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A Partner Qualification Framework to Support Research and Innovation in Technology-Intensive Industries

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“Success consists of going from failure to failure without loss of enthusiasm.”

Winston Churchill

Abstract

In modern economies, where markets and technology are changing rapidly, innovation partnerships are among the major strategic choices for companies to create competitive long term advantages. Especially in high-tech sectors, companies are encouraged to leverage on external sources of knowledge in their R&D activities. Although the number of studies investigating the topic of R&D collaboration from different perspectives has increased over time, the problem of partner selection still lacks comprehensive analyses and operational frameworks to drive innovation alliances to success. In order to address such a gap and to overcome the aforementioned limits this thesis provides a systematic literature review on the R&D partner selection problem and proposes a quantitative and DEA-based decision-making framework to support organizations in identifying, qualifying and selecting the most suitable partners for technological innovation. The framework has been developed together with the innovation department of a large enterprise in the transportation industry, and it has been validated on relevant case-studies of industrial relevance addressing both emerging and mature technologies. Advantages and limitations of the proposed approach in innovation management research and practice are highlighted and discussed.

Keywords: Collaborative R&D, Partner Qualification, Decision Support, Data Envelopment Analysis, Rating, Innovation Performance Evaluation, Open Innovation.

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Table of Contents

List of Figures

List of Tables

CHAPTER 1

1 Introduction

R&D collaboration among organizations is increasingly perceived as a vehicle to enhance innovation through knowledge exchange. The existing link between open innovation and knowledge management is emphasized by the organizations' need for R&D partners to collaborate with in order to share, transfer and exchange novel ideas and knowledge and to be competitive in the market. After a brief description of the R&D collaboration context and the open innovation paradigm, this chapter outlines the objectives of the research and its contribution.

1.1 The R&D Collaboration Context

In modern economies, where markets and technology are changing rapidly, innovation is perceived as a central achievement. Innovation practices involve both large and small organizations refining their products, services and operations in order to create a competitive long term advantage in a fast-paced business environment.

Especially in the hi-tech sectors, where the research and development (R&D) of products and processes is characterized by a high level of complexity and interdisciplinarity, innovative companies can no longer continue to to depend solely on their own skills and resources (Caloghirou, et al., 2004).

Since they cannot always rely on internal R&D resources to achieve their innovation objectives and stay competitive (Miotti & Sachwald, 2003), a very feasible option to speed up the innovation process is for firms to open-up their R&D departments to external sources of novel ideas, methods, tools and products (Chesbrough, 2003a).

In such a context, R&D collaboration plays a key role in enhancing innovation through knowledge exchange.

The possibility to collaborate with external R&D partners (i.e. universities, research institutes or other firms) does not have to be considered as an alternative to in-house R&D. On the contrary, external and internal R&D are complementary to each other because of three main reasons. First of all, there are some cognitive restrictions relating to organizations' access to resources. Secondly, it is too costly for firms to acquire expertise in all the necessary knowledge areas in multi-technology products. Furthermore, it is impossible to be the leader in every area of technology, even if access to resources does not pose a problem. Finally, whilst companies concentrate on their main skills and all the relevant related capabilities, solutions usually call for more (European Commission, 2012).

There are many studies in the literature which highlight the main reasons for R&D collaboration (Miotti & Sachwald, 2003; Nielsen, 2003; Dong & Glaister, 2006; Edwards-Schachter, et al., 2011).

Especially in knowledge-based activities, such as those related to research and development, the likelihood of collaboration success is higher when organizations possess their own R&D departments (Veugelers, 1997). More specifically, in order to acquire knowledge from external sources and to benefit as much as possible from the knowledge exchange, the organizations involved need to possess a certain "absorptive capacity" (Cohen & Levinthal, 1990).

The increasing importance for innovative organizations to establish external linkages is confirmed by a rise in alliances formation and, in turn, in the number of theoretical and empirical studies on knowledge transfer over the last few decades (Hagedoorn, 2002).

Today, the phenomenon of integrating external sources into innovation processes is indicated by the broad term "Open Innovation" (OI) introduced by Chesbrough (2003a,b).

1.1.1 The Open Innovation Paradigm

"Open Innovation is a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firms look to advance their technology" (Chesbrough, 2003a).

Although the open innovation paradigm was not the first to give a detailed description of this idea, over the last ten years, Chesbrough has attracted the attention of researchers and practitioners alike (Nedon, 2015).

Since it was first defined, open innovation has become important in many different sectors of industry - with the aim to obtain external knowledge and integrate it in the internal innovation process ("inbound OI" or "outside-in" approach), or to exploit internal ideas and technologies outside the company ("outbound OI" or "inside-out" approach). According to Gassmann & Enkel (2004), using both outside-in and inside-out OI approaches together, known as the coupled OI approach, allows organizations to optimally exchange knowledge.

Chesbrough (2003b, 2006) uses the term "open innovation" in contrast with "closed innovation", where companies only rely on their own innovation ideas and capabilities in order to implement the innovation process.

The two funnel-shaped diagrams in Figure 1.1 and Figure 1.2 are typically used to represent the open and closed innovation models, respectively, highlighting their differences.

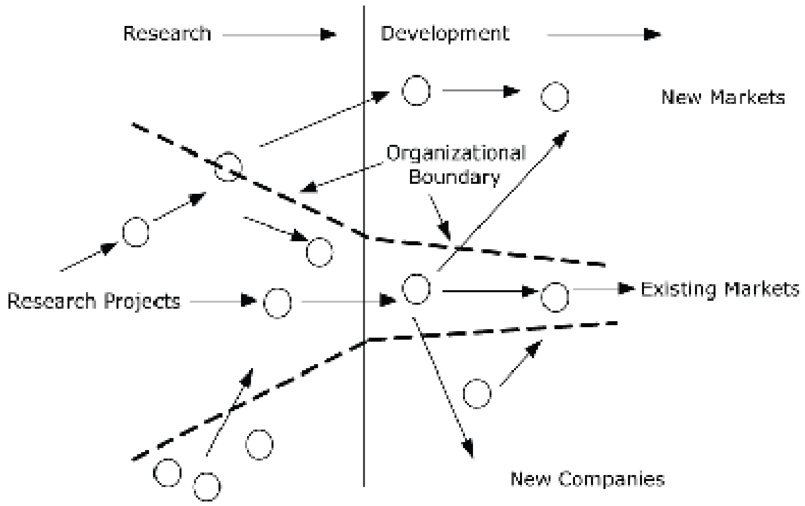

Figure 1.1 - Open innovation model (Source: Chesbrough 2003b)

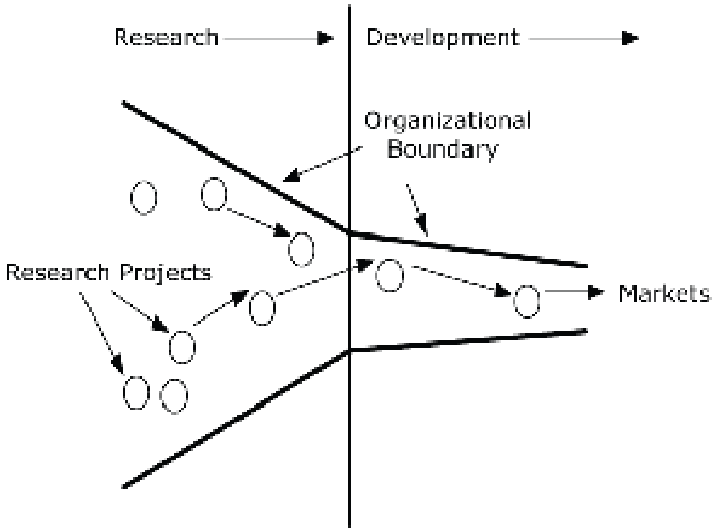

Figure 1.2 - Closed innovation model (Source: Chesbrough 2003b)

The open innovation scenario presents permeable boundaries, indicating the integration of internal and external impulses. More specifically, at the research phase, arrows only enter into the funnel, indicating that the company can rely on both internal and external capabilities to generate new and innovative ideas. At the development phase, arrows can both enter (inflow) and leave (outflow) the funnel. Inflows are possible when the company decides to invest in externally developed innovation in the form of intellectual property (IP) licenses for certain technologies. Alternatively, outflows exist when the company sees the opportunity to create spin-off companies to take on some of its main projects or decides to sell IP licenses that have emerged from the company's own research. Finally, the openness of this process also involves the commercialization phase (Mortara, et al., 2009).

Conversely, concerning closed innovation, the boundaries of the funnel are not "permeable", indicating that innovation processes take place within the firms' departments until the products are introduced into the market, relying only on internal resources.

According to Chesbrough and Brunswick (2013), the shift from closed to open innovation was due to both advances in ICT and the increased mobility of qualified employees, allowing "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough, et al., 2006).

Table 1.1 summarizes the differences between the closed and open innovation models.

Closed Innovation Principles	Open Innovation Principles
• Mostly internal ideas	• Many internal ideas
• Low workforce mobility	• High workforce mobility
• Few new businesses, weak ones	• Many new businesses
• Internal development and usage of technologies	• External options for unused technologies internally
• The experts are working within the company	• Not all the best people are working within and outside the company
• R&D creates profit only when organizations invent, develop and market everything themselves	• External R&D can create remarkable value and has to be integrated with the internal R&D
• Develop the product internally and be the first to market	• R&D can create profit even if not done internally by forming forces with outside parties
• Winner is who gets the innovation to the market first	• Winner is who best uses internal and external ideas
• Have intellectual property under control internally	• Profit from licensing the intellectual property and it supports the business model

Table 1.1 - Closed vs Open innovation (Source: Chesbrough 2003b)

1.2 Research Motivation and Objective

In the current business environment, characterized by continuous and rapid technological changes, innovation partnerships have become part of the major strategic choices by which companies can create a competitive long term advantage.

Both small and large enterprises are encouraged to interact with each other in order to have access to complementary resources and technologies to use for their R&D activities.

Theoretical and practical research on strategic alliances in previous literature has shown that incompatibility of partners is one of the most common reasons for failure

(Sadowskia & Duysters, 2008), resulting in organizations in alliances not always achieving their planned goals. Therefore, in order identify the most appropriate partners to collaborate with, the partner selection process assumes a critical role and must be carefully implemented.

Although the number of studies investigating the topic of R&D collaboration from different perspectives has increased over time (Hagedoorn, 2002), the problem of partner selection needs to be further investigated (Park, et al., 2015) so as to provide efficient comprehensive views and practical frameworks that can influence the success of alliances (Figure 1.3).

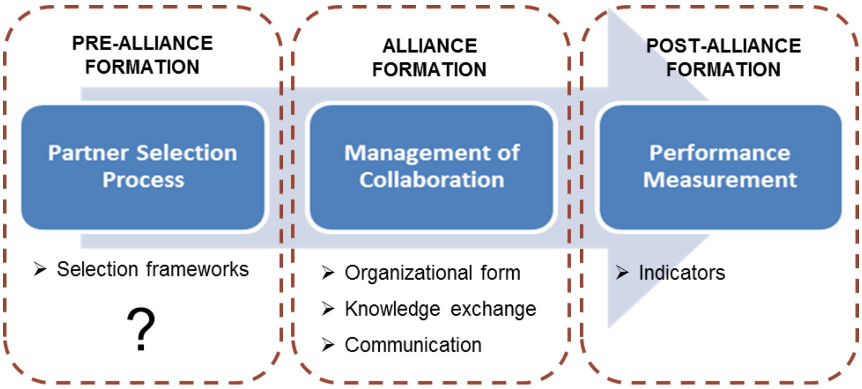

Figure 1.3 - The perspectives of R&D collaboration (Source: own elaboration)

In order to support the open innovation and R&D collaboration practices of technology-intense industries, commonly based on former experience and expert judgement, the aim of this thesis is to define a well-structured R&D partner selection framework to support organizations in identifying and selecting the most suitable partners for technological innovation. Moreover, the decision-making framework allows for the minimization of expert subjectivity, fully satisfying the requirements of replicability, reliability, rationality and transparency.

1.3 Research Approach and Contribution

This thesis is structured into five chapters, with the introduction being the first (Figure 1.4).

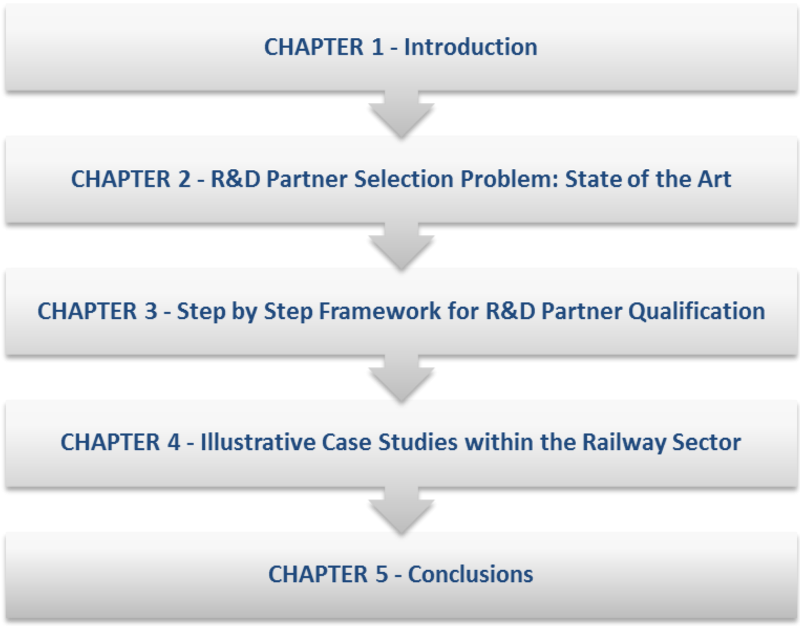

Figure 1.4 - Thesis structure

After discussing the general aspects of the research in this introduction, Chapter 2 goes further into detail about the R&D partner selection problem, through a systematic literature review. The systematic review highlights four main patterns related to the partner selection process (i.e. motivations, partner typologies, selection criteria and methodologies), as well as three major gaps in the literature: 1) the lack of studies considering the limits of using patent data, 2) the lack of studies applying mathematical programming techniques, 3) the lack of studies highlighting the existing relationship between objectives for partnership and technology evolution.

By taking into account the patterns and gaps emerged from the literature review, Chapter 3 proposes a DEA-based framework of four phases (1. Definition of objectives for partnership, 2. Identification of candidate partners (long list), 3. Qualification of candidate partners (short list), 4. Selection of the most appropriate partners) to rationally and objectively support the identification, qualification and selection of collaborative R&D partners.

Chapter 4 aims to test the effectiveness of the proposed framework on real firm practices. The partner selection approach is implemented step-by-step in the case of both emerging and mature technologies of railway interest, in line with the European Research & Innovation roadmap (e.g. Horizon 2020 program - SHIFT²RAIL Joint Undertaking), allowing for a deeper understanding of the existing relationship between technology evolution and R&D collaboration. However, in order to protect information regarding the strategic interests of the company, the list of the candidate partners cannot be disclosed.

Finally, in Chapter 5 the findings of the study are summarized with regard to both academic and managerial implications. The limitations of the study are also highlighted and recommendations for further research are formulated.

CHAPTER 2

2 R&D Partner Selection Problem: State of the Art

As already described in the previous chapter, the need for partnership is increasingly perceived as a key component of organizations' innovation strategies to enhance - through knowledge exchange - their competitive performance in a business environment characterized by fast and continuous technological changes. Although the number of studies investigating the topic of R&D collaboration from different perspectives has increased over time, the problem of partner selection is still described as fragmented and lacks an efficient comprehensive view. To address this gap, the present chapter proposes a systematic review of the literature on R&D partner selection, focusing on four main issues: motivations of R&D collaboration, partners topologies, selection criteria and decision making methodologies.

2.1 A Systematic Literature Review

Due to the dynamic characteristics of the present business environment, where markets and technology are changing rapidly, "collaborative linkages between companies are an important means of improving innovation potential" (Rothwell & Dodgson, 1991). However, managing innovation is not without costs and risks, as it requires a wide range of resources (e.g. financial, technical, organizational and human) that firms do not always possess (Robertson & Gatignon, 1998).

The different kinds of contributions organizations can give within the innovation process is a key aspect behind the need for R&D collaboration in various industries. Especially in high-tech sectors, companies are not always able or flexible enough to develop internally all the complex and multi-disciplinary knowledge, skills and specific capabilities they need to implement all the phases of the innovation process and follow the technological changes (Duysters & de Man, 2003). If firms want to be competitive, they should not rely solely on their internal abilities, but be open to external sources as well (Chesbrough & Brunswicker, 2013). By introducing the open innovation paradigm, Chesbrough (2003a,b) was the first who clearly pointed out that organizations should open their internal R&D activities to external partners for integrating complementary knowledge and technologies. But alliances are not always successful. The percentage of strategic alliances that fail ranges from 50% to 60% (Duysters, et al., 1999; Duysters & de Man, 2003; Sadowskia & Duysters, 2008). This high rate of alliance failure reflects the complexity of the process associated with selecting an alliance partner, and points out the need of a comprehensive study which analyzes all the key aspects that should be taken into account in order to identify the most appropriate collaborative R&D partners.

This section provides a systematic review of the literature accumulated on R&D partner selection and assesses the current knowledge available, outlining potential literature gaps and suggesting directions for future academic and managerial research.

Several scholars have suggested useful guidelines to conduct a systematic literature review (Cronin, et al., 2008; Papaioannou, et al., 2010). Contrarily to a narrative literature review, a systematic literature review adopts a more rigorous approach to collecting and analyzing literature sources in a specific subject area and identifying patterns.

A systematic literature review thus has a number of advantages in comparison to a traditional literature review:

- it is less likely that results from the literature review will be biased by future or different studies;
- some phenomenon can be systematically explored across a wide array of settings and empirical research approaches, either providing robust evidence of consistency or inconsistency of results of the studies available in the existing literature.

According to these guidelines, once the motivation and the objective of the research have been clarified (research question framing), a number of steps that correspond to the following main phases have to be implemented:

1) Search for research materials
2) Review and analysis of content
3) Classification of patterns
4) Identification of findings.

2.1.1 Search for Research Materials

This phases aims at identifying all the relevant scientific outputs referring to R&D partner selection. Initially, the search for research materials was carried out over the period 2003-2014. Then, in order to update and refine the review, the date range was extended to 2015.

All the relevant scientific output referring to R&D partner selection over the period of interest has been identified by using academic search engines such as Scopus, Science

Direct and Web of Science. These data sources have been chosen as they ensure a broad coverage of high-ranking scientific production on management and engineering. Moreover, they were freely available as a research facility in the department.

The bibliographic search on Scopus, Science Direct and Web of Science has been carried out by using keywords such as “R&D”, “research and development”, “innovation”, “technology”, “partnership”, “alliance”, “collaboration”, “cooperation”, “co-operation”, “process”, “framework”, “selection”, “choice”, “evaluation”, “identification” and “partner selection”. These keywords have been properly combined with the logical operators AND and OR.

Although the first sign of an increasing interest in knowledge transfer issues dates back to the 80s (Hagedoorn, 2002), the decision to start the search from 2003 is related to the first publications on the open innovation paradigm by Chesbrough (2003a,b). Since this date, the interest of both researchers and practitioners in open practices has been growing continuously.

The document search over the entire period 2003-2015 has identified 241 articles. This numbers drops to 128 when considering publications only referring to the subject areas of the social sciences and humanities (i.e. business management and accounting, social sciences, decision sciences, computer science, engineering and economics, econometrics and finance).

As shown in Figure 2.1, the R&D collaboration topic appears as a cross-sectional topic within these areas.

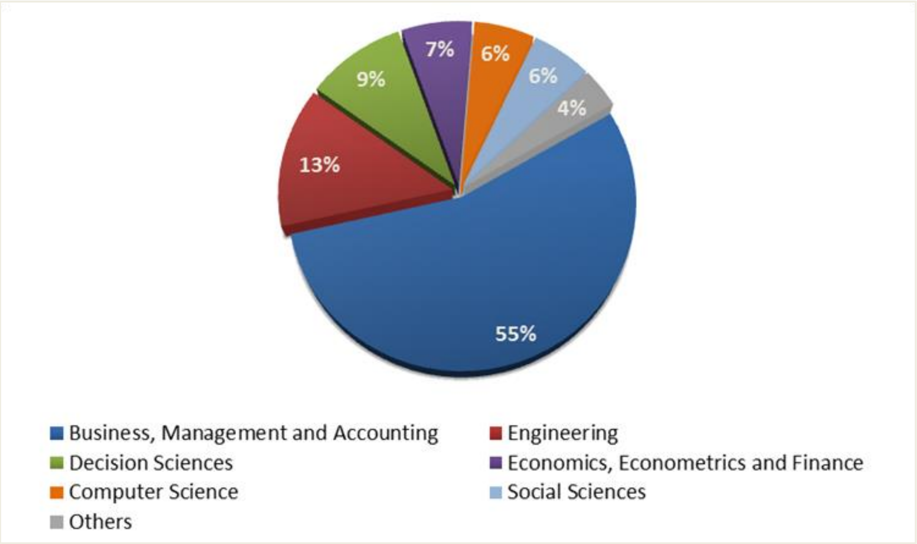

Figure 2.1 - Distribution of articles by subject area

Another important setting concerns the document type (i.e. article, conference paper, review, book chapter, conference review). When limiting the search to articles and conference papers, the number of documents drops from to 128 to 113. Among them, only 109 documents are written in the English language.

The implementation and the results of the material search steps are summarized in Figure 2.2.

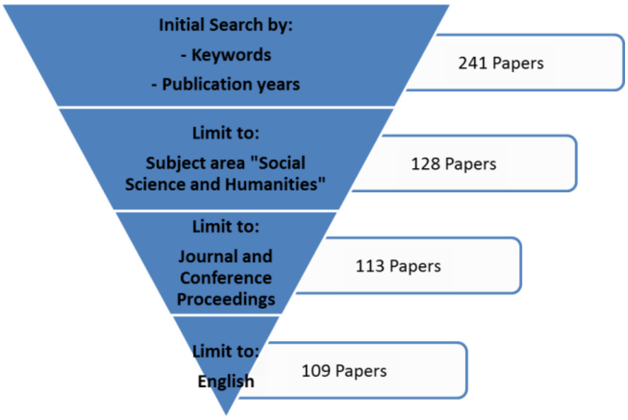

Figure 2.2 - Material search process

2.1.2 Review and Analysis of Content

Due to the large number of issues related to R&D collaboration and open innovation, this phase allows for inclusion and exclusion criteria to be applied in order to focus exclusively on relevant papers with a focus on the R&D partner selection problem (Figure 2.3).

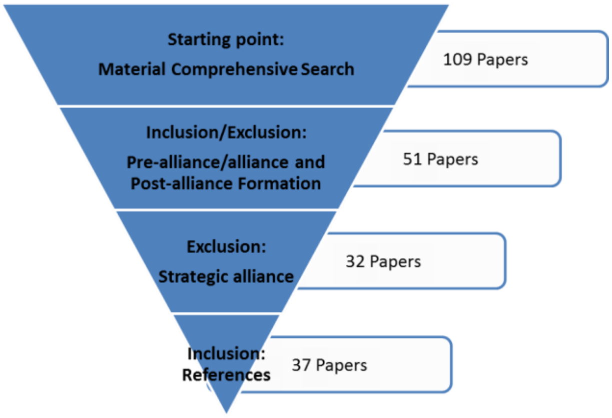

Figure 2.3 - Inclusion/exclusion process

First of all, only the papers whose abstract focuses on the pre-alliance formation phase were selected (51 papers). On the contrary, all the papers focusing on alliance formation and post-alliance formation (e.g. organizational form, knowledge exchange and alliance performance) were excluded (58 papers).

After that, the remaining 51 papers were taken into account for further analysis. More specifically, after reading their full texts, another 19 articles were barred as they were not in line with the purpose of the research. Finally, 5 more papers published from 2003 to 2015 were included in the final sample after analyzing the references of the 32 remaining papers.

The distribution of these 37 papers by journals (Table 2.1) confirms that the R&D partner selection topic covers the subject areas of business, management and accounting, engineering, decision sciences, economics, econometrics and finance, computer science and social sciences.

Scientific Journals	Number of Publications
Research Policy	3
International Business Review	3
Long Range Planning	3
International Journal of Industrial Organization	2
Journal of Technology Transfer	1
Procedia - Social and Behavioral Sciences	1
Technology Analysis and Strategic Management	1
Computers & Industrial Engineering	1
European Management Review	1
European Management Journal	1
Expert system with application	1
Journal of Intellectual Property Rights	1
Journal of Software	1
Journal of Technology Management and Innovation	1
Management Decision	1
Organization Science	1
Physics Procedia	1
Journal of Technology Management and Innovation	1
Technological Forecasting and Social Change	1
Academy of Management Journal	1
Other (Conference papers and proceedings)	6
	37

Table 2.1 - Distribution of papers by journal

At the end of the review and after an analysis of content, the selected papers have been studied in detail.

2.1.3 Classification of Patterns

This fourth step consists of identifying the main issues studied and discussed in the selected papers on R&D collaboration. Through an in depth analysis of the totality of the 37 papers on R&D partner selection, four main issues have emerged:

1. Motivations, including both theoretical and empirical studies analyzing the needs and the objectives for partnerships (9 papers);
2. Partner typologies, including studies which aim at identifying the types of partners that best match with the alliance motivations (11 papers);
3. Selection criteria, including studies focused on the identification of both qualitative and quantitative criteria based on which partners can be selected (21 papers);
4. Methodologies, including studies which provide approaches, methods and techniques for the identification and selection of candidate partners (14 papers).

Figure 2.4 displays the trends of these four issues related to the R&D partner selection problem over the period 2003-2015.

