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Stimulating innovation by user feedback on social media: The case of an online user innovation community

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ABSTRACT

With firms' increasing use of social media platforms, such as online user innovation communities (OUIs), customers are actively participating in firm-sponsored innovation activity by posting and commenting on new ideas for improving the firms' products and services, or to develop new ones. While it has been suggested that OUIs promote user interactions, it is largely unclear how other users' feedback may stimulate a focal user's contribution to such OUIs. Drawing on a media usage theory, we identify multifaceted benefits from user feedback that are cognitive, integrative and affective in the archival comments received by a focal user, and examine their individual and joint impacts on the user's future contribution in terms of both ideating and commenting behavior. We conduct a longitudinal study by collecting a large-scale, quantitative data set from a leading OUI between 2008 and 2015, which reveals novel findings on the nuanced role of user feedback on social media in stimulating innovation.

1. Introduction

Open innovation has received a significant amount of attention from both scholars and practitioners during the past few decades (Chesbrough, 2006; Dong and Netten, 2017). Central to this relatively new paradigm of innovation is that the purposive management of knowledge that flows across organizational boundaries can stimulate both internal innovation and the external use of innovation (Dong et al., 2017; Dong and Yang, 2015, 2016). This implies that firms can and should use both internal and external ideas to innovate. The emerging social media platforms are leading to new opportunities and challenges for open innovation (Ooms et al., 2015; Schemmann et al., 2016). Social media allows interactive online platforms where individual customers can share user-generated content, providing firms with the opportunity to sponsor a community of users who can generate new ideas for improving the firms' products and services or to develop new ones. In particular, online user innovation communities (OUIs) are firm-sponsored communities of users on social media platforms for generating new ideas about the products, services and processes of the firm (Dong and Wu, 2015; West and Lakhani, 2008). In OUIs, users can post, comment on, and vote for new ideas about innovation. Firms select the pertinent ideas from the OUIs for their innovation development to improve their products, services, and processes.

Innovation from OUIs has the potential to generate valuable

commercial outcomes, as ideas proposed by customers could even outperform those of professional developers (Magnusson, 2009) or company employees (Poetz and Schreier, 2012). While industry leaders have increasingly adopted OUIs to crowdsource ideation tasks, including Adobe, BBC, Best Buy, BMW, Dell, LEGO, Salesforce, Sears, and Starbucks, challenges exist in using OUIs for crowdsourcing as in many cases, the number of user-generated ideas declines over time (Huang et al., 2014). Therefore, understanding the drivers and barriers of user contribution to OUIs is critical for the success of crowdsourcing (Nambisan and Baron, 2010). The main courses of behavior by which users contribute to OUIs are, generating new ideas (idea contribution) and co-developing ideas posted by other users by providing feedback (comment contribution). Increasing the accumulation and co-creation of knowledge (Faraj et al., 2011) by stimulating the motivation of users to contribute is one of the biggest challenges for fostering OUIs (Chiu et al., 2006). Since OUIs appear as effective platforms of promoting interactions among users who operate in different social spheres and bring them together to foster innovation (Ooms et al., 2015), it is particularly interesting to study how users' comments may shape recipients' contribution to OUIs (Gebauer et al., 2013). We conduct a longitudinal study by collecting a large-scale, quantitative data set from a leading OUI between 2008 and 2015, which reveals novel findings on the nuanced role of user feedback on social media in stimulating innovation.

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With a focus on the OUIIC context, we identify the multifaceted benefits embedded in user feedback — the cognitive, integrative and affective benefits, based on the uses and gratifications (U & G) framework. Different from prior studies on the benefits with cross-sectional, self-reported survey data (e.g., Nambisan and Baron, 2007, 2009), we capture the benefits in objective archival comments made by users over a long period of time between 2008 and 2015. Furthermore, we examine both the direct effects of these benefits on user contribution to the OUIIC and their nuanced joint effects, which are either complementary or substitutable. To the best of our knowledge, no prior work has examined such joint effects of different benefits. We also measure user contribution to the OUIIC by two different types of behavior — ideating and commenting, which have not been considered separately in prior studies. We find distinct impacts of user feedback on ideating and commenting behavior, suggesting the necessity to separate these two types of user contribution.

The rest of this paper is organized as follows. Next, we present the U & G framework and develop our hypotheses. Following this, the methodology is detailed, and the results are reported. Subsequently, main findings and contributions, theoretical and managerial implications, limitations and directions for future research are discussed.

