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# Crowdsourcing ideas: Involving ordinary users in the ideation phase of new product development

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ABSTRACT

The different roles of users in new product development (NPD) have been extensively described. Currently online idea crowdsourcing, via long-term open idea calls, is increasingly being used by companies to collect new product ideas from ordinary users. Such open idea calls can result in thousands of suggested ideas and detecting the ones that a company wants to implement can be problematic. Empirical research in this area is lacking. We therefore investigate which ideator and idea-related characteristics determine whether an idea for NPD is implemented by a crowdsourcing company. To answer this question, we use a cross-sectional research design to analyse publicly available data from an open idea call, run by an internationally active beverage producer. Our results reveal that ideators paying major attention to crowdsourced ideas of others, the idea popularity, as well as its potential innovativeness positively influence whether an idea is implemented by the crowdsourcing company. Counterintuitively, the motivation of an ideator, reflected in the number of ideas suggested, does not influence the likelihood of an idea being implemented.



## 1. Introduction

Despite the existing research to improve the understanding of new product development and advances made in this area, the failure rate of newly introduced products is still as high as about 40 per cent (Castellion and Markham, 2013). One major problem is to anticipate what the (potential) consumers actually need, i.e. which products they are actually willing to buy. Therefore, knowledge about consumer preferences can importantly contribute to distinguishing product success from product failure. Research on the so-called Front End of Innovation (FEI) has shown that companies can benefit substantially if they effectively manage and improve the early stages of the new product development (NPD)[1] process (e.g. Khurana and Rosenthal, 1998; Reinertsen, 1999; Verworn, 2009). Within the FEI, the most important stages for successful innovation are typically referred to as the ideation phase, where the generation, screening and selection of creative and commercially valuable ideas take place. One way to reduce the risks and uncertainties related to consumer behaviour has been found in a strong user perspective and a deep understanding of user needs during the FEI in general and the ideation phase in particular (Flint, 2002; Kim and Wilemon, 2002; Lüthje and Herstatt, 2004).

Different ways in which users can play an active role in NPD have been emphasized by innovation research over the last 30 years. Ranging from von Hippel's Customer Active Paradigm (von Hippel, 1978a) and customers as a potential source of innovation in Chesbrough's Open Innovation Paradigm (Chesbrough, 2006) to numerous studies which show that some users actively innovate for their own needs in open source software and other user communities, this literature illustrates how users can be a valuable and active resource within the innovation process in general and for NPD in particular.

More recently online idea crowdsourcing for NPD has become very popular among companies in different industries. According to Howe (2006) "crowdsourcing is the act of taking a job traditionally performed by a designated agent (usually an employee) and outsourcing it to an undefined, generally large group of people in the form of an open call". Therefore, crowdsourcing can be used not only for idea generation but for a whole range of tasks. Earlier examples and studies have already highlighted how organizations can potentially benefit from the use of crowdsourcing for different purposes (Kleemann et al., 2008; Brabham, 2009; Poetz

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[1] In this paper, the term 'product' refers to both manufactured products and service products.

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and Schreier, 2012). Hoping to gain direct access to the crowd's knowledge concerning user needs to generate concrete ideas for new products and using the crowd's expertise to solve problems, companies have increasingly made use of crowdsourcing (for an overview see for example Bonabeau, 2009; Haller et al., 2011).

Many online idea crowdsourcing platforms are open to everybody who has access to the Internet and no specific training or expertise is needed to become an ideator and suggest an idea or solution. Unlike open source software or other special interest communities they therefore often attract a large crowd of people consisting of ordinary users and not necessarily experts or lead users. In line with Magnusson (2009), we here define an 'ordinary' user to be a user or potential user who is not a lead user and who is not expected to possess any special expertise in a certain area. While some evidence exists that ordinary users can produce more original and radical ideas than professional developers or users possessing superior knowledge of the underlying technology or product (Kristensson et al., 2004; Magnusson, 2009), research focusing on the involvement of ordinary users is still limited. Our study therefore focuses on the involvement of ordinary users in online idea crowdsourcing.

Thus far, empirical research on online idea crowdsourcing has focused on the following areas: (1) the *motivation of the ideators* (e.g. Frey et al., 2011; Muhdi and Boutellier, 2011; Dahlander and Piezunka, 2014), (2) the *idea generation process*, i.e. the comparison of different idea generation methods (Schweitzer et al., 2012), the design of online idea contests (Boudreau et al., 2011; Walter and Back, 2011) and the effects of crowding on idea selection (Piezunka and Dahlander, 2015) and (3) the *outcome of idea crowdsourcing*, i.e. the market potential and success of crowdsourced ideas (Kornish and Ulrich, 2013; Nishikawa et al., 2013), the influence of ideator expertise on idea quality (Jeppesen and Lakhani, 2010; Poetz and Schreier, 2012; Franke et al., 2014), the influence of cooperative orientation on idea innovativeness in innovation contests (Bullinger et al., 2010) and the factors influencing the originality of crowdsourced ideas (Franke et al., 2013). In sum, scholars focused on ideators' motivation, the crowdsourcing process itself and on explaining the outcome. Although it is highly relevant for the organization to be aware of the factors determining the outcome of crowdsourcing initiatives and particularly the implementation of crowdsourced ideas, knowledge in this area is limited. Our study addresses this research gap. Some of the earlier studies in this area identified ideator or idea-related characteristics that can influence the outcome (e.g. Di Gangi and Wasko, 2009; Bayus, 2013). Importantly, though, with the exception of Piezunka and Dahlander (2015) who included different dimensions of distance, these two groups of characteristics have so far been studied separately. In order to better understand the outcome of idea crowdsourcing initiatives, in particular why some ideas are more likely to be implemented than others, it is necessary to include ideator and idea-related characteristics in the same analyses.

