29)**, it also leads 6 time to the value "*honesty and credibility*" **(32)** and finally this leads 14 times to "*serving to the society*" **(34)**. In the same form, there other elements which are noteworthy for having high frequency in laddering to other elements. Namely, the attribute "*standardized procedures*" **(4)** leads 11 times "*staff efficiency and motivation*" **(28)**, likewise it leads 18 the element "*Passion, Quality and Excellence*" **(33)**, it also leads 9 times to the value "*honesty and credibility*" **(32)** and finally this leads 14 times to the element "*serving to the society*" **(34)**.

According with Reynolds & Gutman (1988) the HVM should include all the direct and indirect relations but specifically in this case of study, only direct relations have been included for this reason: at first the present analysis is going to be complemented with results obtained from our questionnaire. The combined conclusions from questionnaires and ladders are considered to be a more integral approach. In short, the information presented in figure 7.5 is based only in direct relations, which are further complemented with survey results in next chapter.

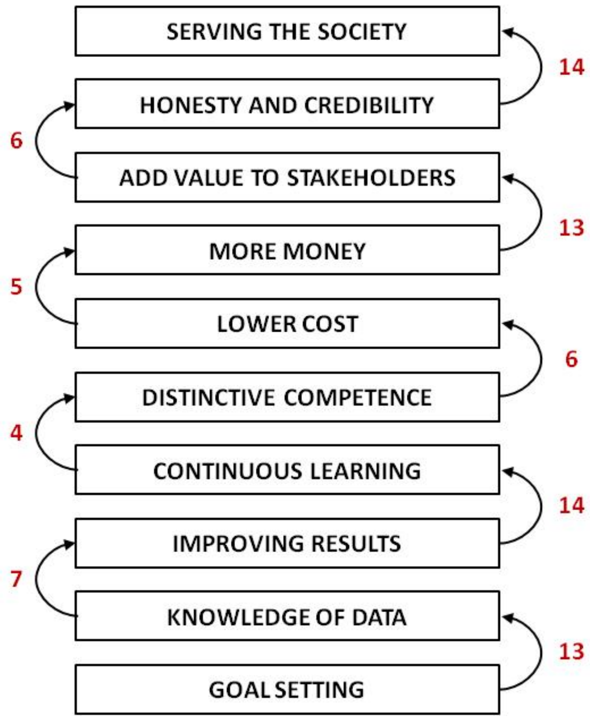

Figure 7.6. Frequency summary for the ladder starting with the attribute "Goal setting"

As it was mention before, the challenge is to compute the number of frequencies that start with the attributes and finish in values. It is clear that the value which receives the highest number of relations is also the most relevant. More specifically, the reader will notice in figure 7.6 that the attribute "*goal setting*" **(3)** leads 13 times to the consequence "*knowledge of data*" **(24)**, likewise it leads 7 times to "*improving results*" **(23)** and this leads 14 times to "*continuous learning*" **(17)**, ant this leads 4 times to "*distinctive competence*" **(18)**, this also leads 6 times to "*lower cost*" **(5)**, this leads 5 times to "*more money*" **(27)**, this also leads 13 times to the value "*add value to stakeholders*" **(29)**, likewise it leads 6 times to the "*honesty and credibility*" **(32)** and finally this leads 14 times "*serving the society*" **(34)**. The cumulative frequency for this ladder is equal to 82. In other words, based on our in-depth interviews there is quantitative evidence to demonstrate that exist a relation between the attribute "*goal setting*" and the value "*serving the society*" which is equals to 82 relations.

As it was mention before, the main goal in this research is to establish quantitative relations between attributes and values, which at first instance are not obvious. In order to achieve this, the starting point is the 10 attributes which have the biggest number of relations. We are defining this number of attributes because they concentrate more than the 90% of the total relations. Considering this a cumulative frequency following the sequence A-C-V was calculated for each attribute. As it can be seen in table 7.3, these overall cumulative frequencies allow us to identify those attributes which have more impact on the ultimate values. It is clear that the higher the cumulative frequency the bigger the impact of the attribute on the ending value.

Table7.3. Relations frequencies for Attribute-Value.

	Personal achivement			Social values				
Attributes	Being a leader	Passion, Quality and Excellence	Total	Communication and trust	add value to stake holders	honesty and credibility	serving the society	Total
Goal setting	61		61		62	68	82	212
Creativity to propose new ideas	56		56		57	63	77	197
information outside the organization	54		54		55	61	75	191
respond more quickly	52		52		55	61	75	191
communication with customers and suppliers	42		42		43	49	63	155
Data is accessible and supports decisions	27		27		45	51	47	143
Enough support		20	20		24	30	44	98
standardized procedures			0		23	29	43	95
Data online		21	21			30	44	74
the most efficient structure		14	14			23	37	60
Total	292	55	347		364	465	587	1416
	17%	**3%**	**20%**		**21%**	**26%**	**33%**	**80%**

Table 7.3 includes also the segmentation criteria proposed by Reynolds & Gutman (1988). According with these authors, the goal of segmentation in the laddering methodology is to cluster the responders with respect to some aspects of their behavior, attitudes or dispositions. Based in our analysis, the six values that received the highest number of relations were segmented in two groups. The first group clustered values related with personal achievement and individual effort, while in the second, values related with teamwork and social iteration were grouped. In short, the first row in table 7.3 presents the classification carried out to the values while the first column shows the 10 attributes with the biggest number of cumulative frequencies. The information contained in this table is relevant because conclusions and findings were drawn from it.

Specifically the attribute "*goal setting*" had the biggest cumulative frequency equals to 212, it was followed by the "*creativity to propose new ideas*" and in third position was "*the information outside the organization*". On the other hand, it seems that socials values are more relevant than personal achievement values because around the 80% of the relations ended in social values while the 20% remaining did it on personal achievement values. Taking more specific look on social values, "*serving the society*" had the highest number of cumulative frequencies equals to 587 and it represents the 33% of all relations finishing in this value. The value "*honesty and credibility*" was found in second place with a cumulative frequency of 465 and it represents the 26% of the all relations finishing in this value. In the third place was found the "*add value to the stakeholders*" with a frequency of 364 which represents the 21% of the computed relations. Note that these three social values together concentrate the 80% of the total relations. In the fourth position was for the value "*being a leader*" and equals to 292 which represent the 17% of the computed relations. These four values, which three are social and only one is personal achievement oriented, concentrate the 97% of the all computed relations.

Otherwise the attribute "*goal setting*" has cumulated the highest number of relations equals to 212 and it represents the 12% of the total. The "*creativity to propose new ideas*" was found in second place with 197 which represent the 11% of the total relations. In third place was the "*information outside the organization*" with 191 which are the 11% of the total relations. The attribute "*responding more quickly*" was ranked in the fourth position with 191 relations. In short the four attributes "*goal setting*", "*creativity to propose new ideas*", *information outside the organization*" and "*respond more quickly*" concentrate the 45% of the total relations. On the other hand four values represent the ending points for 97% of the total relations. Three of these are related with social skills while only one is about personal achievement.

7.4. Conclusions.

The interview process requires a special attention by the researcher in order to obtain accurate results. It is strongly advisable that the interview occurs in a silent and quiet place and any kind of interruptions as phone calls or text messages should be avoided. According with Reynolds & Gutman (1988) while the interview is taking place, the respondent has to feel as if on a voyage of self-discovery and the mean objective of the this voyage is to revisit everyday routines, commonplace experience and examine the assumptions and desires.

The laddering technique is different from other traditional in-depth interviewing methodologies in that it is capable of "*crossing over*" from qualitative to quantitative. This allows for the transformation of soft and unstructured aspects of the adoption of analytical tools in companies, which initially were qualitative, to ones that are structured and quantitative. The hierarchical value map summarizes the quantitative relations between attributes-consequences-values. This map allows us to obtain a better understanding of the triggers (attributes) for the adoption of analytical tools in companies.

Managers, businessmen and practitioners, who are willing to raise the use of analytical tools in their companies, should consider the attributes identified in this research as indispensable elements for success. In addition, it is required the existence of the highlighted values in order to successfully raise the adoption of new analytical tools in companies. This case of study is a novel application of the laddering technique to investigate the impact of values on the level of adoption of analytical tools.

8. Practical guidelines to stakeholders.

This chapter provides guidelines to stakeholders who are interested on expanding the level of adoption of analytical tools. Such guidelines are based on results obtained on previous chapters.

8.1 Introduction.

Throughout this present thesis, the actual practices in the field of business analytics have been described. In chapter 2 was provided a literature review with the most relevant tendencies in the use and adoption of analytical tools in companies. Also in this chapter some of the most important changes in the fields of information technology, communications and statistics applied in business management were described. This literature review brought two important outputs. At first, a conceptual model composed by four key drivers was introduced, (see figure 2.1) and secondly a five-level theoretical scale with the most important features that distinguish any company adopting analytical tools for decision making was proposed (See figure 2.5). With the purpose of complementing our theoretical model and scale, in chapter 3 a compilation of cases of applications of analytical tools was presented. At first instance, this compilation allowed us to retrieve evidence to demonstrate that the adoption of analytical tools is increasing in contemporary business environment. For example, traditional areas which were considered in the past as merely qualitative oriented now have been incorporating new analytical approaches. Human Resources area is a good example of this tendency. In short, chapters 2 and 3 allowed us to understand the phenomenon of the adoption of analytical tools under a theoretical perspective. The next step was to validate the conceptual model and a five level scale with data from the real world. For this validation, it was needed to obtain and analyze data from companies, verify the assumptions which were initially settled in our model and correct the divergences. (See figure 8.1).

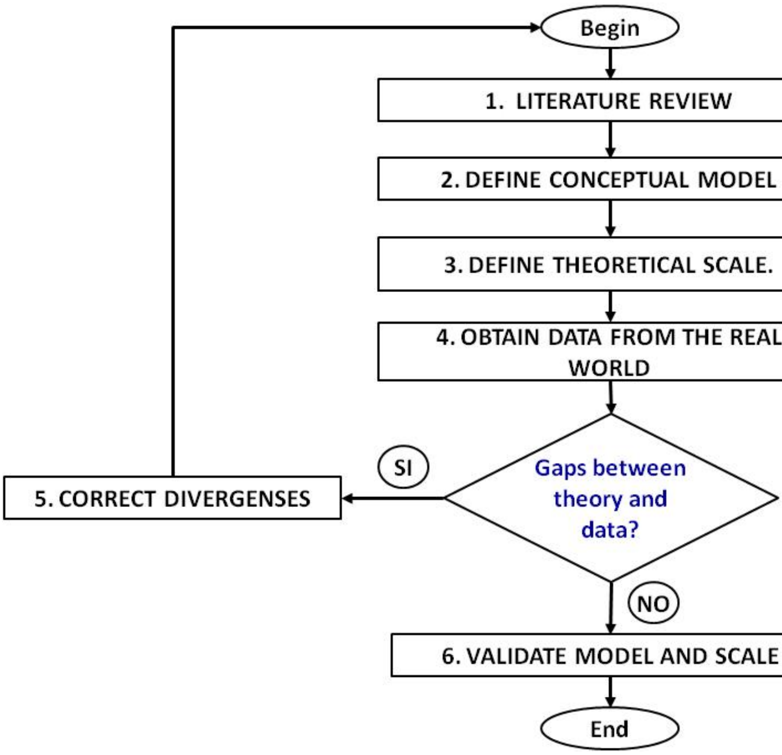

Figure 8.1.Flowchart to validate the proposed model and scale.

In chapter 4, all the steps which were taken in order to design the required instrument are widely described. The goal was to provide reliable and valid assessment of the aspects of the use of analytical tools which are likely to influence companies to incorporate new quantitative methods in their decision making. Based on the previous literature review, the items in the questionnaire were written to address all positive and negative aspects of the adoption of analytical tools in companies. Moreover, this questionnaire was intended to serve as a tool for research and theory development, especially for managers and decision makers who are interested in understanding contextual aspects that may influence the adoption of new analytical tools. This questionnaire was also intended to serve as a diagnostic tool for stakeholders in companies, who are interested in assessing their companies' degree of analytical capabilities, and based on that diagnostic to propose an action-plan to correct deficiencies on factors evaluated as low (See figure 4.4).

Besides, in chapter 4 the exhaustive statistical research related with the factor structure of the dimensions, the reliability test for the scales and the test-retest reliability, coefficients of agreement and convergent validity is performed. At first the coefficient of agreement allowed us to obtain a quantitative measure of the degree of understanding of each item. Secondly, the internal consistency of the scales was quantified for measuring the degree to which each item on the questionnaire statistically fits with other items on its particular scale, and the degree to which the scale fits a confirmatory factor analysis was also calculated. The performed statistical tests allowed us to ascertain that our instrument is reliable and valid. (See figure 4.2 for a complete list with all statistical methods applied in this questionnaire design). The designed instrument is also profitably used in conjunction with interviews to obtain a deeper understanding of the adoption of analytical tools in companies.

Either applied alone or with other methods, our instrument and the conceptual model upon which it is based (See figure 2.1 for the theoretical model) give managers, consultants and academics a path to turn their attention toward the phenomenon of adoption of new analytical tools in companies. Although the instrument was used to assess only companies located in Barcelona area, we consider this a useful beginning, both theoretically and practically. That is to say, in further research the instrument can be applicable beyond this level, for example to compare company divisions, regional areas, cities or countries. It is possible that broader levels in the use of this instrument would increase the error variance of the study, but taking into account the results obtained in validity and reliability tests, it still will be possible to find relevant aspects of the level of adoption of analytical tools as those were discovered at the Barcelona area.

8.2 Practical guidelines for upgrading in the scale.

In chapter 5 it is widely described how the data was analysed and the set of statistical tools used to get relevant conclusions. We decided to use the Statistical Engineering approach as general guide line to analyze and draw conclusions. According with Hoerl & Snee (2010), statistical engineering works by making a practical design of how best to use the existing statistical toolkit for driving improved results. The statistical engineering methodology integrates the existing theory with the cumulative learning from other applications, such as information technology, to create a dynamic theory-practice which generates improved results.

Specifically in this research the statistical engineering approach allowed to create a link between thinking and tools through providing answers to questions like: Why should we use statistics in this thesis? Which statistical tools are the most suitable for getting improved results from our data? What is the main purpose of using this set of statistical tools? By taking in mind answers to these sorts of questions, a design consisted on five-step process which gathered seven different statistical tools was proposed (See figure 5.3). The details about how data was collected are described in section 5.2.2; section5.2.3 explains the confirmatory analysis; sections 5.3.4 and 5.3.5 are reserved to discuss the obtained results. The table 8.1 show the classification performed to the 255 surveyed companies based in our five-level scale.

