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# SMEs' Degree of Openness: The Case of Manufacturing Industries

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**Abstract**

This paper clusters SMEs based on their degree of openness. In addition, it explores both the internal and external determinants of the different clusters obtained. Based on a survey of 1214 firms in manufacturing industries and using both the dimensions of openness, breadth and depth, we find that SMEs could be clustered in four classes, depending on their degree of openness. We find that SMEs could adopt a closed, an open, an interactive or a user approach to innovation. With respect to the determinants of different classes of SMEs, the results of the logistic regression model, developed in this study, show variables such as national and regional proximities that account for explaining the likelihood that SMEs will be in a more open cluster rather than in a low open cluster. Also, this quantitative study shows that external obstacles to innovation may lead these SMEs from a closed approach to innovation to an interactive, user, or open approach to innovation. Finally, we find that the age of the firm is important in explaining the likelihood that SMEs will be in an open cluster rather than in a closed cluster.

**Keywords:** SMEs; open innovation; openness; external sources of information; cluster analysis.

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## Introduction

This paper explores two issues. First, SMEs are clustered in homogeneous groups according to their degree of openness. Secondly, we explore similarities and differences of the determinants of SMEs to determine to which different cluster they belong. To explore these issues, we rely on the dimensions of openness, namely, breadth and depth which reflect one aspect related to the open innovation model.

Firstly, the open innovation model has been described as an inbound and outbound process (Chesbrough and Crowther 2006; Savitskaya et al., 2010) or as an inside-out, outside-in and coupled process (Gassmann and Enkel 2004; Enkel et al. 2009). Recently, in an effort to synthesize the literature on different forms of the open innovation model, Dahlander and Gann (2010) proposed four types of openness. This typology was based on whether the openness is an inbound or an outbound process to innovation and whether the interactions involving the inbound or the outbound process to innovation are pecuniary or non-pecuniary. This categorization yielded, according to these authors, four types of openness: revealing, acquiring, selling, and sourcing. Conceptually, revealing "refers to how internal resources are revealed to the external environment" (Dahlander and Gann 2010, p. 703); acquiring «refers to how firms commercialize their inventions and technologies through selling or licensing out resources developed in other organizations» (Dahlander and Gann 2010, p. 704); selling "refers to acquiring input to the innovation process through the market place" (Dahlander and Gann 2010, p. 705) such as license-in and acquiring expertise from outside; finally, sourcing, according to Dahlander and Gann (2010, p. 704), "refers to how firms can use external sources of innovation" (ESI). In this paper, we are interested in the latest form of openness, which has been linked to the use of ESI (Laursen and Salter 2004; 2006; Leiponen and Helfat 2009; Chiang and Hung 2010; Lee et al. 2010). These authors have used two dimensions to characterize the concept of openness, namely, breadth and depth. In this study, our approach to open innovation is reflected by the openness of SMEs to their use of ESI.

A growing literature has linked the concept of openness to the use of ESI (Laursen and Salter 2004; 2006; Leiponen and Helfat 2009; Chiang and Hung 2010; Lee et al. 2010), because this way of opening-up the process of innovation is informal and does not necessarily require substantial investments (van der Vrand et al. 2009); it is more likely to gain more success among SMEs (van der Vrand et al. 2009). Adopting this view, we try to propose a classification of manufacturing SMEs based on their degree of breadth and depth. To our knowledge, only Keupp and Gassmann (2009) have proposed such a classification using a cluster analysis. In our study, we adopt the same approach to classify firms, but among SMEs in manufacturing industries, which was not the focus of Keupp and Gassmann's study (2009). It is a first explorative study addressing this question in the context of manufacturing SMEs. Moreover, trying to understand a firm's approach to the open innovation model, Lichtenthaler (2008), and Keupp and Gassmann (2009) have only investigated the role of some internal characteristics in the adoption of the open innovation model. In this study, using the cluster analysis results, we use a logit model to identify similarities and differences of the determinants between different clusters of SMEs. Answering this question can provide insights into the factors that enhance the openness of SMEs.

The rest of the paper is organized as follows. In section 2, we discuss issues related to the concept of openness and the classes of SMEs. Section 3 presents the determinants of different classes of SMEs. Next, we provide information about the data and descriptive statistics in section 4. In section 5, we discuss the results and then, in the final section of the paper, we conclude with a discussion of the implications of the results for SMEs and avenues for future research.

## SMEs' degree of openness

Innovation is about introducing new products, processes or services to market. In the case of SMEs, the debate on whether this class of firms is innovative or not is no longer an issue of disagreement between researchers. In fact, studies have shown that SMEs are as innovative as their larger counterparts. In fact, research by Acs and Audretsch (1987a; b; 1988) and Acs (1992) in the U.S. found that SMEs had an innovation rate (the number of innovations per employee) considerably higher than that achieved by larger firms. Also, Pavitt et al. (1987) in the U.K found a higher rate of patents per technical employee and output per dollar expended by smaller firms. However, when it comes to how firms, especially SMEs, deal with the process of innovation, different theories have tried to address this issue. In the past, firms drew heavily on their internal processes to develop innovations (Chesbrough 2003a; van de Vrande et al. 2009). Accordingly, firms pursued a closed approach to innovation (Lichtenthaler 2008). This way of conducting innovation reflects a strong and limited interaction of firms with their environment. Recently, the debate on innovation has evolved around the concept of open innovation. In this matter, Chesbrough (2003a) suggests that many innovative firms have shifted to an 'open innovation' model, using a wide range of external actors and sources to help them achieve and sustain innovation (Chesbrough 2003a; Laursen and Salter 2006; Ozman, 2011). Analyzed mainly in the context of large high-tech multinational firms (van de Vrande et al. 2009), open innovation literature has been expanded to be analyzed in the context of SMEs (Lichtenthaler 2008; van de Vrande et al. 2009; Lee et al. 2010). The use of a large spectrum of ESI to innovate has been proposed by many authors as a way to capture how open a firm is (Laursen and Salter 2006).

Recently, the use of ESI has been linked in the literature to the concept of openness (Laursen and Salter 2004; 2006). This concept has been used as one of the practices related to the open innovation model (Laursen and Salter 2006; Keupp and Gassmann 2009; van de Vrande et al. 2009). The openness of a firm is characterized by two dimensions which reflect the number of ESI used (breadth) and the intensity of use of these ESI (depth).

The first dimension of openness is based on the breadth of use of ESI. Laursen and Salter (2004; 2006) defined breadth as the number of external sources or search channels that firms rely upon in their innovative activities. Thus, the more the firm uses ESI, the more it is seen to have a higher breadth and to be more open. In fact, innovation success in firms has been associated with the use of a large or a wide range of ESI (Schumpeter 1942; Rosenberg, 1982; von Hippel 1988; Freeman and Soete 1997; Boomer and Jalajas 2004; Tidd et al. 2005; von Hippel 2005). According to Burt (1992), access to a larger variety of sources of information provides benefits that are additive rather than redundant, which may encourage firms to use a large spectrum of ESI. This is consistent with the view that ESI don't provide the same kind of knowledge necessary to carry out innovation processes; instead, firms may benefit from complementarities and synergies among knowledge sources (Leiponen and Helfat 2009). For example, users provide feedback regarding problems with, and desired modifications of, existing products (von Hippel 1976). Suppliers provide knowledge regarding inputs, including raw materials, plant and equipment, product components, and subsystems (Leiponen and Helfat 2009).

On the other hand, firms, especially SMEs, may choose to go through some ESI given the complementarity that could exist between these sources (Idrissi et al. 2010), or may not choose to use certain ESI because drawing knowledge from these ESI may be labor-intensive, and requires considerable managerial and financial resources, or may need considerable effort and time to build up an understanding of the norms, habits and routines within different external knowledge sources (Dasgupta and David 1994; Brown and Duguid 2001; Laursen and Salter 2006). Given the context of SMEs, which is characterized by limited resources (Rothwell and Zegveld 1982; Keogh and Evans 1998; Storey 1994; Major and Cordey-Hayes 2003; OCDE, 2005), we therefore believe that these firms will limit their degree of openness.

The second dimension of openness is based on the depth of use of ESI. This dimension has been defined as the extent to which firms draw deeply from different external sources or search channels (Laursen and Salter 2006). Intensively sourcing ideas from a given knowledge source requires that firms maintain strong and frequent contacts with that knowledge source (Leana and Buren 1999; Chiang and Hung 2010) because information is embedded in networks and is derived from networks of relationships (Acs 2000).

The literature on social networks and social capital suggests that strong and frequent contacts with a particular knowledge source can facilitate the transfer of in-depth and fine-grained knowledge from that channel and induces well-defined solutions (Leana and Buren 1999; Dyer and Nobeoka 2000;Chiang and Hung 2010). As stated by Katila and Ahuja (2002), the more frequently a firm has used knowledge, the more deeply it knows it. Collaboration is one way of marinating this frequent contact with some ESI and it is considered to be important for innovation in SMEs because it fills their deficit of resources, skills and knowledge (Rothwell 1991), and overcomes their internal deficiencies (Romijn and Albaladejo 2002). These networks allow to create a climate of confidence and to develop social capital among the actors involved. On the other hand, although collaboration may enhance innovation, especially for SMEs, it certainly brings with it greater risks of opportunistic behavior (Zeng et al. 2010). This is the case where SMEs, especially new ones, are constrained to limit their interactions with their external environment. For example, interactions with external sources within the communities of practice, such as consultants, may leak information about the new venture to incumbents (Brown and Duguid 2000).

