Customer preferences versus managerial decision making in Open Innovation Communities: the case of Starbucks

Customers can participate in open innovation communities posting innovation ideas, which in turn can receive comments and votes from the rest of the community, highlighting user preferences. However, the final decision about implementing innovations corresponds to the company. This paper is focused on the customers' activity in open innovation communities. The aim is to identify the main topics of customers' interests in order to compare these topics with managerial decision making. The results obtained reveal first, that both votes and comments can be used to predict user preferences; and second, that customers tend to promote those innovations reporting them more comfort and benefits. In contrast, managerial decisions are more focused on the distinctive features associated to the brand image.

Keywords – Open Innovation; Innovation policies; Customer communities; Collective intelligence; Decision making

1. Introduction

Organizations have widely acknowledged the role of innovations in economic growth. Technological developments have forced higher competitiveness and shorter innovation cycles and, as a result, companies increase their efforts in innovation activities (Hekkert & Negro, 2009). As a further step, companies have begun to open their innovation processes by incorporating both internal and external resources, leading to the so called open innovation paradigm (Chresbrough, 2003). Open Innovation is a recent strategy related to the management of information in organizations, and relies on the idea that potential opportunities and advantages can be gained outside the formal boundaries of organizations (Huizingh, 2011; Martinez-Torres, 2013; Holzmann, Sailer & Galbraith, 2014). This is especially important in companies offering daily use products, which require a constantly updated external feedback to measure its progress and development.

This paper is focused on a representative example of this kind of organizations: Starbucks. The distinctive element of this company in respect to the competitors is to offer its clients a quality service at all levels. In this line, Starbucks CEO’s and chairman, Howard Schultz, determines the necessity to renovate the company´s image by retracing the company´s steps in the same direction it did from its origin: orienting it to giving personalized attention to each customer. Starbucks, like most companies, is aware of the importance of the new technologies and the diffusion of internet as a tool that can be reached by many customers (Sigala, 2012). The open innovation website is actually a fundamental element in the strategy of restructure. Through "My Starbucks Idea" website, not only users can post and share ideas with the rest of users, but comment and vote other previously posted ideas. These two last forms of participation, commenting and voting, allow users to exert some pressure on the organization highlighting their preferences. However, the organization receives thousands of ideas and must individually asses each one. Moreover, not all the posted ideas, even if they are quite popular, can be implemented by the organization since they can be prohibitive due to its high cost or they can be in conflict with the image and the mission of the organization.

This paper investigates customers' preferences and Starbucks decision making when adopting ideas. More specifically, the paper tries to test to what extent the preferences of customers are influencing the adoption of ideas. Although this research is restricted to the case study of My Starbucks Idea, which is a well-known open innovation platform, the proposed methodology can be easily extended to other similar consumer platforms.

The main contribution of this research is the analysis of open innovation communities from the double perspective of the customers and the company, which can explain some biases in the innovation policy of companies or to what extent customers can influence future innovations. The remainder of the paper is structured as follows: next section explains the concept of open innovation and its implementation through open innovation communities. Section 3 proposes the hypotheses of this study. Section 4 details the methodology for extracting the data from "My Starbucks Idea" website and the variables considered. Section 5 shows the results obtained that are next discussed in section 6. Finally section 7 concludes the paper.

2. Literature review

The term open innovation was coined by Prof. Henry Chesbrough (2003) and refers to the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively. This paradigm assumes that firms can use external ideas and internal ideas, as well as internal and external paths to market in order to advance their technology. In contrast to the traditional innovation model, this paradigm also assumes that the risks derived from opening the innovation, such as the access to valuable information by competitors or the loss of control over the innovation process, can be compensated by a richer number of innovative ideas.

Several classifications have been proposed in the literature about open innovation. Toral et al. (2011) distinguish between product and process innovations. According to the degree of openness in innovation, open innovation strategies can also be classified as outsourcing, crowdsourcing and online contests (Huff et al., 2013). Online contests are intended as competitions among users in order to reach the best idea/proposal and the winner is rewarded (Harland & Nienaber, 2014). However, the generation of ideas through a website can be considered as a form of crowdsourcing, which is not intended as a competition (Martinez-Torres, 2014a). They have been popularized thanks to the emergence of Web 2.0 (Bayus, 2013). Firms such as Microsoft, Dell, IBM, BMW, and Nokia increasingly invest in virtual communities to solicit user contributions as part of their innovation processes. This trend is explained by the increase in digitalization and the decrease in the costs of communication that have lead to an exponential growth of user innovation platforms (Mahr & Lievens, 2009).

