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Triggers of Collaborative Innovation in Online User Communities

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Abstract: This study contributes to the understanding of collaborative innovation in online user communities. Aside from providing evidence for the existence of these communities, prior research focused on users' motivations, backgrounds, and roles at the micro level but largely neglected to examine the effects of individual user activities on joint activities at the community level. By applying a netnographic research design, which is followed by a content analysis step and logistic regression analysis, we explore to what degree different user activities trigger collaborative innovation inside a community. We find two factors inherent to the initial post of a thread, problem complexity and collaboration intention, which explain the probability of collaborative innovation. The likelihood of joint activities is raised significantly if the contribution of a user ranks high on both dimensions. By quantifying collaborative user innovation, we hope to encourage the inclusion of user activities in future policy considerations. Moreover, understanding the effects of individual user activities at the community level may help companies to understand users of technologies better and to identify opportunities for collaboration.

Keywords: user innovation; collaborative innovation; innovation community; community innovation; netnography

1. Introduction

Users rarely innovate in isolation [1,2]. In fact, a plethora of online-based user innovation communities has emerged recently [3]. The dissemination of internet-based settings has massively facilitated this development by increasing connectivity among users worldwide while reducing transaction costs at the same time. To date, new types of digital infrastructures, for example, digital makerspaces, online communities, and work execution forums, provide users with fertile soil to conduct their innovation activities [4–7]. Prior user innovation research extensively discussed the motives of users to join and actively contribute to communities [8], characterized the members' characteristics and motivation [9,10], and examined the structure and composition of online communities [11,12]. Further, we have learned that users are willing to share their ideas and knowledge to assist each other and consequently work on an output collectively [13,14].

Aside from providing evidence, prior research mainly focused on users at the micro level, including their motivation, background, and roles in a community. What we have not yet fully understood is how users' behavior, motivation, and background are related to collaborative innovation activities and the collective output at the community level [15]. We consider, that a deeper understanding of the effects of users' individual activities on collaborative innovation helps to better explain why some communities succeed and others fail and how specific processes in a community are linked to the collective output.

This study aims to understand the triggers of collaborative innovation in user communities. Our research is based on a netnographic study, which is followed by a content analysis step and logistic regression analysis. First, we identify all predominant individual user activities in a community. Second, we analyze the effect of these individual user activities on collaborative innovation efforts in the observed community. Research showed that innovation processes do not always begin with a clear intention to innovate [16]. Accordingly, we analyze the effect of the creation of a thread in a community—the trigger—on collaborative processes occurring later in the respective thread. In doing so, we assume that thread creation is a development step in the overall community evolution. Therefore, we believe that users have a specific intention in mind when they set up a new thread. To enrich our analyses, we include a set of control variables including thread and user characteristics.

In our study, we collect data from the user community OpenEnergyMonitor. The OpenEnergyMonitor has 1464 active community members and is acknowledged to be one of the largest open-source communities in energy-related fields. Prior research presented abundant opportunities to study innovative users in complex product contexts such as energy technologies [17,18]. In a similar vein, the energy segment represents a breeding ground for user innovation as consumer needs are not met by the current smart energy products in the market [19,20].

We contribute to the literature in four ways. First, we identify six individual user activities in online communities: (1) *needing help*, (2) *requesting feedback*, (3) *providing feedback*, (4) *disseminating information*, (5) *sharing developments*, and (6) *calling for action*. Second, we examine the diverging effects of the individual user activities on the probability of collaborative innovation, i.e., the results show that the provision of feedback and the call for other users to innovate increase the probability of collaborative innovation the most among all user activities. Third, we explain the varying effects by two underlying factors inherent to the first post of a thread—problem complexity and collaboration intention. Hence, we argue that collaborative innovation is more likely to take place when the initial post of a thread comprises an appealing and well-sophisticated issue as well as allows for sufficient space for other community members to collaborate. Finally, we identify the critical thread and user characteristics that are significant predictors of collaborative innovation, thereby enriching prior work on this topic [8,21,22]. We conclude our study by discussing our results, drawing managerial and policy implications, presenting the limitations of our work, and providing avenues for future research.

2. Theoretical Background

2.1. Individual User Activities

Prior studies have shown that users rarely innovate in isolation and user innovation motives go beyond personal needs [1,23]. In fact, user–innovators have increasingly organized themselves in communities to achieve their goals [11,13,24]. In most cases, participants are open to sharing their ideas with others in their respective areas of interest and actively promote knowledge diffusion [25–27].

Users usually have the first contact with communities when searching for information they need for private problem-solving activities [28]. Eventually, they realize the additional benefits of user communities, which usually comprise users with complementary capabilities in the form of knowledge, skills, and creativity. Once they identify the connections, community newcomers typically start to communicate and exchange information [1,9].

The dissemination of information and communication technologies (ICT) is a crucial prerequisite for users to organize themselves in online environments and to exchange knowledge, ideas, and opinions [29,30]. The internet has increased connectivity among users, and transaction costs have dropped drastically [30,31]. A recent study showed that ICT even increases users' motivation to support idea generation, to give feedback to others, and to engage in social interactions [32]. The opportunity to codify ideas, comments, and feedback in a written format is thereby vital as it fosters dialogue and ensures connectivity among users [33]. In other words, ICT enables individuals to exchange information with a larger number of people, invokes users to engage in joint activities and thus enhances collective learning [21,34].

A necessary condition for knowledge exchange is the user's willingness to reveal or share information [35]. Interestingly, most users do not expect monetary rewards for revealing their knowledge but rather acceptance and recognition from other community members as well as an increase in their knowledge associated with advancing a technology [1,10,36]. Research has shown that the propensity to reveal freely is higher for community innovators than for users who predominantly work independently. However, [37] have found evidence that even non-collaborating innovators reveal knowledge without expecting monetary rewards. One way to gain recognition is by posting comments on others' ideas and suggestions [32,38]. Therefore, opportunities to comment on other users' work increase the likelihood of collaborating more than extrinsically-based reward systems [39].

