Reducing inferior member community participation using uplift modeling: Evidence from a field experiment

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REDUCING INFERIOR MEMBER COMMUNITY PARTICIPATION USING UPLIFT MODELING: EVIDENCE FROM A FIELD EXPERIMENT

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In their ongoing search for competitive advantage, firms increasingly leverage online innovation communities (ICs). The viability of these ICs may be jeopardized by big data environments and inferior member participation. Therefore, community managers must address poor member participation, together with the data-rich environment. This study examines the viability of a proactive motivational email campaign to reduce inferior member participation using uplift modeling; it also explores optimal treatment characteristics, including message scope (untargeted versus targeted), message content (hedonic, cognitive, and social message), and member profile (self-interest–oriented and positive emotional writing style). The findings indicate that marketing decision makers should use proactive, targeted emails with cognitive motivational elements to mitigate inferior levels of member participation. These findings have important implications for innovation scholars and community managers.

Keywords: proactive email campaign; inferior member participation; uplift modeling; innovation communities

1. INTRODUCTION

In dynamic, innovation-intensive industries, innovation communities (ICs) can grant organizations access to novel knowledge that they can leverage to develop competitive advantages [1,2]. In these private digital networks, companies interact with users to obtain external knowledge [3], as exemplified by Heineken's Idea Brewery, My Starbucks Idea, or Dell's Idea Storm [4]. These ICs attract hundreds of users, generate innovative ideas derived from knowledge collaboration across organizational boundaries [5–7], promote idea diffusion [8], and increase the likelihood of new product success [8]. Despite these great opportunities, this organizational model faces two main challenges [3]. First, ICs operate in a big data digital environment, which makes it difficult for community managers to manage the vast input. Many members post many messages (volume) and nearly instantly provide information (velocity). Even if the interactions tend to be text-based, they also often contain other media sources, such as videos or pictures (variety). Second, these technological challenges occur in parallel with social challenges [9–11]. Online communities are usually self-organized, and the driving force is sociality among members [12]. By encouraging social interactions, organizations can enhance the viability of online communities [13,14], but naturally emerging hierarchical structures among members [15] also can have corrosive effects. An imbalance in power might silence certain members and prevent equal participation [16], which would lead to anomalies, such that only a few members account for the majority of generated data; the 1% rule is a harsh reality for many ICs [17]. When the majority of members falls silent, it constitutes a phenomenon we refer to as *inferior member participation* (IMP), which has several negative consequences. First, [18] show that when member participation is low, it is hard to sustain the flow of ideas for a successful innovation outcome. Second, when data come from only a small minority of members, the risk of idea polarization increases, jeopardizing idea diversity and heterogeneity. Third, when IMP is present in the community, the moderator spends valuable time on member reactivation activities that reduces the time on the innovation task itself [19], while adding new members to the IC is costly and time-consuming. Fourth, online communities might crowd out newcomers, who then become less likely to join, such that the IC comes to rely on the power of the few to persist. Thus there is a strong need to examine how to minimize IMP.

An extensive part of extant literature outlines how individual IC members differ in their intrinsic and extrinsic motivation [20], how relational ties among community members shape their participation [21], and which unique and challenging structural characteristics mark the ICs themselves [5,11]. These studies provide a strong foundation for understanding individual, collective, and structural forces that shape online communities. Yet research that does address how firms might actively influence IMP and community engagement according to the unique challenges of ICs is less widespread. Appendix A gives an overview of extent research papers investigating various firms' intervention strategies on subsequent community behavior. The purpose of our study is to extend this research stream by providing new insights into IMP fighting strategies by diverging from prior approaches and studying community moderators' influence, exerted through email campaigns, as a means to reduce IMP in ICs. Specifically, we rely on the uplift modeling methodology to identify the IC members who are most persuadable in reducing IMP by a moderator's email campaign, and we investigate the viability of such a proactive, motivational, email campaign. To identify optimal communication characteristics, we explore the *message scope* (targeted or untargeted), *message content* (hedonic, cognitive, or social), and *member profiles* (self-interest–oriented and positive emotional writing style). In so doing, this study considers the following research questions:

RQ1a. *Does a proactive untargeted motivational email campaign reduce IMP?*

RQ1b. *Which motivational message in an untargeted proactive email works best?*

RQ2a. *Does a proactive targeted motivational email campaign reduce IMP?*

RQ2b. *Which motivational message in a targeted proactive email works best?*

RQ3. *Which member profiles can be motivated?*

In turn, this study makes three main contributions to information systems (IS) literature. First, with the rise of big data analytics and text mining methods, extant research focusses on the development of community management strategies that rely on extracting information from community posts to identify members with future IMP [3,22]. This article extends this research stream by answering the call for research of [3] to deliver concrete recommendations for proactive communication strategies that improve the long term viability of the ICs. With a real-life field experiment among four ICs, we compare the beneficial impact of proactive untargeted and targeted contact strategies on reducing IMP through uplift modeling. We contribute to IS literature by proving the preference of a targeted over an untargeted approach as a proactive means to reduce IMP.

Second, members' motivational drivers help in developing effective community management strategies [23–26]. Previous studies investigated the cognitive, hedonic and social integrative benefits that members derive from community participation; cognitive or learning benefits reflect the increased acquired knowledge about the products or services that is generated and shared through customer interactions [24], hedonic benefits refer to pleasurable and interesting experiences through conversing with one another about products or services within the communities [27], and social integrative benefits refer to feelings of enhancement of a sense of belongingness or social identity [27,28]. This research study investigates the impact of proactive contact strategies including these motivations in reducing IMP. By comparing motivational emails that leverage cognitive, hedonic, and social arguments, this study contribute to IS literature by concluding that the cognitive motivation offers the best option to proactively reduce IMP in this research context.

Third, previous studies recognized the important signaling role of writing style in community research [22]. In an IC context, [29] investigate the impact of positive emotionality and self-interest oriented writing in detecting IMP. However, no study explored whether such traits offer indicators of persuasion of the proactive contact strategy. With an automated text analysis, we extend current literature by showing that members with a positive emotional writing style are more likely to be positively influenced by a motivational email and thus exhibit larger future constructive community behavior, while self-interest oriented writing tend to have no impact on IMP in this research context.

2. CONTACT STRATEGIES

We build on extant literature to integrate the core concepts underlying contact strategies in ICs: (1) message scope (*whether* targeted or untargeted) [30], (2) message moment (*when* to communicate) [30], (3) message content (*how* to communicate) [31], (4) message profile (to *whom*) [32], and (5) message channel (*where* to communicate) [31]. First, the scope of the message might be untargeted or targeted [30]. In ICs, an untargeted strategy treats all members equally, whereas targeting seeks to identify and treat only specific members on the basis of their prior IMP records.

Second, campaigns can be reactive or proactive, depending on the moment they are issued [30]. Community managers might be reactive and wait for IMP to occur, or else they might be proactive, identify it in advance, and prevent it. Previous research has identified reactive approaches, including both targeted options such as participation feedback [19] or acknowledgement [33] and untargeted versions such as governance policy [34], which take place after the unconstructive behavior has been observed and the community has been affected. In contrast, untargeted proactive approaches might include offline community events like brandfests [35] or reward-based systems [36]. In treating every member equally, theoretically, these approaches could trigger negative reactions. More targeted proactive approaches instead identify members who appear most likely to demonstrate future IMP, using prediction models [2,3]. Here again, the risk is a lower IMP rate if the treatment action triggers negative reactions or involves members who would have participated already on their own accord [37]. Another option is to identify the optimal targets to influence with the treatment using uplift modeling [38,39]. Despite the benefits of proactive strategies, literature on ICs has not confirmed which strategies, targeted or untargeted, are most effective.

Third, the content of the message needs to be relevant to the individual behavior that is being targeted [31]. Aiming to reduce IMP through a treatment campaign in particular involves sending a message that is relevant to the specific member's community participation, which in turn relates directly to the member's participation motives. Previous research explores participation drivers, such as reputation, experience, integration [21], network position [40], relational social capital [41], hobbyism, and firm recognition [42]. In general, members participate if they expect to receive future benefits [28]. Hedonic, cognitive, and social motives help explain member participation [23–26], such that they anticipate benefits from the pleasurable experience, product-related learning, or relational ties over time. However, to the best of our knowledge, no studies explore whether these motives also can function as strategic tools to inform campaign management decisions by community managers.

