Identification of Innovation Solvers in Open Innovation Communities using Swarm Intelligence

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Abstract: Open innovation communities represent an effective strategy to provide organizations with a wider range of ideas, reducing the costs associated to R&D. Its main problem is the large volume of information generated in the form of proposed innovations that should be internally processed and executed by employed experts. The purpose of this work consists of identifying the profiles of the so-called innovation solvers using only their participation characteristics extracted from open innovation communities, which are modelled as social networks, and applying particle swarm optimization. Findings can improve the absorptive capacity of organizations by focusing on those users with more chances of generating potentially adoptable ideas.

Keywords Open innovation; User Innovation Communities; Innovation Solvers; Social Network Analysis; Particle Swarm Optimization.

1. Introduction

Open Innovation represents a new organizational strategy in which organizations make use of internal and external resources to drive their innovation processes, and it is based on the idea that potential opportunities and advantages can be gained from leveraging knowledge and innovation found outside the formal boundaries of organizations (Chesbrough, 2003; Huizingh, 2011; Wang et al., 2015). Instead of using classical procedures like market research or trend scouting, the aim of open innovation is to collect information through the integration of customers or users in all the phases of the innovation process (Lichtenthaler, 2008; Schwab et al., 2011). The first studies in this line (Von Hippel, 1978) signalled that the essential activities at the start of the innovation process are borne by customers instead of manufacturers, and once the manufacturer collects this knowledge from customers, it can start to check the market potential and to develop a marketable innovation. Later studies prefer the idea of the manufacturer and the customer working together cooperatively (Gemünden et al., 1996). The active integration of customers is an essential characteristic of customer oriented innovation processes, which serves to reduce uncertainty about the market (McDermott, 1999). This integration is different from aligning the innovation together with customer needs (in the sense of innovation market research) and means that the customer acts as an active designer in the process of innovation (Parmentier & Mangematin, 2014).

The proliferation of information and communication technologies has made possible the use of Internet as the primary communication channel, leading to virtual customer integration (Rohrbeck et al., 2008; Mortara & Minshall, 2011; Martinez-Torres et al., 2015b). For instance, online communities support discussions between the customer and development engineers (company-to-customer communication) as well as the cooperation among several contributors (customer-to-customer communication). Open innovation communities constitute one of the most successful implementation of the open innovation paradigm. Its main drawback is the large volume of contributions that this approach can generate. This contributions must be individually assessed by the company in order to decide if they can be applied or not, or if they have already been implemented. Typically, only a small fraction of contributions are really attractive for the company. However, this assessment process is a time consuming task, which implies reading the contributions and the debate generated around them (including sometimes a rating given by the rest of the community), deciding about its suitability with some experts of the organization and planning its potential application (Martinez-Torres et al., 2015a). Open innovation is not possible without the absorptive capacity as an internal capability of innovating companies (Vanhaverbeke et al., 2007). The absorptive capacity consists of three dimensions: identification, assimilation and exploitation of external knowledge (Kocoglu et al., 2015). The main bottleneck of open innovation communities is related to the identification dimension, as it is not possible to allocate specific experts of the organization to evaluate any potential innovation proposed by the community.

The analysis of the participation features of community users has been proposed as a possible solution to this problem. According to this approach, best ideas can be extracted through the identification of certain patterns of activity within the community. For instance, von Hippel (1986; 1988) introduced the so-called lead users, who are characterized by their ability to foresee innovations much earlier than the rest of users. One of their distinctive characteristics is that they are looking for obtaining a benefit from their proposed innovations. However, sometimes their interests are not aligned with the strategic policies of the company (Berthon et al., 2007). In this paper, we propose the identification of best ideas through the identification of innovation solvers, which are those users contributing with attractive ideas that have been implemented (or already implemented) by the company. This information is easily accessible through the open innovation community, as companies developing this paradigm usually inform users about the status of their posted ideas. The main difference with respect to lead users is that their proposed innovations are minor modifications, which are usually aligned with the company preferences. When proposing such innovations, they are not trying to anticipate market trends but to provide small solutions that can help other users, and that are the direct result of their experience. They are not only looking for their own benefit, although they can obtain the recognition from other users or from the company. Actually, innovation solvers constitute a wider category than lead users. The prior identification of such kind of users can facilitate the assessment process. The innovation team devoted to analyse posted contributions can save time by prioritizing the evaluation of those contributions generated by users with more chances to be successful. Therefore, the dependent variable of this study, the condition of being or not an innovation solver, is a dichotomic variable that can be easily extracted from open innovation websites, as the status of posted ideas is publicly available. An important peculiarity of this dependent variable is the fact that only a small fraction of shared ideas are finally adopted by the company, causing a dependent variable with excess zeros (Jang, 2005; Lee et al., 2006). In such scenarios, classical statistical methodologies like regression analysis or discriminant analysis are inadvisable (Lambert, 1992). As an alternative, this paper proposes the use of a computational intelligence technique called Particle Swarm Optimization (PSO) to solve the classification problem by obtaining the optimum values of the coefficients of the discriminant function (Del Valle et al., 2008; Majhi and Panda, 2011).

The rest of the paper is structured as follows. Section 2 details previous works related to the open innovation paradigm, its implementation and the identification of users with special profiles. Section 3 introduces the methodology, justifying the necessity of computational intelligence methods, formulating the problem in the form of an optimization problem, and describing the proposed methodology based on swarm intelligence for solving the stated optimization problem. This methodology is applied to the case study of IdeaStorm website, which is introduced in section 4 as well as the SNA features that can be collected from the social network representing open innovation communities. Obtained results and their discussion are included in section 5 and 6, respectively. Finally, conclusions are provided in section 7.