Moreover, the majority of research on idea crowdsourcing focuses on temporary online idea contests. These contests run for a few weeks or months and often search for a single idea or a small number of ideas or solutions to a fairly specific question or problem. Very little research has been conducted on long-term open idea calls, which sometimes over several years generate a large number of ideas of very different quality concerning an often rather broad topic, such as ideas for new products. Examples of such open idea calls can be found in different sectors and countries: in the IT sector the IdeaStorm platform operated by the company Dell has already collected more than 23,000 ideas since 2007, the Japanese household goods manufacturer and retail company Muji has crowdsourced about 8000 ideas so far via its Idea Park platform and the German-based drugstore chain DM has already managed to generate more than 2000 new product ideas for its own natural cosmetics brand. As open idea calls can easily result in hundreds or even thousands of suggested ideas, it can be challenging for the crowdsourcing company to detect those which they find worth implementing. Levitt already stated in 1963 that "[i]deas are useless unless used" (Levitt, 1963, p.79). So, the best proof of an idea's value for NPD is its implementation by the company. In this study we therefore investigate the factors determining whether a crowdsourced idea is implemented. More specifically, our aim is to understand the influence of ideator and idea-related characteristics on the likelihood of an idea being implemented in a long-term open idea call. Accordingly, the question we here address is: *which ideator and idea-related characteristics determine whether an idea suggested in a long-term open idea call is implemented by the crowdsourcing company?*

The contributions of our study are twofold. First, we contribute to the literature on long-term online idea crowdsourcing. Thus far, most studies focus on the temporary idea contests. Also, not much is known about what determines whether an idea is going to be implemented by the crowdsourcing company. Second, the outcomes of our study can provide some useful first insight for companies that consider using long-term open idea calls. More precisely, the results of our study can help to understand which ideator and idea-related characteristics explain the implementation of ideas. Based on our findings, companies can for instance try to attract ideators with specific characteristics that appear to be important for the suggestion of ideas that the company finds valuable. Furthermore, our results offer suggestions for the selection of those ideas that are likely to be implemented.

To shed light on the research question we carried out binary logistic regression analyses on a dataset from one of the currently most widely used idea crowdsourcing platforms, which has been in operation for more than five years. The platform, run by an internationally active beverage producer and retailer, is open to any English-speaking user and contains user ideas and suggestions for product innovations.

The remainder of the paper is structured as follows. Section 2 provides an overview of the literature and the theoretical framework used from which we derive the hypotheses to be tested. Section 3 explains the methodology and Section 4 reports the results obtained. Finally, Section 5 discusses the findings and concludes by highlighting the implications and limitations of the research, as well as areas for future study.

## 2. Theoretical background

Idea crowdsourcing can be seen as a part of Chesbrough's Open Innovation Paradigm, which assumes that companies can and should also use external ideas for their innovation purposes (Chesbrough, 2003). This process is mostly referred to as inbound open innovation (Huizingh, 2011). In the case of crowdsourcing, however, the process builds upon the external ideas of individuals and not of other organizations, such as universities or suppliers (West and Bogers, 2014). To crowdsource ideas for new products, companies can either set up their own online platform to obtain ideas or use an intermediary platform for this purpose. In contrast to ideation which takes place in open source or user innovation communities, it is the crowdsourcing company which controls the ideation process, observes and analyses the user communication and discussion of the ideas suggested and finally decides which ideas will be developed further. The commercialization of the new products is also carried out by the company. The crowdsourcing company also needs to decide whether to use a temporary online idea contest or a long-term open idea call. In our study we focus on the latter.

### 2.1. The value of crowdsourced ideas

Online idea crowdsourcing is likely to generate a large number of very different ideas, especially if it is carried out as a fairly unspecific call that is open to all ordinary users (Blohm et al., 2013). The company then has to filter them with tremendous effort to identify the ones they consider most valuable and therefore worth implementing (Poetz and Schreier, 2012). However, the detection of these potentially valuable ideas is crucial if the crowdsourcing of user ideas is to lead to new products. Thus far, however, little is known about the factors determining which crowdsourced ideas are likely to be implemented. Walter and Back (2011) for instance found that the duration of online idea contests or the strength of the brand have no effect on the average quality of the generated ideas—with the quality being assessed via a crowdsourced rating among the platform users. Moreover, they found that higher rewards offered to successful ideators only lead to a better quality of ideas when offered in highly specific idea contests. In another study Nishikawa et al. (2013) compared the eventual market success of user ideas generated via an idea crowdsourcing platform with those generated by designers. They revealed that products based on the chosen user ideas performed better on the market in terms of sales revenues and were more likely to still be on the market three years after introduction. However, these studies do not provide insight into the characteristics of those ideas that will be implemented by the company.

Research by Franke et al. (2013) points at the importance of idea originality. They found that the originality of any ideators' idea is largely random. Poetz and Schreier (2012) showed in an empirical study on ideas for solving a problem concerning baby products that the ideas of ordinary users scored higher than ideas generated by professionals in terms of novelty and customer benefit, but were somewhat lacking in terms of feasibility. This indicates that idea novelty might impact on the potential idea success, i.e. the chances that an idea will be implemented by the company.

In addition to the importance of idea novelty for the implementation of an idea, research has also shown that it might be important to analyse how popular an idea is among the crowd. In their study on the idea crowdsourcing platform Dell IdeaStorm Di Gangi and Wasko (2009) found some evidence that the ideas which were adopted by the company received more positive votes on average.