Fourth, by understanding the profile of community members, managers can segment them more effectively. Communities are dynamic environments, and their members change over time [11], so dynamic variables such as activity and writing style are more useful segmentation features than traditional characteristics such as demographics [3,33]. Recent literature recognizes that community writing style is an important signaling factor of member participation [33], especially in the form of a self-interest–oriented, positive emotional style [3]. However, it is unclear whether these linguistic traits can serve as indicators to specify which members to motivate using a communication campaign.

Fifth, community members can be reached through many message channels, ranging from physical meetings [35] to virtual discussion forums. Email campaigns are widely used [43]; from an IMP perspective, an email strategy, unlike strategies that are limited to community platform boundaries, facilitates contacts with potential members outside the community platform who are exhibiting IMP and are not motivated enough to enter the platform itself. However, emails also threaten negative side effects, despite their low distribution costs [44], in that they increase members' information processing costs and may lack usefulness. People grow increasingly unwilling to open emails, which reduces their potential positive impact. Therefore, to realize the full potential benefit of email campaigns, community managers need to recognize the optimal message characteristics.

2.1. Proactive email campaigns

Innovation literature mostly explores the concept of proactivity in relation to proactive member contributions, which tend to contain more novel insights than reactive contributions [1], though it also has been suggested as an approach to manage the IC [3,23]. Proactive approaches anticipate future expected events [30] and are preferable to reactive approaches [45]. Proactive treatment campaigns are successful in other domains, such as for reducing customer churn, and seemingly might benefit IMP reduction too. Although the term proactivity often is used somewhat loosely in community literature, it is important to define it explicitly, to highlight its benefit compared with reactive IC management. As depicted in the panels of Figure 1, by relying on [30], we define the task of a motivational email campaign for IMP reduction in ICs according to the following elements:

- Three time stamps appear on the community timeline: the present moment t_0, a point in time in the past p, and a point in time in the future f.
- Member participation behavior is evaluated between the present moment t_0 and some point time in the future f. From a community perspective, the moderator evaluates real member participation behavior at time stamp f as being constructive and useful ($Y = 0$), or useless and inferior ($Y = 1$).
- Member profiling behavior X is evaluated between a point in time in the past p and the present moment t_0.
- Moderators decide to treat and thus send an email to a member ($E = 1$) or leave the member alone ($E = 0$).
- When an email is sent ($E = 1$), it is sent at the treatment date t and includes a motivational message to influence future member participation behavior.

Panel a of Figure 1 visualizes the timeline for a *proactive email campaign*. The moderator analyses past member profiling behavior X to decide to whom a motivational email is sent at the present moment t_0 based on anticipated future participation behavior during the member participation behavior period.

In a reactive approach as depicted in panel b of Figure 1, the moderator must observe the member's behavior first before a motivational email could be send. As a consequence, the moderator could only decide at a future time stamp *f* to treat a member depending on his shown superior ($Y = 0$) or inferior ($Y = 1$) participation behavior.

[INSERT FIGURE 1 AROUND HERE]

Proactive approaches have important benefits over reactive approaches, due to their preventive ability and cost effectiveness [30]. Moderators do not need to engage in damage control and can aim to minimize the impact of observed IMP, while also anticipating "latent" IMP and sending a motivational email to prevent it. Moderators also can avoid other, more expensive treatment actions, because things have not gotten too bad yet. However, when they anticipate future IMP, they are subject to imperfect predictive accuracy [30]. Both cases can produce false negatives, such as when IMP is expected but future participation is constructive ($Y = 0$), and false positives, such as when constructive participation is expected but IMP is observed ($Y = 1$). Some members thus receive an unintended motivational email, increasing email processing costs, while others who should be treated are not, resulting in a loss for the community.

The purpose of the proactive motivational email is to minimize future IMP ($Y = 1$). To evaluate the impact of the campaign, we must distinguish four theoretical outcomes of a treatment action [46], as depicted in Table 1. The "sure things" show always future superior participation behavior whether receiving a motivational email or not. On the contrary, the "lost causes" continue future IMP irrespective of receiving a motivational email by the moderator. Furthermore, the moderator wants to identify and contact the "persuadables" given that the impact of the motivational email is positive on future member participation behavior. These members would show future IMP, but are persuaded to future superior participation behavior in response of the motivational email received. Finally, the moderator wants to avoid emailing the "do-not-disturbs" as these members would show a future superior participation, but change their minds in response to the moderator's email and thus show future IMP. For instance, these IC members could drop out and engage in future IMP, because they are annoyed and tired catching up with the numerous moderator's requests and tasks. The motivational email could be seen as the last straw that breaks the camel's bag. Previous research has shown that these counter-intuitive effects are often context-specific and hard to explain, but are regularly dedicated by the intrusive and excessive character of the communication [46]. To evaluate the parameters of a proactive email treatment campaign, in addition to the cost of community management, we must assess how each approach resonates with the different member profiles.

[INSERT TABLE 1 AROUND HERE]

2.1.1. Proactive untargeted email

A *proactive untargeted email* strategy embraces a "one-size-fits-all" paradigm; the moderator decides to treat all members equally independent of their profile by all sending them the same email campaign. The untargeted approach is straightforward, such that it represents a default way to determine the scope of the campaign. This simplistic approach also is cost effective, because it does not require any decision about whom to treat, so moderators instead can devote their time and resources to innovation tasks. When they receive signals of potential future reduced activity and expect IMP, they can use a proactive untargeted email to motivate the community as a whole. Whether through their experience or by relying on automated tools like language monitoring, moderators can recognize signals of reduced activity, such as low positive emotional community vibes [3] or divergent language styles [33]. However, the assumption of homogeneity manifested in this approach may be difficult to support in an IC. All members are treated equally, even though communities are fluid, and members change over time [11], such that the member base is inherently heterogeneous. Moderators might expect a single, general, positive response from the email, yet negative reactions are possible, as we depict in Table 1. Therefore, in terms of ease of execution, a proactive untargeted email campaign may be highly beneficial, but its ultimate impact suggests the need for caution.

2.1.2. Proactive targeted email

Communities need to avoid allocating untargeted resources to all types of members and instead require heterogeneous treatment approaches [19]. Previous research highlights the benefits of proactive targeted efforts over untargeted ones [45] and the usefulness of direct emailing [47]. This shift toward customer-centric, segmented communication is effectively supported by technology [31], such as big data analytics, that function well in data-rich environments such as ICs [3]. Targeted approaches assume a heterogeneous member base, and recently moderators might rely on analytical models to make objective, cost-effective targeting decisions [3]. With past member profile data and classification techniques, they can construct propensity models to predict future IMP behavior as done in [2] ($P(Y=1|X)$). Then moderators can focus their treatment efforts and target only those members with the highest IMP risk. This first modeling approach anticipates future expected IMP, yet subjecting high-risk members to the treatment still might result in unfavorable outcomes as members could not be persuadable to change their IMP behavior by the treatment [48]. The latter already considers the treatment and then the response to that treatment. In turn, neither modeling approach can distinguish the different treatment outcomes in Table 1 [38].

Noting these flaws of traditional prediction methods, prior studies suggest a new approach to target individuals in a treatment campaign, namely, uplift modeling [39]. It is known by many synonyms, such as net lift modeling, differential response analysis, persuasion modeling or prediction models to predict favorable treatment responses ($P(Y=1|E=1,X)$). In various successful applications, uplift modeling has helped increase the effectiveness of marketing and retention campaigns [49], and it also has huge benefits for direct emailing [38]. With a *proactive targeted email* strategy for IMP reduction, the moderator treats members differently and only targets those who can be positively influenced with an email campaign. Uplift modeling can evaluate the causal impact of a treatment action and distinguish the four member profiles in Table 1 [46]. It enables moderators to decide which members will be positively influenced by the email campaign, avoids annoying the "do-not-disturbs," leaves the "sure things" alone, and prevents any efforts being wasted on "lost causes." For the "lost causes," other treatments might be explored.

Constructing uplift models requires a field experiment that allocates members randomly to either a treatment ($E = 1$) or a non-treatment ($E = 0$) group. In our setting, this comes down to using $P(Y=1|E=0,X)-P(Y=1|E=1,X)$, the uplift modeling technique estimates the decrease in IMP probability if members are sent an email, over the IMP probability if they are not. The model output, or uplift score, reflects the likelihood that a member can be motivated and show less IMP using the motivational email. We also emphasize that the framework of Table 1 with its different member profiles is purely theoretical; a member can never be treated and not treated at the same time. In the modeling process, we construct a prediction model to predict the incremental decrease in IMP by the motivational email, not whether a member belongs to one of the four different member profiles.