2.2. Collaborative Innovation

Reference [40] found that most of the innovative ideas in user activities emerged in collaboration with others. Collaborative prototyping is thereby the critical activity [40,41]. Trial-and-error learning processes usually consist of four steps: design, build, run, and analyze [42,43]. These activities are considered components of the collaborative innovation process. The literature discusses modularity as an essential enabler of collaboration [13]. As complex tasks can be divided into manageable pieces, different users can work on various jobs at the same time.

Reference [44] revealed that the provision of information and knowledge is one of the primary reasons for belonging to a community. This act of revealing knowledge indicates a certain degree of commitment to the community [45]. A recent study supports this argument by proving that more-actively participating users have a higher propensity to share ideas than those who are less active [46]. Another article distinguishes the expected intrinsic and extrinsic benefits [26]. Expected inherent benefits positively affect user willingness to share, whereas expected external benefits may even discourage users from voluntarily sharing their ideas in communities. The characteristics of innovative users are another factor that determines the propensity to reveal freely; for example, professionals usually have a lower motivation to expose their thoughts in communities because they would rather seek extrinsic benefits for their skills [30]. On the contrary, those who describe their innovation activities as a hobby are more likely to share their knowledge.

Innovating in collaboration is beneficial for many reasons. First, financial investments and tasks can be divided among different members of the community, thus reducing transaction costs [14]. Second, the community approach enables quick feedback from others and suggestions for improvements [31]. In a similar vein, users do not innovate from scratch but usually build their ideas on the solutions of others. In this regard, [47] identified various pull effects from organizing user innovation in communities. Third, [47] suggested that user communities foster the dissemination of innovative ideas and consequently create early majorities for new product developments. Therefore, the community approach provokes collective learning and rapid problem-solving [48,49]. Fourth, the presence of users with different educational backgrounds increases the likelihood of success for innovation activities [9,50]. The organization within communities facilitates the recombination of different skills and expertise and consequently creates a vital knowledge pool [49,51].

Prior research described the distinct roles of users in communities [8,10,52]. Users with an elevated level of intrinsic motivation and a strong knowledge base make the most valuable contribution to the community [53]. The possibility of gaining additional knowledge and improving one's own skills motivates highly skilled and active users to complete even mundane tasks, such as providing help to other community members or fixing bugs [28]. Therefore, more knowledgeable users have a higher likelihood of engaging in co-creation activities, whereas novice users are discouraged from participating because of perceived knowledge barriers [54,55]. However, newcomers benefit more from user communities than average users and usually uncover old routines [2].

The quality of interactions among members is shown to be positively related to the level of innovativeness of a community [56]. However, in the two specific extremes of interaction quality, the innovation outcome is maximized. First, when a high degree of cooperation exists, collaborating on a collective output usually results in high innovativeness. Second, in the case of a low degree of collaboration, competition within the community becomes the central motivational driver. A medium degree of interaction quality produces lower levels of innovativeness, as the driving effects of the two extremes are at a minimum [57].

3. Materials and Methods

We identified the field of open-source energy technologies as a useful environment to study user communities, as projects in this context are complex and provide a valuable basis to study collaborative innovation [2,58,59]. This research adopted a combination of netnography [60,61], content analysis [62], and multivariate regression analysis [63]. To gain a deeper understanding of collaborative innovation, a non-intrusive netnographic approach was chosen to obtain less-biased insights [64].

Organizing our research in this way has three advantages. First, the netnographic research design represents an immersive method which allows the uncovering of interaction styles, mutual exchange, and thus forms of collaborative innovation in practice [60]. Second, we opted for an inductive, qualitative-explorative approach as it allows for the disentanglement of the relationship between individual user behavior and collaborative innovation processes in communities and to conceptualize underlying interdependencies. Finally, our multi-method approach helps to provide empirical evidence on the dynamics of user activities and collaborative innovation practices. Building on previous studies [21,22,65], we consider the combination of qualitative and quantitative methods to complement each other, leading to more robust results.

3.1. Setting: Open Energy Monitor

We used the OpenEnergyMonitor for our analysis as the OpenEnergyMonitor has 1464 active community members and could be regarded as one of the largest and most relevant open-source communities in energy-related fields. By extensively analyzing the community content and culture, as well as the community traffic, the data quality was assessed to be at a sufficient level for subsequent analyses [60].

The community describes itself as " ... a project to develop open-source energy monitoring tools that help us relate to our use of energy, our energy systems, and the challenge of sustainable energy" [66]. As every community member is allowed to edit the wiki, the statement can be regarded as having a high level of approval within the community. The initial idea to start the project was developed at a time when no open-source design to build an energy monitor was available. Owing to this circumstance, two students from the United Kingdom began to experiment with Arduino and breadboards to set up their technical solution. In parallel, they created a website documenting and sharing their progress. When the system became increasingly mature, like-minded people began to show interest. Consequently, a forum was created which soon became a marketplace for ideas, experiences, and prototypes. In sum, the OpenEnergyMonitor project portrays a rich case. As the two founders have established an online shop, which is now selling all available components of the OpenEnergyMonitor system, this case also constitutes an example of user entrepreneurship [67–69].

The OpenEnergyMonitor builds on five central units, and both hardware and software solutions are open-source, see Figure 1. The components are mainly the result of the collaborative innovation efforts of the community and can be purchased online. The system enables the monitoring of energy usage and production, temperature, and humidity. Further, the system can collect, store, and visualize all measurements related to home energy flows and consumption.