Also, according to the attention-based theory of the firm, firms «need to concentrate their energy, efforts, and mindfulness on a limited number of issues» in order to achieve a sustained strategic performance (Ocasio 1997, p. 203). Therefore, firms will have problems maintaining strong and frequent contacts with a large number of external sources to locate new ideas for innovation (Chiang and Hung 2010). These arguments suggest that firms, especially SMEs, can only keep up strong and frequents contacts with a restricted and limited number of ESI.

The arguments developed above suggest that firms, especially SMEs, may differ both in the number of ESI they use for their innovative activities as well as in the intensity of use of each of these ESI, consequently their openness. In fact, as stated by Dahlander and Gann (2010), and Chesbrough (2003a) before, "the idea behind openness therefore needs to be placed on a continuum, ranging from closed to open, covering varying degrees of openness". This interesting avenue of investigation suggests theoretically subdividing the openness of SMEs, as defined in this paper, into four classes, depending on their degree of breadth and depth to ESI: Closed SMEs, Interactive SMEs, User SMEs, and Open SMEs.

• Closed SMEs – Class 1- include SMEs that are characterized by the use and interaction with a limited number of ESI. These SMEs still relay on a closed innovation model relying mostly on their internal information to innovate. Although SMEs rarely innovate alone, some of them still relay on their internal capabilities to introduce new products and processes (Albereijo et al., 2009).

• Interactive SMEs - Class 2 - include SMEs that are characterized by the use of limited ESI, but interact mostly with these ESI. In fact, most SMEs use ESI such as suppliers and clients, and interact intensively with these external sources of knowledge.

• User SMEs - Class 3 - include SMEs that are characterized by the use of a large number of ESI but they have limited interactions with these ESI. These SMEs, as Lichtenthaler (2008) stated, have opened their innovation process in one direction. In our case, SMEs are open to use a large number of ESI; however, they are still reluctant to intensively interact with these sources.

• Open SMEs - Class 4 - include SMEs that are characterized by the use of and interaction with a large number of ESI. These SMEs have adopted, according to Chesbrough (2003a), and Laursen and Salter (2004; 2006) an open approach to innovation.

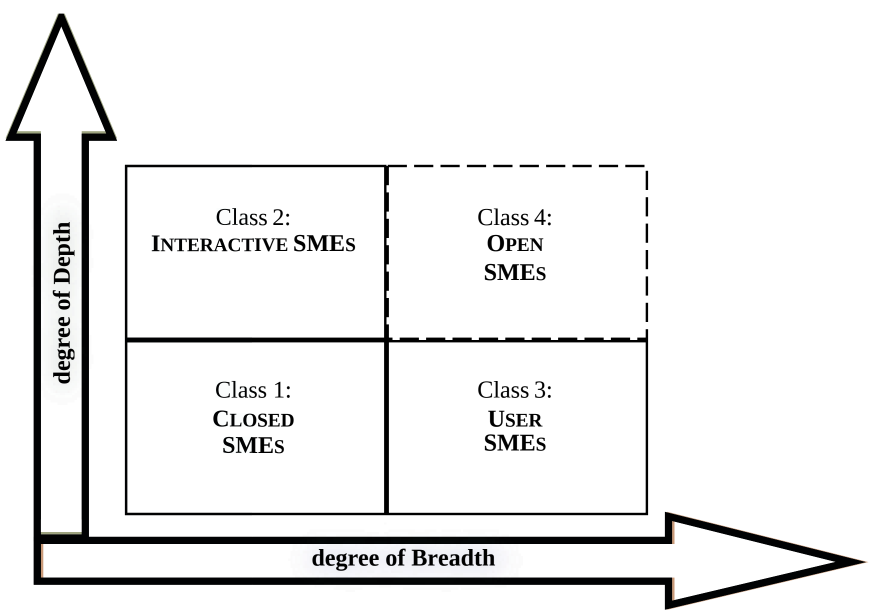


Figure 1. Classes of SMEs based on the dimensions of openness

## Independent variables of SMEs classes

To address the determinants of the adoption of an open approach to innovation, most studies, even if they are scanty, relied on internal factors to explain the adoption of the open innovation model (Lichtenthaler 2008; Keupp and Gassmann 2009). This way of studying firms' approach to open innovation should be analyzed in more detail (Lichtenthaler 2008). Accordingly, this study tries to fill this gap by considering both internal and external context characteristics that could contribute more in explaining a firm's approach to open innovation, as suggested by Huizingh (2011).

## Internal context characteristics

The first variable related to the group of internal factors is linked to the capability of firms to innovate. It is well known that this capability is tied to firms' capacity to recognize the value of new external information, assimilate it, and apply it to commercial ends (Cohen and Levinthal 1990). This capability is related to the concept of absorptive capacity. Since the firm's breadth and depth of the use of external sources of innovation requires extensive effort and time to build up an understanding of the norms, habits and routines within different external knowledge sources (Laursen and Salter 2006), it follows that firms are in need of an absorptive capacity in order to be able to process external information and knowledge. The concept of absorptive capacity has been measured by different indicators such as R&D spending (Lane and Lubatkin 1998; Mowery et al. 1996; Cassiman and Veugelers 2002), skills and human capital (Zahra and George 2002; Zahra and Nielsen 2002; Spanos and Voudouris 2009). Recently, Kostopoulos et al. (in press) used an integrative approach to measure absorptive capacity. In this study, to reflect the presence of absorptive capacity, we consider both the level of skills inside SMEs as reflected by the presence of engineers, technicians, and R&D employees.

The second variable is internal impediments to innovation. The rationale behind this consideration is motivated by the existence of rigidities to innovation, including resistance to change, that exist in each firm (Keupp and Gassmann 2009). These rigidities do not favour innovation, as stated by Blumentritt and Danis (2006). In this sense, Chesbrough (2003b) suggested that firms that are "too focused internally" are prone to miss a number of opportunities that are outside their organizational frontiers because of these rigidities. Accordingly, firms that may face these barriers to innovation could open up their innovation process in order to bypass the effect of these impediments. In fact, Keupp and Gassmann (2009) have suggested that firms that experience such barriers will open up their innovation process compared to firms that do not face these impediments.

Many studies have investigated the effects of different impediments on the innovation process of the firm or the adoption of new technologies (Baldwin and Lin 2002; Galia and Legros 2004). Accordingly, many types of impediments have been grouped inside categories of obstacles. For example, Galia and Legros (2004) have studied complementarities between various groups of impediments, such as economic risk, lack of skilled personnel, innovation costs, lack of customer responsiveness, lack of information on technologies and organizational rigidities. For their part, Baldwin and Lin (2002) have studied the impediments related to the adoption of advanced technology by Canadian firms. They especially studied impediments related to the cost of capital, the cost of technology acquisition, the cost of related equipment acquisition, the cost of related software development, and increased maintenance expenses. Another way to study these impediments is to distinguish between internal and external impediments (Radas and Bozic 2009). Keupp and Gassmann (2009) have only investigated the effect of internal impediments on the approach to open innovation. In this paper, we try to investigate both internal impediments such as those related to humain resources, and external impediments such as those related to cooperation with other firms or research centers.

Finally, recent studies showed that SMEs are starting to adopt an open innovation approach ( van de Vrande et al. 2009; Lee et al. 2010). What we can draw from these studies is that size may influence the adoption of open innovation. For example, van der Vrande et al. (2009), analyzing the adoption of open innovation in manufacturing and services in Deutschland SMEs, found that this approach to innovation is more applied by medium-sized firms. Their results are in line with the survey conducted by Lichtenthaler (2008) among 154 large and medium-sized manufacturing firms. This author has found that firm size has a strong positive impact on the degree of openness. Especially, he found that medium-sized and large manufacturing firms embrace open innovation practices. In the same vein, Keupp and Gassmann (2009) have demonstrated that firm size has a positive and significant effect on the openness of firms. Following this line of research, we want to capture the effect of size on the degree of openness, as defined in this study, in manufacturing SMEs.

## External context characteristics

The first variables related to this group can be derived from the role of proximity of suppliers and clients in the innovation process of firms. The literature on innovation has suggested that regional environments and proximity are vital to the innovation process (Maskell and Malmberg 1999). In fact, proximity is important to access markets, suppliers, and so on. Indeed, based on the investigation of the innovation activities and networking of 53 SMEs, Doloreux (2004) found that the prime location factors for these SMEs is proximity and access to information provided by leading customers. In this study, we try to investigate the impact of three types of proximities, namely, regional, national and international proximities, on the emergence of the four classes of the degree of openness.

