Using Anonymity and Communal Efforts to Improve Quality of Crowdsourced Feedback

Julie Hui,* Amos Glenn,[+] Rachel Jue,[+] Elizabeth Gerber,[§] and Steven Dow[+]

*Northwestern University
juliehui@u.northwestern.edu; egerber@northwestern.edu

[+]Carnegie Mellon University
{amosg,rjue}@andrew.cmu.edu; spdow@cs.cmu.edu

Abstract

Student innovators struggle to collect feedback on their product pitches in a classroom setting due to a lack of time, money, and access to motivated feedback providers. Online social networks present a unique opportunity for innovation students to quickly access feedback providers by leveraging their online social capital. In order to better understand how to improve crowdsourced online feedback, we perform an experiment to test the effect of online anonymity on feedback quality and quantity. We also test a *communal feedback* method—evenly distributing between teams feedback providers from the class's collective online social networks—which would help all teams benefit from a useful amount of feedback rather than having some teams receive much more feedback than others. We found that feedback providers in the anonymous condition provided significantly more *specific criticism* and *specific praise*, which students rated as more useful. Furthermore, we found that the *communal feedback* method helped all teams receive sufficient feedback to edit their innovation pitches. This research contributes an empirical investigation of how online social networks can help student innovators obtain authentic feedback to improve their work.

Figure 1. Student entrepreneurs often fail to collect sufficient feedback before pitching to professionals.

Introduction

Innovators seek specific, diverse, and authentic user feedback throughout their work process to produce and implement high quality products and services (Tohidi et al. 2006a). In professional settings, innovators may readily recruit from dedicated, paid subject pools, or hire trained researchers to perform user testing. However, in educational settings, students lack expertise, time, money, and access to many target user groups, and therefore are often only able to receive feedback from a handful of acquaintances (Dow, Gerber, and Wong 2013; Hui, Gerber, and Dow 2014). To address this problem, crowdsourcing researchers have investigated the efficacy of recruiting feedback providers through crowdsourcing platforms, such as Amazon Mechanical Turk, where feedback is cheap and less biased (Hui, Gerber, and Dow 2014; Xu and Bailey 2012; Xu, Huang, and Bailey 2014). While such an approach supports affordable, quick access to users, feedback from unknown members of the crowd has been found to be superficial and disorganized (Dow, Gerber, and Wong 2013; Easterday et al. 2014; Xu and Bailey 2012). Some design researchers have addressed this issue by creating tools to support structured feedback online (Easterday et al. 2014; Xu, Huang, and Bailey 2014; Luther et al. 2014). We explore the use of social networking platforms, such as Facebook and Twitter, to provide a new opportunity for eliciting feedback from accessible and motivated feedback providers (Ringel Morris, Inkpen, and Venolia 2014).

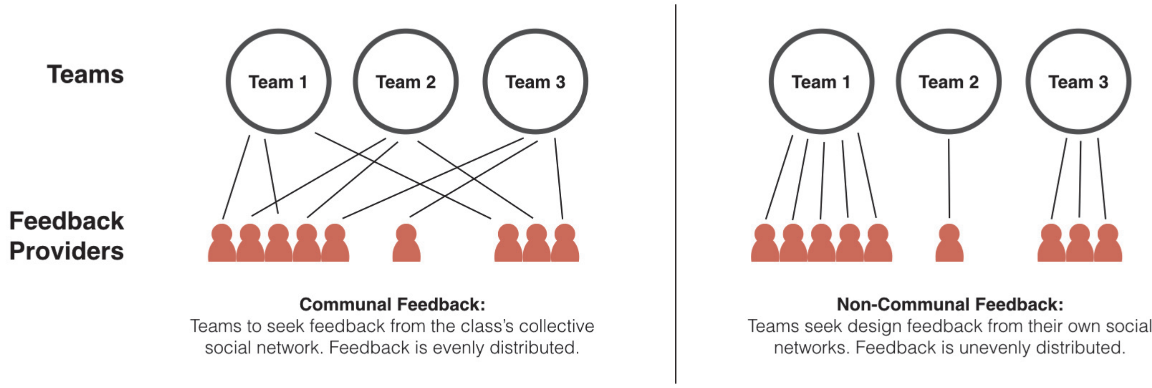

Figure 2. Communal feedback (left) allows all teams to seek a sufficient amount of crowdsourced feedback. Non-communal feedback (right) has teams with more social capital receiving much more feedback than others, which is not ideal in a classroom setting.