2. Theory and hypotheses

2.1. The uses and gratifications framework

While different theoretical frameworks might potentially offer clues about individuals' motivation and behavior, the U & G framework is particularly suitable for studying media usage (Katz et al., 1974). This framework has been widely used in the field of communication studies to identify the different types of benefits that users can obtain from media usage, and to explain how these benefits shape user behavior (e.g., Palmgreen, 1984; Parker and Plank, 2000; Stafford et al., 2004). Thus, the U & G framework focuses specifically on the use of media, including social media, and therefore provides a suitable lens through which to investigate the contribution of OUIIC users. In this study, we choose the U & G framework as the theoretical foundation guiding our theorizing about how different benefits from user feedback influence user contribution in the OUIIC context.

In early research, the U & G framework was mainly applied to study traditional media, based on a qualitative approach whereby statements about which specific needs could be fulfilled by media usage were collected from respondents and grouped into categories (e.g., Katz et al., 1974; Palmgreen, 1984; Palmgreen et al., 1981). Research drawing on the U & G framework has since been extended to social media (e.g., Flanagan, 2005; LaRose et al., 2001; Leung, 2001), which became a powerful means of understanding online users' motivation and behavior (Parker and Plank, 2000; Stafford et al., 2004). In particular, Nambisan and Baron (2007, 2009) applied the U & G framework to investigate the benefits from user interactions on social media platforms based on cross-sectional, self-reported survey data. Our study differs from prior efforts by examining the benefits that users derived from comments in OUIICs based on longitudinal, objective archival data. Because prior work on the U & G framework suggested that the benefits that users obtain from media usage are generated in their actual interactions in media usage (Palmgreen et al., 1981; Perse and Courtright, 1993; Prahalad and Ramaswamy, 2003), self-reported benefits based on perceptions are distinct from the actual benefits that we identify with archival comments.

The U & G framework identifies three types of benefits that users can derive from media use — cognitive, integrative and affective benefits — and proposes that the extent to which media usage offers these benefits will shape their participation in the media (Katz et al., 1974). *Cognitive benefits* relate to strengthening users' understanding of the environment owing to information acquisition; *integrative benefits* relate to strengthening users' credibility, status, confidence, and social ties; *affective*

benefits relate to strengthening users' aesthetic and pleasurable experiences (Katz et al., 1974; Nambisan and Baron, 2009). Next, we explain how such different benefits from other users' feedback influence, individually and jointly, a focal user's contribution to the OUIIC.

2.2. The direct effects of multifaceted benefits from user feedback

Past research has revealed that user feedback plays a key role in shaping individual behavior (Shute, 2008). In an OUIIC, user feedback in the form of comments on ideas represents the information acquired by a recipient in the online interactions. The more information a recipient acquires from other users' feedback, the better the recipient can learn from others (Liu and Carless, 2006; Yoon and Rolland, 2012), to understand other users' preferences in the market environment. As more elaborate comments can better facilitate learning from user feedback, a recipient is likely to gain higher cognitive benefits from the comments, which will enhance the recipient's future usage of the OUIIC by contributing more ideas or comments (Nambisan and Baron, 2009). Thus, we propose that greater cognitive benefits from user feedback associated with longer comments from other users are likely to increase a focal user's future contribution to the OUIIC.

H1. Cognitive benefits from user feedback have a positive effect on a user's future contribution to the OUIIC.

Despite the relative anonymity on online platforms (Lampel and Bhalla, 2007), deriving status benefits is an important reason for users to contribute to online communities (Nambisan and Baron, 2009; Wang and Fesenmaier, 2004). Obtaining a certain reputation or status can subsequently affect user contribution by signaling credibility (Dellarocas, 2005; Resnick and Zeckhauser, 2002). However, most interactions among users of OUIICs occur between those who have never previously interacted, implying that very few users can develop credible social ties with each other. The visible indicators of commenters, such as accumulated reputation and status (Resnick et al., 2000), therefore provide a recipient with a clear signal with which to easily judge their credibility (Brown et al., 2007), which strengthens the recipient's confidence and establishes social ties with commenters by reducing the information asymmetry (Ba, 2001; Nambisan and Baron, 2007), namely personal and social integrative benefits. Thus, we propose that greater integrative benefits from user feedback associated with better commenters' reputation and status are likely to increase a focal user's future contribution to the OUIIC.

H2. Integrative benefits from user feedback have a positive effect on a user's future contribution to the OUIIC.