The second variable related to this group deals with external impediments such as impediments related to external support services (e.g., lack of information on technologies and lack of information on markets). As discussed previously, the presence of such external impediments to innovation may act as motivating factors to push SMEs toward opening up their innovative activities. In fact, as suggested by Veugelers and Cassiman (1999), the presence of such impediments does not deter firms from innovating, but on the contrary, it enhances their awareness to the presence of such obstacles.

Finally, industrial differences may have an impact toward open innovation (van de Vrande et al. 2009). For example, Lichtenthaler (2008) has found an insignificant effect of industry differences. While he stated that this finding is unexpected, and the degree of openness seems to be mainly determined by the individual strategic choice of a company rather than by industry characteristics, Keupp and Gassmann (2009) have found that industrial differences matter in the degree of openness. Precisely, they found that firms in high-tech industries tend to have a higher breadth, whereas firms from the chemical and rubber and plastic industry are characterized by a significant higher depth.

In this study, we use the recent industrial classification proposed by Legler and Frietsch (2007). These authors have proposed an industry classification which is based on the average intensity of R&D in a given sector. Thus, the sector is technologically qualified higher if R&D spending is above 7%, medium if R&D spending is between 2.5% and 7%, and low if R&D spending is below 2.5%.

These two main groups of independent variables may or may not play a significant role in the emergence of specific SMEs classes. This discussion leads us to suggest the framework in Figure 2. To analyze how these variables can influence the emergence of different clusters, a logistic regression was carried out, using data from a study of 451 manufacturing SMEs.

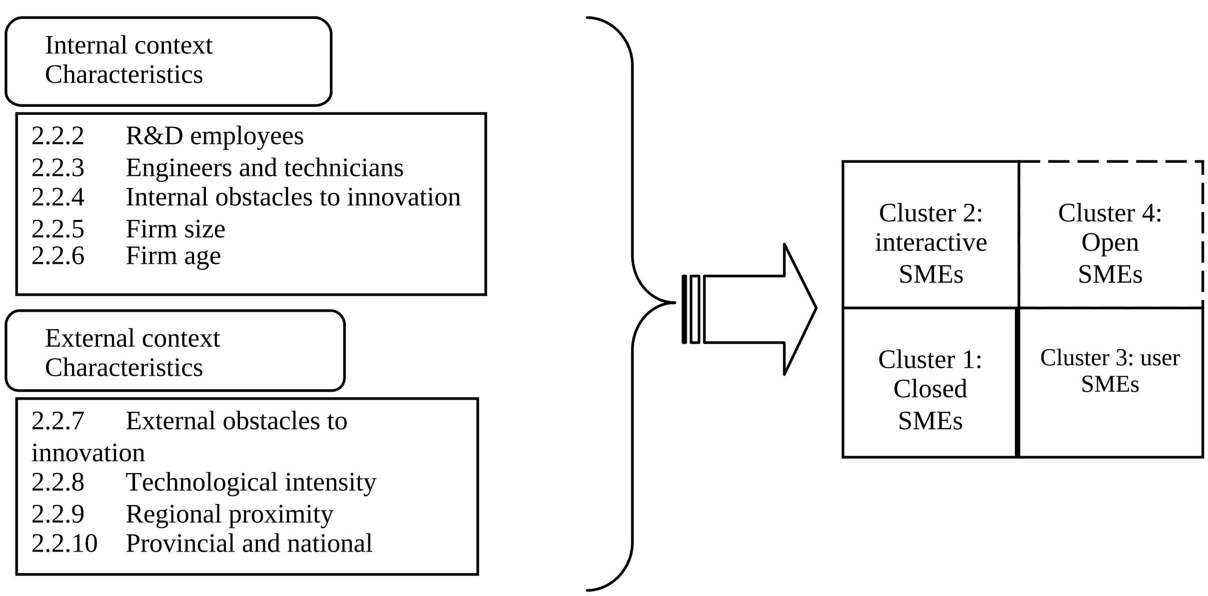


Figure 2. Proposed framework

## Methods

The method used in this paper is presented in three sections. We begin by describing the data used to answer our research questions. Then, we present our dependent and independent variables. Finally, we present in this section our analytical plan which describes the cluster analysis, analytical model and regression results.

## Data

The data used in this study have been collected by a private firm, which conducted computer-assisted telephone interviews from October 09 to December 09, 2003. With a focus on the innovation behaviour of firms, the survey questionnaire derives from the methodology of the Oslo Manual (1997) and is adapted from the Community Innovation Surveys (CIS) and Statistics Canada surveys on innovation. The survey was administered to the whole population of the manufacturing firms operating in manufacturing Canadian region. The population included 1214 firms. Out of this effective population, 332 firms were excluded from the population of the study for different reasons. In the end, the resulting sample consists of 615 firms for a return rate of 69.7%.

In this paper, SMEs are defined as firms where the number of employees is 500 and less. This definition is based on the American Small Business Administration, which is the most prevalent in the literature (Wolff and Pett 2006). This consideration lowered the population under study to 603 firms. Also, in this study, we look at the subset of firms that are innovative, that is, firms that have developed or improved their products or processes during the past three years. This subset amounts to 74.5% (451 firms) of the respondents.

## Data coding

### Dependent variables

There are four dependent variables considered in this study; they describe the degree of openness of SMEs. To obtain the two dimensions characterizing the concept of openness, we draw on the operationalization proposed first by Laursen and Salter (2004; 2006). Hence, the first dimension is termed breadth and is constructed as a combination of the 20 ESI for innovation listed in Table 1. As a starting point, each of the 20 ESI is coded as a binary variable, 0 being no use and 1 being use of the given ESI. Subsequently, the 20 sources are simply added up so that each firm gets a 0 when no ESI is used, while the firm gets the value of 20, when all ESI are used. In other words, it is assumed that SMEs that use higher numbers of sources are more open regarding the dimension of breadth. The dimension obtained is a relatively simple construct, it has a high degree of internal consistency (Cronbach's alpha coefficient = 0.92). As for breadth, the dimension of depth is constructed using the same 20 ESI as those used in constructing breadth. In this case, each of the 20 ESI is coded 1 when the SMEs in question report that they use the source to a high degree and 0 in the case of no, low, or medium use of the given source. As in the case of breadth, the 20 ESI are subsequently added up so that each firm gets a score of 0 when no ESI is used to a high degree, while the SMEs gets the value of 20 when all ESI are used to a high degree (Cronbach's alpha coefficient = 0.82). Again here, it is assumed that SMEs that use higher numbers of sources are more open regarding the dimension of depth.

Furthermore, we used probability plots to determine whether the distribution of each of the two dimensions included in the analysis matches a normal distribution. More specifically, we used the Q–Q plots procedure, which plots the quintiles of a variable's distribution against the quintiles of a normal distribution. In doing so, we found that all dimensions seem to match a normal distribution.

| External sources of information used to create the two dimensions related to the degree of openness | |
|---|---|
| Market sources | 2.2.2 Suppliers<br>2.2.3 Clients<br>2.2.4 Competitors<br>**2.2.5** Related firms in your corporate group<br>**2.2.6** Consultancy firms |
| Research sources | 2.2.7 Universities<br>2.2.8 Community Colleges<br>2.2.9 Technology transfer centers<br>2.2.10 Internet and computer database<br>2.2.11 IP documents |
| Generally available information sources | 2.2.12 Trade fairs and exhibitions<br>2.2.13 Professional conferences, meetings<br>2.2.14 Professional networks<br>2.2.15 Government support agencies |
| Regional sources | 2.2.16 Provincial agencies and research laboratories (CRIQ)<br>2.2.17 Federal government agencies and research laboratories (CNRC/PARI)<br>2.2.18 SITTE/CIMIC<br>2.2.19 CLD<br>2.2.20 SADC<br>2.2.21 Action PME |
| Breadth | SMEs were asked regarding the importance of the role played during the last three years by the following four external sources of information needed for the development of innovations. The firms were asked to rate the importance of these four sources of information on a 5-point scale ranging from 1 (low importance) to 5 (high importance). Each of the 20 ESI used by SMEs in their innovative activities are coded as a binary variable, 0 when no use of ESI and 1 being use of the given ESI. SMEs get the value of 20, when all ESI are used or 0 when no ESI are used. |
| Median | 11.00 |
| Mean | 11.77 |
| Std | 5.85 |
| Minimum | 0 |
| Maximum | 20.00 |
| ChronbachÕs Alpha | 0.92 |
| Depth | SMEs were asked regarding the importance of the role played during the last three years by the following four external sources of information needed for the development of innovations. The firms were asked to rate the importance of these four sources of information on a 5-point scale ranging from 1 (low importance) to 5 (high importance). Each of the 20 ESI are coded with 1 when the SME report that it uses the source to a high degree and 0 in the case of no, low, or medium use of the given source. SMEs get the value of 20, when all ESI are used or 0 when no ESI are used. |
| Median | 1.00 |
| Mean | 2.27 |
| Std | 2.92 |
| Minimum | 0 |
| Maximum | 20.00 |
| ChronbachÕs Alpha | 0.82 |

Table 1. Operational Definitions of the Four Clusters related to the degree of openness: Clusters Are Built Using Two Dimensions

## Independent variables

According to the framework proposed in this study, independent variables are combined in two broad groups: first, internal context characteristics (e.g., internal obstacles to innovation, R&D employees, engineers and technicians, firm size, and firm age) and second, external context characteristics (e.g., external obstacles to innovation, regional proximity, national proximity, world proximity, and technology intensity). In the following section, we respectively introduce measures related to internal context characteristics variables and then measures related to external context characteristics variables.

