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Tournaments to Crowdsource Innovation: The Role of Moderator Feedback and Participation Intensity

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Abstract

Firms increasingly use innovation tournaments to crowdsource innovation ideas from customers. This article uncovers antecedents and consequences of customers' participation intensity over the course of a tournament. More specifically, the authors theorize on the effects that the type and timing of moderating feedback have on tournament participants' participation intensity, as well as the effect of the latter on idea quality. Through two longitudinal experiments using a commercial innovation tournament platform, the authors show that moderating feedback stimulates ideators' participation intensity. They find that negative feedback increases participation intensity, as compared to no feedback and positive feedback. Moreover, negative feedback, either provided in isolation or together with positive feedback, is more effective during the early stages than in the later stages of a tournament. Using a large-scale managerial survey, the authors show that higher participation intensity leads to higher idea quality and better business performance. The effect of participation intensity on idea quality is stronger than the effect of number of ideas and as strong as the effect of number of participants on idea quality.

Keywords

crowdsourcing, idea generation, idea maturation, innovation, innovation tournaments, online idea generation platforms, participation intensity

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Introduction

Firms increasingly use innovation tournaments to crowdsource innovation ideas from customers. In an innovation tournament, firms (1) outsource idea generation and development to a large and undefined group of people (i.e., the "crowd") in the form of an open call (Afuah and Tucci 2012; Bayus 2013; Howe 2006; Nishikawa et al. 2017), and (2) after a prescribed time period following the idea call, select at least one winning idea from those submitted (Wooten and Ulrich 2017; Terwiesch and Ulrich 2009). An example of a nationwide innovation tournament is Staples' *Invention Quest* (Shanler and Martone 2007), hosted for the last several years by the office supply retailer to crowdsource innovative ideas for "America's next breakthrough office products."

Innovation tournaments offer three key advantages for new product development. First, sourcing ideas from a large crowd allows firms to more easily and rapidly generate ideas that require knowledge that falls outside the firm's knowledge base than sourcing ideas from internal experts or outsourcing to specialized contractors (Afuah and Tucci 2012). Second, generating a large number of competing ideas at the onset of an innovation tournament increases the odds of discovering high-quality ideas (Girotra, Terwiesch, and Ulrich 2010). Third, innovation tournaments force firms to apply selection mechanisms that weed out lower-quality ideas and allow only the most promising ones to survive (Terwiesch and Ulrich 2009). Examples of successful new products generated through innovation tournaments include a line of rugged Dell laptops for marine use (Bayus 2013), thematic Lego sets (e.g., *Back to the Future*'s DeLorean, *Ghostbusters*' Ectomobile; Ringen 2015), and Frito-Lay's "Cheesy Garlic Bread," a potato chip

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flavor credited with increasing Lay's sales by 8% in the three months following its launch (BrandIndex 2014).

To help idea contributors, or "ideators," revise and improve their ideas, firms hosting an innovation tournament often interact with and provide feedback to the ideators. Third-party platform providers also design features to provide moderator feedback to ideators. For instance, as part of its business model, Cognistreamer, the platform we use in our experiments, includes paid moderator feedback services for its clients. Feedback—information provided by an agent regarding aspects of another agent's performance—helps ideators assess where they are in terms of achieving their goals (Finkelstein and Fishbach 2012) and evaluate how much effort they need to invest to improve their ideas. Consequently, feedback may help participants remain actively involved in the platform by causing them to visit their own idea page and possibly update their own idea. We refer to such active involvement in the platform as "participation intensity." Prior literature recognizes the importance of number of ideas and number of participants as important drivers of idea quality in innovation tournaments (e.g., Girotra, Terwiesch, and Ulrich 2010; Wooten and Ulrich 2017). However, researchers have placed limited focus on the drivers and consequences of participation intensity. Although we focus specifically on innovation tournaments, feedback and participation intensity are important in any crowdsourcing innovation process. Thus, we complement prior literature in three main ways.

First, we examine the effect of *feedback type* on participation intensity in innovation tournaments. Following Finkelstein and Fishbach (2012), we distinguish *positive feedback* (feedback focused on the accomplishments and strengths of the posted idea) from *negative feedback* (feedback focused on the weaknesses in the idea, the need for idea refinement, or the additional effort needed to strengthen the idea). Prior literature offers potentially competing predictions for the benefits and drawbacks of these two types of feedback. Whereas self-determination theory predicts that positive feedback on progress to date increases participation intensity (Fishbach, Eyal, and Finkelstein 2010; Ryan and Deci 2000), self-discrepancy theory offers the opposite prediction: negative feedback on progress to go (i.e., what the participant still needs to accomplish) increases participation intensity (Fishbach, Dhar, and Zhang 2006; Higgins 1987). Thus, the type of feedback that leads to the highest participation intensity in innovation tournaments is unclear ex ante. Our empirical findings lend support to self-discrepancy theory. For instance, in Study 1 we find that, on average, 10.43% of participants who receive negative feedback update their ideas, whereas only 2.3% of participants who receive positive feedback do the same.

Second, to the best of our knowledge, we are also the first to study the effect of *feedback timing* on participation intensity in innovation tournaments. We draw from the literature on goal pursuit (Fishbach and Dhar 2005; Fishbach, Zhang, and Koo 2009) to argue that the way ideators respond to negative feedback depends on the motivational shifts they experience on their path to the goal. We posit that early in an innovation tournament, participants focus on how the idea still needs to develop to reach the goal, rendering negative feedback congruent with such focus. In contrast, later in the tournament, negative feedback may undermine participants' confidence in their ability to refine their ideas before the deadline. Thus, we predict and find that negative feedback is more effective during the early rather than later stages of a tournament. For example, in Study 2 we find that the percentage of participants who update their ideas when they receive negative feedback close to the end of a tournament is 20% lower than the percentage of participants who update their ideas when they receive negative feedback during the early stages of the tournament.

Third, although practitioners view participation intensity as important, the extent to which participation intensity is an important driver of idea quality and managerially relevant business outcomes is unclear. Prior literature tends to view number of ideas or ideators as the key drivers of idea quality (Bayus 2013; Girotra, Terwiesch, and Ulrich 2010; Terwiesch and Ulrich 2009). This view implicitly assumes that more ideas and participants lead to higher quality ideas, and it overlooks the potential role of ideators' participation intensity over time. We are the first to (1) propose an integrated theoretical framework that extends the concept of *ideation quantity* to include not only number of ideas and number of participants in an innovation tournament but also *participation intensity*, and (2) relate participation intensity to *ideation quality* and business outcomes, namely, *new product performance* and *overall business performance*. In Study 3, we find that the effect of participation intensity on idea quality is stronger than the effect of number of ideas and as strong as the effect of number of participants on idea quality.

Empirically, we examine the role of the type and timing of moderator feedback on participation intensity by conducting two longitudinal experiments (Studies 1 and 2) using a commercial innovation tournament platform, CogniStreamer. We examine the role of participation intensity (as a critical dimension of ideation quantity) on ideation quality and business outcomes using a large-scale survey of innovation managers (Study 3).

Our empirical work provides strong support for four findings: (1) negative feedback is effective in sustaining participation intensity but positive feedback is not, (2) early negative feedback increases participation intensity but late negative feedback does not, (3) participation intensity is a critical driver of idea quality in innovation tournaments, and (4) idea quality increases new product performance and overall business performance.

These findings have important implications for firms. First, firms organizing innovation tournaments and third-party platform vendors should consider training moderators to provide feedback to increase participation intensity. Second, moderators in innovation tournaments should offer negative feedback (i.e., feedback focused on the weaknesses in the idea, the need for idea refinement, or the additional effort needed to strengthen the idea) earlier rather than later in the tournament. Third, firms should go beyond measuring and incentivizing

Table 1. Overview of Empirical Studies on Crowdsourcing Innovation and Innovation Tournaments.

Source	Empirical Approach	Summary of Key Findings
Wooten and Ulrich (2017)	Six field experiments ($N_{Participants} = 245$; $N_{Ideas} = 624$).	Feedback ratings stimulate participation and increase the quality of the ideas in a tournament.
Bockstedt, Druehl, and Mishra (2016)	Secondary data from design contests (Logomyway.com; $N_{Contests} = 1,024$; $N_{Participants} = 2,623$).	Contestants who join early and remain active in a design contest are more likely to succeed. There is a curvilinear relationship between a contestant's number of submissions and success likelihood.
Stephen, Zubcsek, and Goldenberg (2016)	Five controlled experiments ($N = 326$). Participants completed ideation tasks over multiple runs ($N_{ParticipantRuns} = 1,188$).	Higher interconnectivity among customers participating in a crowdsourcing initiative reduces the innovativeness of customers' ideas (due to redundancy in idea generation).
Luo and Toubia (2015)	Two controlled experiments ($N_{Participants} = 708$; $N_{IdeaQualityEvaluators} = 4,412$; $N_{Ideas} = 4,316$).	Allowing customers to see others' ideas is more beneficial for low-knowledge customers. Classifying ideas into categories is more beneficial for high-knowledge ones.
Kornish and Ulrich (2014)	Secondary data (Quirky.com). Data comprises 160 products sold between Mach 2011 and March 2013.	Idea quality matters. The quality of both the raw idea and the final design predict sales outcomes.
Bayus (2013)	Secondary data from Dell's IdeaStorm in the period February 2007 to February 2009 ($N_{Participants} = 4,285$; $N_{Ideas} = 8,801$).	Customers who submit many ideas (serial ideators) are more likely to generate an idea the organization implements. Ideators with past successes are unlikely to repeat their successful ideation.
Boudreau, Lacetera, and Lakhani (2011)	Secondary data (9,661 software development contests posted at TopCoder).	A higher number of participants in a contest leads to better solutions for high-uncertainty problems. For low-uncertainty problems, greater rivalry triggers effort-reducing inefficiencies and backfires.
Kornish and Ulrich (2011)	Classroom data (hypothetical ideas; $N_{Participants} = 279$ students; $N_{Ideas} = 1,368$).	A higher number of ideas increases redundancy. However, redundancy is not detrimental. Non-redundant ideas are not generally the most valuable ones.
Girotra, Terwiesch, and Ulrich (2010)	One controlled experiment ($N_{Participants} = 44$ students; $N_{Ideas} = 443$; $N_{IdeaQualityEvaluators} = 129$).	Ideators working in a hybrid structure (in which they first work individually and then together) generate more and better ideas than those working in teams.

based on number of ideas and number of participants, and they should include participation intensity as a success metric in innovation tournaments.

Research Background

Crowdsourcing Innovation and Innovation Tournaments

The present inquiry complements the extant literature on crowdsourcing innovation and innovation tournaments, which we summarize in Table 1. Prior research in marketing examines the drivers of ideation quantity (i.e., number of ideators or number of ideas) and of ideation quality in crowdsourcing innovation. For instance, Bayus (2013) finds that customers who submit a higher number of ideas to a crowdsourcing platform (serial ideators) are also more likely to generate high-quality ideas (i.e., ideas that are effectively selected and implemented by the company). Luo and Toubia (2015) find that granting access to others' ideas is more beneficial for low-knowledge ideators, whereas classifying ideas into categories is more beneficial to high-knowledge ideators. Stephen, Zubcsek, and Goldenberg (2016) highlight that greater interconnectivity between customers participating in a crowdsourcing initiative reduces the innovativeness of their proposed ideas due to excessive redundancy. However, researchers have placed limited focus on the drivers and the consequences of participation intensity. Herein, we extend crowdsourcing innovation research by examining the effects of feedback type and timing on participation intensity and the consequences of participation intensity on idea quality and key business outcomes.