Some research also analysed ideator-related characteristics of successful ideas. Bayus (2013), who also looked at the crowdsourcing platform Dell IdeaStorm, found that ideators who suggested more than one idea were more likely to generate an idea the company considered worth implementing than ideators who came up with only one idea.

In sum, earlier research in the context of crowdsourcing has shown that it is important to look at the idea novelty and popularity as well as the ideator's activity when aiming to explain the implementation of ideas.

### 2.2. Development of hypotheses

Since empirical research about the outcome of online idea crowdsourcing is still limited, we also use knowledge from three related areas of research to build our hypotheses. Research on (1) user innovation and (2) open source communities has provided important insights concerning the motivation and behaviour of innovating users, and the outcome of (3) creativity research is important for our understanding of idea generation processes.

Research on user innovation has shown that users often play a very active role within product innovation processes (von Hippel, 1978a, 1978b; Baldwin et al., 2006). Cases of such user innovations have, for instance, been described for the development of trend sports equipment (Franke and Shah, 2003), computerized library information systems (Morrison et al., 2000) or banking services (Oliveira and von Hippel, 2011). However, research on user innovation has also shown that successful user innovators possess particular characteristics. von Hippel's lead user concept is therefore based on the assumption that not all users are equally capable of generating and suggesting ideas for new products (Gruner and Homburg, 2000). In contrast to ordinary users those lead users are users who "[. . .] face needs that will be general in a marketplace - but face them months or years before the bulk of that marketplace encounters them, and [. . .] are positioned to benefit significantly by obtaining a solution to those needs" (von Hippel, 1986, p. 796). Therefore, these lead users can not only assist market research as a kind of "need-forecasting laboratory" but they can also serve companies with concrete new product concepts and even designs, as they tend to develop new products to satisfy their own needs (von Hippel, 1986, p.791). Numerous studies on what is often called the lead user method have already proven that the integration of such lead users' ideas and expertise in a company's new product development processes can be very beneficial for the innovation process and its outcome (see for example Herstatt and von Hippel, 1992; Lilien et al., 2002; Lüthje and Herstatt, 2004).

The Internet has enabled user innovators to collaborate in ways never before possible. The development of open source software via an open source community, viz. a crowd of (lead) users who are capable of writing code and therefore of inventing and continuously developing software for their own needs and the needs of other users, is one of the most important and researched areas here. Just as von Hippel proved for the lead users, the contributors to open source products are strongly driven by their own needs for the software they are developing (Hertel et al., 2003; Lakhani and Wolf, 2005).

Following up on these literature strands, our first two hypotheses focus on the influence of ideator-related characteristics on the likelihood of an idea being implemented. They are based on the assumption that not all users within the crowd will be able to generate the same quality of ideas. As we know from the lead user research mentioned earlier, the motivation of such users to come up with ideas and solutions is very high, as they expect to obtain great benefit from the solution to their needs (von Hippel, 1986; Lüthje, 2004). Therefore, they often voluntarily interact with other users or innovate collaboratively in innovation communities (Franke and Shah, 2003). Frey et al. (2011) found that the intrinsic enjoyment of contributing is positively associated with the number of relevant postings i.e. postings that were relevant for the final solution proposal. A high level of intrinsic motivation, which is reflected by the suggestion of more ideas, will therefore result in better ideas. As mentioned above, this is supported by the findings of Bayus (2013) concerning the potential success of ideas obtained from ideators who suggest more than one idea. To assess whether the ideas that are implemented are more likely to come from those ideators within the crowd of ordinary users who suggest many ideas, the first hypothesis to be tested in this paper therefore is:

**H1.** Highly motivated ideators who suggest many ideas are more likely to suggest ideas that are implemented than less motivated ideators who suggest only few ideas.

Research has shown that users who innovate to satisfy their own needs also differ from other users in the way they interact within the community. Franke and Shah (2003) found that within voluntary special-interest sports-related communities those users who improved existing products or even created new products spent significantly more time with the community than users who did not. A study on a community-based innovation contest for student teams carried out by Bullinger et al. (2010) showed that curiosity and support for other ideas were important characteristics of potentially successful ideators. This is in line with a number of studies related to creative processes and idea generation within groups. They have shown that idea sharing and the exposure to other creative ideas can enhance one's own creativity, which eventually leads to the production of not only larger numbers of ideas but also more creative ones (Paulus and Yang, 2000; Garfield et al., 2001; Nijstad and Stroebe, 2006). Despite the risk that the attention towards other ideas and the interaction between ideators might negatively influence the development of ideas, because ideators build on already existing ideas (Girotra et al., 2010), we assume that ideators who pay major attention to the ideas of other ideators will come up with more creative ideas which are therefore more likely to be implemented. This leads to the second hypothesis:

**H2.** Ideators who pay major attention to the ideas of others are more likely to suggest ideas that are implemented than ideators who pay little or no attention to the ideas of others.

As mentioned above, the characteristics of an idea, such as popularity or novelty, can also impact on the likelihood of an idea being implemented. Idea popularity can be important, because it can be seen as an indicator for user interest in the idea and the future product. Therefore, some online idea generation platforms try not only to crowdsource the ideas, but also to involve the crowd of ordinary users in the discussion and pre-selection of ideas. On many idea crowdsourcing platforms users can vote whether they like, or dislike, a proposed idea. Such pre-selection mechanisms are based on the idea of collective intelligence, or the so-called "wisdom of the crowds" as described by Surowiecki (2004). Based on the presentation of very different cases, he argues that decisions based upon the views or votes of a large group of independently deciding individuals are often better and more precise than decisions made by an elite few, no matter how distinguished the latter may be. As mentioned earlier Di Gangi and Wasko (2009) found some evidence that the ideas which were adopted by the company did receive more positive votes on average. The third hypothesis to be tested in this paper therefore is:

**H3.** Ideas that are on average popular with the crowd are more likely to be implemented than ideas which on average were identified as unpopular.