However, both *asking for* and *giving* feedback through online social networks can be problematic. First, the quality and quantity of feedback responses could be limited by one's social capital (Gray et al. 2013; Jung et al. 2013). Social capital – the quantification of one's social network to provide information and support (Putnam 2001; Williams 2006) – is determined by the types of relationships people have with others and how well they are maintained (Ellison, Steinfield, and Lampe 2011; Ellison et al. 2014). Therefore, students with low levels of social capital may not receive sufficient useful feedback from their personal social networks.

Second, to *give* useful and authentic input, feedback providers must feel "license to be critical" (Tohidi et al. 2006b). Existing social relationships may exacerbate participant response bias (Dell et al. 2012; Ren et al. 2012) and self-presentation activities (Erving Goffman 2012), where feedback providers strategically modify their responses to present socially desirable traits and maintain social ties. This could lead feedback providers to offer only affirmative or non-specific feedback to avoid negatively affecting inter-personal relationships. In order to understand how to leverage online social capital while maintaining feedback providers' "license to be critical," we ask the following two questions:

RQ1: How can we leverage student online social capital to seek feedback in the classroom setting?
RQ2: What is the affect of anonymity on feedback from online social networks?

To address the first question, we take a *communal feedback* approach—evenly distributing between teams feedback providers from the class's collective online social networks (Figure 2). This would allow all teams an equal chance to collect a useful amount of feedback, as opposed to the non-communal approach where some teams could end up collecting much more feedback than others. To address the second question, we perform an experiment by testing if feedback provider anonymity has an effect on the feedback quantity, quality, and type given.

The results suggest that the communal approach is a viable way to help more innovation students with various levels of social capital to solicit feedback. In addition, the experimental results suggest that anonymous feedback providers give significantly more specific criticism and specific praise, which students found to be more useful than non-specific feedback. We also provide evidence of how feedback from online social networks influences student innovation work and how students perceive online feedback in comparison to face-to-face user research methods. We emphasize that crowdsourcing feedback from online social networks is not meant to replace, but to supplement current user-research methods, especially in the case where student innovators have limited funds or access to potential feedback providers.

This research makes two contributions to crowdsourcing research: (1) Strategies for innovation teams in a classroom setting to seek a useful amount of critical feedback from online social networks, and (2) An empirical investigation of how crowdsourcing feedback from online social networks can be used to support student innovation.

Related Work

We ground our work and study design decisions based on research on innovation, HCI, and learning sciences.

Challenges with User Feedback

Innovators have long faced challenges obtaining authentic and constructive feedback from users. Feedback providers have been shown to alter their responses depending on their relationship with the person seeking feedback (Paulhus 1991), an effect known as participant response bias. For example, recent HCI work describes how users are 2.5x more likely to favor the designed artifact if they believe the interviewer developed it, and 5x more likely to favor the artifact if the interviewer is also a foreign researcher (Dell et al. 2012). Balance theory (Heider 1958; Holland and Leinhardt 1974) explains how people are more likely to adopt a positive attitudes towards an object if they believe someone else they have positive feelings towards, such as a friend, also thinks positively about the object. Therefore, if a feedback provider believes the feedback seeker has created the artifact and wants to support the feedback seeker, then the feedback provider will sway their opinions positively.