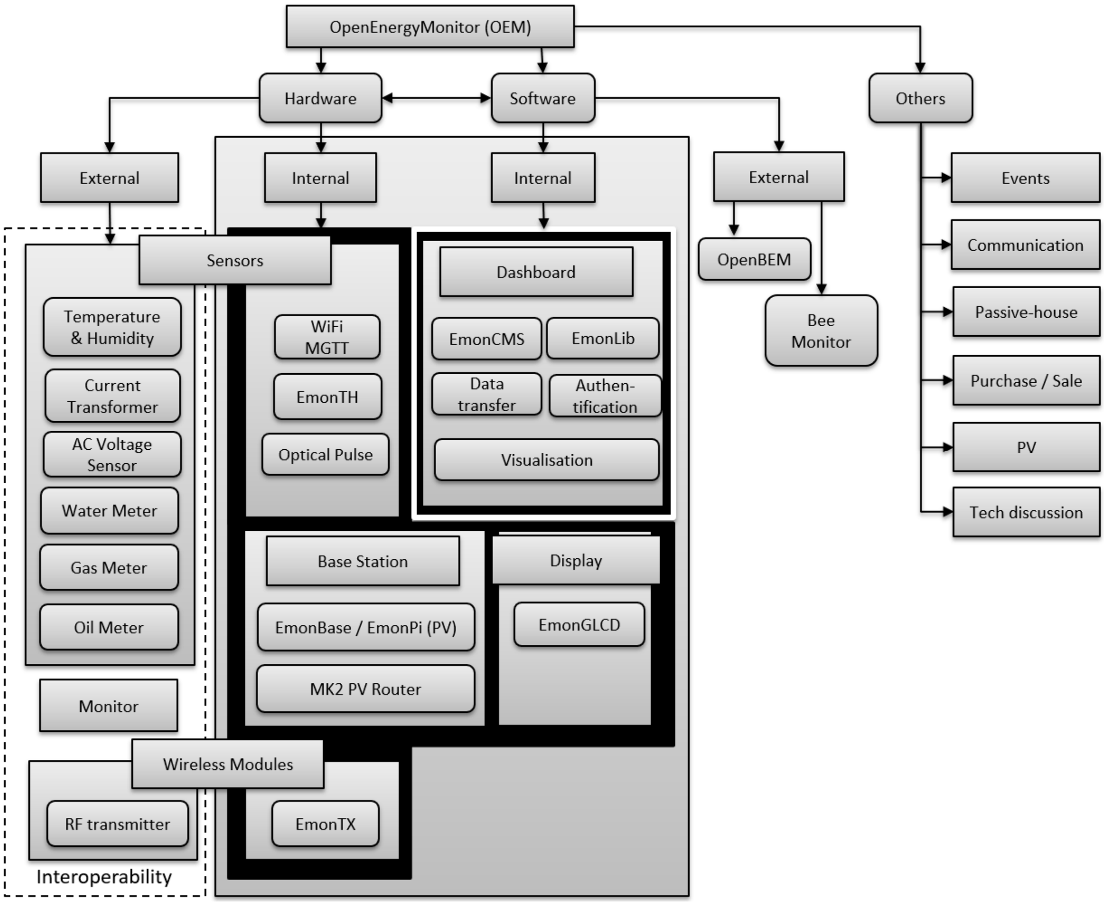

Figure 1. The OpenEnergyMonitor architecture.

3.2. Data Collection and Cleansing

The OpenEnergyMonitor forum can be publicly accessed. We used import.io, a cloud-based web data extraction tool, to collect all the data recorded since the launch of the community in 2011. This gained us access to all posts and threads generated. Using the author ID and name, we could unambiguously match posts to their authors and retrieve their user characteristics (date of registration, number of posts, time active, date of the last post, etc.). This process resulted in 2961 unique threads containing 20,407 posts. A thread is defined as a collection of posts. Each thread is started by one user with an initial post and encompasses all answers to that post, forming a conversation. Non-registered users ("guests") generated 1213 (5.94%) of all posts, 1173 of which were initial posts starting a new thread. Reading these threads carefully enabled us to unambiguously identify another 124 of the "guests" because they registered themselves during the course of the thread and repeatedly engaged in its progression. All the other posts and threads generated by guests were omitted from the analysis because we were not able to generate variables representing their user characteristics as they were not distinguishable by name or author ID. The same is true for the 25 threads that were originally started by a registered user but had only replies from unregistered users; in this case, we were not able to derive user variables at the thread level. Concerns related to potential biases caused by omitting guests from the analysis are addressed in the section on conducted robustness checks. Our final sample contained 1887 threads comprising 15,196 posts.

3.3. Content Analysis

In a next step, we analyzed the first post of each thread to identify its topic and the intended purpose the user had in mind when creating the thread. We argue that the first post in a thread mirrors the intention of the author and thus potentially triggers a community response. We labeled all initial posts as triggers. As we aimed to determine which types of individual user activities increase the probability of collaborative innovation, we inductively derived all different types of triggers [62]. On the basis of our analysis, we constructed the following six triggers: (1) *needing help*, (2) *requesting feedback*, (3) *providing feedback*, (4) *disseminating information*, (5) *sharing developments* and (6) *calling for action*. Applying the consensual agreement technique [70], all three authors coded all threads independently to reduce the probability of reliability issues. Diverging categories were assigned to about 8% of the cases. Discussions on the identified problematic instances resulted in a clear classification of all cases.

