How Co-creation Processes Unfold and Predict Submission Quality in Crowd-based Open Innovation

Completed Research Paper

Introduction

Advanced communication and collaboration technologies, supported by more bandwidth and more computing power, coupled with a demand for more rapid innovation, are driving firms toward crowd-based open innovation. In crowd-based open innovation, organizations generally invite novel contributions from outside the boundaries of the firm via an online platform that enables a large, diverse network of contributors to participate. Unfortunately, little is known about how to best structure and manage information coming from crowds outside of the firm and only a fraction of these efforts succeed. Failures are common, in part, because the ideas submitted are not novel and well-refined and because firms cannot absorb the ideas proffered (Wallin and von Krogh, 2010). Although a number of studies examine strategies of organizations and, at the micro-level, motivations of crowdworkers, we know little about how work is coordinated within the crowd and how to design systems to support higher levels of innovation among crowdworkers. Our goal in this research is to provide a better understanding of how workers collaborate in a crowd-based open innovation community and how these collaboration patterns affect innovation outcomes. Diversity, supported by collaboration and co-creation among community members has been said to be central to the benefits attributed to open innovation (Chesbrough et al., 2006; Ullrich and Vladova, 2016). We aim to unpack the micro-processes of co-creation and how diversity is leveraged in crowd-based open innovation.

Theoretical Background and Hypotheses

Crowd-based open innovation

Open innovation has been broadly defined to include flows of knowledge and ideas both into and outside of the organization (e.g. Dahlander and Gann, 2010; Lichtenthaler, 2011). For our purposes, we are interested in inbound open innovation in which organizations have an explicit policy of, and processes for, acquiring expertise from outside the boundaries of the firm that can then be appropriated for innovating products, processes, and services. This does not necessarily preclude other aspects of open innovation, but allows us to focus, in particular, on how external contributors craft ideas or solutions for the firm. Although an extensive body of research has been published on open innovation, that work has tended to focus on the firm (West et al., 2014) and not at the level of the workers called upon to enact these new forms of work. Research at the firm level concludes that there is promise in open innovation, but challenges abound and most open innovation initiatives fail (Dahlander and Piezunka, 2014).

Open innovation is often coupled with crowdsourcing. As defined by Howe (2009), "crowdsourcing represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined and generally large network of people in the form of an open call." Modern-day inbound open innovation, like that found at Dell IdeaStorm, Threadless, and Local Motors, relies heavily on online communities or crowds as a source for new ideas. To date, the focus of research on crowdsourcing has been largely oriented toward questions of labor abuses and the motivation of contributors. Studies suggest, for example, that monetary payments, when available, increase motivation (e.g. Boudreau et al., 2014; Brabham, 2010, 2008), but that other intrinsic factors, such as being challenged by a complex problem (Boudreau et al., 2014), developing skills (e.g. Brabham, 2010), being identified with the community and forming friendships (e.g. Brabham, 2010; Langer and Seidel, 2015), and having fun (Brabham, 2008) are all equally or more important. These findings align with previous research on open source communities, for example, the Apache and Linux communities, which indicates that being part of the community, and improving and learning new skills are key motivators to contribute (e.g. Hertel et al., 2003; Hars and Ou, 2002; Bonaccorsi and Rossi, 2003; Roberts et al. 2006). Although informative, most studies do not push beyond questions of individual motivation to understand the work itself and few consider how work is coordinated among individuals and contributes to high quality submissions. Further, most studies do not consider interaction patterns over time, thus overlook the possibility that different interaction patterns at different points in the process enable higher quality work (for an exception, see Riedl and Woolley, 2017, discussed later). Hence many questions remain about how workers coordinate among themselves in crowd-based open innovation communities and the effect of these interaction patterns, over time, have on the quality of submissions.

Unpacking co-creation processes in crowd-based open innovation

We are especially interested in co-creation processes. According to Perks and colleagues, co-creation involves the *joint* creation of value. "Innovations are thus the outcomes of behaviors and interactions between individuals and organizations" (Perks et al., 2012: 935). In many crowd-based open innovation communities, despite the competitive nature of contests, contributors help one another to develop their ideas. Participants "interact, collaborate, vote for their favorite idea, discuss various topics by leaving comments on other participants' pin boards, and learn from the aggregate knowledge and feedback of others" (Fuller et al., 2011: 262). This is essential to successful open innovation communities because the ideas are often complex and benefit from input from people with different expertise and functional backgrounds. Thus, even if they have promising ideas for a challenge, creators are not always able, alone, to refine and develop them into coherent submissions (Kittur et al., 2013). To date, most research on co-creation has investigated the individual role of customers and users (e.g., in co-production, user centered design, etc.) and citizens (e.g., Gebauer et al., 2013; Ind and Coates, 2013; Kohler et al., 2011; Vooberg et al., 2015; Riedl and Seidel, 2018). In investigations of co-creation, for example, previous works have explored the emergence of individual psychosocial processes such as personal experiences (Fuller et al., 2011), satisfaction (Grissemann and Stokburger-Sauer, 2012), commitment (Randall et al., 2011), and identification (Langer and Seidel, 2015), and their impact on innovative outcomes. Fuller and colleagues (2011) for example, analyzed the 'Swarovski Enlighted' online contest and found that feelings of creative autonomy, task enjoyment, and a sense of community had a positive impact on the amount and quality of participants' contributions.

Few works, however, have examined *how* heterogeneous actors involved in co-creation collaborate among themselves, how this evolves over time, and the outcomes of these collaborative processes. Such limited attention is striking, considering that one of the premises of crowd-based open innovation is that creativity occurs when there is the possibility of multiple diverse actors collaborating together. One exception is the work of Perks et al. (2012), who investigated the micro-level processes of co-creation and identified two interaction patterns in a network of customers, suppliers, distributors, and intermediaries in the car insurance industry. They found, for example, that successful outcomes often involved high levels of intense interactions among contributors.

