Empowered by Innovation: Unravelling Determinants of Idea Implementation in Open Innovation Platforms

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Abstract: Companies use crowdsourcing to solve specific problems or to search for innovation. By using open innovation platforms, where community members propose ideas, companies can better serve customer needs. So far, it remains unclear which factors influence idea implementation in crowd sourcing context. With the research idea that we present here, we aim to get a better understanding of the success and failure of ideas by examining relationships between characteristics of ideators, characteristics of ideas and the likelihood of implementation. In order to test the methodological approach that we propose in this paper in which we investigate for business relevant innovativeness as well as sentiment based on text analytics, data including unstructured text was mined from Dell IdeaStorm using webcrawling and scraping techniques. Some relevant hypotheses that we define in this paper were confirmed on the Dell IdeaStorm dataset but in order to generalize our findings we want to apply to the Lego dataset in our current work in progress. Possible implications of our novel research idea can be used to fill theoretical gaps in marketing literature, help companies to better structure their search for innovation and for ideators to better understand factors contributing to successful idea generation.

1 INTRODUCTION

The need for innovation is currently a top business priority (Jaruzelski & Dehoff, 2010) and a key issue in academic research (Hauser et al., 2006). On-going technological advances and their enormous influence and use in society have induced considerable changes in people's lifestyles (Romero and Molina, 2011). Therefore, organizations need to adopt innovative business models to engage customers and gain competitive advantage in the marketplace (Zhang et al., 2015). One way organizations can do this is by online co-creation communities (OCC) (Zhang et al., 2015) in the form of crowdsourcing. Majchrzak and Malhotra (2013) define crowdsourcing for innovations as "the public generation of innovative solutions to a complex problem posed by the company sponsoring the challenge call" (p. 258). Companies are nowadays more often looking to generate new ideas or solve specific problems with the help of their customers (Erickson et al., 2012). Companies hope to gain direct access to their customers knowledge concerning user needs to generate ideas for new products and use their expertise to solve problems (Schemmann et al., 2016). This is done in online communities, enabled by companies, where customers are encouraged to share their ideas and thoughts about specific topics (Ye et al., 2012; Schemmann et al., 2016). Customers are not passive targets of marketing action anymore. They are perceived as more active operant resources that determine and create value (Saarijarvi et al., 2013).

Value co-creation has become a key concept within marketing and business management. The focus of value co-creation is to reinvent value in terms of the value creating system itself where different actors like suppliers, business partners, allies and customers, work together to co-produce value. There are a multitude of approaches to value co-creation (Saarijarvi et al., 2013).) The example of Dell's Ideastorm illustrates how customers resources can be engaged in the New Product Development (NPD) (Saarijarvi et al., 2013). Over 50,000 ideas have been generated in the online communities of Dell and Lego

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through crowdsourcing.

Innovative solutions can include new sources of revenue such as new product lines or services, or adapt from existing processes and practices (Dahlander and Gann, 2010). It is thought that a diverse community will develop fundamentally different innovations because they draw from a different knowledge base (Von Hippel, 2005). Diverse expertise may be derived from differences in knowledge domains, context, product usage, discipline or specialty work areas (Schenk and Guittard, 2011). Crowdsourcing has a benefit for both the crowdsourcing company and the user within the online community. Customers' needs are complex and hard to measure (O'Hern and Rindfleisch, 2010). Market research conducted internally would only provide companies a signal of their customers' desires and needs, which still results in a lot of new product failures (Ogawa and Piller, 2006; O'Hern and Rindfleisch, 2010). Organizations have a problem with anticipating what consumers actually need. Through crowdsourcing, ideas come directly from the customers, investing in solving problems that they have and, as a consequence, new product development would become less risky (Lüthje and Herstatt, 2004). Knowledge about consumer preference can contribute to the success of a product. Past research shows that organizations substantially benefit if they effectively manage and improve the earlier stages of the new product development (NPD) process (Verworn, 2009).