3.4. Variables

3.4.1. Dependent Variables

We coded the dependent variable of our model (COLLINNO) as a binary variable that takes a value of one if collaborative innovation was undertaken in the respective thread. One example of a post that lead us to assign a value of one to the variable COLLINNO:

> "[. . .] I followed the instructions from Schism above [. . .] Now I have good news, but I am afraid I still have some bad news too. [. . .] the good news: By using single quotes and a white space after the last backslash in the path strings I can now create feeds with the engines PHPFIWA and PHPTIMESERIES. No more errors anymore with these two engines [. . .]. But now comes the bad news: When I try to use the engine PHPFINA the error message "ERROR: feed could not be created, undefined" still comes up. [. . .]. I've added a screenshot of the feed page and the input page [. . .]". (Tom, 20 March 2014)

3.4.2. Independent Variables

This study focuses on the triggers of collaborative innovation in online communities. Thus, we code the first post in each thread, which is the initial post, as *needing help* (HELP), *requesting feedback* (REQFEED), *providing feedback* (PROVFEED), *disseminating information* (INFO), *sharing developments* (SHAREDEV), and *calling for action* (CALLACT). The variables were coded as dummy variables taking on a value of one if the initial post falls in the respective category. As each initial post can only be attributed to one of the categories, this approach represents a mutually-exclusive codification of all threads. Similar to the dependent variable, the allocation is performed on the basis of the content analysis.

As these triggers constitute a major contribution of our paper, we provide the reasoning behind the classification and provide examples from the community data. Threads started by a user asking for help with a specific problem were categorized as *needing help*, e.g.,

> "Tried Raspberry Pi + Harddrive + Emoncms from emoncms.org, but it did not work as I expected. The new v8 emoncms fascinated me and so I did a complete new installation. The RFM12PI Module did not start and after a bit of searching I added the directory "emoncms" in the file: [. . .] Now I get the data form my sensors into emoncms. [. . .] I'm lost!". (khs, 17 April 2014)

When a user shared a product development simply to inform potentially interested community members without formulating a specific request for any community response, the thread was labeled as development sharing, e.g.,

> "I have been playing with Eagle last couple days and managed to produce an Arduino Shield as EmonTx. [. . .] Here is how it looks, I ordered one PCB and it will be ready the next couple days. I will make a picture and let you know how it works.". (mharizanov, 13 March 2012)

We classified initial posts as *requesting feedback* when a user shared a partially developed product or idea with the intention of receiving constructive feedback from the community, e.g.,

> "I've recently installed an AA battery pack on my emonTX [. . .] The program I am executing on the emonTX is essentially the default CT monitoring one, with a single temperature monitor and battery value added into the payload to be transmitted every 5 s [. . .] Is there anything there that would be consuming the power? I have noticed various sleep commands in other examples—are these commands useful for increasing battery life? [. . .] Any ideas for lowering the power consumption?". (seannation, 21 January 2013)

The trigger *providing feedback* characterizes posts in which users supplied feedback to a product or feature developed by the community, e.g.,

> "I've been posting data from my NanodeRF to emoncms for about a week now. Most of the time it seems to go great, but over the past couple of days the data update rate seemed to be slowing down. [. . .] However, the only thing I had not rebooted was my router. Doing so, the problem went away immediately." (Lloyd, 6 April 2012)

If a user opened a thread to disseminate information they thought was interesting without formulating an expectation of a community reaction, we codified this thread as *disseminating information*, e.g.,

> "Hello to all, The Netduino Plus software for logging your solar panels and/or electric house meter to Emon is now available on http://p1netduinoplus.codeplex.com.". (SolarInKrimpen, 28 October 2012)

Threads that were started by users with a specific idea or problem in mind, prompting the community to develop a solution, were labeled as *calling for action*, e.g.,

> "The hardware is mainly there [. . .] software addition would be required. [. . .] Sorry, I am not a programmer, but maybe someone might like to take this on?" (glyn.hudson, 30 January 2012)

3.4.3. Control Variables

As the likelihood of collaborative innovation is likely determined by other characteristics as well, we included a number of control variables in our model. The control variables were divided into user characteristics and thread characteristics.

First, a variable measuring the user's willingness to assist others is introduced into the model. The variable is measured as the percentage of posts a user contributes in threads that he/she did not start. Subsequently, the variable takes on values between 0 and 1. We argue that this variable also captures the willingness to collaborate as it reflects the user's ability to engage in a potentially vast variety of problems experienced by other users. Following [22], we assume that the higher the willingness of a thread starter to collaborate, the higher the likelihood a collaborative innovation process is started. For each thread, the calculated willingness to assist of all participants is averaged, providing us with the average willingness to assist (ASSIST).

Second, the number of posts of a user overall, divided by the time the user spent in the community, serves as a proxy for the activity level and experience of users. More active and experienced users are more likely to provide new ideas and solutions to existing questions; that is, their level of innovativeness is assumed to be higher than that of less active and experienced users [10,52]. The activity level can also be considered a measure of users' product knowledge as more engaged users may interact in a broader variety of threads; this interaction has been shown to be positively related to users' innovativeness [22]. Further, we include a variable depicting the activity of a user by dividing the number of threads started by a user over the time the user spent in the community. This is to ensure we do not only capture the quantity but also the quality of his/her contributions to the community. We argue that users who repeatedly start threads, contribute to the collaborative processes with a higher quality, than those who predominantly contribute to ongoing discussions. The activity levels of the users measured by posts and threads are averaged over all users active in the respective thread (ACTIVITYPOSTS and ACTIVITYTHREADS, respectively).

Third, we include a variable representing the innovativeness of users: their aptitude to significantly contribute to product innovation [71]. This variable is measured by the number of threads in which a user has contributed to the development process in a significant way divided by the number of threads the user has participated in overall. Again, the average innovativeness of users engaged in a thread is used in the model (INNO).