2.2. Motivational message

Three important motivations lead to community participation: hedonic, social, and cognitive. Members receive hedonic benefits when community participation is fun [24], interesting, pleasurable, and mentally stimulating [23], such that their hedonic engagement evolves over time [25]. Cognitive benefits arise from tapping into knowledge exchanges in the community [24], which might provide information about products, the underlying technology, and their usage [23,50]. Finally, social benefits come from developing social and relational ties over time [23,28] and the "we-intentions" that signal group membership [26]. Because these interactions require beliefs about future benefits [23], firms should take proactive measures and create ICs that contribute to such benefits. This argument suggests proactive stimulation of community members using motivational messages; for example, reminding members about anticipated benefits by citing them in a motivational message, the moderator could directly highlight the reasons for their participation. In contrast with prior research [23] that explores motivations at point t_0 and measures participation behavior at a future point f, we address motivation at point t_0 as a means to influence behavior at a future point f, through a motivational email message.

2.3. Member profile

A self-interested orientation and positive emotionality are crucial to innovation and collaboration [3,13,51]. First, self-interested people focus on pursuing their personal goals and fulfilling their needs, rather than others' [52]. Self-interest drives their future actions [53], so when members exhibit self-interested behavior, it may indicate that they are concerned with their future actions, implying an appropriate moment to influence them. Second, people who exhibit positive emotionality tend to be positive in their affect, which translates into greater cognitive effort [54]. Broaden-and-build process theory [55] suggests that the experience of positive emotions broadens people's attention, cognition, and action, which enhances their physical, social, and intellectual resources. When members express positivity in an IC, it may be an indicator that they have entered a broaden-and-build process, with an appropriate mindset to be influenced by a proactive treatment.

In ICs, in addition to analyzing members' language content (what they say), moderators can analyze their language style (how they say it) to predict future member participation [3,33]. The words people use reveal a lot about their psychological selves [56]. Self-interest–oriented and positive emotional writing styles can be explored by analyzing members' posts, with explicit links to IMP [3].

Because online communities are dynamic environments [11] and self-interest and positive emotionality change over time [52,57], these measures are used to profile IC members. Using the indications provided by their writing style that signal that members are concerned about their future actions, moderators might identify whether members are open to being motivated and persuaded by a motivational email.

3. EXPERIMENTAL SETUP

3.1. Research setting

To implement the research framework as presented in Figure 1 – panel a, a sample, obtained from a European market research consultancy, containing 5,828 posts written by 355 members of four firm-hosted Dutch ICs is used. The market research consultancy organized the ICs, under commission by the companies, and different community topics that correspond with different innovation challenges. The consultancy then recruited members on the basis of their interest in the community topic or extensive usage experience. Members received a small financial incentive to participate, but their ongoing participation mainly reflects their intrinsic motivation. The communities were managed by a moderator, responsible for encouraging participation and guiding the innovation challenge process by introducing questions. In a collaborative manner, members could participate and share their opinions by answering the moderator's questions or responding to other members' posts.

3.2. Experimental timeline

As depicted by Figure 1- panel a, the field test starts at the treatment date t. For each community, t is set at t_0 corresponding to the beginning of a new topic. In each community at t, members were randomly allocated without replacement to one of four groups. Three groups of whom will receive an email ($E = 1$) by the moderator, which varied in the motivational element it featured (i.e., hedonic, social, or cognitive) (see section 3.3. Motivational email). The fourth group is the control group, and these members will not receive any email ($E = 0$). Table 2 lists the characteristics of both the community and the experiment, including the email sent dates.

[INSERT TABLE 2 AROUND HERE]

To ensure sufficient participation, a two-step email procedure implemented at t sought to both encourage participation and reduce IMP in the member participation observation period. At t, the moderator sent a motivational email, followed by a reminder email that contained a copy of the first email and a call to action to participate in active topics. This two-step procedure increases the chances that participants will open the email. The members in the sample opened at least one of the two emails; Table 2 contains the opening rates for the different ICs.

Furthermore, the field experiment spans a three-month period. In line with [3,33], the member profiling period contains two months of past member data before the treatment date *t*. This data is used to create independent variables used in the uplift model (see section 3.4.2. Independent variables). The member participation observation period spans one month after the treatment date *t*. During this period, we observe whether a member's behavior is inferior ($Y = 1$) or superior ($Y = 0$). This information constitutes the dependent variable in the uplift model (see section 3.4.1. Dependent variables). In this overall three-month period, community activity was high, and many new topics were created.

3.3. Motivational email

To motivate members to participate, we created a motivational email campaign to be sent at the treatment date *t* with three types of motivational messages. The general format is the same for all types of emails, expressing the moderator's personal wish for the member to participate constructively in an upcoming period, with a subject line that read "two wishes you have not received." Because the studied ICs use Dutch, the motivational email was also written in Dutch. For the three motivational emails, the two wishes corresponded to the different motivations, or anticipated benefits of community participation provided by [23]. The content also referred to items from scales established by [23], as detailed in Table 3. We used direct translations of the items from prior literature; a pretest among academics confirmed that the motivational emails appeared valid and cited the intended benefit. The email also included a rhetorical question related to the type of anticipated benefit: "Do you think this year will be a pleasurable/educational/social year?" In Appendix B we offer an example of a hedonic motivational email and its reminder.

[INSERT TABLE 3 AROUND HERE]

3.4. Uplift modeling

3.4.1. Dependent variables

To operationalize the dependent variable for the uplift model, we build on a definition of member participation quantity from Coussement et al. [3], which reflects the ratio of active community topics in which a member posts to the total active community topics in a certain period. From Figure 1 – panel a, to gauge the dependent variable, we compared member participation quantity at t_0, i.e. the participation quantity during the member profiling period, with that at f, i.e. the participation quantity during the member participation observation period. If there is a decrease in participation quantity from t_0 to f, the dependent variable equals 1 ($Y = 1$), whereas if there is an increase, it takes a value of 0 ($Y = 0$).

3.4.2. Independent variables

To make targeting decisions, uplift models need information, which in this study pertains to the different variables calculated during the member profiling period: activity, language style, language content, interaction variables, and the treatment variable. As input for direct marketing models, behavioral data are easily accessible and significant, in that they influence the choice of customers [58]. The activity variables are defined as a function of members' posting behavior and relate to recency, frequency, and monetary (RFM) measures, as are widely used in marketing models [59]. To construct the language style variables, we use the LIWC [60], which supports analyses of how members' posts are written. This dictionary-based approach assesses each post according to the percentage of words that belong to respective word categories; it has been widely used in prior academic literature [22,61]. Consistent with prior research, we rely on several word categories as input for member participation models, including emotions [3], cognitive words, and pronouns [33]. The content variables identify the shared content characteristics across members' posts. Identical to the data preprocessing step of [62], we construct the language content variables in accordance with Feldman and Sanger's [63] guidelines. In particular, we employ a bag-of-words approach to convert textual information into numerical information, then turn to latent semantic analysis to construct a low-dimensional matrix. Finally, the binary treatment variable indicates whether a member is sent an email ($E = 1$) or not ($E = 0$).

3.4.3. Algorithm

Most studies that involve uplift modeling feature regression-based and tree-based approaches. We turn to a tree-based approach, which represents an adaption from well-known classification algorithms (e.g., altering the splitting criteria) that accommodates treatment and control groups explicitly. To avoid the problems of single-based decision trees, such as high variance due to the hierarchical nature of the splitting process, multiple decision trees can be effective [49,64]. Accordingly, we use the causal conditional inference forest (ccif) [32], which explicitly provides decision support in marketing interventions and achieved the best performance among alternative methods [32,65]. Furthermore, random forest models are reliable for churn prediction [66]. The ccif classifier offers an improved tree-based ensemble that estimates personalized treatment effects. It solves the problem of the uplift random forest [49], which can lead to overfitting and a selection bias toward covariates with many possible splits. The ccif method implements recursive partitioning in a causal conditional inference framework; that is, it recursively partitions the input space into subgroups with heterogeneous treatment effects. We kindly refer to [49] for more information on ccif. The different split criteria we explore are based on conditional divergence measures, such as Euclidean distance, Kullback-Leibler divergence, chi-squared divergence [38], and the interaction method [67].

Consistent with prior research [68], we use leave-one-out cross-validation to generalize the model over the data set. This method is superior for smaller data sets [69]. This cross-validation scheme iteratively loops through all members, and at each iteration, it takes one member as a test set and the others as the training set. This approach ensures a maximal amount of members to train the model; it also is a deterministic procedure, because it does not use random sampling. Although the approach is computationally intensive, it is feasible for our study context. Finally, to select the final model, by exploring different experimental model parameters in the leave-one-out cross-validation, we seek the model with the best qini performance on the training sample, as detailed subsequently.