To avoid these issues and help obtain more authentic feedback, designers have devised various strategies, including distancing themselves from the artifact by saying someone else had created the artifact (Dell et al. 2012) or seeking feedback on multiple artifacts (Dow et al. 2012; Tohidi et al. 2006b). For instance, Tohidi et al. found that users felt more comfortable providing critical feedback when presented with multiple prototypes compared to just one (Tohidi et al. 2006b). In addition, Dow et al. found that these parallel prototyping strategies also helped designers produce better prototypes by reducing fixation on one design (Dow et al. 2010). Such established techniques reaffirm the ongoing need to identify reliable strategies to seek feedback in new contexts, such as in online social networks.

Anonymous Feedback

Anonymity may help reduce participant response bias, especially in situations where the feedback provider knows the feedback seeker. The anonymous feedback strategy is well understood in peer review contexts where all students create an artifact and anonymously review each others' work (Howard, Barrett, and Frick 2010; Lu and Bol 2007). Lu and Bol found that anonymous peer reviewers provided more negative comments and rated work lower than identifiable peer reviewers (Lu and Bol 2007). Similarly, Howard et al. (Howard, Barrett, and Frick 2010) found that students who anonymously provided feedback through computer-mediated communication on their peers' websites are approximately five times more likely to give critical feedback than students who were identifiable. We expect to observe similar behavior in the online setting, and hypothesize:

H1: Feedback providers are more likely to drop out in the identifiable condition.
H2: Anonymous feedback providers will provide more feedback than identifiable feedback providers.
H3: Anonymous feedback providers will provide more useful feedback than identifiable feedback providers.
H4: Anonymous feedback providers will provide more criticism than identifiable feedback providers.

Prior work has examined the effects of anonymity on feedback through electronic meeting software (Rains 2007), course management systems (Lu and Bol 2007), and other early communication channels like email (Zhao 1998), but not the effect of anonymity on social media feedback. Research shows that communication channel affects how people react and respond to online requests (Leonardi et al. 2012). Furthermore, unlike the previous studied peer and group feedback contexts where the teacher or class peers are required to give feedback to each other, feedback through social media is voluntary. While previous research demonstrates the benefits of anonymous feedback among class peers, it is not immediately clear whether anonymity is beneficial or desirable when seeking feedback from online social networks. Unlike peers whose grades are often determined in comparison to each other, external reviewers have less at stake. Innovators obtaining feedback through social networks may want to identify the feedback provider in order to better contextualize their input (e.g., Does this comment come from mom or a potential user?). Furthermore, feedback providers may actually want to provide their identity so that they may build social capital with the requester. Therefore, we also hypothesize:

H5: Identifiable feedback providers will provide more praise than anonymous feedback providers.

While the affect of anonymity has been studied in the classroom context where peers provide feedback on each other's work, less research has been performed to understand the affect of anonymity on feedback in the online context, and whether it is or is not desirable.

Feedback from Online Crowds and Social Networks

In professional design firms, designers have access to subject pools where people participate in studies for pay. With the growth of online networking platforms, HCI researchers have begun to explore how to use online crowds as participant pools in order to tap into a larger and more diverse population of users (Reinecke et al. 2013), such as soliciting feedback for fashion advice (Ringel Morris, Inkpen, and Venolia 2014), visual design (Luther et al. 2014; Xu and Bailey 2012; Xu, Huang, and Bailey 2014; Xu et al. 2015), and student-created artifacts (Dow, Gerber, and Wong 2013; Hui, Gerber, and Dow 2014; Xu et al. 2015). For instance, Ringel-Morris et al. found that crowdsourced shopping advice was more influential than asking friends for shopping advice (Ringel Morris, Inkpen, and Venolia 2014). Other researchers have explored how to provide meaningful feedback on visual design artifacts for novices (Dow, Gerber, and Wong 2013; Xu and Bailey 2012).

Gathering data online, either friendsourced through online social networks or crowdsourced though Mechanical Turk, has been shown to result in a larger volume of responses than in-person methods (Easterday et al. 2014; Ringel Morris, Inkpen, and Venolia 2014; Xu and Bailey 2012). However, while researchers find use in quantity and diversity of online feedback, there are still discrepancies in quality. Hui et al. (Hui, Gerber, and Dow 2014) noted that crowdsourced feedback can have self-selection biases and provide less in-depth responses than in-person feedback. Seeking quality feedback online can cost money and students are often hesitant to spend money to seek online feedback on their school work (Hui, Gerber, and Dow 2014). Social media provides another large and expansive pool of feedback providers when students can no longer pay for other forms of crowd feedback.