For internal impediments to innovation, each innovative firm was asked to identify the obstacles that slowed down or caused problems when developing new or significantly improved products or processes on a 5-point Likert scale. Table 2 provides results of a principal components factors analysis (PCFA) and internal reliability coefficients (Cronbach's Alpha) for this explanatory variable, with a multiple-item scale. These results indicate that all the multiple-item scale variables satisfy the unidimensionality criterion. Moreover, the values of Cronbach's Alpha show that the items forming the index are reliable. Other internal context variables included in the model are engineers and technicians, R&D employees, firm size, and firm age.

| Internal obstacles to innovation | |
|---|---|
| Items: | Factor loadings |
| Item 1: Lack of skilled personnel; | 0.801 |
| Item 2: Lack of internally qualified personnel; | 0.855 |
| Item 3: Difficulties in training works in the required time; | 0.808 |
| Item 4: Lack of information on technology. | 0.625 |
| Explained variance | 60.37% |
| Eigenvalue | 2.41 |
| ChronbachÕs Alpha | 0.77 |

Table 2. Test of Constructs' Unidimensionality and Internal Reliability Coefficients (Chronbach's Alpha) for Internal Context Variables Including Multiple-Item Scale

Furthermore, we used the probability plots to determine whether the distribution of each of the internal continuous variables included in the model matches a normal distribution. More specifically, we used the Q–Q plots procedure, which plots the quintiles of a variable's distribution against the quintiles of a normal distribution. In doing so, we found that variables related to internal obstacles to innovation seem to match a normal distribution. Also, the observations related to engineers and technicians, R&D employees, firm size, and firm age variables are not clustered around a straight line corresponding to normal distributions. We used a logarithmic transformation for firm size, firm age, engineers and technicians, and R&D employees; the probability plots for the transformed values indicated that the transformed variables did not significantly differ from a normal distribution.

For external impediments to innovation, each innovative firm was asked to identify the obstacles that slowed down or caused problems when developing new or significantly improved products or processes on a 5-point Likert scale. Table 3 provides results of a principal components factors analysis (PCFA) and internal reliability coefficients (Cronbach's Alpha) for this explanatory variable, with a multiple-item scale. These results indicate that all the multiple-item scale variables satisfy the unidimensionality criterion. Moreover, the values of Cronbach's Alpha show that the items forming the index are reliable.

Also, the external variables related to geographical proximity are based on multiple-item scales. Table 3 provides results of a principal components factors analysis (PCFA) and internal reliability coefficients (Cronbach's Alpha) for this explanatory variable, with a multiple-item scale. These results indicate that all the multiple-item scale variables satisfy the unidimensionality criterion. Moreover, the values of Cronbach's Alpha show that the items forming the index are reliable.

| | |
|---|---|
| **External obstacles to innovation** | |
| Items: | Factor loadings |
| Item 1: Lack of cooperation with other firms | 0.613 |
| Item 2: Lack of cooperation with public research centers | 0.874 |
| Item 3: Lack of cooperation with universities, colleges, and technical centers of formation | 0.862 |
| Item 4: Lack of cooperation with regional research centers (CRIQ) | 0.785 |
| Item 5: Lack of cooperation with development | 0.824 |
| Explained variance | 63.52% |
| Eigenvalue | 3.17 |
| ChronbachÕs Alpha | 0.84 |
| **Proximity within 100 km** | |
| Items: | Factor loadings |
| Item 1: Clients located within 100 km of your firm | 0.873 |
| Item 2: Suppliers located within 100 km of your firm | 0.873 |
| Explained variance | 76.28% |
| Eigenvalue | 1.53 |
| ChronbachÕs Alpha | 0.689 |
| **Proximity elsewhere in Canada** | |
| Items: | Factor loadings |
| Item 1: Clients located elsewhere in Quebec | 0.804 |
| Item 2: Suppliers located elsewhere in Quebec | 0.766 |
| Item 3: Clients located elsewhere Canada | 0.837 |
| Item 4: Suppliers located elsewhere Canada | 0.836 |
| Explained variance | 65.82% |
| Eigenvalue | 2.63 |
| ChronbachÕs Alpha | 0.825 |
| **Proximity elsewhere in the World** | |
| Items: | Factor loadings |
| Item 1: Clients located in the U.S.A. | 0.823 |
| Item 2: Suppliers located in the U.S.A. | 0.830 |
| Item 3: Clients located elsewhere in the world | 0.755 |
| Item 4: Suppliers located elsewhere in the world | 0.814 |
| Explained variance | 64.97% |
| Eigenvalue | 2.59 |
| ChronbachÕs Alpha | 0.817 |

Table 3. Test of Constructs' Unidimensionality and Internal Reliability Coefficients (Chronbach's Alpha) for External Context Variables Including Multiple-Item Scale

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For external context characteristics variables, we found that variables related to regional proximity and national proximity seem to match a normal distribution. Nevertheless, the observations linked to external obstacles to innovation and world proximity variables are not clustered around a straight line corresponding to normal distributions. In this case, we used a logarithmic transformation for the world proximity variable and a square root transformation for the external obstacles to innovation variable. The probability plots for the transformed values indicated that the transformed variables did not significantly differ from a normal distribution.

Table 4 provides an overview of the operationalization of the independent variables. As we presented earlier, we conducted a principal components factor analysis (PCFA) and tested the reliability for all independent variable indices based on multiple-item scales, namely, regional proximity (REG_PROX), national proximity (NA_PROX), world proximity (WORLD_PROX), internal obstacles to innovation (OBS_INT), and external obstacles to innovation (OBS_EXT).

| ***Independent variables*** | Measure | Sub-items | Mean (SD) | Percentage (Numbre) | CronbachÕs alpha |
|---|---|---|---|---|---|
| ***Continuous variables*** | | | | | |
| Engineers and technicians [ING&TECH] | Measured as the percentage of the number of technicians and engineers to total number of employees. This variable was matched with the normal distribution using logarithmic transformation. | | 3.40 (6.93) | | |
| R&D employees [PER&D] | Measured as the percentage of the number of R&D employees to total number of employees. This variable was matched with the normal distribution using logarithmic transformation. | | 2.14 (3.04) | | |
| Regional proximity [REG_PROX] | Measured as a weighted index on a Likert scale of the importance of clients and suppliers on a 5-point scale ranging from 1 (low importance) to 5 (high importance) regarding the importance of the role played during the last three years by clients and suppliers located regionally for the development of innovations. | 2.2.2 Clients located within 100 km of your firms<br>2.2.3 Suppliers located within 100 km of your firms | 2.54 (1.04) | | 0.689 |
| Provincial and National proximity [NA_PROX] | Measured as a weighted index on a Likert scale of the importance of clients and suppliers on a 5-point scale ranging from 1 (low importance) to 5 (high importance) regarding the importance of the role played during the last three years by clients and suppliers located at provincial and national level for the development of innovations. | 2.2.4 Clients located elsewhere in Quebec<br>2.2.5 Suppliers located elsewhere in Quebec<br>2.2.6 Clients located elsewhere in Canada<br>2.2.7 Suppliers located elsewhere in Canada | 2.28 (30.96) . | | 0.83 |

| | | | | |
|---|---|---|---|---|
| World proximity [WORLD_PROX] | Measured as a weighted index on a Likert scale of the importance of clients and suppliers on a 5-point scale ranging from 1 (low importance) to 5 (high importance) regarding the importance of the role played during the last three years by clients and suppliers located elsewhere in the world for the development of innovations | 2.2.8 Clients located in U.S.A.<br>2.2.9 Suppliers located elsewhere in U.S.A.<br>2.2.10 Clients located elsewhere in the world<br>2.2.11 Suppliers located elsewhere in the world. | 1.83 (0.93) | 0.82 |
| Internal obstacles to innovation [OBSTINT] | Measured as a weighted index on a Likert scale of relevance of these obstacles regarding the development of innovations on a 5-point scale ranging from 1 (no delay) to 5 (rendered impossible). | 2.2.12 Lack of skilled personnel;<br>2.2.13 Lack of internally qualified personnel<br>2.2.14 Difficulties in training works in the right time;<br>2.2.15 Lack of information on technology. | 1.77 (0.895) | 0.77 |
| External obstacles to innovation [OBST_EXT] | Measured as a weighted index on a Likert scale of relevance of these obstacles regarding the development of innovations on a 5-point scale ranging from 1 (no delay) to 5 (rendered impossible). | 2.2.16 Lack of cooperation with other firms;<br>2.2.17 Lack of cooperation with public research centers;<br>2.2.18 Lack of cooperation with universities, colleges, and technical centers of formation;<br>2.2.19 Lack of cooperation with | 1.16 (0.72) | 0.84 |
| Age [AGE] | Measured as the number of years from which the firm was established to date. This variable was matched with the normal distribution using logarithmic transformation. | | 22.5 (18.07) | |
| Size [SIZE] | Measured as the number of employees in the firms. This variable was matched with the normal distribution using logarithmic transformation. | | 41.3 (70.1) | |
| ***Categorial variables*** | | | | |
| Technological intensiveness [TECH_INT] | Technological intensiveness was measured using three binary variables:<br>1. LOW_TECH is a binary variable coded 1 if the R&D expenditures of the firms are below 2.5%, and coded 0 otherwise;<br>2. MED_TECH, is a binary variable coded 1 if the R&D expenditures of the firms are between 2.5% and 7%, and coded 1 otherwise;<br>3. HIGH_TECH, is a binary variable coded 1 if the R&D expenditures of the firms are more than 7.5%, and coded 1 otherwise. | | 68.1% | |