To better understand co-creation in crowd-based open innovation, we leverage research in organizational behavior on the coordination of creative and complex work. Almost universally, scholars agree that creative work should be coordinated differently from routine work. As early as the 1970's scholars recognized that work characterized by high levels of uncertainty, complexity and interdependence demand more coordination (Van de Ven et al., 1976). Powell (1990), for example, argued that sharing and applying expertise and facilitating innovation require a network rather than a hierarchical form of organizing. The literature on how creative workers build relationships (e.g., Perry-Smith and Shalley, 2003), interact and exchange feedback (e.g., Perlow, 1999; Harrison and Rouse, 2015; Hargadon and Bechky, 2006), and coordinate their efforts (e.g. Bechky, 2006) is well established and offers important insights into collaboration practices that foster innovative outcomes.

A handful of recent studies have also begun to examine interactions in teams composed of crowdworkers (e.g., Retelny et al., 2014; Valentine et al., 2017; Riedl and Wooley, 2017). Riedl and Woolley (2017), for example, conducted a series of experiments to investigate which team processes lead to more innovative performance among crowdworkers. They found that teams having more "burstiness" – defined as the degree to which "members concentrated their communication and work effort during relatively contained time periods versus spreading them out over time more equally" (p. 390) – displayed better performance. Riedl and Woolley also reported that more successful crowdsourcing teams were characterized by "synchrony" dynamics, with members responding rapidly to messages, despite time zone differences between members. Teams that exchanged more diverse information among team members also performed better.

Overall the studies we reviewed suggest that co-creation is characterized by extensive interaction and feedback, and fueled by diversity, but extant research leaves us without a clear understanding of which patterns and sequences of interactions, over time, exemplify co-creation, and their influence on innovation outcomes. The objective of our work is thus to unpack the concept of co-creation and identify the core interaction patterns, or "signatures" that make it successful. We develop a set of specific hypotheses predicting submission quality from the signatures of interaction processes in crowd-based open innovation communities. We focus on submission quality because the literature on online innovation contests has consistently found that ideas submitted have different levels of refinement and quality (Schuhmacher and Kuester, 2012). Obtaining submissions with complete and well-refined ideas is a primary concern for organizations relying on crowd-based open innovation. Thus, we focus on how the co-creation patterns contribute to completion and refinement of ideas, i.e. on submission quality.

Hypotheses

A strong narrative around crowd-based open innovation is that significant benefits come from tapping into a large and diverse, often global, community of contributors. Consistent with that narrative, crowd-based open innovation communities are typically composed of independent professionals, amateurs, learners, company employees, public organizations' representatives and many other different actors (Perks et al., 2012; Fuller et al., 2011; Gebauer et al., 2013). Such diversity represents a unique asset for co-creation processes. Co-creation and innovation more generally, have also been described as depending on the presence of multiple and heterogeneous sources of knowledge and advice, suggesting that the diversity we see in crowd-based open innovation communities may drive better quality submission (e.g., Reidl & Woolley, 2017). Research on diversity and innovation suggests that having inputs from more different people can increase innovation capacity (e.g., Cronin & Weingart, 2007; Dahlin et al., 2005) because it contributes unique information, offers more potential ideas to explore (e.g., Milliken et al.2003), and allows for recombinant juxtaposition of potential ideas (Fleming et al., 2007). We therefore propose that more diverse contributors in the development of a submission will lead to higher submission quality. We also propose, however, that this benefit is greatest earlier in the cycle.

The diverse inputs provided by the comments of heterogeneous community members need to be incorporated into submissions over time. Taking a longitudinal perspective requires us to consider that a creative process is characterized by different phases, i.e. idea generation, elaboration, and evaluation (Amabile, 1988). Successful idea generation is characterized by openness and suspension of judgement and evaluation (e.g., Rouse, 2018; Paulus and Yang, 2000). As the creative process moves from idea generation to idea refinement, convergent thinking, instead of divergent thinking, becomes more important. According to Cropley (2006), "convergent thinking is oriented towards deriving the single best (or correct) answer to a clearly defined question. It emphasizes speed, accuracy, logic, and the like, and focuses on recognizing the familiar, reapplying set techniques, and accumulating information" (p. 392). In contrast, divergent thinking is oriented toward expanding the solution space and generating as many ideas as possible. In co-creation processes, convergent thinking happens when creators move away from generating diverse ideas and start detailing the specific solution they intend to submit. Convergent thinking requires the consolidation of knowledge over time and, we propose, having focused, intense discussions with those community members who are particularly knowledgeable about the design and aware of the design intent.

In particular, as a discussion unfolds, those who have been participating in conversations around an idea have acquired knowledge on, and familiarity with, the idea being developed (Langner and Seidel, 2015). In contrast, those who have participated less have limited knowledge and may offer inputs of less relevance. Therefore, over time, as ideas move from being generated to being refined, the benefits of a diverse set of contributors diminish. On top of this, if creators increasingly receive advice from diverse sources they may face information overload (O'Reilley, 1980; Jones et al., 2004), which makes it difficult to integrate multiple suggestions into a coherent whole. Consistent with this, Jones et al. (2004) found that, in successful online communities, users tend to abandon a topic as the number of posts escalate, leaving a smaller set of users continuing the discussion. We anticipate that the issue of being overloaded with diverse ideas will be more acute as the project progresses and the creator's attention shifts to refining the idea. We thus hypothesize that, as time passes, it is better if the number of unique contributors decreases. To summarize, we hypothesize that:

H1 A submission is more likely to be of higher quality if, over time, the number of different contributors (sources) posting on a design idea decreases.

Using the logic above, we also argue that more posts from a diverse set of contributors is preferable. We also, however, propose that there is a diminishing benefit, over time, to having posts come from a broad set of contributors. It is better, we argue, to have fewer community members who, with their posts, centralize the discussion around an idea. More specifically, in addition to having fewer different people post (H1), having posts concentrated within a decreasing number of people will lead to higher submission quality. In other words, as the idea matures, we anticipate that creators will be better able to complete and refine their ideas if posts are coming from a smaller and smaller number of highly engaged contributors. We thus hypothesize that:

H2 A submission is more likely to be of higher quality if, over time, posts are coming from a smaller number of community members who emerge as proportionately dominant.