Several studies also stress the importance of idea novelty for the success of NPD (e.g. Dahl and Moreau, 2002; Howell, 2005). Despite warning that user involvement during the ideation phase will at best produce very incremental innovations (Alam, 2006), the involvement of users in the generation of ideas for NPD has been proven to enhance the novelty of the ideas produced (Kristensson et al., 2002). As stated in the introduction, the development and introduction of new products is a risky process. To avoid such risks, companies could therefore prefer those ideas which contain little or no innovative potential (e.g. those ideas which ask for the reintroduction of a product or an extension of an already existing service). These are also often easier to implement. However, research by Witell et al. (2011) showed that users were not only capable of coming up with new, potentially innovative product ideas. More importantly they also found that the ideas which were identified as being attractive for NPD were more original than those ideas which were judged to be less promising. Therefore, it can be argued that ideas which possess some innovative potential are more likely to be chosen for implementation than ideas which do not. This leads to the fourth hypothesis:

**H4.** Ideas that are potentially innovative are more likely to be implemented than ideas that are not potentially innovative.

## 3. Methodology

In order to study which ideator and idea-related characteristics determine whether an idea is implemented, we use a cross-sectional research design. The unit of analysis is the crowdsourced idea. While the following insights are based on quantitative analyses, we offer additional anecdotal evidence in order to corroborate our findings from a qualitative perspective.

### 3.1. The dataset

The study uses publicly available data from an online idea crowdsourcing platform run by an internationally active beverage producer and retailer. The launch of the highly popular idea crowdsourcing platform was part of a larger company attempt to focus more on its customers, their needs and their ideas.

The platform is very suitable for the purpose of this research, as it contained about 90,000 crowdsourced ideas at the time of our data collection. Consequently, it constitutes one of the largest open idea crowdsourcing platforms that are publicly available. Moreover, the platform offers the information needed for our analyses. Importantly, the platform publicly states which ideas have been reviewed and whether they have been implemented or rejected. This is essential, because information about rejected ideas is often not available on comparable platforms. Furthermore, it is an open ongoing idea call rather than a temporary idea contest and does not offer any financial rewards to the successful ideators. The platform is open to every (English-speaking) user and no special expertise is needed to suggest an idea. It generates a wide variety of ideas concerning manufactured and service products, as well as processes. It is also attractive because the company is not an IT, software or technical enterprise – whose users might naturally be more open and used to online crowdsourcing – and operates in an industry of the consumer product sector, which offers products used by a very wide and diverse group of customers.

The platform works as follows: all Internet users can register free of charge to become a member of the online community. Members can then share their ideas with the company and other users alike, place comments on other users' ideas, or simply vote whether they like or dislike an idea. These are typical functions of idea crowdsourcing platforms. Members are free to suggest all sorts of ideas for new products or processes. Those members who comment a lot on other users' ideas receive a virtual badge, which is visible to all platform visitors. All comments on ideas are publicly visible and all members can react to other users' comments.

The first step of the company's idea evaluation process consists in identifying a subset of those ideas to be considered in more detail. To this end, the ideas are first evaluated by a selected group of more than forty employees of the crowdsourcing company, who are regarded as experts in their respective fields. There are two ways in which these experts can create a subset of ideas to be considered further. First, the company uses an algorithm that identifies potentially valuable ideas. This algorithm[2] takes into account when the idea was suggested and the number of votes and comments it has received. Second, in addition to this algorithm, the

[2] It can be expected that if the company used a different algorithm, this may well lead to a slightly different subset of crowdsourced ideas considered by the company. However, we think that this would hardly change the results of our study, because – as indicated by the descriptive statistics – the ideas studied vary systematically on all independent variables under investigation. This, in turn, makes it possible to assess the effect of these ideator and idea-related characteristics on the likelihood of implementation.

expert employees are also free to consider any other idea they find promising. The second step consists in the evaluation of the preselected ideas by these experts. The experts will then present the ideas they consider most promising to the company's key decision makers and recommend how the selected ideas can be implemented in a third step. In a forth step, a final decision is taken about the ideas to be implemented. Once this process is completed, all platform visitors can see whether the idea has made it to be reviewed by one of the experts and whether it has been implemented or rejected by the company.

We designed our empirical approach as follows. In spring 2012, we collected publicly available data on 92,382 ideas that were included in the platform at that time. Out of these 92,382 ideas, 348 had already been implemented or were in the process of being implemented, 230 ideas were currently under review and 1108 ideas had been reviewed but were rejected. This implies that the majority of the crowdsourced ideas (namely 90,696 ideas) had not (yet) received any kind of consideration by the company experts. Since this research aims to understand why some ideas are implemented while others are not, only those ideas that have been reviewed can be included in the further analyses. In other words, we had to exclude those ideas that had not been considered by the company at the time we collected the data, because we could not determine whether these ideas would eventually be implemented or rejected. Consequently, the following analyses consider neither those ideas that have not been reviewed by the company experts nor those that were in the process of being reviewed in spring 2012. Therefore, the final dataset used contains those 1456 ideas for which the company's review process was completed.

### 3.2. Measurement

The dependent variable is the company's judgement of an idea to be of value for NPD with the result that the idea is either *implemented or rejected*. Consequently, the dependent variable is dichotomous and is operationalized with the use of the idea status indicated in the platform: ideas which are implemented or in the process of being implemented by the company are coded as 1. Rejected ideas are coded as 0.