Table 8.1.Classification of surveyed companies based on the proposed scale**.**

Level	Freq	Percent
1	65	20%
2	38	15%
3	83	33%
4	52	20%
5	17	7%

It is interesting that the 48% of the companies were ranked in levels 2 and 3. In addition the majority of companies in level 2 recently started to adopt analytical tools and they are receiving the first rewards of making decisions based on quantitative approaches. For example, while a survey was taking place, one participant commented us that he was recently hired as production manager in the company but he came from other company in which data analysis was applied on a daily basis in most of their decisions. He told us that his first reaction was to complain about the large number of decisions that were made using subjective approaches or past experiences in his new position. Later he realized that rather to complain about the lack of analytical culture, he should start his own small analytical project at his department by implementing a basic statistical control process and obtain simple measures as the average of produced goods, standard deviations and control limits. He also told us that, some months later, the staff at his department started to complement these basic analytical approaches with other more sophisticated, and by the end of the first year the analytical project had grown as much as to attract the Senior Management attention. This case illustrates some important features of taking the initiative into analytical projects in small scale. At first, by starting with a small scale project it is possible to learn by doing. Moreover, taking into account that one indispensable requirement to successfully compete with analytics is the experimentation; a small scale beginning permits the possibility of plenty of experimentation. In Davenport and Harris (2007) this is called the "*prove-it*" strategy. There are others advantages of implementing a "*prove-it*" strategy, for example starting by a small scope projects managers can assess the efficiency and effectiveness of the analytical tool at their own department with out to get *buy-in* from some else experience`s. In addition this strategy requires lower levels of initial investment. Here there are relevant guidelines for companies who are willing to consolidate themselves as level 2.

- Identifying sponsors and business problems which are being benefited from the analytical initiatives.
- Producing quantitative measures of the achieved benefits.
- Keeping records during the evolution of the project and share the benefits with key stakeholders.
- Continuing working on the local project until the department or area has cumulated enough knowledge and expertise to spread it to other departments.

In the same way, according with Harris (2009) and Daverport& Harris (2007), it could take between two and three years for a company in stage 2 to acquire the skills and expertise in order to be ready to move up to the next level. In short, by building a string of day-to-day success and keeping records of it, heads of departments can bring the attention of the top management which later can become the needed executive sponsorship for a broader application. This is a clear manifestation that a company is ready to move to level 3.

As it was demonstrated by the logistic regression analysis performed in Chapter 5 (See table 5.5); the top management support is indispensable for moving forward a company to higher levels in the scale. This feature is clearly evidenced by companies in level 3, and according with our results, the 33% of the surveyed companies were ranked in this level, which also represents the biggest group. It is possible to say that broader implementation of analytical projects is the main goal in this stage. When a broader adoption of analytical tools is taking place, the top management becomes the ambassador who promotes and advocates the analytical initiatives with the board of directors, shareholders, suppliers and other stakeholders. One of the most important tasks for companies in level 3 is to create a vision of the benefits expected from the analytical initiatives and then this vision should be shared with all staff in the company. (See section 5.3.5). Backed by a cumulated series of smaller successes, the manager is leading by example and also able to demonstrate advantages of making decisions based on data analysis. At this point the company is ready to launch its first analytical project with impact at operative, tactical and strategic level. In addition the adoption of new analytical tools may require extra resources for example; new software or hiring staff specialized on certain quantitative methods. The top management will be willing to provide those extra resources only if there is convincing evidence which demonstrate that the company is going in the right direction. In the same way, the support from IT is indispensable in launching an analytical project which includes all departments and staff in the company. It's highly advisable that IT area develops a vision and action plan in which are clearly described methods, materials and goals to achieve for the analytical project. According with Harris (2009), it could take between 1 and 3 years for integrating all areas of the company into common analytical vision. The degree of progress will be in function how clear and understandable the metrics and goals are defined. The more the analytical enterprise is addressing the strategic problems, the faster the progress will be.

For the group ranked in stage-four, which represent the 20% of surveyed companies, we consider this famous quote as analogy: "*plan your work and work your plan*". That is to say, if the stage-three is related with planning the broader analytical strategy ("*plan your work*"), in the stage-four the company must put in to action the planed work ("*work your plan*"). Basically, the main goal for companies in the stage-four is to build competitive advantages based on data analysis through the use of analytical tools and therefore the progress must be consequence of the developing in the senior management support, changes in corporative culture, focus on strategic insights and improvements on data management and the information technology. For instance, the emphasis on experimenting new ways of doing things must be a mandatory change in the corporate culture for companies at this level. This new way of thinking will allow the company to learn from each performed analysis. However, the most important challenge in stage-four is to manage the cultural change. For example, differences between the "*drivers of change*" and the "*old guard*" could cause unnecessary spending of time and other resources, or in the worst of the cases, differences between this two groups could cause the failure of the project. A similar challenge is to spread the executive support to the rest of members of the board of directors. For instance, if only one or two senior executives are committed with the expansion in the adoption of analytical tools, the project can easily collapse if they suddenly depart or withdraw. A typical context of companies in stage-four is that the analytical practices are become more sophisticated and complex and therefore more resources are needed. In order to optimize and maximize benefits, companies can put together the most expensive analytical resources into a single group, which provides service to all company. These kinds of practices allow centralizing strategic resources and minimizing their associate costs. According with Harris (2009), it could take between 1 and 2 years to develop an outstanding analytical capability in order to embed it into the most important and critical process of the company. When this is done, the company is ready to reach the highest stage in the scale.

In the last upgrade, analytics in company moves from being an important part of the competitive advantages to a key element of the strategy to reach competitive advantages. A common feature present in companies at level-five is that they routinely reap the benefits of the use and application of analytical tools. Sophisticated and complex metrics have created a strong barrier to present and future competitors. In the same way, the experimentation and testing new ways for improving the key process is an everyday activity in this type of companies. It is possible to reach these levels of excellence and mastery in the use of analytical tools, only if there is the support of the board of directors and whole executive team. The differences between "*drivers of change*" and the "*old guard*" have disappeared and it left place to united team for whom the data analysis is its passion. Some of the everyday practices in companies in level five are: The have mastered critical and complex metrics (e.g. the value of the human resources asset) and are published in the most important documents as the balance sheet and income statement. The language of numbers is predominant in all the company and it is a common denominator for all the staff. Data analysis creates a clear and strong identity for the company, in the same way, that identity provides a strong sense of belonging to all staff of the company. Once levels of mastery and excellence have been reached, a company staged in this level must avoid complacency if they are willing to maintain their competitive advantages. While internal processes are continuously improved by exhaustive data analysis, the external environment must be monitored looking for signals of change. It is important to be vigilant of the environment in order to detect changes in the market which cause to modify the assumptions, models, metrics, quantitative models, methods or rules.

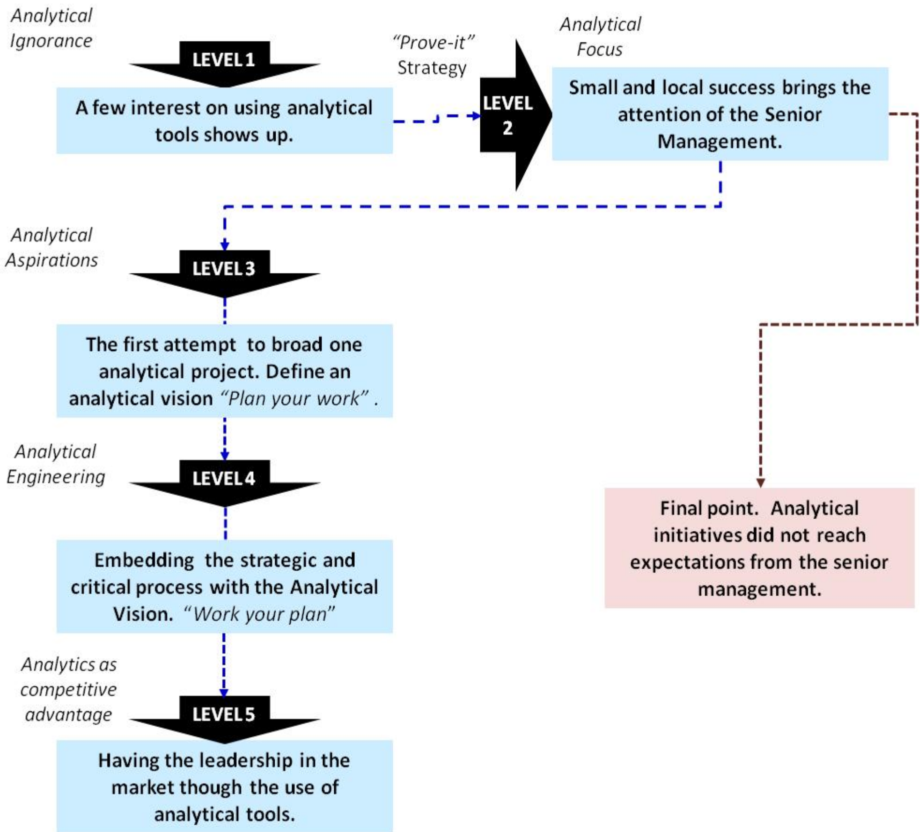

Figure 8.2.Roadmap to transform the use of analytical tools a competitive advantage (Adapted from Davenport & Harris 2007).

In summary, according with Davenport, Harris & Morison (2010) and Harris (2009), the starting point for the analytical development is when a company makes the decision to adopt its first analytical tools. This is called the "*prove it*" strategy. The following is to work locally with discipline, method and keeping records of the progress. At this point, there are two possible situations, either the company is ready to jump to the level 3 or this is the end of the road because the analytical initiatives never reached expectations from the senior management. Once the company achieved the level 3, the challenge is to broad the analytical strategy in all the company. In order to achieve this, changes in corporate culture, process and methods are required. In addition a vision statement with the desired status due to the analytical strategy must be introduced in this stage. When a company can successfully cope with the challenges of the level 3, it is ready to move to the next one. Once in level 4, a company must work on developing their analytical capabilities until the desired status (described in the vision statement) is reached. The highest level in the scale is reached when the company has been doing well for a while and all the analytical practices have embedded the strategic process. If the company is able to maintain the status reached in level 4, continuous improvement cycles are being created and the company inevitably reach a leadership in the industry as direct consequence of reaching maturity in all its analytical practices (See figure 8.3)

8.3 A profile for a highly oriented analytical company.

The starting point for this section is the assessment model which takes the same structure of the questionnaire designed in chapter 4. It is composed by 17 items which are classified in four groups: 1) *Management support on data analysis*, 2) *Data based competitive advantage*, 3) *Systematic thinking* and 4) *Communication outside the company*. The model was assessed according with the size of the companies and following the evidential reasoning approach. (See figure 6.2 for the model)

The reader will find details how these calculations were carried out along the chapter 6. In further lines the discussion is focused on common features which characterize analytical companies.

In the overall assessment, middle-companies obtained highest performance (See figure 6.4). This finding is coherent with results obtained by the Principal Components Analysis carried out in section 5.2.4 in which middle companies also were identified as the most analytical-oriented group. (See figure 5.6). Note that two different analytical methods lead us to similar conclusions. Given the small difference between middle and big companies these conclusions cannot be considered definitive and more research should be conducted in order to confirm our conclusions.

In attributes related with high quality on data once again middle companies received the highest assessment (See figures 6.7A to 6.7D). This result is coherent with the output obtained in the logistic regression analysis, in which features related with data of high quality were identified as significant (See table 5.5). Derived from this, two important features distinguishes highly analytical companies, first *attributes related with data quality* (managing, storing, debugging, sharing, etc) and secondly, *middle companies* have more developed its analytical capabilities.

Similarly, according with results obtained through the logistic regression analysis, two features distinguish the analytical companies. First, the *systematic thinking* is widely developed along this type of companies, and secondly the communication with entities outside the company is strong and efficient (See table 5.5). Similarly, it was found that big companies have the highest evaluation in communication outside whereas middle companies where identified with the highest evaluation in systemic thinking (See figures 6.6A to 6.6D).

Finally, a profile of analytical company is build based on results obtained by different quantitative methods (correspondence analysis, logistic regression, evidential reasoning approach and correlation matrix, among others). At first we identified a cluster of companies which are characterized for selling services, following a differentiation strategy and they are middle size. In contrast, a group of companies which are selling products, with no strategy identified and micro size are the less analytical oriented. In synthesis highly analytical companies tend to be:

- Selling services
- Following a differentiation strategy.
- Middle or big companies.

In contrast the less analytical companies tend to be:

- Selling products
- No competitive advantage strategy defined.
- Micro and small companies.

Until here structured data, which was obtained from our survey have been analysed and interpreted under two different approaches and several quantitative methods. We were able to create a profile which characterizes highly analytical companies. In addition, by applying two different approaches for analyzing our dataset, we were able to ascertain in some extend the validity of our results. Until here there is still more research still to carry out, in order to have a deeper understanding of the level of adoption of analytical tools. The next section is discussed the conclusions derived from the last analysis: in-depth interviews under the laddering methodology.

8.4 Soft and unstructured aspects of the adoption of analytical tools.

Information collected from 10 in-depth interviews was analyzed following the laddering methodology. The reader can find details how interviews were performed and how data was collected, processed and analysed in chapter 7. Now, we are focused in the interpretation of the results, but a detailed description of the methodology is offered in chapter 7. The whole process consisted on building ladders with the form attribute-consequence-values (A-C-V) and then calculating the frequencies. (See figure 7.1). In the same way, a script was prepared which also followed the structure A-C-V. During the drafting process of the script, there were incorporated six different interview techniques proposed by Reynolds & Gutman (1988) to the questions (See table 7.1). The first draft of script contained 33 open questions which were classified in the four groups. In the ending part were including instructions about the script (See appendix B). Each interview lasted between 50 and 80 minutes. Having all the responses digitalized, the next step was to build the ladders. This was done by counting the number of times each attribute, consequence and value was mentioned by the interviewee. Figure 7.3 shows a summary of these frequencies.

The table of frequencies served as the input to the process in which the Hierarchical Value Map was built (HVM). According with Reynolds &Gutman (1988) the HVM is one of most valuable outputs of the laddering technique because it allow us to get a overall perspective of how attributes-consequences-values interact and through the HVM it is possible to easily identify which one are the most relevant values and attributes (See figure 7.5). There are three attributes which deserve special attention: "*goal setting*", "*creativity to propose new ideas*" and "*getting information from outside the company*". On the other hand, with the purpose of obtaining a wider perspective we separated the values in to groups: social values and personal achievement values. For social values is was found that "*serving the society*", "*honesty and creativity*" and "*adding value to the customers*" are the most relevant. On the other hand "*leadership*" is the most relevant value related with personal achievement.