The creator's role, we argue, is also critical to co-creation dynamics. Co-creation is characterized by individuals providing and receiving feedback about their work and ideas. Not only do individuals post an idea to participate in a contest, i.e., act as creators, but also receive feedback to improve their work and expected to engage with that feedback and the one offering it in a constructive way (Langer & Seidel, 2015), ideally using feedback to improve the idea in significant ways. These feedback exchange processes are an important part of innovation practices (e.g. Harrison & Rouse, 2015).

As creators engage in the co-creation process, we argue that they should be present and involved, particularly making clear that they value the feedback (Langner and Seidel, 2015; Fuller et al., 2013; Harrison and Rouse, 2015). We contend, however, that there is a limit to the amount creators should dominate discussion, because those who dominate the conversations around their ideas may inhibit contributions from others. According to Jassawalla and Sashittal (2002), in creative contexts where a member dominates the decision making processes, ideas are less likely to be improved through interaction. In a similar vein, studies on brainstorming show that, when a creator of an idea centralizes attention on his or her proposal and dominates turn-taking, fewer and lower quality ideas are generated (Valachich et al., 1994). Thus, we hypothesize that:

H3 A submission is less likely to be of higher quality if the creator is proportionally dominant, e.g. responsible for the majority of posts.

At the same time, we argue that creators who engage in a dynamic process of co-creation, without dominating the discussion, are more likely to produce high quality submissions. As discussed earlier, innovation tends to follow a sequence from idea generation to elaboration to evaluation (Amabile, 1988). During idea generation, judgment should be suspended to enable the flow of ideas (e.g., Rouse, 2018). We would therefore expect that, in online co-creation, the creator of an idea who receives input from different contributors should suspend immediate evaluation of those ideas, resulting in a relatively low number of interactions with other contributors in these early stages. Over time, however, when the co-creation process moves from idea generation to idea elaboration, we would expect that the creator would have more interaction with contributors, exploring their feedback in more detail and asking more questions. When people reply to feedback they have received, they voice their ideas, crystallize them, and develop them further in interaction with feedback providers (Harrison and Rouse, 2015). Thus, we hypothesize that:

H4 A submission is more likely to be of higher quality if, over time, the creators' responses to posts from community members escalates.

Data and Method

To evaluate our hypotheses, we conducted a study of a crowd-based open innovation community. Using posts from two distinct challenges, we examined the collaboration patterns among community members. We also collected data on which contributors submitted their ideas to the challenge and how the company and others rated the ideas in terms of quality of submissions.

Research Context

Local Motors (LM) is a manufacturing company founded in 2007 with the initial aim of becoming the first organization developing an open-source car in collaboration with an online community. All of the projects carried out by LM have involved an online community, which is composed of approximately 60,000 designers, engineers, and car enthusiasts from all over the world. In the online community, the main projects are initiated by LM as online contests, called challenges. Each challenge is defined and coordinated by a group within LM and lasts between 2 weeks and a few months. A design brief for the challenge, e.g. a document written by a team of Local Motor employees to explain the challenge to the community, provides the context, constraints, and guidelines for the definition of a new vehicle or related technology. Challenges can be highly conceptual (e.g., defining new vehicles for Berlin urban mobility in 2030) or specific (e.g. a product being put into production in the short term). For each challenge, monetary compensation is paid to the winners. Some of the challenges are in collaboration with other companies (e.g., Airbus). LM was an ideal company for our study because crowd-based open innovation is a strategic emphasis, and they are engaged on a day-to-day basis with the contributions from their online community.

This study focused on two challenges, i.e. Project REDACTED (this was its actual name) and the Airbus Cargo Drone Challenge, in order to capture how community members coordinated their work and interacted among themselves and how, thorough such a process, their ideas evolved and became successful. The focus on these specific challenges was driven by their strategic nature for the company. During preliminary interviews with top managers in 2014 and 2015, we came to recognize that the outcomes of both Project REDACTED and the Airbus Cargo Drone Challenge were considered fundamental for the future development of the company. In particular, Project REDACTED was aimed at designing the first road-ready 3D printed car. LM launched the ‘project REDACTED’ challenge in March 2015 and selected the winning design in July 2015. The Airbus Cargo Drone Challenge was aimed at designing a cargo delivery drone for medical uses. The challenged was run in collaboration with Airbus, between April 12 and June 16, 2016.

Data Collection

We collected multiple sources of data, both qualitative and quantitative, to have a rich and detailed understanding of community members’ behaviors.

Data from the Online Platform on Project REDACTED and the Airbus Cargo Drone Challenge

We downloaded all data from the community’s message archives (web log of interactions) during the timeframe of the two contests (i.e., from the initial post of the design brief to the announcement of the winners). In particular, we collected data on all the interactions exchanged by 600 community members and employees during the online contest (consisting of more than 10.000 posts). We automatically downloaded information about the sender of each posting, timing, subject, and message content. We also downloaded demographic and personal information about community members to use as controls.

Interviews with Online Community Members

We conducted 10 interviews with online community members, e.g., external contributors who participated in the challenges. Because of the global distribution of the community, all of these interviews were conducted by Skype. The focus of the interviews was to understand some of the patterns of interactions emerging from the online platform (e.g., why some designs are not ultimately submitted to the competition, how community members perceive feedback, etc.) and to get richer data to understand how their creative work unfolded.

Coding of Data from the Online Platform

To obtain data on the activity sequences of contributors to the online platform, we retrieved data on all posts for the two challenges. Specifically, we collected information on the timestamp, sender, entry, and content of every comment logged across all entries. As an example, if User A left a comment on Submission B at Time T, with Message K, we would log the observed data point as a tuple of information (A, B, T, K). Our full dataset is then a collection of such tuples, which are grouped by entry and sorted by the time of the post.

Measures

The data from the online platform and the coding we performed on it were the input to create the measures we used to test our hypotheses.