Individuals who receive positive feedback can derive more pleasure, whereas negative feedback is more likely to be rejected or ignored by recipients (Greenwald, 1980; Ilgen et al., 1979; Markus, 1977; Tesser and Campbell, 1983). In an OUIIC, positive comments from other users give recipients a feeling of pleasure, because users often seek verification of performance for the ideas that they post (Bayus, 2013; Jeppesen and Molin, 2003). Therefore, positive feedback enhances self-image and leads to a better mood (Brown et al., 1988). Receiving positive feedback can also contribute to experiencing joy (Jeppesen and Molin, 2003) and emotional wellbeing (Ryan and Deci, 2001), thereby generating affective benefits that promote user contribution (Nambisan and Baron, 2007). On the other hand, negative feedback has a detrimental effect on the recipient's contribution (Ilgen and Davis, 2000). Thus, we propose that greater affective benefits associated with more positive comments are likely to increase a user's future contribution to the OUIIC.

H3. Affective benefits from user feedback have a positive effect on a user's future contribution to the OUIIC.

2.3. The interaction effects of multifaceted benefits from user feedback

In this study, we further take into account the nuanced interaction effects of different benefits from user feedback. We propose that cognitive benefits from information acquisition and understanding of the environment owing to user feedback might be strengthened or weakened in the presence of the other two types of benefits. Next, we explain why cognitive benefits are likely to have a negative interaction effect with integrative benefits and a positive interaction effect with affective benefits on user contribution to OUICs. Nevertheless, integrative benefits and affective benefits are unlikely to have an interaction effect, because without cognitive benefits from information acquisition, the information provided by other users cannot generate any benefits that are either social or hedonic. Thus, we focus our theorizing on how cognitive benefits may interact with integrative and affective benefits respectively to influence user contribution to OUICs.

We propose that the impacts of cognitive and integrative benefits from user feedback are likely to be substitutable for each other. A focal user who trusts another commenter with a credible reputation and status does not need to be persuaded by providing a lot of information (e.g., Uzzi, 1997). Because the visible indicators of commenters concerning their reputation and status can overcome information asymmetry in online communities (Bertarelli, 2015), integrative benefits associated with the high status of commenters may substitute the cognitive benefits from elaborate comments. In an OUIC, the cognitive benefits attributable to comment length are, therefore, less effective in determining a focal user's future contribution if the feedback is provided by high status commenters. Thus, we propose a negative interaction effect of cognitive benefits and integrative benefits on user contribution to the OUIC.

H4. Cognitive benefits and integrative benefits from user feedback have a negative interaction effect on a user's future contribution to the OUIC.

Furthermore, we propose that the impacts of cognitive and affective benefits from user feedback are likely to be complementary to each other. Because a recipient accepts positive feedback more readily than accepting negative feedback (Greenwald, 1980; Ilgen et al., 1979; Markus, 1977; Tesser and Campbell, 1983), the positivity of feedback is more effective in influencing user contribution to OUICs if the comments are lengthy and include a number of positive words. In an OUIC, affective benefits attributable to comment positivity are, therefore, more effective in determining a focal user's future contribution in the presence of lengthy comments consisting of more positive words. Thus, we propose a positive interaction effect of cognitive benefits and affective benefits on user contribution to the OUIC.

H5. Cognitive benefits and affective benefits from user feedback have a positive interaction effect on a user's future contribution to the OUIC.

3. Methodology

3.1. Data

We use a large-scale, quantitative data set from a leading OUIC — MyStarbucksIdea (mystarbucksidea.com) — to test our hypotheses. We select MyStarbucksIdea as our research site for four reasons. First, users of MyStarbucksIdea are involved in crowdsourcing for new products, services and processes, with good coverage of different types of innovation. Second, the data are openly available, which allows us to gather complete data for all users since the first day of joining MyStarbucksIdea. Third, Starbucks was one of the earliest adopters of OUICs, beginning on 26 March 2008, so it has been accumulating data for a considerable period of time. Finally, Starbucks is also a successful example of innovating with OUICs, having already implemented approximately 300 innovations, including new coffee flavors, splash sticks, cake pops, sugar-free syrups, mobile phone payment, free Wi-Fi,

free birthday treats, and the introduction of happy hours.