We further control for the length (LENGTH) of a given thread, measured by the number of posts. We can safely assume that the more intensively a thread is discussed, the more likely it is to contain a greater amount of detail and information [21]. Therefore, we expect LENGTH to be positively related to the likelihood of the occurrence of collaborative innovation.

We also control for the number of users that participate in a thread (NUMUSER) as we assume that additional users introduce additional knowledge, which potentially increases the likelihood of collaborative innovation to be initiated.

A summary of all model variables and their corresponding value ranges is presented in Table 1.

Table 1. Description of variables.

Variable	Description	Values/Range	Coding
COLLINNO	A collaborative product development process was started in the respective thread	0 = no; 1 = yes	manually
HELP	Needing help with a specific problem.	0 = no; 1 = yes	manually
REQFEED	Sharing a partially developed product or idea with the intention to receive feedback.	0 = no; 1 = yes	manually
PROVFEED	Supplying feedback to a component or feature developed by the community.	0 = no; 1 = yes	manually
INFO	Providing general (usually external) information without formulating an expectation of a community response.	0 = no; 1 = yes	manually
SHAREDEV	Sharing a product development to inform without a request for community response.	0 = no; 1 = yes	manually
CALLACT	Formulating a specific idea or problem, asking the community to develop a solution.	0 = no; 1 = yes	manually
LENGTH	Number of posts in a thread.	0–872	automated
NUMUSER	Number of individual users that engaged in a thread.	1–60	automated
ASSIST	Average willingness to assist of all users engaged in the thread. Willingness to assist is measured as the percentage of posts a user posted in threads not started by himself.	0–0.98	automated
ACTIVITYPOSTS	Average activity level of all users engaged in the thread. Activity level is measured as the number of posts by a user overall, divided by the number of days spend in the community.	0.000768–2	automated
ACTIVTYTHREADS	Average activity level of all users engaged in the thread. Activity level is measured as the number of threads started by a user, divided by the number of days spend in the community.	0.000946–1.007348	automated
INNO	Average innovativeness of all users engaged in a thread. User innovativeness is measured by the number of threads in which a user has contributed to the development process in a significant way divided by the number of threads the user has participated in overall.	0–0.76	automated

3.5. Regression Analysis

Our dependent variable represents a binary variable. We model the conditional probabilities of the dependent variable COLLINNO with respect to our independent variables x by,

$$\pi_i \equiv Prob(COLLINNO_i = 1|x) = F(x'_i\beta) \quad (1)$$

where x is a $(kx1)$ regressor vector, and β is the $(kx1)$ vector of coefficients to be estimated. Following [63], we specify F as the cumulative distribution function of the logistic distribution. Subsequently, the logit regression model coefficients are estimated using the maximum likelihood approach. The reported standard errors are robust to heteroskedasticity. The variables of main interest, namely, the individual user activities, represent a mutually exclusive categorization of the first post in each thread. Therefore, *needing help* is used as the base category in our analysis. We estimate three specifications of the model where we incrementally include additional control variables. The final model specifications are formulized as follows:

$$\begin{aligned} Prob(COLLINNO_i = 1|x) = \beta_0 + \beta_1 SHAREDEV_i + \ \beta_2 REQFEED_i + \beta_3 PROVFEED_i \\ + \beta_4 INFO_i + \beta_5 CALLACT_i + \ u_i \end{aligned} \quad (2)$$

$$\begin{aligned} & Prob(COLLINNO_i = 1|x) \\ & = \beta_0 + \beta_1 SHAREDEV_i + \ \beta_2 REQFEED_i + \beta_3 PROVFEED_i + \beta_4 INFO_i \\ & + \beta_5 CALLACT_i + \beta_6 LENGTH_i \ + \beta_7 NUMUSER_i + u_i \end{aligned} \quad (3)$$

$$\begin{aligned} & Prob(COLLINNO_i = 1|x) \\ & = \beta_0 + \beta_1 SHAREDEV_i + \ \beta_2 REQFEED_i + \beta_3 PROVFEED_i + \beta_4 INFO_i \\ & + \beta_5 CALLACT_i + \beta_6 LENGTH_i + \beta_7 NUMUSER_i + \beta_8 ASSIST_i \\ & + \beta_9 ACTIVITY_i + \beta_{10} INNO_i + \ u_i \end{aligned} \quad (4)$$

4. Results

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics and variance inflation factors of all model variables. Table A1, see Appendix A, contains the relevant correlation matrix. Of all the 1887 threads in our dataset, about 28% resulted in collaborative innovation activities. Considering the triggers of the threads, most of the threads represent *needing help* (59%), followed by *requesting feedback* (19%), *providing feedback* (7%), *disseminating information* (7%), *sharing developments* (6%) and *calling for action* (3%). On average, a thread was active for 60.5 days and contained eight posts, and three unique users were engaged in the discussion. The longest thread contained 872 posts by 59 unique users.

Table 2. Descriptive statistics and variance inflation factors (VIF).

Variable	N	Mean	SD	Min	Max	VIF [1]
1. COLLINNO	1887	0.276	0.447	0	1	1.17
2. HELP	1887	0.59	0.492	0	1	1.09
3. DEVSHARE	1887	0.057	0.232	0	1	1.1
4. FEEDASK	1887	0.186	0.389	0	1	1.08
5. FEEDGIVE	1887	0.07	0.256	0	1	1.05
6. INFO	1887	0.069	0.253	0	1	2.92
7 CALLACT	1887	0.028	0.164	0	1	3.18
8. LENGTH	1887	8.053	26.356	1	872	1.67
9. NUMUSER	1887	3.045	3.103	1	60	1.49
10. ASSIST	1887	0.597	0.242	0	0.979	1.62
11. ACTLEVELPOSTS	1887	0.435	0.391	0.002	2.382	1.23
12. ACTLEVELTHREADS	1887	0.053	0.142	0.001	1.008	1.17
13. INNO	1887	0.136	0.116	0	1	1.09

[1] Mean VIF is 1.60.