3.4.4. Evaluation

To evaluate the quality of the uplift models, we use the qini coefficient and qini curve [38,65,67]. The qini coefficient is a generalization of the Gini coefficient, which supports analyses of the goodness-of-fit of response models. The qini measure is based on the area under the incremental gains curve, or qini curve [67], which plots the cumulative difference of the IMP rate between the treatment group and control group as a function of the selected proportion of the member base. The qini value is the area underneath the actual gains curve, less the area underneath the diagonal, which corresponds to random targeting. No individual can be both treated and not treated at the same time, so we make no conclusions about whether the individual is a persuadable or sure thing, as in Table 1. Instead, the evaluation takes place at the group level, for each proportion of the member base. With our sparse experimental data, we determine this proportion by quintiles.

3.5. Member profiling

Once the uplift modeling phase is done, each community member is assigned an uplift modeling score showing the impact of the email campaign and community characteristics in reducing IMP. Interestingly, we want to get insight which member profiles tend to result in a higher positive impact of the email campaign in reducing IMP. This is done by finding the relationship between a member's writing style and control variables obtained from the member profiling period and the uplift scores.

To operationalize self-interest–oriented and positive emotional writing styles, we use the operationalization proposed by Coussement et al. [3] and the LIWC [60]. Prior literature defines self-interest as a bipolar continuum, marked by high self-focus and high other-focus as the scale ends [52]. The operationalization of a self-interest–oriented writing style thus depends on the percentage of self-referential (*self*) and other-referential (*other*) words. Both categories contain 12 words ("I," "me," and "mine" versus "her," "they," and "one"). We subtract the average self-referential words and other-referential words used per post in the independent variable period to obtain the variable. For positive emotionality, we rely on both positive and negative affect [70]. The operationalization of positive emotional writing style is similar to that for self-interest–oriented writing style, but we use the positive (*posemo*) and negative (*negemo*) word categories from LIWC. The LIWC dictionary contains 685 positive and 1332 negative emotion words.

As control variables, consistent with [3], we include membership length, member participation quantity, community size, and community participation quantity. Membership length is the number of days the member has been active in the community. Member participation quantity reflects the total number of posts. Community size is the number of active members in the community, and community participation quantity reflects the number of posts in the community.

4. RESULTS

Given that members are randomly assigned to each of the experimental conditions at t_0, the impact of a proactive untargeted email strategy is evaluated by comparing the differences in IMP rates between the treatment groups and the control group. We use a chi-squared test, which offers a non-parametric analysis of group differences when the dependent variable is categorical.

[INSERT TABLE 4 AROUND HERE]

Table 4 reveals the effects of a proactive *untargeted* motivational email campaign, in general and with different motivational elements, and the "no email" strategy. With regard to RQ1a, the IMP rate for the treatment group is 36.50%, whereas the control group has an IMP rate of 25.00% (χ^2=4.05, p<.05). Thus, the average treatment effect of a proactive untargeted motivational email is an 11.5% increase in IMP. When we separate the motivations, to address RQ1b, we find that the IMP rate for the motivational email with a hedonic element is 37.50% (χ^2=3.28, p<.10), that for the cognitive element is 33.33% (χ^2=1.53, p>.10), and that for the social message equals 38.82% (χ^2=3.90, p<.05). The control group has an IMP rate of 25%, so the treatment effect of a proactive untargeted email with a hedonic motivational message constitutes a 12.50% increase in IMP, a cognitive motivational message increases it by 8.33%, and an email with social message leads to a 13.82% increase in IMP.

To investigate the impact of a proactive targeted email campaign, we rely on the outcomes of the ccif uplift model that produces for each of our members in our field test an uplift score. Members with a positive uplift score are expected to be positively influenced by the motivational email and will show thus a reduction in IMP thanks to the email. The higher the uplift modeling score is, the higher the impact of the email in reducing IMP is.

[INSERT TABLE 5 AROUND HERE] [INSERT FIGURE 2-3 AROUND HERE]

Table 5 notes the effect on incremental gains of a proactive *targeted* motivational email campaign across motivational emails (RQ2a) and for each of the motivational email types (RQ2b) for the random and uplift model. A positive incremental gain indicates a positive impact of the email and thus a reduction in IMP rate consequently; a negative incremental gain indicates a negative impact of the motivational email and an increase in IMP rate. Figure 2 visualizes the incremental impact of the email campaign across motivations (RQ2a), while Figure 3 depicts the incremental impacts for each of the motivational emails graphically (RQ2b). Generally speaking treating members with a proactive motivational email and selecting them at random increases the IMP rate; the cumulative incremental gain for 20% of members is -.0230, and that for 40% of members is -.0460. When targeting members by using the uplift model, treating the 20% most persuadable members, i.e. with the highest uplift scores, gives a cumulative incremental gain of -.0027, and for the 40% most persuadable members, this value is -.0411. Thus, a proactive targeted email sent to the most persuadable members based on the uplift model has a less negative impact on the IMP rate than an email sent to a random selection of members, but it still does not achieve positive incremental gains.

Next, treating members with a proactive email with a hedonic motivational message and selecting members at random increases the IMP rate, so for 20% of them, the cumulative incremental gain is -.0250, and for 40% of members, it is -.0500. Treating members with a proactive targeted hedonic motivational email using the uplift model has a similar negative IMP effect. The incremental gain for 20% of the most persuadable members is -.0817, and for the top 40% of members, it is -.0129. Thus, the proactive targeted email using a hedonic motivation sent based on the uplift model performs worse than the random model, without any positive incremental gains.

When targeting members at random using a cognitive motivational message, the IMP rate increases, and the cumulative incremental gain for 20% of members is -.0166, while that for 40% of members is -.0333. Selecting members using the uplift model decreases the IMP rate, such that the cumulative incremental gain for 20% of the most persuadable members is .0129, and that for the top 40% of members is .0297. Thus, using a proactive targeted cognitive email and selecting members through the uplift model performs better than the random model and achieves positive incremental gains.

Finally, treating members at random with a proactive targeted email with a social motivational message increases the IMP rate: For 20% of members, the cumulative incremental gain is -.0276, and for 40% of members, it is -.0552. Selecting members using the uplift model and treating them with an email with a social motivational message increases the IMP rate, such that the cumulative incremental gain for 20% of members is -.0371, and that for 40% of members is -.0485. Thus, the uplift model performs worse than the random model and achieves no positive incremental gains.

In summary, the only way moderators might reduce the IMP behavior of members is by relying on the uplift model and sending them a cognitive motivational email. The results show the positive impact of a proactive targeted cognitive email on a reduction of the IMP rate for both the 20% and 40% of members having the highest uplift scores. In all other contexts, it means that sending a proactive motivational email has an adverse effect on motivating members to participate more. In other words: there appear to be many so-called do-not-disturbs among the top 20% and top 40%, yielding a downlift instead of an uplift.

Table 6 gives insights which member profiles and community characteristics tend to result in a higher positive impact of the email campaign in reducing IMP. It shows the results of the regression of the relationship of a member's writing style and the control variables on the uplift scores. Among all approaches, only the proactive targeted email with cognitive motivation positively influences members, so we focus only on the cognitive email campaign results.

[INSERT TABLE 6 AROUND HERE]

The self-interest–oriented writing style relates non-significantly and negatively to the uplift score (β=-1.32E^{-3}, p>.10); a positive emotional writing style is positively and significantly related to the uplift score (β=8.548E^{-3}, p<.01). Whereas membership length has no significant relationship with the uplift score (β=1.186E^{-5}, p>.10), membership participation quantity has a positive but not significant link to it (β=-8.517E^{-4}, p>.10). Community size is significantly and negatively related (β=-1.462E^{-3}, p<.01), and community participation quantity is significantly and positively related (β=4.376E^{-5}, p<.01), to the uplift score.