In this study, we adopt a longitudinal design because it is critical for testing our hypotheses suggesting that other users' feedback from previous commenting behavior can influence a focal user's future contribution to the OUIC, such as commenting behavior. The focal user's commenting behavior may in turn affect another user's contribution to the OUIC, such as commenting behavior. Testing of such a feedback loop requires longitudinal data over time, to observe the dynamism of user behavior. We collected data by developing a web scraping algorithm that uses the CSS and HTML structure of MyStarbucksIdea website, to download all data to a local database. The comments on an idea from the original poster of that same idea were removed from our analysis, to study the user feedback from others. The comments posted by Starbucks were also removed from our analysis, because they don't belong to user feedback. Our sample consists of 161,135 ideas and 318,581 comments, made between 26 March 2008 and 23 February 2015.

Since the data for each user need to be aggregated within a certain time window to measure the behavior in the next time window, we carefully choose the time window and test the sensitivity of our measures. A narrow time window makes it difficult to measure any behavior changes in each time window, whereas a wide time window leads to a smaller sample with less variance. In both cases the accuracy of the measurements decrease. We followed Bayus (2013) to use a daily time window in main analysis, and use a weekly time window in a supplement analysis. This aggregation process resulted in 326,857 user-day observations. We then excluded the observations without any comment from other users (i.e., no user feedback), thereby generating a final sample of 88,026 observations.

3.2. Measures

3.2.1. Dependent variables

We distinguish the two types of user contribution to the OUIC as ideating and commenting behavior. Count measures are used to capture ideating and commenting behavior (Bayus, 2013; Dong and Wu, 2015). More specifically, we measure *idea contribution* as the number of ideas posted by a focal user in a time window, and we measure *comment contribution* as the number of comments posted by a focal user in a time window. To avoid reverse causality, all other variables are lagged to our dependent variables for one time window.

3.2.2. Independent variables

Since the length of comments indicates the amount of information in user feedback (Joinson, 2001), we take a word count approach to measure *cognitive benefits*. More specifically, we count the number of words in each comment and then take the average as the proxy for cognitive benefits that a focal user receives from other users' comments.

Since commenters' reputation and status indicators provide a recipient with clues about their reputation and credibility (Brown et al., 2007; Dellarocas, 2005; Resnick and Zeckhauser, 2002), we measure *integrative benefits* by combining two indicators showing the reputation and credibility of commenters' previous ideating and commenting behavior. MyStarbucksIdea uses the "idea launched" indicator for users who have posted an idea that has since been implemented by Starbucks, and the "top commenter" indicator for highly active commenters (MyStarbucksIdea, 2015). The two badges are not mutually exclusive, and are visible to other users as they are displayed next to the username. Comments from users with launched ideas bring integrative benefits with good reputation and credibility in terms of ideating behavior. Commenters who have achieved "top commenter" status can show their good reputation and credibility in terms of commenting behavior (Liu and Carless, 2006). We code two binary variables indicating whether a focal user receives any comments in a specific day from other high status users who have previously launched ideas or are top commenters (0 = no; 1 = yes). We then take the average of the two

binary variables as the proxy for integrative benefits that a focal user receives from other users' comments.

Finally, since the positivity of comments is related to the pleasure of a recipient, we adopt a machine learning approach and follow Meyer et al. (2008) to conduct a sentiment analysis for measuring *affective benefits*. To calculate the measure, a Hypertext Preprocessor (PHP) script is created. All punctuation marks are removed from the comments to isolate full words between spaces. Our script selected all words separately from each comment and counted the numbers of words based on a list of positive or negative words from Hu and Liu (2004), resulting in the number of positive words (P) and the number of negative words (N). We then calculate a positivity ratio per comment by $P / (P + N)$. The average positivity ratio of comments in a specific day is used as the proxy for affective benefits that a focal user receives from other users' comments.

3.2.3. Control variables

Since the number of comments may also determine the amount of information in user feedback (Dong and Wu, 2015), we control *feedback amount* by the total number of comments received by a focal user in a specific day. In addition, timely feedback may be more effective than late feedback in shaping user contribution (Hattie and Timperley, 2007; Wooten and Ulrich, 2015). We control *feedback speed* by the average number of days between the dates when ideas were posted by a focal user and the first comments on corresponding ideas were provided by any other users. Table 1 provides the descriptive statistics for all variables, and Table 2 shows the correlations.