Sequence statistics

Because our hypothesized effects concern the progression of behaviors over time, it is important for our analysis to capture the longitudinal relationship between actions. Put another way, we want to use numerical descriptions of past behavior, which we call signatures, to predict future behavior. Accordingly, to examine these signatures or interaction patterns over time, we created sequence statistics that capture interaction events (posts) on a creator's entry over the course of the design challenges. These measures are a post-by-post indicator of who is contributing to an entry. We make use of the platform activity logs to create these measures. The logs store the sender, entry, and the time (or order) the communication was sent. We coded these as relational events (Butts 2008), which are units of data represented as $e = (i, j, t)$. The accumulation of events over time provides data on how the participants interacted with each other via the platform associated with a particular entry. From these sequences, we operationalize a set of path-dependent statistics that represent the tendencies hypothesized. The measures we compute, as well as relevant formulae and descriptions, are presented in Table 1.

For purposes of notation, we denote n_{ijt} as the number of posts by user i on entry j up to time t (where t is relatve to that entry); we denote N_{jt} as the total number of posts on entry j up to time t; we denote C_j as an index referring to the creator of entry j; we denote w^i_{kjt} as the proportion of posts by user k on entry j up to time t, given that user i initiates a new post. Finally, we use the function $1\{\cdot\}$ as an indicator, where it takes a value of 1 if the internal condition is true, and zero otherwise.

Submission Quality

When creating a challenge, Local Motors defines a design brief with a general description of the problem to be addressed and a set of requirements that creators have to follow for their submissions to be 'accepted' for evaluation. The requirements include 1) the specific design constraints (e.g., for REDACTED the car needs to have 4 seats, for Airbus, the drone needs to land vertically); 2) the expected deliverables (e.g., for REDACTED a front view, a rear view, and an interior view; for Airbus, among others, a sheet with geometric and aerodynamic data), 3) some general design guidelines (e.g. keep it simple); and 4) design templates and forms. Of the designs being submitted only 45% followed the requirements and were considered 'complete' and thus accepted for evaluation. When interviewing community members and Local Motors employees we came to recognize that having a 'complete' submission necessitates, on the designers' side, a significant effort of elaboration and refinement of ideas. In other words, according to our informants, only submissions with high quality of work could meet the design brief requirements and be considered finalized submissions to be accepted for evaluation. Acceptance of a design for evaluation is therefore a proxy for submission quality, distinguishing between higher quality submissions (i.e. those meeting the requirements and being accepted for evaluation=1) and lower quality submissions (i.e. those not meeting the requirements and not being accepted for evaluation=0).

Relational Event Modeling Analysis

Our analysis of activity sequences and their implications for submission quality was completed in two steps. First, we defined a general model which describes how sequences of events unfold during the process of completing a submission. Second, we add an additional level to our analysis where we differentiate between entries that were eventually submitted and those that were not. In doing so, we identify behaviors and sequences of events which are positively or negatively indicative of entry completion.

Table 1. Summary of Sequence Statistics		
Measure	**Formula**	**Description**
Time-Variant Effects		
Escalating contributor diversity	$x_1(i,j,t) = -\sum_{k \neq C_j} w_{kjt}^i \log w_{kjt}^i \, 1\{i \neq C_j\}$	The rate of posting is dependent on whether the feedback comes from a diverse source, relative to prior posts
Escalating centralization of contributions	$x_2(i,j,t) = \frac{n_{ijt}}{N_{jt}}$	The rate of posting is proportionate to the fraction of total posts up to that point
Creator post proportion	$x_3(i,j,t) = 1\{i = C_j\}$	The overall rate of the entry's creator posting
Escalating creator response	$x_4(i,j,t) = \frac{\sum_{k \neq C_j} n_{kjt}}{N_{jt}} 1\{i = C_j\}$	The rate of the creator posting is dependent on the proportion of total posts made by others
Time-Variant Controls		
Turn-taking (general)	$x_5(i,j,t) = 1\{(i,j,t-2),(k,j,t-1)\}$	If individual i is followed by individual k in a subsequent post, the likelihood of i making the next post
Turn-taking (creator)	$x_6(i,j,t) = x_5(i,j,t)1\{i = C_j\}$	Turn-taking behavior, where the individual making the repeat post is the entry's creator
Time-Invariant Controls		
Entry length	$length_j = \#$ posts in entry j	The total number of posts on an entry
Entry number of users	$users_j = \#$ unique users in entry j	The total number of users who posted on an entry
Competition version	$version_j = 1\{\text{if } j \text{ is Airbus}\}$	Whether the entry was associated with Airbus (1) or Redacted (0)

Explaining communication sequences

The prevalence of a particular activity sequence can be determined by the relational event model (REM), which is a statistical framework for analyzing sequences of actions and interactions, or relational events (Butts 2008). In this analysis, we focus specifically on ego-centric events, or actions taken by a single actor (Marcum and Butts, 2015). This model builds on temporal social network analytic techniques, but emphasizes the role of short-term linkages occurring in sequence (Quintane et al. 2013). We define the rate of activity by an individual i on a particular forum j as the following:

$$\lambda_{ij}(t) = \exp\left(\sum_{p=1,\ldots,6} \theta_p^{(j)} x_p(i,t)\right)$$

The statistics x are computed from the prior event sequence; in our models, we use operationalizations of our hypothesized mechanisms, as described in Table 1. The variables θ are tuning parameters which determine the influence of a mechanism on the rate of activity. Put another way, if a tuning parameter is positive, then as the corresponding statistic gets larger, the greater the rate of action will become. Thus, the tuning parameters characterize the influence of path-dependent theoretically-based mechanisms on the likelihood of communication. To determine the exact value of the parameters, we use the rate function to specify the probability of the observed sequence $E_j = \{e_1, \dots, e_m\}$ for a given entry j.

$$\Pr(E_j; \theta) = \prod_{e \in E} \lambda_{i_e j} \Big/ \sum_{u \in A_{t_e}} \lambda_u(t_e)$$

Here, the probability of an event occurring is equivalent to the rate of that event, divided by the rates of all possible events contained in the set A_t. In this way, determining the relational event tuning parameters is equivalent to fitting a conditional logit model (Quintane et al. 2014). To determine a set of parameters that best fit the behavioral patterns of the entire collection of entries, we use a multilevel modeling approach (DuBois et al., 2013):

$$\hat{\theta} = \mathrm{argmax}_{\theta} \prod_{j} \Pr(E_j; \theta)$$

The above equation is solved by maximum likelihood estimation. The resulting parameter estimates $\hat{\theta}$ thus capture the overarching patterns observed across entries, as determined by the sequence statistics we previously defined.