However, some major unresolved issues regarding open innovation still remain open. One of them refers to the selection of the best stage in which open innovation can be more effective. In the case of new service development processes, user involvement is often more intense at the initial stages of idea generation and screening, and again at the later stages of test marketing and commercialization. Several studies conclude that it is better involving customers at the earliest stages as they can provide later substantial reductions in time, costs and corrections (Cooper and Kleinschmidt, 1994; Alam, 2006). Another important question refers to managerial decision-making. Gassman et al. (2010) argue that the internal process by which companies manage open innovation is still more trial and error than a professionally managed process. Open innovation can be seen as a support for managerial decision making, problem solving, and opportunity exploiting (Chiu et al., 2014). The collective evaluation system of ideas typically implemented by open innovation communities allows to distinguish customer preferences, and also reveals mismatching between customer preferences and companies' decision making (Martinez-Torres, 2014a). This study goes further in this analysis by first considering the main topics chosen by customers, and then comparing them with the final company decision-making. In contrast to previous papers in this topic that use a qualitative approach (Sigala, 2012), this paper proposes a quantitative approach. Thousands of ideas must be collected and analyzed to obtain the categories or topics they belong to. Although data is publicly available, not all the information contained in web pages is useful and meaningful, and data have to be automatically extracted for each one of the thousands of posted innovations. These data extraction methods can be framed within the Big Data methodologies, which represent an emergent trend within social sciences (Chang et al., 2014; Martinez-Torres, 2014b; Arenas-Marquez et al., 2014).

3. Hypotheses

The two primary forms of participation in online communities consists of commenting and voting. Previous works support that both forms of participation tend to be correlated. For instance, this is the case of Dell Ideas Storm, the open innovation community from Dell, where comments, promotions (positive scores) and demotions (negative scores) has been proved to be correlated (Martinez-Torres, 2014a). Obviously, it is cognitively more complex posting a comment than posting a score, where no justification is required. However, Bajic and Lyons (2011) proposed that collaborative websites allow users to find suggestions similar to their own, hence resulting in more votes and comments per suggestion. Both votes and comments have also been used in open innovation contests as a measure to determine users' design preferences and pre-select the most promising designs for the jury (Füller at el., 2010). Dahlander and Piezunka (2014) obtained a positive relationship between the number of suggestions from external contributors and proactive attention. Other authors have studied how the cognitive and affective feelings influence the evaluation of contributions. Readers of a message will respond to the assertiveness infused into the message as well as to the message itself, and the manner in which the message is presented. Consequently, when messages communicate negative feeling, they are likely to attract negative reactions from the community in terms of votes and comments (Kim & Miranda, 2011).

Although votes and comments are publicly available, there are only few examples of studies that have explored customer generated content in new service development. Li et al. (2010) proposed a news recommendation system based on user comments under the assumption that topic evolution in social media can be reflected by the comments. Therefore, votes and comments can be used as the variables to collect user preferences. Alam (2002) argues that a large number of powerful new service ideas needs to be generated with user contacts and interactions, and customer participation is important for designing distinguishable and unique services. However, customers are able to suggest new services which provide them with values and solutions to their daily problems (Sigala, 2012). It is widely held that service quality is perceived by customers through a comparison between service related expectations and experiences (Grönroos, 2000). These experiences are always relative to what customers consider reasonable based on their prior experiences, service provider's communications, and their own needs and aspirations in a particular situation (Kuusisto, 2008). According to Vargo and Lusch's (2004), services provide customers with value only when they are used. Customer value is hence tied to a customer's meaning attached to the experience with a service. This implies that most customers' proposed innovations are biased by their previous experience, and they are mainly guided by their own needs. According to this, we propose the following hypothesis:

H1: *Users preferences tend to focus on the core activity of the company and on those ideas reporting them more comfort and benefits*

Crowdsourcing has been stated as a source of support for managerial decision making (Brabham, 2013), and open innovation is actually one form of crowdsourcing (Chiu et al., 2014). However, human biases can affect the idea generation process (Bonabeau, 2009). For instance and in the case of the hospitality services, social interference or the consumers' desire for finding a solution fitting their specific needs can lead to ideas far away from the company expectations (Sigala, 2012). In some cases, the company expectations are also drifted by the resistance to change, for instance, selling what we make rather than responding to customer requirements. Online marketing managers often base their decisions on simple heuristics, combined with personal expertise. Personal preferences are still prevalent despite of the volume of data available (Anderl et al., 2013). In the case of hospitality companies, the experience states that they can increase their market share and growth rates by increasing their brand loyal customers (Tepeci, 1999). This is because the hospitality business is a mature industry where it is cheaper to serve current customers rather than acquiring new customers through advertising, promotion, and start-up operating expenses. There are several studies that show the positive relationship between the brand image and customers' perceived value and purchase behaviour (Wu, 2008; Cretu & Brodie, 2007). Thus we propose the following hypothesis:

H2: *Managerial decision making tend to focus on the distinctive features associated to the brand image*.