In our data, 126,108 unique users posted at least one idea in MyStarbucksIdea, with an average of 1.28 ideas per user. The average number of comments received by a user is 5.52, from 63,239 unique commenters. Therefore, approximately half of the users with ideating behavior also contribute by commenting. The average comment length is approximately 44 words. Users with launched ideas and/or who have been recognized as top commenters (henceforth, high status users) posted 10,225 ideas, whereas users without any such indicators (henceforth, low status users) posted 115,883 ideas in MyStarbucksIdea. With respect to commenting behavior, it is almost equally distributed between the two status groups, with high status users providing approximately 49% of comments. The comments in MyStarbucksIdea are more positive than negative with an average positivity ratio of 0.66.

4. Results

4.1. Hypotheses testing

We conducted several diagnostic tests before analyzing the data. First, the Skewness-Kurtosis test for normality was applied to assess the distribution of all variables. It indicated that the distributions of cognitive benefits and feedback amount are very skewed. Consequently, we took the natural logarithm to transform these two variables. Second, we checked whether there is multicollinearity by calculating the variance inflation factors (VIFs), which did not reveal any problems (mean VIF = 1.10, maximum VIF = 1.12). But we found that 27 observations have perfect prediction and therefore dropped them, leading to 87,999

Table 1
Descriptive statistics.

	Obs.	Mean	SD	Min	Max
Idea contribution	326,857	0.071	0.397	0	52
Comment contribution	326,857	0.651	2.601	0	153
Cognitive benefits (non-log)	88,026	47.372	46.736	0	702
Integrative benefits	88,026	0.246	0.347	0	1
Affective benefits	88,026	0.521	0.396	0	1
Feedback amount (non-log)	88,026	1.638	2.041	1	108
Feedback speed	88,026	160.690	345.322	1	2560

Table 2
Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Idea contribution						
(2) Comment contribution	-0.036					
(3) Cognitive benefits	-0.018	0.003				
(4) Integrative benefits	0.040	0.058	-0.058			
(5) Affective benefits	-0.009	-0.004	0.260	-0.119		
(6) Feedback amount	-0.002	0.022	0.089	0.375	-0.068	
(7) Feedback speed	-0.068	-0.048	0.055	-0.425	0.085	-0.197

Note: Correlations in bold are significant with $p < 0.05$.

observations for regression analysis.

Ordinary least squares (OLS) regression is not suitable for our data because the dependent variables have count scales. In this case, Poisson regression or negative binomial regression can be used (Hilbe, 2011). There is overdispersion for both dependent variables as the variance is greater than the mean, so negative binomial regression is appropriate (Gardner et al., 1995). Since our data have a panel structure, fixed effects or random effects model can be used to address potential endogeneity. Because our panel is highly unbalanced, fixed effects model is not able to deal with users who are only observed once and thereby may create sampling bias. Therefore, we estimate a random effects model by negative binomial regression.

The random effects negative binomial regression results are presented in Table 3. Model (1) presents the direct effects, whereas Model (2) includes the interaction effects. In Model (1), contrary to H1, cognitive benefits had a statistically significant and negative effect on idea contribution ($p < 0.05$). However, cognitive benefits also had a statistically significant and positive effect on comment contribution ($p < 0.1$). The results indicate significant opposing effects of cognitive benefits on the two types of user contribution. Thus, H1 was partially supported. Model (1) also verifies that integrative benefits has statistically significant and positive effects on both idea and comment contribution ($p < 0.01$). Thus, H2 was supported. In Model (1), however, affective benefits did not demonstrate any significant effects. Thus, H3 was not supported.

H4 hypothesizes that cognitive benefits and integrative benefits have a negative interaction effect on user contribution. Model (2) shows a statistically significant and negative interaction effect on idea contribution ($p < 0.05$), but not on comment contribution. Thus, H4 was partially supported. H5 hypothesizes a positive interaction effect of cognitive benefits and affective benefits on user contribution. Model (2) indicates a statistically significant and positive interaction effect on idea contribution ($p < 0.05$), but not on comment contribution. Thus, H5 was also partially supported.

The control variable, feedback amount, had statistically significant and negative effects on both idea and comment contribution ($p < 0.01$), which might be driven by information overload problems (Dong and Wu, 2015). Furthermore, feedback speed also had statistically significant and negative effects on both idea and comment contribution ($p < 0.01$), indicating that a prompt response from other users can promote both types of user contribution (Nambisan and Baron, 2009; Wooten and Ulrich, 2015).

4.2. Supplement analysis

We conducted some supplement analyses to offer additional insights from the data. As the results show in Table 4, although most hypotheses

Table 3
Random effects negative binomial regression results for hypotheses testing.