This paper explores an opportunity to leverage online social networks, an environment where people may be more intrinsically motivated to give quality feedback given the relationship to the requestor (Ringel Morris, Inkpen, and Venolia 2014). Soliciting feedback on social networking platforms is not only inexpensive, it may also allow student innovators to tap into relevant domain knowledge present in their immediate social network (Ringel Morris, Inkpen, and Venolia 2014) or seek feedback from people they trust more (Oeldorf-Hirsch et al. 2014; Ringel Morris, Inkpen, and Venolia 2014).

However, not all students benefit equally from using online social networks when gathering feedback. Successfully soliciting feedback from one's network may be dependent on a number of factors, including the way people word their request (Jung et al. 2013) or level of social capital (Gray et al. 2013; Jung et al. 2013). Lampe et al. (Lampe et al. 2011) describe how bridging social capital online allows people access to new ideas whereas bonding social capital yields dense networks of support. In the context of question asking and answering on social networking platforms, Gray et al. found that bridging social capital positively predicted more useful responses (Gray et al. 2013). However, neither bridging nor bonding social capital supported responses to favor requests on social networking platforms (Jung et al. 2013).

In order to build bridging social capital, one must put meaningful effort into relationship maintenance online (Ellison et al. 2014). Ellison et al. describe how the affordances of social networking sites, like Facebook, provide new ways for relationship maintenance and development by connecting people with similar interests and making social information readily available to others (Ellison, Steinfield, and Lampe 2011). Despite efforts to build and use social capital, Rezeszotarski and Ringel-Morris found that at a certain level, people would rather pay a certain monetary cost than endure the social costs of friendsourcing (Rzeszotarski and Morris 2014).

Research on crowdfunding platforms, a type of online innovation community, show that innovators often fail to seek feedback on their pitches before their campaigns launch. Although, crowdfunders seek feedback during their campaign and through social media, they find that failing to make a successful initial first impression hurts their changes of reaching their funding goal. Furthermore, while there exist many online design communities, like Dribbble and Behance, they are used more to show finished work rather than to seek feedback on work-in-progress (Marlow and Dabbish 2014). Xu and Bailey studied a photography critique community and found that quality of feedback was helpful to a degree, but offered few deep insights and with low degree of critique reciprocity (Xu and Bailey 2012). Our work was motivated by seeing student innovators voluntarily post their work on social networks, like Facebook, with requests for feedback. In alignment with recent studies on crowdsourcing, we believe it is imperative to understand the evolving use of social media in modern educational and work practices that lead to better feedback and improved work.

Methods

Our study has two purposes: empirically test the effect of *anonymity* on feedback collected from online social networks while also qualitatively observing the value of the *communal feedback* approach to this activity.

This experiment took place in a class where students were asked to design and pitch a new mobile app. The artifact used in this exercise was each team's written product pitch.

Participants

There are two types of participants in this study. Student participants include 55 undergraduate and masters students enrolled in a mobile application design class during Spring 2014 at a mid-size East Coast university. Students worked in ten teams of four to six students. The class included students with design expertise ranging from less than one year to over four years of experience, and with a wide array of disciplinary backgrounds. Participants were not compensated and participation in the surveys was optional.

Experimental participants included anyone who provided feedback on the student pitches, which were 173 people. These participants were recruited through requests for feedback distributed through social networking platforms by the 55 students in the course. We asked all students to share links to the survey through their online social networks, such as Facebook and Twitter.