5. DISCUSSION

5.1. Treatment scope

Our results indicate that both a proactive targeted and an untargeted motivational email campaign fail to reduce IMP in online innovation communities. Compared with a strategy of sending no motivational email at all, the untargeted email increases the IMP rate by 11.5%. A similar negative impact emerges from the targeted email, sent only to members that seem likely to be positively influenced by the email. Instead, the results indicate the need for greater nuance, because the viability of the treatment scope depends on the email itself and its use of motivational elements. In proactive untargeted emails, all three motivational elements still perform worse than a no-email strategy, increasing the IMP rate anywhere from 8.33% to 13.82%. Proactive targeted emails with hedonic or social motivational elements also are inferior to sending no email; treating even the 20% most persuadable members increases the IMP rate by 8.17% and 3.71%, respectively. The exception is a proactive targeted email with a cognitive motivational element, which reduces IMP in online ICs, by 1.29% if it targets 20% of the most persuadable members or 2.97% by targeting the top 40%. The IMP rate of the control group is relatively high, so these results indicate substantial benefits. Noting that a random selection of 20% of members increases the IMP rate by 1.66% (or 40% of members by 3.33%), we show that the uplift model helps target the right members. By leaving other members alone, this strategy can effectively reduce IMP in online ICs.

Consistent with previous research [45], our results indicate the superiority of the targeted strategy over an untargeted approach. Furthermore, they affirm [47] a negative effect of an untargeted email campaign, compared with a positive effect of a targeted campaign. Despite the benefits of the simplicity and ease of use of an untargeted approach, these results cannot recommend adopting an untargeted motivational email rather than a targeted one, due to the difference in their impacts on the community. The greater effect on the IMP rate stemming from an untargeted approach directly stems from its inability to distinguish between members who need treatment and those who do not. In reducing the IMP rate, the targeted approach leverages uplift modeling to identify the members whose future IMP behavior can be reduced by sending them motivational emails. The ability to treat only these members is especially useful for email campaigns, during which moderators should send motivational emails to the "persuadables" but avoid sending anything to the "do-not-disturbs." The "lost causes" cannot be rescued by a motivational email, but other (more expensive) treatment actions might trigger them. The "sure things" are not bothered by the email, but they do not need to be treated, and ultimately, too many treatments could increase their annoyance with emails and transform them into "do-not-disturb" or "lost cause" members over time.

5.2. Motivational element

The choice of motivational element influences the outcome of email campaigns. In an untargeted approach, emails with all motivational elements perform worse than sending no email. With a targeted approach, emails with hedonic and social elements still fail to exert positive influences, but an email that features a cognitive motivation effectively can decrease the IMP rate by as much as 2.97%. This stronger effect of the cognitive motivation is consistent with prior research [23], including social exchange theory that predicts that community members are motivated to share knowledge in ICs to achieve their personal goal of enhancing their reputation [41]. This study further reveals that IC moderators can anticipate this need and send a cognitive email message to motivate their community participation.

The different outcomes of the three motivational elements might reflect [23]'s findings regarding how product content, member identity, and human interactivity shape benefits. They find that learning benefits depend on product content, not member identity or human interactivity; hedonic and social benefits rely on product content too but also are influenced by product content and human interactivity. The IC moderator has a direct influence on the product content, by organizing and managing innovation challenges [43], but less influence on member identity or human interactivity, which are created by the individual members and their peers. Therefore, a motivational email from the moderator may seem more credible if it cites cognitive motivation, rather than hedonic and social forms.

5.3. Member profile

Moderators cannot use member's self-interest–oriented writing style to identify targets, though a positive emotional writing style can signal their persuadability. [3] similarly find that a member's self-interest–oriented writing style cannot signal future IMP; we advance that insight by noting its inability to determine whether they should be targeted. However, the more positive emotional words a member uses in IC communications, the higher the likelihood that she or he can be motivated with a proactive targeted email with a cognitive message. Relying on the broaden-and-build theory [55], moderators could interpret a positive emotional writing style as a reflection of being in the broaden-and-build process, which indicates that they are broadening their attention, cognition and action. As members with a positive emotional writing style can be motivated using a cognitive motivational message shows that the right profile and moment is found to trigger future constructive participation.

6. CONCLUSION

IMP considerably jeopardizes the viability and sustainability of ICs. By studying, the elements of proactive motivational e-mail campaigns, this study analyzed the effectiveness of such campaigns. By comparing the viability of a targeted and untargeted messages (*message scope*), analyzing the usage of several motivational messages (*message content*) and exploring which member profile can be motivated (*message profile*), we show empirical evidence of optimal characteristics of e-mail campaigns.

Our study makes four important contributions for both academics and practioners. First, when pursuing a proactive motivational e-mail campaign, a targeted treatment scope should be favored over an untargeted approach. While an untargeted proactive e-mail increases the IMP rate, a targeted proactive email using uplift models can identify which members might be positively influenced. By selecting the most persuadable members based on an uplift modeling framework, the moderator can reduce the IMP rate. Second, when choosing the motivational message to feature in the email, hedonic and social motivations will not exert a positive community impact; a cognitive motivational message can achieve the intended campaign purpose. Specifically in this research context, members are triggered to contribute to the innovation task by informing them about the newest trends and developments on the IC subject. For instance, moderators are encouraged to communicate regularly a summary of the latest IC ideas as members seem to respond positively to those intellectual cues. Third, with regard to members' community behavior, a positive emotional writing style indicates a member profile that is more likely to respond to a motivational email. For instance, the community platform provider could opt to develop a sentiment detection dashboard that automatically analyses the positive emotional writing style on IC member level to maximally support the moderator's efforts in reducing IMP. Fourth, community managers need to find an ideal balance between the size and the activation level of the community in order to maximize the impact of proactive targeted email campaigns; when the size of the community increases, the proactive motivational email has a lower impact on decreasing the IMP rate. On the other hand, an increased community size leads to a higher probability of increased community participation activity that has in turn a positive impact on the motivational email in fighting IMP.

Despite these contributions, this study has also some limitations. Notably, we only explore hedonic, cognitive, and social motivations, excluding personal integrative motivation, which [23] propose as a fourth type. Perhaps anticipating reputation benefits would help motivate members to participate. A valuable future research path is to investigate why in general sending a proactive motivational email is worse than sending no email, and why only the cognitive motivation email is effective in this research context. In addition, we rely solely on the uplift method to design the targeted approach, but other models are available, such as regression-based versions. Further research should investigate whether different models lead to better results. Moreover, we focus on motivational emails and thus exclude analyses of other IMP reduction techniques, such as financial incentives. Firms are always on the lookout for improved approaches to managing ICs, and in light of the promise of uplift modeling, further research should reconsider such alternative approaches to design more cost-effective campaigns. Finally, the research study is contextualized in the IC domain, and thus the field test is implemented in four firm-hosted closed online ICs. A valuable path for further research may explore the generalizability of the current study results for other community types.

REFERENCES

[1] D. Mahr, A. Lievens, Virtual lead user communities: Drivers of knowledge creation for innovation, Res. Policy. 41 (2012) 167–177.

[2] S. Debaere, K. Coussement, T. De Ruyck, Multi-label classification of member participation in online innovation communities, Eur. J. Oper. Res. (2018).

[3] K. Coussement, S. Debaere, T. De Ruyck, Inferior Member Participation Identification in Innovation Communities: The Signaling Role of Linguistic Style Use, J. Prod. Innov. Manag. 34 (2017) 565–579.

[4] P.M. Di Gangi, M. Wasko, Steal my idea! Organizational adoption of user innovations from a user innovation community: A case study of Dell IdeaStorm, Decis. Support Syst. 48 (2009) 303–312.

[5] L. Dahlander, L. Frederiksen, The Core and Cosmopolitans: A Relational View of Innovation

in User Communities, Organ. Sci. 23 (2012) 988–1007.

[6] A. Westerski, T. Dalamagas, C.A. Iglesias, Classifying and comparing community innovation in Idea Management Systems, Decis. Support Syst. 54 (2013) 1316–1326.

[7] M. Li, A. Kankanhalli, S.H. Kim, Which ideas are more likely to be implemented in online user innovation communities? An empirical analysis, Decis. Support Syst. 84 (2016) 28–40.

[8] C. Hienerth, C. Lettl, Exploring how peer communities enable lead user innovations to become standard equipment in the industry: Community pull effects, J. Prod. Innov. Manag. 28 (2011) 175–195.

[9] C.E. Porter, N. Donthu, Cultivating Trust and Harvesting Value in Virtual Communities, Manage. Sci. (2008) 113–128.

[10] S. Faraj, S. Kudaravalli, M. Wasko, Leading Collaboration in Online Communities, MIS Q. 39 (2015) 393–412.

[11] S. Faraj, S.L. Jarvenpaa, A. Majchrzak, Knowledge collaboration in online communities, Organ. Sci. 22 (2011) 1224–1239.

[12] S. Faraj, G. von Krogh, E. Monteiro, K.R. Lakhani, Special Section Introduction—Online Community as Space for Knowledge Flows, Inf. Syst. Res. 27 (2016) 668–684.