	(1)		(2)	
	Idea contribution	Comment contribution	Idea contribution	Comment contribution
Cognitive benefits	− 0.038** (0.018)	0.041* (0.023)	− 0.051* (0.030)	0.081** (0.040)
Integrative benefits	0.201*** (0.050)	0.273*** (0.059)	0.503*** (0.148)	0.497*** (0.181)
Affective benefits	0.018 (0.046)	0.072 (0.057)	− 0.304** (0.150)	0.184 (0.192)
Cognitive benefits × integrative benefits			− 0.093** (0.043)	− 0.067 (0.051)
Cognitive benefits × affective benefits			0.103** (0.046)	− 0.035 (0.057)
Feedback amount	− 0.196*** (0.035)	− 0.121*** (0.037)	− 0.183*** (0.035)	− 0.118*** (0.037)
Feedback speed	− 0.001*** (0.000)	− 0.001*** (0.000)	− 0.001*** (0.000)	− 0.001*** (0.000)
Constant	0.049 (0.104)	− 1.184*** (0.097)	0.070 (0.126)	− 1.314*** (0.141)
Wald Chi-square	187.75***	167.18***	199.29***	168.33***

Note: $n = 87,999$. Standard errors are in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

were still supported, weekly aggregated data could explain fewer relationships compared to the daily aggregated data. Interestingly, a statistically significant and positive effect of integrative benefits on comment contribution was also found. Such differences across time windows may be explained by the fact that a longer time lag exists between the benefits from user feedback and ideating behavior compared to commenting behavior (Nambisan and Baron, 2009).

Furthermore, we conducted a subsample analysis across high status users (see Table 5) and low status users (see Table 6). We found the results mostly hold for low status users rather than high status users. A possible explanation is that high status users have higher levels of pre-existing self-efficacy due to enhanced cognitive and integrative benefits derived from past participation in OUICs (Nambisan and Baron, 2007, 2009). Therefore, they may not be influenced by short-term commenting behavior of other users. High status users may also be more motivated to sustain personal integrative benefits that they can derive from their high status, rather than from user feedback.

5. Discussion and implications

5.1. Main findings and contributions

Although OUICs promote the interactions of users, how such interactions shape their motivation and contribution is largely unexplored. This paper contributes to the research on social media and innovation by linking different benefits from user feedback to recipients' future contribution in the OUIC context. Cognitive, integrative and affective benefits are conceptualized and captured in other users' feedback, and these benefits may individually and jointly impact a focal

user's contribution to the OUIC. We conduct a longitudinal study by collecting a large-scale, quantitative data set from a leading OUIC between 2008 and 2015, which reveals new findings on the nuanced role of user feedback on social media in stimulating innovation.

Some interesting and unexpected findings deserve discussion. In particular, we find that cognitive benefits from user feedback can promote a user's contribution in terms of commenting behavior. Contrary to our expectation, however, a negative effect of cognitive benefits on ideating behavior is found. A supplement analysis based on the sub-samples of high and low status users has provided more insight regarding these contradictory effects. The results indicate that the negative effect of cognitive benefits is only significant for high status users, which suggests that cognitive benefits from elaborate comments are not applicable to them. High status users, who are top commenters capable of co-developing ideas, are therefore likely to switch their efforts from ideating to commenting if they better understand other users' preferences in the market environment, by gaining more cognitive benefits from user feedback.

Although no direct effect of affective benefits is observed, we find that affective and cognitive benefits can jointly impact a user's contribution in terms of ideating behavior. This finding provides new insight into how cognitive benefits can be enhanced by affective benefits. Breaking the chain of decreased ideating behavior due to cognitive benefits, but without negatively impacting commenting behavior, can be a fruitful way to increase user contribution to the OUIC. Affective benefits can mitigate the negative effect of cognitive benefits from user feedback on ideating behavior. In other words, if other users' comments are both elaborate and positive, a focal user may increase both ideating and commenting behavior. In addition, cognitive benefits from

Table 4
Random effects negative binomial regression results for weekly data.