4.2. Regression Results

The regression results of our three specifications (1.1, 1.2, and 1.3) are reported in Table 3. The Wald χ^2 test statistics provide some evidence that the models fit the data well, as confirmed by the pseudo R^2 measures. The table reports three different regression specifications as we gradually insert all our control variables. Each model was tested against the nested alternatives containing fewer variables employing likelihood ratio tests [63]. The tests resulted in the rejection of the null hypothesis that the additionally introduced variables have no added explanatory power and do not significantly improve the fit of the model. This strongly indicates that our most sophisticated model specification fits the data significantly better than the nested alternatives.

The results are fairly constant over all model specifications, indicating the robustness of the results. One exception is the coefficient for *sharing developments*, which becomes insignificant after introducing the control variables. This result might be explained by the fact that sharing developments is an activity mostly undertaken by more experienced and sophisticated users. Therefore, the trigger itself is not responsible for the effect but rather the associated user and thread characteristics.

Testing for significant differences in the coefficients by applying Wald tests enables us to sort the triggers with respect to their effect on the probability of collaborative innovation. The probability of collaborative innovation is raised the most by the triggers *calling for action* and *providing feedback*, followed by *requesting feedback*, *needing help*, and *sharing developments*. *Disseminating information* is the trigger with the least effect on the probability of a collaborative innovation process.

Table 3. Logit regressions of the collaborative innovation.

Variables	(1) COLLINNO	(2) COLLINNO	(3) COLLINNO
SHAREDEV	0.952 ***	0.133	−0.444
	(0.214)	(0.301)	(0.313)
REQFEED	1.178 ***	1.241 ***	1.148 ***
	(0.133)	(0.154)	(0.162)
PROVFEED	1.709 ***	2.152 ***	1.710 ***
	(0.191)	(0.211)	(0.219)
INFO	−0.283	−0.483	−0.854 **
	(0.260)	(0.436)	(0.408)
CALLACT	1.952 ***	2.018 ***	1.802 ***
	(0.295)	(0.346)	(0.390)
LENGTH		0.0629 ***	0.0676 ***
		(0.0151)	(0.0154)
NUMUSER		0.501 ***	0.410 ***
		(0.0679)	(0.0669)
ASSIST			2.483 ***
			(0.371)
ACTIVITYPOSTS			−0.586 ***
			(0.209)
ACTIVITYTHREADS			1.522 **
			(0.636)
INNO			2.402 ***
			(0.575)
Constant	−1.482 ***	−3.449 ***	−4.851 ***
	(0.0772)	(0.208)	(0.287)
Observations	1887	1887	1887
Log likelihood	−1024	−784.7	−750.8
Pseudo R2	0.0785	0.294	0.324
Wald χ2 (Δdf)	167.6 (5)	212.5 (7)	285.8 (11)
Wald p-value	<0.0001	<0.0001	<0.0001
LR-Test statistic (*p*-value)	-	478.05 (<0.0001)	67.65 (<0.0001)

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As assumed, the length of the thread has a significant and positive effect on collaborative innovation. Moreover, the number of users has a positive and significant effect on the likelihood of collaborative innovation. The innovativeness and willingness to assist of users participating in a thread are positively and significantly related to collaborative innovation. Additionally, we do find that the activity level of users measured by the number of posts is negatively and significantly impacting the probability of collaborative innovation. The activity level of users measured by the number of started threads, however, positively and significantly increases the likelihood of innovation processes to occur. This lends support to our assumption that the number of posts and the number of threads started measure two distinct aspects of the activity, i.e., quantity and quality, respectively.

4.3. Robustness Checks

First, we re-estimated our models using the standard ordinary least squares (OLS) and probit regressions with heteroscedasticity robust standard errors. The results remain strikingly stable and are available from the authors upon request.

Second, the different model specifications show that the estimated coefficients and standard errors of the main variables (i.e., triggers) remain robust except for the sharing developments variable, for which we provide an intuitive interpretation.

Third, to take into account possible problems due to multicollinearity, the variance inflation factors for all variables in the models were calculated, see Table 2. The average VIF is 1.6 with a maximum of 3.18, which indicates that multicollinearity is not a problem in our sample [72].

Fourth, the fact that our trigger variables represent the initial post of a thread means that the collaboration process naturally occurs at a later point in time, eliminating reverse causality concerns. Nevertheless, the results could suffer from an omitted variable bias. We consider that our non-intrusively observed variables represent many potential confounding effects on our dependent variable. However, collecting a broader set of variables to be considered for the empirical analysis represents a good starting point for future research.

Fifth, the cases in which the thread was started by a non-identifiable user (i.e., a guest) were omitted in the analysis as we aimed to include variables representing user characteristics. This procedure could have introduced selection bias into our results. Unfortunately, we were not able to compare the user variables between registered and non-registered users, as guests were not differentiable in the dataset. Nevertheless, we compared the types of trigger represented by the first post, as they were codified for all threads in the dataset. Independent group *t*-tests for the six triggers confirmed that non-registered users were significantly more likely to need help and were significantly less likely to formulate all other triggers. Furthermore, threads started by registered users were significantly more likely to result in collaborative innovation. As a robustness check, we estimated specifications 1.1 and 1.2, including the cases that were initially started by guests because no user variables were required for these specifications. The results remained qualitatively unchanged, indicating that the bias did not substantially influence our findings.