[13] R.P. Bagozzi, U.M. Dholakia, Open source software user communities: A study of participation in Linux user groups, Manage. Sci. 52 (2006) 1099–1115.

[14] R. Algesheimer, U.M. Dholakia, A. Herrmann, The Social Influence of Brand Community: Evidence from European Car Clubs., J. Mark. 69 (2005) 19–34.

[15] S.L. Johnson, H. Safadi, S. Faraj, The Emergence of Online Community Leadership, Inf. Syst. Res. 26 (2015) 165–187.

[16] S.O. de Almeida, U.M. Dholakia, J.M.C. Hernandez, J.A. Mazzon, The Mixed Effects of Participant Diversity and Expressive Freedom in Online Peer-to-Peer Problem Solving Communities, J. Interact. Mark. 28 (2014) 196–209.

[17] C. Arthur, What is the 1% rule?, Guard. (2006).

[18] B. Langner, V.P. Seidel, Sustaining the Flow of External Ideas: The Role of Dual Social Identity across Communities and Organizations, J. Prod. Innov. Manag. 32 (2015) 522–538.

[19] J. Liao, M. Huang, B. Xiao, Promoting continual member participation in firm-hosted online brand communities: An organizational socialization approach, J. Bus. Res. 71 (2017) 92–101.

[20] A. Kankanhalli, B.C.Y. Tan, K.-K. Wei, Contributing Knowledge to Electronic Knowledge Repositories: An Empirical Investigation, MIS Q. 29 (2005) 113–143.

[21] M.M. Wasko, S. Faraj, Why should I share? Examining social capital and knowledge contribution in electronic networks of practice, MIS Q. 29 (2005) 35–57.

[22] S. Ludwig, K. de Ruyter, D. Mahr, M. Wetzels, E. Bruggen, Take Their Word for It: the Symbolic Role of Linguistic Style Matches in User Communities, Mis Q. 38 (2014) 1201–1217.

[23] S. Nambisan, R.A. Baron, Virtual customer environments: Testing a model of voluntary participation in value co-creation activities, J. Prod. Innov. Manag. 26 (2009) 388–406.

[24] M. Wasko, S. Faraj, "It is what one does": why people participate and help others in electronic communities of practice, J. Strateg. Inf. Syst. 9 (2000) 155–173.

[25] H.J. Schau, A.M. Muñiz, E.J. Arnould, How Brand Community Practices Create Value, J. Mark. 73 (2009) 30–51.

[26] R.P. Bagozzi, U.M. Dholakia, Intentional social action in virtual communities, J. Interact. Mark. 16 (2002) 2–21.

[27] A.M. Muniz, T.C. O'Guinn, Brand community, J. Consum. Res. 27 (2001) 412–432.

[28] S. Nambisan, Designing virtual customer environments for new product development: Toward a theory, Acad. Manag. Rev. 27 (2002) 392–413.

[29] M. Antioco, K. Coussement, Misreading of consumer dissatisfaction in online product reviews: Writing style as a cause for bias, Int. J. Inf. Manage. 38 (2018) 301–310.

[30] R.C. Blattberg, B.-D. Kim, S.A. Neslin, Database marketing: Analyzing and managing customers, Springer, New York, 2010.

[31] V. Kumar, A customer lifetime value-based approach to marketing in the multichannel, multimedia retailing environment, J. Interact. Mark. 24 (2010) 71–85.

[32] L. Guelman, M. Guillén, A.M. Pérez-Marín, A decision support framework to implement optimal personalized marketing interventions, Decis. Support Syst. 72 (2015) 24–32.

[33] S. Ludwig, K. de Ruyter, D. Mahr, M. Wetzels, E. Brüggen, T. de Ruyck, Take their word for it: The symbolic role of linguistic style matches in user communities, MIS Q. 38 (2014) 1201–1217.

[34] J. Preece, Online Communities: Designing Usability and Supporting Socialbilty, 1st ed., John

Wiley & Sons, Inc., New York, NY, USA, 2000.

[35] J.H. McAlexander, J.W. Schouten, H.F. Koenig, Building Brand Community, J. Mark. 66 (2002) 38–54.

[36] M. Antikainen, M. Mäkipää, M. Ahonen, Motivating and supporting collaboration in open innovation, Eur. J. Innov. Manag. 13 (2010) 100–119.

[37] K. Kane, V.S.Y. Lo, J. Zheng, Mining for the truly responsive customers and prospects using true-lift modeling: Comparison of new and existing methods, J. Mark. Anal. 2 (2014) 218–238.

[38] P. Rzepakowski, S. Jaroszewicz, Uplift modeling in direct marketing, J. Telecommun. Inf. Technol. 2 (2012) 43–50.

[39] N.. Radcliffe, P.. Surry, Differential response analysis: modeling true response by isolating the effect of a single action., in: Credit Scoring Credit Control VI, 1999.

[40] L. Dahlander, L. Frederiksen, The core and cosmopolitans: A relational view of innovation in user communities, Organ. Sci. 23 (2011) 988–1007.

[41] C. Wiertz, K. de Ruyter, Beyond the call of duty: Why customers contribute to firm-hosted commercial online communities, Organ. Stud. 28 (2007) 347–376.

[42] L.B. Jeppesen, L. Frederiksen, Why do users contribute to firm-hosted user communities? The case of computer-controlled music instruments, Organ. Sci. 17 (2006) 45–63.

[43] T. Troch, T. De Ruyck, User collaboration through private online communities, in: A. Griffin, C. Noble, S. Durmusoglu (Eds.), Open Innov. New Prod. Dev. Essentials from PDMA, John Wiley & Sons Inc, New York, 2014: pp. 135–172.

[44] O. V. Pavlov, N. Melville, R.K. Plice, Toward a sustainable email marketing infrastructure, J. Bus. Res. 61 (2008) 1191–1199.

[45] T. Coltman, Why build a customer relationship management capability?, J. Strateg. Inf. Syst. 16 (2007) 301–320.

[46] N. Radcliffe, Generating incremental sales: Maximizing the incremental impact of cross-selling, up-selling and deep-selling through uplift modelling, 2007.

[47] T. Reutterer, A. Mild, M. Natter, A. Taudes, A dynamic segmentation approach for targeting and customizing direct marketing campaigns, J. Interact. Mark. 20 (2006) 43–57.

[48] C. Manahan, A Proportional Hazards Approach to Campaign List Selection, in: Proc. Thirtieth Annu. SAS Users Gr. Int. Conf., Philadelphia, 2005.

[49] L. Guelman, M. Guillén, A.M. Pérez-Marín, Random forests for uplift modeling: An insurance customer retention case, in: Lect. Notes Bus. Inf. Process., 2012: pp. 123–133.

[50] S. Nambisan, R.A. Baron, Interactions in virtual customer environments: Implications for product support and customer relationship management, J. Interact. Mark. 21 (2007) 42–62.

[51] H.-T. Tsai, R.P. Bagozzi, Contribution Behavior in Virtual Communities: Cognitive, Emotional, and Social Influences., MIS Q. 38 (2014) 143–163.

[52] B.M. Meglino, M.A. Korsgaard, Considering situational and dispositional approaches to rational self-interest: an extension and response to de Dreu (2006)., J. Appl. Psychol. 91 (2006) 1253–9.

[53] D.T. Miller, The norm of self-interest., Am. Psychol. 54 (1999) 1053–1060.

[54] J.M. Sullivan, M. Conway, Negative affect leads to low-effort cognition: Attributional processing for observed social behavior, Soc. Cogn. 7 (1989) 315–337.

[55] B.L. Fredrickson, The role of positive emotions in positive psychology, Am Psychol. 56 (2011) 218–226.

[56] J.W. Pennebaker, M.R. Mehl, K.G. Niederhoffer, Psychological aspects of natural language use: Our words, our selves, Annu. Rev. Psychol. 54 (2003) 547–77.

[57] P. Kuppens, Z. Oravecz, F. Tuerlinckx, Feelings change: accounting for individual differences in the temporal dynamics of affect., J. Pers. Soc. Psychol. 99 (2010) 1042–1060.

[58] I. Bose, X. Chen, Quantitative models for direct marketing: A review from systems perspective, Eur. J. Oper. Res. 195 (2009) 1–16.

[59] D.L. Olson, B. Chae, Direct marketing decision support through predictive customer response modeling, Decis. Support Syst. 54 (2012) 443–451.

[60] J.W. Pennebaker, LIWC: Linguistic Inquiry and Word Count, LIWC2007 Man. (2007) 1–22.