We also contribute to the nascent literature stream on innovation tournaments (e.g., Girotra, Terwiesch, and Ulrich 2010; Kornish and Ulrich 2011; Kornish and Ulrich 2014). For instance, Wooten and Ulrich (2017) investigate the role of in-process feedback in logo design competitions. They focus on quantitative feedback in the form of ratings and compare directed feedback (i.e., feedback correlated with idea quality) with undirected feedback (i.e., random feedback). They find that directed feedback increases idea quality, whereas undirected feedback does not. A random and uninformative rating does not offer guidance to participants on how to improve their ideas and, as such, does not constitute feedback (Finkelstein and Fishbach 2012). Considering that managers would be more interested in providing direct, high quality feedback rather than undirected feedback unrelated to idea quality, a managerially relevant issue is how a manager should effectively deliver directed feedback (i.e., how feedback type and timing influence ideation quality).

Third-Party Innovation Platforms

There are several key players in any innovation tournament, each of which have different roles. The *hosting firm* sponsors

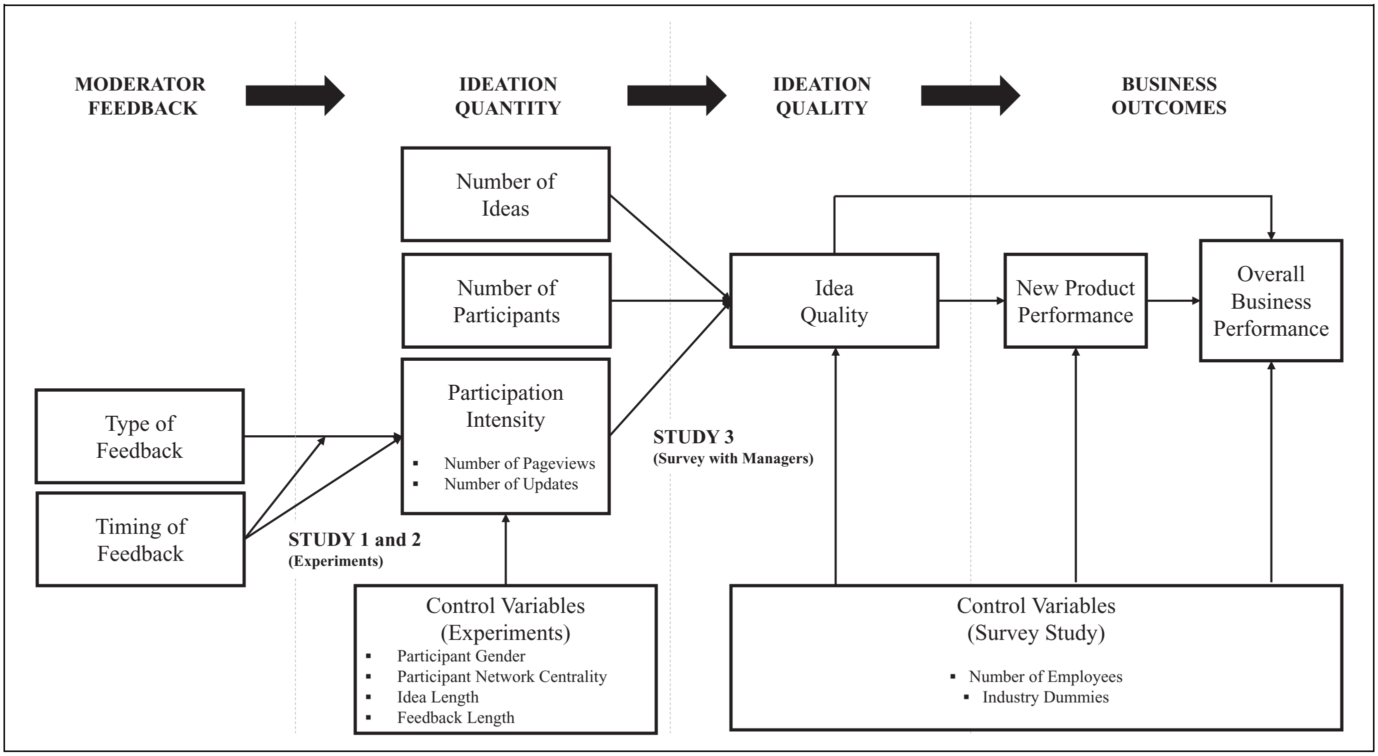

Figure 1. Theoretical framework: Moderator feedback, ideation quantity, ideation quality and business outcomes.

the tournament and typically determines its goals and idea selection criteria. The *ideators* generate and develop their ideas over a prescribed time period. *Third-party innovation platform suppliers* offer online platforms that facilitate the collaboration between the hosting firm and the ideators (Verona, Prandelli, and Sawhney, 2006). Examples of such special-purpose online platforms include CogniStreamer, Darwinator, Hype Innovation, and Spigit.

Innovation platforms provide a means for participants to submit their ideas, receive feedback, and update their ideas (Gliedman 2013). On CogniStreamer, ideators are invited via an idea call. After accepting the call and registering on the platform, participants may then submit their innovation ideas on a special submission form. As part of the submission (which has no word limit), participants can describe their proposed solution and may attach pictures or documents to offer additional documentation about their idea (see Web Appendix 1.1 for additional details and screenshots of the platform).

Once submitted, the idea becomes visible on the platform and the hosting firm or platform supplier can provide moderator feedback. To offer feedback to ideators, a firm may employ specially trained moderators who comment on the ideas in a manner similar to comments on social media platforms. When a moderator leaves a comment, a copy of the comment is also sent to the ideator's email. Ideators can log into the platform at any time to view their idea, view comments left for them, or update their idea by altering the idea's text description or any of its accompanying documents. The hosting firm may allow ideators to also view other participants' ideas. Some firms also encourage ideators to not only view but also comment and possibly even vote on other participants' ideas. On the Cognistreamer platform, social feedback is a feature that can be turned on or off depending on the hosting firm's specification requests.

Participation Intensity

Given that innovation tournaments last for a prescribed time period, some ideators may remain actively involved in developing their ideas over the course of the tournament, whereas others may not. We refer to ideators' sustained involvement in the platform as "participation intensity." Participation intensity manifests itself through repeated ideator activity on the innovation platform, such as when ideators visit their own idea page or update their own idea (Gill, Sridhar, and Grewal 2017). These two metrics of ideator activity in the platform (viewing one's own page and updating one's idea) provide us with an objective and unobtrusive measure of whether the participant remains actively engaged with her own idea. Our key argument is that a firm's design and provision of moderator feedback during an innovation tournament can enhance participation intensity, which in turn may improve the quality of the ideas generated in the tournament by providing new insights or correcting or redirecting the focus of an idea.

Theoretical Framework

Figure 1 depicts our theoretical framework in which we propose that (1) a firm's moderator feedback strategy (i.e., the type and timing of moderators' feedback) drives the level of participation intensity over the tenure of an innovation tournament (examined in Studies 1 and 2), (2) participation intensity is a key driver of the quality of the ideas generated in innovation tournaments, over and above other ideation quantity metrics such as number of ideas and number of participants (examined in Study 3), and (3) idea quality increases new product performance and overall business performance (also examined in Study 3).

Feedback Type and Participation Intensity

We conceptualize the development and refinement of ideas posted on an innovation platform as actions driven by ideators' inherent motivations to participate in the tournament. For instance, an ideator's ultimate goal can be winning a cash prize, gaining status or reputation, or enjoying seeing the firm develop and market her ideas (see Boudreau and Lakhani 2009). Feedback works by reducing the discrepancy between the current state and the desired state on the path to achieving a goal (Hattie and Timperley 2007). Feedback generally focuses on three aspects of this path: how far away the goal is, the progress made toward that goal, and what to do next to reach the goal. Each of these aspects of feedback function at four levels in the ideator's pursuit of a goal: (1) the *task level*, which addresses how to perform the tasks well; (2) the *process level*, which provides an understanding of the process and steps to achieve the goal; (3) the *self-regulation level*, which helps in self-monitoring, directing, and regulating the ideator's actions; and (4) the *self-level*, which involves providing personal evaluations and positive affect about the individual (Hattie and Timperley 2007). Depending on how feedback affects the individual at these four levels, the discrepancy can be reduced either by increasing effort (increased participation intensity) or by blurring, lowering, or completely abandoning the goals (reduced participation intensity). It is precisely because of these impacts that the *type* of feedback on the path to the goal becomes an important determinant of whether the participant reaches her goal of idea development successfully.

Following Finkelstein and Fishbach (2012), we distinguish between two types of feedback: (1) *positive feedback* focused on the accomplishments and strengths of the posted idea and (2) *negative feedback* focused on the weaknesses in the idea, need for idea refinement, or the additional effort needed to strengthen the idea. Like Finkelstein and Fishbach (2012), we maintain that to qualify as feedback, positive feedback must be complimentary without being needlessly flattering, and negative feedback has to offer constructive criticism (i.e., it should not be unnecessarily detrimental). Moreover, to qualify as feedback, a message needs to be "informative" in the sense that it helps participants better pursue their goals (Finkelstein and Fishbach 2012). Taken together, these requirements mean that we define feedback as "positive" when a moderator *compliments* the ideator's idea development to date (i.e., what the participant has already accomplished so far), and we define feedback as "negative" when the moderator challenges the idea and offers *constructive criticism* highlighting the idea development to go (i.e., what the participant still needs to accomplish).

To understand the impact of the type of feedback on participation intensity, we focus on two behavioral motivation theories that provide competing predictions on the nature of such impact. According to self-determination theory (Ryan and Deci 2000), positive feedback works at the self-level and at the self-regulation level and should increase participation intensity. At the self-level, positive feedback increases participants' confidence that they will be able to successfully develop and refine their ideas. At the self-regulation level, positive feedback increases participants' goal commitment. Higher confidence and goal commitment, in turn, allow participants to internalize the goal of idea development and thus stay motivated to pursue their goal going forward (Bandura and Cervone 1983; Fishbach, Eyal, and Finkelstein 2010; Ryan and Deci 2000). This, in turn, increases the intensity of ideators' participation in the innovation tournament. Negative feedback, on the other hand, also works at the self-level and is likely to undermine participants' confidence in their ability to successfully develop their ideas. This demotivates the participants and causes them to abandon or reduce their goals, thereby leading to lower participation intensity.

An alternate literature stream based on cybernetic models of self-regulation provides opposite predictions (Higgins 1987; Kluger and DeNisi 1996). According to self-discrepancy theory (Higgins 1987), positive feedback works at the self-regulation level by providing a signal that the task/goal is being accomplished successfully and thus less effort is needed going forward. This could lead to lower participation intensity. Negative feedback, in contrast, works both at the task level and at the self-regulation level. At the task level, negative feedback highlights weaknesses in the way a task is being performed, signaling the need for corrective action. At the self-regulation level, negative feedback signals that more effort is needed to accomplish the goal of idea development. Thus, according to this viewpoint, negative feedback should encourage higher participation intensity to attain the goal.

There is no clear answer regarding the impact of positive versus negative feedback, which could depend on other factors (see Fishbach, Eyal, and Finkelstein 2010). Thus, we examine the effects of positive feedback and negative feedback on participation intensity. Given the conflicting views discussed previously, we propose the following competing hypotheses for empirical testing:

> $\mathbf{H_{1a}}$: Positive feedback is effective in sustaining participation intensity in an innovation tournament.
>
> $\mathbf{H_{1b}}$: Negative feedback is effective in sustaining participation intensity in an innovation tournament.