2. Related work

There are several possibilities of involving users in the innovation process. The simplest one consists of collecting customer insights, which cover not only their explicit needs and requirements but also their frustrations, sacrifices, and emotional outcomes (Ulwick, 2005). Ideas generation with customers and users is a further step in their integration as part of the innovation process. Brainstorm techniques, open discussions, Delphi techniques and nominal group techniques are typically used to categorize and prioritize ideas for solving the collected customer insights (Weber, 2008). Ideas generation can also be used to capture customer rational and emotional reaction with the aim of testing and improving proposed ideas. For instance, the study made by Yoshida et al. (2014) simulated a mechanism of user innovation generation and diffusion within a mountain climbing product market by applying agent-based simulation and data acquired from a questionnaire survey. The study revealed that the diffusion of user innovation is supported by the community but it does not always mean an improvement in the quality of user innovation.

The effectiveness of these previous schemes can be increased through the use of Open Innovation communities. Their virtual character allows to overcame physical (spatio-temporal) barriers, reaching a large variety of potential users and customers. Some authors also argue that innovation is mostly the result of the cooperation among several contributors. Cooperation acts as an innovation stimulus and is expected to bring benefits such as achieving economies of scale and of scope, reducing uncertainty, gaining access to new markets or accessing complementary knowledge (Miotti & Sachwald, 2003; Parmentier & Mangematin, 2014). Open innovation communities promote the generation of new ideas, the interactions among users as well as the interactions among the development team and customers (Di Gangi and Wasko, 2009). Interactions among users enable them to build on one another's knowledge and experiences, which plays a critical role in developing ideas (Rowley et al., 2007). Besides, emerged discussions from posted ideas also contributes to concept testing through the comments posted by other users or through a scoring system. However, the practical implementation of open innovation communities demonstrates that they tend to generate a huge volume of information that can be difficult to manage. In general, they implement some kind community-based idea evaluation to facilitate the process of identifying the ‘best’ ideas (Berg-Jensen et al. 2010), which can be considered as a collective judgment task (Zigurs and Buckland 1998; Leimeister, 2010). The community evaluation acts as filter between the community and the company, thus enhancing the quality of the knowledge transmission between the community as sender and the company as receiver of ideas (Blohm et al., 2011).

Rating scales (Di Gangi and Wasko 2009; Riedl et al. 2010) and prediction markets (Soukhoroukova et al. 2011) have been researched as the two major mechanisms for collective idea evaluation. The main disadvantage of collective evaluation is that popular ideas among consumers are not always attractive for the company. Additionally, the criteria for voting are often left vague leading to implicit variations in criteria used for voting, from likelihood of purchase to ‘‘coolness’’ of idea to feasibility (Majchrzak & Malhotra, 2013). Consequently, the ideas that are voted as most popular may not be the most innovative ideas. For instance, one of the most popular ideas at My Starbucks Idea, the open innovation site of Starbucks, is about coffee ice cubes for iced drinks. This idea received more than 70 thousands votes but the company did not implement it because the cost of such innovation was far beyond the reasonable limits. In general, the company’s management is usually better able than the crowd to assess the fit of the proposed solutions within the context of the company’s unique needs (Wei, 2013). Moreover, because voters are exposed to previous votes, phenomena such as the “rich get richer” and “social influence bias” diminish the importance from all but very few of the earlier posts (Muchnik et al., 2013).

Instead of focusing on the judgement of the crowd, a different approach consists of focusing on special profiles of users able to find the greatest value when they suggest solutions instead of simply describing problems or stating customer requirements. Therefore, other authors propose that the identification of best ideas can be done through the identification of the lead users.

According to von Hippel's lead user theory (1986; 1988), lead users experience certain needs that will diffuse in a marketplace significantly earlier than the bulk of that marketplace and they are positioned to benefit notably from gaining innovative solutions to those needs. Previous studies have recognized their potential impact on the development of valuable innovation knowledge (Morrison et al., 2004; Lettl, 2007; Mahr and Lievens, 2012). Due to their innovative, future-oriented character, lead users can not only detect problems but also look for and propose solutions (Lüthje, 2004; Schreier and Pruegl, 2008). If they develop solutions for their own needs, the solutions might also be suitable for future problems in the mass market. Besides, previous research on this topic has shown that lead users, who are characterized by high betweenness centrality, tend to take the position of boundary spanners (Kratzer and Lettl, 2009). However, the main limitation of the lead user method is precisely the proper identification of lead users, and this difficulty has been claimed to be one of the barriers for organizations to adopt the lead user concept (Olson and Bakke 2001; Westerski et al., 2013).

FIGURE 1

This paper changes the focus and, instead of trying to identify lead users, the study tries to obtain the common patterns of participation of those users that have already been recognized as innovators by the company. Therefore, the paper is focused on the stage of idea evaluation and screening of the process of ideation shown in Figure 1. The recognition of innovation solvers by their participation patterns can help the company to assess thousands of received ideas. Instead of manually assessing each posted innovation, the company can pre filter received ideas using the proposed methodology. Additionally, innovation solvers interact with other members of the open innovation community, so they contribute to the dissemination of information through the social network. To this aim, open innovation communities have been modelled as a social network where nodes represent the community users and arcs the interactions through the posted ideas and comments. The distinction between those nodes that are innovators and those that are contributors is provided by the status of their posted ideas according to the evaluation performed by the company. The topological characteristics of nodes can be extracted using Social Network Analysis techniques. Features like degree, centrality, connectivity or the clustering coefficient have been previously used in several studies that analyse the participation in virtual communities (Wang & Chen, 2004; Ganley & Lampe, 2009; Martinez-Torres, 2012). Therefore, this paper tries to answer two research questions:

RQ1: What an innovation solver is and how he can be distinguished from a lead user?

RQ2: Which are the activity patterns of innovation solvers?