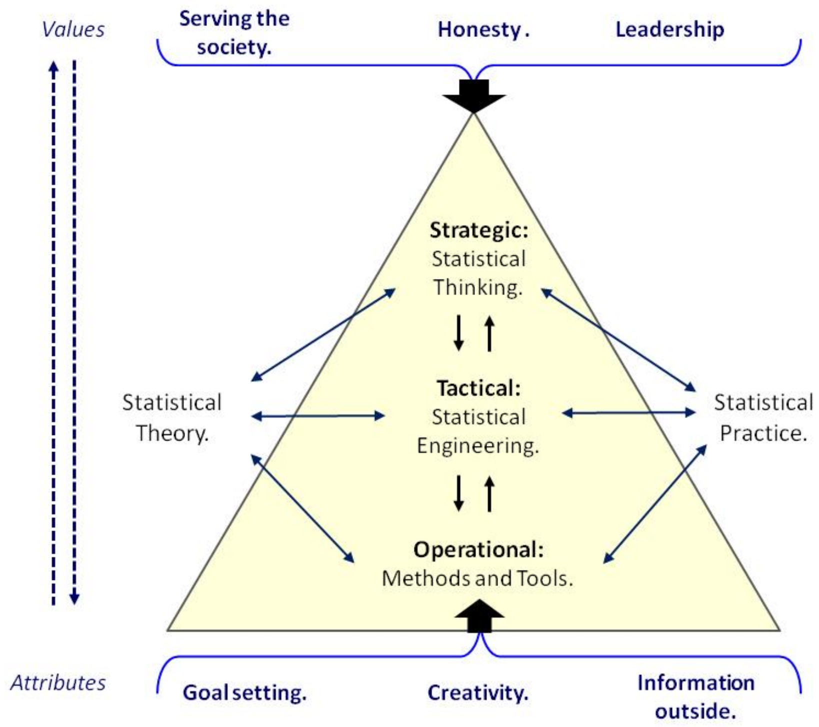

Figure 8.4. Main values and attributes that influence the adoption of analytical tools. (Adapted from Hoerl and Snee 2010).

According with Thompson & McEwen (1958) it is almost impossible that a company can continue indefinitely if goals are formulated arbitrarily or without deep knowledge of how the company works. There is a strong relationship between gathering information from along the company and the goal setting process. Shalley (1995) suggest that one of the most important aspects to guarantee the survival of the company in the long term is the capacity to accurately respond to changes in the business environment and this can only be achieved by retrieving information which is the input for a truthful goal setting process. In the same way, Locke & Latham (1990) suggest that there is a direct relationship between goal setting and productivity. That is to say, the goal setting increases productivity when individuals accept and commit to specific difficult goals and receive feedback concerning their performance. The results obtained in this particular case of study demonstrate that goal setting is an outstanding attribute for increasing the level of adoption of analytical tools.

The second attribute is related with creativity. In Amabile et al (1996) creativity is defined as the production of novel and useful ideas in any domain. In other words, creativity by individuals and teams is the starting point for innovation and therefore for experimentation, which has a strategic importance in increasing the use of analytical tools. In this particular context innovation and experimentation are also defined as the successful implementation of creative ideas to solve problems or generate improved results. Given this, it is evident that creativity is another indispensable element to increase the use of analytical tools.

The third most important attribute is related with the capacity of monitoring the business environment. For the purpose of this thesis, the term environment is related more with the business environment (e.g. suppliers, customers, society, economic conditions, etc.) and is not restricted only to ecological and environmental aspects. According with Roome (1992), the complexity in the business environment impacts the management practices, technology available and company's structure and considering this, it is necessary to constantly monitor the business environment to access reliable information from outside the company. Ruff (2006) proposes to screen the environment in three levels: products and services, markets and industries and the macro-environment issues, which include politics and economic factors.

The obtained results regarding with the importance of the goal setting process, the creativity and information from outside the company are coherent with is was found in literature. In the next part of this chapter we are discussing results related with values.

We define values as outstanding and lasting beliefs of ideals that are shared by member of a country, culture or company. Values refer to what is good or bad, desirable or undesirable, acceptable or unacceptable. Values are similar to norms in having a moral and regulatory role. ("Values", 2013). In this particular context, three values were identified as key elements in increasing the use of analytical tools: serving to the society, honesty and leadership. Additionally, there is plenty of literature which discusses the influences of leadership on business analytics and competitive advantage in Eisenbeiss et al (2013), Porter (1996) and Lowe, Kroeck & Sivasubramaniam (1996), similarly the value of honesty and its influence on business administration is discussed in Becker(1998), Evans et al (2001) and Forehand & Grier (2003), and the value serving the society is commented in Perry-Smith & Shalley (2003). What it was found in literature is coherent with our results, which remarks the critical importance of these three values on the adoption of analytical tools.

As it is shown in figure 8.4, there is a double effect in the adoption of analytical tools, which is produced by both values at the strategic processes whereas attributes impact operational processes. More specifically, serving the society, honesty and leadership are influencing the strategic part of the data analysis (*the statistical thinking*). On the other hand, at the bottom of the company`s structure: goal setting, creativity and information outside the company are influencing operational aspects of the adoption of analytical tools (*the methods and tools).* At the middle level of the structure the statistical engineering is found, which establishes a strong links between attributes/operational-process and values/strategic-process. In this way, the bigger picture of the adoption of analytical tools in companies is composed.

Considering the elements shown in picture 8.4 and its interrelations, the initiatives for expanding the adoption of analytical tools should be divided in two major groups. At first with the purpose of impacting the operational levels in the company, actions should be focus on:

- Improving the ***goal setting process***.
- Stimulate the ***creativity*** in all staff.
- Improving the processes related with gathering ***information from outside***.

Secondly, the strategic processes in the company should be based on instilling values. More specifically, senior management should be a reference by conducting the following actions.

- Making sure and demonstrating that the company is ***adding value to the society***.
- Assuring that ***honesty*** is a “big issue” in the company and everybody in the company share this belief.
- Demonstrating ***leadership*** and commitment by providing all the needed support in order to promote and stimulate the use of analytical tools in the company.

In chapter 1, were introduced six general objectives for this thesis. In table 8.2 is shown each one of the settled objectives and the corresponding chapter in which it was developed.

Table 8.2. Thesis objectives and chapter in which were developed**.**

Thesis objective.	Chapter in which it was developed
1. Propose a theoretical scale to measure the level of adoption of analytical tools in companies.	2,3
2. Design a reliable and valid instrument to collect data from a sample of companies located in Barcelona, Spain.	4
3. Analyze data collected from the surveyed companies, in order to draw conclusions about the level of adoption of analytical tools in Barcelona by applying the ***Statistical Engineering*** approach.	5
4. Rank the sampled companies in the five levels scale by applying the ***Evidential Reasoning*** approach.	6
5. Conduct in-depth interviews with managers, consultants and academics with the purpose of finding out soft and unstructured aspects about the level of adoption of analytical tools in Barcelona by applying the ***Laddering Methodology***.	7
6. Merge findings from questionnaires and in-depth interviews in order to get complementary and unique conclusions about the level of adoption of analytical tools in Barcelona, Spain.	8

Having considered that the objectives were achieved; now it is beyond the scope of this thesis to find out deeper how these attributes and values can be quantified and successfully deployed in the company. Although it was offered an explanation how those attributes and values affect the analytical capabilities in the company at operational, tactical and strategic levels; and supportive literature was also provided, it is clear that this description is far from being exhaustive. We are considering the design of a mathematical formulation, which widely describes relations between this attributes-values and operative-strategic processes for a topic of further research. In the last chapter of this thesis are described the future lines of research, which also are based in findings obtained until this point.

9. Further lines of research.

This chapter describes a future line of research, which is derived of results obtained through this thesis.

9.1. Introduction.

The complex contemporary economic environment, globalization in markets, emergence of more powerful computers, intricate internet-based systems, and the proliferation of real-time communication channels are transforming the way organizations make decisions. The first immediate consequence of those changes is the accumulation of massive amounts of data. According with Gantz & Reinsel (2012) from 2005 to 2020 the data accumulated will grow by a factor of 300, this is from 130 exabytes to 40,000 exabytes, or 40 trillion of gigabytes. Regarding with its composition, around of 68% of the information worldwide will be created and consumed by consumers doing several activities as watching digital TV, interacting in social networks, sending images and videos, among others. Additionally private and public organizations will own nearly 80% of the data in the "digital universe" at the same they will have to deal with issues as security, privacy, copyright, and compliance with regulations.

Considering the exponential grow in data available, it is clear organizations should respond to these changes. It is a fact that traditional decision making approaches, usually based intuitive judgements and past experiences, are gradually becoming inadequate guides for dealing with the increasingly complexity. The challenge is to find new approaches for extracting relevant information from the enormous amounts of data available and making more accurate decisions. In contemporary globalized markets competitive advantages will be given by the ability to analyze data and create value in order to successfully respond to the expectations of customers, suppliers, staff, shareholders and society. The emergence in 2006 of the evidence-based management (EBMgt) concept makes clear this tendency. According with Rousseau (2006) EBMgt is defined as the discipline of making the most accurate organizational decisions by the application of science and research principles and it is only possible to achieve when the principles and values are credible, the evidence is clear and findings are interpretable by all stakeholders. A second movement introduced as response to the mentioned tendencies is the predictive analytics. Basically, it deals with extracting valuable information from data, in order to predict trends, behaviours and patterns. The main concept behind predictive analytics relies in establishing relations between explanatory and predicted variables ("Predictive analytics", 2013). Here only two movements were briefly discussed in order to illustrate what is doing by experts and practitioners as response to the necessity of taking advantage of the "*big data*". An extensive discussion about these changes and tendencies can be found in Davenport, Harris & Morison (2010), Lynch (2008), Scott, A. J. (2012) and Anderson-Cook et al (2012). In further lines the discussion is centred on how real-world data was obtained in order to validate what it is stated in our literature review. Having both: the literature review and real-world data, at the end of this section our research objectives are introduced.

At this point is clear the importance of investigating how organizations can improve their analytical capabilities and obtain more benefits from data available. In Barahona & Riba (2011) it was proposed a five-level scale to measure the level of adoption of analytical tools and later it was applied to a sample of 255 organizations. The analysis of these data allowed us to formulate guidelines in order to assist them to improve their analytical capabilities. Later our survey was complemented with in-deep interviews with managers, consultants, academics and practitioners. A total of 10 interviews were carried out and results allowed us to propose an additional scale. Based on these two sources of data with different scales, the first composed into a five-level scale while the second formulated on a three-level, the challenge is to provide a generic framework that allows us to obtain unique and relevant conclusions while losing information is preventing. In order to deal with this problem, a novel structure should be developed as it is stated in the following research objectives.

- Based in the principles stated in Yang et al (2011), analyze scales from questionnaires and in-depth interviews in order to propose a unique framework for both of them.
- Apply the evidential reasoning approach for calculating the overall performance, comparing alternatives and perform sensitivity tests.
- Offer relevant guidelines to organizations that are interesting in improving their analytical capabilities.

Having settled the objectives for this research proposal, in following lines the methodology is discussed in detail.

9.2. Methodology.

The evidential reasoning (ER) approach is a generic *evidence-based* type of multi criteria decision analysis (MCDA). It can be used for dealing with problems which are composed of both quantitative and qualitative information or be applied to support several decision making problems, assess and evaluate alternatives such as business activities, environmental impact, quality models, among others. According with Yang & Singh (1994) the evidential reasoning approach is different from conventional MCDA methods in that it uses *evidence-based* reasoning process to reach a decision. One of the most important contributions of this method is its capacity to describe a scenario by using belief structures or belief decision matrices, on where each alternative is assessed by a vector of paired elements. Basically the ER approach uses a non-linear process to aggregate attributes. The non linearity is given by the weights of criteria, and the form each criterion is assessed.

In this research the ER will be applied for prioritizing the level of adoption of analytical tools in organizations. Yang et. al (2011) define prioritizing as ranking the alternatives on a given individual criteria or on the overall criterion. For example, a simple approach for ranking the level of adoption of analytical tools is to quantify each value on the scale to a certain fixed value, calculate its mean and then rank the different alternatives based on their mean values. As it will be shown in further lines, the problem with this procedure is that it can only produce a narrow sense of mean and richer information contained in the data is eventually lost. A solution to this problem is proposed in Yang et. al (2011) which consist on utilizing a generic framework. This method does not require the assessment grades to be quantified to fixed values, instead it allows to them to take any values that suit their qualitative definitions and meanings. The way this methodology can be implemented to our data is explained in following paragraphs.

In figure 9.1, the model for this research is presented. The level of adoption of analytical tools may be assessed through one or more ways. For this specific case it is assessed in two ways, at first questionnaires collect quantitative and structured aspects and secondly in-depth interviews are focused on qualitative and unstructured features. Both approaches are complementary and they allowed us to get a deeper understanding of how and why analytical tools in organizations are adopted.

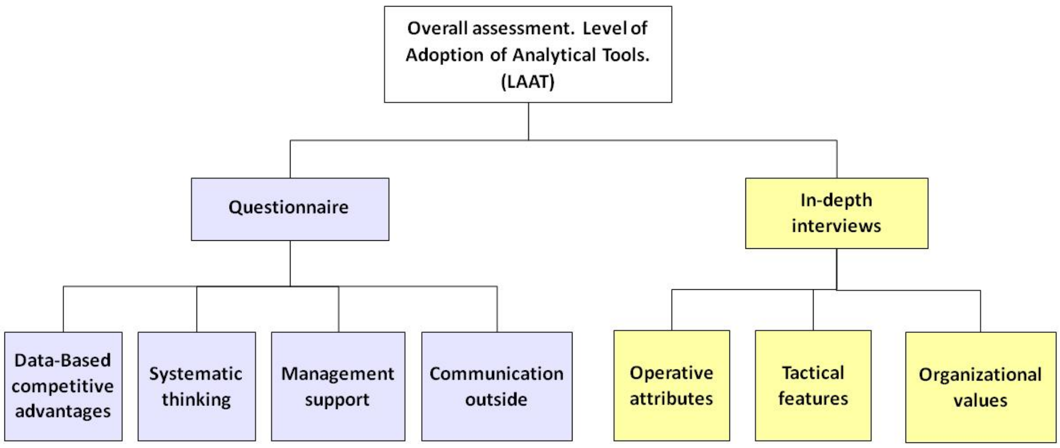

Figure 9.1. A common framework for obtaining the overall assessment of the level of adoption of analytical tools.

Based on the principles proposed by Yang (2001), multiple criteria (from both questionnaires and in-depth interviews) can be handling to generate appropriate evidence for assessing and finally prioritizing the level of adoption of analytical tools. This means that the problem can be tackled as a sort of multi-level multi-criteria decision analysis (MCDA) problem.