Table 4. Definitions of Independent variables

As recommended by Field (2009), before running the binary logit models, we checked for assumptions related to the logistic regression, namely, linearity between dependent variables and independent variables, independence of errors, and multicollinearity between independent variables. We found that all the assumptions were respected, which suggests that the binary logit models could be run in our case.

Finally, the correlation matrix relating the independent variables used in the regression models (Table 5) indicates that the highest correlation coefficient is between regional proximity (REG-PROX) and world proximity (WOR_PROX) variables. This correlation coefficient is equal to .514. The second column of Table 5 also reports tolerance statistic values for all continuous predictors used in the regression models. Tolerance statistic values, which are the reciprocal of Variance Inflation Factors (VIF), indicate whether a predictor has a strong linear relationship with the other predictors. It can be seen that all the tolerance statistic values are much higher than .2. This ensures that there is no multicollinearity concern (Menard 1995; Field 2009).

| | Tolerance statistics | WORLD_ PROX | NA_ PROX | REG_ PROX | OBST_INT | OBST_EXT | ING&TECH | PER&D | SIZE | AGE |
|---|---|---|---|---|---|---|---|---|---|---|
| WORLD_PROX | 0.408 | 1 | 0.514 | 0.206 | 0.106 | 0.049 | 0.062 | -0.134 | 0.455 | 0.171 |
| PR&NA_PROX | 0.752 | | 1 | 0.402 | 0.093 | 0.039 | 0.115 | -0.051 | 0.278 | 0.107 |
| REG_PROX | 0.400 | | | 1 | 0.021 | 0.006 | 0.004 | 0.083 | - 0.147 | - 0.107 |
| OBST_INT | 0.885 | | | | 1 | 0.258 | 0.091 | 0.011 | 0.210 | 0.070 |
| OBST_EXT | 0.922 | | | | | 1 | 0.008 | 0.032 | - 0.008 | 0.044 |
| ING&TECH | 0.725 | | | | | | 1 | 0.439 | 0.007 | - 0.179 |
| PER&D | 0.652 | | | | | | | 1 | - 0.344 | - 0.257 |
| SIZE | 0.788 | | | | | | | | 1 | 0.424 |
| AGE | 0.557 | | | | | | | | | 1 |

Table 5. Correlations and Tolerance statistics Between Explanatory Variables

## Analytical plan

Our analytical plan is carried out in two stages. First, we use a cluster analysis in order to group SMEs into homogeneous categories with respect to two dimensions related to the concept of openness, namely, breadth and depth. Second, we use a multinomial regression model and a binary logit model to establish the determinants of the various classes of SMEs obtained from cluster analysis and ascertain how the most favourable classes compare to the others.

## Cluster analysis

There are three general classes of methods of classifying objects in the social and behavioral sciences: univariate, bivariate, and multivariate methods (Robins et al. 1998). In the first method of classifying objects, the sample is divided into subgroups based on ad-hoc cut off scores. Thus, taking a median split is a typical classification method used in psychology and in social sciences too (see Amara and Landry 2005). According to Mandara (2003), this method is purely for convenience, and can never be considered as a reliable means of typology development. In the second method of classifying objects, two dimensions are crossed to form quadrants, and objects falling into the formed quadrants are considered to be members of a type. This method is based on an arbitrary cut of scores (Mandara 2003), suggesting that objects may be forced into groups. Thus, multivariate analyses are proven to be an empirical approach to the classification of objects. The third method of classifying objects begins by measuring each case on a set of relevant variables in a traditional-centered way (Mandara 2003). Then, the data matrix is transposed so that each case's scores are represented in a column and each variable's scores are in a row. Thus the unit of analysis shifts from variables to cases. Then, the profile or pattern of scores is assessed and cases with similar patterns are classified into types. The number of types and each type's prototypical pattern of behaviour are not known beforehand (Mandara 2003).

There are many multivariate methods of classification such as Cluster Analysis, Discriminant Analysis, Automatic Interaction Detection (Punj and Stewart 1983), Multidimensional Scaling (Borg and Groenen 1997), Configural Frequency Analysis (von Eye 2002), and Latent Class Analysis (Clogg 1995). While discriminating analysis and automatic interaction detection methods require to know group membership for the cases used to derive the classification rule, cluster analysis makes no prior assumptions about important differences within a population (Punj and Stewart 1983). Also, given our subject of study, that is to say the degree of openness of SMEs, the nature of variables which are continuous ones, and the number of variables of the study, the analysis method used to derive a typology is the cluster analysis method.

The cluster analysis is a statistical method of classification that regroups variables or observations into homogeneous categories. In this study, we are interested in classifying manufacturing SMEs into groups that are homogeneous in their degree of openness. Similar approaches were developed by different authors (Lichtenthaler 2008; Keupp and Gassmann 2009; van de Vrande et al. 2009). In our study, we adopt the same approach used by Keupp and Gassman (2009), but using 20 ESI instead of 13, and proposing a more complete and comprehensive cluster analysis than they did. Although cluster analysis has become a common tool for marketing research (Punj and Stewart 1983) and innovation studies, its use to study open innovation classes of firms, especially SMEs, is still scanty.

In this study, cluster analysis (Punj and Stewart 1983; Aldenderfer and Blashfield 1984) was used to classify SMEs into groups based on their degree of openness as measured by breadth and depth. Specifically, breadth and depth scores for each of the 451 SMEs were computed and provided the basis for a two-step clustering procedure (Punj and Stewart 1983). Because cluster analysis is sensitive to outliers (de Jong and Marsili 2006), we first assessed the outlying observations obtained from standardized variables. Values exceeding +3.0 and below -3.0 are potential outliers (Singh 1990). Upon examination, it was determined that none of the observations could be classified as potential outliers. Thus it appeared safe to conduct cluster analysis with the entire data (Singh 1990).

In the cluster analysis, we combined hierarchical and non-hierarchical techniques. According to Milligan and Sokol (1980), and Punj and Stewart (1983), this helps to obtain more stable and robust taxonomies. Ward's (1963) hierarchical clustering method with squared Euclidean distances was used independently with each sample to obtain an initial description of potential clusters within the data. This initial analysis suggested four and five clusters, as proposed by the dendogram (Lichtenthaler 2008; Keupp and Gassmann 2009) and elbow method (Ogawa 1987). A non-hierarchical k-means clustering procedure (MacQueen 1967) was then used to develop four and five-cluster solutions based on the earlier hierarchical clustering. As suggested by McIntyre and Blashfield (1980), cross-validation is recommended here. This procedure is carried out, first, on one half of the observations available for analysis. Once a statistically significant clustering solution has been identified, centroids describing the clusters are obtained. Objects in the holdout data set are then assigned to one of the identified clusters on the basis of the smallest Euclidean distance to a cluster centroid vector. The degree of agreement between the nearest-centroid assignments of the holdout sample and the results of a cluster analysis of the holdout sample are an indication of the stability of the solution. This cross-validation procedure was carried out, in our case, for the four and five-cluster solutions respectively. To assess which solution was most stable, we computed kappa, the chance corrected coefficient of agreement (Singh 1990), between each initial and final solution. The four-cluster solution appeared to be optimal (k =0.89, while k =0.85 for the other solution). The four-cluster solution obtained in this study and the cluster description are shown in Table 6.

| Dimension of the degree of openness | Cluster 1 (n=30) | Cluster 2 (n=111) | Cluster 3 (n=181) | Cluster 4 (n=129) |
|---|---|---|---|---|
| Breadth | 1.03 | 2.12 | 2.50 | 2.83 |
| Depth | 0.09 | 1.00 | 0.22 | 1.83 |

Table 6. Clusters description

Based on the relevant cluster means associated with the two dimensions breadth and depth, the four classes of the degree of openness of SMEs are:

• Closed SMEs (6.7% of SMEs): SMEs in this cluster have both a low degree of breadth and depth.
• Interactive SMEs (24.6% of SMEs): SMEs in this cluster have a high degree of depth and a low degree of breadth.
• User SMEs (40.1% of SMEs): SMEs in this cluster have a high degree of breadth and a low degree of depth.
• Open SMEs (28.6% of SMEs): SMEs in this cluster have both a high degree of breadth and depth.