Differentiating Quality Submissions

To capture the differences in behaviors on creators' entries that produced high-quality submissions vs. those that did not, we introduce random effects at the second level the relational event model. Effectively, we want to determine if there are significant deviations in behavioral patterns across entries, after controlling for differences in entry length, popularity of the entry, and topic of submission. This approach is similar to the ANCOVA methodology used by Johnson and Faraj (2011) to delineate network patterns across online communities, as well as the moderation approach of Schecter et al. (2017) to characterize behaviors of teams based on variations in emergent constructs. We anticipate that while general turn-taking tendencies will be similar across entries, the four main effects will differ based on characteristics of the sequence, as well as completion status. Accordingly, we model the relational event parameters for $p = 1, \dots, 4$ in terms of random effects across entries:

$$\theta_p^{(j)} = \mu_p + \beta_{1p} length_j + \beta_{2p} users_j + \beta_{3p} version_j + \beta_{4p} z_j + \varepsilon_{pj}$$

Here, μ_p is the average level of statistic p, i.e., the main effect. The next three terms are time-invariant controls based on descriptions of the entries. Finally, z_j is a binary variable indicating whether or not entry j was of high-quality (value of 1) or not (value of 0). Thus, the sign and significance of β_{4p} is a statistical measure for whether or not pattern p is expressed differently across entries of varying quality.

We differentiate our approach from a typical causal inference model; rather than predict the outcome as a function of some antecedents, we characterize an outcome by the underlying process associated with it. In this way, we avoid claiming that a pattern or measure is better or worse, or that a specific sequence leads to a specific result. Rather, we determine if specific variations in certain behaviors are systematically associated with different outcomes.

Hypothesis Testing & Goodness of Fit

To empirically test our four main hypotheses, we fit the above multilevel model using various combinations of terms, including time-variant and time-invariant measures, as well as an indicator for entry completion. The sign and significance of the main effect μ_p is interpreted as the prevalence of a behavioral pattern in entries that are not submitted. On the other hand, the sign and significance of β_{4p} is indicative of how the behavioral pattern is expressed differently in completed entries, net of control variables.

We evaluate the fit of each model using the deviance, AIC, and BIC measures to account for possible overfitting. Using a step-wise progression, we ensure that each additional model term significantly improves the model fit using a Chi-square test on the reduction in model deviance.

Results

Descriptive Analysis

Table 2a contains summary statistics and correlations among these metrics for all entries from both the Project REDACTED and Airbus entries. The correlations among entry metrics are shown in the final two columns. All correlations were found to be significant.

Table 2a. Descriptive statistics and correlations among entry-level metrics. N = 482 (62 REDACTED, 420 Airbus), all correlations are significant at p < 0.05

Metric	Mean	SE	Min.	Max.	1.	2.
1. Submission Status	0.45	-	-	-	-	
2. Total Number of Posts	15.68	19.81	1.00	171.00	0.54	-
3. Total Number of Users	7.91	7.24	1.00	53.00	0.57	0.91

Table 2b reports descriptive statistics and correlations of the sequence statistics used in relational event modeling. The subscript "t" denotes the temporal dependence of certain event metrics. We describe the values of each measure for each observed event. As with Table 2a, the last two columns show the event metrics' correlations, and all correlations are significant. However, note that there is not a correlation between Creator Post Proportion and Escalating Creator Response, because based on Table 1, Escalating Creator Response is nonzero if and only if the indicator $1\{i = C_j\}$ equals 1, in which the jth entry's creator is the sender of the message post.

Table 2b. Descriptive statistics and correlations among event-level metrics. N = 6520 events, all correlations are significant at $p < 0.05$

Variable	Mean	SE	Min.	Max.	1.	2.
1. Escalating Contributor Diversity $_t$	0.13	0.48	0.00	3.39	-	
2. Escalating Centralization of Contributions $_t$	0.13	0.16	0.00	0.50	-0.14	-
3. Creator Post Proportion $_t$	0.32	0.47	0.00	1.00	-0.19	0.62
4. Escalating Creator Response $_t$	0.32	0.34	0,00	1.00	-0.18	0.52

Hypothesis Testing

To test our four main hypotheses, we conduct relational event analysis. We apply a step-wise approach in which we add additional model terms and determine if there is significant improvement in fit. Our first model (Model 1) contains only the main effects, measured across all entries. Our second model includes these main effects, but includes number of posts, number of users, and competition version as cross-entry controls (Model 2). Finally, our third model includes all prior terms and also differentiates between completed entries and those that were not completed (Model 3). The parameter results for these models are presented in Table 3. Based on reduction in deviance, AIC, and BIC values, we conclude that Model 3 provides the strongest fit to our data.

Looking first at the main effects (Model 3), we see that, overall, entries tended to have increasing diversity over time. That is, over time, different contributors posting to creators' entries escalated. Similarly, over time, creators tended to respond more within their own entries, suggesting that they may have increased their engagement with contributors providing feedback. There are no significant effects for escalating centralization of contributions or for the creator increasing dominance, suggesting that these patterns were not reflected in the overall sample.