4. Methodology

This study follows a grounded theory approach, which is a general methodology for developing theory that is grounded in data systematically gathered and analyzed (Strauss & Corbin, 1998; Toral et al., 2009). This methodology has been used as a marketing research methodology for studying customer involvement in new service developments (Sigala, 2012) or for analysing the publicly available information in online communities (Kozinets, 2002). The first step to apply this methodology consists of finding an online community appropriate for the research aims. This is the case of My Starbucks Idea, which is an open innovation website where users can score and comment innovations, and where the company makes public and visible those ideas finally adopted. The second step consists of data collection. Starbucks' open innovation website identifies members' contributions as ideas. When posting an idea, registered users have to choose one of the fifteen subcategories that respond to three basic aspects of the company: product, experience and involvement ideas, Table 1.

Table 1. Categories and subcategories of posted ideas.

Product ideas	**Coffee & Espresso Drinks**
	Frappuccino & Beverages
	Tea & other drinks
	Food
	Merchandise & Music
	Starbucks Card
	New Technology
	Other Product Ideas
Experience ideas	**Ordering or Payment & Pick-Up**
	Atmosphere & Locations
	Other Experience Ideas
Involvement ideas	**Buiding Community**
	Social Responsability
	Other Involvement Ideas
	Outside USA

Once an idea is submitted and shared, community users can vote and comment posted ideas. Commenting an idea means that the users attach comments below the posted idea in the form of a thread of discussion. In general, comments can support, criticize or refine the idea shared and, as a result, a debate among users can emerge through these comments. Even the original author of the idea can participate answering some questions. Voting an idea consists of adding or subtracting 10 points to its current score. As long as ideas receive more votes, they are promoted to top positions in terms of popularity within the web. There is a separate category, called Ideas in Action, which shows those ideas that either have already been launched (adopted by the company) or that are currently coming soon. Therefore, this category includes those ideas that have been considered by Starbucks for their implementation.

Three variables have been considered in this study: Votes, which refers to the current score of each idea; Comments, defined as the number of received comments by each idea shared; and Size, which refers to the number of characters of the ideas shared. The three variables have been extracted using our own crawler. A crawler is a computer program that follows the hyperlink structure of the web. In this case, the crawler is used to collect data from a specific website (Youtie et al., 2012). As the source code of each website has a different structure and style, there is no standard way of browsing through them. As a consequence, it is necessary to program a hand-made crawler. In this paper, the crawler was programmed in R, which is a free software environment for statistical computing. The base package of R contains the function *readLines()*, which reads data from a URL. This function was used to access the shared reviews. However, webpages are formatted in HTML code, and accessed data contains both the webpage content and the HTML tags. Therefore, it is necessary to parse the HTML file using the *htmlParse()* function. This function generates an R structure representing the HTML tree. Once online webpages are available as an R structure, meaningful data can be easily identified using regular expressions that are also supported in R, for instance, in packages such as XML. As a result, a total of 99528 ideas distributed over the fifteen categories of Table 1 were collected. Additionally, the category of Ideas in Action was also crawled. In this case, the number of ideas is 897. For each one of them, the number of comments received and its size was captured (the number of votes is not available in this case), as well as the categories under which these ideas were classified by Starbucks. Once data is collected, the paper first analyses the activity of users in open innovation communities in the different categories where they can post innovations. The results obtained are then compared with those ideas actually implemented by the company.

5. Results

A correlation analysis among the three extracted variables for the fifteen categories of ideas has been performed. Results obtained in Table 2 show that participation through voting and commenting are positively correlated, while the size of ideas shared is not correlated with the other two variables.

	Votes	Size	Comments
Votes	**1,000**	**-,027****	**,487****
Size	**-,027****	**1,000**	**,101****
Comments	**,487****	**,101****	**1,000**

** Correlation is significant at the 0,01 level (2-tailed).

Table 2. Correlation among variables.