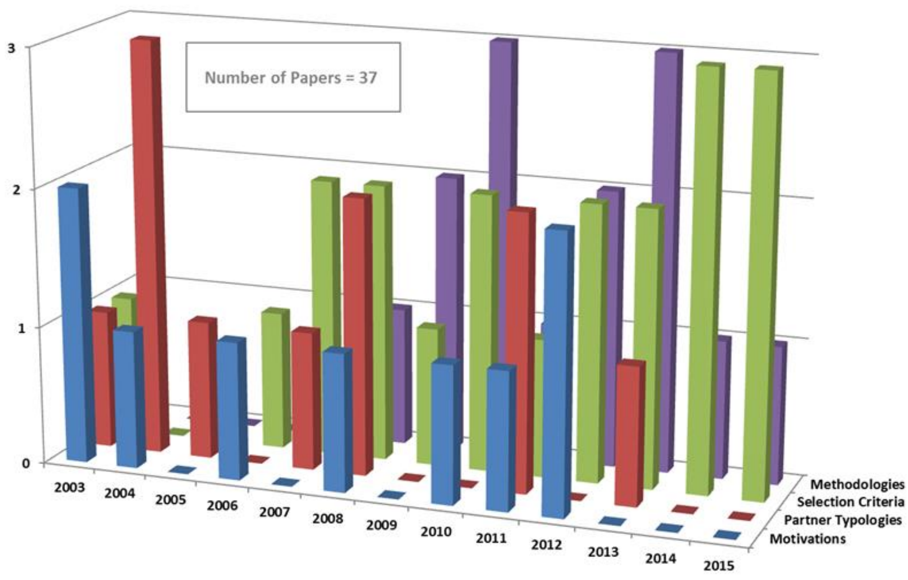

Figure 2.4 - Distribution of issues over time

The papers analyzing motivational issues have been distributed between 2003 and 2012. From 2013, the number drops to zero. With regard to partner typologies, the number of studies is limited across the entire period. Furthermore, the graph indicates a continuous interest in selection criteria, which peaked in 2014. Finally, the interest in methodologies has increased over time, highlighting the emerging managers' need of new frameworks to support the identification and selection of the most appropriate partners to collaborate with.

Table 2.2 summarizes all the references analyzing the main issues concerning the R&D partner selection problem.

	References	Motivations	Partner Typologies	Criteria	Methodologies
1	Miotti & Sachwald (2003)	•	•		
2	Nielsen (2003)	•		•	
3	Belderbos et al. (2004a)		•		
4	Belderbos et al. (2004b)		•		
5	Narula (2004)	•	•		
6	Veugelers & Cassiman (2005)		•		
7	Dong & Glaister (2006)	•		•	
8	Bierli III & Gallagher (2007)			•	
9	Nieto & Santamaria (2007)		•		
10	Nielsen (2007)			•	
11	Li et al. (2008)		•		
12	Arranz & de Arroyabe (2008)		•	•	
13	Chen et al. (2008)	•		•	•
14	Holmberg & Cummings (2009)				•
15	Wu et al.(2009)			•	•
16	Chen et al. (2010)	•		•	•
17	Lee et al. (2010)			•	•
18	Zhang & Geng (2010)				•
19	Edwards-Schachter et al. (2011)	•			
20	Huang & Yu (2011)		•	•	
21	Jeon et al. (2011)				•
22	Perkmann et al. (2011)		•		
23	Cumming & Holmberg (2012)	•		•	
24	Tai et al. (2012)			•	•
25	Wang (2012)				•
26	Nielsen & Gudergan (2012)			•	
27	Zhang & Yin (2012)	•			
28	Garcez & Sbragia (2013)		•	•	
29	Geum et al. (2013)			•	•
30	Lee & Yoon (2013)				•
31	Li (2013)				•
32	Capaldo & Petruzzelli (2014)			•	
33	Reuer & Lahiri (2014)			•	
34	Yang et al. (2014)			•	•
35	Hu et al. (2015)			•	
36	Park et al. (2015)			•	•
37	Ramli & Senin (2015)			•	
		9	11	21	14

Table 2.2 - Distribution of papers by issue

Although the majority of the selected studies do not analyze all the issues that have been identified, motivations, partner typologies, selection criteria and methodologies can be considered together as running phases of the partner selection process (Figure 2.5).

Figure 2.5 - The four phases of the partner selection process

Therefore, after having clearly defined the motivations that drive the need for partnership (issue 1), as well as the most suitable partner typologies to meet the objectives for partnership (issue 2), all potential partners can be explored based on the set of selection criteria that best reflect the need for collaboration (issue 3). Once all the information regarding potential partners has been collected, the identification and evaluation of the most appropriate partners can be performed by using several methodologies (issue 4).

The four issues are presented in more detail in the following section.

2.1.3.1 Motivations

The logic for the pursuit of technological alliances is multi-faceted, as there is no single reason why firms choose to open up their innovation practices. With regard to cooperation involving R&D and innovation, the literature on motivational issues distinguishes three main theoretical perspectives driving the search for partners.

The most common approach used in R&D collaboration is the transaction cost view. This theory highlights the importance of transaction cost minimization and economic exchange as the motivations driving strategic collaboration (Williamson, 1981). Another approach is the resource-based view, according to which competitive advantages in the market can be obtained by exchanging complementary technologies and resources among different firms (Tsang, 1998), as well as sharing costs and risks (Lavie, 2006).

Finally, the knowledge-based view focuses on acquiring knowledge skills and knowledge capabilities from external partners (Hamel, 1991). This view highlights knowledge as the most important strategic resource for innovation (Grant, 1996) in order to create new products and processes or improve existing ones in a more efficient and effective way (Nonaka & Takeuchi, 1995).

Minor perspectives include the strategic management theory (Dogson, 1992), the industrial organization theory (Hagedoorn, et al., 2000), the market-power theory (Porter, 1980), the game theory (Sanna Randaccio & Veugelers, 2001) and the social exchange theory (Das & Teng, 2001).

In summary, one of the main motivations for creating alliances is the wish to gain some advantages of adopting a global strategy. Another is that forming alliances can make up for any weakness that an organization may have concerning an important asset or capability which is required for innovation. Examples of benefits that firms gain from alliances involve faster access to technological expertise, access to new technologies, access to new markets, gaining comparative advantage, sharing costs and risks, and increasing internal innovativeness. These potential benefits cannot be acquired easily. However, having clear motivations and objectives allow firms to better evaluate the capabilities of potential partners (Nielsen, 2003) and, in turn, to successfully select the most appropriate to collaborate with.

Studies analyzing motivational issues in the literature are both theoretical and empirical.

One of the first empirical studies published between 2003-2015 which analyzes the motivation for partnership is the one proposed by Miotti & Sachwald (2003). The two authors developed an integrated resource-based framework to investigate the factors influencing the selection of partners in a sample of 4215 French manufacturing firms over the period 1994-1996. According to the results of their study, the wish to acquire new technology is not the main motivation of R&D collaboration. Vice versa, regarding the resource-based theory, the results strongly confirm the necessity of firms to be able to access complementary R&D resources, especially in the R&D intensive sector (high-tech and mid-high-tech). Other significant motivations of R&D collaboration are access to public funding and market share. Furthermore, costs reduction and risks sharing are not very significant. The results also showed that the need for complementary capabilities decreases as firms become smaller in size.

Focusing on international strategic alliances, Nielsen (2003) identified market-based factors, sharing R&D costs, development and application of new technology and exchanging existing technology as the main motivations for R&D collaboration. The author also highlighted the positive effect of having a clear motivation and choosing appropriate criteria on alliance outcome.

Narula (2004) highlighted the main interests of large and small firms in undertaking R&D collaboration. The results of a survey conducted in the ICT sector showed that both SMEs and large firms are more interested in complementary technologies and tacit knowledge acquisition than in risks or costs reduction. Based on managers' perceptions, firms mainly undertake partnerships when focusing on applied research and product development, with the aim to reduce the time needed for innovation.

Dong and Glaister (2006) conducted an empirical research to examine the strategic motivation and partner selection criteria by administering a questionnaire to 203 Chinese international strategic alliances. The results show that the strategic motives of Chinese firms are mainly market-based, i.e. maintaining their place in the market, growing internationally and exchanging technology.

According to Chen et al. (2008, 2010), in order to identify the proper alliance partners for a successful collaboration, a firm must clearly define its aims and priorities. After presenting a brief review on the studies analyzing the need for partnership, the authors identified four main motivation classes that can be used for selecting partners: (1) the "strategy-oriented" approach which aims at obtaining a competitive advantage by maximizing profits and economies of scale and reducing the time necessary to introduce new products in the market; (2) the "cost-oriented" approach which aims at reducing the risks of investments and costs of research; (3) the "resource-oriented" approach which aims at both increasing the availability of critical resources (human resources and/or equipment) and at accessing new markets and channels for distribution; (4) finally, the "learning-oriented" approach which aims at acquiring new knowledge through technological information exchange and direct contact during the development of new technologies. These motivations are taken into account by the authors for the implementation of partner selection frameworks based on the Analytic Network Process (Chen, et al., 2008) and Analytic Hierarchy Process (Chen, et al., 2010), respectively.

Based on previous research, the most important strategic benefits from resource-sharing alliances were identified by Cumming and Holmberg (2012). Firstly, by mixing partnering firms' complementary resources and abilities, synergistic benefits can be acquired. Secondly, partner firms are able to specialize even more so than previously. Furthermore, firms, through collaboration, can avoid irreversible sunk-cost investments yet, still access new capabilities and not have to face as many inertial constraints against change. Finally, partners can increase the speed at which they achieve their various aims if they have successful collaboration.

Through an empirical analysis, Zhang & Yin (2012) studied the relationship between R&D motivations (complementary resources, risk sharing, economies of scale, market access, government relationships) and functions (research-oriented and development-oriented) in Chinese alliances. The results of the Chi-square test indicate that, regarding the development-oriented function, Chinese firms look for complementary resources, economies of scale and government relationships. On the contrary, firms seek to share risks and access new market when focusing on basic or applied research.

Finally, through an empirical study, Edwards-Schachter et al. (2011) examined the motives as to why Spanish and Argentine firms generally collaborate. According to the results of the analysis, the main motivations are market oriented (i.e. access to new markets, commercialization and distribution of new products to the market).

Firms also look for new technologies which allow improvements to be made to the productive process (through a new quality system, stock reduction, etc.). Finally, access to resources and organizational improvements do not seem very significant.

Although all the 9 papers highlight motivations classes that make sense theoretically and intuitively, there are overlapping perspectives. By merging all the motivations suggested in the literature which are consistent with the innovation process flow, a classification in three main perspectives is proposed, allowing for a better distinction among motivation classes (Table 2.3).

Motivations	Description	References
Research-based	• Access to complementary resources and capabilities • Technology exchange • Tacit knowledge acquisition • Increasing the availability of critical resources (human resources or equipment)	Miotti & Sachwald (2003), Nielsen (2003), Narula (2004), Cumming & Holmberg (2012), Zhang & Yin (2012), Chen et al. (2008), Chen et al. (2010)
Saving-based	• Access to public funding • Cost reduction and risk sharing • Reduction of time of innovation • Reduction of time to market • Maximizing profits and economies of scale	Miotti & Sachwald (2003), Nielsen (2003), Narula (2004), Chen et al. (2008), Chen et al. (2010), Cumming & Holmberg (2012), Zhang & Yin (2012), Dong & Glaister (2006)
Market-based	• Access to new markets and channels for distribution • Maintaining a market position • Obtaining a competitive advantage	Miotti & Sachwald (2003), Nielsen (2003), Chen et al. (2008), Chen et al. (2010), Zhang & Yin (2012), Dong & Glaister (2006)

Table 2.3 - Motivations for R&D collaboration

According to the above classification, the identified motives for opening up collaborative R&D practices can be research-based, including the need for complimentary knowledge and technology sources, saving-based, focusing on cost and risk reduction, and market-based linked to the need for market growth and competitive advantage.

2.1.3.2 Partner Typologies

As R&D collaboration always involves specific aims, selecting a particular partner depends on the kind of complementary R&D resources the firm is seeking to have access to (Arranz & de Arroyabe, 2008)**.** The literature on partner selection is full of studies identifying the main R&D partner typologies (customers, suppliers, competitors, firms, universities and research institutes) and analyzes how they can contribute to meeting alliance objectives (Miotti & Sachwald, 2003; Belderbos, et al., 2004a; Belderbos, et al., 2004b; Nieto & Santamaria, 2007).

By following a research-based view, Miotti & Sachwald (2003) studied the relationship between the needs for complementary or similar resources and the motives for selecting certain R&D partners. Through an empirical analysis, they analyzed how collaboration with different partners gives different innovative results. Specifically, the most common R&D partnership involves vertical collaboration. In terms of new products, collaborating with suppliers of components and equipment is quite efficient, but is unhelpful for carrying out research regarding front-end technologies or for granting patents. Vice versa, being able to access science research capabilities and increasing the ability of a firm to generate patents are benefits of collaborating with public institutions. Furthermore, clients are an attractive source of market information. Finally, there is no significant impact on innovation when collaborating with rivals rather than with other partner profiles.

According to Narula (2004), in the case of R&D collaboration, the preferred partner typologies are research institutes and universities, as they decrease the likelihood of giving away their own technology to a competitor, or potential competitor.

Belderbos et al. (2004a,b) analyzed the existing relationship between four typical partner typologies involved in R&D collaboration (competitors, suppliers, customers, and universities and research institutes) and the performance of the collaboration, in terms of labor productivity and productivity in innovative sales. Through an empirical study on innovative Dutch firms over the period 1996-1998, the authors confirmed that alliances with competitors and suppliers are generally preferred when the focus of the collaboration is on improving process performance and firm productivity (incremental innovation). If the objective of the collaboration is related to sales and the introduction of new products in the market, the authors indicated competitors and universities as suggested partners. Finally, informal R&D collaborations, such as those with customers and universities, represent important sources of market knowledge.

With regard to Spanish manufacturing firms, Nieto & Santamaria (2007) analyzed both theoretically and empirically the relationship between the different partner typologies and how novel their innovation products were. The analysis reveals that the innovation process is negatively affected by collaboration with competitors. Vice versa, the process is positively affected when collaboration involves with suppliers, clients and research institutions. Finally, collaboration involving different kinds of partners (collaborative networks) has the most positive effect on innovation.

Veugelers & Cassiman (2005) focused on R&D collaboration between Belgian manufacturing firms and universities. Through an econometric analysis, the authors found universities to be complementary to other partner typologies. In addition, the strongest industry-science links mainly involve sectors, such as the chemical and pharmaceutical ones, characterized by high costs of innovation. On the contrary, industry-science links are not very common when firms look for partners with whom to share the risks. Finally, collaboration with universities are more likely to involve large firms, as they usually possess the internal R&D capabilities to efficiently communicate with scientific institutes and implement successful collaboration.

According to Arranz & de Arroyabe (2008) and Perkmann et al. (2011), collaboration with research institutes also seem to be the best match for companies looking for basic knowledge and research capabilities in order to acquire a better understanding of scientific changes.

With regard to R&D collaboration with suppliers, customers, rivals, universities and research institutes, researchers have distinguished three types of alliance: “vertical”, “horizontal” and “institutional” (Miotti & Sachwald, 2003; Arranz & de Arroyabe, 2008; Garcez & Sbragia, 2013). Vertical alliances mainly involve suppliers and customers. More specifically, vertical collaboration with suppliers promote new product development, allowing firms to be able to access various resources such as those related to technology, the market and its demands/requirements. Vertical collaboration with customers reduce the uncertainties of the market, positively influencing the likelihood of success of new products to be launched.

On the other hand, horizontal alliances are generally those with competitors. Such alliances seek to both reduce financial, technical and business risks and increase market concentration and economies of scale. However, the main limits of this kind of collaboration is related to the risk of knowledge appropriability. Lastly, as previously mentioned, when firms wish to obtain funding for their research and development, collaboration with institutions are rather attractive as governments give financial aid to public-private alliances.

Another existing classification is the one proposed by Li et al. (2008). Based on an analysis of 1159 R&D alliances, the authors categorized potential partners into three groups (i.e. friends, acquaintances and strangers) based on prior alliance experience and level of trust. Two partners are friends when they have developed a high level of trust through multiple previous interactions. If the number of prior interactions is low and, therefore, there is limited trust, partners are acquaintances. Finally, the authors defined partners as strangers when they do not know each other and, therefore, the level of trust between them is low.

Furthermore, by considering both the main partner typologies and the motivations behind the need for R&D collaboration, Huang & Yu (2011), for example, distinguished alliances as “non-competitive”, referring to the ones with universities and research institutes, and those involving inter-firm collaboration as “competitive”. According to the authors, innovation performance is higher concerning competitive collaboration and, more specifically, when the firms involved have their own R&D

departments. However, the classification of vertical, horizontal and institutional collaboration remains the most common one.

Table 2.4 indicates the references concerning the partner typology issues for each of these three categories.

Partnership Typologies		Related Motivations	References
Vertical Collaborations	Customers	• Sources of market knowledge	Miotti & Sachwald (2003), Balderbos et al. (2004a,b), Nieto & Santamaria (2007)
	Suppliers	• Access to knowledge and technology capabilities • Process performance and firms' productivity, • Technology development	Miotti & Sachwald (2003), Balderbos et al. (2004a,b), Nieto & Santamaria (2007), Cassiman et al. (2005)
Horizontal Collaborations	Competitors	• Process performance and firms' productivity • Introduction of new product in the market	Balderbos et al. (2004a,b), Miotti & Sachwald (2003), Balderbos et al. (2004a,b), Arranz & de Arroyabe (2008)
Institutional Collaborations	Universities	• Access to basic knowledge and technology complementarity • No risk of technology appropriability • Introduction of new product in the market • Access to market information • Sharing costs	Miotti & Sachwald (2003), Narula (2004), Balderbos et al. (2004a,b), Veugelers & Cassiman (2005)
	Research Institutes	• No risk of technology appropriability • Access to basic knowledge and technology complementarity	Narula (2004), Nieto & Santamaria (2007), Cassiman et al. (2005), Arranz & de Arroyabe (2008) & Perkmann et al. (2011)

Table 2.4 - R&D partnership typologies

2.1.3.3 Selection Criteria

The third issue concerning the partner selection process refers to the selection criteria to be taken into account in order to compare and select the most suitable partners to collaborate with. Partner selection criteria are closely linked to both the objectives that underlie the need for collaboration and the partner typology (Garcez & Sbragia, 2013). As selecting the right partner is an important determinant for the likely outcome of the relationship between parties, it is important to identify the criteria that better mitigate the companies' difficulties and compensate for their lack of skills and resources (Dong & Glaister, 2006; Wu, et al., 2009).

As previously mentioned, incompatibility of partners is one of the main factors contributing to R&D collaboration failure, resulting in the alliance partners not always achieving their planned goals. Therefore, in order to identify the most appropriate partners to collaborate with, the partner selection process assumes a critical role and must be carefully implemented.

The choice of the most appropriate partners for a successful R&D collaboration has been examined by both researchers and practitioners. Through surveys and interviews with industry experts, the most significant factors that drive the choice have been highlighted, identifying the criteria and sub-criteria to take into account for selecting the most appropriate partners to collaborate with. Due to the large number of selection criteria, several authors have grouped them into categories. One of the most cited classifications is the one introduced by Geringer (2001) concerning "task-related" and "partner-related" factors. According to the author, task-related factors refer to specific operational skills and resources such as the ability to provide technical expertise, financial resources, highly qualified staff, access to new market and distribution channels, which are necessary in order to be successful. Conversely, partner-related factors concern the general efficiency and effectiveness of collaboration. This category includes the existence of prior collaboration and, in turn, trust between parties, similarity and/or complementarity of partners' culture, organizational size and structure.

Through an empirical analysis of the criteria adopted by Danish firms for choosing partners for international strategic alliances, Nielsen (2003) found that the best way to effectively drive managers to find the proper partners for future alliances consists of using both task-related and partner-related criteria at the same time. In addition, because potential partners often meet only some of these criteria, and the need for certain partners' capabilities may change depending on the availability of internal resources, the author suggested ranking the preferred task-related and partner-related criteria case by case, according to the weight they have in achieving the alliance's strategic objectives. Special attention was given to previous alliance collaborations, experience with foreign partners, and administrative governance structure.

Dong & Glaister (2006) confirmed Geringer's assumption that the partner-related selection criteria are less specific than the task-related ones. Furthemore, by examining 203 Chinese international strategic alliances, task-related criteria appear to be more significant than partner-related.

In their comprehensive partner selection framework, Cumming & Holmberg (2012) proposed "learning-related" and "risk-related" criteria, in addition to the task and partner-related ones. The learning-related tasks focus on the extent to which potential partners are favorably disposed to share their knowledge (both tacit and explicit), to leverage their knowledge network, and to indicate directions for future developments in R&D, technologies, customers, foreign markets and distribution areas. On the other hand, the risk-related tasks focus on the extent to which potential partners can address both the risks that come from taking part in an alliance (“alliance risks”) and the ones that come from possible alliance activities sought after by others (“non-partnering risks”).

Through an empirical study using the techniques of multinomial logistic regression and binomial logistic regression, Garcez & Sbragia (2013) outlined the existing relationship among task-related and partner-related criteria and both partner typologies (universities and research institutes, customers, competitors, suppliers, and consulting companies) and type of innovation project (incremental, platform, radical, basic science).

The purpose of the article by Bierly III & Gallagher (2007) is to provide a clear understanding of the degree to which strategic fit, trust and expediency impact a firm's alliance partner selection in the presence of uncertain and external time constraints. According to the authors, although strategic fit is undoubtedly required, it is not always a sufficient motive for partner selection. In addition, trust is more significant when the level of uncertainty is high.

Nielsen (2007) proposed an empirical study on international strategic alliances. Based on a web-survey, the author investigated Danish partner firms involved in both equity and non-equity joint ventures with international partners. The author distinguished the selection criteria with respect to the two phases of the collaboration development: pre-alliance formation factors and post-alliance formation factors. Among the pre-alliance formation criteria, reputation and prior experience are particularly significant for partner selection. When the alliance is formed, collaborative know-how, trust, complementarity become more important in order to improve alliance performance.

Arranz & de Arroyabe (2008) studied the R&D collaboration among Spanish firms. They used a logit regression in order to identify the main variables affecting the choice for partners. More specifically, the results of their analysis indicates that the technology level of the sector, the integration of the firm into a group, the size of the firm, and the availability of public funding positively affect the innovation process and the likelihood of partnership success.

Chen et al. (2008, 2010) classified partner selection criteria in four main categories: corporation capability, technology capability, resources for R&D and financial condition. According to the authors, these criteria are strongly related to the motivations that drive the need for partnership. In order to better express this relationship, the authors proposed the use of a weighting process in which the two factors mutually affect each other. Specifically, motivations affect the weighting process for criteria and the priority of motivations is shown through the weighting process.

Referring to R&D in the high-tech sector, Wu et al. (2009) proposed to classify criteria in five criteria, each including few related sub-criteria: (1) characteristics of the partners, including competencies, management style, strategic objectives and technical capabilities; (2) market knowledge capability, including organizational culture, expertise, control and flexibility; (3) intangible assets, including proprietary knowledge, reputation, alliance experience, technical skills; (4) complementary capabilities, including market share, export opportunities, local knowledge of business practices; (5) degree of fitness, including managerial capabilities, market coverage, diversity of customers, quality of distribution system.

Based on a massive literature review, Lee et al. (2010) proposed a set of four-fold decision criteria for selecting strategic partners for collaborative R&D: technology strength, R&D openness, R&D linkage, and collaboration effects. For each class, the authors defined fourteen patent and publication indexes which were also used for further study by Geum et al. (2013).

In order to select the right R&D partners for SMEs, Tai et al. (2012) summarized a set of nineteen criteria, clustered in three main factors: (1) complementarity (manufacturing complementarity, technology complementarity, marketing complementarity, share brand name, finance complementarity, patent sharing and government policy), (2) mutual trust (experience in external collaboration, predominance to collaboration, reputation for keeping promises, placing high importance on the collaboration, taking a key position in the market and willingness to take risks), and (3) communication between partners (similarity in products or customers, consensus with vision collaboration, existing communication channel between members, the intention to involve new partners, similarity in firm size and geographic closeness). According to the authors, mutual trust is the most important factor affecting small firms' alliance performance, followed by reputation.

According to the detailed literature survey by Yang et al. (2014), cooperative willingness, financial ability, complementary resources and technological ability - and their relative sub-criteria - are the main factors to be considered when looking for favorable partners to collaborate with. In order to evaluate technological capabilities the authors used patent data. The use of patents as criteria for partner identification is one of the most common factors for objectively evaluating technology partners (Park, et al., 2015). Together with publications they are sources of quantitative information.

According to Nielsen & Gudergan (2012), the variables with a higher impact on knowledge exchange and alliance performance are prior experience, competence similarity, cultural distance and partner trust effect. Focusing on competence similarity, the authors found that this variable is more significant when researching new products and technologies (scope) than when exploiting existing knowledge in new markets (scale).

Finally, there are also studies indicating internal capabilities as the main factor for improving innovation performance that should be consistent in the selection process. An example is the empirical study by Huang & Yu (2011) which highlighted a positive correlation between internal R&D (expressed by the ratio of the number of full-time engineers and scientists to the total number of employees) and firms' innovation performance. Previous literature also points out the key role of internal R&D in enhancing an organization's capability of acquiring, assimilating, transforming and exploiting knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002).

Reuer & Lahiri (2014) focused their attention on the role of geographical proximity in R&D alliance formation. Through an empirical study, they found geographic distance to negatively affect the likelihood of alliance formation. This effect decreases when the organizations involved in the partnership have the same objective and priorities. However, despite the negative effect of spatial proximity, a noticeable increase in maximum distance between partners since 1980 has been observed (Waltman, et al., 2011)**.**

Another study analyzing the effect of geographical proximity on alliance formation is the one by Capaldo & Petruzzelli (2014). The authors highlighted the negative effect of geographical distance on innovative performance. In addition, through a statistical analysis, they found that this negative effect can be reduced in the presence of organizational proximity, i.e. the capacity of organizations to interact with each other (Crespin-Mazet, et al., 2013)**.**

Hu et al. (2015) proposed both a conceptual and a structural equation model in order to describe the impact of selection criteria on alliance performance. According to their model, the criteria affecting technological alliance performance can be classified as either "congenital" or "posterior" factors. Criteria such as compatibility, reputation, technical capability and market capability are included in first class. Vice versa, criteria such as trust, information exchanging and shared problem solving are included in the second class.