5. Discussion

Our findings reveal that individual user activities increase the likelihood that collaborative innovation activities in user communities are triggered in very different ways. Moreover, our results illustrate the important effects of user and thread characteristics on the probability to start joint innovation efforts. In the following section, we explain our findings by placing them in the context of the literature as well as present a framework synthesizing our results.

5.1. Effects of Individual User Activities on Collaborative Innovation

The activities *providing feedback* and *calling for action* raise the probability of collaborative innovation activities in user communities the most among all user activities. Therefore, not only does the provision of feedback by users help to solve problems with existing components or features of the system but it is also an important trigger for collaborative innovation in the community to improve the current version. A clear call for action towards community members to work on specific aspects of the system is an important driver in activating other community members to join collective activities that add new features or components.

The next most important trigger for collaborative innovation is *requesting feedback*. In this case, users create a thread to share their work on their own ideas and ask the community for their feedback. Interestingly, the intention to ask others for feedback significantly increases the probability of having sequential collaborative innovation that is based on the initial user idea. Therefore, user communities are a vital environment for users to share their innovative ideas [1]. The initially personal idea establishes public interest and is included in the collective output produced by the community.

Sharing developments only triggers collective innovation efforts more than needing help when further control variables depicting user characteristics are not included. This finding can be explained by the fact that sharing developments is an activity mostly undertaken by innovative users who are also willing to assist others [55]. Therefore, the post itself is not the one responsible as a trigger in this case but rather the associated user characteristics.

Disseminating information is the activity that has the least effect on subsequent collaborative innovation activities. Moreover, this action even has a weaker effect as a trigger than simply needing help. As we controlled for activity levels, the degree of innovativeness, and the willingness to assist each other, this result indicates that the contributions of actors from the community periphery do not seem to influence the overall community development and critical innovation efforts in particular.

5.2. Explaining Collaborative Innovation in User Communities

Figure 2 shows our framework explaining the diverging effects of individual user activities on the probability of collaborative innovation. The x-axis describes the degree of collaboration intention the user has when starting a new thread. While an appeal to start a collaborative project would rank high on this measure, just providing mere information without the intent for further collaboration would rate rather low. The y-axis represents the diverse set of pull-factors inherent to the first post of a thread itself, which we call problem complexity. This includes the complexity, appeal, and maturity level of the topic. While an elaborate request to develop a new feature or component to solve an existing and well-defined problem would score high, a simple request for help, addressing an issue of low complexity, would score rather low on this axis.

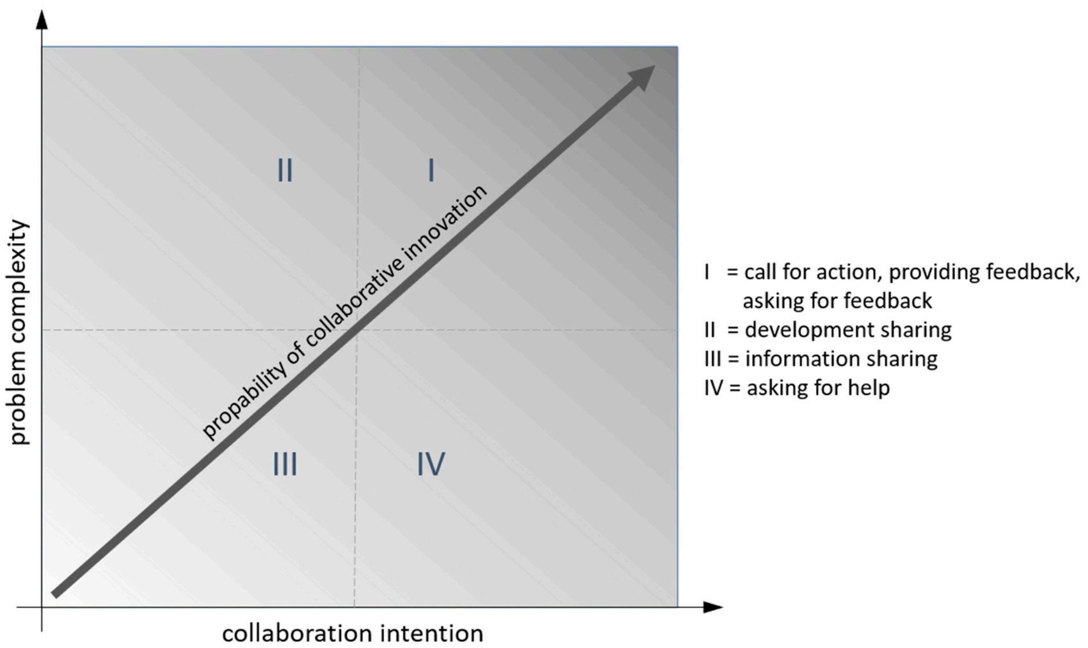

Figure 2. Impact of factors inherent to the initial post of a thread on the probability of collaborative innovation.

We propose that the likelihood of collaborative innovation increases in each factor individually. Nevertheless, we argue that collaborative innovation is more likely to take place when a thread ranks high on both axes, i.e., is placed in the first quadrant. Complementing previous studies which described the effects of user characteristics on collaborative innovation activities [8,55], our results show the effect of thread-inherent factors on the probability of collaborative innovation in user communities. Hence, the likelihood of joint activities increases when the contribution in the format of a new thread is appealing and thus incorporates a certain degree of complexity on the one hand and offers sufficient room for other community members to collaborate on the other hand.

5.3. The Importance of the Written Format and User Characteristics

As regards the other thread variables, the length of the thread has a significant and positive effect on collaborative innovation. From our perspective, this finding shows that a comprehensive discussion in written format is essential to share and improve ideas and to begin joint activities [33]. Furthermore, the number of involved users in a thread has a positive effect on the likelihood of collaborative activities. This finding is in accordance with the literature claiming that various actors bring diverse educational and social backgrounds and skills that positively affect community innovation [21,53].