9.2.1 Written questionnaire.

A questionnaire was designed to investigate the level of adoption of analytical tools. In order to guarantee its reliability and validity several statistical test were performed, among them the coefficient of agreement proposed by Fleiss (1971), a measure of reliability in the scale proposed by Cronbach (1951) and a test to measure the degree of association between items suggested by Shrout & Fleiss (1979). Once the draft was finished, a principal components analysis was performed in order to confirm the original design. All statistical tests were satisfactory according with parameters suggested in the mentioned literature, and this allowed us to move forward by sending the questionnaire to the sampled companies (See table 9.1 for the questionnaire structure).

Table 9.1. Questionnaire structure**.**

Section	Number of items
Categorical questions	3
Data Based Competitive Advantage	5
Management Support Data Analysis	6
Systemic Thinking	5
Communication outside the company	1
Total	**20**

We invited to 6,064 companies to participate in the study by sending to them a questionnaire. The questions used a five-level scale and related about features and good practices in data exploitation and analysis. All the invited companies are located in Barcelona, Spain and it was sent electronically. The questionnaire was addressed to the information technology manager, quality manager or manager director and it asked to be redirected proper person when necessary. Additionally, we offered to any interested company diagnostic about its analytic capabilities for free in order to maximize the number of responses. In the same way, we stated in the cover letter our open intention to share the final results and conclusions with anyone interested. Considering that responses were given on the basis of an ordinal scale with five assessment grades, they are subjective in nature. The employed scale can be represented in the following way:

$$\begin{aligned} H_1 = \{ &'H_{1,1} - Dissatisfied\ Completely', 'H_{1,2} - Dissatisfied', \\ &'H_{1,3} - Neutral', 'H_{1,4} - Satisfied\ ', \\ &'H_{1,5} - Satisfied\ Completely'\} \end{aligned} \tag{1}$$

According with expression (1), a manager may chose to tick one of the grades in order to assess the level of adoption of analytical tools in his/her company. Considering that K companies participated in our study and $k_{l,n}$ of them selected a grade $H_{1,n}$ for assessing the company in the category A_l , then the degree of belief $\beta^l_{1,n}$ to which a company is assessed by the whole group of managers to the grade $H_{1,n}$ on the category A_1 is given for the following expression.

$$\beta^l_{1,n} = \frac{k_{l,n}}{K} \tag{2}$$

The evaluation rating of a company on the category A_l by the whole group of companies which were surveyed is given by the following expression.

$$S(A_l) = \{(H_{1,1}, \beta^l_{1,1}), (H_{1,2}, \beta^l_{1,2}), (H_{1,3}, \beta^l_{1,3}), (H_{1,4}, \beta^l_{1,4}), (H_{1,5}, \beta^l_{1,5}), (H_1, \beta^l_{H_1})\} \tag{3}$$

In expression (3), $0 \le \beta^l_{1,n} \le 1$. Additionally $\sum_{n=1}^{5} \beta^l_{1,n} \le 1$ and $\beta^l_{H_1} = 1 - \sum_{n=1}^{5} \beta^l_{1,n}$ provides a measure of companies who did not provide any assessment on the category A_l. That is to say, $\beta^l_{H_1}$represents the amount of missing information or the degree of ignorance for the category A_l . According with Yang (2001) and Yang et al (2011) it is possible to ascertain that expression (3) adequately records the collected assessment information and keeps the diversity of each questionnaire, and thus it generates suitable information for further decision analysis. Moreover, considering that our data comes from a survey, it results helpful to calculate the mean for the distributed assessment as simpler indicator of the performance. If $u(H_{1,n})$ is the utility given to $H_{1,n}$ and there is not missing information, so that $\beta^l_{H_1} = 0$ the mean for the distribution (3) is given by:

$$u(S(A_l)) = \sum_{n=1}^{5} \beta^l_{1,n}\, u(H_{1,n}) \tag{4}$$

The evaluation obtained in (4) provides relevant information about the level of adoption of analytical tools. For instance, if a company is given a high mean on any particular category, it means that this company should work in maintain the achieved strength. On the other hand, if the company obtains a low mean on a given category, it means that this category should be paid high priority so that, the company and overcome this weakness. In short, it is possible to apply the expressions (1) to (4) to our survey data in order to collect relevant evidence regarding with the level of adoption of analytical tools, which includes distributed assessments for each company, its means and performs comparisons among companies on a given category. In the next subsection the in-depth interviews and its assessment distribution are discussed.

9.2.2 In-depth interviews.

With the purpose of investigating soft and unstructured features of the level of adoption of analytical tools, a set of in-depth interviews were performed. Prior the elaboration of the interviews, a script was prepared. Although these were unstructured interviews, the script let us keep a general guideline while each of them was performed. The script and interviews were designed by following the laddering methodology proposed by Reynolds & Gutman (1988). The term "*laddering*" refers to an in-depth, one-to-one interviewing technique, which is applied to understand how customers transform attributes of any given product or service into meaningful associations with respect to self by following the Means-End theory. In this research proposal we are focused on investigating the scales, but a detailed explanation of both, laddering technique and Means-End theory can be found in Herrmann et al (2000), Reynolds & Gutman (1984) and Reynolds & Gutman (1988). Basically, the core idea behind the laddering technique is eliciting elements in a sequential order from the bottom to the top. The bottom is given by the less abstracted elements while the top is composed for the most abstracted. Three levels of abstraction follow an order of "*attributes*" → "*tactical features* → "*values*". In addition, Deming (2000) states that values have the biggest positive impact in adopting analytical tools in companies while attributes have the lowest impact. Under this perspective, a three level scale is defined as follows:

$$H_2 = \{'H_{2,1} - Minimal\ impact', 'H_{2,2} - Average\ impact' \\ 'H_{2,3} - Highest\ impact'\} \qquad (5)$$

Comparable with the expression of the questionnaires, in (3) the distributed assessment for the in-depth interviews in the category A_l is given by:

$$S(A_l) = \{(H_{2,1}, \beta_{2,1}^l), (H_{2,2}, \beta_{2,2}^l), (H_{2,3}, \beta_{2,3}^l), (H_2, \beta_{H_2}^l)\} \qquad (6)$$

Where $\beta^{l}_{2,n}$, n=1,2,3 is calculated like it was performed with expression (2). In addition $\beta^{l}_{H_2}$ is a measure of ignorance, $0 \leq \beta^{l}_{2,n} \leq 1$ and $\sum_{n=1}^{3} \beta^{l}_{2,n} \leq 1$. On the other hand $u(H_{2,n})$ is the utility assigned to $H_{2,n}$. If we assume it is a complete distribution, so that $\beta^{l}_{H_2} = 0$, then the mean value is given by:

$$u\big(S(A_l)\big) = \sum_{n=1}^{3} \beta^{l}_{2,n}\, u\big(H_{2,n}\big) \tag{7}$$

Similarly to the mean for questionnaires, the expression (7) can be assessed to whether a criterion should be given high priority, or it can be employed for comparing a position of a company with respect its competitors on a given criterion. For instance, if a company receive higher accumulated degree of belief to the top grade (ie $H_{2,3}$ in (6)) then this criterion should be given high priority in order to maintain the company strengths. On the other hand, if a company received higher accumulated degree of belief to the bottom grade (ie $H_{2,1}$ in (6)) then this criterion should be given high priority for improving the company weakness.

As it was illustrated in previous subsections, the scales presented in (1) and (5) have to be transformed into a common scale for the purpose of obtaining a richer assessment of the level of adoption of analytical tools. This enriched assessment will be a helpful in making decisions about how to improve analytical capabilities in companies. In following paragraphs a set of rule based techniques are proposed to transform our data from their original scales into a common scale.

9.2.3 A common framework.

As it was mention in our research objectives, the challenge is how to use two sources of information, and investigate them under a single framework to support the prioritization of the level of adoption of analytical tools in companies while losing or distorting information is prevented. In Yang et al (2011), Yang (2001) and Liu et. al (2008) is demonstrated that expert judgments are routinely used in industry for interpreting data from surveys. In this proposal the roll of the experts is not deeply discussed; although it is clear for us that expertise and knowledge from judgments will successfully provide key information for enriching the distributions assessments. In further lines we centred our attention in detailing the process, which will be used to interpret our data systemically in order to propose a unique frame work.

By gathering evidence from expert knowledge the proposed scale should preserve original information from questionnaires and in-depth interviews while it is understandable and easy to use. In addition, the gathered evidence should provide set of common sense rules that could be used during the transformation process in a flexible form. Considering the above, a five-level monotonic scale is suggested in the following way:

$$\begin{aligned} H_1 = \{ &\text{´}H_1 - Analytics\ Ignorance\text{´}, \text{´}H_2 - Analytics\ focused\text{´}, \\ &\text{´}H_3 - Analytical\ aspirations\text{´}, \text{´}H_4 - Systemic\ analytics\text{´}, \\ &\text{´}H_5 - Analytics\ as\ competitive\ advantages\text{´}\} \end{aligned} \tag{8}$$

A complete and specific definition of the scale, including each one of its five levels, will be provided during the implementation of this research. This is part of the operative definition of variables which was previously done in order to gather the required evidence. In addition, the distributed assessment of a company (for both: questionnaires and in-depth interviews) on the category A_l is expressed as:

$$S(A_l) = \{(H_1, \beta^l_{1,}), (H_{,2}, \beta^l_{,2}), (H_{,3}, \beta^l_{,3}), (H_{,4}, \beta^l_{,4}), (H_{,5}, \beta^l_{,5}), (H, \beta^l_H)\} \tag{9}$$

The expressions (8) and (9) represent the common framework on which data from questionnaires and in-depth interviews will be transformed. At this point is necessary offer a set of rule based techniques in order to complete the transformation process.

9.2.4 Qualitative transformation for questionnaires

The scale utilized for questionnaires can be transformed almost directly to the new common scale. That is to say, considering both scales have five grades with logic behind "*higher is better*", it makes the transformation easy to implement. The following equivalence of rules are proposed for carrying out the transformation.

$'H_{1,1} - Dissatisfied\ Completely'$	→	$'H_1 - Analytics\ Ignorance'$
$'H_{1,2} - Dissatisfied',$	→	$'H_2 - Analytics\ focused'$
$'H_{1,3} - Neutral'$	→	$'H_3 - Analytical\ aspirations'$
$'H_{1,4} - Satisfied\ '$	→	$'H_4 - Systemic\ analytics'$
$'H_{1,5} - Satisfied\ Completely'$	→	$'H_5 - Analytics\ as\ competitive\ advantages'$

For the purpose of this research, the symbol '→' means 'is equivalent" in terms of utility. The implementation of these rules doesn't imply changes in the utilities. For instance if $u(H_n)$ is defined as the utility of H_n then, $u(H_{1,1}) = u(H_1)$, $u(H_{1,2}) = u(H_2)$, $u(H_{1,3}) = u(H_3)$, $u(H_{1,4}) = u(H_4)$ and $u(H_{1,5}) = u(H_5)$. It is important to mention that we assume that the grades are evenly distributed in the assessment space with H_1 with the lowest utility while H_5 associated to the highest.

9.2.5 Qualitative transformation for in-depth interviews

On the other hand, data from in-depth interviews is based on three levels and this implies to expand it to a five levels, which represent an additional degree of complexity. Basically the two extra grades should be added to the former scale. Similarly to questionnaires, the scale for the interviews is following a logical order "*higher is better*" and anchoring points are not required for carrying out the transformation. The following equivalence of rules are proposed for in-depth interviews.

$'H_{2,1} - Minimal\ impact'$	→	$'H_1 - Analytics\ Ignorance'$
$0.5\ 'H_{2,1} - Minimal\ impact'$ & $0.5\ 'H_{2,2} - Average\ impact'$	→	$'H_2 - Analytics\ focused'$
$'H_{2,2} - Average\ impact'$	→	$'H_3 - Analytical\ aspirations'$
$0.5\ 'H_{2,2} - Average\ impact'$ & $0.5\ 'H_{2,3} - Highest\ impact'$	→	$'H_4 - Systemic\ analytics'$
$'H_{2,3} - Highest\ impact'$	→	$'H_5 - Analytics\ as\ competitive\ advantages'$

In this case the introduction of the proposed rules implies changes in the utilities. More explicitly, we have that $u(H_{2,1}) = u(H_1)$, $0.5u(H_{2,1}) + 0.5u(H_{2,2}) = u(H_2)$, $u(H_{2,2}) = u(H_3)$, $0.5u(H_{2,2}) + 0.5u(H_{2,3}) = u(H_4)$ and $u(H_{2,3}) = u(H_5)$. The assumption of evenly distributed grades is also done in this second transformation.

9.2. Procedure for the implementation

The new assessment distribution with the sum of both transformations is not developed in this proposal, but it will be fully developed during the postdoctoral work. In the same way, a complete description of how the evidential reasoning will be adapted in this analysis is also provided during the postdoctoral outputs. Finally a “big picture” of the implementation process was prepared with the purpose of illustrate the sequence and logical order that will be followed.

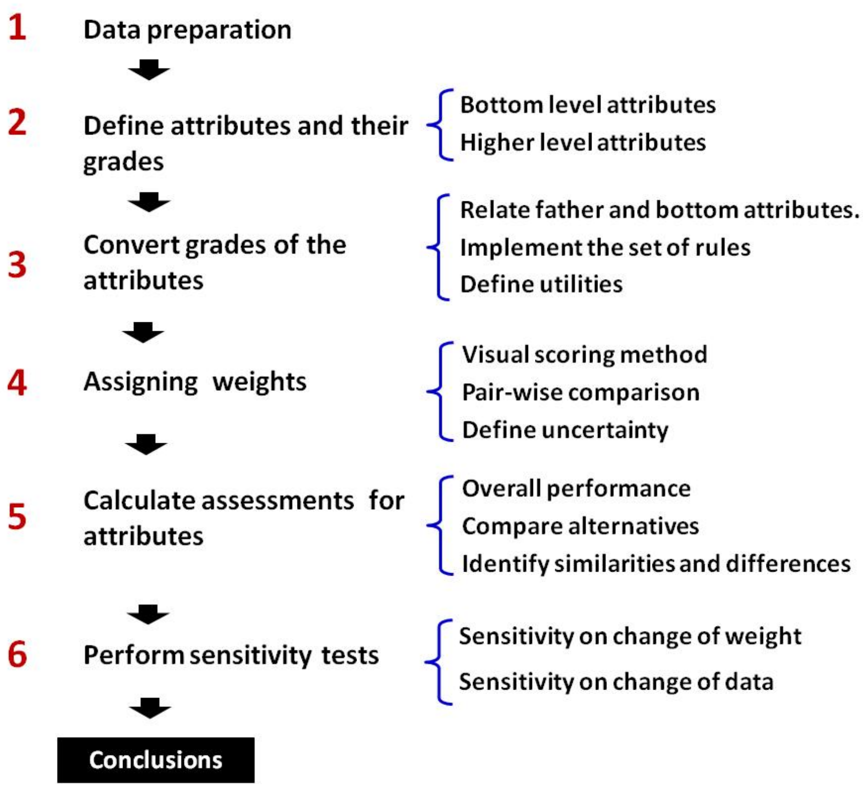

Figure 9.2. The implementation process for the described methodology.