3. Lead users and innovation users

User-centred innovation is a phenomenon to acquire innovation-related information of products and services (Von Hippel, 2005). Those new product ideas are based on information collected from current or potential users typically within open innovation communities (Lilien et al., 2002). In order to clarify how the best ideas are identified, this section provides an overview of different characteristics of the lead users and innovation solvers, as they represents two possible alternatives from whom collecting information.

On the one hand, according to the definition by von Hippel (1986) lead users are those members of a user population who (1) anticipate obtaining relatively high benefits from obtaining a solution to their needs and so may innovate and (2) are at the leading edge of important trends in a marketplace under study and so are currently experiencing needs that will later be experienced by many users in that marketplace. Subsequent studies have recognized their potential impact on the development of valuable innovation knowledge and highly novel product ideas (Morrison et al., 2004; Lettl, 2007; Mahr and Lievens, 2012; Franke et. al 2006; Schreier et al., 2007). Due to their innovative, future-oriented character, lead users can not only detect problems but also look for and propose solutions (Lüthje, 2004; Schreier and Prügl, 2008). If they develop solutions for their own needs, the solutions might also be suitable for future problems in the mass market. Likewise, innovations reported by lead users are judged to be commercially attractive and have actually been commercialized by manufacturers. Besides, previous research on lead user has shown that lead users, who are characterized by high betweenness centrality, tend to take the position of boundary spanners (Kratzer and Lettl, 2009).

On the other hand, despite the fact that some studies show that innovation solvers share some of characteristics of lead users (Herstatt and von Hippel 1992; Olson and Bakke 2001; Lilien et al. 2002; Franke and Shah 2003; von Hippel, 2005), lead users are only a small fraction of users who are highly likely to innovate (von Hippel, 1986). Thus, innovation solvers are the remainder, the mass users, who freely share innovations. The first characteristic of innovation solvers is that they provide solutions to problems broadcasted by companies. The authors Terwiesch and Xu (2008) designate as solvers to those users who face an innovation-related problem posted in an innovation contest by a firm or seeker and then provide the best solution. In this line, the study conducted by Franke and Sah (2003) also provides a better understanding of the so-called innovators by bringing attention of how those users contribute within the innovation process. Moreover, according to Lüthje (2004) innovating users are the ones who are also consumers of the product and whose new product ideas are likely to be implemented as little innovations of a product. Likewise, the findings founded by Shah (2000) revealed that end users, who had no formal organizational structure, were always the developers of the first versions of the basic equipment in sports such as snowboarding, skateboarding and windsurfing. As an additional characteristic, they also enjoy the process of solving a problem. Above all in the field of leisure time activities, where several commercially successful new products were developed by the users of these goods.

The innovation solvers inventions gathered in the literature range from the field of OPAC (Online Public Access Catalog) information search systems (Morrison et al., 2000) to outdoor products in Germany (Lüthje, 2004), where innovation solvers generated ideas for improved or new products. Furthermore, innovations made by these users tends to be broadly distributed rather than concentrated among just a very few users (von Hippel, 2005) such as the lead users.

In fact, little innovations or modifications of a product made by innovation solvers are usually those adopted by a company. For instance, on February 16, 2007, Dell invited end users to share their ideas and collaborate with Dell to create or modify new products and services through its new open innovation online community IdeaStorm. One of the first ideas proposed the option to have the three most popular Linux distributions pre-installed on all Dell PCs. After the idea refinement, on May 24, 2007 Dell announced the implementation of this idea (Di Gangi and Wasko, 2009). This implies that companies can identify and therefore utilise innovation solvers as a resource for the development of new products and services. In that line, the research conducted by Bretschneider et al. (2015) also explores the motives encouraging these users to support product innovation, which they described as self- marketing, fun, contact to peers, recognition, product improvement and enhancement, and learning.

4. Methodology

The fact that only a small fraction of shared ideas are finally adopted by the company causes a dependent variable with excess zeros, which is the value assigned to non-innovator users. This kind of problems where the dependent variable contains a disproportionally high number of zeros are known as zero inflated problems, and they can lead to biased/inconsistent parameter estimates, inflated standard errors and invalid inferences if classical discriminant analysis or regression models are used. Zero inflated models have been proposed to solve this problem. They consider a mixture of models to deal with the excess zeros because zero values can be structural zeros, which are inevitable, or sampling zeros, which occur by chance. However, in the case of open innovation communities all the zeros are sampling zeros, because all the ideas are shared with the expectation of being adopted by the company. Therefore, zero inflated models are not appropriate in this case. As an alternative, this paper proposes the search of discriminant functions using a computational intelligence technique called Particle Swarm Optimization. The main advantage of this technique is that it does not require any previous assumption about the data so it can deal with problems with excess zeros. Additionally, it can find new relationships within a large set of data by performing a guided search, being less resource intense than other alternatives such as decision trees. The disadvantage is that it does not guarantee that the global optimum will be reached since they are probabilistic algorithms that must be stopped according to a certain convergence criteria (if they were run for an infinite amount of time, the global optimum would be found). Next subsection formulates the problem as a classification optimization problem that will be solved using Particle Swarm Optimization.

3.1 Formulation of the problem

The purpose of this work consists of identifying the profiles of users whose ideas have been adopted or partially adopted in open innovation communities. More specifically, the purpose consists of deriving a set of discriminant functions over a set of users' features obtained by modelling communities as social networks, so that the coefficients of obtained discriminant functions can maximize innovation solvers identification.