As we can see from our results, open SMEs represent more than a quarter of the sample of SMEs. However, Keupp and Gassmann (2009) have found less than 1% of firms that are open. Also, using technology exploitation and exploration as dimension of the openness of firms Lichtenthaler (2008) found a small amount of firms that are open. These differences is due to the use of different variables to define the openness of the firms (Lichtenthaler, 2008), the use of different clustering techniques when using the same definition of openness (Keupp and Gassman, 2009), and finally, in this study, we used only SMEs that are innovative and consequently they are more open to the use of ESI.

To check for validity of cluster solutions, we tested variables used to develop the four-cluster solutions. As suggested by Hair et al. (1998), one should find significant differences between the variables used to develop the clusters. Kruskal–Wallis tests confirmed this for the two variables (Table 7). In fact, results in Table 7 indicate which class has the highest degree of openness, namely, the cluster with the highest mean rank. In this case, cluster 4 has the highest degree of openness and cluster 1 has the lowest degree of openness.

Until now, the cluster analysis allowed to identify empirically four homogeneous groups of SMEs based on their degree of openness. In the following section, the four-cluster solutions will be used as our dependent variables to analyze the likelihood that SMEs would have a high degree of openness rather than a low degree of openness.

| Dimension of the degree of openness | Cluster 1 (n= 30) | Cluster 2 (n = 111) | Cluster 3 (n =181) | Cluster 4 (n = 129) | KruskalÐWallis $\chi^2$ (df =3) |
|---|---|---|---|---|---|
| Breadth | 24 | 148 | 231 | 331 | 196.48*** |
| Depth | 107 | 254 | 124 | 371 | 318.79*** |

Table 7. Incidence of the degree of openness across the four clusters

## Regression models

Five situations were considered relevant in our investigation aiming to identify the factors which would increase the likelihood that SMEs would have a high degree of openness rather than a low degree of openness: 1) a cluster of open SMEs rather than a cluster of closed SMEs; 2) a cluster of open SMEs rather than a cluster of interactive SMEs; 3) a cluster of open SMEs rather than a cluster of user SMEs; 4) a cluster of interactive SMEs rather than a cluster of closed SMEs; and 5) a cluster of user SMEs rather than a cluster of closed SMEs. A multinomial logit regression was estimated to ascertain the first three situations, while two bivariate logit regressions were estimated to identify the factors increasing the likelihood that closed SMEs move to interactive and user SMEs clusters.

## Multinomial logit regression model

For the multinomial logit regression, the dependent variable used is the degree of openness characterized by the dimensions of breadth and depth determined by the cluster analysis method presented previously. The four alternative clusters are 1, 2, 3 and 4, with 1 being the closed SMEs (low breadth and low depth); 2 the interactive SMEs (low breadth and high depth); 3 the user SMEs (high breadth and low depth); and 4 the open SMEs (high breadth and high depth), identified as the reference category in our model.

The probability of choosing a cluster category k (k=1, 2, 3, 4) is given by:

$$\mathbf{Prob}_{ik} = \frac{e^{\beta_k X_i}}{1+\sum_{k=1}^{4} e^{\beta_k X_i}} \qquad 1$$

Where Xi is the matrix of cluster dimensions and βk is m * 1 vector of parameters.
As is the case of bivariate logit models, coefficients for reference choice are set equal to zero. Such a normalization will be taken into account when interpreting the rest of the model coefficients. In our case, the cluster corresponding to open SMEs is taken as a reference category and, as a consequence, the estimated parameters will be interpreted as follows:

$$\frac{\mathrm{Prob}_{i1}}{\mathrm{Prob}_{i4}} = \frac{e^{\beta_1 X_i}}{e^{\beta_4 X_i}} = e^{(\beta_1-\beta_4)Xi} = e^{\beta_1 X_i}$$

$$\frac{\mathrm{Prob}_{i2}}{\mathrm{Prob}_{i4}} = \frac{e^{\beta_2 X_i}}{e^{\beta_4 X_i}} = e^{(\beta_2-\beta_4)Xi} = e^{\beta_2 X_i} \qquad 2$$

$$\frac{\mathrm{Prob}_{i3}}{\mathrm{Prob}_{i4}} = \frac{e^{\beta_3 X_i}}{e^{\beta_4 X_i}} = e^{(\beta_3-\beta_4)Xi} = e^{\beta_3 X_i}$$

Or

$$\mathrm{Ln}\left(\frac{\mathrm{Prob}_{i1}}{\mathrm{Prob}_{i4}}\right) = (\beta_1\text{-}\beta_4)\,X_I = \beta_1\,X_I$$

$$\mathrm{Ln}\left(\frac{\mathrm{Prob}_{i2}}{\mathrm{Prob}_{i4}}\right) = (\beta_2\text{-}\beta_4)\,X_I = \beta_2\,X_I \qquad 3$$

$$\mathrm{Ln}\left(\frac{\mathrm{Prob}_{i3}}{\mathrm{Prob}_{i4}}\right) = (\beta_3\text{-}\beta_4)\,X_I = \beta_3\,X_I$$

From equation 3, the estimated coefficients, for instance, β1j (j = 1,….,m), are interpreted as the marginal change in the logarithm of the odds that the SMEs were described as closed ones over the category indicating that they were described as open SMEs, due to a marginal change in the attribute j. However, while marginal changes in the logarithm of the odds are not always intuitively understandable, we can use the exponential of parameters, also referred to as odds ratios. They offer a straightforward model interpretation. Indeed, exp (β1j) is the factor by which the odds change when the jth independent variable increases by one unit. If b1j is positive, this factor, e.g., exp (β1j), will be higher than 1, which means that the odds are increased. On the contrary, if β1j is negative, exp (β1j) is less than 1, implying that the odds are decreased. And if β1j is 0, exp (β1j) is equal to 1, which leaves the odds unchanged. In an analogous way, if attribute j is a dummy variable, the exponential of parameters, e.g., exp (β1j), measures the factor of change in the odds with respect to the reference variable.

## Binary logit models

Since the Multinomial logit regression permits a comparison only with regard to one reference category like we did by using the cluster of open SMEs as a reference category, two bivariate logit regressions are also estimated to capture two other relevant situations that refer to the likelihood that closed SMEs be either in the interactive or user SMEs cluster.

For each of these two situations, the following equation was estimated:

$$\mathrm{Log}(P_i/1\text{-}P_i) = \beta_0 + \beta_1 \mathrm{REG\_PROX} + \beta_2 \mathrm{NA\_PROX} + \beta_3 \mathrm{WORLD\_PROX} + \beta_4 \mathrm{OBS\_INT} + \beta_5 \mathrm{OBS\_EXT} + \beta_6 \mathrm{RPER\&D} + \beta_7 \mathrm{ING\&TECH} + \beta_8 \mathrm{AGE} + \beta_9 \mathrm{SIZE} + \beta_{11} \mathrm{HIGH\_TECH} + \beta_{12} \mathrm{MED\_TECH}$$

Where, βi (i= 0…….11) are the coefficients and log (Pi/1-Pi) is the logarithm of the ratio of the probability that SMEs in a closed cluster be in the cluster of interactive or user SMEs relative to the probability that SMEs in the same cluster don't move.

## Descriptive statistics

Table 4 reports the descriptive statistics of the explanatory variables used in this study. Overall, each SME has invested 4.66% of its sales in R&D activities and allocated 2.14% of its employees to R&D.

Also, SMEs in this region ranked 2.54 out of a possible maximum of 10 on the scale of geographical proximity within 100 km of clients and suppliers, ranked 2.28 out of a possible maximum of 20 on the scale of geographical proximity to clients and suppliers located elsewhere in Quebec and Canada, and ranked 1.83 out of a possible maximum of 20 on the scale of geographical proximity to clients and suppliers located in the U.S. and elsewhere in the world.

Likewise, for the independent variables related to obstacles to innovation, namely internal obstacles to innovation and external obstacles to innovation, SMEs in this region ranked 1.77 out of a possible maximum of 20, and 1.16 out of a possible maximum of 25. Finally, innovative SMEs in this region had 41.3 employees and are an average of 22.5 years old. Overall, 68.1% of the SMEs were in the low-technology sector, 15.3% in the medium-technology sector and 16.6% in the high-technology sector, according to the classification of Legler and Reichter (2007).

## Results of the Multinomial logit regression

The regression results of the logit models corresponding respectively to the three first situations comparatively to the bench mark situation (Open cluster) are summarized in Table 8. As we can see, the model has acceptable predictive power, with 54.7% of correct predictions. The value of the Nagelkerke R2 is 0.425, which is very good for qualitative dependent variable models. Furthermore, the computed value of the likelihood ratio (e.g., 199.13) is much larger than the critical value of the chi-squared statistic at the 1 percent level, with 33 degrees of freedom. This suggests that the null hypothesis, that all the parameter coefficients (except the intercept) are all zeros, is strongly rejected. Consequently, the model is significant at the 1 percent level.