Table 3. Relational Event Model Results

	Model 1		Model 2		Model 3	
Variable	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
Escalating contributor diversity	0.39	(0.02)***	1.27	(0.09)***	1.44	(0.09)***
Escalating centralization of contributions	-0.79	(0.13)***	0.20	(0.38)	-0.70	(0.40)
Creator post proportion	0.80	(0.13)***	-0.47	(0.45)	0.16	(0.46)
Escalating creator response	1.58	(0.15)***	3.19	(0.53)***	2.56	(0.54)***
Escalating contributor diversity x Quality (H1)					-0.32	(0.06)***
Escalating centralization of contributions x Quality (H2)					1.57	(0.26)***
Creator post proportion x Quality (H3)					-1.20	(0.29)***
Escalating creator response x Quality (H4)					1.21	(0.35)***
Turn-taking (general)	1.50	(0.05)***	1.54	(0.05)***	1.53	(0.05)***
Turn-taking (creator)	-0.47	(0.06)***	-0.51	(0.07)***	-0.50	(0.07)***
Random Effect Controls	No		Yes		Yes	
Deviance	143,700.9		143,003.5		142,944.8	
Deviance Reduction			$\chi^2_{18} = 697.4$***		$\chi^2_4 = 58.7$***	
AIC	143,712.9		143,051.5		143,000.8	
BIC	143,769.5		143,278.1		143,265.2	

*Notes. Significance codes * p < 0.05, ** p < 0.01, *** p < 0.001. Degrees of freedom for Chi-square test are equal to number of added parameters. In total there were 6,520 events and 93,210 possible events across 482 entries, 216 of which were completed.*

From Table 3, we can also draw a number of conclusions related to our hypotheses. Specifically, we look to the interaction effects in Model 3 to differentiate patterns indicative of high-quality submissions. First, we find that in high quality submissions as compared to low quality submissions, over time, the diversity of contributors to the entry increases at a lower rate ($\beta_{41} = -0.32, p < 0.001$). Put another way, as time passes, in high quality entries, as compared to low quality entries, it is more likely that feedback originates from a smaller number of individuals other than the creator. This finding lends support to Hypothesis 1, suggesting escalating diversity in the larger sample, but much less so in high quality submissions. Second, we find a positive and significant tendency in high quality as compared with low quality submissions for centralization of contributors to increase over time ($\beta_{42} = 1.57, p < 0.001$). This result indicates that as interactions revolving around a high quality submission progress, feedback is significantly more likely to originate from a small number of active contributors, proving support for Hypothesis 2. Third, as hypothesized (H3), we observe that in high quality entries, the creator has a lower overall tendency to post, relative to other contributors ($\beta_{44} = -1.20, p < 0.001$). In other words, for high quality submissions, the creator of an entry does not dominate the discussion of their own idea. Finally, we find a positive and significant tendency for creators to respond to feedback more in high quality submissions, as compared with low quality submissions ($\beta_{43} = 1.21, p < 0.001$). Thus, as an entry accumulates more contributor feedback over time, creators of high quality submissions are more likely to respond to and engage with the feedback, e.g. in the later stages of the context. This result lends support to Hypothesis 4.

We also performed additional analyses for robustness which are not included in this manuscript for sake of brevity. We tested a variety of interaction terms, as well as a curvilinear effect for diversity. We found that none of the variance associated with these terms across entries explained variance in outcomes among the entries. Surprisingly, this analysis suggests that there is not a point at which increasing diversity has a positive effect. That is, even small amounts of increasing diversity were associated with lower submission quality.

Discussion

Crowd-based open innovation provides a unique context in which to examine collaboration in an online environment, especially when the goal is to develop novel ideas. We set out to better understand how workers collaborate in crowd-based open innovation communities and how these collaboration patterns affect innovation outcomes. In particular, we examined co-creation processes and how these vary over time as the innovation process moves from idea generation to elaboration. Through the use of relational event modeling, we were able to capture interaction patterns between creators and community members over the course of two contests and use these interaction patterns to predict the quality of creators' submissions.

Our findings describe unique signatures of interaction for submissions of high quality. With regard to diversity, our results show that there is a tendency in the overall sample for more unique contributors to flock to an entry over time, but the entries that are most successful have fewer contributors over time. We also show that, in high quality submissions, feedback to the creator tends to originate from a smaller number of individuals, and these individuals are significantly more active relative to other contributors as the project moves from idea generation to elaboration. Essentially, a small group of engaged people provide significant feedback to the submission toward the later stages of higher quality submissions. Further, we observe that the creators of more successful submissions, while not dominating the discussion, are particularly responsive to feedback in later stages. This tendency paints a picture of a creator who actively engages in discussion with community members while refining the idea, but who does not crowd out potential contributors. We find that these patterns are significant net of differences in number of posts, number of unique contributors, and the particular contest.

One of the primary contributions of this research is that we were able to detect different interaction patterns over time and their effects. This is in contrast to more static research which captures data at a single point in time. Our research suggests that static approaches may run the risk of drawing inaccurate conclusions. Static research on diversity, for example, might conclude that diversity has positive or negative effects, but obscures the fact that the phase of the project matters. Our findings suggest that, for crowd-based open innovation, diversity is better earlier rather than later in the contest. Similarly, we find that the creator should be more active later in the project. Data exclusively from early stages in a project might erroneously conclude that the creator should be minimally active. Our results clearly indicate that collaboration processes are sensitive to project phase and should be examined temporally.

We also contribute to burgeoning research on open innovation and collaboration in online communities. Little is yet known about how collaboration works when crowds of people are drawn together, often from very diverse backgrounds and geographies, to interact in a loosely coupled way in an online platform. We add to this growing body of research on collaboration in online communities. While much of the existing research has employed more experimental methods and created online tasks and teams (e.g. Retelny, et al., 2014; Valentine, 2017; Reidl & Woolley, 2017), we examined the dynamics that occurred with real community members on real projects. Although we sacrificed experimental control, doing so enabled us to see the interaction between members of the community, many of whom were long-time members, as they engaged in contests that they knew were going to be implemented.