Mathematically, the optimization problem can be formulated as follows:

$$User^{*}_{isolvers} = \begin{cases} 1 & if\ \prod_{i=1}^{n} \theta_i\, Var_i + C > 0 \\ 0 & otherwise \end{cases} \quad (1)$$

where $\mathrm{User}^{*}_{\mathrm{isolvers}}$ are those users whose ideas could be potentially adopted, Var_i are the set of features (variables) characterizing those users, θ_i are the set of coefficients for each variable and C is a constant term. If $\mathrm{User}_{\mathrm{isolvers}}$ represent the vector of users whose ideas have been actually implemented according to the available information, the optimization problem consists of selecting a set of θ_i values so that the confusion matrix between $\mathrm{User}^{*}_{\mathrm{isolvers}}$ and $\mathrm{User}_{\mathrm{isolvers}}$ maximize the identification ratios.

[TABLE 1]

Table 1 details the confusion matrix. *TP* and *TN* are true positives and negatives, respectively, and they refer to those innovation/non-innovation solvers that were correctly classified while *FP* and *FN* are false positives and negatives, respectively, and they refer to innovation/non-innovation solvers incorrectly classified. The rightmost column of Table 1 details the TN rate, TP rate, and the percentage of correct classification. This last metric has been used as the cost function for the optimization problem. The coefficients of the obtained discriminant function determine if they affect positively or negatively to the identification of innovation solvers.

3.2 Proposed methodology: Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a computational intelligence technique developed by Eberhart and Kennedy (1995), which was inspired by the social behaviour of bird flocking and fish schooling. It is based on the swarm intelligence concept, which refers to artificial intelligence systems where the collective behaviours of unsophisticated agents that are interacting locally with their environment create coherent global functional patterns. Basically, PSO uses a population of particles that fly through the problem hyperspace. All the particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. These velocities are stochastically adjusted according to the historical best position for the particle itself and the neighbourhood best position. The particles fly through the problem space by following the current optimum particles.

Mathematically, PSO is formulated as follows. First, a set of P particles (population) is randomly initialized, where the position of each particle represents a solution to the problem, represented by a d-dimensional vector in problem space $s_i= (s_{i1}, s_{i2},..., s_{id})$, $i =1, 2,...,P$, $s\in\Re$. Thus each particle is randomly placed in the d-dimensional space as a candidate solution, and its performance is evaluated using a predefined fitness function. The velocity of the i-th particle $v_i=(v_{i1}, v_{i2},..., v_{id})$, $v\in\Re$, is defined as the change of its position.

The information available for each individual is based on its own experience and the knowledge of the performance of other individuals in its neighbourhood. Therefore, each particle adjusts its trajectory based on its own previous best position and the previous best position attained by any particle of the swarm, namely p_{id} and p_{gd}. The velocities and positions of particles are updated using equations (2) and (3), respectively:

$$v_{id}(t+1) = w\, v_{id}(t) + c_1 rand_1\big(p_{id} - s_{id}(t)\big) + c_2 rand_2(p_{gd} - s_{id}(t)) \tag{2}$$

$$s_{id}(t+1) = s_{id}(t) + v_{id}(t) \tag{3}$$

where t is the iteration counter, w is the inertia weigh, c_1 and c_2 are the acceleration coefficients, and $rand_1$, $rand_2$ are two random numbers in [0, 1]. The inertia weight w controls the impact of previous histories of velocities on current velocity, and it is used to control the convergence behaviour of the PSO (Yang, 2007). To reduce this weight over the iterations, allowing the algorithm to exploit some specific areas, the inertia weight w is updated according to equation (4):

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}}\, iter \tag{4}$$

where w_{max}, w_{min} are the maximum and minimum values that the inertia weight can take, $iter$ is the current iteration of the algorithm and $iter_{max}$ is the maximum number of iterations. The acceleration coefficients c_1 and c_2 control how far a particle will move in a single iteration. Typically, these are both set to 2, although assigning different values to c_1 and c_2 sometimes leads to improved performance. The velocity update equation in (2) has three major components. The first one is the inertia, which models the tendency of the particle to continue in the same direction it has been travelling. The second component is usually referred as memory, and it is the linear attraction towards the best position ever found by the given particle p_{id} scaled by a random weight $c_1 rand_1$. Finally, the third component usually referred as cooperation or social knowledge is the linear attraction towards the best position found by any particle p_{gd}, scaled by another random weight $c_2 rand_2$.

The newly formed particles are evaluated according to the fitness function and the algorithm iterates for a predetermined number of iterations, or until a convergence criterion has been met. Finally, the best solution obtained across all iterations is returned. The following pseudo code details a PSO implementation:

1) Initialize the swarm by assigning a random position in the problem hyperspace to each particle.

2) Evaluate the fitness function for each particle.

3) For each individual particle, compare the particle's fitness value with its p_{id}. If the current value is better than the p_{id} value, then set this value as the p_{id} and update the current particle's position.

4) Identify the particle that has the best fitness value. The value of its fitness function is identified as p_{gd}.

5) Update the velocities and positions of all the particles using equations (1) and (2).

6) Repeat steps 2–5 until a stopping criterion is met (maximum number of iterations or a sufficiently good fitness value).

There are two kinds of population topologies for the particle swarm optimization: the global best (gbest) population topology and the local best (lbest) population topology (Engelbrecht, 2007). In the *gbest* neighbourhood, the particles are attracted to the best solution found by any member of the swarm. This represents a fully connected network in which each particle has access to the information of all other members in the community. In the *lbest* approach, each particle has access to the information corresponding to its immediate neighbours, according to a certain swarm topology. An error gradient tolerance combined with a fixed maximum number of iterations without error gradient change is used as the convergence criterion. That means that PSO is stopped if the *gbest* value does not change by at least the fixed lowest error gradient tolerance for the fixed maximum number of iterations.