Despite being well-recognized in the industry, limited academic research is done to study OCCs as a technology driven innovation concept (Bugshan, 2014). It remains unclear how specific characteristics of ideators and ideas might influence the likelihood of idea implementation. Also, little is known about long-term open idea calls. These idea calls can result in thousands of ideas and detecting the ones to implement can be difficult for companies. The IdeaStorm platform operated by the organization Dell has collected more than 23,000 ideas since 2007 (Schemmann et al., 2016). Empirical research in this field is lacking (Schemmann et al., 2016). This study addresses this research gap. The aim of this research is to estimate whether the characteristics of the ideator and comments provided by other ideators can influence the success of an idea. The contributions of this research are twofold. First, we contribute to the literature about long-term online idea crowdsourcing. Not much is known about which factors contribute to the likelihood that an idea gets implemented. Our second contribution is a methodological advancement by providing a new approach to study this topic. We provide a technique to disentangle unstructured idea and comment texts to identify innovative efforts and sentiment in comments. This is the first study to our knowledge that uses text analysis on crowdsourcing ideas and comments.

2 THEORETICAL DISCUSSION

Idea crowdsourcing can be seen as a part of Chesbrough's Open Innovation Paradigm. This assumes that organizations can and should use ideas from external stakeholders to innovate (Chesbrough, 2006). In the case of crowdsourcing the process of innovation builds upon the external ideas of individuals. The crowdsourcing organization controls the ideation process, observes and analyses the communication and discussion of ideas and finally decided which ideas will be implemented (Schemmann et al., 2016). The online idea crowdsourcing is likely to generate a large amount of ideas. Therefore, the company needs to filter out with tremendous effort to identify which ideas will be most valuable. Previous research suggests that successful ideators possess certain characteristics (Von Hippel, 2005). However, thus far little is known about the factors determining which ideas are most likely to be implemented (Schemmann et al., 2016). The first two hypotheses of this research focus on the influence of ideator related characteristics on the likelihood of idea implementation. Not all users within a community are able to generate the same quality ideas. Characteristics that might influence the likelihood of idea implementation are activity (Bayus, 2013) and popularity (Gangi and Wasko, 2009) of an ideator. Shah (2003) found that more active ideators produce more valuable ideas. However, Schemmann et al., (2016) found that ideators who post more ideas are not more likely to generate implemented ideas than ideators who suggest only one idea. Due to the mixed results we look once again into the relationships between ideator characteristics (i.e. the amount of comments given and received) and idea implementation.

Ideator Activity.
The starting point of our investigation is to create a link between the activity of an ideator in the past and the quality of the idea that (s)he generates. The exposure to other creative ideas can enhance one's own creativity which leads to the production of more creative ideas (Nijstad and Stroebe, 2006). By commenting upon other ideas an ideator's knowledge

base will be more diverse. More alternative and creatives ideas can be formulated by combining, recycling, and further developing pieces of information (Fleming and Szigety, 2006). Research recognizes that interaction and idea exchange among ideators will facilitate the retrieval of relevant and diverse knowledge during idea generation (Kohn and Smith, 2011). A fundamental believe of brainstorming is that interactions with diverse others can stimulate associations in the memory that lead to higher quality ideas (Osborn, 1953). Interaction with others help ideators to generate alternatives, upgrade their own knowledge, get to know more diverse customer needs and therefore create more innovative and original ideas. Innovation is thought to play an important role in idea implementation (Schemmann et al., 2016). Original ideas are found to be more attractive by company experts than less original ideas (Witell et al., 2011). Schemmann et al., (2016) find that the odds of implementation increase when an idea is more innovative. Combining the insights of ideator activity and innovative idea generation, we propose the following hypothesis:

H1: The number of comments that an ideator had given in the past has a positive effect on the extent to which other customers find his/her idea to be innovative.