Feedback Timing and Participation Intensity

We also study the impact of providing different types of feedback *over time* throughout an innovation tournament. Recall that positive feedback focuses on the idea development to date, whereas negative feedback highlights idea development to go. Given that innovation tournaments last for a prescribed time period, the participants' focus on accomplishments to date versus efforts to go may shift over time. Thus, we posit that as a participant's tournament tenure (i.e., the amount of time a participant spent in the tournament) increases, the effect of different types of feedback on participation intensity may change. This is in line with the literature on goal pursuit, which predicts that the way individuals respond to positive and negative feedback depends on the motivational shifts experienced on their path to the goal (Fishbach and Dhar 2005; Fishbach, Zhang, and Koo 2009). Thus, one may posit that during the early stage of a tournament, participants focus on idea development to go, and negative feedback is thus congruent with such focus. That is, during the early stage of a tournament, negative feedback that encourages participants to focus on idea development increases participation intensity to attain the goal. However, at the later stage of the tournament, participants may focus more on the looming deadline. At that point, negative feedback may undermine participants' confidence in their ability to successfully refine their ideas before the end of the tournament. This would render negative feedback at a later stage of a tournament less effective than negative feedback at an early stage of a tournament. Therefore, we propose the following hypothesis:

> **H_2**: Negative feedback is more effective in sustaining participation intensity early, rather than late, in an innovation tournament.

It should be noted that we do not hypothesize differences in the impact of positive feedback *over time* throughout an innovation tournament. This is because, in contrast with negative feedback, it would be difficult to form a directional hypothesis for the moderating effect of time on the impact of positive feedback on participation intensity. Specifically, it is possible that positive feedback is most effective early in an innovation tournament when participants who recently joined the tournament may need signals that reinforce their commitment to the tournament and its goal (e.g., Fishbach, Eyal, and Finkelstein 2010). However, it is equally possible that positive feedback is most effective late in an innovation tournament because it may restore the participant's depleted internal energy (Schmeichel and Vohs 2009). We thus leave the impact of providing positive feedback *over time* throughout an innovation tournament as an empirical question.

The Effect of Participation Intensity on Idea Quality

Prior research especially emphasizes the importance of the number of ideas or participants (ideation quantity) in increasing the odds of discovering truly exceptional ideas (Girotra, Terwiesch, and Ulrich 2010; Terwiesch and Ulrich 2009). Consequently, researchers have focused on seeding stimulus ideas or adapting and structuring the ideation tasks with the specific objective of stimulating a high number of ideas or attracting a high number of participants (Luo and Toubia 2015; Hoffman, Kopalle, and Novak 2010; Stephen, Zubcsek, and Goldenberg 2016). We complement this viewpoint by arguing that participation intensity is also a key driver of idea quality. That is, we argue that the higher the ideators' participation intensity throughout an innovation tournament, the higher the quality of the output ideas. We make this argument for two main reasons. First, ideators with a greater participation intensity (i.e., those who repeatedly view or update their ideas) may be better able to learn from the information generated in the tournament environment than ideators with a lower participation intensity (Bockstedt, Druehl, and Mishra 2016). For instance, repeatedly viewing one's idea may help participants better interpret moderator feedback, thus providing new insights to participants and helping them correct or redirect the focus of their ideas. Second, participants' sustained involvement in the platform—namely, repeated updates of their ideas—helps them clarify and mature their ideas even in the absence of moderator feedback. It is well known that initial submissions to a crowdsourcing platform are typically vague and immature (Bayus 2013). Updating one's idea allows an ideator to gain experience with the idea maturation task. Prior literature shows that ideators with more experience in a given task are better able to retain their ideas in their memory, increasing their capacity to mature them into novel and useful ideas (Gino et al. 2010). Taking these two arguments into account, we hypothesize:

> **H_3**: The higher the ideators' participation intensity, the higher the quality of the ideas in an innovation tournament.

The Effect of Idea Quality on Firm Performance

Prior empirical evidence suggests that idea quality is a significant predictor of market outcomes (Kornish and Ulrich 2014), and customers are more likely to adopt and purchase higher quality ideas (Girotra, Terwiesch, and Ulrich 2010). Therefore, we expect higher quality ideas to contribute to a firm's new product performance with regard to indicators such as profit, sales, and market share (Moorman 1995), which should contribute to improve the overall business performance of the firm (Jaworski and Kohli 1993). Thus, we hypothesize that:

> **H_4**: The greater the quality of the ideas in an innovation tournament, the greater (a) the firm's new product performance and (b) the firm's overall business performance.

Overview of Studies

To test our theoretical framework (see Figure 1), we conducted two longitudinal experiments (Studies 1 and 2) and one large-scale managerial survey (Study 3). Studies 1 and 2 allow us to examine the effect of *feedback type* and *feedback timing* on participation intensity (H_1 and H_2). Study 1 is a longitudinal classroom experiment in which student participation was required, which reduces concerns about self-selection bias but lowers realism. Study 2 is a real innovation tournament organized by one of our schools for its centennial anniversary in

Table 2. Overview of Studies and Summary of Key Results.

Study	Theoretical Effects Tested	Methodology	Details on Study Design	Summary of Key Results
1	Moderator feedback ↓ Participation intensity	Experimental	In-class experiment with students. We ran the tournament using a real innovation tournament platform (CogniStreamer). To reduce endogeneity concerns, moderator feedback type is exogenously manipulated and feedback timing is orthogonal to feedback type (i.e., we randomly assign participants to feedback treatments at each round). Student participation was required, which reduces self-selection bias concerns.	• *Positive feedback* has no influence either on the number of pageviews or on idea updating. • *Negative feedback* increases the number of pageviews and idea updating, but late negative feedback may lead participants to disengage from the tournament. • *Positive plus negative feedback* increases the number of pageviews and idea updating but such beneficial effects attenuate as the tournament progresses.
2	Moderator feedback ↓ Participation intensity	Experimental	Real innovation tournament organized by one of our schools for the centennial anniversary of the school. The experimental design and innovation tournament platform are the same used in Study 1, but participation in the tournament is voluntary to enhance the realism of the experiment. To save on degrees of freedom, we do not manipulate positive feedback.	• *Negative feedback* increases idea updating and the number of pageviews, but its effect on idea updating attenuates as the tournament progresses. • Nonsignificant effect of *positive plus negative feedback* on the number of pageviews. • Positive effect of *positive plus negative feedback* on idea updating, but this effect attenuates as the tournament progresses.
3	Ideation quantity (Nr. ideas, nr. participants and participation intensity) ↓ Idea quality ↓ Business outcomes	Survey	Large-scale survey with managers (N = 1,519) to guarantee generalizability and test whether participation intensity drives idea quality and business outcomes in a large variety of industries. Out of the 1,519 respondents, 516 (33.97%) indicated that their firms had already organized an innovation tournament on an online platform. Econometric controls included to reduce concerns with common method bias and self-selection bias.	• *Participation intensity* is a significant driver of idea quality in innovation tournaments, over and above number of ideas and number of participants. • The effect of *participation intensity* on idea quality is stronger than the effect of number of ideas and as strong as the effect of number of participants on idea quality. • *Idea quality* increases new product performance and overall business performance.

which participation was voluntary, which enhances the realism of our experiment. The use of these longitudinal experiments helps us establish the causality between the type and timing of moderator feedback and participation intensity by reducing the influence of unobservable factors or endogeneity (Chen, Wang, and Xie 2011). Study 3 then tests the postulated effect of participation intensity on the quality of the ideas in an innovation tournament (H_3) and validates that higher idea quality enhances business outcomes (e.g., Kornish and Ulrich 2014), namely, new product performance (H_{4a}) and overall business performance (H_{4b}). To do this, we use a large-scale survey of 1,519 innovation managers across a large number of innovation tournaments and industries. We present an overview of the three studies and a summary of our findings in Table 2.

Study 1: Longitudinal Classroom Experiment with Required Participation

Overview and Procedure

The goal of Study 1 is to test H_{1a}, H_{1b}, and H_2 using a controlled experiment with required participation. The experiment was conducted as part of a marketing strategy course taught at Erasmus School of Economics, Erasmus University Rotterdam, the Netherlands. We organized an innovation tournament to crowdsource ideas for the future of the school from the students. Students were encouraged to find breakthrough ideas capable of innovating the school's offering to boost its impact on students, faculty, or society as a whole by 2030 across four domains: education, knowledge creation, knowledge dissemination, and internationalization. We used the following procedure, which lasted for seven weeks (see Web Appendix 1.2).

First, we issued an idea call two weeks before the start of the tournament informing all enrolled students that, to receive their course credit, they would be required to submit an idea to this tournament. We also informed students that they would mature their ideas over a period of four weeks and that they would receive feedback from selected moderators to help them develop their ideas. Note that, in this tournament, idea submission was required but participation intensity (i.e., viewing and updating one's idea) was not required for the course credit, which allowed us to investigate the impact of moderator feedback on participation intensity. Moreover, students were also informed that they had to submit a final idea proposal at the end of the innovation tournament and that the five students with the best ideas would be rewarded with a bonus on their grade.

Next, the experiment proceeded with an idea development phase that lasted for four weeks and included multiple rounds of feedback. In each of the experiment's rounds, we trained a set of six moderators who would provide feedback to participants on the following topics and in the following sequence, one per experimental round: (1) value creation; (2) strengths, weaknesses, opportunities, and threats analysis (external and internal environment); (3) competition; (4) branding; and (5) feasibility. Besides focusing on the effect of positive versus negative feedback, we also examined the effect of positive and negative feedback given *simultaneously*, as platform moderators can offer positive feedback on one aspect of the idea and negative feedback on another aspect. This is somewhat similar to what is called a "sandwich feedback strategy" in business practice (Schwarz 2013). Therefore, in each experimental round, we randomly assigned participants to one of four between-subject conditions: (1) "no feedback," (2) "positive feedback," (3) "negative feedback," and (4) "positive plus negative feedback."

In the "no feedback" condition, moderators provided an uninformative message expressing appreciation for the participation but no information about the participant's idea. A message that is uninformative about the participant's idea does not help participants pursue their goals more effectively and, as such, does not constitute "feedback" (Finkelstein and Fishbach 2012). Thus, participants assigned to this "no feedback" condition constitute our control group. In the "positive feedback" condition, moderators pointed out the strengths of an idea and highlighted positive aspects of an idea (i.e., aspects in which the participant already did a good job). In the "negative feedback" condition, moderators pointed out the weaknesses of an idea and highlighted idea development to go (i.e., corrective actions that participants could implement to improve their ideas). In the "positive plus negative feedback" condition, moderators combined positive and negative feedback in the same message (see examples in Web Appendix 1.2).

Finally, one week after the last feedback was provided, students were required to submit an idea pitch, which we used to select the five best ideas and reward the winners with a grade bonus.

Data

Table 3 summarizes the measures of key variables we obtained from this experiment. We summarize the descriptive statistics of the key variables of this study in Web Appendix 2 (Table 2.1). In total, 93 students (37 female and 56 male) submitted 93 ideas to this innovation tournament and received moderating feedback across five feedback rounds (see Figure 1.2a in Web Appendix 1). The average length of the initially submitted ideas—measured by the log of the number of characters before they receive their first feedback—is 7.30 (SD = 1.03). On average per each feedback round, participants viewed their own ideas 1.40 times (SD = 2.74), and we observed an update in 17% of the idea rounds (SD = .37).

Participation intensity. Measures for the level of participation intensity are constructed using time stamped participant behaviors found on the tournament platform. Following Chatterji et al. (2016), we use two measures of participation intensity: (1) the number of pageviews on an idea i made by the idea creator after receiving t-th feedback but before (t+1)-th feedback,[1] and (2) a dummy variable indicating whether a participant updated her idea after receiving t-th feedback and before (t+1)-th feedback (yes = 1; no = 0).

Controlling for social motivations. Prior research suggests that social motivations play two important roles in human behavior that may influence ideators' participation intensity in innovation tournaments. First, a person's agency–communion orientation (i.e., her tendency to focus on the self or others) may determine her feelings of responsibility towards others and whether or not she engages in impression management efforts (Kurt, Inman, and Argo 2011). Feelings of responsibility toward others and impression management concerns, in turn, may influence ideators' participation intensity. Prior research uses gender as a proxy for agency–communion orientation (see Kurt, Inman, and Argo 2011). In line with this literature, we expect communal participants (i.e., women) to show a higher level of concern for others and to have a higher need for impression management than agency-oriented participants (i.e., men; Gneezy, Niederle, and Rustichini 2003). Therefore, we control for participant gender in our model, which we measured through an intake survey to all participants.