Table 2.5 summarizes the main selection criteria identified in the literature on R&D partner selection, by distinguishing them in qualitative criteria (i.e. partners' characteristics and innovative capabilities) and qualitative criteria (i.e. degree of fitness and strategic capabilities).

Selection Criteria Classes	Criteria	References
Quantitative	**PARTNERS' CHARACTERISTICS** • Organizational size • R&D efforts (R&D resources and expenses) • Geographical distance • Market coverage • Previous collaborations	Nielsen (2003), Dong & Glaister (2006), Cumming & Holmberg (2012), Garcez & Sbragia (2013), Arranz & de Arroyabe (2008), Chen et al. (2008), Chen et al. (2010), Wu el al. (2009), Huang & Yu (2011), Reuer & Lahiri (2014), Capaldo et al. (2014), Huang & Yu (2011)
	INNOVATIVE CAPABILITIES • Publications • Patents • Quality of research	Garcez & Sbragia (2013), Chen et al. (2008), Chen et al. (2010), Lee et al. (2010), Huang & Yu (2011), Tai et al. (2012), Geum et al. (2013), Yang et al. (2014), Park et al. (2015)
Qualitative	**DEGREE OF FITNESS** • Organizational proximity • Flexibility • Reputation • Trust • Complementarity • Similarity • Symmetry of scale and scope	Nielsen (2003), Dong & Glaister (2006), Cumming & Holmberg (2012), Garcez & Sbragia (2013), Nielsen (2007), Bierly III & Gallagher (2007), Chen et al. (2008), Chen et al. (2010), Wu et al. (2009), Lee et al. (2010),Cumming & Holmberg (2012), Tai et al. (2012), Nielsen & Gudergan (2012), Geum et al. (2013), Huang & Yu (2011)
	STRATEGIC CAPABILITIES • Market knowledge • Distribution system • Access to funding • Financial ability	Nielsen (2003), Dong & Glaister (2006), Chen et al. (2008), Chen et al. (2010), Cumming & Holmberg (2012), Garcez & Sbragia (2013), Arranz & de Arroyabe, Yang et al. (2014)

Table 2.5 - R&D selection criteria

2.1.3.4 Methodologies

Methodologies are the last key issue of the partner selection problem emerging from the literature review, which refer to the usage of approaches, methods and techniques for the identification and selection of the most suitable R&D partners.

As many studies on the topic highlight that a careful and systematic implementation of the partner selection processes may result in a decrease in the rate of R&D alliance failure, the interest of scholars in methodologies has increased over time.

In particular, recent research is full of studies suggesting guidelines for creating successful alliances, as well as developing new quantitative partner selection frameworks to overcome the limitations of R&D collaboration practices, which are mainly based on expert judgment and lack of objective perspective.

Holmberg & Cummings (2009), in order to support the creation of successful R&D collaboration, provided a conceptual framework for partner selection consisting of four steps. According to the authors, after aligning corporate and strategic alliance objectives (step 1), selection criteria have to be drawn up (step 2). Once the first two steps have been implemented, candidate partners can be mapped (step 3), and finally the potential of each candidate has to be evaluated (step 4).

However, when potential R&D partners are unknown, they first have to be identified. In that sense, the recourse to sources of technological information is needed for searching and identifying potential candidates with complementary capabilities.

In order to identify potential technology partners, Jeon et al. (2011) developed a patent based approach. The process for searching potential technology includes three phases. First of all, patent data are collected from the USPTO database. As the patent data are unstructured, they need to be pre-processed in order to eliminate unnecessary information. The second step consists of creating co-occurrence vectors by using text mining and domain experts. Finally, potential technology partners are identified by using similarity indicators.

The framework proposed by Wang (2012) is also based on the use of patents as an information source of technological complementarity when firms have insufficient information on who may possess them.

Another example is the recent paper by Park et al. (2015). In order to examine suitable future partners for R&D collaboration, the authors provided a new systematic methodology which seeks technological and semantic similarity of patents.

In addition to the identification on partners, Chen et al. (2008) proposed the use of an analytic network process (ANP) approach for partner selection whereby relative weights of criteria and motivations for forming strategic alliances are determined simultaneously. Two years later, having the same motivations and criteria in mind, Chen et al. (2010) implemented the analytic hierarchy process (AHP).

For selecting strategic alliance partners, the use of ANP was also advised by Wu et al. (2009). The methodology is implemented in eight steps: (1) break down the problem, (2) outline partner selection criteria, (3) structure the hierarchy, (4) perform pairwise comparison and prioritization, (5) calculate the weights of the criteria, (6) rate the alternative partners, (7) calculate the potential partners' overall score of each prospective partners, (8) make final decision.

Lee et al. (2010) developed a framework for strategic partner selection for collaborative R&D based on literature, enabling a wide range search for potential partners and an understanding of their characteristics. After a massive literature review aimed at identifying the main decision criteria for selecting the strategic partners for collaborative R&D, the importance of each criterion is determined by the

AHP technique based on expert opinion. The proposed framework was also implemented by Geum et al. (2013).

A fuzzy-AHP model was instead proposed by Yang et al. (2014). The authors used it for identifying and selecting candidate partners to work with on Chinese mega projects. The AHP model considers three hierarchical levels: organizational characteristics, evaluation criteria and sub-criteria. Relative weights are assigned to each criteria.

Tai et al. (2012) suggested the use of a hybrid approach to select small firms' collaborative R&D partners, in the presence of multiple criteria. More specifically, they proposed applying a two-phase framework, combining fuzzy, Delphi method and AHP.

To find the perfect balance between partners and companies' needs, Lee & Yoon (2013), after identifying the technology field of interest by using patent roadmapping and listing the candidate SME partners for collaboration, suggested the use of a Bayesian model for obtaining rankings. According to the authors, the Bayesian model is the most appropriate one when considering many criteria and their relationship to each other.

Zhang & Geng (2010) proposed the use of a multi-agent simulation method in order to select R&D partners in virtual enterprises. According to the authors, the limitations of the simplex quantitative analysis can be overcome by using this method.

In order to support organizations in choosing the most appropriate partners and making cooperative innovation more efficient, Li (2013) proposed a decision-making methodology of few steps, integrating fuzzy logic and the TOPSIS method. First of all, the main factors influencing the cooperation strategy are identified and the criteria system of partner selection is set up. Then, the fuzzy weight and fuzzy assessed value can be acquired by considering the linguistic variable and triangular fuzzy number. Finally, in order to obtain a ranking of partners, the TOPSIS method is used.

Table 2.6 summaries the results of the literature review with regard to the methods used for selecting R&D partners.

Methods for R&D Partner Selection	References
Analytic Network Process (ANP)	Chen et al. (2008), Wu et al. (2009)
Analytic Hierarchy Process (AHP)	Chen et al. (2010), Lee et al. (2010), Geum et al. (2013), Yang et al. (2014), Tai et al. (2012)
Bayesian	Lee & Yoon (2013)
Multi-Agent	Zhang & Geng (2010)
Fuzzy Hybrid	Tai et al. (2012), Yang et al. (2014), Li (2013)

Table 2.6 - Methods for R&D partner selection

As shown in the table, most of the papers propose the use of multi-criteria decision making (MCDM) techniques, i.e. ANP and AHP developed by Saaty (1980, 2001). The use of both AHP and ANP is also integrated with the use of the fuzzy logic (Tai, et al., 2012; Yang, et al., 2014), which allows for making decision in the presence of vagueness and uncertainty.

In order to select the most appropriate collaborative R&D partners, there is also one study proposing the use of artificial intelligence (i.e. Bayesian model) as a decision making technique, and another one applying the multi-agent simulation.

However, in contrast with the overall literature on partner selection, no studies applying mathematical programming emerge when focusing on R&D.

2.1.4 Identification of Findings

This final phase consists of a critical analysis of the research materials in order to highlight findings and gaps in the literature.

The in depth analysis of the selected papers has highlighted the existence of a strong relationship between motivations, partner typologies and selection criteria (Figure 2.6).

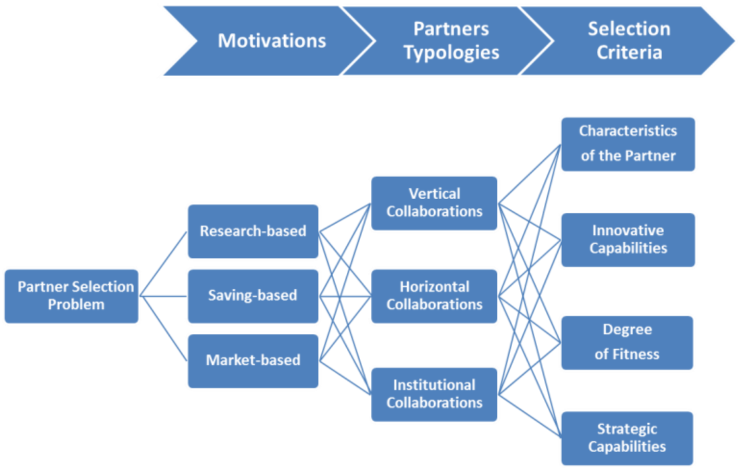

Figure 2.6 - Links among motivations, partners typologies and selection criteria

A clear understanding of the motivations for partnership, the identification of the proper partner typology based on motivations, as well as the selection of the right criteria to be taken into account to assess potential partners, are extremely important in order to guide the development and implementation of partner selection methodologies.

As already emphasized, the interest in methodologies has increased over time due to the emerging managers' need of new frameworks to support the identification and selection of the most appropriate partners to collaborate with, as they positively affect the success of R&D collaboration. Therefore, in order to better manage the variety of R&D objectives and the many characteristics that drive the choice for a partner, the studies identified through the systematic literature review have proposed the combined use of different decision making methodologies, mainly including multi-criteria decision making techniques, such as AHP and ANP. On the contrary, the use of data envelopment analysis (DEA) is not mentioned. This finding contradicts the overall literature on decision-making methodologies for partner selection, according to which DEA is one of the most popular linear programming techniques (Ho, et al., 2010; Wu & Barnes, 2011; Chai, et al., 2013; Govindan, et al., 2015). This, therefore, represents the first gap of the literature related to the R&D partner selection problem.

Another emerging gap refers to selection criteria. More specifically, the systematic literature review has highlighted patents to be a common source of technological information about candidate partners for R&D collaboration. In particular, the number of patents is often used as criteria for evaluating technology complementarity and/or similarity of partners. By using patents as a criteria, researchers do not consider their limitations. First of all, not all of the know-how is eligible for patent protection (i.e. technologies at the early stages of their life cycle). In addition, some organizations may decide to protect their technological know-how in other ways, such as trade secrets or trademarks (Ernst, 2003). Therefore, even though patents represent an objective measure of R&D activities, only using patent data may automatically exclude or at least under-estimate some relevant R&D potential partners.

The last gap emerging from the literature on the R&D partner selection problem refers to motivations and preferred partner typologies issues. In contrast with the overall literature on innovation and technology management, when focusing on the R&D partner selection problem, researchers do not consider the existing link between the two issues and the technology life cycle (Kapoor & McGrath, 2014). More specifically, although the importance of R&D collaboration to achieve competitive success in a market characterized by rapid and continuous technological changes has been highlighted, there are no studies explaining the different motivations and the roles served by the different kinds of partner typologies during the evolution of technology from an initial emerging stage characterized by a high degree of uncertainty, to subsequent stages of growth and maturity in which the degree of uncertainty is much lower.

In the light of these findings, the next chapter proposes a framework for identifying and selecting R&D partners by taking into account a preliminary analysis of the technology of interest and its life cycle. Furthermore, in order to overcome the limitations of patents, the framework considers selection criteria and variables of interest based on both patent and publication data. Finally, the use of data envelopment analysis is used as a decision making technique in order to fill the last gap in the literature, providing a further significant contribution to the research on the topic.

CHAPTER 3

3 Step by Step Framework for R&D Partner Qualification

Although the number of studies investigating the topic of R&D collaboration and, more specifically, the R&D partner selection process, has increased over time, findings from the literature review (chapter 2) highlight some relevant gaps to be filled. First of all, the need for a preliminary analysis of the technology of interest has emerged in order to better define the motivations, partner typologies and selection criteria. In addition, with regard to the identification of partners and their selection, a lack of studies applying mathematical programming techniques, such as data envelopment analysis, has been highlighted. In this chapter, in order to overcome these limits, a new quantitative decision-making framework, which takes into account technological issues, is provided to support organizations in evaluating and selecting the most suitable R&D partners for technological innovation. Advantages of adopting this approach in innovation management research and practice are also highlighted.

3.1 The Strategic Role of Technology Analysis

The investments and efforts made in recent decades by companies, research centers, and local governments in the race for the technological innovation of products and processes have been enormous. Despite the improvement of technological performance, it is increasingly difficult to meet the needs of customers increasingly oriented towards products with a high quality to price ratio. The reduction of the technology life cycle also makes the choice of the right time to enter into the market increasingly difficult.

In this panorama of ongoing technological transformation, the analysis of technology has a key role in managing innovation. The literature on technology management is full of studies highlighting the strategic use of technology analysis and its significant implications for firm strategies and industry evolution.

When referring to technology analysis, one of the most common approaches is the "technology future analysis" (TFA) or "future-oriented technology analysis" (FTA). The main aims of TFA are allowing for a clearer understanding of the directions that existing trajectories will take and creating an improved future through making better decisions related to the future. A variety of activities are involved in TFA and are known as technology foresight, forecasting, intelligence, roadmapping and assessment (Technology Futures Analysis Methods Working Group, 2004) .

Another common technique to be used together with TFA is patent analysis. The use of patent data is becoming increasingly popular within Innovation Management, especially in high-tech sectors (Jeon, et al., 2011; Jeong & Yoon, 2015). Ernst (1997) proposed the use of patents for drawing the curve of the evolution of technology, known as the technology life cycle.

3.1.1 Technology Life Cycle

In order to measure technological changes, Arthur D. Little (1981) introduced the notion of the technology life cycle (TLC), distinguishing four different stages (i.e. emerging, growth, maturity and saturation) based on two dimensions (i.e. the competitive influence/effect and integration in products or processes). According to Arthur's definition:

- at the emerging stage the technology is novel with both low competitive and impact and integration in processes or products;
- at the growth stage there are pacing technologies with high competitive impact that still have to be integrated in new products or processes;
- at the maturity stage they become key technologies, and are integrated into products or processes, and maintain their high level of competitive impact;
- at the saturation stage the technology loses its competitive impact and becomes a base technology, and a new technology may take its place.

TLC assumes the general form of an S-curve, indicating that the technology progression "advances slowly at first, then accelerates, and then inevitably declines" (Foster, 1986).

As highlighted by Taylor & Taylor (2012) regarding the concept of technological life cycle, a common interpretation of the S-curve plots the cumulative adoption of a technology over a certain amount of time, which leads to what often termed the diffusion model (Nieto, et al., 1998).

Ernst (1997) used the S-curve to display technological performance, in terms of patent data, both over time and in terms of cumulative R&D efforts (Figure 3.1).

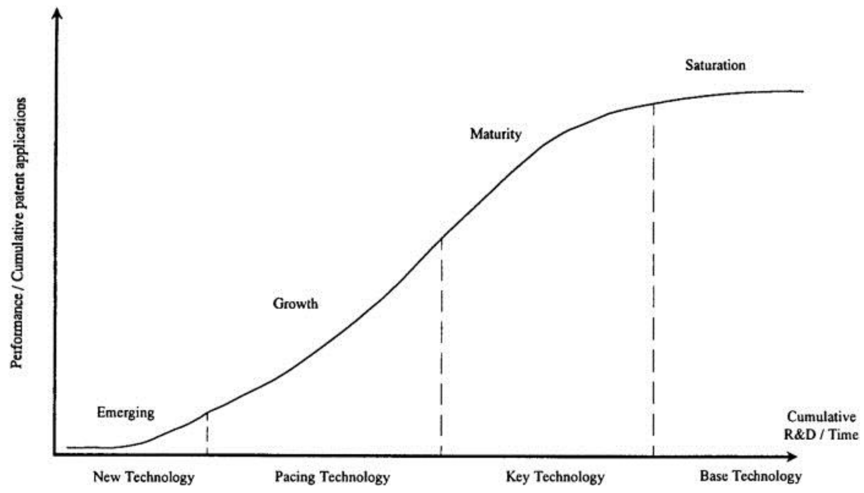

Figure 3.1 - The Technology Life Cycle (Source: Ernst, 1997)

Further studies suggested drawing the S-curve by using patent data together with some other bibliometric indicators, such as the number of articles and citations (Haupt, et al., 2007; Gao, et al., 2013).

However, during the emerging stage of the technology life cycle, when the basic technology principles have been partially understood, the growth of the curve is slow. This initial stage is characterized by a high degree of risk, related to the uncertainty of identifying interesting technology solutions that allow firms to respond to the emerging needs of the market. Vice versa, during the subsequent stages of growth and maturity, the degree of uncertainty is much lower. Once a deeper knowledge of technology has been acquired, its improvement becomes faster. This period of quick growth precedes an inflection point and slower growth as a period of maturity begins. At a certain point, when the advances in research and development approach their natural limit or the technology becomes obsolete, the innovative performance declines, resulting in the emergence of new technologies.

Moreover, due to rapid and continuous technological changes, the life cycle of advanced technology becomes shorter. In order to reduce the high level of uncertainty coming from these changes, companies have to do their best in order to reduce research and development costs, to identify market needs, to find the right distribution channel and, finally, to make the most of the competitive advantage through providing new and effective technologies.

In such a context, R&D collaboration represents a great opportunity to innovate. In order to make the collaboration successful, the innovation process needs to be managed properly at all stages of the technology life cycle.

Therefore, the evolution of technology will be taken into account for the development of the partner selection framework described in the next sections. By doing so, it is possible to respond to and fill one of the gaps that emerged from the literature review.

3.2 The Four Steps

The partner selection problem is one of the most critical aspects in the establishment of R&D collaboration (Geringer, 2001). When the selection process is implemented well, the partner choice can lead to important competitive advantages. On the other hand, when the partners have not been selected properly, failures can occur from the beginning of the alliance.

Many studies highlight the existing relationship between partner selection and alliance performance. According to Nielsen (2003), alliances would be more successful if the selection process were more structured and started by looking at the motivations and intentions of an alliance. Holmberg & Cummings (2009) suggested the application of analytic and systematic methods for partner selection as a precondition to increase the success rate of alliances.

In order to support organizations in selecting the proper partners for successful collaboration, a new quantitative framework, structured in only a few phases, is proposed in this section. More specifically, this decisional framework allows experts (e.g. firms’ managers) to rationalize the selection of technological partners by identifying and classifying them based on proper criteria and methods. However, once the final list of candidate partners has been elaborated, the effective choice is made by managers autonomously.

The proposed framework has been developed based on the results of the literature review on R&D collaboration (i.e. the existence of four main issues) and on the emerged findings (the need for technology considerations). Therefore, the partner selection is defined here as a process of four phases in which, after clearly defining the alliance purpose, in terms of technology of interest, motivations and preferred partner typologies, candidate partners can be identified utilizing a set of criteria objectively describing their characteristics. Finally, based on the relative importance of these factors, appropriate partners to collaborate with can be evaluated and selected (Figure 3.2).

Figure 3.2 - The four steps framework

Each of the four phases has been rationally structured, in order to make the framework simple to implement and reliable at the same time. In addition, the use of information and data available online allows the identification of candidate partners to be objective and replicable.

Finally, the decision making methodologies suggested for both the qualification and final selection phases have been chosen with the aim to minimize expert subjectivity, and to speed-up the analysis, whilst taking into account a large set of candidate partners.

3.2.1 The Partner Selection Team

According to Baker et al. (2002), before starting any decision process, a decision making team should be identified in order to reduce possible disagreements about problem definition, requirements, goals and criteria.

In order to identify and select the most appropriate partners to collaborate with, the creation of a partner selection team responsible for the full implementation of the four-step framework is important. More specifically, the members of the team must have a certain amount of experience in the field of R&D, as well as being up to date with the latest advances in innovation. In addition, some familiarity with the main scientific search engines is essential.

3.3 Objectives of the Innovation Strategy (Step 1)

When defining the objectives of the innovation strategy, having a clear idea of the real interests of the company is crucial in order to identify the main sources of knowledge and expertise about a certain technology (i.e. universities, research centers and/or other firms).

Firstly, all the objectives related to the technology of interest, such as the sector of interest and the life cycle phases, must be clarified. Once the technology of interest is known, the motivations underlying the need for R&D collaboration and the most favorable partner typologies can be identified. Finally, previous collaboration (if any) on the topic should be indicated.

For practical purposes, the creation of an objectives chart is suggested (Table 3.1).

OBJECTIVES FOR PARTNERSHIP	# 1
Technology of Interest	Technology 1
Preferred Sector	Sector 1, Sector 2, …
Description	Keyword 1, Keyword 2, …
Life cycle Phase	Emerging/ Growth/ Maturity/ Saturation
Main Motivations	Research-based/ Development-based/ Market-based
Preferred Partners Typologies	Universities and Research Institutes/ Firms

Table 3.1 - Example of a chart of the company's objectives for partnership

3.3.1 Technology of Interest, Motivations and Partner Typologies

A very significant contribution to the literature highlighting the significant role of the technology of interest and its evolution is given by Kapoor & McGrath (2014). Through a study analyzing more than 2,000 articles presented in industry technical conferences on semiconductor technologies, the two authors "unmasked" the existence of the relationship between technology evolution, and R&D collaboration. More specifically, they highlighted that the preferred partner typology for R&D collaboration (i.e. research organizations, users, suppliers and rivals) changes when shifting from the initial emergence stage of the technological life cycle to the growth and maturity stages.

Therefore, according to Kapoor and McGrath's findings, in order to develop a new R&D partner selection framework which takes into account the technology issue, the following assumptions are applied:

- During the emerging stage of the technology life cycle, organizations are strongly orientated toward basic research. R&D efforts mainly involve internal

R&D departments and collaboration with research organizations, such as universities and research institutes.

- Throughout the growth and maturity stages of the technology life cycle, with the increasing need for collaborative development and integration of complementary technology, R&D collaboration with suppliers is on the rise. Institutional collaboration continues to exist.
- Finally, collaboration with competitors are stable, ranging from research-based motivations (i.e., using collaboration to learn and accumulate knowledge), to saving-based (i.e. sharing R&D resources to generate economic efficiencies), and to market-based (i.e. introduction of new products into the market).

3.4 Identification of Candidate Partners (Step 2)

The second step of the R&D framework consists of identifying a long list of potential partners to be selected for R&D collaboration.

The partner search involves different kinds of organizations from all over the world, that can be found by using both publications and patent data. The search for R&D potential partners starts from publications or patents, depending on the objectives for partnership (technology of interest, motivations and preferred partner typology) and, therefore, on the relative importance of partner selection criteria.

3.4.1 Selection Criteria and Variables of Interest

Defining criteria poses one of the greatest difficulties regarding partner selection problems (Ávila, et al., 2012). Partner selection criteria are closely linked to innovation strategy goals. The literature on open innovation and R&D collaboration is full of studies identifying the most significant criteria for partner selection (Nielsen, 2003; Dong & Glaister, 2006; Bierly III & Gallagher, 2007; Arranz & de Arroyabe, 2008).

However, the systematic literature review has highlighted the emerging need for selection approaches based on more objective data. Consequently, the second step of the framework proposes the use of quantitative selection criteria and variables of interest (i.e. partners' characteristics and innovative capabilities) that can be measured without relying on expert opinion. Rather, these quantitative variables are based on data to be collected by making use of the more common online data sources.

Based on the concept of "innovative performance" (Hagedoorn & Cloodt, 2003), R&D inputs (as cost factors) and R&D outputs (as benefit factors) can be considered. The benefit factors refer to innovative capabilities, such as research output and quality of research of potential partners. On the other hand, the cost factors take into account collaboration experience and co-authorship.

Table 3.2 provides a brief overview of the variables of interest.

	Variables of Interests	
BENEFITS (R&D Outputs)	**Research Output**	
	Pub	Total number of publications with a focus on the technology of interest, published over a certain period of time
	Spat	Total number of patent data with a focus on the technology of interest, published over a certain period of time
	Epat	Total number of patent data published over a certain period of time with a focus on the subject areas in accordance with the technology of interest
	Kdecay	Publications (or patents) decay over a certain period of time
	Quality of Research	
	Cit	Total number of citations received by publications about the technology of interest over a certain period of time
	HTind	H-technology index of potential partners calculated focusing on publications about the specific technology of interest over a certain period of time
COSTS (R&D Inputs)	**Collaboration Experience**	
	Coll	Total number of collaborations established over a certain period of time
	Eucoll	Total number of collaborations established with European organizations over a certain period of time
	Iucoll	Total number of collaborations established among universities/research centers and industries over a certain period of time
	Co-authorship	
	Auth	Number of authors involved in the publications about the technology of interest over a certain period of time

Table 3.2 - Variables of interest for R&D partner selection

Each of these variables is described in further detail below.

3.4.1.1 Benefit Criteria: Research Output and Quality of Research

According to the literature on R&D partner selection, collaboration among organizations and/or between individuals represents an important source of knowledge that allows firms to stay competitive in the current dynamic business environment. More specifically, R&D collaboration allows firms to take advantage of the expertise of many researchers and, in turn, to increase their innovative and technological capabilities.

In order to evaluate and select the most favorable potential partners to collaborate with, the benefit criteria have been distinguished in two classes: (1) research output and (2) quality of research.