As with any study, ours has limitations. First, despite analyzing data over time, we must still be cautious about making causal claims. We have controlled for a variety of factors, but cannot with certainty claim that the collaboration patterns we observed caused, or were simply associated with other latent unobserved factors that caused, low or high quality submissions. We also gathered our data from a single collaboration platform, hosted by Local Motors. Every open innovation platform has particularly design features and often different cultures fostered by the hosting organization. Local Motors, for example, has historically encouraged active collaboration among community members. Other crowd-based open innovation platforms have different design features and foster different, perhaps more openly competitive, cultures. Future research should examine collaboration patterns in other open innovation communities with different features and cultures. Finally, in the analyses we reported, we examined only submission quality. Future research would benefit from exploring the effect of these collaboration patterns on a wide variety of outcomes, including novelty of the ideas submitted, future participation of members in the community, improvement of ideas over time, etc.

References

Amabile, T. M. 1988. "A model of creativity and innovation in organizations," in Research in Organizational Behavior, Staw, B. M. and Cummings, L. L. (eds.), Vol. 10, JAI Press, Greenwich, CT, pp. 123-167.

Bechky, B. A. 2003. "Sharing meaning across occupational communities: The transformation of understanding on a production floor," *Organization Science* (14:3), pp. 312-330.

Bonaccorsi, A., and Rossi, C. 2003. "Why open source software can succeed," *Research policy* (32: 7), pp. 1243-1258.

Boudreau, K., Gaule, P., Lakhani, K. R., Riedl, C. and Woolley, A. W. 2014. "From Crowds to Collaborators: Initiating Effort & Catalyzing Interactions Among Online Creative Workers," *Harvard Business School Working Paper*, No. 14-060.

Brabham, D. C. 2008. "Moving the crowd at iStockphoto: The composition of the crowd and motivations for participation in a crowdsourcing application, " *First Monday* (13:6).

Brabham, D. C. 2010. "Moving the crowd at Threadless: Motivations for participation in a crowdsourcing application, " *Information, Communication & Society*, (13:8), pp.1122-1145.

Butts, C. T. 2008. "A relational event framework for social action," *Sociological Methodology* (38:1), pp. 155-200

Camacho, L. M., and Paulus, P. B. 1995. "The role of social anxiousness in group brainstorming," *Journal of personality and social psychology*, (68:6), p. 1071.

Chesbrough, H., Vanhaverbeke, W., and West, J. (eds.). 2006. *Open innovation: Researching a new paradigm*, Oxford University Press on Demand.

Cronin, M. A., and Weingart, L. R. 2007. "Representational gaps, information processing, and conflict in functionally diverse teams," *Academy of Management Review* (32:3), pp. 761-773.

Cropley, A. 2006. "In praise of convergent thinking," *Creativity Research Journal*, (18:3), pp. 391-404.

Dahlander, L., and Gann, D. M. 2010. "How open is innovation?, " *Research Policy* (39:6), pp. 699-709.

Dahlander, L., and Piezunka, H. 2014. "Open to suggestions: How organizations elicit suggestions through proactive and reactive attention, " *Research Policy (*43:5), pp. 812-827.

Dahlin, K. B., Weingart, L. R., and Hinds, P. J. 2005. "Team diversity and information use," *Academy of Management Journal* (48:6), pp. 1107-1123.

DuBois, C., Butts, C. T., McFarland, D., and Smyth, P. 2013. "Hierarchical models for relational event sequences," *Journal of Mathematical Psychology* (57:6), pp. 297-309.

Faraj, S., and Johnson, S. L. 2011. "Network exchange patterns in online communities," *Organization Science* (22:6), pp. 1464-180.

Fleming, L., Mingo, S., and Chen, D. 2007. “Collaborative brokerage, generative creativity, and creative success,” *Administrative Science Quarterly* 52(3), pp. 443-475.

Füller, J., Hutter, K., and Faullant, R. 2011. "Why co-creation experience matters? Creative experience and its impact on the quantity and quality of creative contributions," *R&D Management* (41:3), pp. 259-273

Gebauer, J., Füller, J., and Pezzei, R. 2013. "The dark and the bright side of co-creation: Triggers of member behavior in online innovation communities, " *Journal of Business Research* (66:9), pp. 1516-1527.

Grissemann, U. S., and Stokburger-Sauer, N. E. 2012. "Customer co-creation of travel services: The role of company support and customer satisfaction with the co-creation performance, " *Tourism Management* (33:6), pp. 1483-1492.

Hargadon, A. B., and Bechky, B. A. 2006. "When collections of creatives become creative collectives: A field study of problem solving at work, " *Organization Science* (17:4), pp. 484-500.

Harrison, S. H., and Rouse, E. D. 2015. "An inductive study of feedback interactions over the course of creative projects," *Academy of Management Journal* (58:2), pp. 375-404.

Hars A. and Ou S. 2002. "Working for free? Motivations for participating in open-source projects," *International Journal of Electronic Commerce*, (6:3), pp. 25-39.

Hertel, G., Niedner, S., and Herrmann, S. 2003. "Motivation of software developers in Open Source projects: an Internet-based survey of contributors to the Linux kernel, " *Research Policy* (32:7), pp. 1159-1177.

Howe, J. 2009. Crowdsourcing: Why the Power of the Crowd Is Driving the Future of Business, New York (NY): Crown Busines.

Ind, N., and Coates, N. 2013. "The meanings of co-creation," *European Business Review* (25:1), pp. 86-95.

Jassawalla, A. R., and Sashittal, H. C. 2002. "Cultures that support product-innovation processes," *The Academy of Management Executive* (16:3), pp. 42-54.

Jones, Q., Ravid, G., and Rafaeli, S. 2004. "Information overload and the message dynamics of online interaction spaces: A theoretical model and empirical exploration," *Information Systems Research* (15:2), pp. 194-210.

Kittur, A., Nickerson, J. V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J., Lease, M., and Horton, J. 2013. "The future of crowd work," In *Proceedings of the 2013 Conference on Computer Supported Collaborative Work*, pp. 1301-1318.

Kohler, T., Fueller, J., Matzler, K., Stieger, D., and Füller, J. 2011. "Co-creation in virtual worlds: The design of the user experience, " *MIS Quarterly* (35:3), pp. 773-788.

Langner, B., and Seidel, V. P. 2015. "Sustaining the flow of external ideas: The role of dual social identity across communities and organizations, " Journal of Product Innovation Management (32:4), pp. 522-538.