The independent variable *ideator motivation* (see H1) is measured as the total number of ideas suggested by the respective ideator. For each idea the ideator suggested on the platform the respective idea receives 1 point. In order to correct for the skewed distribution of values on the variable, the respective square root values are calculated and used in the analyses.

The independent variable *attention paid to other ideas* (see H2) is operationalized on the basis of the commenting behaviour of each ideator. The platform enables every member to read all ideas and to comment on them. Members who are very active in commenting are publicly acknowledged by the company. The *attention paid to other ideas* variable is thus dichotomous and assumes a value of 1 if the ideator of the respective idea has been acknowledged for his or her active commenting behaviour and a value of 0 if this is not the case.

To operationalize the third independent variable, we use the voting behaviour of the crowd. All registered users have the opportunity to vote once on every idea posted, indicating whether they like or dislike it. Each positive vote counts 10 points and each negative vote counts −10 points, which implies that most ideas obtain either a positive or a negative final result. An average outcome of 0 points, i.e. the same amount of positive and negative votes or no votes at all, is rare (only 71 ideas). The independent variable *idea popularity* (see H3) is therefore a dichotomous variable, with a value of 1 for all ideas that receive overall a positive voting result and a value of 0 for all ideas that overall receive a negative voting result. The 71 ideas which have been reviewed by the company but have received neither a positive nor a negative result have been discarded from the analysis, as we cannot determine the popularity of these ideas.

The ideas generated via the online platform differ regarding their novelty and potential innovativeness. The ideas were therefore analysed to assess whether, or not, they contained any innovative potential. It was assumed that some users also used the crowdsourcing platform to publish their complaints concerning goods or services, or to ask the company for price reductions. Such suggestions are, in our view, not innovative. The same holds for crowdsourced ideas that ask for the reintroduction of products that were offered by the company in the past. Based on these assumptions, we analysed the ideas by their title and coded them on the basis of whether they are potentially innovative. Ideas with the following suggestions or requests are considered not to be innovative: reintroduction of previous products, simple price reductions or products for free, feedback, customer complaints or criticism, requests for additional store locations, for more products of an already existing kind or for an extension of an already existing service. On the other hand, ideas with the following suggestions or requests are considered to be potentially innovative: introduction of products or processes that are new (to the company), advertising or pricing ideas which go beyond a simple price reduction or a request for free products, suggestions for improvements of existing products or processes, products for a new target group, new product combinations within the existing product range, and technological advancements or ideas concerning the company's corporate social responsibility. For 369 ideas it is not possible to determine whether they are potentially innovative according to the aforementioned parameters. These ideas are therefore coded as "not possible to determine".

Even though no particular expert knowledge of the beverage and retail sector is needed to code the various ideas according to these parameters, we also asked a marketing expert of the food sector to code a subset of the ideas according to the aforementioned parameters in order to cross-check our classification. An interrater reliability analysis using the Cohen's Kappa statistic was performed to determine consistency among coders. The interrater reliability was found to be Kappa = .653 ($p < .001$,), which shows that there was substantial agreement between the two raters. The differences between the two raters occurred mainly in cases that were coded as not identifiable by rater 1 versus not potentially innovative by rater 2. We decided to follow the more conservative coding. The independent variable *idea innovativeness* (see H4) is therefore dichotomous with a value of 1 if the idea is potentially innovative and a value of 0 if this is not the case. Ideas which do not allow for such judgement by their title are coded as missing values (counts for 25.3% of the cases).

To control for unobserved temporal factors which might influence the number of ideas implemented, such as the amount of attention that the company paid towards the crowdsourced ideas in different years or when different annual budgets for NPD were available, we added time as a control variable into our analyses. To this end, we constructed dummy variables for each year of the idea call. More concretely, all ideas suggested in the first calendar year of the call receive a value of 1; all ideas suggested in the second calendar year receive a value of 2 and so forth. We compared the results obtained from controlling for time on the basis of separate year dummies with the results obtained when a single time dummy, ranging from 1 to 5, was used. As we observed no differences in the results based on these alternative controls, we decided to use the single variable for reasons of simplicity.

**Textbox 1**

**Sample idea to illustrate an idea that was reviewed and implemented**

Idea title: *"Bite size pastries"*

The idea asks the company to introduce bite size pastries with new flavours. It was proposed by an ideator who suggested 61 ideas via this platform. This ideator also paid major attention to other ideas. The idea of bite size pastries was popular among the crowd and received overall 605* * positive votes. Given that the idea suggests a potentially new product, we coded the idea as potentially innovative. The company decided to implement this idea.

**Sample idea to illustrate an idea that was reviewed and rejected**

Idea title: *"Have the previous logo on the *COMPANY NAME* drinks"*

This idea asks for the re-introduction of the previous company logo on a certain product range. The ideator did not suggest any other idea and did also not pay major attention to other ideas. The idea was unpopular among the crowd and received overall 15* * negative votes. We coded this idea as not be innovative, because it merely asks to bring back something that already existed in the past. The company rejected this idea.

* * One-tenth of the number of positive or negative points that an idea received.

To enable a better understanding of the ideas suggested on the platform and of the variables used in our analyses, we report two sample ideas in Textbox 1.