3.4.1.1.1 Research Output

In order to evaluate the technological capabilities of potential partners, one of the main aspects to take into account is their research output. It can be evaluated in terms of the number of publications and patents they have published (Li, et al., 2008; Lee, et al., 2010; Wu, et al., 2009; Jeon, et al., 2011).

Usually, publications are more significant when collaborations are established with universities or research centers, whereas patents are preferred in the case of collaboration among industries (Geum, et al., 2013).

In addition to the number of publications and patents, the use of a new variable termed "knowledge decay" is proposed. The details of these variables are given below.

Total number of publications (Pub). The total number of published papers is the first variable to consider as a research output. In order to select the most suitable R&D partners, it is advisable to collect publication data on the specific technology of interest.

Specifically, this variable is able to quantify the innovation and technological capabilities of candidate partners.

The number of publications can be collected by using bibliographic data sources, such as Scopus and Web of Science, and by setting a period of time ranging from five to ten years (Geum, et al., 2013; Wu, et al., 2009).

Total number of patents (Spat). The total number of published patents is the last variable to consider as a research output. As in the case of publications, it refers to a period of time ranging from five to ten years (Hagedoorn & Cloodt, 2003; Ernst, 2003; Jeon, et al., 2011).

In order to select the most suitable R&D partners, it is advisable to collect patent data on the specific technology of interest (Spat). When the number of specific patents is not significant enough to differentiate the candidates, the patents collection can be extended to the subject areas (i.e. engineering and computer science) to which the technology of interests refers (Epat). In any case, the patents count is a measure of the technological capabilities of candidate partners.

As indicate by the World Intellectual Property Organization (WIPO), patent data can be collected by using several online database services, such EPO Espacenet, Google Patents and Thomson Innovation (WIPO, 2010).

As already discussed, not all technological innovations are eligible for patent protection (Ernst, 2003) and registered in all countries. These limitations may automatically exclude or at least under-estimate some relevant organizations. For these reasons, it is important to carefully evaluate the use of this variable.

Knowledge decay (Kdecay). When the number of publications or patents do not significantly differentiate the potential partners, the use of a new variable, called "knowledge decay", is proposed. It reminds the patent indexes proposed in the literature by Flaming (2001).

The knowledge decay variable is based on the idea that the innovative relevance of the publications (or patents) changes over the period of interest and, more specifically, it decreases in the case of less recent publications (or patents).

According to this assumption, in the case of publication data, the Kdecay values can be measured by using the following exponential decay formula:

$$\sum_{t=0}^{t=n} Pub(t) * e^{-kt}$$

where *Pub(t)* is the number of publication at time *t*, and *n* indicates the years from the latest to the earliest one (for example, n = 2015 for t = 0 and n = 5 for t = 2010). Furthermore, *k* is the rate of decay of knowledge.

According to Mansfield (1968), the rate of decay of the knowledge produced by firms ranges between 0.04 and 0.07. About ten years later, referring to traditional capital and research, Griliches (1980) suggested the use of a rate of decay k = 10.The knowledge decay can also be measured by using a formula equivalent to the one used in economics, finance, and accounting for the calculation of the Net Present Value (NPV), as follows:

$$\sum_{t=0}^{t=n} Pub(t) * (1/1 + k)^{t}$$

However, in the case of patent data, the number of publications *Pub(t)* in the two formulations above must be replaced by the number of patents *SPat(t)*.

3.4.1.1.2 Quality of Research

The most common indicators used in the literature to measure the quality of research are h-index and both publications and patents citations (Hagedoorn & Cloodt, 2003).

Even though the use of patents citations is suggested by many researchers, the present framework does not take them into account. This choice is related to the research objectives, which mainly focus on the research and development phase of the innovation process. More specifically, because during these phases organizations are still working on a better understanding of the basic technology principles, the number of patents is too limited to make the usage of patent citations worthwhile.

With regard to the h-index, it was introduced by Hirsch (2005) to evaluate the scientific productivity and the apparent scientific impact of a scientist's research. More specifically, the h-index is based on the set of a researcher's most cited papers and the number of times they have been cited in other people's publications.

The present framework does not use the h-index in its original formulation, but proposes an alternative use of it. The new indicator is called "h-technology index".

Thus, the quality of research will be measured in terms of the number of citations and by using the h-technology index.

H-Technology index (HTindex). In order to select R&D partners, an alternative use of the h-index is proposed. The new indicator is called "h-technology index" in order to underline the fact that it does not refer to the overall publications of individual researchers, but only to the papers published by each candidate partner about the technology of interest. The h-technology values can be measured candidate partner by candidate partner by using bibliographic data sources. More specifically, the h-technology index value is obtained by sorting the candidates' publications about the technology of interest by number of citations and taking the number of publications N having the number of citations ≥ N.

Total number of article citations (Cit). When the h-technology index is not likely to differentiate the various candidate partners, it is possible to resort to counting the number of article citations. The use of the citations of articles as an indicator of the quality of the research is very common in the literature (Lee, et al., 2010; Geum, et al., 2013). In particular, this value can be measured by using bibliographic data sources, in order to assess the relevance of research concerning specific technologies of interest.

3.4.1.2 Cost Criteria: Collaborations and Co-Authorship

The choice of R&D partners does not have to be based solely on innovative performance of research. On the contrary, when looking for collaborative R&D partners, in addition to the advantages of R&D cooperation, firms must also take into account the "hidden" costs associated with R&D collaboration (Amoroso, 2014).

Concerning the transaction cost perspective, these costs are associated to personnel management and monitoring (Williamson, 1981). In this section, collaboration experience and co-authorship have been chosen as cost criteria to use for the identification and selection of proper potential partners.

The collaboration experience can be measured in terms of the total number of collaborations created between each candidate partner of the long list and other organizations. On the other hand, the co-authorship criteria is evaluated in terms of the number of researchers involved in the papers published by each organization of the long list.

Some additional information about the indicators used to measure the cost criteria are given below.

Total number of prior collaborations (Coll). According to the literature on R&D partner selection, the collaboration among organizations represents an important source of capabilities that allows firms to stay competitive in the current dynamic business environment (Chen, et al., 2008; Garcez & Sbragia, 2013).

Despite the evident advantages to gain from R&D collaboration, when organizations work together in order to achieve common goals, they must create a structure to efficiently support knowledge transfer and allow the involved parties to communicate with each other. Of course, managing communication and knowledge exchange in the presence of organizational, cultural and proximity distance (Capaldo & Petruzzelli, 2014; Reuer & Lahiri, 2014) requires an additional workload or R&D effort (Caloghirou, et al., 2004), that can be assumed as a collaboration related investment.

Based on this assumption, the collaboration experience can be regarded as a cost. As already mentioned, it is measured in terms of total number of collaborations in which potential partners have been involved in publishing papers.

As already done for some of the variables of benefit, all the information related to this variable of cost can be collected by using bibliographic data sources, such Scopus and Web of Science.

However, based on the objectives for partnership, the data collection can also be limited to the collaboration only between European organizations (Eucoll), or to the partnerships between industries and universities or research institutions (Iucoll).

Total number of authors (Auth). The second cost criteria to be taken into account is co-authorship. It is evaluated through the measurement of the number of researchers involved by each candidate partner in the publication of papers. In accordance with this definition, it is also considered as an indicator of the research capabilities based on which the candidate partners can be evaluated and selected (Chen, et al., 2008; Chen, et al., 2010).

The use of this variable is related to the concept of workload, according to which the R&D efforts can be measured in terms of working hours. As it is not possible to obtain information about the exact amount of working hours dedicated to the implementation of each article, it has been assumed that the higher the number of researchers involved in the publication of papers is, the higher the costs of the collaborative research are.

3.4.2 Data Collection

Many studies on partner selection show that firms often base the search for potential partners on previous partners, relying on expert knowledge to identify and select the most suitable candidates. In order to create greater synergies, firms should also look for unexpected and unknown potential partners, by exploiting knowledge from outside databases and incorporating quantitative data.

In order to obtain all the information needed for partner selection, the use of online data sources for patents and publications is advised.

The “Guide to technology databases” by WIPO (2010) provides an exhaustive list of the existing patent and publication data sources, classifying them in various groups.

With regard to patents, the data sources can be distinguished in three categories:

- Free databases provided by WIPO, national and regional offices, such as Espacenet by the European Patent Office (EPO);
- Free-of-charge commercial databases, such as Google Patents;
- Fee-based commercial databases, such as Thomson Innovation.

Likewise, with regard to the publication data sources, the WIPO guide distinguishes them in:

- Free-of-charge search services, such as Google Scholar;
- Fee-based search services, such as Scopus and Thomson Innovation;
- Free-of-charge journal databases, such as Science Direct.

Table 3.3 summarizes the main technology databases.

DATA SOURCES	PUBLICATIONS	PATENTS	FREE SOURCE
Google Scholar (http://scholar.google.com)	•		•
ScienceDirect (http://www.sciencedirect.com)	•		
Scopus (http://www.scopus.com)	•	•	
Thomson Innovation (www.thomsoninnovation.com)	•	•	
Google Patents (http://www.google.com/patents)		•	•
EPO Espacenet (http://www.espacenet.com/access)		•	•

Table 3.3 - Main data sources for patents and publications

These databases can be used to create the long list of potential partners and, subsequently, to collect all the data needed to evaluate and identify the most appropriate partners to collaborate with.

In order to create the database of the long list of candidate partners, the choice of the first document typology (patents or publications) to be considered for the data collection depends on the objectives of the collaboration and, therefore, on the partner typology of interest.

Generally, in the case of universities or research centers, the use of publications is preferred, whereas patent data is preferred regarding firms (Geum, et al., 2013). Moreover, when publications are preferred, the data collection starts from a bibliographic data source and then patent information are integrated into the existing database of potential partners (long list). Vice versa, if patents are preferred.

Figure 3.3 represents a flow chart showing the data collection phase activity by activity, when starting the search from bibliographic data.

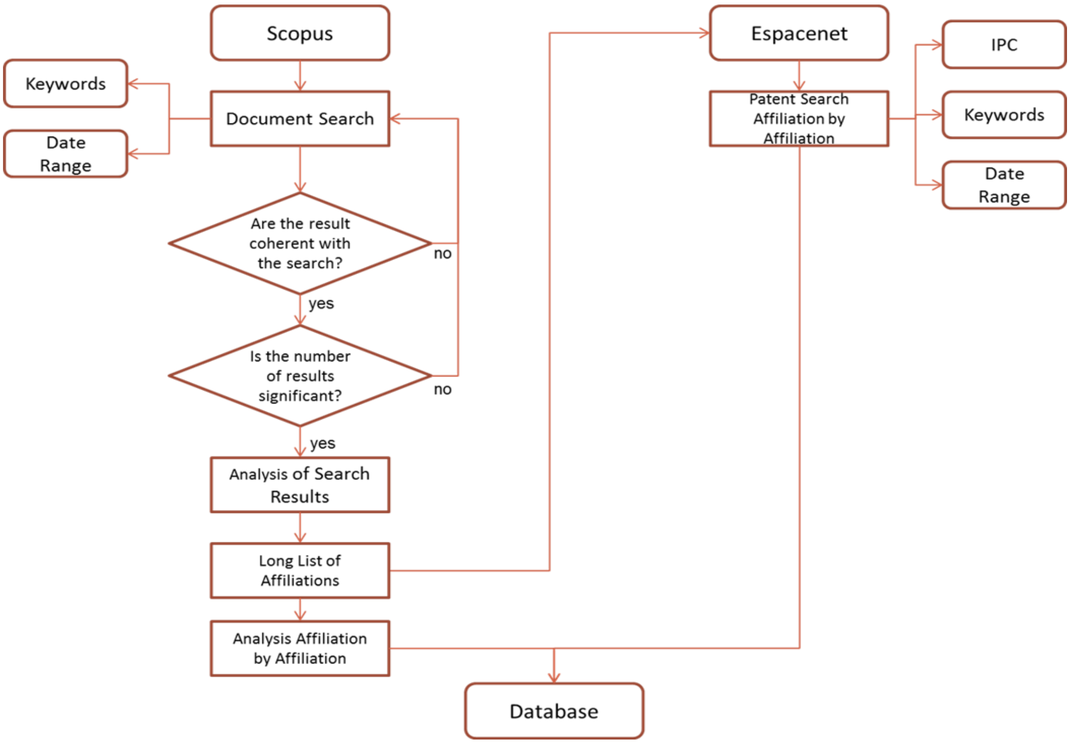

Figure 3.3 - Flow chart of the data collection phase

The partner selection team is responsible for implementing each stage of the data collection. In particular, a focus group is advisable for the identification of the most appropriate keywords to use for the document search.

In the following section, the use of Scopus and Espacenet for data collection is described. However, according to Table 3.3, any other online data source can be used to obtain the needed bibliometric and patent information.

3.4.2.1 Use of Scopus

Together with Web Of Science (WOS) from Thomson Innovation, Scopus is one of the largest databases on various scientific fields, commonly used for searching the literature (Guz & Rushchitsky, 2009). In addition, its user friendly interfaces and the possibility to manage and refine the search results make this database one of the most appropriate for data collection.

Scopus also performs a citation analysis and, therefore, can be used in order to collect data such as h-index and number of citations for each potential partner. Lastly, Scopus provides a link to the Espacenet database for patent research.

The data collection by Scopus can be implemented in three main phases:

1. Document search
2. Potential partner search
3. Affiliations data collection

Scopus uses the term “affiliation” to indicate every organization producing a scholarship output. Therefore, from now on, the words “affiliation” and “organization” will be used interchangeably.

At the end of the three phases indicated above, a long list of potential partners is available for further evaluation.

3.4.2.1.1 Document search

The document search allows for the identification of all the publications focusing on the technology of interest, through the use of a set of keywords properly combined with the logical operators AND and OR.

In order to identify the best combination of keywords to find the greatest number of items that are in line with the specific technology of interest, it is advisable to implement the following steps:

- Going on Scopus and clicking on the “document search” tab (Figure 3.4);

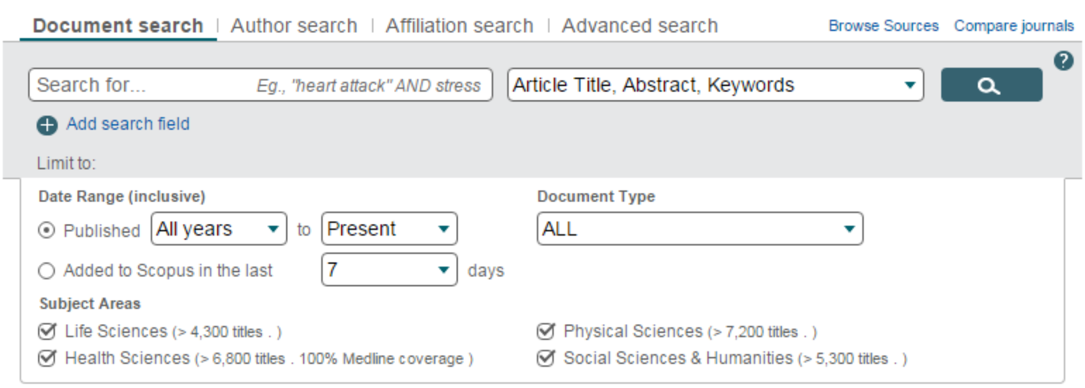

Figure 3.4 - Scopus document search

- Writing a combination of keywords in the “search for…” field that describe the technology of interest well (it is possible to add new search fields, if necessary) and limiting the search to article title, abstract and keywords;
- Identifying synonyms and combining, by trial and error, old and new keywords in order to obtain only the documents which are consistent with the objectives of the search;
- Eliminating redundant keywords (search results should not change).

Once the best keywords have been identified, all the documents matching the search settings are displayed (Figure 3.5). From them, it is possible to select only those included in the preferred publication date range, document type, subject areas and language.

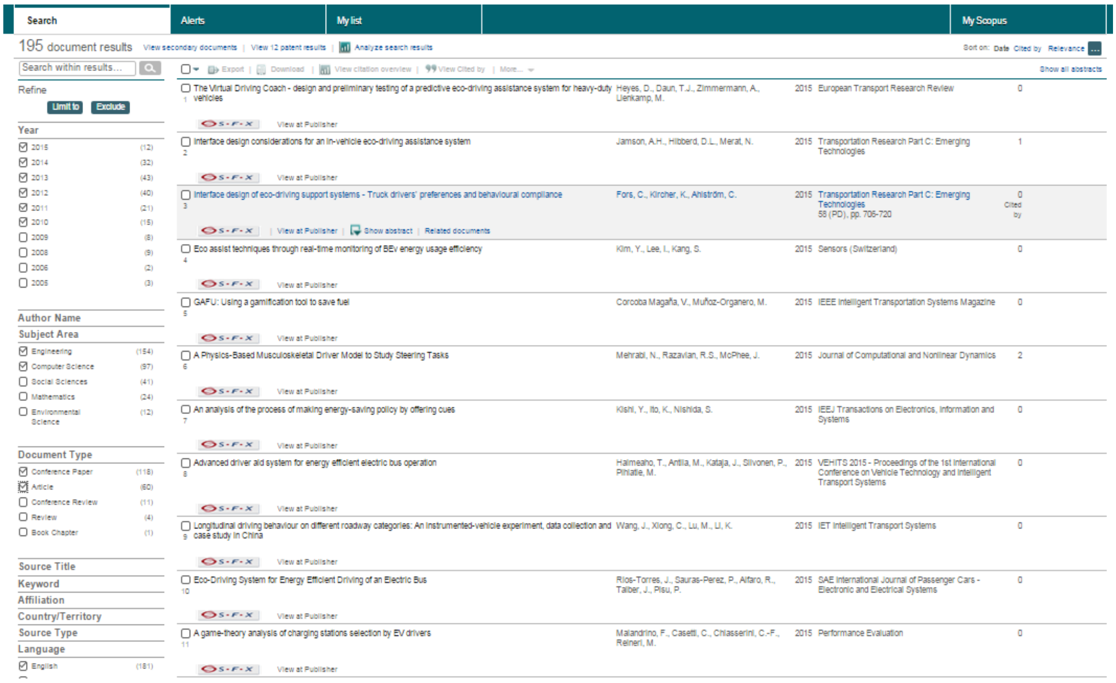

Figure 3.5 - Document search results

Finally, when the documents of interest have been found, the next step consists of identifying a long list of potential partners.

3.4.2.1.2 Potential partners search (long list)

In order to identify a preliminary group of potential partners to collaborate with, the document search results have to be analyzed and classified partner by partner. This can be carried out by selecting "analyze result search" (Figure 3.5).

This function displays the analysis of the search results by Scopus. It shows the number of documents categorized (on different tabs) by year, source title, author name, affiliation name, country, document type and subject area.

In order to identify the main affiliations working on the specific technology of interest, the first tab to explore is the affiliation one (Figure 3.6). These affiliations represent the long list of potential partners to be considered for data collection and, later, for performance benchmarking and ranking.

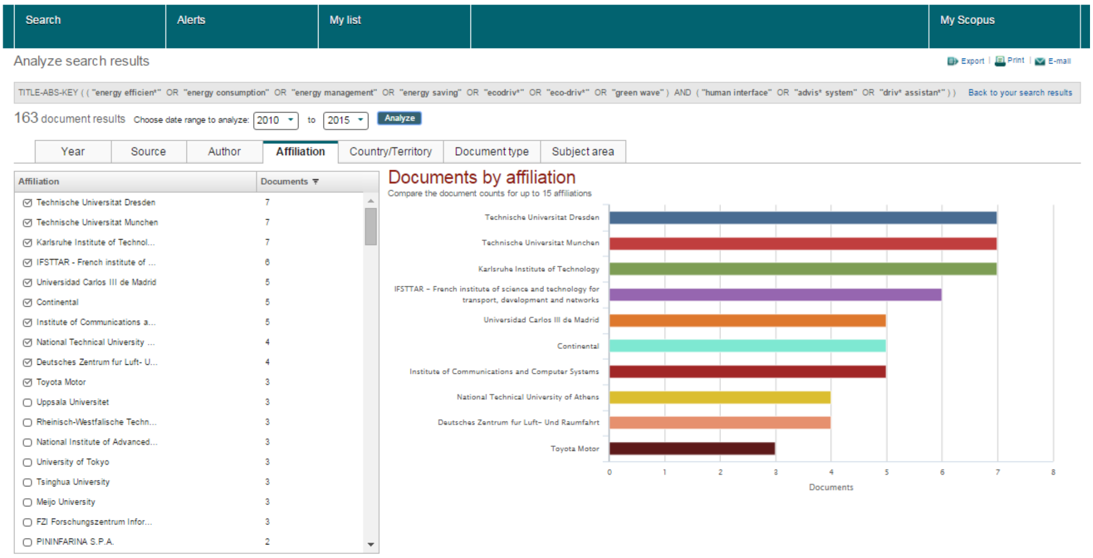

Figure 3.6 - Analysis of search results

3.4.2.1.3 Data collection affiliation by affiliation

By clicking on every single affiliation's name and the related number of documents, it is possible to obtain and collect more general information about the potential partners (Figure 3.7), as well as a list of documents matching the specific search in a new window affiliation by affiliation (Figure 3.8).

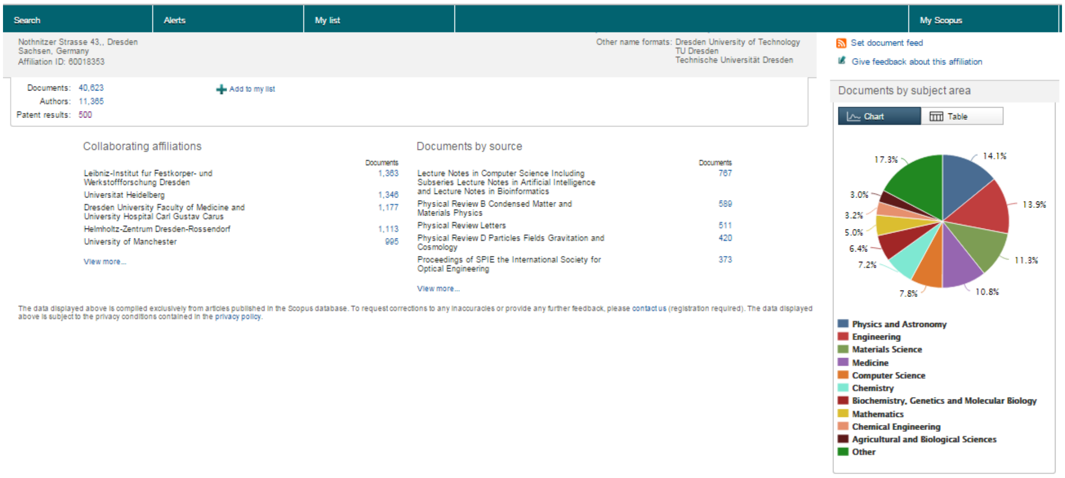

Figure 3.7 - Affiliations' information

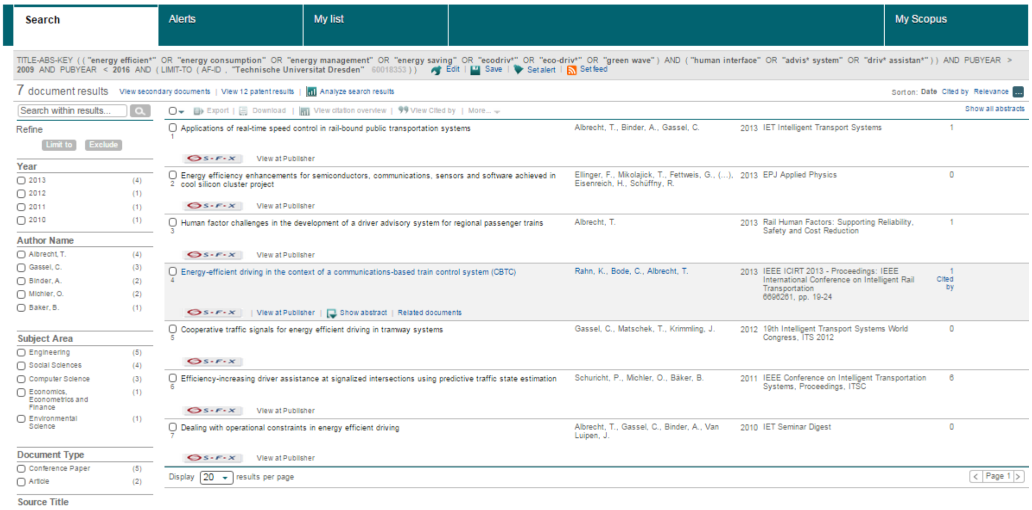

Figure 3.8 - Documents by affiliation

Specifically, looking at the window with all the documents matching the specific search, it is possible to collect data about the h-technology index and documents citations. As already stated, the h-technology index value is obtained by sorting the candidates' publications about the technology of interest by number of citations and taking the number of publications N having the number of citations ≥ N.

Then, by clicking “analyze search results” and looking at the country/territory and affiliation tabs, it is possible to collect more information, such as the number of collaborations. Furthermore, all the information needed is categorized year by year or over the entire period of interest.

For practical purposes, it is advisable to summarize the keywords and the settings in a table (Table 3.4).

SCOPUS DATA COLLECTION	
Keywords	Keyword 1, Keyword 2, …
Additional settings	• Years: 2010-2015 • Subject areas: Humanities and Social Science • Document type • Language: English

Table 3.4 - Scopus search settings

3.4.2.2 Use of Espacenet

Espacenet is an online service developed by the European Patent Office (EPO) for searching patents and patent applications. It is free and which records more than 90 million patent publications. Using EPO is the best option when firms have to market their technology not in the US, but in Europe, or when the size of the markets using the technologies is greater than in the US, even though it is the US which is the largest technology market (Kim & Lee, 2015).

As is the case with Scopus, the document search on Espacenet starts with the identification of a set of keywords that better describe the technology of interest (Figure 3.9).