This result suggests that those ideas that receive a higher number of votes are also generating a debate around them. Therefore, both votes and comments can be considered relevant information to identify users' preferences. However, the size of ideas is not relevant for identifying good ideas.

The distribution of the three variables considered over the fifteen categories of ideas has been first analysed. Figure 1 illustrates the mean value and confidence intervals of the variable Votes in each of the fifteen categories of ideas. This figure highlights that the categories *Starbucks cards*, *Ordering*, *Payment & Pick up and Coffee & Espresso Drinks* are the three ones that receive more votes, while *New Technology* is clearly the worst evaluated category by users. These results suggest that Starbucks customers are more biased towards the core activity of Starbucks, which are basically coffee and the ordering processes. Starbucks card refers to the loyalty program of the company and its associated advantages. Taking into account that the Starbucks Card is the rewarding system to the loyalty of users and the fact that the majority of the ideas provided by the community in this category demands extending its owner's benefits, there's an obvious tendency among My Starbucks Idea members to support and vote these ideas, as stated in hypothesis H1.

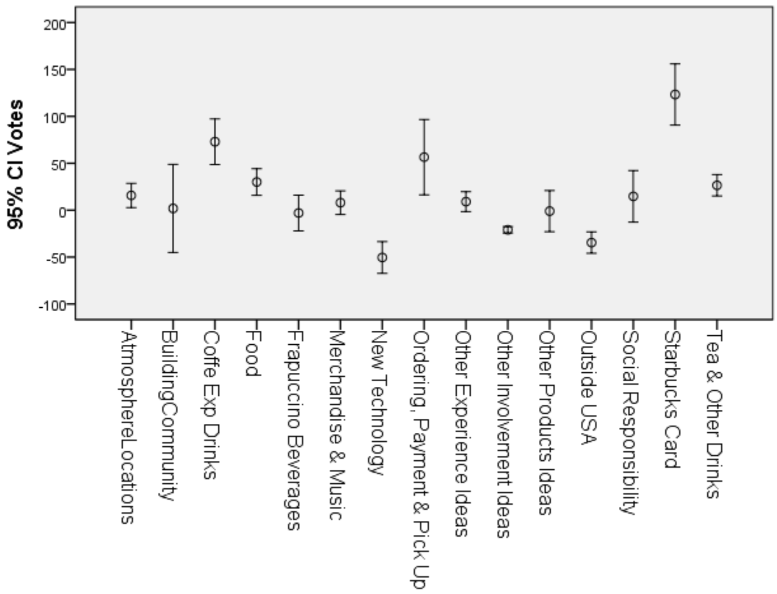

Figure 1. Mean value and confidence intervals of Votes.

Figure 2 details the mean value and confidence intervals of the variable Size. In this case, three categories (*Frapuccino, New technology and Outside USA*) show the highest values. The rest of them are more or less similar in size. This result can be explained because this particular categories have a wider scope, and consequently ideas need to be more precise and require longer explanations.

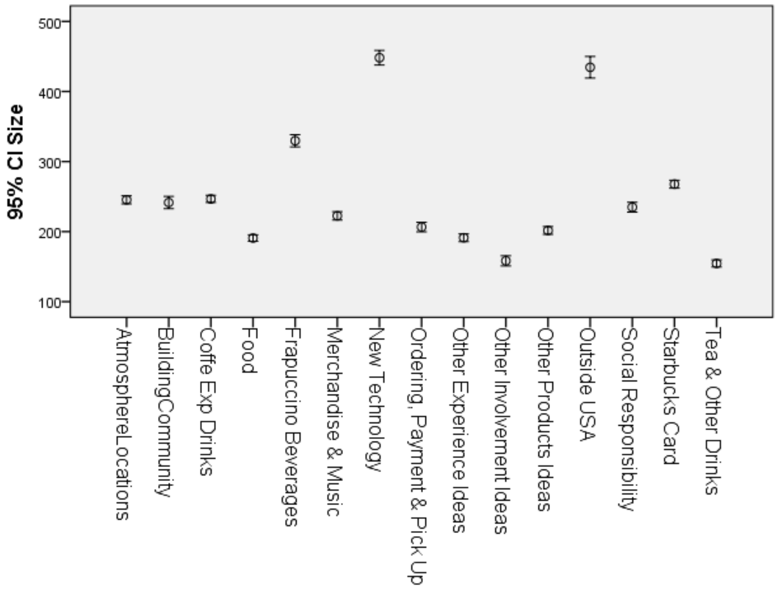

Figure 2. Mean value and confidence intervals of Size.