The level of innovativeness of a user is positively related to collaborative innovation. The result indicates that threads in which many innovative community members are involved have a higher likelihood of triggering collaborative innovation than threads involving less creative users. This finding underlines the leading role of some principal actors in the community influencing the overall community development [26,50,52]. Moreover, users' willingness to assist significantly increases the likelihood of a subsequent collective effort. We explain these two findings by assuming a reputational effect originating from active users [73,74]. The reputation of some users signifies quality and significance to other users in the community.

6. Conclusions

This study helps to improve the understanding of collaborative innovation in user communities. Our results show that a considerable number of threads trigger collaborative innovation (28% of all threads). In the context of new types of digital infrastructures [7], users play an increasingly central role in innovation processes in situations in which the market cannot serve consumer needs. An exclusive focus on companies and research institutions may result in a distorted supporting scheme that neglects extra-organizational innovation, such as open-source communities. On the basis of the vitality of collaborative user innovation, we encourage policymakers to support extra-organizational activities. These activities may include offering financial assistance that facilitates costly hardware innovation and ensuring the regulatory and organizational freedom-to-operate for user initiatives.

The main reason why policy support is lacking thus far is that user innovation activities remain largely excluded from official statistics [75]. We hope that our attempt to quantify collaborative innovation encourages the aim of including user innovation activities in future policy considerations regarding statistics and innovation framework programs. Furthermore, our study provides an example of how an initial user effort can result in user entrepreneurship and, therefore, economic growth and welfare [69,76]. We believe that digitization (i.e., new digital infrastructures or layered modular architectures) can provoke a massive increase in user innovation, community formations, and user-initiated entrepreneurship [6,77,78].

Our findings are also relevant to the business sector. First, we recommend that companies more closely monitor user-initiated innovation communities. These communities usually arise when the products available in the market fail to meet customer needs [43] or when consumers actively reject innovations because of disenchantment [19]. Therefore, monitoring communities such as the OpenEnergyMonitor helps innovative companies identify and better understand customer needs in specific technology fields.

Second, user communities can be a vital pool of radical ideas that are outside a company's scope of innovation efforts. We believe that user activities are particularly relevant for medium-sized and large enterprises that are imperiled by digitization and disruptive technologies [77,79,80]. In a similar vein, companies can learn about workflow management from user communities. The OpenEnergyMonitor case demonstrates how flexible organizational structures facilitate effective and efficient prototyping and result in rapid problem-solving mechanisms.

Finally, insights from this study can help companies to identify opportunities to interact with user communities. Prior research comprehensively discussed synergies between users and producers [30,81,82]. However, these studies focused on firm-initiated communities. We assume that firms' interaction opportunities and organizations are different in user-initiated communities. The most relevant questions are how companies should approach these communities and how a co-creation process could be organized without destructing the user innovation culture.

6.1. Limitations and Future Research

Although we applied well-established research methods, some limitations suggest opportunities for future research. First, our netnographic study focused only on one single official community. This framework inevitably causes a generalizability problem in our findings. Therefore, we encourage other researchers to adopt our research design and to apply it to other communities. Second, following a non-intrusive approach enables the analysis of unaffected data and fully spontaneous user activities from the community. Nevertheless, direct interactions with the community members in the form of interviews or dialogues could have further strengthened the robustness of our results. Future research may take this opportunity and follow an intrusive approach. This research design may enable researchers to focus on the social structure of user-driven communities and linkages between collaborative innovation activities and social relationships among community members. Third, the content analysis step produces a valuable dataset of individual user activities and potential collaborative innovation processes. Although we tried to ensure a satisfactory level of objectivity and unambiguity by involving three researchers in the coding process, this step of our research design is undoubtedly subject to some degree of misperception or false interpretation of user statements and their respective intentions. An avenue addressing this issue can be found in computer-assisted coding processes using machine-learning algorithms. Recent research has shown how these methods can be used to identify user ideas in unstructured texts [83]. Applying this technique to user communities may help to analyze communities more efficiently.

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Appendix A

Table A1. Correlations (N = 1887).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. COLLPROT												
2. HELP	−0.243 ***											
3. DEVSHARE	0.052 *	−0.295 ***										
4. FEEDASK	0.159 ***	−0.573 ***	−0.118 ***									
5. FEEDGIVE	0.173 ***	−0.330 ***	−0.068 **	−0.132 ***								
6. INFO	−0.079 ***	−0.326 ***	−0.067 **	−0.130 ***	−0.075 **							
7 CALLACT	0.128 ***	−0.202 ***	−0.042	−0.081 ***	−0.046 *	−0.046 *						
8. LENGTH	0.239 ***	−0.095 ***	0.137 ***	0.044	−0.017	−0.023	0.048 *					
9. NUMUSER	0.410 ***	−0.135 ***	0.159 ***	0.073 **	−0.023	−0.042	0.107 ***	0.804 ***				
10. ASSIST	0.300 ***	−0.226 ***	0.145 ***	0.023	0.108 ***	0.130 ***	0.051 *	0.150 ***	0.289 ***			
11. ACTLEVELPOSTS	0.033	−0.045 *	0.015	0.0331	−0.031	0.078 ***	−0.035	0.062 **	0.078 ***	0.204 ***		
12. ACTLEVELTHREADS	−0.069 **	0.0162	−0.002	0.008	−0.016	−0.032	0.010	−0.054 *	−0.091 ***	−0.335 ***	0.423 ***	
13. INNO	0.232 ***	−0.245 ***	0.274 ***	0.0178	0.135 ***	0.054 *	0.011	0.120 ***	0.179 ***	0.309 ***	0.055 *	−0.010

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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