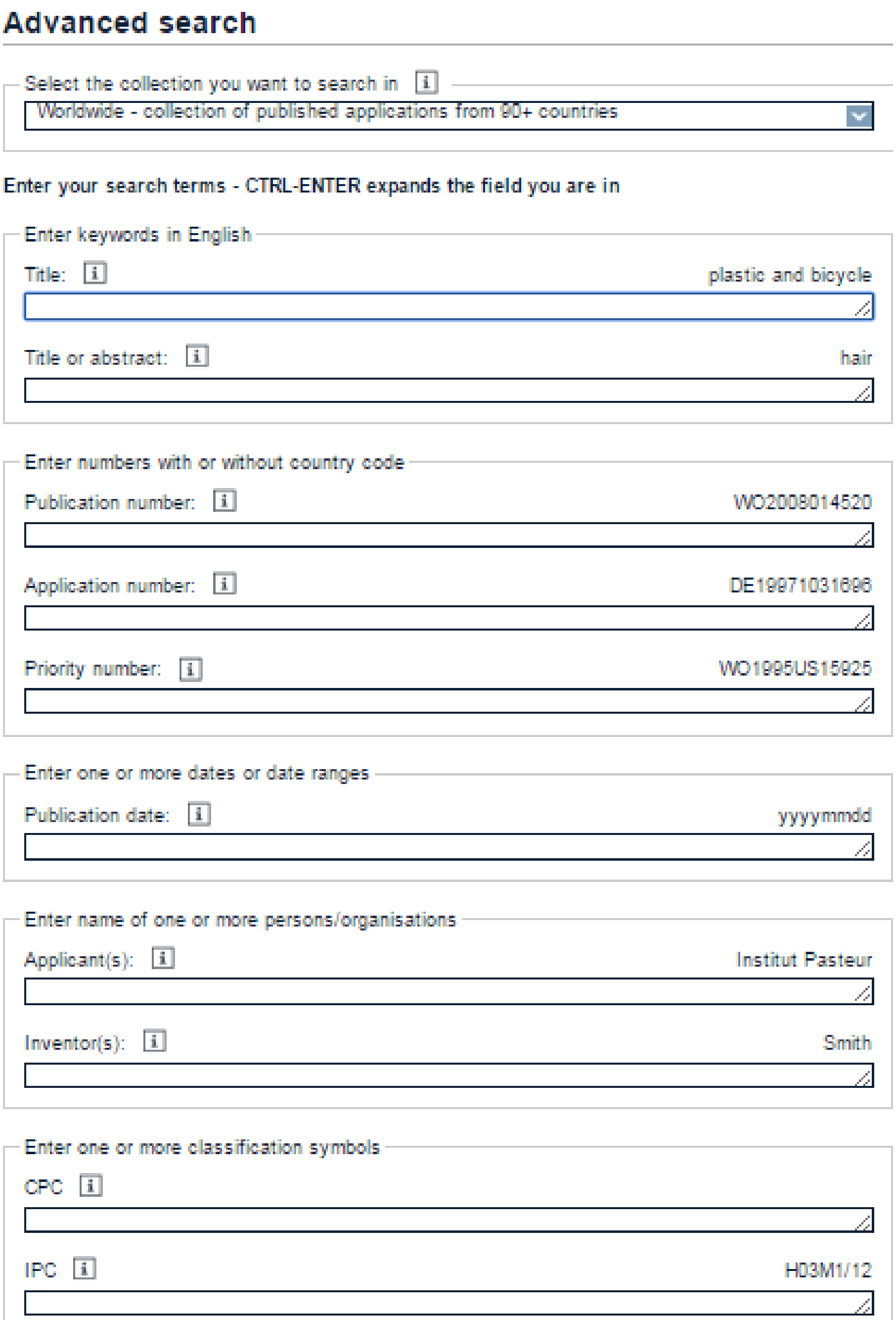

Figure 3.9 - Espacenet patent advanced search

In addition, in order to find the right documents, the patent advanced search allows the setting of one or more classification classes symbols from the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC) systems.

The IPC is a hierarchical patent classification system which is applied in more than 100 countries to classify the content of patents in a uniform manner. The IPC classification symbols are made up of a letter denoting the IPC section (e.g. B), followed by a number (two digits) denoting the IPC class (e.g. B60) and a letter denoting the IPC subclass (e.g. B03W). A number (variable, 1-3 digits) denotes the IPC main group (e.g. B60W1), a forward slash `/`, and a number (variable, 1-3 digits) denotes the IPC subgroup (e.g. B60W1/32).

Conversely, CPC system has been jointly developed by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). It is mainly based on the previous European classification system (ECLA), which itself was a more specific and comprehensive version of the International Patent Classification (IPC) system. As with the IPC, the CPC system also has a hierarchical structure which consists of sections, classes, subclasses, groups and subgroups.

Once keywords and patent classes have been defined, date ranges can be assigned too. Moreover, when looking for patents after publications, the patent search has to be implemented candidate partners by candidate partners (from the long list by Scopus). In this case, the candidate partners' name can be set in the field "Applicant(s)". On the contrary, when data collection starts from the patent search, the assignee field does not need to be set.

For practical purposes, it is advisable to summarize keywords, patent classes and other parameters in a table (Table 3.5).

ESPACENET DATA COLLECTION	
Keywords	Keyword1, keyword2, …
IPC symbols	IPC1, IPC2, …
CPC symbols	CPC1, CPC2, …
Additional settings	• Years: 2010-2015 • Subject areas: Engineering and Computer Science

Table 3.5 - Patent search settings

3.5 Qualification of Candidate Partners (Step 3)

The qualification phase is the third step of the partner selection framework proposed in this thesis. It consists of obtaining a smaller set of potential partners by first reducing the larger one (de Boer, et al., 2001).

According to Sarkara & Mohapatra (2006), the qualification of candidate partners is a prerequisite for creating successful relationships among parties.

In the general literature on the partner selection problem, the techniques identified for the partners' qualification are several. According to the review by de Boer et al. (2001), the techniques that are particularly suitable for pre-qualification of suppliers are cluster analysis, case-based reasoning, and data envelopment analysis. Wu & Barnes (2011) also indicated the use of categorical methods.

Among the above techniques, data envelopment analysis (DEA) is one of the most flexible, as it is able to manage a large set of decision alternatives (i.e. candidate partners) and minimize expert subjectivity, fully satisfying the requirements of replicability, reliability, rationality. Moreover, the data envelopment analysis model fits perfectly with the idea of evaluating the candidate partners based on both benefit and cost factors.

Finally, the use of the DEA technique for the qualification of R&D potential partners contributes to responding to the lack of studies in the literature applying mathematical programming techniques.

The models and the usage of DEA are described in detail below.

3.5.1 Data Envelopment Analysis (DEA)

The Data Envelopment Analysis is a non-parametric technique initially introduced by Charnes et al. (1978) and built around the concept of "technical efficiency" of a set of decisional entities, known as decision making units (DMUs).

The technical efficiency of DMUs (i.e. potential partners) can be calculated as the ratio of the weighted sums of benefit criteria (to be considered as outputs) to the weighted sums of cost criteria (to be considered as inputs).

Figure 3.10 provides a graphical representation of a typical decision making problem analyzed by using DEA.

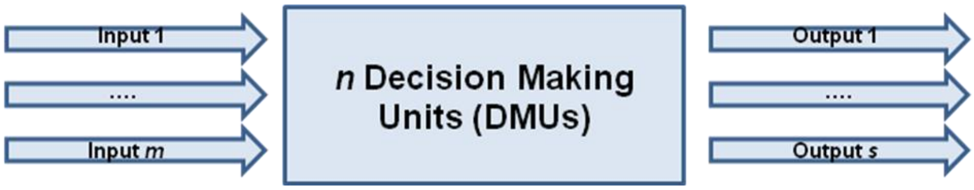

Figure 3.10 - Representation of a typical DEA process

When DEA is used, the decision-making problem can be analyzed from two different points of views: “output-oriented” and “input-oriented”. The output-oriented model maximizes the amount of outputs produced by a certain DMU whilst controlling the set of consumed inputs. Vice versa, in the case of an input-oriented model, DEA measures the ability of DMUs to produce a given set of outputs with the minimum amount of inputs.

Either way, DEA helps the decision-makers to classify the DMUs in efficient and inefficient, based on the technical efficiency score (TE). All the efficient DMUs receive a TE of 1, whereas the inefficient ones have a TE score positive and lower than 1.

The efficient DMUs define the so-called “efficient frontier”. An example of the efficiency frontier in the case of maximization of outputs is shown in Figure 3.11.

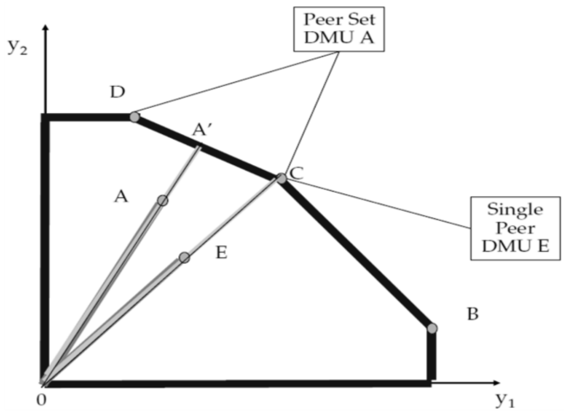

Figure 3.11 - DEA efficiency frontier

The radial distance of an inefficient DMU (A or E) from the nearest efficient DMU on the frontier (B, C or D) indicates the direction and amount of possible improvements to be made in each output and input in order for it to become efficient.

Consider a set of n of DMU using m inputs (costs) to produce s outputs (benefits). Let y_{rq} and x_{iq} denote the amount of the rth output (r = 1,2,...,s) and of the ith input (i = 1,2,...,m) produced and consumed by the DMU q, respectively. Also, v_r and u_i are the weights given to output r and input i, respectively.

The original Charnes-Cooper-Rhodes (CCR) model of DEA, used to obtain the technical efficiency of the DMU q, is formulated in terms of the following fractional programming:

$$Max \quad \frac{\sum_{r=1}^{s} v_r y_{rq}}{\sum_{i=1}^{m} u_i x_{iq}}$$

$$s.t. \quad \frac{\sum_{r=1}^{s} v_r y_{rj}}{\sum_{i=1}^{m} u_i x_{ij}} \leq 1 \qquad \text{j} = 1,\ldots,n \tag{1}$$

$$v_r, u_i \geq 0 \qquad \text{r} = 1,\ldots., s, \ \text{i} = 1,\ldots,m$$

So that the relative efficiency scores of all the DMUs can be identified, the problem has to run n times.

According to the formulation (1), the technical efficiency scores (TE) range from 0 to 1. If the TE = 1, the DMU is efficient, whereas if TE < 1, the DMU is inefficient. Furthermore, with regard to weights, this method does not require an a priori assignment. On the contrary, the set of weights for the DMU q are determined as the those which maximize its TE score on the condition that the efficiency of other DMUs (calculated using the same set of weights) are limited to values zero to one.

It is also important to highlight that there is no unique set of weights for all the DMUs, but rather the weights assigned should be flexible and reflect the requirement of individual DMUs. For example, a potential partner that has a good reputation in terms of number of publications will likely attach higher weights to this kind of output. On the other hand, a candidate that has a higher number of published patents would probably assign a greater weight to this output category. In other words, the weights, which are one of the most important issues of the DEA assessment, are assigned by DEA as a unique set of weights for each DMU.

The original CCR fractional programming can be converted into a linear programming model, known as the primal CCR model. In turn, the primal model can be converted in its dual, which has a lower number of constraints.

Because, in general, the more constraints a linear problem has, the more difficult it is to solve, it is usual to solve the dual DEA model.

The dual CCR output-oriented model, is formulated below:

$$
\begin{aligned}
& Max \ \ \phi_q \\
& s.t. \ \ \sum_{j=1}^{n} x_{ij}\lambda_j \le x_{iq} && \mathrm{i} = 1, \ldots, m \\
& \qquad \sum_{j=1}^{n} x_{rj}\lambda_j \le \phi_q y_{rq} && \mathrm{r} = 1, \ldots, s \qquad (2) \\
& \qquad \lambda_j \ge 0 && \mathrm{j} = 1, \ldots., n
\end{aligned}
$$

where φ_q represents the technical efficiency score of the specific DMU q, and λ_j is the weight assigned to the DMU j.

3.5.1.1 DEA Methods for Qualification

In the previous section, the basic DEA model has been described, showing how its implementation groups the DMUs in two sets, i.e. those that are efficient and those that are inefficient.

Starting from the original data envelopment analysis model, many researchers have tried to better the differential capabilities of DEA, developing both rating and ranking methods.

As reviewed by Adler et al. (2012), and later by Khodabakhshia & Aryavash (2012), in the context of data envelopment analysis, the most common methods for ranking are:

- Cross-efficiency, first proposed by Sexton et al. (1986) and which ranks DMUs based on both self and peer evaluations;
- Super efficiency, introduced by Andersen and Petersen (1993), consisting of ranking DMUs by excluding the unit being scored from the DEA dual model;
- Benchmarking, providing a full ranking of efficient DMUs by counting the number of times each DMU acts as a peer benchmark for inefficient DMUs (Torgersen, et al., 1996).

On the other hand, as a rating method, Barr et al. (1994) introduced the DEA Peeling method. DEA Peeling provides a classification of inefficient DMUs by grouping them based on demonstrated levels of achievement ("rating tiers").

One of the main differences between the above methods is related to their capabilities to differentiate the DMUs' efficiency scores. Thus, the choice to use one method rather than another depends on the level of differentiation required by the problem.

The qualification problem, which aims at reducing the long list of potential partners to consider for further analysis by "sorting" rather than ranking the candidates (de Boer, et al., 2001), does not require a high degree of differentiation. Therefore, the rating provided by DEA Peeling is more appropriate for the implementation of the qualification phase of the framework.

3.5.1.1.1 DEA Peeling

DEA Peeling was introduced by Barr et al. (1994) based on the idea of "peeling the DEA onion". The method was then validated as a tool for DMU classification by (Bougnol & Dula, 2006).

According to Gedranovich & Salnykov (2012), the peeling procedure, as proposed by Bougnol and Dula (2006), is a "very intuitive process" that aims to exclude efficient units from the original dataset stage-by-stage. In other words, at each iteration all the efficient DMUs (TE=1) are "peeled" away from the respective efficient frontier.

More specifically, the first stage consists of applying DEA by considering the entire data set, so that all the efficient DMUs at this stage form the first rating tier. Then, efficient DMUs are taken away from the data set and another DEA analysis is launched.

The next group of efficient DMUs make up the second rating tier which is then taken away from the data set. DMUs in rating tier two are deemed inefficient in comparison with those in rating tier one, but efficient in comparison with all the others.

The process is repeated until all the DMUs in the data set have been assigned to a rating tier. However, the number of stages depends on the number of DMUs and the dimensionality of output space.

Figure 3.12 shows an example of the three ~~stages~~ peeling procedure, regarding the DEA output-oriented formulation, allowing for a clearer understanding of the procedure.

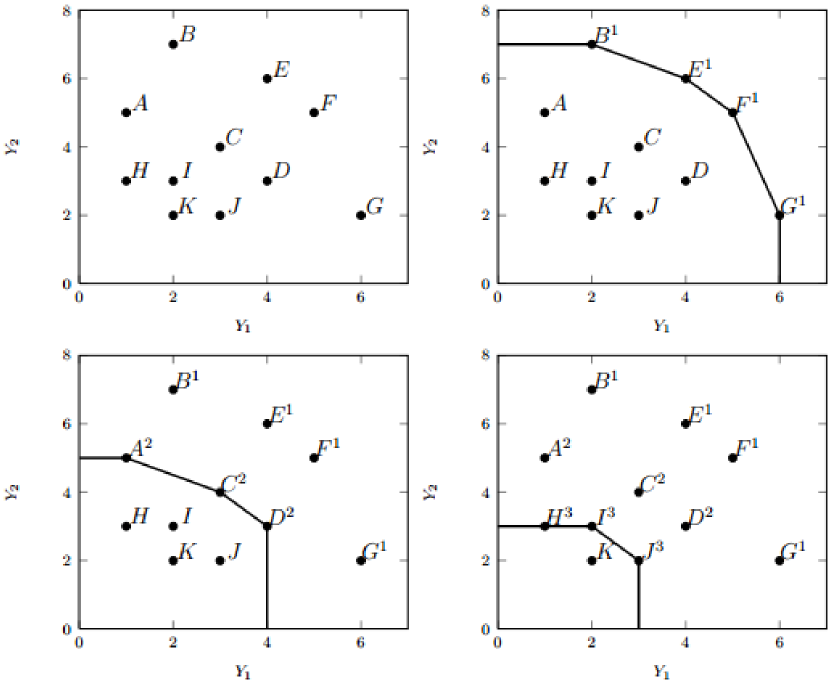

Figure 3.12 - DEA peeling procedure (Source: Gedranovich & Salnykov, 2012)

As shown, the top left hand box displays the initial set of 11 DMUs (A-K) on the output space.

According to the output-oriented approach, the top right hand box shows the efficient frontier obtained connecting all the efficient units (B, E, F and G) of the first DEA peeling stage. These efficient units form the first DEA peeling rating tier to be excluded from the initial set of DMUs before implementing the second DEA peeling stage.

The bottom left hand box shows A, C and D to be efficient, and they form the second rating tier of DMUs to be peeled away before implementing the third DEA peeling stage. Finally, in the bottom right hand box the efficient DMUs are H, I, and J.

After a certain amount of stages, a short list of the highest performing partners can be created. In comparison with the original list of potential partners, the short list is simpler to manage in order to support the final partner choice.

3.6 Selection of The Most Appropriate Partners (Step 4)

Once the short list of partners has been obtained, the final selection phase can begin. According to the general literature analyzing the partner selection problem, three main categories of techniques for the final partner selection can be distinguished (Ho, et al., 2010; Wu & Barnes, 2011; Chai, et al., 2013; Govindan, et al., 2015):

- Multi-criteria Decision Making (MCDM) techniques, including analytic hierarchy process and analytic hierarchy Network;
- Mathematical Programming (MP) techniques, such as data envelopment analysis;
- Artificial Intelligence (AI) techniques, such as neural network and Bayesian network.

The above techniques are often integrated with the use of the fuzzy set theory. In addition, Wu & Barnes (2011) also identified some studies applying the linear weighting which do not require the user to learn any optimization techniques. Within the literature in R&D partner selection, the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) developed by Saaty (1980, 2001) are commonly used for criteria weighting (Chen, et al., 2008; Chen, et al., 2010; Lee, et al., 2010; Geum, et al., 2013). In particular, they compare two criteria according to a numerical scale from one to nine, indicating how much one element dominates another. This scaling process is then translated into priority weights.

With regard to AI techniques, Lee & Yoon (2013) proposed the use of Bayesian networks to support the partner selection process when there are many interrelated criteria.

However, when focusing on MP techniques, such as data envelopment analysis, a lack of studies on the R&D partner selection problem emerges in the literature. In order to fill this emerging gap, the use of DEA is proposed.

So far, data envelopment analysis has been proposed as a technique to be used when minimizing subjectivity is required. However, DEA can also allow decision makers to make more focused evaluations by assigning a priori relative weights, prices or priorities of inputs and/or outputs (Bogetoft & Otto, 2011).

In the light of this consideration, the DEA method selected for the final partner choice is Revenue Efficiency.

In comparison with the other DEA models introduced in the section referring to the qualification phase, the particularity of Revenue Efficiency is that a preliminary assignment of criteria weights is required. This characteristic allows for a higher level of flexibility, i.e. the possibility to better respond to the dynamism of high-technology markets and, in turn, to the fast-changing needs of organizations.

3.6.1 DEA Revenue Efficiency

Revenue Efficiency is a particular output-oriented DEA model that can be used in order to support the final choice of R&D partners, by taking into account experts opinion regarding the relative importance of the outputs (benefits) of the selection problem.

This method has been commonly applied to evaluate the efficiency of banks and other financial institutions (Kočišová, 2014; Sahoo, et al., 2014), providing revenue efficiency scores (RE) indicating to what extent a DMU is predicted to perform well in terms of revenue in comparison with others in the same period, producing the same set of outputs. However, it is possible to extend its usage to other kinds of DMUs, i.e. candidate R&D partners.

The overall revenue efficiency (RE) is defined as the ratio of observed revenue to optimal revenue for the DMU. More specifically, y^*_{rq} and y_{rq} indicate the maximum and observed revenue vectors of output quantities for DMU q, respectively, and p_{rq} refers to the vector of output priorities of DMU q, as expressed by experts.

The RE of DMU q is expressed by the following ratio:

$$RE_q = \frac{\sum_{r=1}^{s} p_{rq} y_{rq}}{\sum_{r=1}^{s} p_{rq} y_{rq}^{*}} \tag{3}$$

It reflects the ability of a DMU to produce the optimal proportion of output, given the experts' priorities.

As the maximum revenue vectors of output quantities for DMU q are unknown, in order to calculate the above RE ratio, it is necessary to solve the following DEA model for revenue maximization (Coelli, et al., 2005):

$$\begin{aligned} & Max \ \sum_{r=1}^{s} p_{rq} y_{rq}^{*} \\ & s.t. \ \sum_{j=1}^{n} x_{ij} \lambda_j \leq x_{iq} \qquad \mathrm{i} = 1,\ldots,m \\ & \sum_{j=1}^{n} y_{rj} \lambda_j \leq y_{rq}^{*} \qquad \mathrm{r} = 1,\ldots,s \\ & \lambda_j \geq 0 \qquad \mathrm{j} = 1,\ldots.,n \end{aligned} \tag{4}$$

where x_{iq} represents the input levels, and λ_j is the weight assigned to the DMU j

The use of such a method in an innovation context, characterized by continuous and rapid technological changes, is very useful in order to consider the partner selection process as a dynamic one because the relative importance of the variables can change depending on objectives and innovation strategies.

CHAPTER 4

4 Illustrative Case Studies within the Railway Sector

In this chapter, the DEA-based framework proposed in chapter 3 is implemented step by step. In order to test the effectiveness of the proposed approach on real firm practices, two technological case-studies of railway interest, in line with the European Research & Innovation roadmap (e.g. Horizon 2020 program - SHIFT²RAIL Joint Undertaking) have been used. The choice to analyze an emerging technology (eco-driving) and a mature one (satellite) allows for a deeper understanding of the existing relationship between technology evolution and R&D collaboration practices.

4.1 SHIFT²RAIL Research Program

SHIFT²RAIL is an industrial driven multiannual research program which focuses on all the areas of the European railway market (i.e. High Speed/Mainline, Regional, Urban/Metro & Suburban, and Freight).

It is the first large-scale European program and is in line with the objectives of the EU 2011 White Paper on Transport and the Framework Program for Research and Innovation Horizon2020 which aims to attract passengers and businesses to rail transport and make the EU rail industry more competitive, by speeding up the integration of new and advanced technologies into innovative rail product solutions, whilst supporting energy efficiency and reliability of next generation products.

The program is co-financed by both the private sector and the European Commission, with an overall budget of about 1 billion euros which will be used to reduce the life cycle cost of railway transport by as much as half, and to increase railway capacity, reliability and punctuality by 50%.

Five Innovation Programs (IPs) make up the SHIFT²RAIL program:

- IP1 - Energy & Mass Efficient Technologies for High Capacity Trains
- IP2 - Advance Traffic Management & Control Systems
- IP3 - Cost efficient - High Capacity Infrastructure
- IP4 - IT Solutions for a Seamless Attractive Railway
- IP5 - Technologies for Sustainable & Attractive European Freight (UNIFE - The European Rail Industry, 2014).

Among the several technologies related to each of the above IPs, eco-driving (IP1) and satellite (IP2) have been chosen in order to test the partner qualification framework proposed in chapter 3, as they are at two different stages (i.e. emerging and mature, respectively) of the technology life cycle.

The illustrative case studies referring to both eco-driving and satellite technologies are presented in the following sections, with research-based motivations driving the search for R&D partners.

Both the applications have been implemented by a partner selection team, composed of engineers from the innovation department of a railway company, and of university researchers from a department of industrial engineering. More specifically, the former provided in depth knowledge about the latest advances in innovation technologies and managerial practices, whereas the latter contributed their background in decision making methodologies and a great deal of experience using scientific data sources for research.

4.2 Case study #1: Eco-driving Technology

The first case study refers to IP1, which focuses on developing the future generation of trains that will be lighter and more energy efficient while reducing current travel times, track damage and negative effect on the environment, resulting in a reduced life cycle cost.

With regard to energy efficiency, one of the main goals of the railway industry is to encourage a shift away from less efficient and carbon-intensive modes (TSLG, 2012). In this context, eco-driving plays an important role.

As shown in Figure 4.1, the eco-driving technology is at the emerging phase of its life cycle.

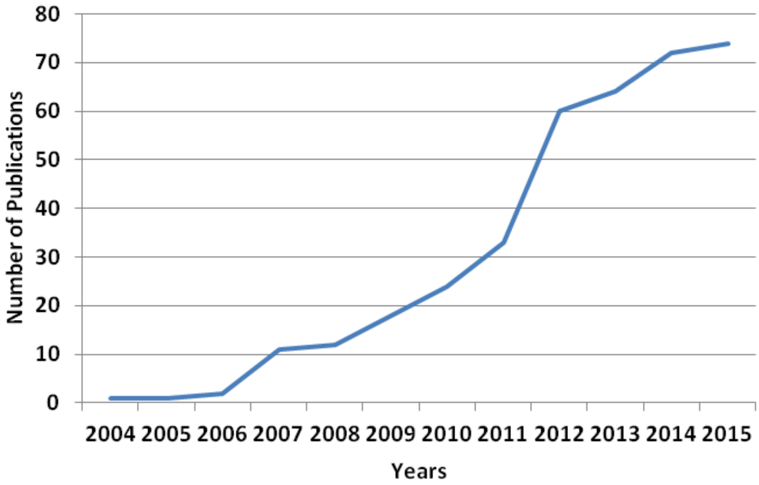

Figure 4.1 - Eco-driving TLC (Source: own elaboration using data retrieved from Scopus)

Also, Figure 4.2 indicates the maturity of energy efficiency technologies.