With regard to the external context characteristics variables explaining the likelihood that SMEs being in an open cluster rather than in any of the three other clusters, five out of the six variables related to this category explain the likelihood that SMEs be in an open cluster rather than in an interactive or user clusters. More specifically, the two variables related to proximity, namely, regional proximity and national proximity, have a significant impact in the three clusters considered in our model. The results show that a decrease in the index of regional and national proximities of SMEs increases the likelihood that SMEs be in an open cluster rather than in a closed, interactive or user cluster.

The variables related to the external obstacles to innovation have a significant impact on the two clusters considered in our model. More specifically, an increase in the index of external obstacles to innovation of SMEs increases the likelihood that SMEs be in an open cluster rather than in a closed or interactive cluster. While these results seem somewhat counterintuitive at first sight, firms that find high obstacles (e.g., risks and costs) to innovation are more likely to innovate (Veugelers and Cassiman 1999). This result seems to be in line with the results of Keupp and Gassmann (2009) who find that firms experiencing impediments to innovation are more likely to have a more open degree of openness (both breadth and depth).

The results also show that variables related to technological intensity have a significant impact on the likelihood that SMEs have a high degree of openness rather than a low degree of openness. More specifically, being in medium technology sectors instead of being in low technology sectors increases the likelihood that SMEs be in an open cluster rather than in a closed, interactive, or user cluster. Also, being in high technology sectors instead of being in low technology sectors increases the likelihood that these firms be in an open cluster rather than in an interactive cluster or user cluster.

For variables related to the internal context characteristics variables explaining the likelihood that SMEs be in an open cluster rather than in any of the three other clusters, four out of the six variables related to this category explain the likelihood that SMEs be in an open cluster rather than in an interactive or user cluster. In fact, an increase in the index of internal obstacles to innovation increases the likelihood that SMEs be in an open cluster rather than in a user cluster. This result confirms the results of Keupp and Gassmann (2009) who find that firms whose internal innovative activities are confronted with impediments to innovation are more likely to have a more open degree of openness (both breadth and depth). Also, an increase in the percentage of engineers and technicians increases the likelihood that SMEs be in an open cluster rather than in an interactive or user cluster.

Finally, an increase in the size of the firm increases the likelihood that SMEs be in an open cluster rather than in a closed cluster. This result confirms previous results (Laursen and Salter 2004; 2006; Lichtenthaler 2008; Keupp and Gassmann 2009) which indicate that large companies are more likely to adopt an open innovation approach to innovation than SMEs. Unlike Keupp and Gassman (2009), we find that the age of the firm has a significant impact on one cluster considered in our model. More specifically, we find that a decrease in the age of the firms decreases the likelihood that SMEs be in an open cluster rather than in a closed cluster. This result suggests that aging provides SMEs with the experience needed to forge more relations and trust with external partners and to be more open.

| | Multinomial Logit Estimation | | | | | | Binary Logit Estimation | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | Low breadth & Low depth/ High breadth & High depth | | Low breadth & High depth / High breadth & High depth | | High breadth & Low depth/ High breadth & High depth | | Low breadth & Low depth/ Low breadth & High depth | | Low breadth & Low depth/ High breadth & Low depth | |
| | Closed to open **[MODEL 1]** | | Interactive to open **[MODEL 2]** | | User to open **[MODEL 3]** | | Closed to interactive **[MODEL 4]** | | Closed to user **[MODEL 5]** | |
| Independent variables | **Coeff. β** | **Exp (β)[a]** | **Coeff. β** | **Exp (β)** | **Coeff. β** | **Exp (β)** | **Coeff. β** | **Exp (β)** | **Coeff. β** | **Exp (β)** |
| **Constant** | -6.457*** | 0.001 | -6.413*** | 0.002 | -8.493*** | 0.000 | 0.247 | 1.280 | 3.050 | 21.118 |
| WORLD_PROX | 0.229[NS] | 1.257 | 0.382[NS] | 1.465 | -0.498[NS] | 0.607 | -.677[NS] | .508 | .998[NS] | 2.713 |
| PR&NA_PROX | 2.470*** | 11.822 | 1.058*** | 2.881 | 1.198*** | 3.313 | 1.538** | 4.655 | 1.651** | 5.211 |
| REG_PROX | 1.304*** | 3.684 | 0.272** | 1.313 | 0.520*** | 1.682 | 1.009** | 2.743 | .722** | 2.058 |
| OBST_INT | 0.045[NS] | 1.046 | 0.006[NS] | 1.006 | 0.319** | 1.375 | -.176[NS] | .839 | -.166[NS] | .847 |
| OBST_EXT[b] | 1.581** | 4.860 | 0.431[NS] | 1.539 | 0.427* | 1.533 | 1.299** | 3.666 | 1.520** | 4.574 |
| ING&TECH | 0.596[NS] | 1.815 | 1.130** | 3.096 | 0.704** | 2.028 | -.677[NS] | .508 | .105[NS] | 1.110 |
| PER&D[c] | -0.003 | 0.997 | 0.099[NS] | 1.104 | -0.039[NS] | 0.962 | .009[NS] | 1.009 | -.067[NS] | .935 |
| SIZE[c] | .372* | 1.451 | -0.039[NS] | 0.962 | -0.046[NS] | 0.955 | .512** | 1.669 | .429** | 1.535 |
| AGE[c] | -1.083** | 0.338 | -0.368 | 0.692 | 0.319[NS] | 1.375 | -.244 | .784 | -2.497*** | .082 |
| HIGH_TECH[d] | 0.746[NS] | 2.108 | 3.119*** | 22.629 | 1.946** | 7.001 | -3.646** | .026 | -.301[NS] | .740 |
| MED_TECH[d] | 1.693* | 5.436 | 1.599** | 4.950 | 1.335** | 3.800 | -.437[NS] | .646 | .632[NS] | 1.882 |
| *N (total= 451)* | 29/125 | | 101/125 | | 173/125 | | 130/141 | | 202/211 | |
| Chi-square (d.f.) | 199.13 (33) | | | | | | 44.61 (11) | | 55.53 (11) | |
| Nagelkerke $R^2$ (Pseudo R square) | .405 | | | | | | .444 | | .429 | |
| Percentage of correct predictions | 54.7% | | | | | | 85.4% | | 88.1% | |

[a] Exp(β) is the factor change in the odds of the dependent variable, due to a one unit increase in the specific independent variable.
[b] Sr indicates the logarithmic transformation of the variable whose name it precedes
[c] LN indicates the logarithmic transformation of the variable whose name it precedes
[d] Low-tech is the category reference
[NS]: non significant
*, ** and *** indicate that variable is significant at the 10 %, 5 % and 1 % level respectively. NS indicate that the variable is not significant at the 10 % level.

Table 8. Estimation of multinomial and binary Logit Models of Factors Affecting the degree of openness of SMEs in traditional manufacturing industries.

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## Results of the binary logit regression

The regression results of these binary logit models are also summarized in Table 8. The computed value of the Chi-square statistics for each of the two logit regressions is greater than its critical value (e.g., 44.61; 55.53) with 11 degrees of freedom at the 1% level. The two equations have good predictive power, with 85.4% and 88.1% of overall correct predictions for being in an interactive cluster rather than in a closed cluster, and for being in a user cluster rather than in a closed cluster. Finally, the value of Nagelkerke pseudo R2 is 0.444 for the first binary logit regression and 0.429 for the second.

As in the multinomial regression model, we first report the results of the external context characteristics variables. More specifically, variables related to regional and national proximities have a significant impact on the two clusters considered in our model. The results show that these variables explain the likelihood that SMEs be in an interactive or user cluster rather than in a closed cluster. Also, the variable related to the external obstacles of innovation has a significant impact on the two clusters considered in these regressions. In fact, an increase in the index of this variable increases the likelihood that SMEs be in an interactive or user cluster rather than in a closed cluster.

According to these results, variables related to high technology intensity have a significant impact on the cluster considered in our model. More specifically, being in a high technology sector decreases the likelihood that SMEs be in an interactive cluster rather than in a closed cluster (e.g., binary logit estimation).