[61] S. Ludwig, K. De Ruyter, M. Friedman, More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates, J. Mark. 77 (2013) 87–103.

[62] K. Coussement, D.F. Benoit, M. Antioco, A Bayesian approach for incorporating expert opinions into decision support systems: A case study of online consumer-satisfaction detection, Decis. Support Syst. 79 (2015) 24–32.

[63] R. Feldman, J. Sanger, The text mining handbook: advanced approaches in analyzing unstructured data, Imagine. 34 (2007) 410.

[64] M. Soltys, S. Jaroszewicz, P. Rzepakowski, Ensemble methods for uplift modeling, Data Min. Knowl. Discov. 29 (2015) 1531–1559.

[65] F. Devriendt, D. Moldovan, W. Verbeke, A Literature Survey and Experimental Evaluation of the State-of-the-Art in Uplift Modeling: A Stepping Stone Toward the Development of Prescriptive Analytics, Big Data. 6 (2018) 13–41.

[66] K. Coussement, K.W. De Bock, Customer churn prediction in the online gambling industry: The beneficial effect of ensemble learning, J. Bus. Res. 66 (2013) 1629–1636.

[67] N. Radcliffe, P. Surry, Real-world uplift modelling with significance-based uplift trees, White Pap. TR-2011-1, Stoch. (2011) 1–33.

[68] W. Buckinx, G. Verstraeten, D. Van den Poel, Predicting customer loyalty using the internal transactional database, Expert Syst. Appl. 32 (2007) 125–134.

[69] C. Goutte, Note on Free Lunches and Cross-Validation, Neural Comput. 9 (1997) 1245–1249.

[70] R.M. Kowalski, “I was only kidding!”: Victims’ and perpetrators’ perceptions of teasing, Personal. Soc. Psychol. Bull. 26 (2000) 231–241.

[71] N. Stokburger-Sauer, Brand community: Drivers and outcomes, Psychol. Mark. 27 (2010) 347–368.

[72] C. Homburg, L. Ehm, M. Artz, Measuring and Managing Consumer Sentiment in an Online Community Environment, J. Mark. Res. 52 (2015) 629–641.

[73] C.E. Porter, N. Donthu, W.H. MacElroy, D. Wydra, How to Foster and Sustain Engagement in Virtual Communities, Calif. Manage. Rev. 53 (2011) 80+.

[74] H. Liu, J. Zhang, R. Liu, G. Li, A Model For Consumer Knowledge Contribution Behavior: The Roles Of Host Firm Management Practices, Technology Effectiveness, And Social Capital, Inf. Technol. Manag. 15 (2014) 255–270.

[75] L. Chen, J.R. Marsden, Z. Zhang, Theory and Analysis of Company-Sponsored Value Co-Creation, J. Manag. Inf. Syst. 29 (2012) 141–172.

[76] P. Huang, A. Tafti, S. Mithas, Platform Sponsor Investments And User Contributions In Knowledge Communities: The Role Of Knowledge Seeding, Mis Q. 42 (2018) 213–240.

TABLE 1
MEMBER RESPONSE TYPES TO (NON)TREATMENT IN PROACTIVE EMAIL CAMPAIGNS

		Future member participation when no motivation email sent ($E = 0$)	
		Superior ($Y=0$)	Inferior ($Y=1$)
Future member participation when motivation email sent ($E = 1$)	Inferior ($Y=1$)	*Do-not-disturbs*	*Lost causes*
	Superior ($Y=0$)	*Sure things*	*Persuadables*

TABLE 2
DESCRIPTIVE AND EXPERIMENTAL CHARACTERISTCS OF EACH COMMUNITY

Id	Sector	Purpose	Members ($\boldsymbol{E = 1}$)	Members ($\boldsymbol{E = 0}$)	Open rate	Posts	First email ($\boldsymbol{t_0}$)	Second email
1	FMCG	New marketing strategy	61	18	67.77%	951	09/03/2016	23/03/2016
2	Technology	Improvements to online consumer platform	45	20	58.44%	1266	11/04/2016	13/04/2016
3	FMCG	New shop design and footwear	42	16	71.18%	449	29/03/2016	12/04/2016
4	FMCG	New food products	115	38	79.31%	3162	21/03/2016	23/03/2016

Notes: FMCG = fast moving consumer goods.

TABLE 3
ITEMS FOR THE MOTIVATIONAL EMAILS

Benefit	Moderator whishes	Items
Hedonic	"I hope you will get a lot of **enjoyment** from **co-developing** and **influencing new concepts and ideas** in the world of <domain>" "I hope you will experience **fun** and **receive pleasure** from your **participation** in the community and you will be **entertained** through all the **brainstorms and challenges** that we have created for you"	• Derive enjoyment from problem solving, idea generation, etc. • Derive fun and pleasure. • Entertain and stimulate my mind.
Social	"I hope that because of your participation in this community you **will meet plenty of new people** or even make **extra friends** for life" "I hope that we can make you **feel at home**, so you will become **more involved** and **experience yourself as one of us**"	• Expand my personal/social network. • Enhance my sense of belongingness with this community. • Enhance the strength of my affiliation with the customer community.
Cognitive	"I hope that through all the brainstorms and challenges we have created for you, you will become better **informed** about the existing <domain> **concepts, ideas** and **daily usage**" "I hope you will gain more **information** about the **newest trends** and **developments** in the world of <domain>"	• Enhance my knowledge about the product and its usage. • Enhance my knowledge about advances in product, related products, and technology.

TABLE 4
INFERIOR MEMBER PARTICIPATION RATE, UNTARGETED PROACTIVE MOTIVATIONAL EMAIL

	General	Hedonic	Cognitive	Social
Treatment	36.50%**	37.50%*	33.33%	38.82%**
Control	25.00%			

** *p* < .05; **p* < .10.

TABLE 5
CUMULATIVE INCREMENTAL GAIN OF THE PROACTIVE TARGETED MOTIVATIONAL EMAIL ON INFERIOR MEMBER PARTICIPATION RATE

	% of members	General	Hedonic	Cognitive	Social
Random	**20%**	-.0230	-.0250	-.0166	-.0276
model	**40%**	-.0460	-.0500	-.0333	-.0552
Uplift	**20%**	-.0027	-.0817	.0129	-.0371
model	**40%**	-.0411	-.129	.0297	-.0485

TABLE 6
REGRESSION RESULTS OF THE RELATIONSHIP BETWEEN MEMBER PROFILE AND UPLIFT SCORE

Variable	Uplift score
Self-interest oriented writing style	-1.32E-03
Positive emotional writing style	8.548E-03**
Membership length	1.186E-05
Member participation quantity	-8.517E-04
Community size	-1.462E-03**
Community participation quantity	4.376E-05**

** *p* < .05. **p* < .10.

FIGURE 1
PROACTIVE VS. REACTIVE INFERIOR MEMBER PARTICIPATION REDUCTION

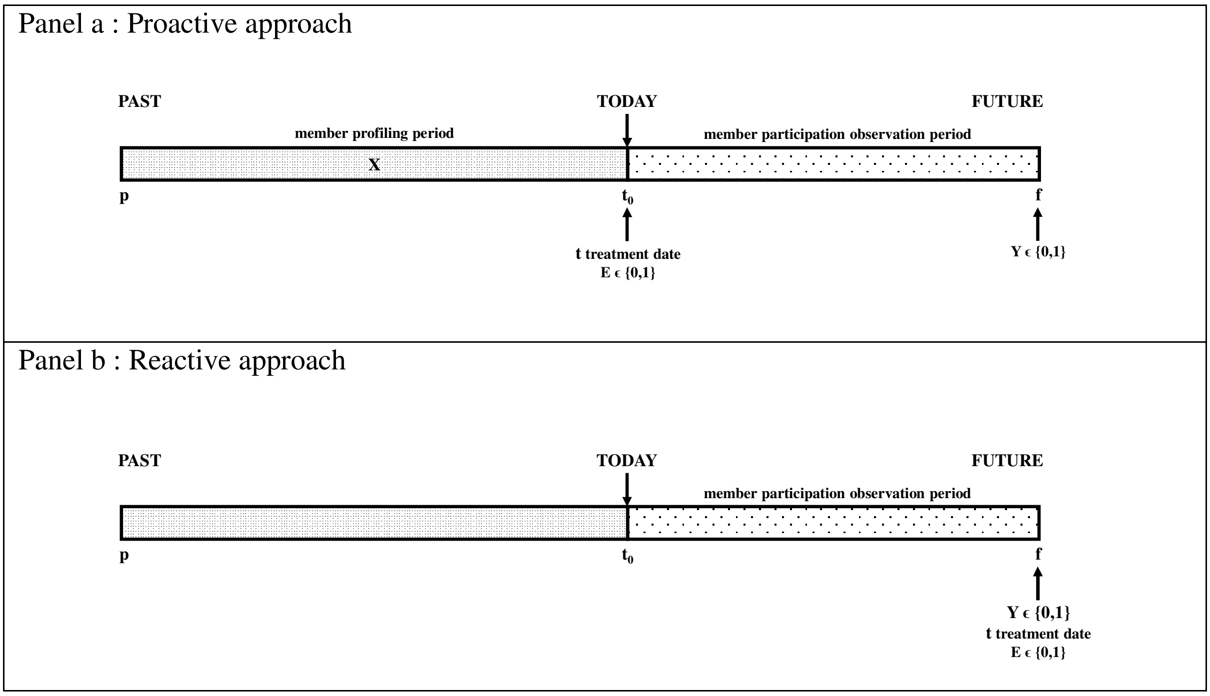


FIGURE 2
QINI CURVE OF A MOTIVATIONAL EMAIL CAMPAIGN (RQ2a)