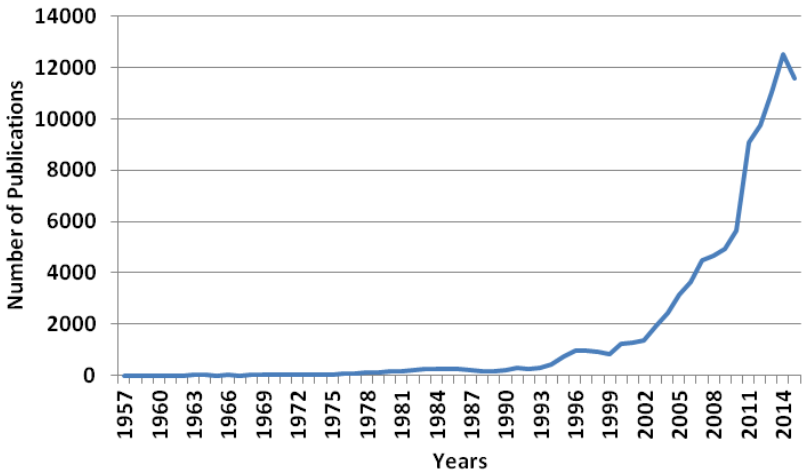

Figure 4.2 - Energy efficiency TLC (Source: own elaboration using data retrieved from Scopus)

These considerations regarding the TLC phases are taken into account during the step-by-step implementation of the framework.

4.2.1 Step 1: Objectives of the Innovation Strategy

According to the assumptions made in chapter 3, during the emerging stage of the technology lifecycle, organizations are strongly oriented toward basic research, with university and research centers being the preferred partners typologies (TSLG, 2012).

Table 4.1 summarizes the partner selection team’s objectives for collaborations on eco-driving.

OBJECTIVES FOR PARTNERSHIP	#1
Technology of Interest	Eco-driving
Preferred Sector	Transportation
Description	Energy efficiency, eco driving, display, interface
Lifecycle Phase	Emerging
Main Motivations	Research-based
Preferred Partners Typologies	Universities, Research Centers

Table 4.1 - Objectives chart (eco-driving)

Even though it has been highlighted that, in the case of research-based motivations, collaborating with universities and research centers has the highest impact on the innovation process, in order to test the framework industries will also be taken into account.

4.2.2 Step 2: Identification of Candidate Partners

In order to create the database with all the information related to a first list (long list) of candidate partners, Scopus and Espacenet have been chosen as data sources for publications and patents, respectively.

Table 4.2 and Table 4.3 indicate Scopus and Espacenet settings.

SCOPUS SETTINGS	
Keywords	“energy efficien*”, “energy consumption”, “energy management”, “energy saving”, “ecodriv*”, “eco-driv*”, “green wave”, “human interface”, “advis* system”, “driv* assistan*” (in title, abstract or keywords)
Limitations	• Years: 2010-2015 • Subject areas: Engineering and Computer Science • Source Type: Conference Proceedings and Journals • Language: English

Table 4.2 - Scopus settings (eco-driving)

ESPACENET SETTINGS	
Keywords	“energy”, “advisor”, “assistan*”, “driv*” (in the title or abstract)
Patent Classes	B61L, B60W, B60K (as IPC classification)
Limitations	• Years: 2010-2015 • Subject areas: Engineering and Computer Science

Table 4.3 - Espacenet settings (eco-driving)

With regard to the patent classes settings, B60 refers to vehicles in general, and B61 to railway. Additional details are summarized in Table 4.4.

PATENT CLASSES DEFINITIONS	
B60W	Conjoint control of vehicle sub-units of different type or different function; control systems specially adapted for hybrid vehicles; road vehicle drive control systems for purposes not related to the control of a particular sub-unit
B60K	Arrangement or mounting of propulsion units or of transmissions in vehicles; arrangement or mounting of plural diverse prime-movers in vehicles; auxiliary drives for vehicles; instrumentation or dashboards for vehicles; arrangements in connection with cooling, air intake, gas exhaust or fuel supply of propulsion units, in vehicles
B61L	Guiding railway traffic; ensuring the safety of railway traffic

Table 4.4 - Patent classes definitions (eco-driving) (Source: Espacenet website)

By using the above Scopus settings, a long list of 131 candidate partners (40 firms and 91 universities/research centers) distributed across Europe (60%), Asia (28%) and America (12%) has been identified (Figure 4.3).

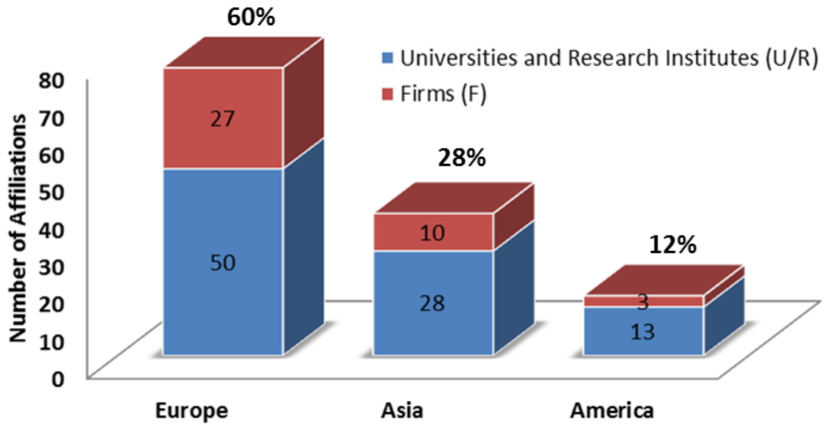

Figure 4.3 - Distribution of the 131 candidate partners (eco-driving)

In order to protect information regarding the strategic interests of the railway company, the list of the candidate partners is not disclosed. However, as shown in Table 4.5, most of the candidate partners are located in Europe across 14 countries, followed by Asian affiliations (over 7 countries) and American ones in Canada and in the US.

EUROPE		ASIA		AMERICA	
Austria	3	**China**	7	**Canada**	2
Belgium	1	**India**	1	**US**	14
Finland	1	**Iran**	2		
France	10	**Japan**	22		
Germany	33	**Singapore**	2		
Greece	2	**South Korea**	2		
Hungary	2	**Taiwan**	2		
Italy	5				
Netherlands	3				
Spain	3				
Sweden	4				
Switzerland	1				
Turkey	1				
UH	8				
Total	**77**		**38**		**16**

Table 4.5 - Candidates' distribution across geographical areas (eco-driving)

For each affiliation of the long list, the database also includes the values of the related benefits (i.e. research output and quality of research) and costs (i.e. collaboration experience and co-authorship) to be considered for the qualification and selection of the most suitable partners to collaborate with (Table 4.6).

	Variables of Interests	
BENEFITS (R&D Outputs)	**Research Output**	
	Pub	Total number of publications with a focus on eco-driving, published between 2010 and 2015
	Kdecay	Decay of eco-driving publication over the period 2010-2015
	Spat	Total number of patent data with a focus on eco-driving, published between 2010 and 2015
	Epat	Total number of patent data with a focus on engineering and computer science, published between 2010 and 2015
	Quality of Research	
	Cit	Total number of citations received on eco-driving publications between 2010 and 2015
	HTind	H-technology index of potential partners calculated focusing on eco-driving publications between 2010 and 2015
COSTS (R&D Inputs)	**Collaboration Experience**	
	Coll	Total number of collaborations with other organizations in publications on eco-driving from 2010 to 2015
	Eucoll	Total number of collaborations established with European organizations in publications on eco-driving from 2010 to 2015
	Iucoll	Total number of collaborations established among universities/research centers and industries in publications on eco-driving from 2010 to 2015
	Co-authorship	
	Auth	Number of authors involved in publications on eco-driving from 2010 to 2015

Table 4.6 - Benefit and cost factors (eco-driving)

The above information has been collected and/or measured by making use of the more common bibliographic databases and other online data sources. More specifically, as the main motivations underlying the need for collaborative R&D partners are research-based, Scopus has been used for both identifying the long list of candidate partners and collecting publication data (i.e. number of publications and knowledge decay, number of authors and collaborations) related to them. Conversely, Espacenet has only been used for patent data collection.

Table 4.7 summarizes the collected data, indicating some statistics of all the cost and benefit variables, by geographical area.

		Auth	Coll	Eucoll	Iucoll	Pub	Kdecay	Cit	HTind	Epat	Spat
EUROPE	mean	4,92	1,27	0,82	0,61	1,51	1,19	2,00	0,51	80,45	0,35
	st dev	3,87	1,39	1,27	1,05	1,18	0,91	4,18	0,68	302,83	1,99
	max	29,00	7,00	6,00	5,00	7,00	5,42	27,00	3,00	2385,00	17,00
	min	1,00	0,00	0,00	0,00	1,00	0,61	0,00	0,00	0,00	0,00
ASIA	mean	5,03	1,34	0,89	0,53	1,63	1,30	4,16	0,71	101,39	0,08
	st dev	3,62	1,28	1,16	0,89	1,34	1,04	6,77	0,77	448,39	0,49
	max	23,00	5,00	5,00	4,00	6,00	4,47	34,00	3,00	2753,00	3,00
	min	2,00	0,00	0,00	0,00	1,00	0,61	0,00	0,00	0,00	0,00
AMERICA	mean	3,38	0,44	0,31	0,31	1,13	0,87	1,06	0,38	236,94	0,00
	st dev	1,54	0,63	0,60	0,48	0,34	0,28	1,65	0,50	634,04	0,00
	max	6,00	2,00	2,00	1,00	2,00	1,64	5,00	1,00	2259,00	0,00
	min	1,00	0,00	0,00	0,00	1,00	0,61	0,00	0,00	0,00	0,00

Table 4.7 - Statistics relative to the long list of candidates, by geographical area (eco-driving)

The highest standard deviation is related to the variable Epat. For instance, the number of patents varies from 0 to 2385 in Europe, from 0 to 2753 in Asia, and from 0 to 2259 in America. On the contrary, all the other variables present a low standard deviation of the variables, indicating that candidate partners do not differ to a large extent. However, there are differences among geographical areas.

Data also show that not all the variables are significant, such as Spat. Therefore not all the collected data are going to be used for the qualification and the selection of the most suitable partners to collaborate with on eco-driving.

However, as there are certain characteristics of data that may not be acceptable for the implementation of data envelopment analysis, before the qualification and selection phases, all the available data related to the benefit and cost variables of interest have to be preliminarily treated and selected.

In particular, according to the guidelines by Sarkis (2002), the data set can be prepared for DEA by eliminating zero values and normalizing it in order to balance their magnitude. It is also required to eliminate both redundant and non-significant input and output factors, and evaluate their cause-effect relationship by using correlation analysis. Finally, the right number of inputs and outputs for a certain amount of DMUs must be considered.

Figure 4.4 summarizes this preliminary processes.

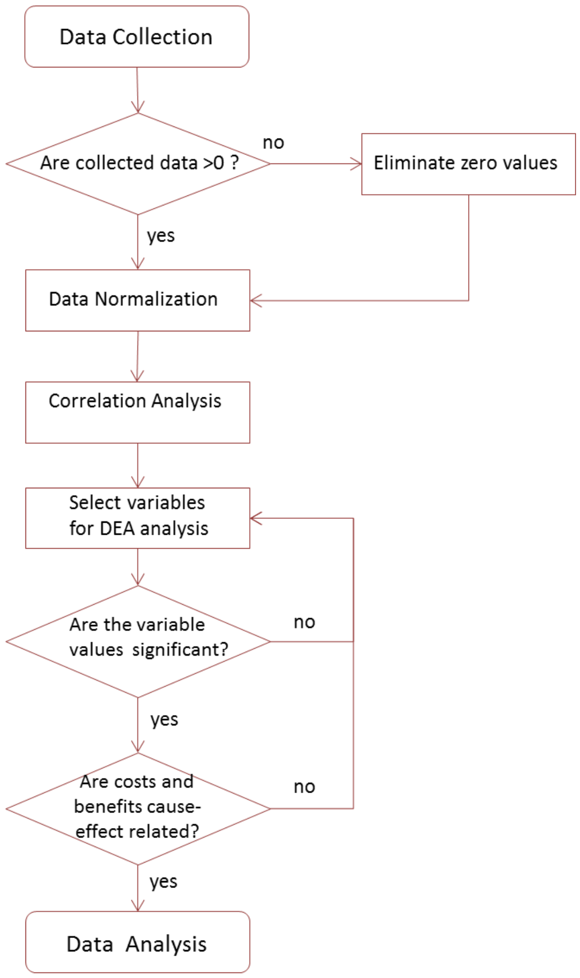

Figure 4.4 - Flow chart for preliminary data analysis process

With regard to the eco-driving data treatment and selection, the zero values have been eliminated by adding one unit to the entire data set.

Table 4.8 displays the results of the correlation analysis performed on the entire set of data.

	Auth	Coll	Eucoll	Iucoll	Pub	Kdecay	Cit	HTind	Epat	Spat
Auth	1,000	0,678*	0,696*	0,672*	0,746*	0,721*	0,430*	0,307*	0,062	0,114*
Coll	0,678*	1,000	0,818*	0,720*	0,525*	0,500*	0,278*	0,340*	-0,094	-0,041*
Eucoll	0,696*	0,818*	1,000	0,748*	0,615*	0,577*	0,381*	0,458*	-0,085	0,007*
Iucoll	0,672*	0,720*	0,748*	1,000	0,513*	0,465*	0,242*	0,238*	-0,014	0,029*
Pub	0,746*	0,525*	0,615*	0,513*	1,000	0,989*	0,400*	0,460*	0,028	0,133*
Kdecay	0,721*	0,500*	0,577*	0,465*	0,989*	1,000	0,362*	0,428*	0,022	0,119*
Cit	0,430*	0,278*	0,381*	0,242*	0,400*	0,362*	1,000	0,632*	-0,083	-0,011*
HTind	0,307*	0,340*	0,458*	0,238*	0,460*	0,428*	0,632*	1,000	-0,131	-0,039
Epat	0,062	-0,094	-0,085	-0,014	0,028	0,022	-0,083	-0,131	1,000	0,499*
Spat	0,114*	-0,041*	0,007*	0,029*	0,133*	0,119*	-0,011*	-0,039	0,499*	1,000

* indicates significant correlation at five percent (P < 0.05)

Table 4.8 - Pearson's coefficients (eco-driving)

The correlation between two variables is considered "very high" for Pearson's coefficients ranging from 0.90 to 1, "high" from 0.70 to 0.90, "moderate" from 0.50 to 0.70, "low" from 0.30 to 0.50 and "negligible" from 0 to 0.30 (Mukaka, 2012).

Based on the results of the correlation analysis, the collaboration experience factors Coll, Eucoll and Iucoll are highly correlated with each other. Also, Pub is very highly correlated to Kdecay. With regard to the quality of research, Cit and HTind are moderately correlated. These correlations are statistically significant as they present values of probability lower than 0.05 (Nuti, et al., 2011).

Among the correlated variables, Coll, Kdecay and Cit are taken into account as they are able to better differentiate the candidate partners from each other.

With regard to patent variables, even though Epat and Spat are not correlated, only the latter is taken into account given that most of the Spat values are equal to each other.

According to the preliminary data process, Table 4.9 indicates the benefit and cost factors that are going to be used for the qualification phase.

BENEFIT FACTORS		COST FACTORS	
Pub		**Coll**	●
Kdecay	●	**Eucoll**	
Spat	●	**Iucoll**	
Epat		**Auth**	●
Cit	●		

Table 4.9 - Selected benefit and cost factors

Finally, as benefits mainly increase when costs increase, they can be assumed as outputs and inputs of the DEA analyses, respectively.

In summary, the variables to be considered as benefits (outputs) are knowledge decay, number of citations and patents focusing on engineering and computer science subject areas. On the other hand, the total number of collaborations and authors involved in publishing papers on eco-driving represent the variables of cost (inputs) to be used to assess potential partners such as universities, research centers and industries.

4.2.3 Step 3: Qualification of Candidate Partners

As suggested in chapter 3, a short list of partners can be created from the long one by implementing the DEA Peeling procedure. In comparison with the original list of potential partners, the short list is simpler to manage in order to support the final partner selection.

Figure 4.5 summarizes the variables and the DMUs to be considered for the DEA Peeling process.

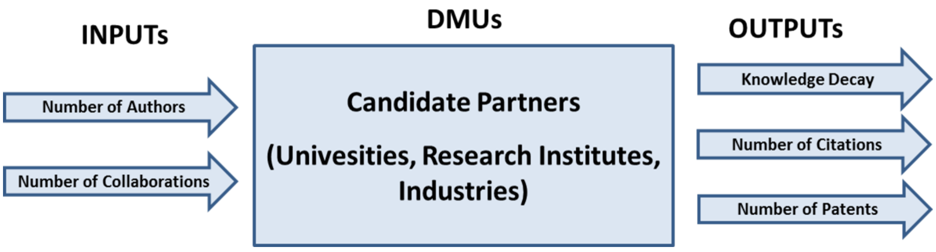

Figure 4.5 - DEA inputs, outputs and decision making units

The DEA Peeling procedure has been implemented by using the Benchmarking package for R software.

The efficient DMUs of each DEA Peeling stage form different rating tiers, which are generally characterized by a decreasing level of mean technical efficiency (TE) when moving from the first to the last tier. The mean TE has to be calculated during the first peeling stage.

Table 4.10 displays the DMUs rating tier by rating tier, as well as the related mean technical efficiency and % change.

	DMUs	Mean Technical Efficiency (TE)	% Change
Rating Tier 1	7, 9, 10, 78, 90, 94, 99, 110, 123, 127, 128 (11 DMUs)	1,00	-
Rating Tier 2	11, 16, 18, 21, 23, 24, 53, 82, 92, 93 (10 DMUs)	0,71	-0,29
Rating Tier 3	27, 28, 29, 31, 41, 97, 98, 100, 117, 121 (10 DMUs)	0,60	-0,16
Rating Tier 4	1, 3, 19, 43, 48, 50, 63, 65, 77, 124, 125, 130 (12 DMUs)	0,49	-0,18
Rating Tier 5	4, 6, 13, 25, 33, 45, 60, 73, 74, 84, 88, 91, 107, 120 (14 DMUs)	0,52	0,05
Rating Tier 6	5, 20, 26, 36, 38, 40, 46, 49, 55, 72, 76, 79, 85, 86, 101, 108, 109, 112, 114 (19 DMUs)	0,47	-0,10
Rating Tier 7	12, 14, 22, 62, 69, 87, 105, 106, 111, 113, 116, 122 (12 DMUs)	0,41	-0,12

Rating Tier 8	30, 67, 68, 71, 80, 95, 96, 119, 129, 131 (10 DMUs)	0,41	-0,01
Rating Tier 9	15, 32, 34, 42, 44, 47, 56, 61, 66, 81, 83, 102, 104, 118 (14 DMUs)	0,39	-0,04
Rating Tier 10	2, 8, 35, 51, 52, 54, 57, 64, 103, 115, 126 (11 DMUs)	0,32	-0,19
Rating Tier 11	17, 37, 39, 58, 59, 70, 75, 89 (8 DMUs)	0,30	-0,05

Table 4.10 - Peeling procedure (eco-driving)

The full peeling procedure consists of 11 stages. However, after the fifth rating tier, the mean technical efficiency scores stabilize, with the innovative performance of the candidate partners included in tiers 6, 7, 8, 9, 10 and 11 ranging from around 40% to 30%. Therefore, in order to create the short list of potential partners, only the rating tiers from 1 to 5 have been taken into account, for a total of 57 candidate partners. Among them, a total amount of 42 candidate partners are universities and research centers, whereas only 15 candidates are industries. Most of them are located in Europe (65%), followed by Asia (28%) and America (7%).

4.2.4 Step 4: Selection of the Most Appropriate Partners

As suggested in chapter 3, in order to support the final selection of R&D partners, the DEA Revenue Efficiency has to be applied. In comparison with the other DEA models, it allows the partner selection team to make more focused evaluations by taking into account a priori relative priorities of outputs. Furthermore, the possibility of assigning priorities makes the selection process a dynamic one, as the relative importance of benefit criteria can change depending on the objectives of the innovation strategies. Finally, by taking into account different sets of priorities, a sensitivity analysis can be used to evaluate the robustness of the classification.

Table 4.11 shows two different sets of priorities - related to the output variables - to be used for the Revenue Efficiency analysis on eco-driving, firstly giving more relevance to publication data (priorities set 1) and, then, to patent data (priorities set 2).

OUTPUTS	PRIORITIES SET 1	PRIORITIES SET 2
Knowledge Decay	0,7	0,3
Number of Citations	0,2	0,2
Number of Patents	0,1	0,5

Table 4.11 - Criteria priorities

The above priorities have been set based on the individual judgments of the partner selection team members. More specifically, the Super Decision software (http://www.superdecisions.com) developed by Saaty (1980, 2001) has been used for comparing the selected benefit criteria (i.e. knowledge decay, number of citations, and number of patents) with respect to the overall objectives for partnership.

Figure 4.6 and Figure 4.7 show the criteria pairwise comparison and the overall inconsistency index related to the assignment of each priorities set. The inconsistency values lower than 10% confirm the coherence of the judgments.

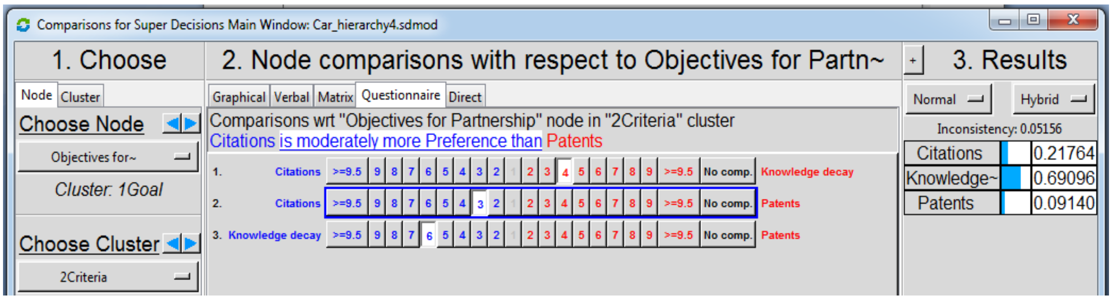

Figure 4.6 - Criteria pairwise comparison (priorities set 1)

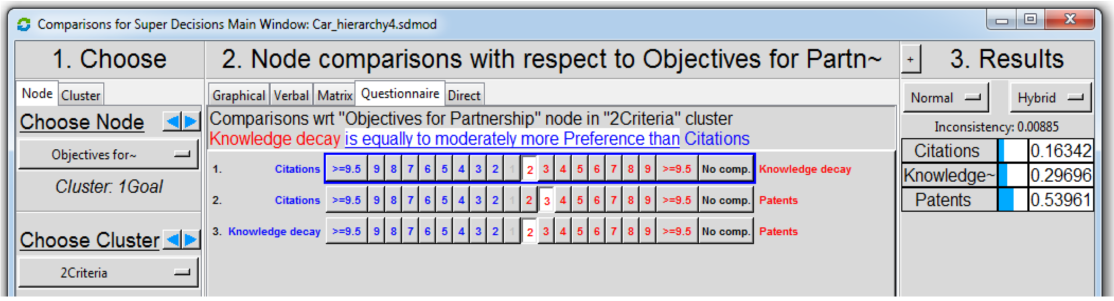

Figure 4.7 - Criteria pairwise comparison (priorities set 2)

Once the relative output priorities are expressed, the Revenue Efficiency score (RE) of the short list of candidate partners can be calculated reflecting on the ability of each DMU to produce the optimal proportion of outputs.

Figure 4.8 displays both the TE and RE trends for the two set of priorities. In particular, RE 1 indicates the revenue efficiency of the long list of candidate partners when considering the first set of priorities, whereas RE 2 refers to the second priorities set.

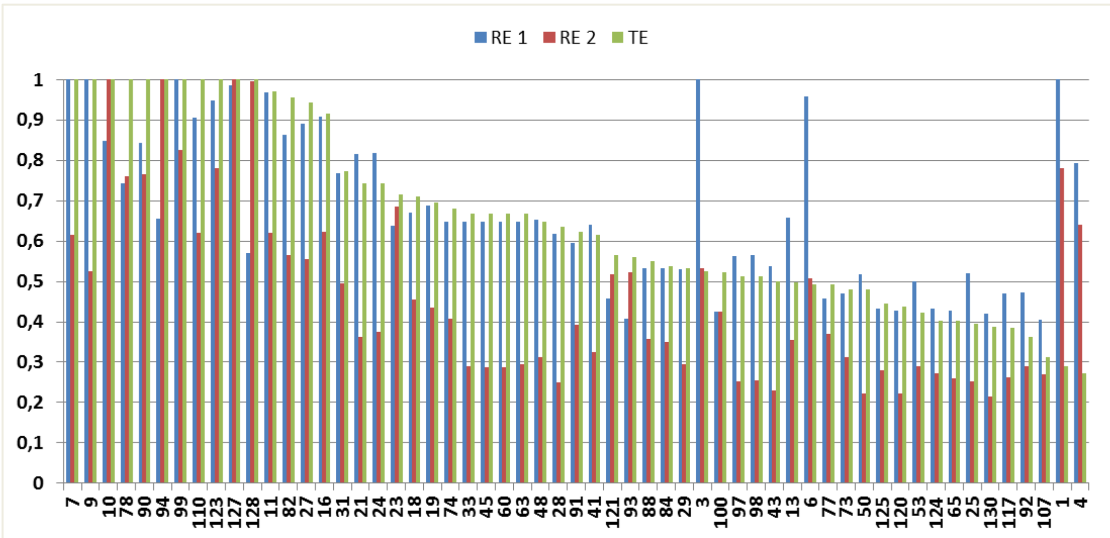

Figure 4.8 - Efficiency scores of the short list of candidates (eco-driving)

Table 4.12 also summarizes the candidate partners' efficiency statistics.