According with the figure 9.2, a process composed of six stages will be followed in order to implement the explained methodology. In the first, stage activities related with data debugging will be performed. The second stage is related with the model definition, through the implementation of the rules and the conversion of grades. In the third step the weights of each attribute will be defined. At the stage five the interpretable results are expected to be obtained. Finally, in order to complement our findings in the last step a set sensitivity of tests will be performed.

References

Amabile, T. M., Conti, R., Coon, H., Lazenby, J., & Herron, M. (1996). Assessing the work environment for creativity. *Academy of Management Journal, 39*(5), 1154-1184.

Anderson-Cook, C. M., Lu, L., Clark, G., DeHart, S. P., Hoerl, R., Jones, B., et al. (2012). Statistical Engineering-Forming the Foundations. *Quality Engineering, 24*(2), 110-132.

Ang, J. S. K., Sum, C.-C., & Yeo, L.-N. (2002). A multiple-case design methodology for studying MRP success and CSFs. *Information & Management, 39*(4), 271-281.

Banks, D. (1993). IS INDUSTRIAL STATISTICS OUT OF CONTROL. *Statistical Science, 8*(4), 356-377.

Barahona, I., & Riba, A. (2012). Applied Statistics on Business at Spain: A Case of Statistical Engineering. In ASA (Ed.). In *2012 Joint Statistical Meetings*. Vol. Book of abstracts, pp. p 246). San Diego CA:(ASA).

Barlow, W., Lai, M. Y., & Azen, S. P. (1991). A COMPARISON OF METHODS FOR CALCULATING A STRATIFIED-KAPPA. *Statistics in Medicine, 10*(9), 1465-1472.

Becker, T. E. (1998). Integrity in organizations: Beyond honesty and conscientiousness. *Academy of Management Review, 23*(1), 154-161.

Bhatt, G. D., & Grover, V. (2005). Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of Management Information Systems, 22*(2), 253-277.

Blanchard, D. (2010). *Supply chain management best practices*. Hoboken, New Jersey: John Wiley & Sons Ltd; Edición: 2nd Revised edition.

Boen, J. R., & Zahn, D. A. (1982). *The human side of statistical consulting*. Belmont, CA: Lifetime Learning Publications Belmont.

Brenneman, W. A., & Joner, M. D., Jr. (2012). Setting Appropriate Fill Weight Targets-A Statistical Engineering Case Study. *Quality Engineering, 24*(2), 241-250.

Bryant, F. B., Yarnold, P. R., & Michelson, E. A. (1999). Statistical methodology: VIII. Using confirmatory factor analysis (CFA) in emergency medicine research. *Academic Emergency Medicine, 6*(1), 54-66.

Bryman, A. (2012). *Social research methods*. New York, NY: Oxford University Press.

Burby, J., & Atchison, S. (2007). *Actionable web analytics: using data to make smart business decisions*. Indianapolis, IN: Sybex.

Checkland, P. (1999). *Systems thinking, systems practice: includes a 30-year retrospective*. West Sussex, England: John Wiley & Sons.

Cohen, J. (1960). A COEFFICIENT OF AGREEMENT FOR NOMINAL SCALES. *Educational and Psychological Measurement, 20*(1), 37-46.

Cohen, J. (1968). WEIGHTED KAPPA - NOMINAL SCALE AGREEMENT WITH PROVISION FOR SCALED DISAGREEMENT OR PARTIAL CREDIT.*Psychological Bulletin, 70*(4), 213-220.

Conger, A. J. (1980). INTEGRATION AND GENERALIZATION OF KAPPAS FOR MULTIPLE RATERS. *Psychological Bulletin, 88*(2), 322-328.

Cortina, J. M. (1993). WHAT IS COEFFICIENT ALPHA - AN EXAMINATION OF THEORY AND APPLICATIONS. *Journal of Applied Psychology, 78*(1), 98-104.

CRM. Customer Relationship Manager (2013). Retrieved April 12 of 2013, 2013, from http://www.answers.com/topic/customer-relationship-management

Cronbach, L. J. (1951). COEFFICIENT ALPHA AND THE INTERNAL STRUCTURE OF TESTS. *Psychometrika, 16*(3), 297-334.

Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: the new science of winning*. Boston MA: Harvard Business Press.

Davenport, T. H., Harris, J. G., & Morison, R. (2010). *Analytics at work: smarter decisions, better results*. Boston, MA: Harvard Business Press.

Deming, W. E. (1993). *The New Economics: For Industry, Government, Education*. Cambridge, MA: Massachusetts Institute of Technology, Center for advanced engineering study.

Deming, W. E. (2000). *Out of the Crisis*. Cambridge, MA: Massachusetts Institute of Technology, Center for Advanced Engineering Study.

Dempster, A. (2008). Upper and Lower Probabilities Induced by a Multivalued Mapping. In R. Yager & L. Liu (Eds.), *Classic Works of the Dempster-Shafer Theory of Belief Functions* (Vol. 219, pp. 57-72): Springer Berlin Heidelberg.

Donner, A. (1985). THE ANALYSIS OF INTRACLASS CORRELATION IN MULTIPLE SAMPLES. *Annals of Human Genetics, 49*(JAN), 75-82.

Donner, A., & Klar, N. (1996). The statistical analysis of kappa statistics in multiple samples. *Journal of Clinical Epidemiology, 49*(9), 1053-1058.

Eisenbeiss, S. A., & Boerner, S. (2013). A Double-edged Sword: Transformational Leadership and Individual Creativity. *British Journal of Management, 24*(1), 54-68.

Engineering (2013). Retrieved January 14 of 2013, 2013, from http://www.answers.com/topic/engineering

Evans, J. H., Hannan, R. L., Krishnan, R., & Moser, D. V. (2001). Honesty in managerial reporting. *Accounting Review, 76*(4), 537-559.

Fleishman, J., & Benson, J. (1987). USING LISREL TO EVALUATE MEASUREMENT MODELS AND SCALE RELIABILITY. *Educational and Psychological Measurement, 47*(4), 925-939.

Fleiss, J. L. (1971). MEASURING NOMINAL SCALE AGREEMENT AMONG MANY RATERS. *Psychological Bulletin, 76*(5), 378-382.

Fleiss, J. L. (1981). *Statistical methods for rates and proportions*. New York, NY: John Wiley & Sons.

Fleiss Joseph L, L. B., Paik Myunghee Cho. (2003). *Statistical methods for rates and proportions* (3rd ed. ed.). New York, NY: Hoboken John Wiley & Sons.

Flynn, B. B., Schroeder, R. G., & Sakakibara, S. (1994). A framework for quality management research and an associated measurement instrument.*Journal of Operations management, 11*(4), 339-366.

Forehand, M. R., & Grier, S. (2003). When is honesty the best policy? The effect of stated company intent on consumer skepticism. *Journal of Consumer Psychology, 13*(3), 349-356.

Futami, R. (1986). The outline of seven management tools for QC. *Reports of Statistical Application Research, Union of Japanese Scientists and Engineers, 33*, 7-26.

Gantz, J., & Reinsel, D. (2012). THE DIGITAL UNIVERSE IN 2020: Big Data, Bigger Digital Shadows, and Biggest Grow in the Far East. (EMC Corporation).

Garvin, D. A. (1984). JAPANESE QUALITY MANAGEMENT. *Columbia Journal of World Business, 19*(3), 3-12.

Garvin, D. A. (1986). QUALITY PROBLEMS, POLICIES, AND ATTITUDES IN THE UNITED-STATES AND JAPAN - AN EXPLORATORY-STUDY. *Academy of Management Journal, 29*(4), 653-673.

Gengler, C. E., Klenosky, D. B., & Mulvey, M. S. (1995). Improving the graphic representation of means-end results. *International Journal of Research in Marketing, 12*(3), 245-256.

Ghemawat, P. (2007). *Redefining Global Strategy: crossing borders in a world where differences still matter*. Boston MA: Harvard Business Press.

Ghemawat, P., Mark, K. A., & Bradley, S. P. (2004). *Wal-Mart Stores in 2003*. Boston MA: Harvard University School Pub.

Goodman, M. T., Nomura, A. M. Y., Wilkens, L. R., & Kolonel, L. N. (1990). AGREEMENT BETWEEN INTERVIEW INFORMATION AND PHYSICIAN RECORDS ON HISTORY OF MENOPAUSAL ESTROGEN USE. *American Journal of Epidemiology, 131*(5), 815-825.

Greenacre, M., & Hastie, T. (1987). The geometric interpretation of correspondence analysis. *Journal of the American Statistical Association, 82*(398), 437-447.

Gruber, T., Szmigin, I., & Voss, R. (2009). Developing a deeper understanding of the attributes of effective customer contact employees in personal complaint-handling encounters. *Journal of Services Marketing, 23*(6-7), 422-434.

Grunert, K. G., & Grunert, S. C. (1995). Measuring subjective meaning structures by the laddering method: Theoretical considerations and methodological problems. *International Journal of Research in Marketing, 12*(3), 209-225.

Gutman, J. (1982). A MEANS-END CHAIN MODEL BASED ON CONSUMER CATEGORIZATION PROCESSES. *Journal of Marketing, 46*(2), 60-72.

Hahn, G. J., Doganaksoy, N., & Hoerl, R. (2000). The evolution of six sigma. *Quality Engineering, 12*(3), 317-326.

Hair, J. F., Black, B., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate Data Analysis.* Upper Saddle River,NJ: Pearson Education.

Hamada, C. A., & Hamada, M. S. (2012). Illustrating the Practice of Statistics as a Stepping Stone to Statistical Engineering. *Quality Engineering, 24*(2), 184-192.

Harris, J. G., Craig, E., & Egan, H. (2009a). How to Create a Talent-Powered Analytical Organization. *research report, Accenture Institute for High Performance*.

Harris, J. G., Craig, E., & Egan, H. (2009b). *How to Create a Talent-Powered Analytical Organization*. research report, Accenture Institute for High Performance. Retrieved March 19th of 2013, 2013, from http://www.accenture.com/SiteCollectionDocuments/PDF/Accenture_How_to_Create_a_Talent_Powered.pdf

Harvey, R. J., Billings, R. S., & Nilan, K. J. (1985). CONFIRMATORY FACTOR-ANALYSIS OF THE JOB DIAGNOSTIC SURVEY - GOOD-NEWS AND BAD NEWS. *Journal of Applied Psychology, 70*(3), 461-468.

Hass, K. B. (2011). *The Enterprise Business Analyst: Developing Creative Solutions to Complex Business Problems*. Vienna, VA: Management Concepts.

Henneberg, S. C., Gruber, T., Reppel, A., Ashnai, B., & Naude, P. (2009). Complaint management expectations: An online laddering analysis of small versus large firms. *Industrial Marketing Management, 38*(6), 584-598. Retrieved Aug-Sep, from Article; Proceedings Paper database.

Herrmann, A., Huber, F., & Braunstein, C. (2000). Market-driven product and service design: Bridging the gap between customer needs, quality management, and customer satisfaction. *International Journal of Production Economics, 66*(1), 77-96.

Hershock, R. J., Cowman, C. D., & Peters, D. (1994). From experience: action teams that work. *Journal of Product Innovation Management, 11*(2), 95-104.

Hinkin, T. R. (1998). A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires. *Organizational Research Methods, 1*(1), 104-121.

Hoerl, R., & Snee, R. D. (2012). *Statistical thinking: improving business performance* (Vol. 58). Hoboken, New Jersey: John Wiley & Sons.

Hoerl, R. W., Hooper, J. H., Jacobs, P. J., & Lucas, J. M. (1993). Skills for industrial statisticians to survive and prosper in the emerging quality environment. *The American Statistician, 47*(4), 280-292.

Hoerl, R. W., & Snee, R. (2010). Statistical Thinking and Methods in Quality Improvement: A Look to the Future. *Quality Engineering, 22*(3), 119-129.

Hoerl, R. W., & Snee, R. D. (2010a). Closing the Gap: Statistical Engineering Can Bridge Statistical Thinking with Methods and Tools,. *Quality Progress*, 52-53.

Hoerl, R. W., & Snee, R. D. (2010b). Moving the Statistics Profession Forward to the Next Level. *American Statistician, 64*(1), 10-14.

IDESCAT (2013). *Companies in Barcelona.*: IDESCAT. Retrieved April 30th of 2013, 2013, from http://www.idescat.cat/pub/?id=aec&n=974&lang=es

Ishikawa, K. (1985). *What is total quality control? The Japanese way*. New York. NY: Prentice-Hall.

Jackson, M. C. (1992). *Systems methodology for the management sciences*. New York, NY: Springer.

Janis, A. (2008). *Making Progress: The State of Marketing Analytics in the Twin Cities*. Evantage Consulting. Retrieved February 14-th of 2013, 2013, from http://www.evantageconsulting.com/sites/default/files/Marketing_Analytics_Whitepaper.pdf

Johnson, G., Melin, L., & Whittington, R. (2003). Micro strategy and strategizing: Towards an activity-based view - Guest Editors' Introduction.*Journal of Management Studies, 40*(1), 3-22.

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis.*Psychometrika, 23*(3), 187-200.

Kassarjian, H. (1977). Content Analysis in Consumer Research. *Journal of Consumer Research*(4), 8--18.

Kaushik, A. (2011). *Web Analytics 2.0*. Indianapolis, IN: Editions Eyrolles.

Kaushilk, A. (2011). *How to Choose a Web Analytics Tool: A Radical Alternative*. Retrieved March 15-th of 2013, 2013, fromhttp://www.kaushik.net/avinash/how-to-choose-a-web-analytics-tool-a-radical-alternative/

Kim, J. O., & Mueller, C. W. (1978). *Introduction to Factor Analysis: What It Is and How To Do It*. Beverly Hills, CA: SAGE Publications.

King, W. R. (2009). *Knowledge Management and Organizational Learning* (Vol. 4). Pittsburg PA: Springer.

Kong, G., Xu, D.-L., Liu, X., & Yang, J.-B. (2009). Applying a belief rule-base inference methodology to a guideline-based clinical decision support system. *Expert Systems, 26*(5), 391-408.

Kotler, P., Keller, K., Brady, M., Goodman, M., & Hansen, T. (2009). *Marketing management: first European edition*. Essex, UK: Pearson.

Krzanowski, W. (2000). *Principles of Multivariate Analysis* (2, revised, illustrated, reprint ed.). Oxford UK: Oxford University Press.

Krzanowski, W. J., & Krzanowski, W. J. (1996). *Principles of multivariate analysis*: Oxford University Press.