Second, a person's position in the network of participants in an innovation tournament can also increase her exposure to other participants' behavior, thereby influencing participation intensity. Prior research shows that network position is a good predictor of ideators' behavior and ideation performance because it reflects the richness and diversity of information resources ideators can access (Ransbotham, Kane, and Lurie 2012). Similarly, Mallapragada, Grewal, and Lilien (2012) show that in the community of open source software developers, the network centrality of innovators (which the authors capture using degree centrality and betweenness centrality in the social network of developer users) can be an important driver of project success.[2] More recently, Stephen, Zubcsek, and Goldenberg (2016) show that the interconnectivity of a participant in a crowdsourcing initiative, which the authors

[1] Note that although participants can also view other participants' ideas, pageviews on others' ideas may be driven out of curiosity and competitive concerns and do not necessarily reflect an objective measure of a participant's engagement with her own idea.

[2] Degree centrality refers to the number of ties, or neighbors, an ideator has in her network. Betweenness centrality refers to how importantly or strategically placed her ties are (i.e., an ideator with high betweenness centrality has a stronger influence in the network because a large number of ties "pass through" this ideator).

Table 3. Measurement (Study 1 and Study 2).

Conceptual Variable	Notation	Measured Variable	Data Source
Participation Intensity			
Pageviews of own idea	Pageviews_{it}	The number of pageviews of an idea i by the creator of the idea between feedback at t and feedback at t + 1	Time-stamped browsing data in the platform
Idea updating	Idea update_{it}	1 if an idea i is updated between feedback at t and feedback at t + 1, 0 otherwise	
Feedback Type			
	$\text{Positive feedback}_{it}$	1 if positive feedback was provided to an idea i at round t, 0 otherwise	Experimentally manipulated
	$\text{Negative feedback}_{it}$	1 if negative feedback was provided to an idea i at round t, 0 otherwise	
	$\text{Positive plus negative feedback}_{it}$	1 if positive plus negative feedback was provided to an idea i at round t, 0 otherwise	
Feedback Timing	$\text{Tournament tenure}_{it}$	The log of the duration of the time (measured in seconds) between feedback at t provided to an idea i and the creator of idea i's registration in the tournament	Measured
Social Motivations			
Agency–communion orientation	Gender_{i} (proxy)	1 if the creator of idea i is female (communion-oriented), −1 if he is male (agency-oriented)	Measured using self-reported data
Network centrality	Degree_{i}	Degree centrality of the creator of idea i in the social network of all participants in the tournament	
	Betweenness_{i}	Betweenness centrality of the creator of idea i in the social network of all participants in the tournament	(Study 1) and Facebook data (Study 2)
	Clustering_{i}	Clustering coefficient of the creator of idea i in the social network of all participants in the tournament	
Other Control Variables			
Length of the initial idea	Idea length_{i}	The length of the initially submitted idea i (measured by the log of the number of characters before it receives its first feedback)	Time-stamped data in the platform
Length of feedback	$\text{Feedback length}_{it}$	The length of the feedback provided to idea i at round t (measured by the log of the number of characters)	
Extrinsic recruitment	Extrinsic_Rec_{i}	1 if the creator of idea i was recruited by an extrinsic reward, −1 otherwise (Study 2 only)	Coded
Multiple idea submission	$\text{Multiple ideas}_{i}$	1 if the creator of idea i submitted multiple ideas, −1 otherwise (Study 2 only)	

capture through the clustering coefficient,[3] can negatively influence the innovativeness of her idea. This is because those who are highly interconnected to others tend to come up with similar and redundant ideas due to their ideation resources being more clustered than those who are not highly interconnected to others.

We control for the effect of a participant's network centrality on participation intensity. We used dyadic friendship questions to infer each participant's friendship network and compute network centrality scores (Eagle, Pentland, and Lazer 2009). Specifically, right after the end of the tournament, students indicated whether they knew each of their classmates in person. We say that a friendship link exists between participants i and j if either i responded "yes" to this question about j, or vice versa. We then used these self-reported friendship ties to construct each participant's social network and calculate her network metrics including degree centrality, betweenness centrality, and clustering coefficient. We only employ degree centrality and clustering coefficient to express a participant's network connectivity, because the betweenness centrality is highly correlated with degree centrality. Our results are robust to the usage of different sets of network position metrics (see Web Appendix 3.1).

Controlling for other variables. We control for other variables potentially related to participation intensity, namely, the length of the raw idea (i.e., the length of the initial submission) and the length of each feedback received. We also control for carryover effects (i.e., whether prior participation intensity affects subsequent participation intensity) by including lagged terms for idea viewing and idea updating in our models.

[3] Clustering refers to the density of an ideator's network of neighbors, such that a higher clustering coefficient refers to denser networks with higher interconnectivity among neighbors (see Stephen et al. 2016).

Model

We model pageviews on a participant's own idea page with a zero-inflated negative binomial model and idea updating with a binomial logit model.

Pageviews model. To accommodate the excess number of zeros (54% of observations of the pageviews of a participant's own idea page) and the overdispersion in the pageview data, we employ a zero-inflated negative binomial model (Greene 2003).[4] To incorporate unobserved factors associated with each participant, we allow for participant-level random effects (independent standard normal random variable). We specify the probability of the creator of idea i making y_{it} pageviews on her own idea during the feedback round t as follows:

$$\Pr(Y_{it} = y_{it}) \sim \begin{cases} 0 \text{ with probability } w_{it}, \\ \text{Negative Binomial } (\lambda_{it}) \text{ with probability } (1 - w_{it}) \end{cases}, \quad (1)$$

where w_{it} is the zero-inflation parameter capturing the likelihood to observe excess zeros in pageviews, $0 < w_{it} < 1$; λ_{it} is the parameter capturing the count of pageviews, which follows a negative binomial model; and $\lambda_{it} \geq 0$.

The zero-inflated negative binomial model is particularly well suited to our context. Specifically, by specifying the supplementary zero-inflation process for the excess zeros, which occur with probability w_{it}, our model accommodates the fact that some participants may, at any point in time, disengage and stop participating in the tournament, thereby generating excess zeros. We predict the zero-inflation parameter w_{it} as a function of the same set of variables that predict the number of pageviews. Specifically, we estimate w_{it} as a function of the (1) type of moderator feedback, (2) timing of moderator feedback (i.e., tournament tenure, which is the elapsed time between the participant registering in the platform and receiving each round of feedback), (3) interaction effects between the type and timing of moderator feedback, (4) participant gender, (5) network centrality metrics, (6) carryover effect of lagged pageviews on the participant's own idea, and (7) remaining control variables, including round-specific fixed effects. Our final specification is as follows:

$$\log\left(\frac{w_{it}}{1 - w_{it}}\right) = \mathbf{x_{it}}'\boldsymbol{\gamma} + \alpha_{1i}, \quad (2)$$

where α_{1i} captures the participant-level random effect with $\alpha_{1i} \sim N(0, \sigma_1^2)$ and $\mathbf{x_{it}}$ captures the independent variables just described.

Likewise, we estimated the mean of the count in the negative binomial model λ_{it} as a function of the same set of variables described previously as follows:

$$\log(\lambda_{it}) = \mathbf{x_{it}}'\boldsymbol{\delta} + \alpha_{2i}, \quad (3)$$

where α_{2i} captures the participant-level random effect with $\alpha_{2i} \sim N(0, \sigma_2^2)$.

Idea updating model. We model the probability that the creator of idea i updates her idea during the feedback round t as a binomial logit model with random effects.[5] We model the indirect utility for the creator of idea i updating her idea during feedback round t as follows (where $\mathbf{x_{it}}$ captures the same independent variables described previously):

$$U_{it} = \mathbf{x_{it}}'\boldsymbol{\beta} + \alpha_{3i} + \varepsilon_{it}, \quad (4)$$

where α_{3i} is the participant-level random effect and $\alpha_{3i} \sim N(0, \sigma_3^2)$, and ε_{it} follows an i.i.d. Type 1 extreme value distribution.

The probability that the creator of idea i updates her idea during round t is given by:

$$\Pr(Y_{it} = 1) = \frac{\exp(U_{it})}{\exp(U_{it}) + 1}. \quad (5)$$

Results

Table 4 presents the results of the zero-inflated negative binomial and the binomial logit models. We discuss our key findings in detail subsequently.

Impact of feedback type on pageviews of own idea. Table 4, Panel A depicts the results from our pageviews model. We standardize the tournament tenure variable and interpret the parameter estimates of feedback type as the "simple effects" of different types of feedback for a participant with an average tenure in the tournament (see Spiller et al. 2013).[6] We find that, for a participant with an average tournament tenure, positive feedback has no significant effect on a participant's number of own idea pageviews ($\delta = .20$, $p > .10$). In contrast, we find that negative feedback is effective in encouraging participants to increase their own idea pageviews ($\delta = .49$, $p < .05$). We find that positive plus negative feedback is also effective in encouraging participants to increase pageviews of their own idea page, even

[4] Zero-inflated count models extend standard count models by supplementing the standard count process with a secondary binary process that distinguishes "excess zeros," which occur as a realization of the binary process, from "standard zeros," which occur as a realization of the count process (Cameron and Trivedi 2005). We considered the following alternative models: Poisson model, negative binomial model, and zero-inflated negative binomial model. Using the goodness-of-fit indicators, we concluded that a zero-inflated negative binomial model is the most appropriate for our data (see more discussion in Web Appendix 3.2). We thank an anonymous reviewer for these suggestions.

[5] Given the excess zeros in our data, we considered both a logit model and a Scobit model, but a likelihood ratio test indicated that the logit model is more appropriate for our data (see Web Appendix 3.1).

[6] Given that we standardize the tournament tenure variable, the interaction effects can be interpreted as the effects of different types of feedback when a participant's tenure is at one standard deviation above the mean of the tournament tenure.