Finally, Figure 3 shows the mean value and the confidence intervals of the variable Comments. The most popular categories in this case are *Coffee & Espresso Drinks*, *Frapuccino* and *New technology*. It is interesting to notice that *Coffee & Espresso Drinks* occupies a relevant position in both Votes and Comments. This could be because Coffee is the main product of Starbucks, and people tend to associate the image brand to coffee. Therefore, this is perhaps the main category in which users are more involved in. It is also interesting to see that *New technology* is in general the worst evaluated/scored category, although it arouses an important debate among users. This point can be explained by the specificity of contributions related to this category. In contrast, the debate in the categories *Outside USA, Food and Merchandise & Music* is noticeably lower.

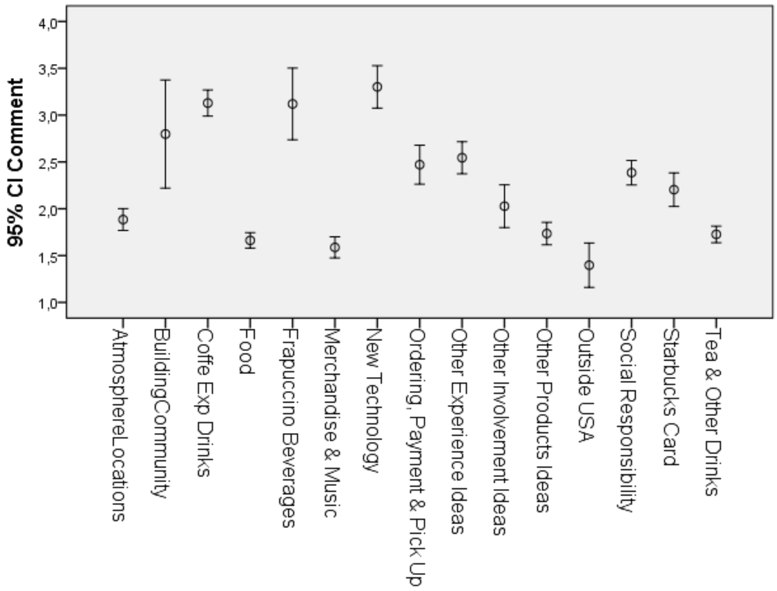

Figure 3. Mean value and confidence intervals of Comment.

A Kruskal-Wallis test has been performed to test the equality of means of the three variables considered in each of the fifteen categories of ideas. The Kruskal–Wallis test is a nonparametric version of one-way analysis of variance. The assumption behind this test is that the measurements come from a continuous distribution, but not necessarily a normal distribution. The test is based on an analysis of variance using the ranks of the data values, not the data values themselves. The low *p* value in Table 3 for each variable suggests that the null hypothesis can be rejected, so it can be concluded that the obtained mean values in Figures 1-3 are significantly different.

	Votes	**Size**	**Comments**
Chi-square	**4713,32**	**6046,31**	**2507,39**
df	**14**	**14**	**14**
p	**0,000**	**0,000**	**0,000**

Table 3. Kruskal-Wallis test.

Any of the previous ideas belonging to the fifteen categories have the opportunity of becoming a reality. If the contribution is viable and it is considered interesting by Starbuck's quality team support, it can reach the *Idea in Action* status. This category actually represents the managerial decision making, as ideas reach this status after been evaluated by the innovation department or some experts of the company. Although the final decision about ideas can be influenced by the community evaluation, it is actually an independent and autonomous decision of the company.

Figure 4 shows the distribution of the number of Ideas in Action per category of Ideas. *Coffee & Espresso Drinks*, with 190 ideas in Action, is clearly the category in which more ideas have been selected by Starbucks. Again, this result is in line with the main product offered by the company, which is also the most closely associated to the brand image. The second and third places correspond to *Other Experience Ideas* and *Social Responsibility*.