Landis, J. R., & Koch, G. G. (1977). MEASUREMENT OF OBSERVER AGREEMENT FOR CATEGORICAL DATA. *Biometrics, 33*(1), 159-174.

Langfield-Smith, K., & Greenwood, M. R. (1998). Developing co-operative buyer-supplier relationships: A case study of Toyota. *Journal of Management Studies, 35*(3), 331-353.

Lawler Iii, E. E., & Ledford Jr, G. E. (1985). Skill-Based Pay: A Concept That's Catching on. *Personnel, 62*(9), 30-37.

Lewis, M. M. (2003). *Moneyball: the art of winning an unfair game*. New York, NY: W W Norton & Company Incorporated.

Lin, L. I. (1989). A CONCORDANCE CORRELATION-COEFFICIENT TO EVALUATE REPRODUCIBILITY. *Biometrics, 45*(1), 255-268.

Liu, X.-B., Zhou, M., Yang, J.-B., & Yang, S.-L. (2008). Assessment of strategic R&D projects for car manufacturers based on the evidential reasoning approach. *International Journal of Computational Intelligence Systems, 1*(1), 24-49.

Locke, E. A., Latham, G. P., Smith, K. J., Wood, R. E., & Bandura, A. (1990). *A theory of goal setting & task performance* (Vol. 21): Prentice Hall Englewood Cliffs, NJ.

Long, J. S. (1983). *Confirmatory Factor Analysis: A Preface to LISREL, Issue 33*. Beverly Hills, CA: SAGE Publications.

Lowe, K. B., Kroeck, K. G., & Sivasubramaniam, N. (1996). Effectiveness correlates of transformational and transactional leadership: A meta-analytic review of the MLQ literature. *Leadership Quarterly, 7*(3), 385-425.

Lynch, C. (2008). Big data: How do your data grow? *Nature, 455*(7209), 28-29.

Maani, K. E., & Maharaj, V. (2004). Links between systems thinking and complex decision making. *System Dynamics Review, 20*(1), 21-48

McDonough, B. (2009). *Improving Organizational Performance Management Through Pervasive Business Intelligence.*: International Data Corporation (IDC). Retrieved March 14-th of 2013, 2013, from http://www.sap.com/canada/industries/retail/pdf/Improving_Organizational_Performance.pdf

McDonough Iii, E. F. (2000). Investigation of Factors Contributing to the Success of Cross-Functional Teams. *Journal of product innovation management, 17*(3), 221-235.

Me too's product (2013). Retrieved march 21 of 2013, 2013, from http://www.answers.com/topic/me-too-product

Menor, L. J., & Roth, A. V. (2007). New service development competence in retail banking: Construct development and measurement validation.*Journal of Operations Management, 25*(4), 825-846.

Mian, I. U. H., & Shoukri, M. M. (1997). Statistical analysis of intraclass correlations from multiple samples with applications to arterial blood pressure data. *Statistics in Medicine, 16*(13), 1497-1514

Michie, S., Johnston, M., Abraham, C., Lawton, R., Parker, D., Walker, A., et al. (2005). Making psychological theory useful for implementing evidence based practice: a consensus approach. *Quality & Safety in Health Care, 14*(1), 26-33.

Morgan, S. P., & Teachman, J. D. (1988). Logistic regression: Description, examples, and comparisons. *Journal of Marriage and the Family*, 929-936.

Morris, H., Moser, K., Vesset, D., Blumstein, R., Andersen, P., Martinez, N., et al. (2002). The financial impact of business analytics. *IDC White Paper, 28pp*.

NHS (2013). *Clinical Trails*. Retrieved April 30th of 2013, 2013, from http://www.nhs.uk/Conditions/Clinical-trials/Pages/Definition.aspx

Nydick, R. L., & Hill, R. P. (1992). Using the Analytic Hierarchy Process to Structure the Supplier Selection Procedure. *International Journal of Purchasing and Materials, 28*, 2.

Perry-Smith, J. E., & Shalley, C. E. (2003). The social side of creativity: A static and dynamic social network perspective. *Academy of Management Review, 28*(1), 89-106.

Petroni, A., & Braglia, M. (2000). Vendor selection using principal component analysis. *Journal of supply chain management, 36*(2), 63-69.

Pfeffer, J., & Sutton, R. I. (2006). *Hard facts, dangerous half-truths, and total nonsense: Profiting from evidence-based management*: Harvard Business Press.

Pocinki, S. B., Scinto, P. R., & Wilkinson, R. G. (2012). The Q.LIFE (R) Engine: A Work of Statistical Engineering. *Quality Engineering, 24*(2), 215-226.

Poon, P., & Wagner, C. (2001). Critical success factors revisited: success and failure cases of information systems for senior executives. *Decision Support Systems, 30*(4), 393-418.

Porter, M. E. (1990). THE COMPETITIVE ADVANTAGE OF NATIONS. *Harvard Business Review, 68*(2), 73-93.

Porter, M. E. (1996). What is strategy? *Harvard Business Review, 74*(6), 61-&.

Porter, M. E. (2008). *Competitive Advantage: Creating and Sustaining Superior Performance*. New York, NY: Simon and Schuster.

Powell, T. C., & DentMicallef, A. (1997). Information technology as competitive advantage: The role of human, business, and technology resources. *Strategic Management Journal, 18*(5), 375-405.

Predictive analytics (2013). Retrieved 20 of june of 2013, 2013, fromhttp://www.answers.com/topic/predictive-analytics

Ray, G., Barney, J. B., & Muhanna, W. A. (2004). Capabilities, business processes, and competitive advantage: Choosing the dependent variable in empirical tests of the resource-based view. *Strategic Management Journal, 25*(1), 23-37.

Reynolds, T. J., & Gutman, J. (1984). Laddering: Extending the Repertory Grid Methodology to Construct Attribute-Consequence-Value Hierarchies. In *in Personal Values and Consumer*. (Books).

Reynolds, T. J., & Gutman, J. (1988). LADDERING THEORY, METHOD, ANALYSIS, AND INTERPRETATION. *Journal of Advertising Research, 28*(1), 11-31.

Richmond, B. (1997). The thinking in systems thinking: how can we make it easier to master. *The Systems Thinking, 8*(2), 1-5.

Roberts, H. V. (1990). Applications in business and economic statistics: some personal views. *Statistical Science, 5*(4), 372-390.

Roome, N. (1992). Developing environmental management strategies. *Business Strategy and the Environment, 1*(1), 11-24.

Rousseau, D. M. (2006). Is there such a thing as" evidence-based management"? *Academy of Management Review, 31*(2), 256-269.

Ruff, F. (2006). Corporate foresight: integrating the future business environment into innovation and strategy. *International Journal of Technology Management, 34*(3-4), 278-295.

Saaty, T. L. (1986). Axiomatic foundation of the analytic hierarchy process. *Management science, 32*(7), 841-855.

SCM. Supply Chain Management. (2013). Retrieved January 12 of 2013, 2013, from http://www.answers.com/topic/supply-chain-management

Scott, A. J. (2012). Moneyball: Message for Managers [Marketing paper]. Pennsylvania:(University of Pennsylvania ScholarlyCommons).

Senge, P. M., & Sterman, J. D. (1992). SYSTEMS THINKING AND ORGANIZATIONAL LEARNING - ACTING LOCALLY AND THINKING GLOBALLY IN THE ORGANIZATION OF THE FUTURE. *European Journal of Operational Research, 59*(1), 137-150.

Shafer, G. (1976). *A Mathematical Theory of Evidence*. Sheffield UK: Princeton University Press.

Shalley, C. E. (1995). EFFECTS OF COACTION, EXPECTED EVALUATION, AND GOAL-SETTING ON CREATIVITY AND PRODUCTIVITY. *Academy of Management Journal, 38*(2), 483-503

Shrout, P. E., & Fleiss, J. L. (1979). INTRACLASS CORRELATIONS - USES IN ASSESSING RATER RELIABILITY. *Psychological Bulletin, 86*(2), 420-428.

Siegel, S., & Castellan, N. J. (1988). *Nonparametric statistics for the behavioral sciences* (2, illustrated, reprint ed.). New York. NY: McGraw-Hill.

Sila, I., & Ebrahimpour, M. (2003). Examination and comparison of the critical factors of total quality management (TQM) across countries. *International Journal of Production Research, 41*(2), 235-268.

Steinberg, D. M., Bisgaard, S., Doganaksoy, N., Fisher, N., Gunter, B., Hahn, G., et al. (2008). The future of industrial statistics: A panel discussion. *Technometrics, 50*(2), 103-127.

Streiner, D. L. (2003). Starting at the beginning: An introduction to coefficient alpha and internal consistency. *Journal of Personality Assessment, 80*(1), 99-103.

Stubbs, E. (2011). *The value of business analytics: identifying the path to profitability series*. Hoboken, New Jersey:: John Wiley & Sons Ltd.

Tague, N. R. (2005). *The Quality Toolbox*. Milwaukee,WI: American Society for Quality Press.

Takeuchi, H. (1981). PRODUCTIVITY - LEARNING FROM THE JAPANESE. *California Management Review, 23*(4), 5-19.

Tallon, P. P., Kraemer, K. L., & Gurbaxani, V. (2000). Executives' perceptions of the business value of information technology: A process-oriented approach. *Journal of Management Information Systems, 16*(4), 145-173.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53-55.

Thompson, J. D., & McEwen, W. J. (1958). ORGANIZATIONAL GOALS AND ENVIRONMENT - GOAL-SETTING AS AN INTERACTION PROCESS. *American Sociological Review, 23*(1), 23-31.

Tian, L. L. (2005). On confidence intervals of a common intraclass correlation coefficient. *Statistics in Medicine, 24*(21), 3311-3318.

Tort-Martorell, X., Grima, P., & Marco, L. (2011). Management by facts: The common ground between total quality management and evidence-based management. *Total Quality Management & Business Excellence, 22*(6), 599-618.

Values (2013). Retrieved April 18 of 2013, 2013, from http://www.answers.com/topic/values-5

Verma, R., & Pullman, M. E. (1998). An analysis of the supplier selection process. *Omega, 26*(6), 739-750.

von Krogh, G., Ichijo, K., & Nonaka, I. (2000). *Enabling Knowledge Creation: How to Unlock the Mystery of Tacit Knowledge and Release the Power of Innovation*: Oxford University Press, USA.

Walker, B. A., & Olson, J. C. (1991). MEANS-END CHAINS - CONNECTING PRODUCTS WITH SELF. *Journal of Business Research, 22*(2), 111-118.

Wang, R. Y., Kon, H. B., & Madnick, S. E. (1993, 19-23 Apr 1993). *Data quality requirements analysis and modeling.* Paper presented at the Data Engineering, 1993. Proceedings. Ninth International Conference.

Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of management information systems*, 5-33.

Wang, Y.-M., Yang, J.-B., Xu, D.-L., & Chin, K.-S. (2009). Consumer preference prediction by using a hybrid evidential reasoning and belief rule-based methodology. *Expert Systems with Applications, 36*(4), 8421-8430.

Webster, A. L. A., García, Y. M., & Lozano, C. L. (2000). *Estadística aplicada a los negocios y la economía*: McGraw-Hill.

Weir, J. P. (2005). Quantifying test-retest reliability using the intraclass correlation coefficient and the SEM. *Journal of Strength and Conditioning Research, 19*(1), 231-240.

Xu, D.-L. (2012). An introduction and survey of the evidential reasoning approach for multiple criteria decision analysis. *Annals of Operations Research, 195*(1), 163-187.

Xu, D.-L., McCarthy, G., & Yang, J.-B. (2006). Intelligent decision system and its application in business innovation self assessment. *Decision Support Systems, 42*(2), 664-673.

Xu, D. L., & Yang, J.-B. (2001). Introduction to multi-criteria decision making and the evidential reasoning approach. *Manchester School of Management, University of Manchester Institute and Technology*.

Xu, D. L., & Yang, J. B. (2003). Intelligent decision system for self-assessment. *Journal of Multi‐Criteria Decision Analysis, 12*(1), 43-60.

Yang, J.-B. (2001). Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. *European Journal of Operational Research, 131*(1), 31-61.

Yang, J.-B., & Sen, P. (1994). A general multi-level evaluation process for hybrid MADM with uncertainty. *Systems, Man and Cybernetics, IEEE Transactions on, 24*(10), 1458-1473.

Yang, J.-B., & Singh, M. G. (1994). An evidential reasoning approach for multiple-attribute decision making with uncertainty. *Systems, Man and Cybernetics, IEEE Transactions on, 24*(1), 1-18.

Yang, J.-B., & Xu, D.-L. (2002a). Nonlinear information aggregation via evidential reasoning in multiattribute decision analysis under uncertainty.*Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 32*(3), 376-393.

Yang, J.-B., & Xu, D.-L. (2002b). On the evidential reasoning algorithm for multiple attribute decision analysis under uncertainty. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 32*(3), 289-304.

Yang, J. B. (2001). Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. *European Journal of Operational Research, 131*(1), 31-61.

Yang, J. B., Liu, J., Wang, J., Sii, H. S., & Wang, H. W. (2006). Belief rule-base inference methodology using the evidential reasoning approach - RIMER. *Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 36*(2), 266-285.

Yang, J. B., Xu, D. L., Xie, X., & Maddulapalli, A. K. (2011). Multicriteria evidential reasoning decision modelling and analysis-prioritizing voices of customer. *Journal of the Operational Research Society, 62*(9), 1638-1654.

Yeo, K. T. (1993). Systems thinking and project management—time to reunite. *International journal of project management, 11*(2), 111-117.

Yule, G. U., & Kendall, M. G. (1950). *An Introduction to the Theory of Statistics*: C. Griffin.

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Appendix A.

The questionnaire.

3. GENERAL INFORMATION

Directions:

- Please answer all questions.
- Read each statement carefully and choose the best option that corresponds to your company´s situation.

3.1. Please, Write the name of your Company. (This is an elective question)

3.2. Select the size of your company according to the number of employees.

Micro (1 to 10 employees)	
Small (11 to 50 employees)	
Medium (51 to 200 employees)	
Big corporation (201 employees or more)	

3.3. Select your company's economic activity.

Research development	
Medical and health care	
Environmental Care	
Consulting and advisory services	
Agriculture	
Mining	
Livestock	
Forestry	
Food processing	
Steel	
Chemicals manufacturing	
Textile Manufacturing	
Production of goods and services	
Information technology (hardware and software)	
Consumer goods sales	
architecture and design	
Construction	
Goods and services trading	
Communications	
Goods transportation	
Leisure and entertainment.	

3.4. How old is your business? (Select one age´s range)

From 0 to 5 years	
Between 6 and 10 years	
Between 11 and 20 years	
Between 21 and 30 years	
Between 31 and 40	
Between 41 and 50 years	
Between 51 and 60	
Between 61 and 70 years	
Between 71 and 80 years	
Between 81 and 90 years	
Between 91 and 100 years	
100 years old or more	

3.5. The competitive advantage of your company lies in:

- ☐ That our prices and costs are lower than our competitors
- ☐ That our products and services are considerably different and better
- ☐ We have the loyalty of a specific market niche
- ☐ We have a privileged location

We still have not identified any competitive advantage other (Which one?)