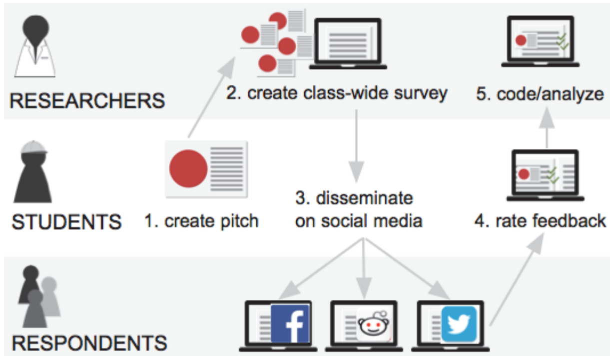

Figure 3. Procedure for collecting and analyzing communal feedback from the class's collective online social network.

Procedure

The instructor of the mobile service design class assigned teams of students to draft a short pitch (1-3 paragraphs) for their final product concept to eventually be posted in a crowdfunding campaign. In order to carry out the *communal approach* to soliciting feedback, a member of the research team compiled all the draft pitches into a single Qualtrics survey that all students would distribute to their connections on social networking platforms (Figure 3).

To experimentally control for anonymity, the survey software randomly assigned each feedback provider to the anonymous or identifiable condition. Before beginning the survey, those in the anonymous condition were told that no identifying information would be collected and their feedback would remain anonymous. Those in the identifiable condition were required to provide either a name or email address before proceeding.

The survey asked all responders to provide feedback on randomly selected pitches from two out of the class's ten teams. As feedback providers were shown each written pitch, they were asked to offer feedback by responding to a single open-ended question: "What edits would you make to this pitch to make it more effective? Effective means catchy, easy to understand, or exciting."

All students in the class received the same survey link, which they used to recruit feedback providers. Students were told to post the link on Facebook and any other social network site they would find useful, and ask their connections to help their class obtain feedback through the survey link. Students informed feedback providers that the product pitches they would review were randomly selected from the classroom and were not necessarily their own products. Students were also given the freedom to word their request in order to have the request be as authentic as possible. The survey was available for 5 days, from Wednesday at noon through Monday at 9 AM in May 2014. Following feedback collection, students were asked to complete a follow-up survey to reflect on their experiences.

Whole Comment	Individual Idea Units	Feedback Type
This is an amazing idea and would be an extremely helpful app/product. There should be some sort of back up system in place in the event a particular food cannot be identified. There would also need to be some sort of system by which [your service] could check all restaurants and eat outs for updated menus.	This is an amazing idea.	Praise (non-specific)
	would be an extremely helpful app/product.	Praise (non-specific)
	There should be some sort of back up system in place in the event a particular food cannot be identified.	Directive suggestion
	There would also need to be some sort of system by which [your service] could check all restaurants and eat outs for updated menus.	Directive edit

Table 1. Separating whole comments from online participants into individual idea units, with categories of feedback type based on (Cho et al., 2006).

Analysis

Once the survey was closed, researchers collected the feedback from the survey and distributed them to each team for evaluation. Each member of each team was asked to rate the usefulness of each feedback comment (from 1=very useless to 7=very useful). "Usefulness" was defined for students as "specific, actionable, and thoughtful," inspired by Cho et al.'s previous work on gathering feedback on written work (Cho, Schunn, and Charney 2006). All feedback comments were kept anonymous during student evaluation in order to reduce bias from student usefulness rating.

To help us understand the feedback content, two members of the research team (agreeing over 90% of the time with 25% of the data) disaggregated all of the feedback comments into "idea units," also as inspired by Cho et al. (Cho, Schunn, and Charney 2006). Idea units are the individual thoughts that together make up a comment—each idea unit is a phrase containing a single piece of feedback within the whole comment (Table 1).