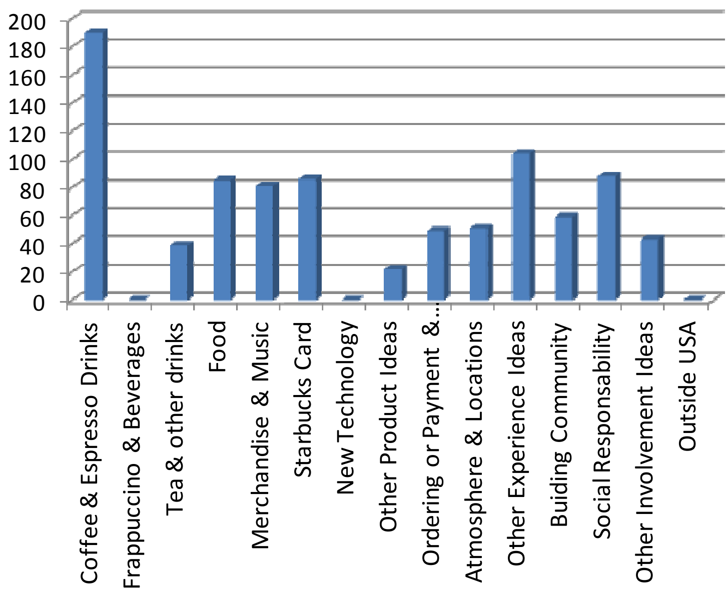

Figure 4. Distribution of Ideas in Action per category.

Other experience ideas category provides space for those comments not instinctively classifiable in the other categories, such as partners (workers, baristas), other types of rewarding loyalty, or decoration changes. This category includes the feeling of users about Starbucks, and this is an issue prioritized by the company, which considers the experience of taking a coffee in Starbucks as a distinctive experience. The same can be said about social responsibility. Starbucks aims to be an environmental-friendly green brand, concerned about social problems both in the whole world and in every single neighborhood. The three most adopted categories are those more closely related to the brand image of the company, as hypothesized in H2.

6. Discussion and implications

Although there are several methods for importing external ideas through the scheme of open innovation, this study is specifically focused on open innovation web communities, which have gained popularity with the emergence of user generated content (Martinez-Torres, 2015).

Results obtained show there is a gap between customer preferences and managerial decision making in open innovation communities. This gap can be explained because companies involved in open innovation are not still completely confident about the open innovation results. However, this is precisely contrary to what the literature has established in the sense that users are better in identifying useful ideas because these are not usually easy to implement by firms (Poetz and Schreier, 2012). Although customer preferences under the scheme of open innovation can overcome some resistance to change, there is still some biases in managerial decision making, as it can be observed in the results obtained. As a result, companies can miss some important disruptive innovations that can be competitive advantages for the future.

In order to overcome these problems, it is important for companies performing open innovation schemes to introduce some monitoring activities about the decision making processes, able to detect some biases. At this point, this paper offers a methodological contribution by using some methods for data collection in social media. The main advantage of the proposed method is that it can work with the whole data set instead of a sample, as information about all previous posted innovation can be easily accessed using computer based tools. The comparison between customer and company preferences can detect areas of innovations not considered previously. Moreover, customer preferences can also be analyzed through the different categories in which they can post innovations. The selection of the categories is made up by the company, and it is important to decide which areas are available, since they guide in some way the customers' contributions.

The results obtained in this study show that customers tend to focus on the core activity of the company, coffee and food, and on those ideas reporting them more comfort and benefits, for instance, those ideas related to ordering and payment, or loyalty cards (Vargo and Lusch, 2004). This means that customers value not only the final product but also the surrounding and the experience associated to them. Actually, the website distinguish between product, experience and involvement ideas, as shown in Table 1. As a difference, the company is focused on the distinctive features associated to the brand image. According to Cretu & Brodie (2007), the brand's image has a more specific influence on the customers' perceptions of product and service quality. It is worth mentioning that the *New Technology* group of ideas receive many comments, but they are evaluated with low scores. This point can be explaining because those authors posting technological ideas are more sensitive to intellectual property issues and they can be resilient to make open their contributions without any kind of rewards, as may happen in other open innovation schemes. Open innovation communities like My Starbucks Idea can only provide intangible rewards such as community cooperation, learning new ideas and having entertainment (Antikainen et al., 2010). Additionally, technological innovations require high investments that are not usually considered by hospitality companies.

Several limitations and future research works can be addressed. The paper is limited to a case study. Therefore, the work could be extended by analyzing some other open innovation communities and confirming if managerial decision making is also biased in the same way. Another limitation is that the paper is only focused on the activity of customers when posting, commenting or scoring innovations. However, the content of contributions was not considered. Research methods coming from Social Media analytics have been used for data extraction. But some other research methods could be applied to go further in the analysis of open innovation communities. For instance, the content of posted contributions could be processed using semantic analysis techniques to obtain the main topics (Martinez-Torres et al., 2013), both from the side of customers and from the side of the company. In this way, the study would not be limited to the categories or tags selected by the company, as it is the case in this work. Moreover, this analysis could also be used to check whether the tags selected by the company actually fit the real contributions of customers or they are actually constraining their creativity. Finally, the study could be extended to other types of open innovation schemes with a stronger link between the company and contributors, for instance, through rewards or compensation to the participants.