### 3.3. Analysis

Given that the dependent variable is a binary variable, we conduct a binary logistic regression analysis. We run three different models. In the first model, we only include the control variable, i.e. time. In the second model, the independent variables are included. Finally, the third model includes the control variable together with the independent variables. Consequently, the binary logistic regression analysis of model 3 reads as follows:

$$\text{Odds}_{\text{implemented idea/rejected idea}} = \frac{P_{\text{implemented idea}}}{P_{\text{rejected idea}}}$$

$$P_{\text{implemented idea}} = \frac{1}{1 + e^{-(b0+b1\,x1+b2\,x2+b3\,x3+b4\,x4+b5\,x5)}}$$

$$P_{\text{rejected idea}} = 1 - P_{\text{implemented idea}}$$

where $x_1$ is the ideator motivation (number of ideas suggested by respective ideator [continuous]), $x_2$ is the attention paid to other ideas (ideator has been acknowledged for his/her intensive commenting behaviour [binary]), $x_3$ is the popularity of an idea (idea received overall a positive voting result [binary]), $x_4$ is the idea innovativeness (idea is potentially innovative [binary]), $x_5$ is the time (year of the idea call when idea was suggested [continuous]).

In addition to conducting these quantitative analyses, we also offer some systematic anecdotal evidence illustrating our findings in a qualitative manner.

## 4. Results

Table 1 provides an overview and descriptive statistics of the variables used. It shows that about a quarter of the ideas were judged as valuable and therefore implemented. Interestingly, only a small number of the ideas were suggested by ideators who paid a lot of attention to other ideas. Furthermore, about 2/3 of the ideas were popular and almost half of the ideas were innovative.

The results for the binary logistic regression are shown in Table 2.

The tests of all models against the respective constant-only model are statistically significant, indicating that the predictors together reliably distinguished between an idea being implemented or not. Nagelkerke's $R^2$ is .208 for model 1, and .193 for model 2 and .295 for model 3.

In an assessment of the predictive power of each independent variable for model 3 the Wald criterion shows that the variables *attention paid to other ideas*, *idea popularity*, *idea innovativeness* and the *time control* variable made a significant contribution to the prediction. These findings are in line with model 2 and model 1. Only the independent variable *ideator motivation* is not statistically significant. The results regarding the control variable *time* remain largely unchanged and significant at a .01 confidence level for both model 1 and model 3. The results for model 3 show that the odds of an idea being implemented decrease by a factor of .552 when time increases by 1, keeping other variables constant. In other words, at the start of the crowdsourcing platform more ideas were implemented. Therefore, it is also important to control for time.

Following hypothesis H1, we would expect that ideas which are implemented are more likely to come from highly motivated ideators who suggest many ideas than from less motivated ideators who seldom suggest ideas. The results however show that there is no empirical support for this hypothesis at a .05 confidence level. We find no indication that the motivation of the ideator to suggest many ideas determines whether an idea is implemented. Thus H1 is not supported by empirical evidence.

Hypothesis H2 leads to the expectation that ideas that are implemented are more likely to come from ideators who have paid major attention to other ideas. Net of other variables, the results show that the odds of an idea being implemented are 2.774 times higher for ideas that are suggested by ideators who pay major attention to the ideas of others when compared to ideas that are suggested by ideators who pay little or no attention to the ideas of others. Empirical support for this hypothesis is found at a .05 confidence level.

Following hypothesis H3, we would expect that ideas that are implemented are more likely to be popular with the crowd of users than ideas which are judged not valuable. The results shown in Table 2 support this hypothesis by empirical evidence at a .01 confidence level. Net of other variables, the results show that the odds of an idea being implemented are 3.787 times higher for ideas that are on average popular with the crowd when compared to ideas that are on average unpopular with the crowd. In line with hypothesis H3, we thus find that the popularity of an idea actually determines whether an idea is implemented.

Hypothesis H4 leads to the expectation that ideas that are potentially innovative are more likely to be implemented by the company. The results show that the potential innovativeness of an idea significantly increases the likelihood of the idea being implemented. Thus, empirical evidence also supports H4 at a .01 confidence level. Net of other variables, the results show that the odds of an idea being implemented are 2.57 times higher for ideas that are potentially innovative when compared to ideas that are not innovative.

We also conducted the following three types of robustness checks in order to assess the sensitivity of the results to changes in model specifications.

Due to the fact that some ideas which were analysed had been suggested by the same ideators, the observations for the independent variables *ideator motivation* and *attention paid to other ideas* might not be completely independent. In order to control for this, we also ran the analysis with clustered robust standard errors. The results remained the same.

As already mentioned in the operationalization section we also replaced the continuous *time* control variable with a categorical dummy variable for each calendar year. This, too, does not lead to any significant differences in the results based on the alternative controls for time.

In our models we omitted those 71 ideas which had neither a positive nor a negative popularity score. To assess their impact on

**Table 1**
Summary statistics for dependent, independent and control variables.

| Variables | *N* | Minimum | Maximum | Mean | Std. deviation |
|---|---|---|---|---|---|
| Dependent variable | | | | | |
| Idea implemented or rejected | 1456 | 0 | 1 | .24 | .427 |
| Independent variables | | | | | |
| Ideator motivation* | 1456 | 1 | 23.19 | 1.79 | 2.299 |
| Attention paid to other ideas | 1456 | 0 | 1 | .07 | .248 |
| Idea popularity | 1385 | 0 | 1 | .66 | .473 |
| Idea innovativeness | 1087 | 0 | 1 | .44 | .497 |
| Control variable | | | | | |
| Time | 1456 | 1 | 5 | 3.40 | 1.213 |

* The independent variable was normalized using a square root transformation in order to produce a less skewed and leptokurtic distribution.