Lichtenthaler, U. 2011. "Open innovation: Past research, current debates, and future directions, " *The Academy of Management Perspectives* (25:1), pp. 75-93

Marcum, C. S., and Butts, C. T. 2015. “Constructing and Modifying Sequence Statistics for relevent Using informR in R.,” *Journal of Statistical Software* (64:5), p. 1-36.

Milliken, F., Bartel, C.A. and Kurtzberg, T. 2003. “Diversity and Creativity in Work Groups: A Dynamic Perspective on the Affective and Cognitive Processes That Link Diversity and Performance,” in Group Creativity, P. B. Paulus and B. Nijstad (eds.), Oxford, England: Oxford University Press, pp. 32-62.

O'Reilly III, C. A. 1980. "Individuals and information overload in organizations: is more necessarily better?," *Academy of Management Journal* (23:4), pp. 684-696.

Østergaard, C. R., Timmermans, B., and Kristinsson, K. 2011. "Does a different view create something new? The effect of employee diversity on innovation," *Research Policy* (40:3), pp. 500-509.

Paulus, P. B., and Yang, H. C. 2000. "Idea generation in groups: A basis for creativity in organizations, " *Organizational Behavior and Human Decision Processes* (82:1), pp. 76-87.

Perks, H., Gruber, T., and Edvardsson, B. 2012. "Co-creation in radical service innovation: a systematic analysis of microlevel processes, " *Journal of Product Innovation Management* (29:6), pp. 935-951

Perlow, L. A. 1999. "The time famine: Toward a sociology of work time," *Administrative Science Quarterly* (44:1), pp. 57-81.

Perry-Smith, J. E., and Shalley, C. E. 2003. "The social side of creativity: A static and dynamic social network perspective, " Academy of Management Review (28:1), pp.89-106.

Powell. W.W. 1990. "Neither market nor hierarchy: Network forms of organization," *Research in Organizational Behavior* (12), pp. 295-336

Riedl, C., and Seidel, V. 2018. "Learning from Mixed Signals in Online Innovation Communities," *Organization Science*, forthcoming

Quintane, E., Conaldi, G., Tonellato, M., and Lomi, A. 2014. "Modeling relational events: A case study on an open source software project," *Organizational Research Methods* (17:1), pp. 23-50.

Quintane, E., Pattison, P. E., Robins, G. L., and Mol, J. M. 2013. "Short-and long-term stability in organizational networks: Temporal structures of project teams," *Social Networks* (35:4), pp. 528-540.

Randall, W. S., Gravier, M. J., and Prybutok, V. R. 2011. "Connection, trust, and commitment: dimensions of co-creation?," *Journal of Strategic Marketing* (19:1), pp. 3-24.

Retelny, D., Robaszkiewicz, S., To, A., Lasecki, W. S., Patel, J., Rahmati, N. Doshi, T., Valentine, M., and Bernstein, M. S. 2014. "Expert crowdsourcing with flash teams," in *Proceedings of the 27th annual ACM symposium on User interface software and technology*, pp. 75-85.

Riedl, C., and Woolley, A. W. 2017. "Teams vs. Crowds: A Field Test of the Relative Contribution of Incentives, Member Ability, and Emergent Collaboration to Crowd-Based Problem Solving Performance, " *Academy of Management Discoveries* (3:4), pp. 382-403

Roberts, J. A., Hann, I. H., and Slaughter, S. A. 2006. "Understanding the motivations, participation, and performance of open source software developers: A longitudinal study of the Apache projects, " *Management Science* (52:7), pp. 984-999.

Rouse E. 2018. "Where you end and I begin: Understanding intimate co- creation," *Academy of Management Review*, forthcoming

Schecter, A., Pilny, A., Leung, A., Poole, M. S., and Contractor, N. 2017. "Step by step: Capturing the dynamics of work team process through relational event sequences," J*ournal of Organizational Behavior*, forthcoming

Schuhmacher, M. C., and Kuester, S. 2012. "Identification of lead user characteristics driving the quality of service innovation ideas," *Creativity and Innovation Management* (21:4), pp. 427-442.

Sutton, R. I., and Hargadon, A. 1996. "Brainstorming groups in context: Effectiveness in a product design firm, " *Administrative Science Quarterly*, pp. 685-718.

Ullrich, A., and Vladova, G. 2016. "Weighing the pros and cons of engaging in Open Innovation," *Technology Innovation Management Review* (6:4).

Valacich, J. S., Dennis, A. R., and Connolly, T. 1994. Idea generation in computer-based groups: A new ending to an old story," *Organizational Behavior and Human Decision Processes* (57:3), pp. 448-467.

Valentine, M. A., Retelny, D., To, A., Rahmati, N., Doshi, T., and Bernstein, M. S. 2017. "Flash Organizations: Crowdsourcing Complex Work by Structuring Crowds As Organizations, " in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 3523-3537.

Van der Vegt, G. S., and Janssen, O. 2003. "Joint impact of interdependence and group diversity on innovation," *Journal of Management*, (29:5), pp. 729-751.

Van de Ven, A. H., Delbecq, A. L., and Koenig Jr, R. 1976. "Determinants of coordination modes within organizations," *American Sociological Review*, pp. 322-338.

Voorberg, W. H., Bekkers, V. J., and Tummers, L. G. 2015. "A systematic review of co-creation and co-production: Embarking on the social innovation journey," *Public Management Review* (17:9), pp. 1333-1357.

Wallin, M.W., and von Krogh, G. 2010. "Organizing for open innovation: Focus on the integration of knowledge, " *Organizational Dynamics* (39:2), pp. 145-154

West, J., and Bogers, M. 2014. "Leveraging external sources of innovation: a review of research on open innovation, " *Journal of Product Innovation Management* (31:4), pp. 814-831

West, J., Salter, A., Vanhaverbeke, W., and Chesbrough, H. 2014. "Open innovation: The next decade, " *Research Policy* (43:5), pp. 805-811