	TE	RE 1	RE 2
mean	0,655	0,670	0,464
st dev	0,230	0,195	0,224
max	1,000	1,000	1,000
min	0,272	0,405	0,216
no. 100% efficient candidates	11	5	4

Table 4.12 - Efficiency statistics (eco-driving)

By comparing the three trends it is possible to highlight that the number of efficient candidate partners decreases when priorities are assigned to the benefit variables. More specifically, there are eleven TE efficient potential partners (DMUs 7, 9, 10, 78, 90, 94, 99, 110, 123, 127, 128). This number drops to five (DMUs 7, 3,1, 9, 99) and four (DMUs 127, 94, 10, 128) when the first and second sets of priorities are assigned, respectively.

Even though there are some differences related to the assignment of relative priorities, the TE and RE 1 measurements have similar trends for the aggregate sample. Conversely, RE 2 shows a lower efficiency performance trend. More specifically, the mean TE, RE 1 and RE 2 efficiency scores are 65.5%, 67.0% and 46.4%, while the lower TE, RE 1 and RE 2 efficiency scores are 27.2%, 40.5% and 21.6%, respectively.

The drop in the mean efficiency performance, when taking into account the second set of priorities, confirms the assumption that, in the case of emerging technologies, the organizations are more focused on basic research.

TE, RE 1 and RE 2 are also displayed in relation to geographical areas (Figure 4.9 to Figure 4.11) and partner typologies, i.e. universities/research centers and industries/firms (from Figure 4.12 to Figure 4.14).

With regard to the distribution by geographical area, the TE trend (Figure 4.9) shows that the eleven 100% efficient candidates are distributed across Asia (DMUs 10, 94, 128, 78, 99, 123) and Europe (DMUs 127, 9, 7, 110, 90).

The results change when priorities are assigned to the benefit variables. In particular, when publication data are preferred (Figure 4.10), the majority of efficient candidates are located in Europe (DMUs 7, 3, 1, 9) and only one efficient candidate is located in Asia (DMU 99). Conversely, when considering RE 2 (Figure 4.11), the efficient candidates are mainly located in Asia (DMUs 94, 10, 128) and only one in Europe (DMU 127).

The improvement of Asian performance, when shifting from the first to the second priorities set, can be related to some differences in policies and mechanisms that are used to protect intellectual property.

Finally, the TE and RE 1 scores of American candidates range from 65% and 75%, whereas the RE 2 scores range from 25% to 50%.

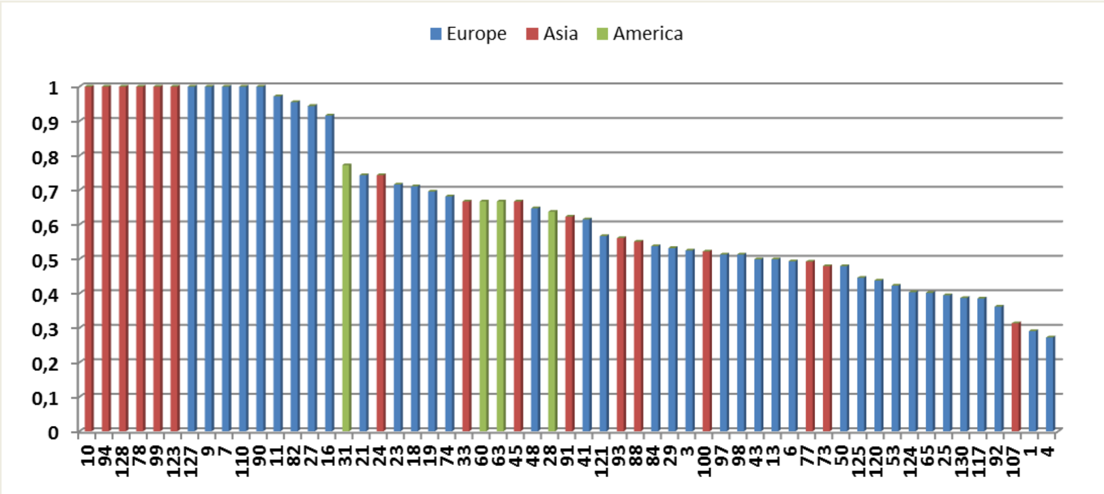

Figure 4.9 - TE by geographical area (eco-driving)

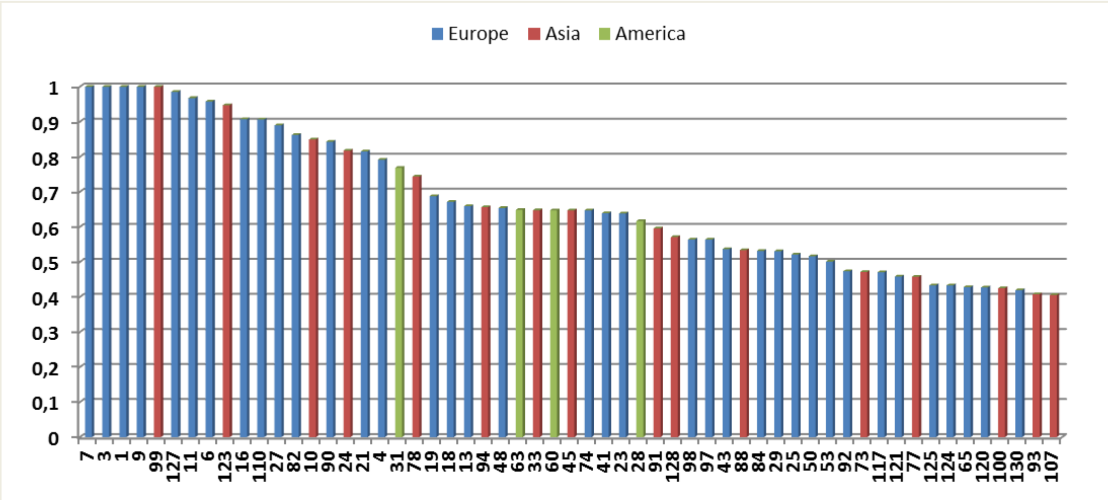

Figure 4.10 - RE 1 by geographical area (eco-driving)

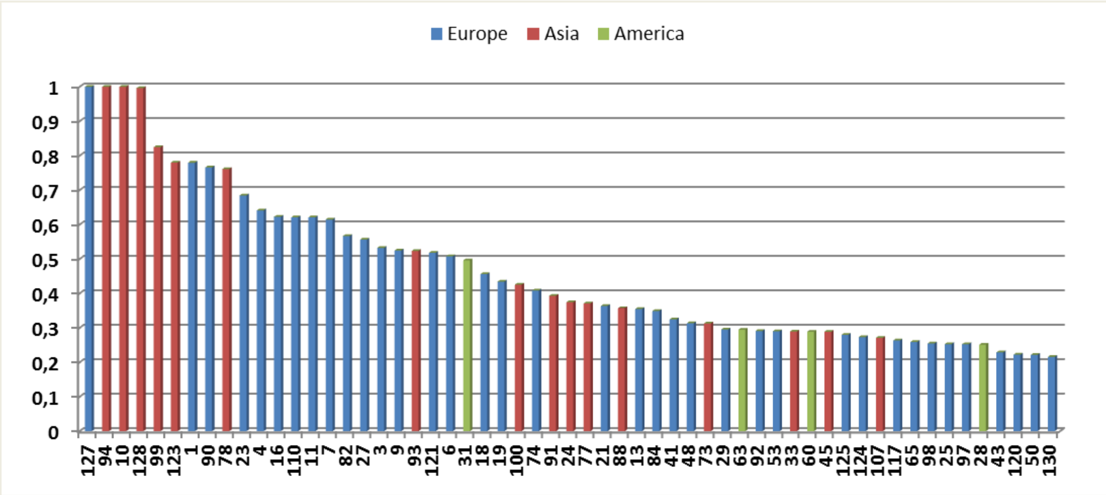

Figure 4.11 - RE 2 by geographical area (eco-driving)

With regard to the trends by partner typologies, when referring to TE (Figure 4.12), the 100% efficient candidates are about equally distributed between U/R and F: six efficient candidates are universities and research institutes (DMUs 78, 99, 9, 7, 110, 90), whereas five are firms (DMUs 10, 94, 128, 123, 127).

The revenue efficiency distributions highlight that the number of efficient firms decreases when changing the priority set from the first to the second one. More specifically, when more importance is given to publication data (Figure 4.13), the five 100% efficient candidates are all universities and research institutes (DMUs 7, 3, 1, 9, 99). Vice versa, when assigning the second set of priorities (Figure 4.14), according to which patent data are more relevant than publications, there are no efficient universities and research centers, and only four efficient firms (DMUs 127, 94, 10, 128). Also, when switching from TE and RE 1 to RE 2, the mean efficiency score of U/R decreases from about 65% to 40%, whilst from about 65% to 57% in the case of firms.

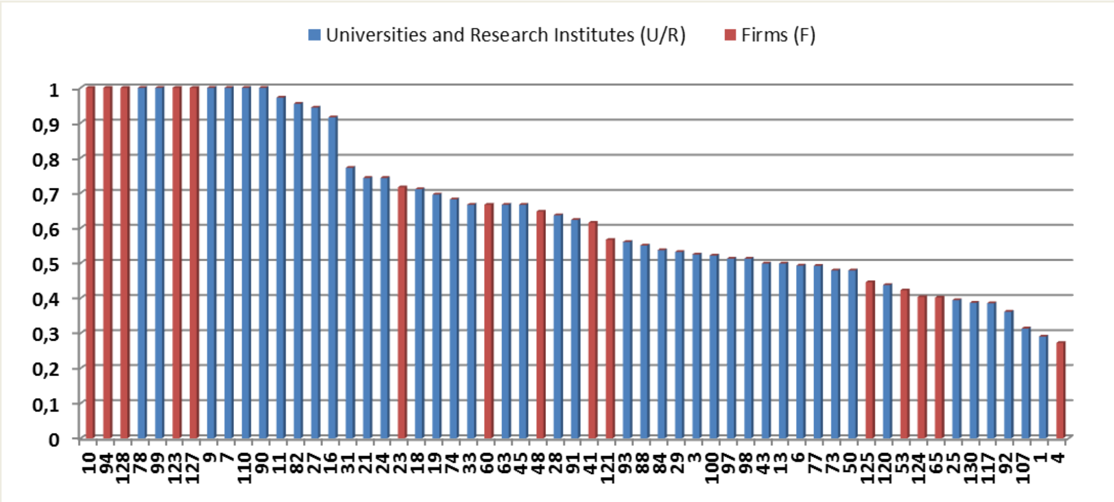

Figure 4.12 - TE by partner typology (eco-driving)

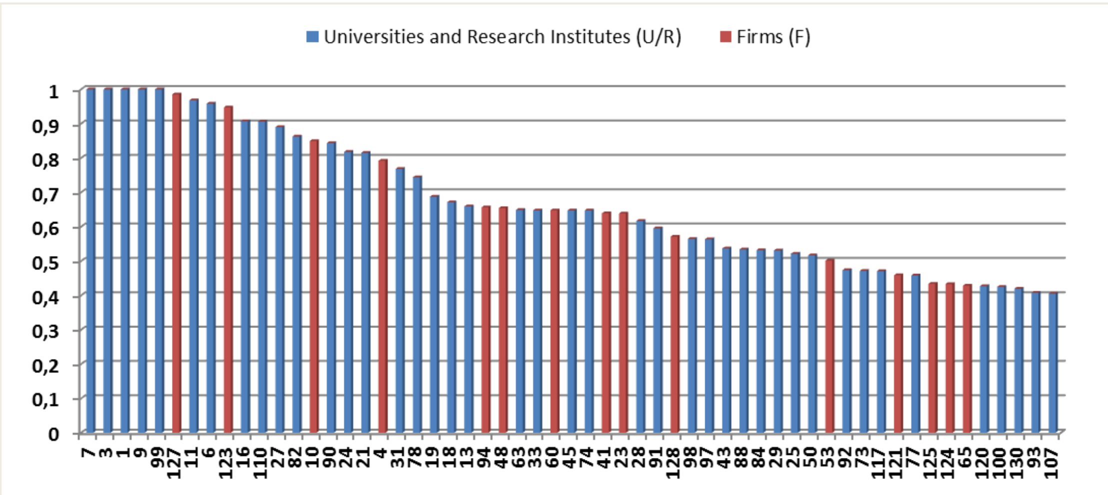

Figure 4.13 - RE 1 by partner typology (eco-driving)

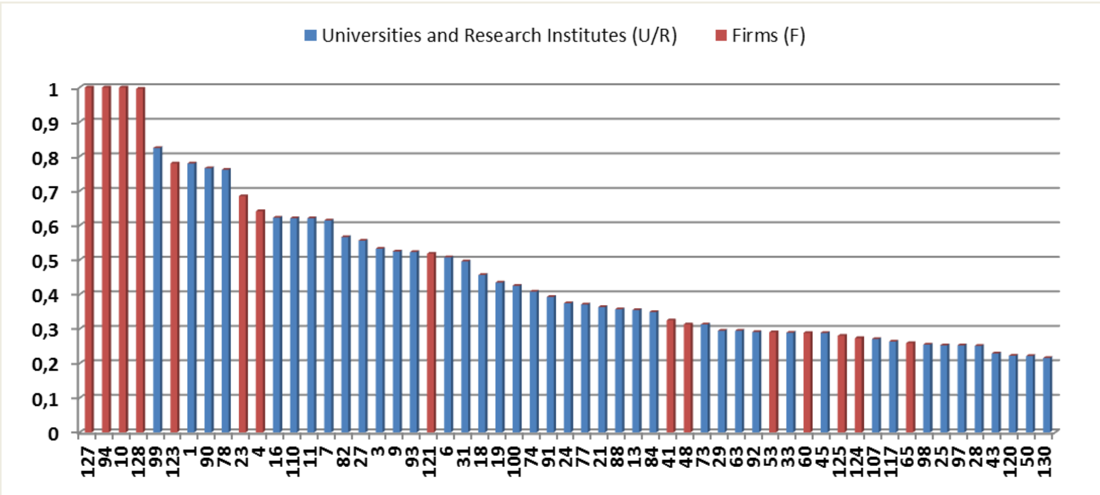

Figure 4.14 - RE 2 by partner typology (eco-driving)

These results confirm the initial assumption that the use of publication data is more significant when assessing universities and research centers, whilst patent data are more relevant in the case of industries and firms.

4.3 Case study #2: Satellite Technology

The case study on satellite technologies refers to IP2, which focuses on developing a new generation of signaling and control systems, building on current ERTMS to enable intelligent traffic management with automatically driven trains and to optimize capacity, reliability and minimize life cycle cost (TSLG, 2012).

In the context of advance traffic management and control systems, satellite and positioning play a key role, and therefore the interest in these technologies has increased over time (Figure 4.15).

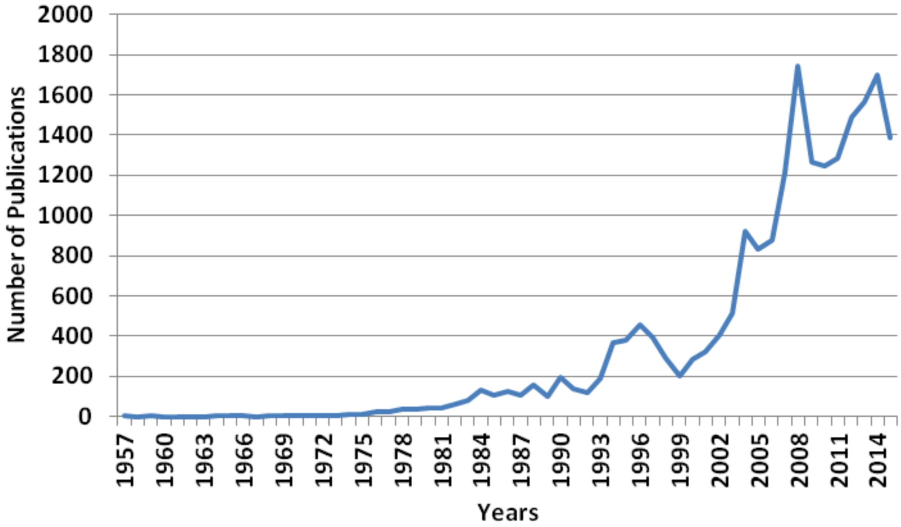

Figure 4.15 - Satellite TLC (Source: own elaboration using data retrieved from Scopus)

By looking at the above S-curve, the satellite technology is clearly at the mature phase of the technology life cycle.

4.3.1 Step 1: Objectives of the Innovation Strategy

According to the assumption made in chapter 3, throughout the growth and maturity stages of the technology lifecycle, with the increasing need for collaborative development and integration of complementary technology, R&D collaboration with suppliers is on the rise.

Table 4.13 summarizes the partner selection team's objectives for collaborations on satellite.

OBJECTIVES FOR PARTNERSHIP	# 2
Technology of Interest	Satellite
Preferred Sector	Transportation
Description	Satellite, positioning, safety, reliability
Lifecycle Phase	Mature
Main Motivations	Research-based
Preferred Partners Typologies	Firms

Table 4.13 - Objectives chart (satellite)

However, as the case study considers the research-based perspective, even though the preferred partnership typology at the mature TLC stage is that with firms, in order to validate the framework, universities and research centers are also taken into account.

4.3.2 Step 2: Identification of Candidate Partners

As with the first case study, in order to identify candidate partners and to collect all the information and data needed for partner selection, Scopus and Espacenet have been chosen as data sources for publications and patents, respectively.

Table 4.14 and Table 4.15 indicate Scopus and Espacenet settings.

SCOPUS SETTINGS	
Keywords	"satellite", "positioning", "safety", "reliability", "dependability", "trustworthiness", "integrity", "protection level", "GNSS", "GPS", "LAAS", "SBAS", "RAIM" (in title, abstract or keywords)
Limitations	• Years: 2010-2015 • Subject areas: Engineering and Computer Science • Source Type: Conference Proceedings and Journals • Language: English

Table 4.14 - Scopus settings (satellite)

ESPACENET SETTINGS	
Keywords	"satellite", "positioning" (in the title or abstract)
Patent Classes	G01S19/00 (as IPC classification)
Limitations	• Years: 2010-2015 • Subject areas: Engineering and Computer Science

Table 4.15 - Espacenet settings (satellite)

With regard to the patent classes settings, G01S19/00 refers to satellite radio beacon positioning systems, which determine position, velocity or attitude using signals transmitted by such systems.

By using the above Scopus settings, a long list of 130 candidate partners (26 firms and 104 universities/research centers) have been identified. Also in this case, they have not been revealed for data protection reasons. However, 55% of the candidates are located in Europe, 24% in Asia, 17% in America, and the remaining 4% in Africa and Oceania (Figure 4.16).

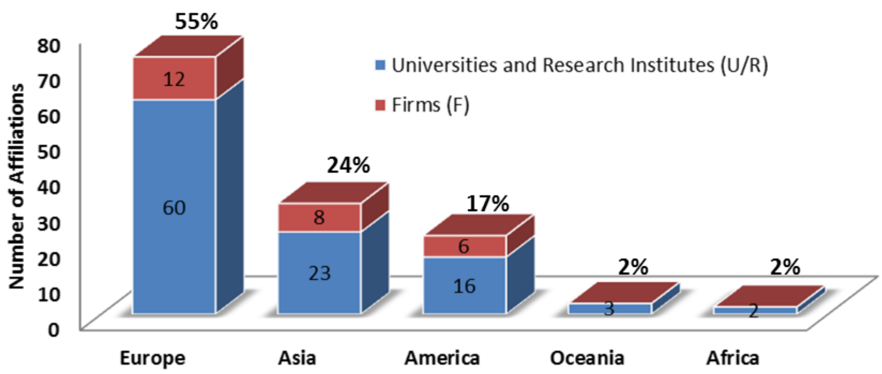

Figure 4.16 - Distribution of the 130 candidate partners (satellite)

More specifically, as shown in Table 4.16, the candidate partners are distributed in Europe over 16 countries, in Asia over 6 countries, and in America over 3 countries.

In Oceania and Africa the candidates are located only in Australia and South Africa, respectively.

EUROPE		ASIA		AMERICA		OCEANIA		AFRICA	
Austria	2	**China**	17	**Brazil**	1	**Australia**	3	**South Africa**	2
Czech Republic	3	**India**	2	**Canada**	3				
Denmark	1	**Japan**	7	**US**	18				
Finland	1	**South Korea**	3						
France	12	**Taiwan**	1						
Germany	15	**Thailand**	1						
Hungary	1								
Italy	11								
Netherlands	3								
Norway	1								
Poland	2								
Portugal	3								
Spain	6								
Switzerland	3								
Turkey	1								
UK	7								
Total	**72**		**31**		**22**		**3**		**2**

Table 4.16 - Candidates' distribution across geographical areas (satellite)

Table 4.17 shows statistics relative to the data collected on Scopus and Espacenet about the long list of candidate partners working on satellite technologies, by geographical area.

		Auth	Coll	Eucoll	Iucoll	Pub	Kdecay	Cit	HTind	Epat	Spat
EUROPE	mean	5,57	4,69	1,65	1,25	3,71	3,04	15,18	1,29	7,99	1,64
	st dev	4,32	4,60	2,21	1,69	3,03	2,49	29,98	1,11	19,61	3,51
	max	23,00	20,00	14,00	9,00	17,00	14,20	188,00	5,00	151,00	23,00
	min	2,00	0,00	0,00	0,00	1,00	0,68	0,00	0,00	0,00	0,00
ASIA	mean	4,42	2,77	0,19	0,68	2,77	2,22	3,68	0,61	217,61	9,13
	st dev	3,93	2,04	0,54	1,17	2,62	2,19	8,42	0,76	577,33	27,88
	max	18,00	7,00	2,00	6,00	16,00	13,36	41,00	2,00	3039,00	153,00
	min	2,00	0,00	0,00	0,00	1,00	0,75	0,00	0,00	0,00	0,00
AMERICA	mean	3,77	4,68	0,91	0,68	2,77	2,12	26,77	1,27	30,95	3,18
	st dev	2,54	5,89	1,93	0,84	1,74	1,23	49,61	1,24	66,42	5,40
	max	10,00	22,00	7,00	2,00	8,00	5,73	189,00	5,00	307,00	23,00
	min	2,00	0,00	0,00	0,00	1,00	0,91	0,00	0,00	0,00	0,00
OCEANIA	mean	6,33	3,00	0,67	0,67	5,33	4,53	28,00	2,33	6,00	1,33
	st dev	5,13	1,00	1,15	0,58	4,04	3,52	26,00	1,53	5,57	1,53
	max	12,00	4,00	2,00	1,00	10,00	8,60	54,00	4,00	11,00	3,00
	min	2,00	2,00	0,00	0,00	3,00	2,34	2,00	1,00	0,00	0,00
AFRICA	mean	4,50	0,00	0,00	0,00	2,00	1,44	0,00	0,00	0,00	0,00
	st dev	0,71	0,00	0,00	0,00	0,00	0,10	0,00	0,00	0,00	0,00
	max	5,00	0,00	0,00	0,00	2,00	1,51	0,00	0,00	0,00	0,00
	min	4,00	0,00	0,00	0,00	2,00	1,37	0,00	0,00	0,00	0,00

Table 4.17 - Statistics relative to the long list of candidates, by geographical area (satellite)

The meaning of the variables in the table has already been indicated in the previous case study on eco-driving technologies (see Table 4.6).

Data indicate that the highest standard deviation is related to the number of patents (Epat) of Asian candidate partners, ranging from 0 to 3039. The Epat values differ to a large extent in the case of American affiliations (from 0 to 307), as well as for European affiliations (from 0 to 151). The other variables present a low standard deviation.

As in the previous illustrative case study, according to the preliminary data process, only knowledge decay, number of citations and patents focusing on engineering and computer science subject areas are significant benefits. On other hand, the significant cost variables are the total number of collaborations and authors involved in publishing papers on satellite.

Table 4.18 shows the results of the correlation analysis.

	Auth	Coll	Eucoll	Iucoll	Pub	Kdecay	Cit	HTind	Epat	Spat
Auth	1,000	0,206*	0,330*	0,383*	0,637*	0,622*	0,114	0,232*	0,169	0,150
Coll	0,206*	1,000	0,779*	0,627*	0,528*	0,489*	0,777*	0,669*	-0,019	0,028
Eucoll	0,330*	0,779*	1,000	0,593*	0,574*	0,538*	0,614*	0,581*	-0,060	-0,043
Iucoll	0,383*	0,627*	0,593*	1,000	0,509*	0,484*	0,452*	0,362*	-0,016	0,041
Pub	0,637*	0,528*	0,574*	0,509*	1,000	0,988*	0,484*	0,682*	-0,013	0,009
Kdecay	0,622*	0,489*	0,538*	0,484*	0,988*	1,000	0,441*	0,651*	-0,017	0,000
Cit	0,114	0,777*	0,614*	0,452*	0,484*	0,441*	1,000	0,729*	-0,011	0,021
HTind	0,232*	0,669*	0,581*	0,362*	0,682*	0,651*	0,729*	1,000	-0,070	-0,023
Epat	0,169	-0,019	-0,060	-0,016	-0,013	-0,017	-0,011	-0,070	1,000	0,910*
Spat	0,150	0,028	-0,043	0,041	0,009	0,000	0,021	-0,023	0,910*	1,000

* indicates significant correlation at five percent ($P < 0.05$)

Table 4.18 - Pearson's coefficients (satellite)

4.3.3 Step 3: Qualification of Candidate Partners

The DEA Peeling procedure has been used to create the short list of potential partners to collaborate with on satellite technologies.

By taking into account costs and benefits as input and output variables, respectively, the full peeling procedure consists of 10 stages (Table 4.19).