Table 4. Effects of Feedback on Participation Intensity in a Required-Participation Tournament (Study 1; N = 465).

a. Pageviews Model

	Zero-Inflation Model (Disengagement)		Negative Binomial Model (Number of pageviews)	
(Number of Pageviews)	Estimate	SE	Estimate	SE
Intercept	1.58	2.31	−1.77	.85
Idea update$_{it−1}$	−1.44	.90	−.73	.16***
Pageviews$_{it−1}$	−.07	.09	.03	.01***
Positive feedback$_{it}$ (base: no feedback condition)	.28	.64	.20	.21
Negative feedback$_{it}$ (base: no feedback condition)	−.43	.76	.49	.21**
Positive plus negative feedback$_{it}$ (base: no feedback condition)	.71	.84	.46	.25*
Tournament tenure$_{it}$	−.10	.98	.44	.25*
Positive feedback$_{it}$ × Tournament tenure$_{it}$	.36	.66	−.14	.17
Negative feedback$_{it}$ × Tournament tenure$_{it}$	2.93	1.23**	.01	.16
Positive plus negative feedback$_{it}$ × Tournament tenure$_{it}$	1.29	.88	−.27	.16*
Gender$_i$ (1 = female; −1 = male)	.14	.24	.06	.11
Idea length$_i$	−.38	.21*	.33	.10***
Feedback length$_{it}$	−.33	.32	−.20	.10**
Degree$_i$	−.35	.27	.06	.11
Clustering$_i$	.13	.25	.01	.12
Overdispersion parameter			.04	.02
Log likelihood	−538			

b. Idea Updating Model	Estimate	SE
Intercept	−13.30	3.46***
Idea update$_{it-1}$	−2.98	.85***
Pageviews$_{it-1}$	.24	.09***
Positive feedback$_{it}$ (base: no feedback condition)	.12	.80
Negative feedback$_{it}$ (base: no feedback condition)	1.72	.77**
Positive plus negative feedback$_{it}$ (base: no feedback condition)	1.39	.82*
Tournament tenure$_{it}$	1.41	.97
Positive feedback$_{it}$ × Tournament tenure$_{it}$	.26	.93
Negative feedback$_{it}$ × Tournament tenure$_{it}$	−1.12	.73
Positive plus negative feedback$_{it}$ × Tournament tenure$_{it}$	−1.28	.74*
Gender$_i$ (1 = female; −1 = male)	−.15	.28
Idea length$_i$	1.29	.33***
Feedback length$_{it}$	.11	.25
Degree$_i$	−.12	.28
Clustering$_i$	−.32	.30
Log likelihood	−161	

Notes: We standardize the tournament tenure variable, which allows us to interpret the feedback parameters as the "simple effects" of different types of feedback for a participant with an average tenure in the tournament. Both pageviews and idea updating models include four dummy variables to capture the fixed effect of each feedback round. None of the dummy variables are significant.
*$p < .10$; **$p < .05$; ***$p < .01$. All p values are two-sided.

though the effect is only significant at the 10% level ($\delta = .46$, $p < .10$). This finding suggests that positive plus negative feedback is not more effective than negative feedback in isolation. To facilitate comparison of the relative sizes of the different effects, we use the estimated parameters to compute the probability that a participant with an average tenure in the tournament views her idea at least once, conditional on the type of feedback received (Hoetker 2007). For example, we find that 95.04% of participants with an average tournament tenure and who receive negative feedback view their idea at least once in a feedback round, whereas only 86.4% of participants who do not receive feedback do the same. These probabilities show that our effect sizes are meaningful, but for brevity we discuss all remaining effect sizes in Web Appendix 4.1.

Impact of feedback timing on pageviews of own idea. In terms of feedback timing, we find a positive interaction between a participant's tenure in the tournament and negative feedback in the zero-inflation model ($\gamma = 2.93$, $p < .05$), indicating that negative feedback late in the tournament (i.e., at 1 SD above the mean of tournament tenure, which means close to the end of the tournament) is more likely to trigger a participant to disengage than negative feedback early in the tournament (i.e., at the mean of tournament tenure, meaning halfway through the tournament or earlier). We also find a negative interaction between a participant's tenure and positive plus negative feedback in the negative binomial model, even though the effect was significant only at the 10% level ($\delta = -.27, p < .10$). Thus, although the effects of negative feedback and positive plus negative feedback on the number of pageviews of one's own idea page are positive early in the tournament, such beneficial effects attenuate as a participant approaches the end of the tournament.

Impact of feedback type on idea updating. Table 4, Panel B, depicts the results from our idea updating model. We find that whereas positive feedback does not drive idea updating ($\beta = .12$, $p > .10$), negative feedback and positive plus negative feedback increase the likelihood that a participant updates her idea ($\beta = 1.72, p < .05$ for negative feedback; $\beta = 1.39, p < .10$ for positive plus negative feedback), as compared to the no feedback condition. In terms of the magnitude of these effects, we find that the probability that a participant with an average tenure in the tournament who receives no feedback updates her idea is 2.04%. If moderators provide positive feedback, the updating probability is 2.3% (which is not significantly different from 2.04%). However, if moderators provide negative feedback, the updating probability is 10.4%, and if moderators provide positive plus negative feedback, the updating probability is 7.73%, showing that these effects are meaningful (for a more detailed discussion, see Web Appendix 4.1).

Impact of feedback timing on idea updating. We find that the effect of positive plus negative feedback on idea updating decreases as participants' tenure in the tournament increases ($\beta = -1.28, p < .10$). Thus, positive plus negative feedback is less effective in enhancing idea updating late in the tournament than feedback provided earlier in the tournament.[7] In terms of negative feedback, we find an interaction effect that approaches significance at the 10% level in the predicted negative direction ($\beta = -1.12$, $p = .12$). In contrast, we do not find an interaction effect between tournament tenure and positive feedback ($\beta = .26$, $p > .10$).

Hypothesis testing. Our findings across our pageviews and idea updating models suggest that positive feedback is not an effective driver of participation intensity either early or late in the tournament, leading us to reject H_{1a}. In contrast, negative feedback is effective in enhancing participation intensity, both when provided in isolation or together with positive feedback. These results lend support to the alternative hypothesis H_{1b}. We also find that positive plus negative feedback is not more effective than negative feedback provided in isolation, which casts doubt on the benefits of the often used "sandwich feedback" strategy. In terms of feedback timing, we find partial support for H_2. Specifically, the effectiveness of negative feedback in stimulating pageviews decreases as the tournament progresses (which is in line with H_2), and its effectiveness in stimulating idea updates also decreases as the tournament progresses but does so at a low p-value ($p = .12$). In addition, we find that positive plus negative feedback is more effective early rather than late in the tournament.

Social motivations and other variables. We did not find significantly higher participation intensity by women or by participants with higher network centrality. Given our sample size and number of feedback treatment conditions, this is possibly due to low degrees of freedom. Thus, this is a conservative test and these effects could possibly be captured in an experiment with higher degrees of freedom. We discuss the results of these and all other control variables in detail in Web Appendix 4.2.

Study 2: Longitudinal Experiment with Voluntary Participation

Overview and Procedure

Being a classroom experiment with required participation, Study 1 provided us with an opportunity to test the causal effects of the type and timing of moderating feedback on participation intensity in innovation tournaments without the threat of selection bias. At the same time, however, the classroom setting and required participation pose a threat to the external validity of our study. To alleviate these concerns, in Study 2, we ran a longitudinal experiment in a real innovation tournament conducted at Erasmus School of Economics. The tournament was branded "ESE Innovation Tournament" (ESE stands for Erasmus School of Economics).

We used the following procedure. First, at the occasion of its centennial celebration, the school invited students to contribute ideas for the future of the school with the same focus of boosting the school's impact by 2030 and along the same domains we used in Study 1. Given the voluntary participation, we conducted an in-campus marketing campaign to raise awareness for the tournament and recruit participants. Apart from voluntary participation, the tournament was very similar to the one in Study 1 (see Web Appendix 1.2). Specifically, we told participants they would mature their idea over a period of five (rather than four) weeks and that they would receive feedback from selected moderators to help them develop their ideas (feedback content was the same as in Study 1, but because we gave participants one additional week, they received six rather than five feedback messages, with moderators focusing the additional feedback on improving participants' pitches). We also informed participants that a jury of senior officials, including the dean, would select the top three ideas, and that we

[7] Due to the nonlinearity in the idea updating models, the sign and significance of interaction coefficients between feedback type and feedback timing (i.e., tenure) may not indicate the true statistical significance of the interaction effect (Ai and Norton 2003). Thus, following Zelner (2009), we further examined the interaction effects in idea updating models by simulating the marginal effects of feedback type on the probability that a participant updates an idea across different levels of her tenure (see Web Appendix 3.3). This analysis shows that none of our effects are driven by the nonlinearity of the logit specification, even though some effects (e.g., the interaction between tournament tenure and negative feedback in Study 2) become significant only at the 10% level.

would reward the winners with a recommendation letter from the dean and a cash reward of €500.

Similar to Study 1, six selected moderators trained on the different feedback types provided the feedback. However, to conserve degrees of freedom, we excluded the positive feedback treatment in the present study. Therefore, at each experimental round, we randomly assigned participants to three different treatments: (1) a "no feedback" condition, (2) a "negative feedback" condition, and (3) a "positive plus negative feedback" condition.

Data

In total, 104 participants (39 female and 65 male) submitted 142 ideas at this innovation tournament and received moderating feedback across six feedback rounds. On average, participants viewed their own ideas .87 times per feedback round (SD = 2.54), and in 15% of the idea-rounds we observed an update (SD = .36). We summarize the descriptive statistics for this study in Web Appendix 2 (Table 2.2).

We used the same measures as in Study 1, with the following exceptions. In Study 2, we obtained participants' genders and network centralities by tracking their Facebook profile pages. For those who did not disclose their gender on Facebook (N = 17, out of 106), we inferred their gender according to whether their first name is commonly used for men or women.[8] For network centrality, we inferred the position of a participant in the network of all participants from the friendship network of all participants on Facebook. Specifically, we obtained participants' lists of friends from their public Facebook profile pages.[9] Using the lists of friends elicited from Facebook profiles, we constructed the social network of participants and calculated network metrics for each participant including degree centrality, betweenness centrality, and clustering coefficient.

Model

Our model specifications remain the same as the ones used in Study 1, with the following exceptions. First, we included a "multiple idea" control variable because, in this tournament, some participants submitted more than one idea. Second, we included a dummy to control for recruitment through extrinsic rewards because we used small gifts (e.g., Ben & Jerry's ice cream) in some of our in-campus marketing efforts to recruit students. Third, we removed the "positive feedback" treatment variable, as it was not manipulated in the present study.

Results

Table 5 presents the estimated coefficients from pageviews and idea updating models.

Impact of feedback type on pageviews of own idea. Table 5, Panel A depicts the results of our pageviews model. As in Study 1, we standardize the tournament tenure variable. Similar to our findings from Study 1, we find that negative feedback is effective in stimulating a higher number of pageviews, which is an effect that is significant at the 10% level ($\delta = .52, p < .10$). We do not find a significant effect of positive plus negative feedback on pageviews.

Impact of feedback timing on pageviews of own idea. In contrast with Study 1, we do not find a significant interaction between the type and timing of feedback on the number of pageviews.

Impact of feedback type on idea updating. Similarly to Study 1, in Study 2 we find that, when compared with participants assigned to the control condition, participants receiving negative feedback and positive plus negative feedback are more likely to update their ideas ($\beta = 5.35$, $p < .01$ for negative feedback; $\beta = 5.35$, $p < .01$ for positive plus negative feedback).

Impact of feedback timing on idea updating. We again find that feedback timing matters. Specifically, we find that the positive effects of negative feedback and of positive plus negative feedback on idea updating decrease as participants' tenures in the tournament increase ($\beta = -4.51$, $p < .01$ for negative feedback; $\beta = -4.94$, $p < .01$ for positive plus negative feedback).

Hypothesis testing. Taken together, the results from our pageviews and idea updating models reinforce the results of Study 1. Specifically, we find that negative feedback is an effective driver of participation intensity, in line with H_{1b}. We also find that positive plus negative feedback is not more effective than negative feedback in isolation. In fact, positive plus negative feedback is not effective in driving pageviews, whereas negative feedback provided in isolation is. These results cast doubt on the effectiveness of the sandwich feedback strategy. In terms of feedback timing, the results of the idea updating model suggest that negative feedback, either provided in isolation or together with positive feedback, should be provided early rather than late in the tournament, lending support to H_2.[10]

Social motivations and other variables. With three exceptions, our results for other variables beyond feedback type and timing

[8] We obtained the data about the probability of a first name to be used for boys or girls from http://www.gpeters.com/names/baby-names.php.

[9] For those who did not allow access to their list of Facebook friends (N = 35), we detected their friendship only when we found them in someone else's list of friends.

[10] Note that our key question of interest is whether different types of feedback increase or decrease participation intensity in any of its manifestations (i.e., either pageviews or idea updating). Taken together, the results of Study 2 on these different manifestations reinforce those of Study 1. We thank an anonymous reviewer for pointing this out.