**Table 2**
Binary logistic regression of ideator motivation, attention paid to other ideas, idea popularity and idea innovativeness on idea implementation (results of binary logistic regression analyses: odds ratio Exp(*b*) presented).

| 0 = Rejected ideas<br>1 = Implemented ideas | Model 1<br>(control variable only) | | Model 2<br>(all independent variables) | | Model 3<br>(full model) | |
|---|---|---|---|---|---|---|
| | *b* | Exp(*b*) | *b* | Exp(*b*) | *b* | Exp(*b*) |
| Constant | 1.326** | | −2.892** | | −.444 | |
| H1: ideator motivation | | | −.085 | .919 | −.135 | .874 |
| H2: attention paid to other ideas | | | .907* | 2.476* | 1.020* | 2.774* |
| H3: idea popularity | | | 1.893** | 6.638** | 1.332** | 3.787** |
| H4: idea innovativeness | | | 1.033** | 2.809** | .944** | 2.570** |
| Control: time | −.744** | .475** | | | −.595** | .552** |
| ***N*** | 1037 | | 1037 | | 1037 | |
| $R^2_{\text{Nagelkerke}}$ | .208 | | .193 | | .295 | |

Model 1: chi-square = 161.260, $p < .000$ with df = 1. Model 2: chi-square = 148.656, $p < .000$ with df = 4. Model 3: chi-square = 237.363, $p < .000$ with df = 5.
* Is significant at a .05 confidence level.
** Is significant at a .01 confidence level.

the results, we first coded these 71 ideas as having received a positive popularity score. When re-running the analyses, the results remained stable. We obtained similarly stable results when subsequently re-running the analyses while including the same ideas after having assigned them a negative popularity score.

Overall, these additional analyses demonstrate the robustness of the results reported in Table 2.

Based on a Mill's method of difference design (see Hancké, 2009), the following anecdotal evidence corroborates our quantitative findings from a qualitative perspective. First, let us consider the examples of an implemented and a rejected idea each that, regarding our independent variables only differ in the attention that the ideator paid to other ideas. The implemented idea with the title "*Bring back the 'real' *REGISTERED TRADEMARK* bears.*" was suggested by an ideator who paid major attention to other ideas. The rejected idea "*Gold Card choices! offer some different rewards Please!*", on the other hand, was suggested by an ideator who paid no major attention to the ideas of others. Both ideas were proposed by ideators who suggested a similar number of ideas each and both ideas received a similar number of positive votes. Both ideas were considered non-innovative, as they asked for the reintroduction of a product and for free products, respectively. These two samples illustrate our quantitative finding that ideas from ideators who paid major attention to other ideas are more likely to be implemented than ideas from ideators who did not do so.

Second, let us turn to two sample ideas which, regarding our independent variables, differ only in terms of their popularity. The idea "*What about coffee + alcohol?*" received 26 negative votes and was rejected by the company, whereas the idea "*Sell reusable sleeves*" received 3298 positive votes was implemented. Both ideas were proposed by ideators who suggested two ideas each and paid no major attention to other ideas. Both ideas were considered potentially innovative as they suggested a possibly new product offer. Consequently, these two sample ideas illustrate the positive effect of an idea's popularity we observed in the quantitative analyses.

Third, let us finally turn to two sample ideas which, regarding our independent variables, differ only in their potential innovativeness. The idea "*Please bring back the former paper cup (or cup manufacturer)*" was considered non-innovative and rejected by the company, whereas the idea "*polycarbonate-free travel cups*", which was considered potentially innovative, was implemented. Both ideas came from ideators who suggested a similar number of ideas and neither ideator paid major attention to other ideas. Both ideas received a similar number of positive votes. These examples illustrate our quantitative finding that potentially innovative ideas are more likely to be implemented than non-innovative ideas.

## 5. Discussion and conclusion

Our paper provides insight into the ideator and idea-related characteristics that determine whether an idea suggested by an ordinary user in a long-term open idea call is implemented.

We first assessed two important ideator-related characteristics: ideator motivation and attention paid towards other ideas. Our results show that – contrary to our expectations – highly motivated ideators who suggest many ideas are not more likely to generate ideas that are implemented than those users who only suggest one or a few ideas. The intrinsic enjoyment of the ideator to contribute ideas to a crowdsourcing platform does not lead to the generation of 'better' NPD ideas for the crowdsourcing company. This challenges the findings of Bayus (2013), who found that those ideators who suggested two or more ideas to the Dell IdeaStorm platform were more likely to suggest an idea the organization finds valuable enough to implement than those ideators who suggested only one idea[3]. The different outcomes of our study and the study by Bayus might be explained by the fact that an open idea call for IT goods and services might attract a different kind of crowd than an open call for food, beverage and retail ideas. Possibly the former attracts more users with special expertise than the latter.

Regarding the second ideator-related characteristic, we find – in line with creativity research – that the ideator's attention paid to other ideas positively influences the likelihood of an idea to be implemented. Our findings are also in line with the findings of Franke and Shah (2003) and Bullinger et al. (2010), who saw similar effects for ideation in special-interest sports-related communities and an idea competition for university students. Our results indicate that this does not only hold for users with a certain expertise but also for the ordinary users in online idea crowdsourcing.

Furthermore, our results show that idea popularity, based on a simple like or dislike rating mechanism, indeed constitutes an important characteristic of ideas that are to be judged as valuable for NPD by the company. While not every ordinary user might be able to come up with innovative or valuable ideas, the crowd of ordinary users is collectively capable of identifying those ideas that are valuable for the company. An area that needs further assessment is to what extent a high number of positive votes also exerts some pressure on the company, thus increasing the likelihood of such ideas being implemented.