5. Case study

Dell IdeaStorm (www.dellideastorm.com) is an open innovation community where end users freely reveal innovative ideas with community members and Dell (Di Gangi and Wasko, 2009). This website represents a new way to listen to customers on how to build the best products and services. Through IdeaStorm, customers can post their ideas about existing or new Dell products, services and operations (Lambropoulos et al., 2009). Moreover, users have the option of voting for the best or the worst ideas as well as discussing the ideas with other users. Using this information, Dell shares the ideas with top management, department managers, and key employees that work within relevant subject domains. Users can comment on ideas by other (identified by an alias) as well as promote or demote ideas using the IdeaStorm scoring feature. Promotion means adding ten points to the current rating of the idea while demotion means subtracting ten points. Dell development team also takes part in the community commenting ideas through a specific user.

Using the proposed approach, the community can be modelled as a graph considering community users as nodes and arcs as interactions among users. Using comments, promotions and demotions to set arcs among nodes, up to three graphs representing the community can be obtained: 1) comment network, 2) promotion network, and 3) demotion network. All of them are directed networks, which means that arcs go from that author commenting, promoting or demoting an idea to that other author who originally posted this idea. A web crawler was programmed to collect information from IdeaStorm website and build these networks. The html content of the site was extracted using the *readLines()* function from the base package of R, which reads data from a URL. The html content is then parsed using the *htmlParse()* function, which generates an R structure representing the html tree. Finally, the meaningful data to build the previous social networks (alias and interactions through comments and ratings) can be easily identified using the regular expressions that are also supported in R, for instance, in packages such as XML. As a results and during the period 2008-2010, a total of 6720 ideas posted by 3987 different users were obtained as well as the different types of interactions around them. Using this data, the three mentioned social networks were built. Figure 2 illustrates the case of the comment network. The total size of the network (number of nodes) is 5489 (which includes the 3987 users who have posted ideas plus the rest of users who have only commented ideas). Figure 2 also represents the size of nodes proportional to the number of posted ideas. It can be observed that there is a participation inequality typical of other online communities, in the sense that only a small fraction of users are responsible for the majority of posted ideas (Toral et al., 2010).

FIGURE 2

The following set features listed in Table 2 can be extracted for each user of the innovation community.

TABLE 2

N_ideas is the number of ideas posted by each user and *Votes* is the number of votes that posted ideas have received. *Cat* is the number of tags covered by the ideas posted by a given author. Whenever a user posts an idea to the IdeaStorm website, it should be classified attending to a limited number of tags. The rest of variables of Table 2 are related to topological features of users as part of one of the derived social networks:

Degree of nodes: it is defined as the number of lines incident with a node, and it is a measure of the connectivity of each node (Toral et al., 2009a). In case of directed networks, in and out degree can be distinguished depending on the direction of the arcs, and both values can be calculated for the three considered networks. For instance, the in-degree of each node in the comment network, labelled as *IndCN* in Table 2, is the number of comments this user has received through his posted ideas, while the out-degree (*OutdCN* in Table 2) is the number of comments this author has sent to the ideas posted by other authors. Similar variables have been extracted for the promotion and demotion networks.

Closeness centrality: it is an index of centrality based on the concept of distance. The closeness centrality of a node is calculated considering the total distance between one node and all other nodes, where larger distances yield lower closeness centrality scores (Toral et al., 2009b).

Betweenness centrality: it is a measure of centrality that rests on the idea that a person is more central if he or she is more important as an intermediary in the communication network (Nooy et al., 2005). The centrality of a node depends on the extent to which this node is needed as a link to facilitate the connection of nodes within the network. If a geodesic is defined as the shortest path between two nodes, the betweenness centrality of a node is the proportion of all geodesics between pairs of other nodes that include this node (Martinez-Torres, 2012).

1-neighbourhood connectivity: it is the number of arcs among users in 1-neighborhood of a given user (Nooy et al., 2005). It is a structural property of each node that gives an idea of how the 1-neighbourhood of a given user is connected.

Clustering coefficient: It measures whether first degree neighbours of a particular node interact with each other. Basically, the clustering coefficient is a measure of local cohesiveness through the neighbour interactions of a node (Durugbo, 2012). It is defined as the ratio of the number of links to the total possible number of links among its neighbours.

Considering all previous SNA variables, the optimization problem consists of distinguishing those users whose ideas have been adopted by Dell from the rest of the community. The first group are the innovation solvers ($User_{id\_adopted}$), and they can be easily extracted from IdeaStorm website through the status field of their posted ideas. The estimation of innovation solvers are given by $\mathrm{User}^{*}_{\mathrm{id\_adopted}}$ and they are defined by equation (1), where *Var*$_i$ refers to the list of variables detailed in the first column of Table 2, and θ_i refers to the variable coefficients detailed in the third column of the same table. The cost function for the optimization problem is the percentage of correct classification shown in the confusion matrix of Table 1.

6. Results

Particle swarm optimization has been applied to find the optimum rules able to distinguish between innovation and non-innovation solvers. PSO parameters settings are detailed in Table 3.

TABLE 3

FIGURE 3

PSO found the best solution in 200 out of the 400 maximum number of iterations, which means that the *gbest* value didn't change during the last 40 iterations. Figure 3 illustrates the evolution of the *gbest* value over the set of iterations. The maximum possible value of *gbest* is 2 since the fitness function was defined as the percentage of correct classification of innovation and non-innovation solvers using the confusion matrix of Table 1. The optimum value obtained by PSO is 1.4637, which is given by the following confusion matrix:

TABLE 4

The resulting values of coefficients are detailed in Table 5. These coefficients define the discriminant functions able to distinguish innovation from non-innovation solvers.