7. Conclusions and implications

This paper is focused on the open innovation community of Starbucks, which is based on sharing ideas through a specific website run by this company.

The aim of the paper is to distinguish between users and company preferences when deciding about the most interesting shared ideas. Both of them are logically focused on the main product of the company: coffee and espresso drinks. However, users tend to promote those ideas reporting them more comfort and personal benefits, while the company is more focused on those issues related to the brand image, like the beliefs and feeling associated to the experience of taking a coffee.

References

[1] Alam, I. 2002. An exploratory investigation of user involvement in new service development, *Academy of Marketing Science*, 30, Iss. 3: 250-261.

[2] Alam, I. 2006. Removing the fuzziness from the fuzzy front-end of service innovations through customer interactions, *Industrial Marketing Management*, 35. no. 4: 468-80.

[3] Anderl, E., Becker, I., Wangenheim, F. V., & Schumann, J. 2013. Putting attribution to work: A graphbased framework for attribution modeling in managerial practice. *Social Science Research Network*, 2343077.

[4] Antikainen, M., Mäkipää, M., & Ahonen, M. 2010. Motivating and supporting collaboration in open innovation. *European Journal of Innovation Management*, 13, Iss. 1: 100-119.

[5] Arenas-Marquez, F. J., Martinez-Torres, M. R., Toral, S. L. 2014. Electronic word of mouth communities from the perspective of Social Network Analysis, *Technology Analysis & Strategic Management*, 26, Iss. 8: 927-942.

[6] Bajic, D. and Lyons, K. 2011. Leveraging social media to gather user feedback for software development, *Proceedings of the 2nd International Workshop on Web 2.0 for Software Engineering, Web2SE '11*, pp. 1-6.

[7] Bayus, B. L. 2013. Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community, *Management Science*, 59, Iss. 1: 226-244.

[8] Bonabeau, E. 2009. Decisions 2.0: the power of collective intelligence, *MIT Sloan Management Review*, 50, Iss. 2: 45–52.

[9] Brabham, D.C. 2013. *Crowdsourcing*, The MIT Press, Boston, MA.

[10] Chang, R. M., Kauffman, R. J., Kwon, Y. 2014. Understanding the paradigm shift to computational social science in the presence of big data, *Decision Support Systems*, 63: 67-80.

[11] Chiu, C.-M., Liang, T.-P., Turban, E. 2014. What Can Crowdsourcing Do for Decision Support?, *Decision Support Systems*, 65:40-49.

[12] Chresbrough, H. 2003, *Open innovation: The New Imperative For Creating and Profiting from Technology*, Harvard Business School Press, Boston.

[13] Cooper, R.G. and Kleinschmidt, E.J. 1994. Determinants of timeliness in product development, *Journal of Product Innovation Management*, 11, no. 5: 381-96.

[14] Cretu, A. E, Brodie, R. J. 2007. The influence of brand image and company reputation where manufacturers market to small firms: A customer value perspective, *Industrial Marketing Management*, 36, Iss. 2: 230–240.

[15] Dahlander, L., and Piezunka, H. 2014. Open to suggestions: How organizations elicit suggestions through proactive and reactive attention, *Research Policy*, 43, Iss. 5: 812–827.

[16] Füller, J., Möslein, K., Hutter, K., Haller, J. 2010. Evaluation Games - How to Make the Crowd your Jury, 40th Annual Conference: Informatik 2010: Service Science- Neue Perspektiven für die Informatik, Gesellschaft für Informatik, Leipzig, Germany, pp. 955-960.

[17] Gassmann, O., Enkel, E., Chesbrough, H.W. 2010. The future of open innovation, *R&D Management*, 40, Iss. 3: 213–221.

[18] Grönroos, C. 2000. *Service Management and Marketing – A Customer Relationship Management Approach*. John Wiley & Sons Ltd, Chichester, England.

[19] Harland, P. E., & Nienaber, A. M. 2014. Solving the matchmaking dilemma between companies and external idea contributors, Technology Analysis & Strategic Management, 26, Iss. 6, 639-653.