	DMUs	Mean Technical Efficiency (TE)	% Change
Rating Tier 1	6, 7, 11, 13, 23, 34, 39, 51, 54, 55, 77, 81, 103, 113 (14 DMUs)	1,00	-
Rating Tier 2	2, 8, 12, 14. 22, 28, 43, 52, 80, 82, 86, 91, 105, 109 (14 DMUs)	0,85	-0,15
Rating Tier 3	4, 15, 32, 33, 40, 53, 119 (7 DMUs)	0,67	-0,21

Rating Tier 4	1, 9, 24, 29, 30, 31, 41, 42, 57, 59, 76, 99, 102 (13 DMUs)	0,61	-0,09
Rating Tier 5	17, 19, 26, 37, 44, 45, 47, 49, 68, 70, 74, 84, 88, 93, 110, 111, 112, 117, 121, 124, 128 (21 DMUs)	0,54	-0,12
Rating Tier 6	3, 60, 69, 72, 73, 85, 90, 97, 98, 101, 107, 118, 125, 129 (14 DMUs)	0,44	-0,18
Rating Tier 7	5, 10, 16, 18, 20, 21, 27, 48, 61, 75, 78, 79, 87, 92, 100 (15 DMUs)	0,43	-0,03
Rating Tier 8	35, 56, 66, 89, 95, 96, 106, 116 (8 DMUs)	0,39	-0,11
Rating Tier 9	25, 36, 38, 46, 58, 63, 65, 67, 71, 83, 114, 126, 127, 130 (14 DMUs)	0,32	-0,17
Rating Tier 10	62, 64, 94, 104, 108, 115, 120, 122, 123 (9 DMUs)	0,25	-0,21

Table 4.19 - Peeling procedure (satellite)

From rating tier 6 onwards, the mean technical efficiency scores become more stable, resulting in a short list of 49 candidate partners included in the tiers 1, 2, 3 and 4 to be taken into account for collaborating on satellite. Among them, a total of 47 candidate partners are universities and research institutes, whereas only two candidates are firms. They are located in Europe (49%), in Asia (33%), in America (10%), in Africa (4%) and in Oceania (4%).

4.3.4 Step 4: Selection of the Most Appropriate Partners

As already done for first case study on eco-driving technologies, the DEA Revenue Efficiency has been applied in order to support the final selection of R&D partners.

The same two sets of criteria assigned during the case study on eco-driving technologies have been taken into account (see Table 4.11).

The results of the RE analysis of the candidates are displayed below. In particular, Figure 4.17 compares the technical efficiency scores (TE) of the candidate partners of the short list with the revenue efficiency scores RE 1 and RE 2, calculated for the first and second sets of priorities, respectively.

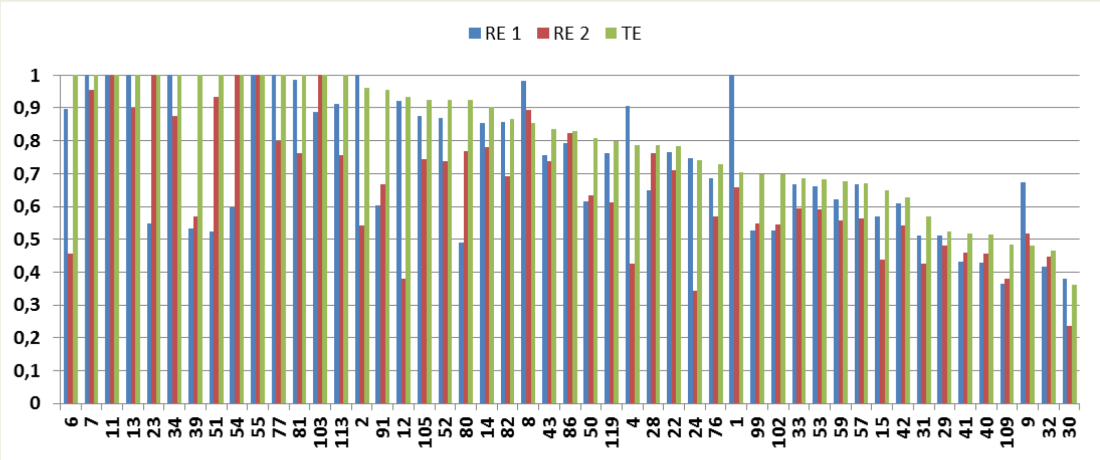

Figure 4.17 - Efficiency scores of the short list of candidates (satellite)

Table 4.20 also summarizes the candidate partners' efficiency statistics.

	TE	RE 1	RE 2
mean	0,803	0,726	0,659
st dev	0,185	0,202	0,201
max	1,000	1,000	1,000
min	0,363	0,366	0,235
no. 100% efficient candidates	14	8	5

Table 4.20 - Efficiency statistics (satellite)

By comparing the trends and the statistics, it is possible to highlight that the candidate partners present the highest mean efficiency scores in the case of TE measurements. In particular, the mean TE, RE 1 and RE 2 efficiency scores are 80.3%, 72.6% and 65.9%, while the lower TE, RE 1 and RE 2 scores are 36.3%, 36.6% and 23.5%, respectively.

It is interesting to highlight that, in contrast with the previous case study on emerging technologies, in the case of satellite there is not a relevant drop in the mean efficiency performance when taking into account the second set of priorities. This is because the technology is mature and the organizations focus on applied research and development.

Also, the number of 100% efficient candidates is maximum when measuring the technical efficiency. In this case there are fourteen efficient candidates (DMUs 6, 7, 11, 13, 23, 34, 39, 51, 54, 55, 77, 81, 103, 113). The number decreases when priorities are assigned to the benefit variables. More specifically, for the first set of priorities, there are eight efficient candidate partners (DMUs 7, 11, 1, 77, 2, 55, 13, 34), whereas for the second set this number drops to five (DMUs 11, 23, 103, 55, 54). However, RE 1 and RE 2 present similar trends for the aggregate sample.

The trends of TE, RE 1 and RE 2 are also displayed in relation to geographical areas (from Figure 4.18 to Figure 4.20) and partner typologies, such as universities/research centers and firms (from Figure 4.21 to Figure 4.23).

With regard to the distribution by geographical area, the TE 100% efficient organizations for both the priorities sets (Figure 4.18) are located in Europe, followed by Asia, America and Oceania. More specifically, there are eight 100% efficient candidates in Europe (DMUs 7, 11, 13, 34, 55, 77, 81, 113), four in Asia (DMUs 54, 23, 51, 103), one in America (DMU 39), and one in Oceania (DMU 6).

When considering the revenue efficiency scores the results change. By taking into account the first priorities set (Figure 4.19), the number of European 100% efficient candidates decreases to seven (DMUs 7, 11, 1, 77, 55, 13, 34) and the number of efficient Asian candidates drops to one (DMU 2). Furthermore, there are no efficient candidates in America, Oceania and Africa.

Conversely, if the second priorities set is assigned (Figure 4.20), the number of efficient European candidates decreases to two (DMUs 11 and 55), whereas the number of efficient Asian candidates become three (DMUs 23, 103, 54).

Finally, with regard to African affiliations, TE, RE 1 and RE 2 scores range from 80% to 70%, from 75% to 65%, and from 60% to 55%, respectively.

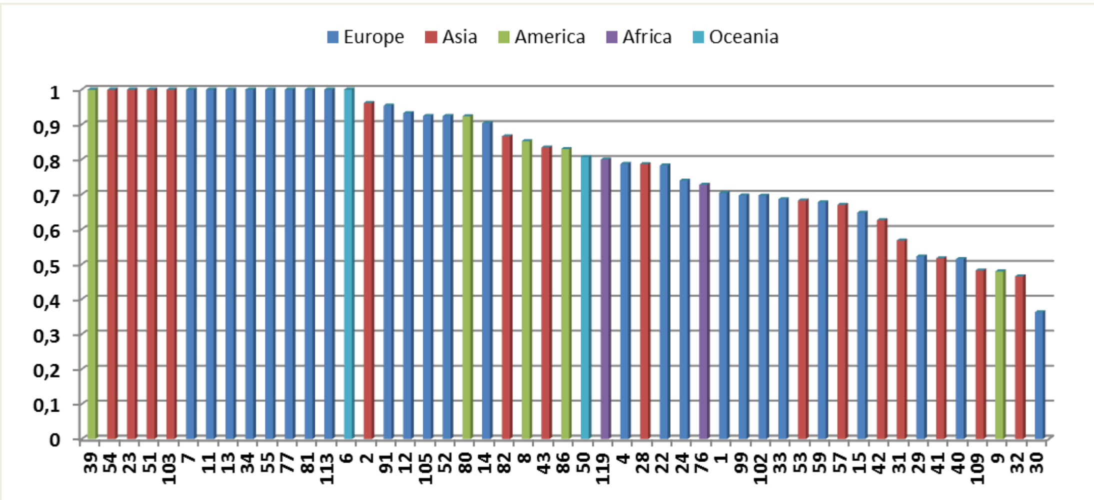

Figure 4.18 - TE by geographical area (satellite)

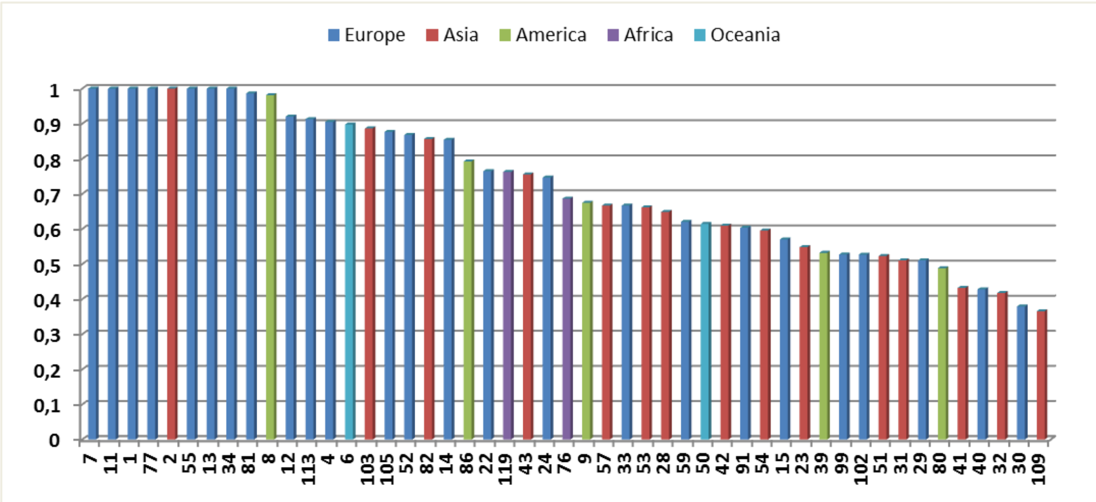

Figure 4.19 - RE 1 by geographical area (satellite)

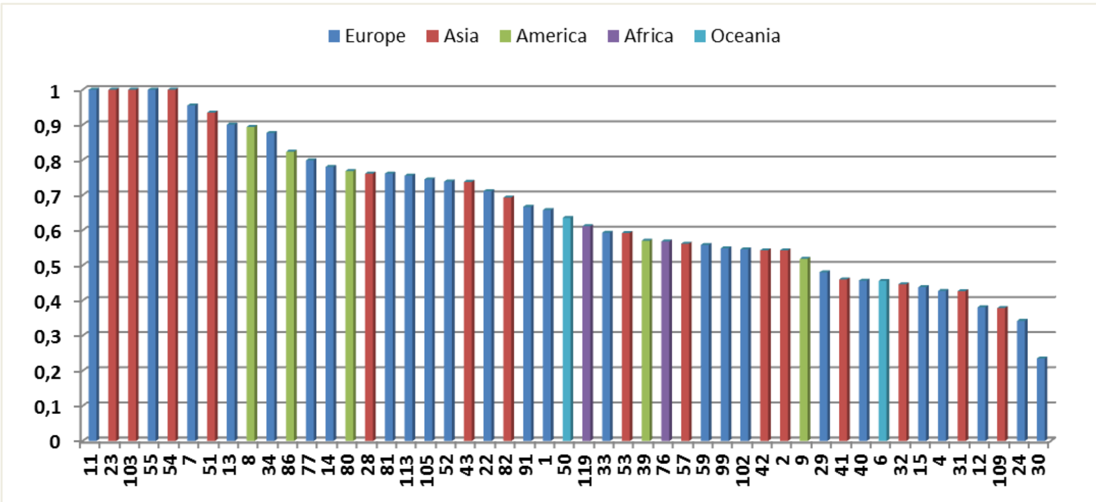

Figure 4.20 - RE 2 by geographical area (satellite)

With regard to the distributions by partner typology, most of the 100% efficient candidate partners are universities or research centers. In the case of technical efficiency (Figure 4.21), there are thirteen efficient U/R candidates (DMUs 39, 54, 23, 51, 103, 7, 11, 13, 34, 55, 77, 81, 113, 6) and one efficient firm (DMU 54).

For the first priority set (Figure 4.22), all eight efficient candidates are universities and research institutes (DMUs 7, 11, 1, 77, 2, 55, 13, 34).

This number drops to four (DMUs 11, 23, 103, 55) when giving more importance to patent data (Figure 4.23). In the case of RE 2, there is also an efficient firm in the sample (DMU 54).

Furthermore, when switching from the first to the second priorities sets, the mean RE efficiency score of U/R decreases from 73% to 65%, whereas the mean RE efficiency score of industries and firms increases from 6% to 9%.

Also in this case, the result confirms that the use of patent data is more significant when assessing organizations such as industries and firms.

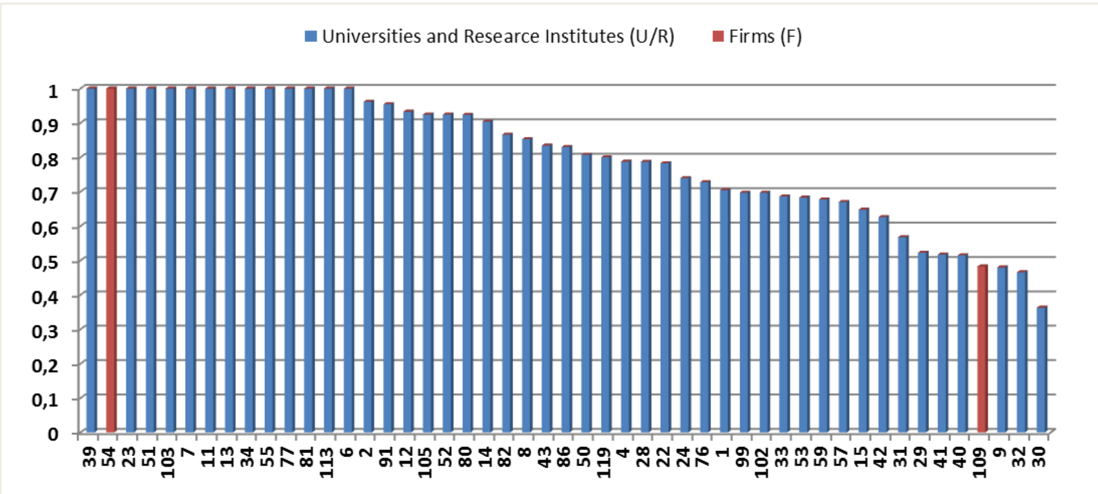

Figure 4.21 - TE by partner typology (satellite)

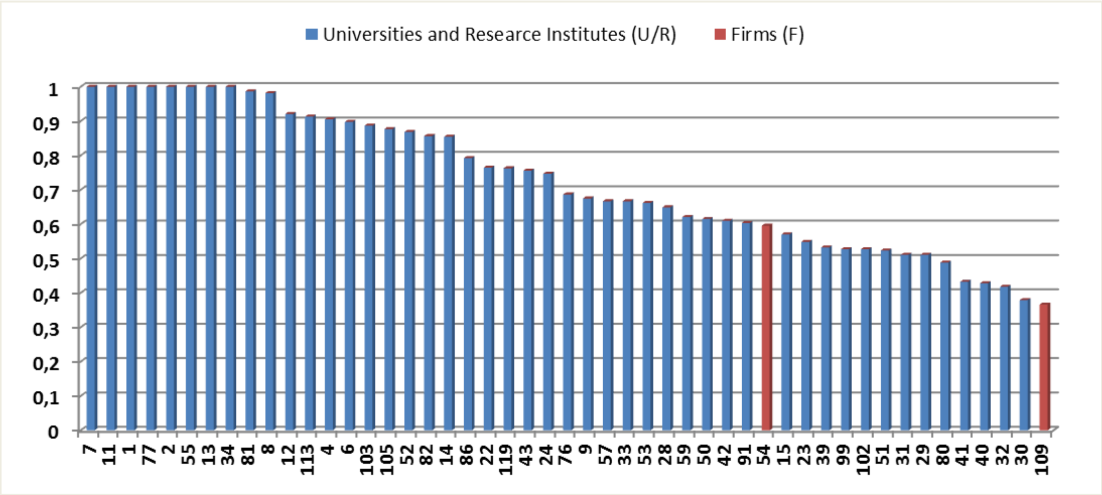

Figure 4.22 - RE 1 by partner typology (satellite)

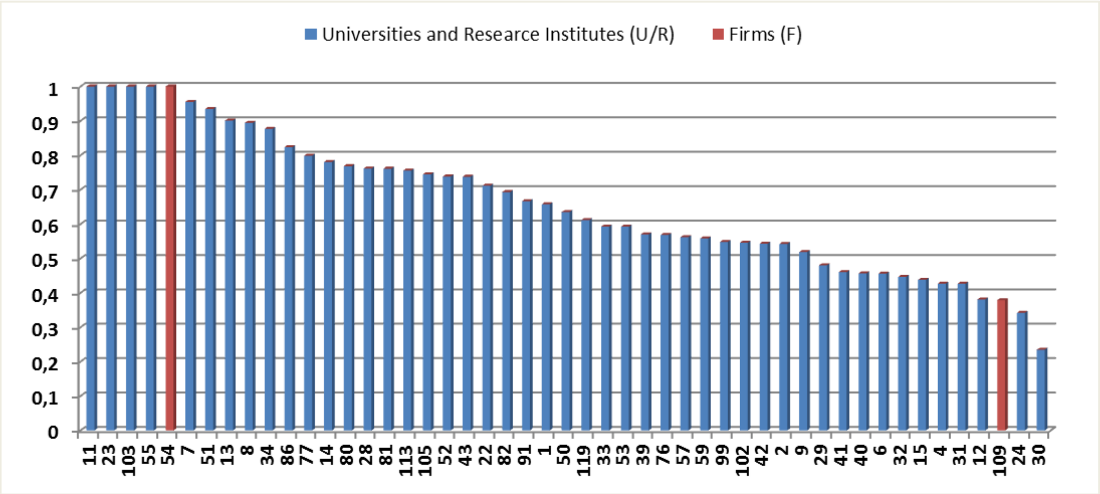

Figure 4.23 - RE 2 by partner typology (satellite)

CHAPTER 5

5 Conclusions

This final chapter discusses the findings emerged from the research, highlighting their contribution to both academic research and managerial practices. The research is inevitably subject to some limitations, despite its valuable contribution, and can consequently be taken into consideration for further research.

5.1 Main Outcomes of The Research

In modern economies, where markets and technology are changing rapidly, exchanging knowledge and acquiring technologies through R&D collaboration among organizations is increasingly perceived as a vehicle to enhance innovation and be competitive.

Despite the benefits of R&D collaboration, the identification and the selection of the most suitable partners still remains an open question that catches the interest of both academics and practitioners.

One of the main points of discussion is related to the use of effective information (i.e. qualitative or quantitative) and methods based on which candidate partners have to be identified, qualified and selected.

In order to significantly contribute to the open innovation research and R&D collaboration practices of technology-intense industries - commonly based on former experience and expert judgement - this thesis provides a well-structured partner qualification framework to both academics and practitioners, which is able to fully satisfy the requirements of replicability, reliability, rationality and transparency, as well as minimize the need for expert opinion. Furthermore, the framework development allows the gaps that emerged in the literature on R&D collaboration to be filled.

5.1.1 Academic and Managerial Contributions

This thesis work contributes to both academic research and managerial practices in several ways. First of all, from an academic point of view, in order to develop the partner qualification framework, a systematic literature review on the R&D partner selection problem was carried out, highlighting four main issues to be taken into account during the definition of the framework: motivations (i.e. research-based, saving-based and market-based), partner typologies (i.e. vertical, horizontal and institutional collaborations), selection criteria (i.e. qualitative and quantitative), and methodologies.

It is interesting to note that although these four issues are strongly linked to each other and can be considered as running phases of the partner selection process, the majority of the analyzed papers focus on just one or two of the them.

As a result of the systematic review, three major gaps emerged in the literature. The first gap refers to the lack of studies considering the limits of using patent data when the candidate partners have to be identified. First of all, not all of the know-how is eligible for patent protection (i.e. technologies at the early stages of their life cycle) and secondly, some organizations may decide to protect their technological know-how with other means. These limitations may automatically exclude or at least underestimate some relevant organizations.

The second gap concerns the decision making methodologies used for the qualification and selection of partners. When studying the partner selection problem in the case of R&D collaboration, no authors suggest using data envelopment analysis (DEA). This finding contradicts the overall literature on decision-making models for partner selection (e.g. suppliers, vendors), in which DEA appears as one of the most popular approaches.

Finally, the third gap emerging from the literature on the R&D partner selection problem refers to the lack of studies highlighting the existing relationship between objectives for partnership and technology evolution.

The results of the literature review are the starting point for the development of the partner qualification framework. The framework consists of the following four phases:

1. Definition of the objectives of the innovation strategy;
2. Identification of candidate partners (long list);
3. Qualification of candidate partners (short list);
4. Selection of the most appropriate partners.

More specifically, the first phase of the framework allows the third gap in the literature to be filled by suggesting a preliminary analysis of the technology of interest and its life cycle. For instance, the choice of partner typologies (e.g. universities and research centers or industries) changes when shifting from the emerging to the maturity stages of the TLC. In that sense, it is assumed that during the emerging stage of the technology life cycle, R&D collaboration mainly involves universities and research institutes, whereas in the case of mature technologies R&D collaboration with suppliers is preferred.

The second phase of the framework allows for the filling of the first gap emerged in the literature, suggesting the use of both patent and publication data in order to identify the long list of partners, as well collecting the information needed to measure some of the variables of interest. In particular, it is assumed that publication data are more significant when looking for partners such as universities and research centers, whereas patent data are more relevant when searching and selecting firms.

Finally, the use of DEA as a data analysis technique during phase 3 and phase 4 fills the second literature gap. More specifically, the rating procedure DEA Peeling is implemented in order to create a short list of partners (qualification phase). In order to reduce the number of initial candidate partners, the choice of this procedure is appropriate as it does not assign a specific rank position to the candidates, rather it classifies them in different levels of efficiency, allowing for a simpler and faster reduction of the long list. Furthermore, from a more practical point of view, as DEA Peeling does not require any definition of a priori weights, the partner qualification allows for the minimization of expert subjectivity, fully satisfying the requirements of replicability, reliability, rationality and transparency.

The DEA Revenue Efficiency implemented during the fourth phase of the framework is used to obtain a more focused evaluation of the candidate partners, by assigning a priori relative weights, prices or priorities of inputs and/or outputs. The use of priorities in this final phase allows for more flexibility, i.e. the possibility to better respond to the dynamism of high-technology markets and, in turn, to the fast-changing needs of industries.

Moreover, by using DEA and open data sources, the proposed framework fulfills the requirements of being low-cost and user-friendly.

Finally, in order to test the effectiveness of the proposed partner qualification framework on real firm practices, two case studies of railway interest, in line with the European Research & Innovation roadmap (e.g. Horizon 2020 program - SHIFT²RAIL Joint Undertaking), were carried out. The choice to analyze an emerging technology (eco-driving) and a mature one (satellite) allows for a deeper understanding of the existing relationship between technology evolution and R&D collaboration. These two case studies were tested only for research-based motivations.

With regard to the two case studies, the results of both the applications on eco-driving and satellite technologies confirm the assumption that the use of publication data is more significant when assessing universities and research centers, whilst patent data are more relevant in the case of industries and firms.

Furthermore, the differences in the mean efficiency performance when switching from the first to the second priorities sets confirm the assumption that, in the case of eco-driving technologies, the organizations are mainly focused on basic research. Conversely, in the case of mature technology the interest is on both basic and applied research.

Finally, the results also highlight the existence of a relationship between the two sets of priorities and the location of the efficient candidate partners. In particular, Asian partners seems to be more appropriate when the preferential selection criteria are patents. Vice versa, European candidates are preferred when more relevance is given to publications.

5.2 Limitations and Suggestions for Further Research

Whilst the results of this research provide significant insights into the open innovation and R&D collaboration fields, this study is subject to some limitations.

First of all, although the qualification framework has been developed to respond to the general search for R&D partnerships, it has only been tested on high-technologies of railway interest and, therefore, in order to investigate whether the findings related to emerging and mature technologies can be generalized, it is advisable to test the proposed framework across different sectors, using other technologies.

Also, the two applications on eco-driving and satellite technologies have only analyzed the case of research-based motivations, which gives more relevance to publication data. In that sense, it could be interesting to implement the step-by-step framework when starting the data collection process from patent data sources, analyzing the changes in the long list of candidate partners, in terms of distribution by geographical area and partner typology. Moreover, other variables - both qualitative and quantitative - could be taken into account in order to test the framework in the case of saving-based and market based-motivations.

With regard to the data analysis, in order to get a deeper understanding of the candidate partners' characteristics that most affect their efficiency performance, it is possible to integrate the use of the implemented DEA models with different ones. For instance, a regression analysis can be performed by setting as dependent variable the efficiency scores obtained by implementing the bootstrapped DEA model.

Finally, even though the proposed framework has been developed and implemented in the context of a tool for decision making in a real industrial setting based on quantitative data, it is important to highlight that it does not provide an optimal solution but, rather, it serves to support the search for collaborative R&D partners.

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