Giving comments is a signal that an author invests in the community and spends more time reading other ideas and commenting upon others. This will increase the visibility of the ideator among other customers. Arguably, when the ideator posts a new idea, other customers would acknowledge the ideator as a valuable member of the customer community and would be more inclined to contribute to improve the idea. Based on this mechanism, we propose the second hypothesis:

H2: The number of comments that an ideator had given in the past has a positive effect on the number of comments that the ideator would receive.

Signalling Theory.

Next, we will investigate how innovativeness and comments that an idea had received can be linked to the likelihood of its implementation. An underlying mechanism which explains the relationship between the attributes of an idea and idea implementation can be found within the Signaling theory by Spence (1973). This theory explains how people make decisions based on signals of quality, particularly when quality is difficult to ascertain. The lower the ability of the decision maker to evaluate all available information, the more important the presence of signals will be (Spence, 1973). Signaling theory has been applied in customer research. Through these signals people can predict the quality of for example a product (Cheung et al., 2014). One could argue that it is hard for companies to process all available ideas because of an information overload. Furthermore, since the ideas in crowdsourcing are still in ideation phase, it is arguably difficult to ascertain the quality of the idea. Therefore, the company has to rely on signals to determine the quality of the idea.

Innovativeness.

The first signal that we propose is idea innovativeness. The innovativeness of an idea can possibly be found within the comments that other customers give to the proposed idea. Previous studies have not investigated the strength of the text of comments upon idea implementation. But as previous research found that innovative ideas are more likely to be implemented (Schemmann et al., 2016), we expect that comments which imply that an idea is innovative will be seen as a signal for companies that the idea is indeed innovative. Therefore, we expect:

H3: The extent to which other customers find an idea to be innovative as expressed in the comments has a positive effect on the likelihood of an idea being implemented.

Other Customers' Interest.

The next signal that we propose is other customers' interest towards the idea quantified from the number of comments. When ideas receive more comments this can be interpreted as a signal of high quality. The Prospect theory adds to this logic by stating that people are risk-averse (i.e. avoid uncertainty) and therefore make decisions based on potential gains and losses (Tversky and Kahneman, 1992). One could argue that ideas with lots of comments are less risky to implement, because managers already have an indication that these ideas will be popular among potential users.

H4: The number of comments that an idea receives has a positive effect on the likelihood of the idea being implemented.

Sentiment.

Besides looking at comments we study the sentiment in comments. To our knowledge no studies have established the relationship between the sentiment of the comments and the likelihood of implementation. It is important to study sentiment because it expresses the attitude of ideators about an idea from another ideator. Attitude is defined as “the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question” (Ajzen, 1991, p. 188). A positive sentiment means a positive emotion. This research aims to identify the attitude of fellow ideators towards ideas. Comments can give useful insights into why certain ideas will be accepted and others not. To improve the existing literature, we propose that comments must be analyzed with a sentiment analysis. It is not enough to look at the amount of comments when sentiment in comments could influence the likelihood of implementation. Based on the underlying mechanisms explained in the Signaling theory and Prospect theory, we propose the following:

H5: A positive sentiment within the comments given to an idea has a positive effect on the likelihood of the idea being implemented.

3 METHODOLOGY

Data.

The data source of this study is the Dell IdeaStorm website (ideastorm.com) that is commonly applied in this research context (Bayus, 2013; Gangi and Wasko, 2009). The study uses data mined through web crawling and scraping with scrapy (Kouzis-Loukas, 2016) in Python. The database consists of 844 ideas that were available online at the moment of data mining (46% implemented/partially implemented), in overall as well as 24 categories of product ideas, Dell ideas and topic ideas, posted between 2007 and 2018, by 622 ideators. The ideators received 277 votes and 70 comments on average. The ideas received 98 votes and 14 posts on average (193 and 25, respectively, for implemented/partially implemented ideas). We process the texts of the ideas and comments using text-mining techniques with library 'tm' in R, version 3.4.3. This library contains a procedure to identify frequently mentioned terms in texts. For pre-processing, we clean the review texts from punctuations, numbers, multiple blank spaces and stop words.