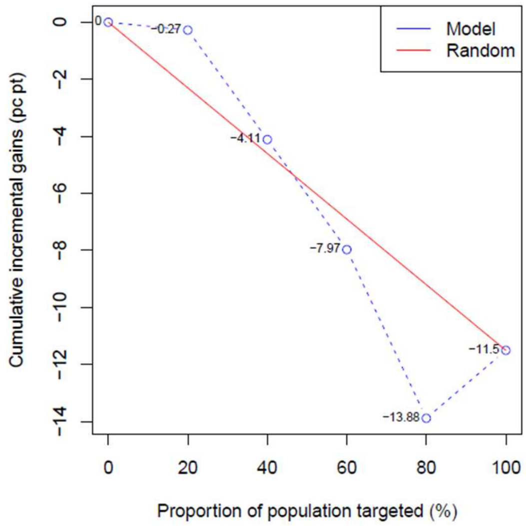
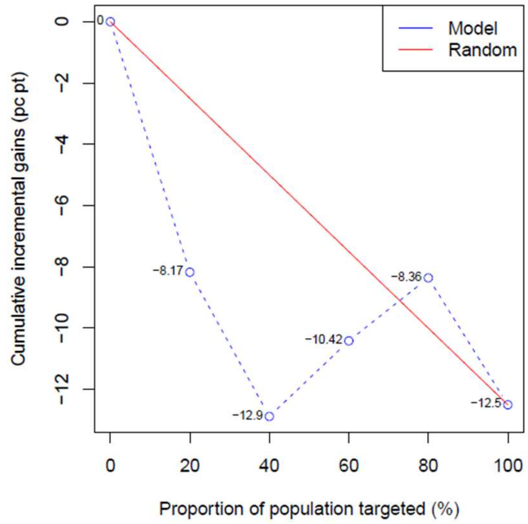
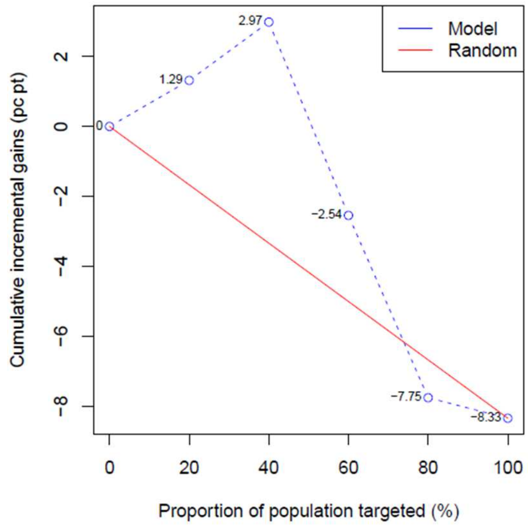


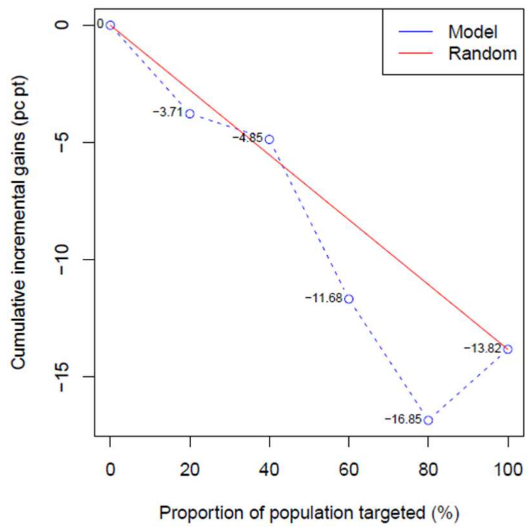
FIGURE 3
QINI CURVE OF A MOTIVATIONAL EMAIL CAMPAIGN (RQ2b)
A. HEDONIC MOTIVATIONAL MESSAGE



B. COGNITIVE MOTIVATIONAL MESSAGE



C. SOCIAL MOTIVATIONAL MESSAGE



APPENDIX A. Literature Review of Firm Initiatives to Stimulate Community Participation

Reference	Research context	Description of the approach	Key findings
[19]	Seven firm-hosted online brand communities: Xiaomi, Meizu, Vivo, Huawei, Oppo, Oneplus, and Smartisan	Socialization techniques: member education, interaction support, and participation feedback	Member education, interaction support and participation feedback have a positive influence on community participation intention.
[9]	Five firm-hosted virtual communities: Dell Community Forum, PalmOne Inc., Customer Community, HP/Compaq Customer Community, and REI Online Community	Providing quality content, fostering embeddedness, and encouraging interaction	Efforts in providing quality content and fostering embeddedness have a positive impact on the community, but efforts in encouraging interaction do not.
[71]	One brand community: Unknown brand	Organizing an event (offline) and making available online bulletin boards and expert chats (online)	Compared with online activities, offline activities are more effective in strengthening community integration and the consumer–brand relationship.
[72]	Ten online community forums: one DIY company, five airlines, and four hotels	Firms' online engagement: reply interactivity	A certain level of replies has a positive influence on the community, while excess replies decreases customer sentiment.
[35]	One brand community: Jeep.	Organizing offline brand fest activities	Organizing brand fests has a positive impact on the community.
[36]	Three open innovation collaborative platforms: Crowdspirit, FellowForce, and Owela.	Developing extrinsic (e.g. monetary rewards) and intrinsic (e.g. stimulation of community cooperation) motivational tools	Exploratory case study analysis shows that monetary rewards are not always valuable, while developing intangible drivers (community cooperation, learning new ideas and having entertainment) is beneficial.
[73]	Random sample of members from sixty firm-hosted communities	Encouraging users to contribute high-quality content, cultivating connections among members, and creating enjoyable experiences for community users.	All three sponsorship efforts have shown to have a positive impact on community participation.
[74]	One firm-hosted online community: A global appliance brand headquartered in China	Promoting interaction, organizing offline activities, and providing explicit incentives	Promoting user interaction and organizing offline activities have a positive impact on users' contributions, while providing incentives has a detrimental effect.
[75]	One online brand community: Dell's IdeaStorm	Delivering (swift) firm feedback	Delivering (swift) feedback by the community host encourages the community members to contribute.
[76]	One online knowledge community: SAP	Knowledge seeding	Knowledge seeding strategies induced by the hosting firm positively impacts the community's knowledge contributions.

APPENDIX B. Example Email with Hedonic Motivational Message

EMAIL 1

Two Wishes You Never Got...

Hello you there,

Now that you have been active with the <name of community> for some time, I would like to take a quick look at some of the community wishes I have had for a while.

1. I hope you will get a lot of **satisfaction** by working out and **influencing new concepts and ideas** in the wonderful world of <domain>.

2. I hope you will experience a lot of **fun** and **enjoyment** through your participation in this community and that you will be **fully integrated** with all the brainstorms and challenges we have for you.

Do you think this year may also be a **PLEASURABLE** <name of community> Year?

I sincerely hope so!

Let's start working on it in the coming days and weeks. Let's do this! We will succeed.

Thank you very much.

Greetings,
<name of the moderator>

EMAIL 2

Are The 2 Wishes Coming To It?

Hello you there,

Do you remember the email that I sent you back a while? Do you think these two wishes are already coming true for you?

With our last topic <URL to last topic> we can make this all the way.

I'm curious!!

Greetings.
<name of the moderator>

<Copy of email 1>