	(1)		(2)	
	Idea contribution	Comment contribution	Idea contribution	Comment contribution
Cognitive benefits	− 0.048*** (0.011)	0.019** (0.009)	− 0.057*** (0.017)	0.023 (0.015)
Integrative benefits	0.214*** (0.038)	− 0.488*** (0.035)	0.230** (0.109)	− 0.421*** (0.117)
Affective benefits	− 0.040 (0.028)	0.037 (0.023)	− 0.108 (0.090)	0.044 (0.079)
Cognitive benefits × integrative benefits			− 0.005 (0.033)	− 0.020 (0.032)
Cognitive benefits × affective benefits			0.022 (0.027)	− 0.002 (0.023)
Feedback amount	− 0.453*** (0.026)	0.372*** (0.011)	− 0.452*** (0.026)	0.372*** (0.011)
Feedback speed	0.001*** (0.000)	− 0.000*** (0.000)	0.001*** (0.000)	− 0.000*** (0.000)
Constant	0.095 (0.062)	0.137*** (0.041)	0.118* (0.072)	0.126** (0.055)
Wald Chi-square	1769.67	1433.66	1770.97	1435.47

Note: $n = 46,846$. Standard errors are in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table 5
Random effects negative binomial regression results for high status users.

	(1)		(2)	
	Idea contribution	Comment contribution	Idea contribution	Comment contribution
Cognitive benefits	− 0.081** (0.041)	0.004 (0.036)	− 0.130* (0.068)	0.052 (0.065)
Integrative benefits	0.184* (0.112)	0.130 (0.092)	0.192 (0.308)	0.295 (0.273)
Affective benefits	− 0.087 (0.106)	0.082 (0.094)	− 0.490 (0.348)	0.274 (0.310)
Cognitive benefits × integrative benefits			− 0.001 (0.089)	− 0.051 (0.077)
Cognitive benefits × affective benefits			0.128 (0.105)	− 0.061 (0.093)
Feedback amount	− 0.115* (0.063)	− 0.179*** (0.053)	− 0.107* (0.064)	− 0.180*** (0.053)
Feedback speed	− 0.001*** (0.000)	− 0.002*** (0.000)	− 0.001*** (0.000)	− 0.002*** (0.000)
Constant	0.323* (0.195)	− 0.679*** (0.142)	0.448* (0.246)	− 0.825*** (0.219)
Wald Chi-square	40.71***	82.80***	42.65***	83.38***

Note: $n = 8786$. Standard errors are in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table 6
Random effects negative binomial regression results for low status users.

	(1)		(2)	
	Idea contribution	Comment contribution	Idea contribution	Comment contribution
Cognitive benefits	− 0.028 (0.020)	0.067** (0.028)	− 0.032 (0.034)	0.101** (0.049)
Integrative benefits	0.221*** (0.056)	0.345*** (0.075)	0.593*** (0.167)	0.537** (0.239)
Affective benefits	0.037 (0.050)	0.071 (0.070)	− 0.254 (0.167)	0.178 (0.238)
Cognitive benefits × integrative benefits			− 0.115** (0.049)	− 0.058 (0.068)
Cognitive benefits × affective benefits			0.093* (0.051)	− 0.034 (0.071)
Feedback amount	− 0.239*** (0.042)	− 0.096* (0.051)	− 0.224*** (0.042)	− 0.094* (0.051)
Feedback speed	− 0.001*** (0.000)	− 0.001*** (0.000)	− 0.001*** (0.000)	− 0.001*** (0.000)
Constant	− 0.050 (0.127)	− 1.718*** (0.133)	− 0.052 (0.152)	− 1.827*** (0.183)
Wald Chi-square	164.72***	109.76***	175.17***	110.02***

Note: $n = 79,213$. Standard errors are in parentheses.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

elaborate comments, and integrative benefits from low status users, reinforce each other in their joint impact on ideating behavior. In line with our theory, low status users may compensate for their lack of credibility and trustworthiness by posting more elaborate ideas.

Our contributions to the literature are threefold. First, with a focus on the OUI context, we identify the multifaceted benefits embedded in user feedback — the cognitive, integrative and affective benefits, based on the U & G framework. Different from prior studies on such benefits, which relied on cross-sectional, self-reported survey data (e.g., Nambisan and Baron, 2007, 2009), we capture the benefits from objective archival comments made by users over a long period of time between 2008 and 2015. Second, we examine both the direct effects of these benefits on user contribution to OUIs and their nuanced joint effects, which are either complementary or substitutable. To the best of our knowledge, no prior work has examined such joint effects of different benefits. Finally, we measure user contribution to OUIs by two different types of behavior — ideating and commenting, which have not been considered separately in prior literature. We find distinct impacts of user feedback on ideating and commenting behavior, suggesting the necessity of separating these two types of user contribution. Overall, we extend the U & G framework by better capturing the multifaceted benefits in the OUI context, considering both their direct and interaction effects on user contribution, while providing new insights into their distinct impacts in shaping users' ideating and commenting behavior.