TABLE 5

According to the definition of the fitness function, a positive coefficient value means the corresponding variable positively discriminates innovation solvers while the negative coefficient value acts in the opposite direction. Consequently, innovation solvers are defined by the following features:

Number of posted ideas: the number of posted ideas is a measure of activity and involvement of users within the community. Although it is not the only way in which users can participate, it is obviously the most creative one. Creativity and active participation are two of the distinctive characteristics of lead users according to von Hippel's lead user theory (1986).

In degree (Comment network): the in-degree of the comment network represents the number of comments posted by the rest of the community over a particular posted idea. It is the measure of the debate generated around posted ideas. In accordance with obtained results, innovation solvers are not only characterized by posting ideas, but also by posting ideas that generate a debate around them.

In and Out closeness centrality (Comment network): the topological position of users in terms of distance is relevant for distinguishing innovation solvers. The position of users in open innovation communities has been identified as relevant for distinguishing lead users in previous works (Morrison et al., 2004).

1-neighbourhood connectivity: One of the characteristics of innovations solvers is the high connectivity in their 1-neighborhood. This feature means that innovation solvers are active users which interact with other active users.

Clustering coefficient (Comment network): The clustering coefficient averages connectivity with the maximum number of possible connections among neighbours. A high value of the clustering coefficient means innovation solvers interact with a reduced group of other active users densely connected among them.

In degree (Promotion network): promotions represent a way of evaluating potential solutions using collective intelligence. It is based on the idea that the crowd can do a better evaluation than individuals since they own a group-based intelligence, which can outperform individual knowledge (Surowiecki, 2004). The positive coefficient value for promotions means that this evaluation based on collective intelligence is working properly in the case of IdeaStorm open innovation community, and it is one of the variables that can discriminate innovation solvers.

Out degree (Demotion network): this variable means innovation solvers are critical with other posted ideas.

As a difference, the following characteristics are not applicable to innovation solvers:

Votes: Ideas that receive a high number of votes are those ideas who satisfy to the majority of users, but they are usually difficult to be adopted by the company. Notice that innovation solvers are those users proposing ideas finally adopted by Dell. However, strategic innovation policies of Dell are not always aligned with users' desires. Some non-affordable ideas can be excellent for users but prohibitive for the company.

Number of categories covered by posted ideas: the number of categories shows the scope of the posted ideas. The obtained result is that those ideas with a wider scope are less likely to be adopted by the company. This result can be explained because the list of tags provided by Dell is short and they refer to clearly independent areas or products, so those ideas focused on several tags tends to be quite generic.

Out degree (Comment network): the fact of being active commenting ideas does not imply being an innovation solver. They are more focused on their topics of interest rather than commenting many different ideas.

Betweenness centrality (Comment network): it is a measure of the intermediate role played by innovation solvers. Obtained results show that this is not a distinctive feature of innovation solvers. The central position of innovators as stated by the lead user theory (Von Hippel, 1986) is in terms of distance rather than in terms of mediation.

Out degree (Promotion network): Again, innovation solvers are more focused on their topics of interest than in promoting other users ideas.

In degree (Demotion network): Receiving demotions is not compatible with ideas posted by innovation solvers. Demotions represent the dual way of evaluating potential solutions using collective intelligence.

A sensitivity analysis has also been done to address the influence of parameter selection. This analysis consists of comparing the evolution of PSO using different swarm sizes: 50, 75, 100 and 200. Figure 4 shows that the curves associated to 75, 100 and 200 converge to a similar optimum value, while the curve corresponding to 50 particles stops earlier in a sub-optimum solution.

FIGURE 4

7. Discussion and implications

From a theoretical point of view, this paper examines the collective intelligence mechanisms for ideas evaluation and von Hippel's theory about lead user identification. Mostly of von Hippel’s empirical studies have been progressively extended, with the purpose of widening their application beyond business-to-business settings. Although various studies have investigated the collaboration with lead users yielding commercial success for companies (Antorini et al., 2012; Franke and Shah, 2003; Ogawa and Piller, 2006), only recently they have captured the interest of lead users in online communities around a topic, idea, or product innovation (Franke and Piller, 2004; Jeppesen and Fredriksen, 2006; Lüthje, 2004). Nevertheless, despite the lately attention paid to online communities, studies are still missing about determining potential innovative users who provide organizations with new ideas in the specific context of open innovation communities. In that regard, this paper contributes to the lead-user literature in several important ways. For instance, obtained results show that innovators can be more successfully identified following participation features rather than using data from collective evaluation. Indicators such as the number of posted comments, in-degree of the comments are able to discriminate innovators. Promotions network and centrality show that creativity, popularity and a central position are several of the identified innovators characteristics as they were stated in von Hippel's previous works (von Hippel, 1986; 1988).

Nevertheless, despite this relevant literature on user creativity and all the findings within this paper where successful ideators might focus on their own ideas and topics of interests rather than on commenting on other people's ideas, there is a stark disparity to an alternative perspective of the study conducted by Bayus (2013). This author analyses the Dell IdeaStorms community, where about 4% of all ideas proposed were implemented. This author highlights that the so-called "serial ideators" are more likely to produce a successful idea compared to the "one time ideators". Once an ideator had been successful, the likelihood of coming up with another successful idea decreases because past success leads to less diverse ideas. The paper supports the idea that such a functional fixedness is reduced in the case of diverse commenting activities. However, according to the afore shown results within this paper it can be noticed that innovation solvers share several of the features previously defined for lead users, like creativity, active participation and centrality. Innovator solvers also exhibit a high connectivity and interactivity with other active users within the community. They are more involved with a reduced part of the network (not the whole network), which is related to their specific topics of interest. As it is shown by the clustering coefficient, they tend to group in smaller sub networks within the community. On the contrary, lead users are not interested in inter actuating with other community members. Besides, obtained results emphasize that collective evaluation techniques are not useful for identifying innovator solvers.