Variables.

Dependent Variable.

We measure the effect of the independent variables on the idea implementation, our dependent variable. Per idea the website indicated whether an idea is implemented or rejected. The dependent variable is operationalized with the use of the idea status indicated on the platform (Schemmann, et al., 2016). This information was also scraped.

Independent Variables.

The first independent variable in this research is ideator activity that is measured by the number of comments that authors receive and give to ideas of others.

The second independent variable, sentiment, was operationalized with sentiment score for each comment using SentiStrength software, a tool for processing different types of information contained in text. SentiStrength estimates the strength of positive and negative sentiment in a text by using a predefined sentiment word list (Thelwall et al., 2010). This software is free for academic research and has been tested and validated in previous research (Thelwall et al., 2010; Thelwall and Buckley, 2013). SentiStrength analyses text based on a 1-5 scale.

For the third independent variable, innovation, we created a document text matrix using the tm library in R to determine the most frequently mentioned innovative words. We asked two linguistic experts in the field of communication science to indicate, out of a list of words, the degree in which these words were good synonyms for both innovative and not innovative. With these words we are able to quantify the level of innovativeness of the idea by the number of associated words expressed in the comments. In total 73 words were selected. After forming the lists, the experts assigned scores to these words based on the degree of innovativeness. The score assignment process is similar to the sentiment analysis which is based on a 1-5 scale. 1 means the word has little innovativeness and 5 means that the words has a high degree of innovativeness. To quantify innovativeness the authors replaced the sentiment word list with the innovativeness word list in SentiStrength. This provided the authors with the innovativeness score of the comments.

Control Variables.

In the text analysis and modelling, we add the word length of the idea title and the idea text and the number of votes that the idea received as control variables.

Analysis.

Hypotheses 1 and 2 will be tested through an OLS regression in SPSS with the innovativeness of the comment and the number of comments received as dependent variables; while the number of comments that the authors had given in the past as the independent variable.

Binary logistic regression will be performed in SPSS to test Hypotheses 3, 4, and 5 because whether an idea is implemented is a binary variable. The formula for the binary logistic regression is:

$$Probability(Accepted)_i = \phi(\alpha_0 + \alpha_1.NumberComments_i + \alpha_2.NumberPastComments_i + \alpha_3.Sentiments_i + \alpha_4.Innovativeness_i + \alpha_5.LengthTitle_i + \alpha_6.LengthText_i + \alpha_7.Votes_i + \varepsilon_i)$$

4 RESULTS

The results show that the number of comments that an ideator had given in the past has a positive effect on the extent to which other customers find his/her idea to be innovative (β = .136, t = 3.981, p < .00). H1 is confirmed. The number of comments that an ideator had given in the past has a positive effect on the number of comments that the ideator received (β = .015, t = 2.285, p < .05). H2 is also confirmed.

Table 1: Logistic regression results.

Variables	Coefficient	S.E.	
Constant	-1,174	.207	***
N. of Past Comments	.002	.000	***
N. of Comments	.039	.008	***
Average Innovation	.621	.166	***
Average Positive Sentiment	.391	.127	*
Name Length	.016	.014	
Elaboration Length	.-002	.001	
Votes	.001	.001	

*is significant ant the .050 level (2-tailed).
** is significant at the .010 level (2-tailed).
*** is significant at the .001 level (2-tailed).