4. DATA BASED COMPETITIVE ADVANTAGE

Directions:

- Please answer all questions.
- Read each statement carefully and choose the best option that corresponds to your company´s situation.

4.1. DB-CA1. Does the top management at your company understand the benefits of analytical tools for extracting valuable information from the data?

☐ Yes, they understand the benefits ALL the time

☐ Yes, they understand the benefits MOST OF the time

☐ Yes, they understand the benefits, but ONLY HALF OF the time

☐ Yes, they understand the benefits, but ONLY OCCASIONALLY

☐ No, they NEVER understand the benefits

4.2. DB-CA2. At your company, you improve your products or services using data analysis and statistical techniques?

☐ Yes, we use data analysis and statistics ALL the time

☐ Yes, we use data analysis and statistics MOST OF the time

☐ Yes, we use data analysis and statistics HALF of the time

☐ Yes, we use data analysis and statistics OCCASIONALLY

☐ No, we NEVER use data analysis and statistics

4.3. DB-CA3 In general, you think the use of statistics, is helping you to build a competitive advantage in your business?

☐ Yes, statistics help us to improve the competitive advantages ALL the time

☐ Yes, statistics help us to improve the competitive advantages MOST OF the time

☐ Yes, statistics help us to improve the competitive advantages HALF OF the time

☐ Yes, statistics help us to improve the competitive advantages OCCASIONALLY

☐ No, statistics NEVER helps us to improve competitive advantages

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4. DB-CA4 The use of data and statistical techniques. How important are they for the decision-making in your business?

- ☐ Yes, data analysis and statistical techniques are VERY IMPORTANT
- ☐ Yes, data analysis and statistical techniques are IMPORTANT
- ☐ Yes, data analysis and statistical techniques are important HALF OF TIME
- ☐ Yes, data analysis and statistical techniques are of MINOR IMPORTANCE
- ☐ No, data analysis and statistical techniques are UNIMPORTANT

5. DB-CA5 In your company, is there a work environment that encourages the use of statistical techniques and data analysis?

- ☐ Yes at the company, ALL of us encourage the use of statistical techniques
- ☐ Yes at the company, MOST of us encourage the use of statistical techniques
- ☐ Yes at the company, HALF of us encourage the use of statistical techniques
- ☐ Yes at the company, ONLY A SMALL MINORITY of us encourage the use of statistical techniques
- ☐ NOBODY encourage the use of statistical techniques

5. MANAGEMENT SUPPORT

Directions:

- Please answer all questions.
- Read each statement carefully and choose the best option that corresponds to your company´s situation.

5.1. MS-DA1 Does your company provide training to employees related with analytical tools and data analysis?

☐ Yes, the company provides training to ALL of us

☐ Yes, the company provides training to THE MAJORITY of us

☐ Yes, the company provides training to THE HALF of us

☐ Yes, the company provides training only to THE MINORITY of us

☐ No, the company NEVER provides training

5.2. MS-DA2 At your company. Is the new knowledge in relation with data analysis applied and implemented?

☐ Yes, ALL the new knowledge is implemented.

☐ Yes, MOST OF the new knowledge is implemented

☐ Yes, but ONLY HALF of the new knowledge is implemented

☐ Yes, but ONLY A SMALL PART of the new knowledge is implemented

☐ No, the new knowledge is NEVER implemented

5.3. MS-DA3 At your company, is there a process for data collection and application of analytical tools?

☐ Yes, this process exists and it is applied in ALL departments

☐ Yes, this process exists and it is applied in MOST OF departments

☐ Yes, this process exists and it is applied in HALF OF departments

☐ Yes, this process exists and it is applied in ONLY ONE OR TWO departments

☐ No, this process does not exist in the company

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5.4. MS-DA4 At your company, is there a defined budget for projects related to data analysis and applied statistics?

- ☐ Yes, there is a budget and ALL departments can use it
- ☐ Yes, there is a budget and MOST OF departments can use it
- ☐ Yes, there is a budget, and A HALF OF departments can use it
- ☐ Yes, there is a budget, but ONLY ONE OR TWO departments can use it
- ☐ No, there is no budget for data analysis and applied statistics

5.5. MS-DA5 At your company, are the required technological resources for implementing statistical techniques and data analysis available to everyone?

- ☐ Yes, EVERYONE has access to technology for data analysis
- ☐ Yes, MOST OF us have access to technology for data analysis
- ☐ Yes, HALF OF us have access to technology for data analysis
- ☐ Yes, but only A MINORITY has access to technology for data analysis
- ☐ No, NOBODY have access to technology for data analysis

5.6. MS-DA6 At your company. Do you investigate the evolution of your competitors, based on data analysis?

- ☐ Yes, we investigate and it is STRONGLY based on data analysis
- ☐ Yes, we investigate and it is MODERATELY based on data analysis
- ☐ Yes, we investigate and it is POORLY based on data analysis
- ☐ Yes, we investigate, but we DO NOT USE the data analysis
- ☐ No, we NEVER investigate the evolutions of competitors

6. SYSTEMIC THINKING

Directions:

- Please answer all questions.
- Read each statement carefully and choose the best option that corresponds to your company´s situation.

6.1. SYS1. At your company, are the efforts for increasing the use of analytical tools in decision making, recognized and appreciated?

☐ Yes, the efforts are recognized and appreciated ALL the time

☐ Yes, the efforts are recognized and appreciated MOST OF the time

☐ Yes, the efforts are recognized and appreciated HALF OF the time

☐ Yes, the efforts are recognized and appreciated but ONLY OCCASIONALLY

☐ No, the efforts NEVER are recognized and appreciated

6.2. SYS2. At your company, is the mission statement and vision known and understood for everyone?

☐ Yes, ALL of us know and understand the mission and vision

☐ Yes, MOST OF us know and understand the mission and vision.

☐ Yes, HALF OF us know and understand the mission and vision

☐ Yes, but ONLY A MINORITY of us know and understand the mission and vision

☐ No, THERE ARE NOT Mission and Vision at the company.

6.3. SYS3 At your company, is communication open and is it stimulating for using data and statistical techniques?

☐ Yes, communication is open and it stimulates ALL of us

☐ Yes, communication is open and it stimulates MOST OF us

☐ Yes, communication is open and it stimulates A HALF OF us

☐ Yes, communication is open and it stimulates ONLY A MINORITY of us

☐ No, communication is not open, and it don't stimulate

4. SYS4 At your company, is there a teamwork culture?

- ☐ Yes, there is a strong teamwork culture in ALL the company
- ☐ Yes, there is a strong teamwork culture in MOST of the company
- ☐ Yes, there is a strong teamwork culture in A HALF of the company.
- ☐ Yes, there is a strong teamwork culture, but only in ONE OR TWO departments
- ☐ No, a strong teamwork culture does not exist

5. SYS5 Do top management give you a suitable work environment for making decisions, through analyzing data and using statistical techniques?

- ☐ Yes, top management reinforce the use of data analysis ALL the time
- ☐ Yes, top management reinforce the use of data analysis MOST OF the time
- ☐ Yes, top management reinforce the use of data analysis HALF OF the time
- ☐ Yes, top management reinforce the use of data analysis but ONLY OCCASIONALLY
- ☐ No, top management NEVER reinforce the use of data analysis

7. COMMUNICATION OUTSIDE COMPANY

Directions:

- Please answer all questions.
- Read each statement carefully and choose the best option that corresponds to your company´s situation.

7.1. COM-OUT. At your company, is it a priority to be in constant communication with suppliers and customers?

- ☐ Yes, it is the MOST IMPORTANT
- ☐ Yes it is an IMPORTANT PRIORITY, but not the greatest
- ☐ Yes it is a MEDIUM PRIORITY; there are other issues with equal importance
- ☐ Yes it is a LOW PRIORITY; there are other issues with more importance
- ☐ No, communication with customers and suppliers don’t have priority

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Appendix B.

The script for the in-depth interviews.

The in-depth interviews.

Objective: To Identify qualitative aspects ("soft" and “not structured”) regarding to the use and application of analytical tools in business management

Overview: The laddering methodology for variables consist in carrying out in-depth interviews in order to find out and understand how are related the individual values with the five 5 drivers of the level of adoption of analytical tools. (LAAT)

Script of the interview

The interview is divided in 5 parts. That is one part for each key driver of the LAAT. There are not right or wrong questions. All the responses are based on personal values, judgements and perceptions.

1. Competitive advantage.

1. What do you think the competitive advantages (CVS) at your company are?
2. Why do you think those CVS are important?
3. Which attributes and characteristics in those CVS are important?
4. Why do you think the mentioned attributes are important?
5. Explain briefly 2 positive consequences that the previously discussed attributes have at the company.
6. Now explain 2 negative consequences.
7. Why do you think those consequences are important?

2. Data usage and exploitation.

1. Explain briefly how the data usage and exploitation is at your company
2. What attributes and characteristics have the use of the data at your company?
3. Why do you think the attributes previously mentioned are important?
4. Explain briefly 2 positive consequences that the previously discussed attributes have at the company.
5. Now comment 2 negative consequences
6. Why do you think those consequences are important?

3. Management support

1. Explain briefly how the management support related with the use of data is at your company.
2. What attributes and characteristics in the management support at your company are related with the data usage and exploitation?
3. Explain briefly 2 positive consequences that the previously discussed attributes have at the company.
4. Now comment 2 negative consequences.
5. Why do you think those consequences are important?

4. Systematic vision of the company

How at your company are?

1. The Vision and Mission statements
2. The communication between all the departments.
3. The teamwork.

What attributes and characteristics have?

4. The communication between all the departments
5. The communication with clients and suppliers.
6. The teamwork

Why do you think the attributes and characteristics previously discussed are important?

7. Explain briefly 2 positive consequences for the attributes before mentioned
8. Now comment 2 negative consequences.
9. Why do you think those consequences are important?

5. The use of Statistical Methods.

1. Explain and comment briefly about the knowledge of Statistical Methods that your company has.
2. What attributes and characteristics at your company are related with the use of Statistical Methods?
3. Why do you think those attributes are important?
4. Explain briefly 2 positive consequences that the previously discussed attributes have at the company.
5. Now comment 2 negative consequences.
6. Why do you think those consequences are important?

General remarks

- Each interview is between 40 and 60 minutes long. (Approximately among 8 and 10 minutes per section)
- All the responses are confidential and anonymous.
- Digital records will be made for each interview. (This must be previously asked and authorized by the interviewed)

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Appendix C.

Definition operational of the variables.

Appendix C.

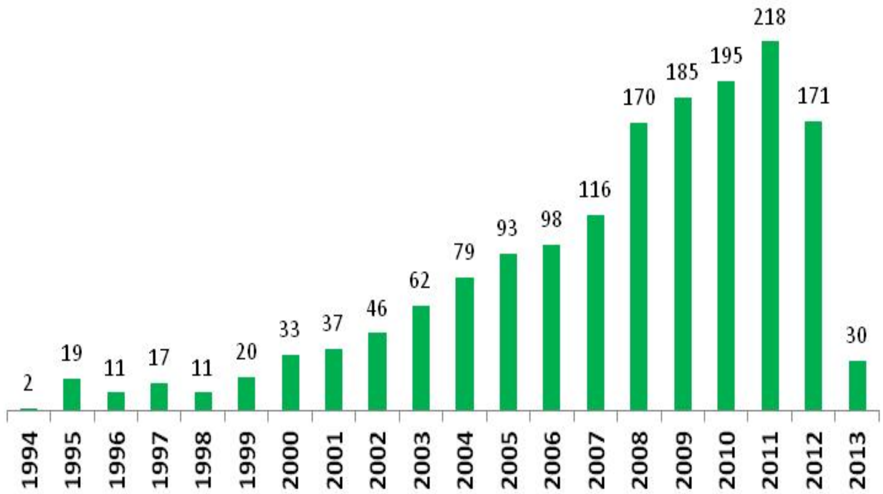
Code	Measurement ITEMS	Supportive literature.
3.5	The competitive advantage of your company lies in	Porter (1996) and Porter(2008)
DB-CA1	Does the top management at your company understand the benefits analytical tools for extracting valuable information from the data?	Tort-Martorell, Grima, & Marco (2011)
DB-CA2	At your company, you improve your products or services using data analysis and statistical techniques?	Hoel & Snee (2010) and Garvin (1986)
DB-CA3	In general, you think the use of statistics, is helping you to build a competitive advantage in your business?	Hoel & Snee (2010) and Hoel & Snee (2007)
DB-CA4	The use of data and statistical techniques. How important are they for the decision-making in your business?	Deming (2000)
DB-CA5	In your company, is there a work environment that encourages the use of statistical techniques and data analysis?	Deming (2000) and Wang & Strong 1996).
MS-DA1	Does your company provide training to employees related with analytical tools and data analysis?	Deming (2000) Tort-Martorell et al (2011)
MS-DA2	At your company. Is the new knowledge in relation with data analysis applied and implemented?	Davenport, & Harris (2007)
MS-DA3	At your company, is there a process for data collection and application of analytical tools?	Sila & Ebrahimpour (2003)
MS-DA4	At your company, is there a defined budget for projects related to data analysis and applied statistics?	Wang & Strong (1996)
MS-DA5	At your company, are the required technological resources for implementing statistical techniques and data analysis available to everyone?	Burby & Atchison (2007)
MS-DA6	At your company. Do you investigate the evolution of your competitors, based on data analysis?	Davenport, Harris & Morison (2010)
SYS1	At your company, are the efforts for increasing the use of analytical tools in decision making, recognized and appreciated?	Locke et. at. (1990)
SYS2	At your company, is the mission statement and vision known and understood for everyone?	Deming (2000)
SYS3	At your company, is communication open and is it stimulating for using data and statistical techniques?	Checkland (1999)
SYS4	At your company, is there a teamwork culture?	Gruber, Szmigin & Voss, (2009)
SYS5	Do top management give you a suitable work environment for making decisions, through analyzing data and using statistical techniques?	Davenport, Harris & Morison (2010)
COM-OUT	At your company, is it a priority to be in constant communication with suppliers and customers?	Perry-Smith & Shalley (2003)
X Removed	Does your company puts in practice the acquired knowledge about statistics and data analysis?	Hoel & Snee (2010) and Banks. (1993)
X Removed	Does your company have agreements with Universities and Research centres, which bring analytical knowledge?	Ruff, F. (2006)
X Removed	In your company, are the departments provided with the needed technology to share data, audio and video?	Davenport, Harris & Morison (2010)

Appendix D.

Bibliometric Report.