From a methodological point of view, this paper proposes modelling open innovation communities as two separate social networks, one considering user interactions through comments and the other one considering interaction through evaluation activities. Both of them are clearly differentiated activities. The former requires a better knowledge and understanding of the commented idea, and suppose a bigger degree of involvement with the community. The latter is much easier to perform, as users only have to promote or demote an idea without providing any justification for his or her decision. Sometimes, users do a promotion or a demotion following an internal feeling rather than an accurate analysis of what it has been proposed. This fact explains why users' in-degree in the comment network exhibit a higher positive coefficient than their in-degree in the promotion network. A second important contribution in the methodological part is the proposal of a novel technique based on computation intelligence to find the discriminant functions that optimize the classification problem of innovators and non-innovators. This problem has an inherent difficulty due to the excess of zeros in the dependent variable. Zero inflated dependent variables advise against the use of traditional statistical techniques like regression models or discriminant analysis. Moreover, zero inflated models also fails due to the random nature of zeros in this specific problem. The proposed methodology overcomes these problems using a guided search over all the possible discriminant rules, and optimizing the classification rates. Although previous studies like Kratzer et al. (2015) also follows a network analytics approach, they only consider the social networking behaviour of users in forums, while this study also considers other forms of participation like promotion and demotion of ideas. Additionally, this study only considers the degree centrality and the betweenness centrality and determine their influence on lead userness. This study goes further by considering a complete set of networking activities. Moreover, the aim is finding the thresholds values for this set of variables that optimize the discovery of innovation solvers. The advantage of the applied methodology is its ability to find solutions and relationships beyond the knowledge of researchers. Some other alternatives like decision trees might be impractical due to the large dataset.

Finally, from the practical implications perspective, this study shows several ways in which organizations interested in the open innovation paradigm can improve its implementation through online communities. First, collective judgement schemes have been shown to be inappropriate for finding the most innovative users. Second, the proposed methodology establishes an alternative way of finding this set of desirable users. A better performance in the procedure of ideas evaluation improves the knowledge absorptive capacities of the organization (Pandza & Holt, 2007; Lewin et al. 2011), avoiding the loss of valuable information.

This study is limited to the analysis of a specific case study and only considers the participation characteristics of community users. However, Dell IdeaStorm is an open innovation community considered and studied many times in previous studies, such as Bayus (2013) or Di Gangi and Wasko (2009). Moreover, the proposed methodology could fail to identify the new innovation solvers (the so called "one time ideators"), above all in case they do not have previous interactions with other users. In terms of future work, we envision to extend the study to other innovation communities and to include new measures related to the content of posted messages using semantic analyses techniques. Additionally, the proposed methodology could be complemented with collective judgment mechanisms to improve the discovery rate of innovation solvers and more specifically the group of one-time ideators.

8. Conclusion

This paper proposes the use of swarm intelligence to the problem of obtaining the optimum discriminant functions able to distinguish between innovation and non-innovation solvers. More specifically, PSO provides the optimum coefficient values for these discriminant functions. Obtained results provide new insights about the features of innovation solver profiles, facilitating the evaluation of ideas by the company's innovation team. The advantage of identifying innovation solvers is that they provide ideas aligned with the strategic innovation policies of the company. The proposed methodology can be extended to the identification of user profiles in other online communities.

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Tables

Table 1. Confusion matrix.

<table>
<tr><td rowspan="3" colspan="2">Observed</td><td colspan="3">Estimated</td></tr>
<tr><td colspan="2">Innovation solvers $\mathrm{User}^{*}_{\mathrm{isolvers}}$</td><td rowspan="2">Percentage correct</td></tr>
<tr><td>,00</td><td>1,00</td></tr>
<tr><td rowspan="2">Innovation solvers $\mathrm{User}_{\mathrm{isolver}}$</td><td>,00</td><td>TN</td><td>FP</td><td>$\mathrm{TN}/(\mathrm{TN}+\mathrm{FP})$</td></tr>
<tr><td>1,00</td><td>FN</td><td>TP</td><td>$\mathrm{TP}/(\mathrm{FN}+\mathrm{TP})$</td></tr>
<tr><td colspan="2">Total percentage correct</td><td></td><td></td><td>$\mathrm{TN}/(\mathrm{TN}+\mathrm{FP})+\mathrm{TP}/(\mathrm{FN}+\mathrm{TP})$</td></tr>
</table>

Table 2. SNA variables describing the behavior and activity of IdeaStorm users

Variable	**Description**	**Coefficients (θ_i)**
N_ideas	Number of posted ideas	Nid
Votes	Total number of votes received	Vt
Cat	Number of categories covered by posted ideas	Cat
IndCN	In-degree, comment network	InD-CN
OutdCN	Out-degree, comment network	OutD-CN
IncloCN	In-closeness centrality, comment network	IncloCN
OutcloCN	Out-closeness centrality, comment network	OutcloCN
BetCN	Betweeness centrality, comment network	BetCN
NL1neigh	1-neighbourhood connectivity	NeighCN
CC-CN	Clustering coefficient, comment network	CC-CN
IndPN	In-degree, promotion network	InD-PN
OutdPN	Out-degree, promotion network	OutD-PN
IndDN	In-degree, demotion network	InD-DN
OutdDN	Out-degree, demotion network	OutD-DN

Table 3. PSO parameter settings.

Parameter	**Value**
Number of particles	75
PSO Mode	Common PSO with inertia weights
Acceleration constants [c_1, c_2]	[2.1,2.1]
Inertia weights [w_{max}, w_{min}]	[0.9,0.3]
Error gradient tolerance	1e-6
Iterations without error gradient change	40
Maximum number of iterations	400

Table 4. Confusion matrix obtained by PSO.