Finally, our results illustrate that ideas that are potentially innovative are more likely to be implemented than ideas that are not innovative. Academics who are sceptical about the involvement of ordinary users during the ideation phase warn that this will not lead to the implementation of really new ideas (Bennett and Cooper, 1981; Alam, 2006). Our study, however, demonstrates that too much scepticism is unfounded. While we cannot determine how radically innovative – and therefore "risky" – the crowdsourced ideas are, our results show that crowdsourcing during the ideation phase of NPD leads to the generation of ideas that are potentially, at least, new to the company – and thus valuable for the company. No indication was found that online idea crowdsourcing mainly leads to the implementation of "safe" ideas which contain no innovative potential at all. Our findings therefore show that the usefulness of idea crowdsourcing goes beyond improving a company's customer orientation image (Fuchs and Schreier, 2011) or being an online campaign that helps to gain publicity and visibility (Djelassi and Decoopman, 2013).

Like all research, our study also has its limitations and raises suggestions for further research.

First of all, the study is solely based on the publicly available data generated from a single platform of an international player in the beverage production and retail industry. Even though the data used is extensive and the platform used is one that had been in operation for 5 years at the time of the analysis, our findings may not be completely applicable to idea crowdsourcing in other industries. As mentioned above, our findings concerning ideators who suggest many ideas differ from the findings of Bayus (2013) in the IT sector. But with respect to similar open idea calls in comparable industries we consider our results to be applicable. We consider those open idea calls to be similar that are comparable regarding the predicted outcome of the task that the crowd has been given, regarding the kind of crowd involved to fulfil this task, and regarding the degree to which the individual crowd members depend upon each other to do so. These considerations are based on Whitley's (2000) framework for understanding the different properties of idea generation stating that differences in knowledge development can be conceptualized along the dimensions of 'task uncertainty' and 'mutual dependency'. 'Task uncertainty' concerns the unpredictability of task outcomes. While all idea generation activities are fundamentally uncertain since outcomes are not repetitious and predictable, some ideation tasks are inherently more uncertain than others. Some crowdsourcing tasks are very standardized, and there is an (implicit) understanding of the types of solution required. Since in our study the call was relatively open and scarcely standardized there is greater uncertainty due to a wider scope of different types of contributions. 'Mutual dependency' refers to the extent to which a community relies upon knowledge provided by others inside and outside the community in order to make a significant contribution (Whitley, 2000). In this sense, the outcome of an idea generation activity depends on strength of connection and frequency of interaction. In our study, though, we focus rather on ordinary users who do not actively accumulate knowledge but perform tasks alone, needing no specific training or expertise to become an ideator. Analyses of data from other long-term open idea calls in comparable and different industries will be useful to verify our claims.

Second, our study only uses data, which was publicly available on the platform. This already provides interesting insight into the effect of ideator and idea-related characteristics on idea implementation. More refined measures of ideator-related characteristcs (for instance the exact number of comments made by an ideator) or idea-related characteristics (for instance the actual innovation potential of the ideas suggested) might be useful to gain even deeper insights. Along those lines, further research on ideator and commenter behaviour and interaction on such platforms would be interesting. Even though our dichotomous variable that measured the attention ideators paid to other ideas is useful as a starting point, additional behaviour and interaction-related measurements might lead to greater insights.

Third, because the participants of such open idea calls are usually allowed to stay anonymous, data on the personal characteristics of ideators – such as their age, gender or location – were not available to us. Nevertheless, it could certainly be valuable to assess how such additional control variables impact on the results obtained.

Last, in this quantitative research we were interested in the relationships in terms of effects between ideator and idea-related characteristics and idea implementation. Future qualitative research may provide insights in the underlying mechanisms, thus complementing our results.

Despite these limitations, our study contributes to a better understanding of ordinary user involvement in NPD via online idea crowdsourcing. Most of the previous idea crowdsourcing research focused on temporary idea or problem-solving contests rather than ongoing idea calls. Given that such competitions often attract experts who compete for suggesting the best solution to a specific problem, our paper contributes novel insight with regard to crowdsourcing new product ideas from ordinary users. Consequently, our findings do not only speak to the literature on idea crowdsourcing but also to those literature strands that investigate the role of users within the innovation process, most notably the literatures on (lead) user innovation and open source innovation. More concretely, we contribute to these research strands by investigating whether the involvement of ordinary users can be valuable, and in what way, during the ideation phase of NPD. In particular, we illustrate which ideator and idea-related characteristics can help to identify those user-generated ideas that are of potential interest for companies. Due to the large

[3] Due to the fact that the ideator motivation variable was not far off being significant at .05 confidence level in model 3 and also indicated a negative relationship with the dependent variable, we also tested a different model in which we replaced the original continuous ideator motivation variable with a dichotomous variable analogous to the one used by Bayus. The result, which was significant at .01 confidence level, showed that ideas which were implemented were in fact less likely to come from ideators who suggested more than one idea than those ideas, which were rejected (Exp($b$) = .536).

numbers of ideas that are often being generated, this is crucial for the success of the crowdsourcing and therefore the NPD process.

The findings of our paper, therefore, also bear some practical and managerial implications for companies or organizations that consider using open calls to crowdsource ideas for their NPD. First, companies should be aware that those ideators who suggest many ideas on such platforms are not necessarily the most useful for obtaining the kind of ideas that the company wants to implement. Thus, incentives that reward the suggestion of a large number of ideas by the same ideator might only result in more ideas which are not necessarily those that the company perceives as valuable. Instead, ideators should rather be stimulated to pay attention to the ideas suggested by others, as this seems to have a positive effect on the quality of the ideas suggested. Second, given that the "wisdom of the crowd" helps to identify ideas that are perceived as valuable, even simple online voting systems can constitute a meaningful tool for platform-integrated market research.

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