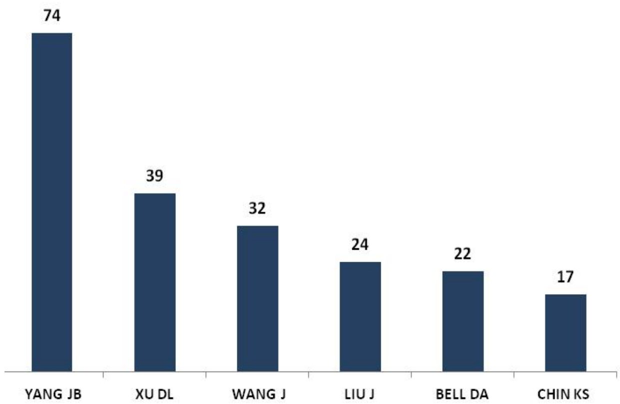
1. Number of citations which the topic “Evidential reasoning” has had since 1994

Year	Citations per year
1994	2
1995	19
1996	11
1997	17
1998	11
1999	20
2000	33
2001	37
2002	46
2003	62
2004	79
2005	93
2006	98
2007	116
2008	170
2009	185
2010	195
2011	218
2012	171
2013	30
Total	1613



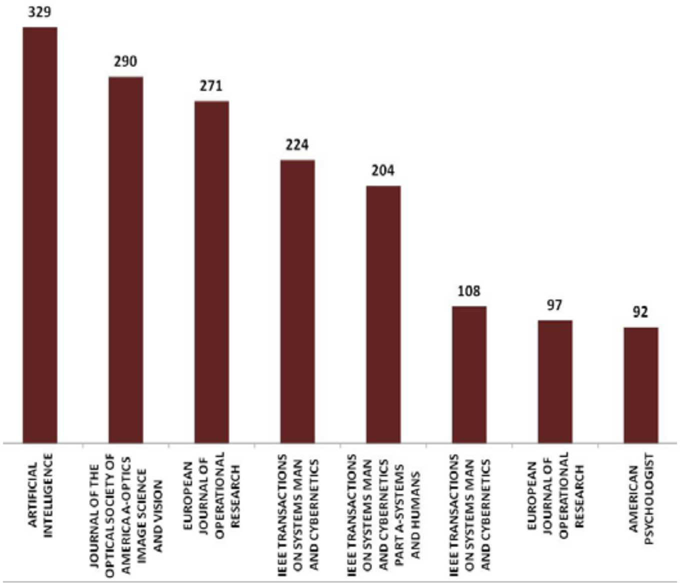
2. Authors and number of publications with the topic “Evidential reasoning”

Author	Number of publications	Sum of the Times Cited	h-Index	Average Citations per Item
YANG JB	74	1968	23	26,59
XU DL	39	829	12	21,26
WANG J	32	516	13	16,12
LIU J	24	364	10	15,17
BELL DA	22	76	4	3,45
CHIN KS	17	325	9	19,12



3. Journals and number of citations with the topic “Evidential reasoning”

Source Title	Total Citations	Average per Year
ARTIFICIAL INTELLIGENCE	329	19,4
JOURNAL OF THE OPTICAL SOCIETY OF AMERICA A-OPTICS IMAGE SCIENCE AND VISION	290	17,1
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	271	15,9
IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS	224	13,2
IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS PART A-SYSTEMS AND HUMANS	204	12,0
IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS	108	6,4
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	97	5,7
AMERICAN PSYCHOLOGIST	92	5,4
Total	1615	



4. List of papers and number of citations.

(1) Yang, J. B., & Singh, M. G. (1994). AN EVIDENTIAL REASONING APPROACH FOR MULTIPLE-ATTRIBUTE DECISION-MAKING WITH UNCERTAINTY. Ieee Transactions on Systems Man and Cybernetics, 24(1), 1-18. Times cited 173

(2) Yang, J. B., & Xu, D. L. (2002b). On the evidential reasoning algorithm for multiple attribute decision analysis under uncertainty. Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 32(3), 289-304. Times cited 167

(3) Gordon, J., & Shortliffe, E. H. (1985). A METHOD FOR MANAGING EVIDENTIAL REASONING IN A HIERARCHICAL HYPOTHESIS SPACE. Artificial Intelligence, 26(3), 323-357. Times cited 164

(4) Yang, J. B. (2001). Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. European Journal of Operational Research, 131(1), 31-61. Times cited 138

(5) Pearl, J. (1987). EVIDENTIAL REASONING USING STOCHASTIC SIMULATION OF CAUSAL-MODELS. Artificial Intelligence, 32(2), 245-257. Times cited 110

(6) Yang, J. B., & Sen, P. (1994). A GENERAL MULTILEVEL EVALUATION PROCESS FOR HYBRID MADM WITH UNCERTAINTY. Ieee Transactions on Systems Man and Cybernetics, 24(10), 1458-1473. Times cited 93

(7) Yang, J. B., & Xu, D. L. (2002a). Nonlinear information aggregation via evidential reasoning in multiattribute decision analysis under uncertainty. Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 32(3), 376-393. Times cited 74

(8) Murphy, R. R. (1998). Dempster-Shafer theory for sensor fusion in autonomous mobile robots. Ieee Transactions on Robotics and Automation, 14(2), 197-206. Times cited 68

(9) Wang, Y.-M., Yang, J.-B., & Xu, D.-L. (2006). Environmental impact assessment using the evidential reasoning approach. European Journal of Operational Research, 174(3), 1885-1913. Times cited 68

(10) Yang, J. B., Wang, Y. M., Xu, D. L., & Chin, K. S. (2006). The evidential reasoning approach for MADA under both probabilistic and fuzzy uncertainties. European Journal of Operational Research, 171(1), 309-343. Times cited 65

(11) Wang, J., Yang, J. B., & Sen, P. (1995). SAFETY ANALYSIS AND SYNTHESIS USING FUZZY-SETS AND EVIDENTIAL REASONING. Reliability Engineering & System Safety, 47(2), 103-118. Times cited 61

(12) Yang, J. B., Liu, J., Wang, J., Sii, H. S., & Wang, H. W. (2006). Belief rule-base inference methodology using the evidential reasoning approach - RIMER. Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 36(2), 266-285. Times cited 59

(13) Cheng, J., & Druzdzel, M. J. (2000). AIS-BN: An adaptive importance sampling algorithm for evidential reasoning in large Bayesian networks. Journal of Artificial Intelligence Research, 13, 155-188. Times cited 53

(14) Pearl, J. (1986). ON EVIDENTIAL REASONING IN A HIERARCHY OF HYPOTHESES. Artificial Intelligence, 28(1), 9-15. Times cited 51

(15) Wang, Y.-M., Yang, J.-B., Xu, D.-L., & Chin, K.-S. (2006). The evidential reasoning approach for multiple attribute decision analysis using interval belief degrees. European Journal of Operational Research, 175(1), 35-66. Times cited 47

(16) Gong, P. (1996). Integrated analysis of spatial data from multiple sources: Using evidential reasoning and artificial neural network techniques for geological mapping. Photogrammetric Engineering and Remote Sensing, 62(5), 513-523. Times cited 45

(17) Wang, J., Yang, J. B., & Sen, P. (1996). Multi-person and multi-attribute design evaluations using evidential reasoning based on subjective safety and cost analyses. Reliability Engineering & System Safety, 52(2), 113-128. Times cited 44

(18) Yang, J. B., & Sen, P. (1997). Multiple attribute design evaluation of complex engineering products using the evidential reasoning approach. Journal of Engineering Design, 8(3), 211-230. Times cited 40

(19) Buede, D. M., & Girardi, P. (1997). A target identification comparison of Bayesian and Dempster-Shafer multisensor fusion. Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 27(5), 569-577. Times cited 38

(20) Kim, H., & Swain, P. H. (1995). EVIDENTIAL REASONING APPROACH TO MULTISOURCE-DATA CLASSIFICATION IN REMOTE-SENSING. Ieee Transactions on Systems Man and Cybernetics, 25(8), 1257-1265. Times cited 31

(21) Liu, J., Yang, J. B., Wang, J., & Sii, H. S. (2005). Engineering system safety analysis and synthesis using the fuzzy rule-based evidential reasoning approach. Quality and Reliability Engineering International, 21(4), 387-411. Times cited 31

(22) Pal, N. R., Bezdek, J. C., & Hemasinha, R. (1993). UNCERTAINTY MEASURES FOR EVIDENTIAL REASONING .2. A NEW MEASURE OF TOTAL UNCERTAINTY. International Journal of Approximate Reasoning, 8(1), 1-16. Times cited 31

(23) Yang, J. B., Dale, B. G., & Siow, C. H. R. (2001). Self-assessment of excellence: an application of the evidential reasoning approach. International Journal of Production Research, 39(16), 3789-3812. Times cited 29

(24) Liu, J., Yang, J. B., Wang, J., Sii, H. S., & Wang, Y. M. (2004). Fuzzy rule-based evidential reasoning approach for safety analysis. International Journal of General Systems, 33(2-3), 183-204. Times cited 27

(25) Tang, W. H., Spurgeon, K., Wu, Q. H., & Richardson, Z. J. (2004). An evidential reasoning approach to transformer condition assessments. Ieee Transactions on Power Delivery, 19(4), 1696-1703. Times cited 22

Appendix E.

SPSS outputs. Principal components analysis

E.1 Matrix of components.

In the following figure the Principal Component Analysis (PCA) is shown. For simplification purposes loadings values lower than 0.30 were removed from the analysis. Note that, three items are highlighted in red squares because they show conflictive loadings in different components.

Figure E1. The initial matrix of rotated components.

Matriz de componentes rotados[a]

	Componente			
	1	2	3	4
DB_CA1	,757			
DB_CA2	,756	,310		
DB_CA3	,831			
DB_CA4	,806			
DB_CA5	,659	,479		
MS_DA1		,826		
MS_DA2	,486	,723		
MS_DA3	,597	,527		,313
MS_DA4		,837		
MS_DA5	,456	,622		
MS_DA6		,561	,737	
SYS1	,581	,461	,595	
SYS2			,693	,406
SYS3	,437	,444	,571	
SYS4			,764	
SYS5	-,684	-,455	,534	
COM_OUT	,313			,852

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 5 iterations.

E.2 Tests of adequacy and communalities.

Below figures for test of adequacy and communalities are shown. As it was explained in chapters 4 and 5, the values on these test allowed us to ascertain the suitability of the data for the factor analysis.

Figure E2-A KMO test of adequacy.

KMO y prueba de Bartlett

Medida de adecuación muestral de Kaiser-Meyer-Olkin.		,927
Prueba de esfericidad de Bartlett	Chi-cuadrado aproximado	1622,635
	gl	136
	Sig.	,000

Figure E2-B Communalities

Comunalidades

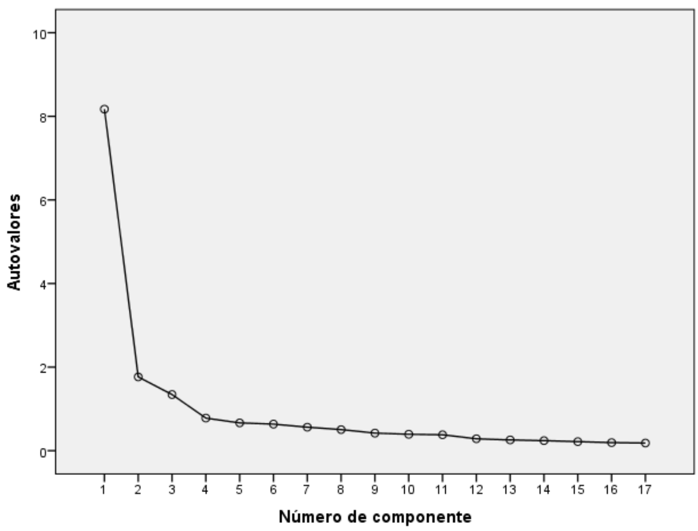
	Inicial	Extracción
DB_CA1	1,000	,691
DB_CA2	1,000	,717
DB_CA3	1,000	,699
DB_CA4	1,000	,735
DB_CA5	1,000	,737
MS_DA1	1,000	,710
MS_DA2	1,000	,774
MS_DA3	1,000	,735
MS_DA4	1,000	,734
MS_DA5	1,000	,654
MS_DA6	1,000	,582
SYS1	1,000	,650
SYS2	1,000	,695
SYS3	1,000	,718
SYS4	1,000	,632
SYS5	1,000	,741
COM_OUT	1,000	,859

Método de extracción: Análisis de Componentes principales.

E.3 The scree plot for the Exploratory analysis

In the next figure is presented scree-plot. Note that the first four components concentrate around the 71% of the total variance.

Figure E3. The scree plot for the PCA.



E.4 Variance explained for each factor.

In the following figure is shown the explained variance for each component. The second column represents the percentage of the variance while the third column the cumulated variance is presented.

Figure E4. Variance explained on each factor.

Total explained variance

Component	Enginvectors			Sum of saturations	
	Total	% of variance	% cumulated	Total	% of variance
1	8,171	48,067	48,067	8,171	48,067
2	1,766	10,386	58,453	1,766	10,386
3	1,344	7,904	66,358	1,344	7,904
4	,780	4,589	70,946	,780	4,589
5	,666	3,915	74,862		
6	,636	3,739	78,601		
7	,563	3,311	81,912		
8	,505	2,970	84,882		
9	,421	2,475	87,357		
10	,393	2,312	89,669		
11	,380	2,238	91,906		
12	,285	1,679	93,585		
13	,257	1,512	95,097		
14	,240	1,414	96,511		
15	,216	1,270	97,781		
16	,194	1,140	98,922		
17	,183	1,078	100,000		

E.5 Final arrangement of the Exploratory analysis.

In the following figure is presented the final arrangement of the items after the principal component analysis. The criterion of the researched, based on an exhaustive literature review and an operative definition of variables, was applied for grouping the three conflictive items.

Figure E5. Final arrangement of items after PCA.

Quetionnaire ITEM	Factor1	Factor2	Factor3	Factor4
Understanding benetifs DB_CA1	0.757			
Product Improvement DB_CA2	0.756			
Statistics Support DB_CA3	0.831			
Statistics Importance DB_CA4	0.806			
Statistics Encouragement DB_CA5	0.659			
Staticstics Training MS_DA1		0.826		
New knowledge implementation MS_DA2		0.723		
Data collection process MS_DA3		0.527		
Budget for projects MS_DA4		0.837		
Technological resources MS_DA5		0.622		
Competitor's Investigation MS_DA6		0.561		
Efforts recognition SYS1			0.595	
Mission understanding SYS2			0.693	
Communication openness SYS3			0.571	
Teamwork culture SYS4			0.764	
Reinforcement on data usage SYS5			0.534	
Communication suppliers/customers COM_OUT				0.852