[20] Hekkert, M. P. & Negro, S. O. 2009. Functions of innovation systems as a framework to understand sustainable technological change: Empirical evidence for earlier claims, *Technological Forecasting and Social Change*, 76, Iss. 4: 584-594.

[21] Holzmann, T., Sailer, K., & Galbraith, B. 2014. Matchmaking for open innovation – theoretical perspectives based on interaction, rather than transaction, Technology Analysis & Strategic Management, 26, Iss. 6: 595-599.

[22] Huff, A., Moslein, K., Reichwald, R. 2013. *The Future of Crowdsourcing: From Idea Contests to MASSive Ideation Leading Open Innovation*, In: Leading Open Innovation, MIT Press, pp. 241-261.

[23] Huizingh, E. K. R. E. 2011. Open innovation: State of the art and future perspectives, *Technovation*, 31, no. 1: 2-9.

[24] Kim, S., Miranda, S. 2011. Seeds of Change: Substance and Influence in Brand Communities, *Thirty Second International Conference on Information Systems*, Shanghai 2011, paper 30.

[25] Kuusisto, A. 2008. Customer roles in business service production - implications for involving the customer in service innovation, in A. Kuusisto and S. Päällysaho 2008. *Customer Role in Service Production and Innovation - Looking for Directions for Future Research*, Lappeenranta University of Technology, Faculty of Technology Management Research, report 195.

[26] Mahr, D., Lievens, A. 2012. Virtual lead user communities: Drivers of knowledge creation for innovation, *Research Policy*, 41, Iss. 1: 167-177.

[27] Martinez-Torres, M. R. 2013. Application of evolutionary computation techniques for the identification of innovators in open innovation communities, *Expert Systems with Applications*, 40, Iss. 7: 2503-2510.

[28] Martínez-Torres, M.R., Toral, S. L., Barrero, F., Gregor, D. 2013. A text categorisation tool for open source communities based on semantic analysis, *Behaviour & Information Technology*, 32, Iss. 6: 532-544.

[29] Martinez-Torres, M. R. 2014a. Analysis of Open Innovation Communities from the perspective of Social Network Analysis, *Technology Analysis & Strategic Management*, 26, Iss. 4: 435-451.

[30] Martinez-Torres, M. R. 2014b. Analysis of Activity in Open Source Communities using Social Network Analysis Techniques, *Asian Journal of Technology Innovation*, 22, Iss. 1: 114-130.

[31] Martinez-Torres, M. R. 2015. Content analysis of open innovation communities using latent semantic indexing, *Technology Analysis & Strategic Management*, doi: 10.1080/09537325.2015.1020056.

[32] Poetz, M. K., and Schreier, M. 2012. The Value of Crowdsourcing: Can Users Really Compete with Professionals in Generating New Product Ideas?, *Journal of Product Innovation Management*, 29, Iss. 2: 245–256.

[33] Sigala, M. 2012. Social networks and customer involvement in new service development (NSD), *International Journal of Contemporary Hospitality Management*, 24, no. 7: 966-990.

[34] Strauss, A. & Corbin, J. M. 1998. *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*, SAGE Publications, Thousand Oaks, CA, USA.

[35] Tepeci, M. 1999. Increasing brand loyalty in the hospitality industry, *International Journal of Contemporary Hospitality Management*, 11, Iss. 5: 223-230.

[36] Toral, S. L., Martínez-Torres, M. R., & Barrero, F. 2009. Modelling mailing list behaviour in open source projects: the case of ARM embedded Linux. *Journal of Universal Computer Science*, 15, Iss. 3: 648-664.

[37] Toral, S., Martinez-Torres, M. R., Di Gangi, P. 2011. User Innovations Through Online Communities From the Perspective of Social Network Analysis, *The First International Conference on Advanced Collaborative Networks, Systems and Applications, COLLA 2011*, pp. 40-45.

[38] Vargo, S.L. and Lusch, R.F. 2004. Evolving to a new dominant logic for marketing, *Journal of Marketing*, 68: 1-17.

[39] Wu, W. C., 2008. The Study of Influence of Brand Equity, Customer Value, Customer Satisfactions and Customer Loyalty —A Case Study of Wretch, *MA Taiwan: Department of Communications Management,* Ming Chuan University.

[40] Youtie, J., Hicks, D., Shapira, P. & Horsley, T. 2012. Pathways from discovery to commercialisation: using web sources to track small and medium-sized enterprise strategies in emerging nanotechnologies, Technology Analysis & Strategic Management, 24, Iss. 10: 981-995.