Table 5. Effects of Feedback on Participation Intensity in a Voluntary Tournament (Study 2; N = 803).

a. Pageviews Model

	Zero-inflation model (Disengagement)		Negative binomial model (Number of pageviews)	
	Estimate	SE	Estimate	SE
Intercept	6.38	2.13***	−2.97	.78***
Idea update$_{it-1}$	−1.68	1.33	−.54	.15***
Pageviews$_{it-1}$	−.58	.22***	.03	.01***
Negative feedback$_{it}$ (base: no feedback condition)	.20	.90	.52	.29*
Positive plus negative feedback$_{it}$ (base: no feedback condition)	−.22	.99	.29	.31
Tournament tenure$_{it}$	−.58	.78	−.07	.31
Negative feedback$_{it}$ × Tournament tenure$_{it}$	.65	.77	−.12	.30
Positive plus negative feedback$_{it}$ × Tournament tenure$_{it}$	1.13	.78	.04	.30
Gender$_{i}$ (1 = female; −1 = male)	−.08	.24	.16	.09*
Extrinsic_Rec$_{i}$	.72	.42*	−.35	.36
Idea length$_{i}$	−.74	.22***	.38	.09***
Feedback length$_{it}$	−.11	.70	.17	.21
Multiple ideas$_{i}$	−.61	.24***	−.01	.10
Degree$_{i}$	−.02	.28	.22	.10**
Clustering$_{i}$	.32	.31	−.17	.14
Overdispersion parameter			.13	.05***
Log likelihood	−628			

b. Idea Updating Model

	Estimate	SE
Intercept	−20.78	3.01***
Idea update$_{it-1}$	−.78	.49
Pageviews$_{it-1}$	.00	.04
Negative feedback$_{it}$ (base: no feedback condition)	5.35	1.89***
Positive plus negative feedback$_{it}$ (base: no feedback condition)	5.35	1.90***
Tournament tenure$_{it}$	4.28	1.93**
Negative feedback$_{it}$ × Tournament tenure$_{it}$	−4.51	1.92**
Positive plus negative feedback$_{it}$ × Tournament tenure$_{it}$	−4.94	1.93**
Gender$_{i}$ (1 = female; −1 = male)	.89	.20***
Extrinsic_Rec$_{i}$	−.57	.46
Idea length$_{i}$	1.77	.28***
Feedback length$_{it}$	−.52	.56
Multiple ideas$_{i}$	.46	.24*
Degree$_{i}$	1.16	.25***
Clustering$_{i}$	−.86	.32***
Log likelihood	−189	

Notes: We standardize the tournament tenure variable, which allows us to interpret the feedback parameters as the "simple effects" of different types of feedback for a participant with an average tenure in the tournament. Both the pageviews and idea updating models include five dummy variables to capture the fixed effect of each feedback round. Except for the dummy variable for round 2 feedback (strengths, weaknesses, opportunities, and threats) in the negative binomial component of the pageviews model, none of the dummy variables are significant. Note that we have 803 idea round observations because, unlike in Study 1, Study 2 has an unbalanced panel. This imbalance occurs because some participants joined after the first feedback round due to the voluntary nature of this tournament.
*$p < .10$; **$p < .05$; ***$p < .01$. All p values are two-sided.

reflect those of Study 1 (see Web Appendix 4.2 for a detailed discussion). First, unlike Study 1, we find a significantly higher participation intensity by female (vs. male) participants, and by participants with high (vs. low) degree or betweenness centrality. Second, we also find a significantly lower participation intensity by participants with high (vs. low) clustering coefficients. These results reinforce the possibility that the lack of significant effects of these social motivation variables in Study 1 was possibly driven by the study's low degrees of freedom. Third, in contrast with Study 1, we do not find a significant effect of the length of feedback on the number of pageviews ($\delta = .17$; $p > .10$).

Study 3: Large-Scale Managerial Survey

Purpose and Study Design

The purpose of Study 3 is to test H_3 and H_4. In other words, Study 3 examines (1) whether participation intensity drives the quality of the ideas emerging from innovation tournaments over and above the number of ideas and the number of participants and (2) whether idea quality has a positive influence on new product performance and on overall business performance. We used a large-scale managerial survey for two key reasons. First, a large-scale managerial sample allows us to observe variations in ideation quantity (i.e., number of ideas, number of participants, and participation intensity), ideation quality, and business outcomes across a large number of innovation tournaments and firms. Such data enable us to obtain direct insights into the effect of participation intensity on the quality of ideas generated in innovation tournaments and of idea quality on new product performance and overall business performance. Second, a large-scale managerial survey provides evidence of the effects examined in this study across a variety of firms and industries, thereby enhancing the external validity of our arguments.

To recruit participants to our online survey, we contracted Research Now, a leading online sampling company that manages a large executive panel and constantly monitors the quality of its panels to ensure sample representativeness and respondents' attention and motivation. In total, Research Now solicited 4,773 innovation managers from among its panel members. Respondents worked in a variety of industries, such as automotive, engineering, food/beverages, information/media, retail/wholesale, and telecommunications, to name a few (see Web Appendix 6 for the distribution). We considered respondents eligible if (1) they were sufficiently knowledgeable about innovation in their firm (i.e., if they had a score of six or higher on knowledge of innovation) and (2) they had been working at their current company for at least four years (see Homburg et al. 2012 for how these factors increase accuracy). We excluded respondents working for a firm active in finance/banking, insurance, or consulting, as firms in these industries typically position themselves as expert advisors to their customers, making it more difficult for these firms to crowdsource new products and services from their customers. Of the 4,773 solicited responses, 1,871 were eligible. Out of these, 352 exited the study early, leaving us with 1,519 eligible and complete respondents. Out of these, 516 (33.97%) indicated that their firm had already run an innovation tournament on an online platform.

Some firms may have better capabilities and resources for innovation and are thus more likely to run innovation tournaments because they expect such tournaments to deliver high quality ideas. To control for this potential endogeneity problem, we employed Heckman's (1979) two-step procedure. To do this, we collected information about the innovation capabilities and firm resources for all firms, including the 1,003 firms that had not run an innovation tournament on an online platform, and we used a two-step Heckman (1979) correction to demonstrate that our results in the subset of firms that had already run an innovation tournament on an online platform ($N = 516$) are robust and not threatened by selection bias, as recommended in the extant literature (Sande and Ghosh 2018). We offer a detailed description of our two-step Heckman correction in Web Appendix 5.4. In short, we first ran a probit selection model for each respondent in which we regressed the firm's decision to run an innovation tournament (firm had already run an innovation tournament = 1, firm had not yet run an innovation tournament = 0) on covariates explaining the selection decision (i.e., innovation capabilities and resources available for the firm to successfully deploy such an innovation tournament). Next, we used the probit estimates to calculate the Heckman correction factor, or inverse Mills ratio (λ). Finally, following Heckman (1979), and in line with recent marketing literature (Wetzel, Hammerschmidt, and Zablah 2014), we augmented our structural equation model (SEM) by including the inverse Mills ratio as an additional predictor of idea quality.

Questionnaire Composition and Measurement

Structure of the questionnaire. In the first part of the questionnaire, we gathered our screening questions and two control variables: industry and firm size. Given that creating and developing high quality ideas may be easier in certain industries than in others, we control for the industry sector a firm operates in. Moreover, even though prior research has found mixed results regarding the effect of firm size on innovation performance (Chandy and Tellis 1998; Cohen and Levin 1989), we also control for the effect of firm size (which we proxy using number of employees). In this part of the questionnaire, we also measured the business outcomes in our conceptual framework, namely new product performance and overall business performance.

In the second part of the questionnaire, we provided respondents with clear and simple definitions of our key terms, such as innovation tournaments and online innovation platforms. We then measured whether a respondent's firm had ever run an innovation tournament on an online innovation platform. For respondents whose firms had already run an innovation tournament, we measured participation intensity, number of ideas, and number of participants in the firm's latest innovation tournament. Finally, we measured the quality of the ideas emerging from the firm's latest innovation tournament.

Measures. We describe the measurement of all constructs, including all items, source(s), and reliability measures in Web Appendix 5.1. In Web Appendix 5.2, we show that our measures are unidimensional and reliable, that they exhibit divergent and convergent validity, and that common method variance and multicollinearity do not pose a threat in this study.

We developed three new scales for participation intensity (three items; $\alpha = .86$), number of ideas (three items; $\alpha = .88$), and number of participants (three items; $\alpha = .86$). To develop these new scales, we domain-sampled the constructs from extant literature in marketing and innovation and examined the reliability and validity of proposed measures to guarantee the purity of our scales (as recommended by Churchill 1979).

For all other constructs, we used existing scales published in the marketing literature as the basis and inspiration for our scales. For instance, following Luo and Toubia (2015), we measured idea quality by asking respondents to rate, using seven-point scales, whether the ideas generated in the latest innovation tournament at their firm were novel, insightful, valuable for customers, and well-articulated ($\alpha = .82$). We also collected an alternative measure of idea quality that considers the ideas' technical feasibility, novelty, specificity, and potential market demand (see Girotra, Terwiesch, and Ulrich 2010; Luo and Toubia 2015). We show in Web Appendix 5.3 that our results are robust to the usage of either of the two measures of idea quality. To measure new product performance, we used a five-item scale developed by Moorman (1995; $\alpha = .93$), and to measure overall business performance we used a three-item scale adapted from Jaworski and Kohli (1993; $\alpha = .88$).

Model Formulation and Estimation

We tested our hypotheses using a Bayesian SEM estimated on the subsample of firms that had already run an innovation tournament on an online platform (N = 516). Bayesian estimation is increasingly recognized as a more flexible approach to the estimation of theory-driven structural equation models than maximum likelihood (Muthén and Asparouhov 2012). We depict the descriptive statistics and bivariate correlations among all constructs in our model in this subsample of firms in Web Appendix 2. To compute these correlations, we averaged respondents' answers to the items in each of the scales to produce summated scales for each construct. In doing so, we followed the standard argument in psychometrics (Nunnally and Bernstein 1994) and in marketing research textbooks (Iacobucci and Churchill 2010) that it is both safe and useful to treat summated Likert scales as interval scales. For technical details about the econometric specification and estimation of our model, see Web Appendix 5.5.

Model Fit

We compared the fit of different models using the deviance information criterion (DIC), for which lower values indicate a better fit (Spiegelhalter et al. 2002). Individual DIC values are hard to interpret in absolute terms, and the Bayesian literature recommends comparing the differences in DIC between models ($\Delta_{\text{Avs.B}} = \text{DIC}_{\text{A}} - \text{DIC}_{\text{B}}$; Burnham and Anderson 2004), with a model (A) considered as having more support than an alternative model (B) if its DIC is more than 10 points below the DIC of the alternative model (i.e., $\Delta_{\text{Avs.B}} < -10$). We compare four models. Model 0 is a baseline model with only the control variables (i.e., number of employees and industry dummies) and where idea quality is not allowed to influence new product performance and overall business performance ($\text{DIC}_{\text{M0}} = 23{,}558$). In Model 1, we allow idea quality to influence new product performance and overall business performance but keep only number of employees and industry dummies as drivers of idea quality, which significantly improves model fit ($\text{DIC}_{\text{M1}} = 23{,}463$; $\Delta_{\text{1vs.0}} = -95$). In Model 2, we introduce the effects of number of ideas and number of participants on idea quality, which again leads to a significant improvement in model fit ($\text{DIC}_{\text{M2}} = 23{,}319$; $\Delta_{\text{2vs.1}} = -143$). When we introduce the effect of participation intensity in Model 3, the fit of the model again improves significantly ($\text{DIC}_{\text{M3}} = 23{,}278$; $\Delta_{\text{3vs.2}} = -42$; $\Delta_{\text{3vs.1}} = -185$; $\Delta_{\text{3vs.0}} = -280$). Thus, the optimal model, based on minimum DIC, is Model 3. We also estimate these same models using ordinary least squares models estimated using each construct's summated scales. Again, our full model shows the best fit (see Web Appendix 5.6).