With regard to variables related to the internal context characteristics, according to our results, the variable related to the size of SMEs has a significant impact on SMEs being in a user cluster rather than in a closed cluster. Precisely, an increase in the index of this variable increases the likelihood that SMEs be in a user cluster rather than in a closed cluster. Finally, a decrease in the age of the SMEs decreases the likelihood that SMEs be in a user cluster rather than in a closed cluster.

| | Multinomial Logit Estimation | | | | | | Binary Logit Estimation | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | Low breadth & Low depth/ High breadth & High depth | | Low breadth & High depth / High breadth & High depth | | High breadth & Low depth/ High breadth & High depth | | Low breadth & Low depth/ Low breadth & High depth | | Low breadth & Low depth/ High breadth & Low depth | |
| | Closed to open [MODEL 1] | | Interactive to open [MODEL 2] | | User to open [MODEL 3] | | Closed to interactive [MODEL 4] | | Closed to user [MODEL 5] | |
| Independent variables | Coeff. β | Exp (β)a | Coeff. β | Exp (β) | Coeff. β | Exp (β) | Coeff. β | Exp (β) | Coeff. β | Exp (β) |
| Constant | -5.908*** | 0.003 | -2.972*** | 0.051 | -3.953*** | 0.019 | -3.319** | 0.036 | -2.859** | 0.057 |
| PR&NA_PROX | 1.048*** | 2.852 | 1.005*** | 2.732 | 0.964*** | 2.622 | 1.270** | 3.561 | 1.511** | 4.531 |
| REG_PROX | 2.616*** | 13.681 | 0.226** | 1.254 | 0.482*** | 1.619 | 1.010** | 2.746 | 0.628** | 1.873 |
| OBST_EXT[b] | | | | | | | 1.181** | 3.258 | 0.828** | 2.889 |
| SIZE[c] | | | | | | | 0.378** | 1.459 | 0.079 NS | 1.082 |
| HIGH_TECH[d] | | | | | | | -1.954** | 0.142 | | |
| MED_TECH[d] | 0.732 NS | 2.079 | 0.184 NS | 1.202 | 0.510* | 1.665 | | | | |
| N (total= 451) | 30/129 | | 111/129 | | 181/129 | | 131/141 | | 204/211 | |
| Chi-square (d.f.) | 150.58 (9) | | | | | | 42.88 (5) | | 36.83 (4) | |
| Nagelkerke R2 (Pseudo R square) | 0.309 | | | | | | 0.428 | | 0.296 | |
| Percentage of correct predictions | 53.2% | | | | | | 85.5 % | | 85.3% | |

[a] Exp(β) is the factor change in the odds of the dependent variable, due to a one unit increase in the specific independent variable.
[b] Sr indicates the logarithmic transformation of the variable whose name it precedes
[c] LN indicates the logarithmic transformation of the variable whose name it precedes
dLow-tech is the category reference
NS: non significant
*, ** and *** indicate that variable is significant at the 10 %, 5 % and 1 % level respectively. NS indicate that the variable is not significant at the 10 % level

Table 9. Re-estimation of multinomial and binary logit models with only the significant factors affecting the degree of openness of SMEs in traditional manufacturing industries.

To assess the robustness of the results of estimation of the multinomial and binary logit models reported in table 8, we re-estimated five logit models that excluded the insignificant parameters found in the initial estimations. Overall, the results obtained and reported in table 9 did not show significant variations between the two sets of estimations. More specifically, SMEs belonging to the medium technology intensity rather than being in low technology industries became insignificant to explain the likelihood that SMEs move from a closed or interactive cluster to a more open cluster (MODELS 1 and 2). Also, firm size became insignificant to explain the likelihood that SMEs move from a closed cluster to an interactive cluster (MODEL 4). All other variables found significant in the initial set of estimations were still significant from the 1% to 10% levels in the second set of estimations.

## Discussions and conclusions

Starting from the operationalization of openness, proposed by Laursen and Salter (2004; 2006), this article has investigated many gaps related to the literature on openness. Hence, using the dimensions of breadth and depth, we were able, using cluster analysis, to classify, in homogeneous groups, SMEs in manufacturing industries into four groups which differ in their degree of openness. Our cluster analysis results differ to some extent from those proposed by Keupp and Gassmann (2009). In fact, these authors have suggested four archetypes: Scouts, Professionals, Explorers, and Isolationists. In our study, the cluster formed by Isolationists refers to a closed cluster, the cluster formed by Scouts corresponds to a user cluster, and the cluster formed by Professionals refers to an open cluster. However, we were not able to confirm the existence of the last group, namely Explorers, and this is because of the way we measure the degree of openness of SMEs to ESI. By adopting this way of considering the open innovation model, the present study has verified that SMEs used different modes to open up their innovation process, namely, by becoming more interactive or more user. Such a perspective of investigating the degree of openness allows us to consider factors that would increase the likelihood that SMEs be in a more open cluster rather than in a less open cluster. In this study, as suggested by Huizingh (2011), we consider two broad factors, namely, external and internal context characteristics variables.

The results of the regression models suggest that variables related to external context characteristics have significant power to explain the move of SMEs to open up their innovative activities. Indeed, regional and national proximities, and external obstacles to innovation are the major drivers of SMEs being open in their innovative activities. Also, we did find some significant differences across the four clusters related to industries, unlike Lichtentahler (2008) who finds an insignificance of industry differences. Specifically, we find that being in high technology industries rather than low technology industries increases the likelihood that SMEs move from interactive and user clusters to an open cluster. Likely, being in medium technology industries rather than low technology industries increases the likelihood that SMEs move from closed, interactive and user clusters to an open cluster.

For variables related to internal context characteristics, the results suggest that the variable size and age are significant to explain the likelihood that SMEs move from a cluster with a less degree of openness to a cluster with a higher degree of openness. Especially, the increase in size helps SMEs to move from a closed cluster to interactive, user, and open clusters. Likely, the decrease in age does not favor SMEs to move from a closed cluster to user and open clusters. Variables related to absorptive capacity, namely, R&D employees and engineers and technicians, seem to have, in our study, a limited explaining force. In fact, the presence of R&D employees does not explain at all any of the clusters which may be explained by the fact that SMEs in this region have a strong “not-invented-here” syndrome which is related to a more closed approach to innovation (Laursen and Salter 2006; Lichtenthaler 2008). However, engineers and technicians explain only the likelihood that SMEs move from interactive and user clusters to an open cluster. These SMEs may have a less strong “not-invented-here” syndrome which allows them to open up more their innovative process.

Taking all these results together, we were able to show that adopting a higher degree of openness can be explained both by internal and external factors and not only by the internal environment of firms (Keupp and Gassmann 2009), which shows a strong contribution toward investigating more the factors that explain the adoption of an open innovation model.

The results driven by our study could be interesting for managers. Firstly, using our framework, managers, in these SMEs, could identify to which cluster their firm belongs and take concrete approaches to develop their SMEs' adoption of the open innovation model.

Second, managers may pay more attention in monitoring their proximities with regional and national external knowledge sources in the sense that interactions with these ESI can raise transaction costs (Chesbrough 2003a) which can have negative returns (Laursen and Salter 2006; Keupp and Gassmann 2009). In doing so, managers should enhance their social capital with these ESI because the latter contributes to reduce transaction costs between firms and between external actors (Amara and Landry 2005).

Third, managers in these SMEs should also pay attention to external obstacles to innovation by looking for more alternatives to open up their innovative process. As Keupp and Gassman (2009), we believe that openness is a strategic response to overcome these impediments to innovation.

Fourth, managers should be aware of the importance of the age of the firm in approaching openness. In fact, managers in SMEs should open up their innovative process progressively, because opening up the process of innovation implies building relations and trust between the firm and its external partners. Trust is developed over time through continuing interactions which may need more time to be established (Amara and Landry 2005). So managers have to be aware of the limit of the size of their firms if they consider opening up their innovation process.

Fifth, according to the attention-based theories of the firm (Simon 1979; Ocasio 1997), managerial attention is the most precious resource inside the firm. Small firms are extremely resource-constrained, which may lead managers in these firms to a lack of time and attention to be more open to the use of ESI. This way mangers should consider the complementarily or substitutions effects that may exists between the use of different ESI.

Finally, managers have to pay attention to the "not-invented-here" syndrome which might be developed by the technical staff towards opening up the firm's process of innovation. In this sense, managers can invite staff to look closely at the benefits of interacting and collaborating with external partners to cope with the risks related to the process of innovation.

Of course, our study suffers from limitations that are at the heart of the debate on the concept of openness. First, future studies should use finer measurements related to openness to cluster SMEs in homogeneous groups. Measurements, as those proposed by van de Vrande et al. (2009), such as venturing, outward and inward IP licensing, employee involvement, customer involvement, external networking, external participation, and outsourcing R&D might be more reliable to cluster SMEs. Second, future research should extend the variable list, such as the strategic orientation variable, which may be the cornerstone in the decision to adopt a more open approach to innovation (Lichtenthaler 2008; Keupp and Gassmann 2009; Huizingh 2011). Third, our study did not investigate the costs related to the adoption of different profiles by SMEs. Future research should tackle this issue by providing insights in which case the cost of being open is less fruitful for SMEs than the cost of being user and so on.

Finally, our data investigate SMEs in manufacturing region in Canada. It is convenient to underline the exploratory nature of this study as it is one of the few that have empirically considered the effect of both external and internal context characteristics variables to explain why SMEs adopt different degrees of openness. Therefore, the generalization of these results should be applied to other contexts with precaution. Future research should consider a cross-national survey, on the degree of openness, to have a complete picture of how and what factors explain the adoption of a high degree of openness among manufacturing SMEs.

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