5.2. Managerial implications

Our study provides a number of actionable implications for

managers in design and management of OUIs for crowdsourcing, which may be applicable to other firms' OUIs (e.g., Dell IdeaStorm and LEGO Ideas). However, it should be stressed that managers need to be cautious when generalizing these implications to other types of social media platforms, such as online innovation contest communities (OICCs).¹ We expect that in OICCs (e.g., IdeaConnection and InnoCentive), most users are professionals rather than customers, and the inherent fierce competition for rewards may inhibit the provision of, and benefiting from, user feedback.

To design and manage OUIs, first, a word limit for comments could be used to reduce the negative effect of cognitive benefits on the ideating behavior of high status users, while reducing the commenting behavior of low status users in the meantime. However, as low status users in OUIs cannot compensate for their lack of credibility and trustworthiness by writing elaborate comments, any such word limit could be implemented only for high status users. In addition, because the positive effect on a user's idea contribution of receiving elaborate and positive comments cannot be sustained (the direct effect of cognitive benefits is much weaker than the interaction effect of cognitive benefits and affective benefits), it could be argued that the imposition of a word limit could be detrimental. Perhaps the safest policy would be to stimulate low status users to post elaborate comments.

Second, managers should aim to increase the feedback comments of high status users in OUIs, because these comments have a strong positive impact on other users' contribution. The downside, however, is

¹ We thank one anonymous reviewer who suggested this point.

that it will also promote the commenting behavior of low status users, which subsequently can have a negative impact on other users' contribution. Because elaborate, positive comments promote ideating behavior, and will potentially overcome the negative effect of cognitive benefits, they need to be encouraged.

Third, managers may also consider integrating some status indicators into OUIs. This would allow users to derive integrative benefits from such indicators, and in the meantime, would encourage these highly valuable individuals to join OUIs. The practical implementation of such a design leaves room for managerial creativity, but this could include status indicators such as “education level”, “marketing specialist”, “financial specialist”, and “innovation specialist”, among others. However, a robust screening protocol should be in place, because without a certification system any such status indicators would not work efficiently.

Finally, managers could alter the standard order in which ideas are displayed in OUIs. In MyStarbucksIdea, the default sortation is based on idea popularity, though there are alternative ways in which users can alter this manually. The current standard sortation facilitates user feedback on the most popular ideas. However, as the results indicate, user feedback is not always beneficial to a user's contribution to OUIs. In fact, as shown in this study, it can even have a detrimental effect. For example, the speed of the receipt of any feedback is a strong determinant of user contribution, so managers could alter the standard sortation to a recency order and thereby stimulate prompt responses from users.

5.3. Limitations and future research

This study has some limitations. First, the generalizability of our results is limited by OUIs. Other types of social media platforms, such as OICs, may attract different types of users. Following the model of Füller (2010), who differentiated between four user types with distinct motivations — reward-oriented, intrinsically interested, curiosity-driven, and need-driven — it is likely that we do not observe the behavior of the first category because MyStarbucksIdea does not offer extrinsic rewards. In OICs, professionals compete for extrinsic rewards, such as monetary incentives or career opportunities offered to the best solutions, which may discourage users from providing useful feedback to others. Moreover, some social media platforms may allow users to participate in the later stages of the innovation process, such as product development, testing or commercialization.² Future research could examine our findings in other social media contexts.

Second, the individual characteristics of users are not taken into account in our analysis due to data availability. However, they are important for processing feedback (Shute, 2008). For example, Nambisan and Baron (2009) suggested that individuals might differ in the amount of pre-existing self-efficacy that affects user interactions. Although random effects model can partly address this issue by controlling the omitted variables that are time-invariant but vary between individuals and the omitted variables that are time-variant but fixed between individuals (Greene, 2000), individual differences may be potential confounding factors. Future research could incorporate more variables, if possible, to better control for individual differences.

Finally, our supplement analysis indicates some potentially fruitful directions for future research. We have found clear differences in the effects of the benefits from user feedback on different status user groups. While possible explanations have been provided in the discussion, however, more research is needed to be conclusive. In addition, the counter-intuitive results regarding the control variables, such as the negative impact of the number of received comments on both ideating and commenting behavior, suggest interesting directions for future research.

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