Observed		Estimated		
		Innovation solvers $User^{*}_{isolvers}$		Percentage correct
		,00	1,00	
Innovation solvers $User_{isolver}$	,00	2419	1340	0.6435
	1,00	41	187	0.8202
Total percentage correct				1.4637

Table 5. Coefficients' optimum values.

Coefficients	Value	Coefficients	Value
Nid	3,9396	**BetCN**	-3,7729
Vt	-3,9976	**NL1neighCN**	4,1684
Cat	-0,5523	**CC-CN**	2,6107
InD-CN	9,6235	**InD-PN**	3,8001
OutD-CN	-2,4347	**OutD-PN**	-0,903
IncloCN	2,2314	**InD-DN**	-6,4569
OutcloCN	1,4867	**OutD-DN**	1,5878
Constant	-8,2973		

Figures

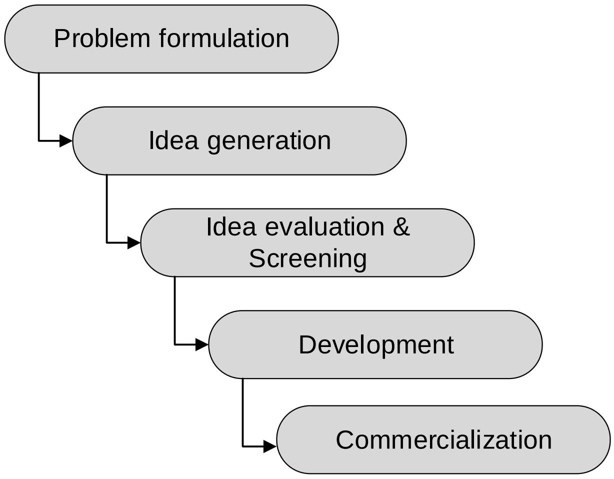

Figure 1. Process of ideation.

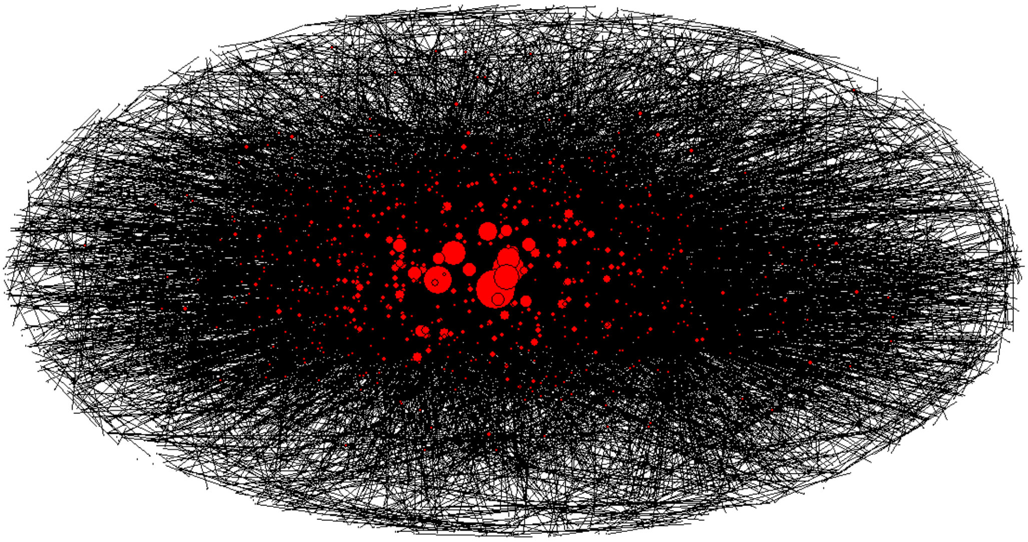

Figure 2. Comment network modeling IdeaStorm open innovation community

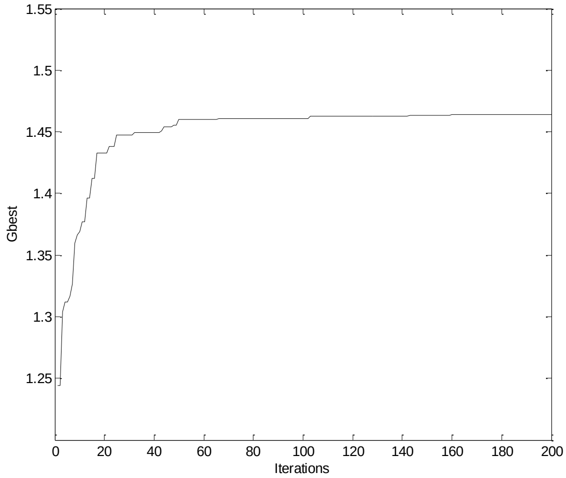

Figure 3. Evolution of the gbest value.

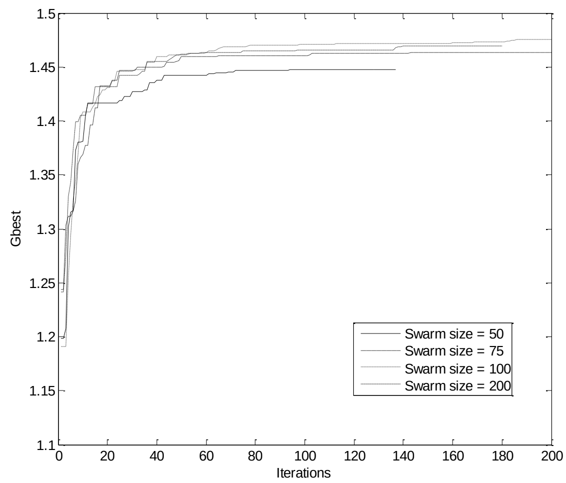

Figure 4. Comparison of different swarm sizes on PSO evolution.