Table 6. Bayesian SEM Results (Study 3; N = 516).

	Path Coefficients (Posterior Means)
Ideation quantity → Ideation quality	
Participation intensity → Idea quality	.45***
Number of ideas → Idea quality	.15
Number of participants → Idea quality	.35***
Ideation quality → Business outcomes	
Idea quality → New product performance	.73***
Idea quality → Overall business performance	.32***
New product performance → Overall business performance	.58***
Other variables	
Number of employees → Idea quality	.01
Number of employees → New product performance	−.13***
Number of employees → Overall business performance	.01
Industry dummies ‡ → Idea quality	See Web Appendix 6
Industry dummies ‡ → New product performance	See Web Appendix 6
Industry dummies ‡ → Overall business performance	See Web Appendix 6

Notes: We let all models converge and run each of our Bayesian SEM models for 35,000 draws with two chains. We then discarded the first 10,000 draws for burn-in and used the remaining 5,000 thinned draws for posterior inference (we used every 10th draw in each of the two chains to reduce autocorrelation). The parameter estimates reported in the second column are the posterior means of the path coefficients across all Markov chain Monte Carlo draws, excluding burn-in draws. We use "***" to indicate that the 99% credible interval of a parameter does not contain zero, "**" to indicate that the 95% credible interval does not contain zero, and "*" to indicate that the 90% credible interval does not contain zero.

‡The model controlled for industry dummies. See Web Appendix 6.

Results

Ideation quantity and ideation quality. We summarize our results in Table 6. In line with H_3, we find that the higher the participation intensity, the higher the quality of the ideas emerging from an innovation tournament ($\beta = .45$; 95% CI = [.27, .63]). In addition, we find that the number of participants enrolled in the tournament also has a positive effect on the ultimate quality of the ideas emerging from an innovation tournament ($\beta = .35$; 95% CI = [.12, .58]). In contrast, controlling for participation intensity and for number of participants, the number of ideas generated in the tournament does not have a significant impact on the ultimate quality of the ideas emerging from the tournament (β = .15; 95% CI = [–.11, .43]).

Ideation quality and business outcomes. In support of H_4, we find that the higher the quality of the ideas emerging from an innovation tournament, the higher a firm's new product performance ($\beta_{.}$ = .73; 95% CI = [.64, .83]) and the higher a firm's overall business performance ($\beta_{.}$ = .32; 95% CI = [.21, .42]). In addition, we find that the higher the new product performance, the higher the overall business performance (β = .58; 95% CI = [.47, .69]).

Other variables. We do not find a significant effect of firm size (i.e., number of employees) on the quality of the ideas emerging from an innovation tournament ($\beta_{.}$ = .01; 95% CI = [–.05, .06]). We find 12 (out of 39) significant industry-specific effects, seven of which are on new product performance and five of which are on idea quality. None of the industry-specific dummies had a significant effect on overall business performance (see Web Appendix 6 for details).

Discussion

Implications

Our work raises several important implications that are relevant to both theory and managerial practice. From a theoretical perspective, we highlight the importance of participation intensity in innovation tournaments as an important antecedent for idea quality, over and above number of ideas and number of participants, which are the more commonly used ideation quantity metrics in extant research (Bayus 2013; Girotra, Terwiesch, and Ulrich 2010; Terwiesch and Ulrich 2009). In addition, our research examines the key roles that the type of feedback and the timing of feedback play in affecting participation intensity in innovation tournaments. Whereas extant research focusing on feedback and goals provides conflicting expectations regarding the impact of type of feedback (positive versus negative) and timing of feedback (early versus late), our research provides clear confirmation and insights into why negative feedback early in an innovation tournament has a positive impact on participation intensity. These insights, although theoretically important, also have important managerial significance.

For example, for firms organizing and hosting innovation tournaments, these results document the value of feedback provision, whether internally provided or externally sourced. For third-party providers of innovation platforms, these results provide evidence they can present to their clients when they aim to sell moderator feedback services to their clients.

Moreover, our result that participation intensity is an important driver of idea quality, more so than number of ideas and number of participants, has implications regarding the measures on which firms should focus. Firms now routinely monitor only number of ideas and number of participants but do not always consistently monitor participation intensity. Our research calls for firms to pay more attention to participation intensity as a behavior to monitor, a metric to report, and an outcome to incentivize.

Practically, this may lead to many specific actions. To name just a few: Firms hosting innovation platforms may seed among ideators the expectation that ideators will view and update their idea over several rounds. Hosting firms may also consider stimulating updating behavior in ideators who show low participation intensity (i.e., who rarely visit the platform after submission) by using email campaigns, flyers, calls, or other forms of communication. Hosting firms should demand that third-party platform providers report participation intensity routinely (e.g., at the end of every day), rather than only reporting number of ideas and number of participants. Hosting firms may also use participation intensity as one of the key performance indicators for measuring the success of the tournament, and they may even negotiate with third-party platform providers to establish payment schedules that depend on participation intensity, especially if they have also secured moderator feedback services from that platform provider. When designing a request for quotation for third-party platform providers, and at these providers' pitch meetings, organizers of innovation tournaments should also push for historical evidence that a platform can generate and sustain participation intensity and make this metric a dimension on which they score or compare vendors.

Our findings also show that negative feedback beats positive feedback with regard to sustaining ideators' participation intensity in innovation tournaments. These findings enable firms organizing and hosting innovation tournaments that adopt moderator feedback to choose the right type of feedback to steer participation intensity. Innovation tournament organizers and firms supplying such services should train moderators to challenge participants' ideas and highlight the work that still needs to be done for the idea to be successful. Unambiguously signaling that more effort is needed for a participant to accomplish her goals, in turn, leads her to increase her efforts. We find in our study that positive feedback, in contrast, may not be as effective in driving participation intensity. Despite its potentially positive effects on motivation, positive feedback may have a deleterious influence on participation intensity by signaling that participants are already close to reaching their goals. We also find that negative feedback does not need to be sandwiched between positive feedback to be effective. These results demonstrate to companies that in the context of innovation tournaments, the "sandwich feedback strategy" (Craig 2016) is not more effective than negative feedback only.

Finally, moderators should frontload their criticism of ideas to the early rather than late stages of an innovation tournament, as the effectiveness of criticism on participation intensity seems to attenuate over time. This finding has several implications. For moderator training, it would imply that moderators should be instructed to adjust the timing of the feedback according to the feedback type, providing more negative feedback as early as possible. Also, innovation tournament organizers should think about the optimal timing of feedback rounds given the timeline of the tournament. Specifically, hosting firms should allow for a sufficient number of early rounds of feedback so that moderators have sufficient opportunity to detect and raise critical shortcomings in time for participants to still be able to update their idea to its full potential. Once the initiative nears its end, we find that feedback effectiveness diminishes. Given there will always be a cost associated with providing feedback, organizers can economize feedback by providing it only earlier in the tournament.

Limitations and Further Research

Our study has a few limitations that offer opportunities for future research. The first issue concerns the generalizability of our results to other contexts. Randomized field experiments in a real company context, although difficult to implement given a typical firm's strategic agenda when implementing an innovation tournament, would be very valuable. Also, it would be valuable to analyze historical data from one platform vendor, for instance, across many campaigns. Future research could confirm the generalizability of our findings to other types of crowdsourcing innovation beyond innovation tournaments, such as collaboration-based crowdsourcing (Afuah and Tucci 2012).

In our research, we did not study the impact of other participants' feedback (i.e., social feedback) on participation intensity. Thus, we cannot conjecture on the effect of social feedback and whether it is similar to the effect of moderator feedback. Research testing the generalizability of our findings to social feedback may yield valuable insights and provide new research topics to study such as feedback reciprocity, dyad (i.e., the person giving and the person receiving feedback) concordance or discordance effects, and the role of network position and other descriptors of the person giving feedback, to name just a few.

A related issue is whether the effects of internal feedback are different from those of external feedback. In reality, firms can choose to have their own staff provide feedback, which would ensure moderators with a strong firm identification, or have external staff without such firm identification provide feedback. Future research that clarifies whether moderators' identification with the firm makes a difference for the participation intensity on the platform may provide useful insights for firms as they deliberate whether to let an outside agency deliver feedback or assign internal resources to such feedback provision.

Our research did not measure the cost of feedback, nor did it estimate a model that allows trading off feedback cost and the increased idea quality one obtains thanks to such feedback. Therefore, although we can firmly say feedback can positively affect idea quality through participation intensity, we cannot infer the return on investment such feedback provision delivers. An analysis on the return on investment of different moderation strategies may provide firms with valuable insights on innovation tournament design. Beyond participation intensity, such analysis could include other dimensions of ideation quantity, such as number of participants, that also come at a cost (e.g., employee time).

We model pageviews and idea updating decisions as separate processes. Like all models, this is an abstraction of reality. In reality, it is more likely that these decisions are sequential. Participants first view their own idea and may then decide to update the idea. More generally, a participation episode in a crowdsourcing platform may follow an even richer sequence of different actions, such as a participant viewing her own idea, viewing feedback, viewing another participant's idea, returning to her own idea, viewing still another idea, updating her own idea, etc. Future research that conceptualizes the different participation patterns in a typology and models such patterns (e.g., as one would do with clickstream data) would allow studying additional research topics. For such inquiries, one would ideally have richer data than ours both in dimensionality (e.g., the number of movements throughout the platform) and in number of ideas or participants to enable sufficient statistical power to estimate more complex model structures.

One of the important findings in our research is that positive feedback is ineffective, which disconfirms what one may expect from self-determination theory. However, this finding rests mostly on the results of our Study 1, given that in Study 2 we did not manipulate positive feedback in isolation. Also note that in Study 2, we did manipulate negative plus positive feedback and did not find it to be more effective than negative feedback provided in isolation, which may reduce concerns about the possibility that positive feedback provided in isolation could be an effective driver of participation intensity in this study. Still, future research that manipulates all three types of feedback would offer a more rigorous replication and a valuable validation of the current findings. Moreover, future researchers may develop more variations in which positive feedback can be provided and examine whether some types of positive feedback are more effective than other types of positive feedback. Further validation across contexts and with different styles of positive feedback could thereby confirm, qualify, or complement the findings we report herein, thereby enriching the implications we present to firms as they consider their feedback strategy.

Finally, future research should explicitly test the mediating effect of participation intensity on the effect of feedback on idea quality. Formally examining the mechanisms through which feedback influences idea quality is a highly important theoretical question. Future experimental research could, for instance, not only experimentally manipulate feedback and measure participation intensity but also measure the quality of the output ideas in an innovation tournament. Such data would allow for a formal mediation analysis of the mechanism linking feedback to idea quality. We hope that this study will fuel the future research agenda of scholars in the crowdsourcing area, in which the managerial interest is currently still very much on the rise.

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References

Afuah, Allan, and Christopher L. Tucci (2012), "Crowdsourcing as a Solution to Distant Search," *Academy of Management Review*, 37 (3), 355–75.

Ai, Chunrong, and Edward C. Norton (2003), "Interaction Terms in Logit and Probit Models," *Economics Letters*, 80 (1), 123–29.

Bandura, Albert, and Daniel Cervone (1983), "Self-Evaluative and Self-Efficacy Mechanisms Governing Motivational Effects of Goal Systems," *Journal of Personality and Social Psychology*, 45 (5), 1017–28.

Bayus, Barry L. (2013), "Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community," *Management Science*, 59 (1), 226–44.

Bockstedt, Jesse, Cheryl Druehl, and Anant Mishra (2016), "Heterogeneous Submission Behavior and its Implications for Success in Innovation Contests with Public Submissions," *Production and Operations Management*, 25 (7), 1157–76.

Boudreau, Kevin, Nicola Lacetera, and Karim Lakhani (2011), "Incentives and Problem Uncertainty in Innovation Contests: An Empirical Analysis," *Management Science*, 57 (5), 843–63.