The logistic regression model for H3, H4, and H5 was significant ($\chi^2(8)$ = 243.831, p < .005) in explaining the likelihood of an idea getting accepted. The model predicts 33.5 percent of the likelihood that an idea will be implemented. The results show that the extent to which other customers find an idea to be innovative expressed in the comments (β =.621, p <.000) has a positive effect on the likelihood that an idea gets implemented. H3 is confirmed. The number of past comments (β =.002, p <.000) and positive sentiment (β =.391, p <.000) within the comments have a positive effect on the likelihood of an idea being implemented. H4 and H5 are also confirmed. For the model details see Table 1.

5 CONCLUSIONS

Recently, online idea crowdsourcing for new product ideas has become widely used by companies (Bayus, 2013; Schemmann, 2016). Companies are nowadays more often looking to generate new ideas or solve specific problems with the help of their customers. It is thought that a diverse community will develop fundamentally different innovations because they draw from a different knowledge base (Von Hippel, 2005). Companies aim to develop and produce exactly what consumers want, but this is become increasingly difficult to attain, since customers' quickly changing preferences and the heterogeneity of their demands. Newly launched products suffer from high failure rates. The main problem is the faulty understanding of customer needs (Ogawa and Piller, 2006). Only customers know their specific needs and problems. Companies can adapt their products based on this knowledge (Bogers et al., 2010; Schemmann et al., 2016). By integrating customers in the innovation process, ideas come directly from customers (Ogawa and Piller, 2006). Therefore, new product development would become less risky (Lüthje and Herstatt, 2004). On the other end of the spectrum, the customers who generated the idea benefit by receiving economic incentives, gaining self-worth, or obtaining the solution for their problem (Estellés Arolas and González Ladrón-de-Guevara, 2012).

The results of this study show that the ideator and idea related characteristics influence the likelihood of an idea being implemented. There is a significant effect of the number of past comments of an ideator on the extent to which others in the community find his/her idea to be innovative (H1) and the number of comments that the ideator would receive in the community (H2). Furthermore, we found a significant effect of the extent to which other customers in the community find an idea to be innovative (H3), the number of comments that an idea receives in the community (H4) and the extent to which the comments have a positive sentiment on the likelihood than an idea will be implemented (H5). We explained these effects by the Signaling Theory (Spence, 1973) and the Prospect Theory (Tversky & Kahneman, 1992).

The findings of this study have several implications for the existing literature. It contributes to the literature by researching the effect of ideator and idea characteristics on the likelihood that an idea will be implemented. It also has a methodological contribution by applying advanced techniques for text mining and text analytics that provide the opportunity to extract innovativeness and sentiment from comments that are placed by ideas.

The results have practical implications that provide useful insights for management. First, some characteristics of ideators and ideas have a positive effect on the likelihood of an idea being implemented. Management could use these characteristics to search for more promising ideas on a crowdsourcing website. Online crowdsourcing via long-term open idea calls can result in thousands of ideas (Blohm, et al., 2013; Schemmann et al., 2016). For an organization it can be problematic to detect the ones it wants to implement (Schemmann et al., 2016). This research makes the crowdsourcing process for companies more effective and less demanding. Second, the failure rate of newly introduced products is still about 40% (Castellion and Markham, 2013). One problem for an organization is to anticipate what the customers actually need and want (Schemmann et al., 2016). This research helps companies to better understand and serve the needs of their customers. This makes new product implementation less risky.

However, as with any other studies, this research has some limitations and raises suggestions for further research. First, this research is solely based on publicly available data generated for a single crowdsourcing platform from a specific company. Therefore, our findings may not be completely applicable to crowdsourcing in other industries. Future studies could research other platforms from companies from different industries. Second, this study uses data from a publicly available platform. This provides interesting insights, however more refined measures of ideator related characteristics (for example, gender, age and location) or idea related characteristics (for instance, the quality of an idea) might benefit further research. Finally, future research could also get insights from the interaction between ideators which can be displayed in the comments.

Regardless of these limitations, this preliminary study contributes to the understanding of user involvement via online idea crowdsourcing and helps companies to get a better understanding of which ideator and idea characteristics will influence the likelihood of idea implementation.

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