Boudreau, Kevin, and Karim Lakhani (2009), "How to Manage Outside Innovation," *MIT Sloan Management Review*, 50 (4), 69–76.

BrandIndex (2014), "Crowdsourcing Campaign Appears to Boost Brand Perception for Lay's," *Forbes*, (October 11), https://www.forbes.com/sites/brandindex/2014/10/11/crowdsourcing-campaign-appears-to-boost-brand-perception-for-lays/#481d0354571d.

Burnham, Kenneth P., and David R. Anderson (2004), "Multimodel Inference: Understanding the AIC and BIC in Model Selection," *Sociological Methods Research*, 33, 261–304.

Cameron, A. Colin, and Pravin K. Trivedi (2005), *Microeconometrics: Methods and Applications*. Cambridge, UK: Cambridge University Press.

Chandy, Rajesh K., and Gerard J. Tellis (1998), "Organizing for Radical Product Innovation: The Overlooked Role of Willingness to Cannibalize," *Journal of Marketing Research*, 35 (4), 474–87.

Chatterji, Aaron K., Michael Findley, Nathan M. Jensen, Stephan Meier, and Daniel Nielson (2016), "Field Experiments in Strategy Research," *Strategic Management Journal*, 37 (1), 116–32.

Chen, Yubo, Wang Qi, and Jinhong Xie (2011), "Online Social Interactions: A Natural Experiment on Word of Mouth versus Observational Learning," *Journal of Marketing Research* 48 (2), 238–54.

Churchill Jr., Gilbert A. (1979), "A Paradigm for Developing Better Measures of Marketing Constructs," *Journal of Marketing Research*, 16 (1), 64–73.

Cohen, Wesley M., and Richard C. Levin (1989), "Empirical Studies of Innovation and Market Structure," in *Handbook of Industrial Organization*, Vol. 2, R. Schmalensee and R.D. Willig, eds. Amsterdam: Elsevier Science Publishers, 1059–61.

Craig, William (2016), "How to Boost Your Constructive Criticism Skills," *Forbes*, (February 2), https://www.forbes.com/sites/williamcraig/2016/02/02/how-to-boost-your-constructive-criticism-skills/#5987375d6289.

Eagle, Nathan, Alex (Sandy) Pentland, and David Lazer (2009), "Inferring Friendship Network Structure by Using Mobile Phone Data," *Proceedings of the National Academy of Sciences*, 106 (36), 15274–78.

Finkelstein, Stacey R., and Ayelet Fishbach (2012), "Tell Me What I Did Wrong: Experts Seek and Respond to Negative Feedback," *Journal of Consumer Research*, 39 (1), 22–38.

Fishbach, Ayelet, and Ravi Dhar (2005), "Goals as Excuses or Guides: The Liberating Effect of Perceived Goal Progress on Choice," *Journal of Consumer Research*, 32 (3), 370–77.

Fishbach, Ayelet, Ravi Dhar, and Ying Zhang (2006), "Subgoals as Substitutes or Complements: The Role of Goal Accessibility," *Journal of Personality and Social Psychology*, 91 (2), 232–42.

Fishbach, Ayelet, Tal Eyal, and Stacey R. Finkelstein (2010), "How Positive and Negative Feedback Motivate Goal Pursuit," *Social and Personality Psychology Compass*, 4 (8), 517–30.

Fishbach, Ayelet, Ying Zhang, and Minjung Koo (2009), "The Dynamics of Self-Regulation," *European Review of Social Psychology*, 20 (1), 315–44.

Gill, Manpreet, Shrihari Sridhar, and Rajdeep Grewal (2017), "Return on Engagement Initiatives: A Study of a Business-to-Business Mobile App," *Journal of Marketing*, 81 (4), 45–66.

Gino, Francesca, Linda Argote, Ella Miron-Spektor, and Gergana Todorova (2010), "First, Get Your Feet Wet: The Effects of Learning from Direct and Indirect Experience on Team Creativity," *Organizational Behavior and Human Decision Processes*, 111 (2), 102–15.

Girotra, Karan, Christian Terwiesch, and Karl T. Ulrich (2010), "Idea Generation and the Quality of the Best Idea," *Management Science*, 56 (4), 591–605.

Gliedman, Chip (2013), "The Forrester Wave: Innovation Management Tools," (July 11), http://goodies.hypeinnovation.com/hs-fs/hub/314186/file-350087413-pdf/collateral/The_Forrester_Wave_Innovation_Management_Tools_Q3_2013.pdf.

Gneezy, Uri, Muriel Niederle, and Aldo Rustichini (2003), "Performance in Competitive Environments: Gender Differences," *The Quarterly Journal of Economics*, 118 (3), 1049–74.

Greene, William H. (2003), *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

Hattie, John, and Helen Timperley (2007), “The Power of Feedback,” *Review of Educational Research*, 77 (1), 81–112.

Heckman, James J. (1979), “Sample Selection Bias as a Specification Error,” *Econometrica*, 47 (1), 153–61.

Higgins, E. Tory (1987), “Self-Discrepancy: A Theory Relating Self and Affect,” *Psychological Review*, 94 (3), 319–40.

Hoetker, Glenn (2007), “The Use of Logit and Probit Models in Strategic Management Research: Critical Issues,” *Strategic Management Journal*, 28 (4), 331–43.

Hoffman, Donna L., Praveen K. Kopalle, and Thomas P. Novak (2010), “The ‘Right’ Consumers for Better Concepts: Identifying and Using Consumers High in Emergent Nature to Further Develop New Product Concepts,” *Journal of Marketing Research*, 47 (5), 854–65.

Homburg, Christian, Martin Klarmann, Martin Reimann, and Oliver Schilke (2012), “What Drives Key Informant Accuracy?” *Journal of Marketing Research*, 49 (4), 594–608.

Howe, Jeff (2006), “The Rise of Crowdsourcing,” *Wired*, 14 (6), 1–4.

Iacobucci, Dawn, and Gilbert A. Churchill, Jr. (2010), *Marketing Research: Methodological Foundations*, 10th ed. Stamford, CT: Cengage Learning.

Jaworski, Bernard J., and Ajay K. Kohli (1993), “Market Orientation: Antecedents and Consequences,” *Journal of Marketing*, 57 (3), 53–70.

Kluger, Avraham N., and Angelo DeNisi (1996), “The Effects of Feedback Interventions on Performance: A Historical Review, a Meta-Analysis and a Preliminary Feedback Intervention Theory,” *Psychological Bulletin*, 119 (2), 254–84.

Kornish, Laura J., and Karl T. Ulrich (2011), “Opportunity Spaces in Innovation: Empirical Analysis of Large Samples of Ideas,” *Management Science*, 57 (1), 107–28.

Kornish, Laura J., and Karl T. Ulrich (2014), “The Importance of the Raw Idea in Innovation: Testing the Sow’s Ear Hypothesis,” *Journal of Marketing Research*, 51 (1), 14–26.

Kurt, Didem, J. Jeffrey Inman, and Jennifer J. Argo (2011), “The Influence of Friends on Consumer Spending: The Role of Agency–Communion Orientation and Self-Monitoring,” *Journal of Marketing Research*, 48 (4), 741–54.

Luo, Lan, and Olivier Toubia (2015), “Improving Online Idea Generation Platforms and Customizing the Task Structure on the Basis of Consumers’ Domain-Specific Knowledge,” *Journal of Marketing*, 79 (5), 100–114.

Mallapragada, Girish, Rajdeep Grewal, and Gary Lilien (2012), “User-Generated Open Source Products: Founder’s Social Capital and Time to Product Release,” *Marketing Science*, 31 (3), 474–92.

Moorman, Christine (1995), “Organizational Market Information Processes: Cultural Antecedents and New Product Outcomes,” *Journal of Marketing Research*, 32 (3), 318–35.

Muthén, Bengt, and Tihomir Asparouhov (2012), “Bayesian SEM: A More Flexible Representation of Substantive Theory,” *Psychological Methods*, 17 (3), 313–35.

Nishikawa, Hidehiko, Martin Schreier, Christoph Fuchs, and Susumu Ogawa (2017), “The Value of Marketing Crowdsourced New Products as Such: Evidence from Two Randomized Field Experiments,” *Journal of Marketing Research*, 54 (4), 525–39.

Nunnally, Jum C., and Ira H. Bernstein (1994), *Psychometric Theory*, 3rd ed. New York: McGraw-Hill.

Ransbotham, Sam, Gerald C. Kane, and Nicholas H. Lurie (2012), “Network Characteristics and the Value of Collaborative User-Generated Content,” *Marketing Science*, 31 (3), 387–405.

Ringen, Jonathan (2015), “How Lego Became the Apple of Toys,” *Fast Company*, (January 8), https://www.fastcompany.com/3040223/when-it-clicks-it-clicks.

Ryan, Richard M., and Edward L. Deci (2000), “Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being,” *American Psychologist*, 55 (1), 68–78.

Sande, Jon Bingen, and Mrinal Ghosh (2018), “Endogeneity in Survey Research,” *International Journal of Research in Marketing*, 35 (2), 185–204.

Schmeichel, Brandon J., and Kathleen Vohs (2009), “Self-Affirmation and Self-Control: Affirming Core Values Counteracts Ego Depletion,” *Journal of Personality and Social Psychology*, 96 (4), 770–82.

Schwarz, Roger (2013), “Giving Feedback: The ‘Sandwich Approach’ Undermines Your Feedback,” *Harvard Business Review Blog*, (April 19), https://hbr.org/2013/04/the-sandwich-approach-undermin/.

Shanler, Amy, and Mari Martone (2007), “Staples Announces 2007 Staples Invention Quest Kid, Adult, and Associate Winners: Three Individuals Lauded as America’s Next Great Inventive Minds; Winners Selected by Expert Judges and America’s Vote,” (April 24), https://www.businesswire.com/news/home/20070424006005/en/Staples-Announces-2007-Staples-Invention-Quest-Kid.

Spiegelhalter, David J., Nicola G. Best, Bradley P. Carlin, and Angelika van der Linde (2002), “Bayesian Measures of Model Complexity and Fit,” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 64 (4), 583–639.

Spiller, Stephen A., Gavan J. Fitzsimons, John G. Lynch Jr., and Gary H. McClelland (2013), “Spotlights, Floodlights, and the Magic Number Zero: Simple Effects Tests in Moderated Regression,” *Journal of Marketing Research*, 50 (2), 277–88.

Stephen, Andrew T., Peter P. Zubcsek, and Jacob Goldenberg (2016), “Lower Connectivity is Better: The Effects of Network Structure on Redundancy of Ideas and Customer Innovativeness in Interdependent Ideation Tasks,” *Journal of Marketing Research*, 53 (2), 263–79.

Terwiesch, Christian, and Karl T. Ulrich (2009), *Innovation Tournaments: Creating and Selecting Exceptional Opportunities*. Boston, MA: Harvard Business School Press.

Verona, Gianmario, Emanuela Prandelli, and Mohanbir Sawhney (2006), “Innovation and Virtual Environments: Towards Virtual Knowledge Brokers,” *Organization Studies*, 27 (6), 765–88.

Wetzel, Hauke A., Maik Hammerschmidt, and Alex R. Zablah (2014), “Gratitude versus Entitlement: A Dual Process Model of the Profitability Implications of Customer Prioritization,” *Journal of Marketing*, 78 (2), 1–19.

Wooten, Joel O., and Karl T. Ulrich (2017), “Idea Generation and the Role of Feedback: Evidence from Field Experiments with Innovation Tournaments,” *Production and Operations Management*, 26 (1), 80–99.

Zelner, Bennet A. (2009), “Using Simulation to Interpret Results from Logit, Probit, and Other Nonlinear Models,” *Strategic Management Journal*, 30 (12), 1335–48.