Once the idea units were identified, the two researchers (agreeing over 90% of the time with 25% of the data) categorized each idea unit into one of eight types: Praise (specific), Praise (non-specific), Criticism (specific), Criticism (non-specific), Directive edits, Directive suggestions, Questions, and Off-topic. These eight types were also inspired by Cho et al. (Cho, Schunn, and Charney 2006) but were modified to fit the qualities important to pitch feedback. For example, we divided Cho et al.'s original codes of "praise" and "criticism" into "praise (specific/non-specific)" and "criticism (specific/non-specific)" because only the specific comments allow the student innovators to

Feedback Type	Definition	Example idea unit
Praise (Specific)	Describes a specific part positively.	"'And we know eating sesame chicken for the 10^{th} time this month isn't the healthiest option out there.' This is a great line."
Praise (Non-Specific)	Describes a non-specific part positively.	"Good."
Criticism (Specific)	Describes a specific part negatively.	"Logo is not related to clothes."
Criticism (Non-Specific)	Describes a non-specific part negatively.	"No one will adopt it."
Directive Edit	Suggests a change and provides a written-out alternative.	"Your pitch should be to both the consumers and producers. Something like, 'Do you know your city better than all your friends? Meet new people, and make some extra cash.'"
Directive Suggestion	Suggests a change, but does not provide a written-out alternative.	"The logo and name on the left needs a tagline to give a quick idea of what it is (otherwise I'll click away)."
Question	Provides a question to encourage further thinking on a certain topic.	"How do you plan on making money?"
Off topic	Comment does not fit any of the code categories, is ambiguous, or does not make sense.	"Ditto."

Table 2. Definition of feedback types inspired by (Cho et al., 2006) with examples from data.

know what part of their pitch works or does not work well. Furthermore, much of pitch feedback is provided through questions to encourage further thinking. Therefore, we added the code, "question," to categorize these idea units. Table 2 describes our eight codes.

Results

Students recruited a total of 173 feedback providers via social networking platforms. Feedback providers were brought in through Facebook (126), Reddit (26), Quora (3), and email lists (18). Their ages ranged from 13 to 53, skewed towards those in their 20's (the median age is 24). All feedback providers were randomly assigned to either the anonymous condition or the identifiable condition.

Participants who did not complete the survey remain in the dataset in accordance with intention-to-treat (ITT) analysis methods (Fergusson et al. 2002). ITT analysis includes subjects according to treatment randomly assigned instead of treatment received, essentially ignoring factors after randomization (Fergusson et al. 2002). We chose ITT methods because we are interested in authentic feedback, and so are more interested in including all real data as collected by students than excluding data that deviates from an ideal setting. All statistical analyses were performed in R.

Anonymity: Effect on Dropout Rate, Overall Feedback Quantity and Quality

Through a t-test, we find that feedback providers were more likely to drop out in the identifiable condition [$t(125.40)=3.04$, $p<0.05$], lending support to H1. In regard to the quantity of feedback, a single sample Mann-Whitney-Wilcoxon Test (t-test for non-parametric data) finds no significant difference in either the overall number of words ($p>0.5$) or number of idea units ($p>0.5$) given by feedback providers between the anonymous and identifiable conditions. Therefore, H2 is not supported. There is also no significant difference found in the overall usefulness of the feedback between conditions ($p>0.5$) based on student ratings, meaning H3 is also not supported.

Anonymity and Types of Feedback

A Kruskal-Wallis test (ANOVA for non-parametric data) was conducted to compare the effect of anonymity (IV) on the number of idea-unit occurrences of feedback types (DV). In other words, did feedback providers tend to give different types of feedback in different conditions? We used non-parametric tests because we compared feedback type counts rather than ratios where each feedback provider more often provided none of a certain feedback type rather than a lot. We find that there is significantly more *total criticism* (*specific criticism* and *non-specific criticism*) in the anonymous condition [$H(1,48) = 6.35$, $p<0.05$], lending support to H4. Breaking *total criticism* down into its component parts, we find that feedback providers in the anonymous condition gave significantly more *specific criticism* [$H(1,48) = 4.4711$, $p<0.05$], but not necessarily more *non-specific criticism* (Table 3). We perform the same analysis with praise and find that although there is no significant difference in the amount of *total praise* between conditions, feedback providers in the anonymous condition were more likely to give *specific praise* [H(1,48)

Feedback Type	Anonymous	Identifiable	p-value
# idea units	**188**	**137**	
Praise (specific)	**0.15**	**0.02**	**< 0.05 d = 0.13**
Praise (non-specific)	0.55	0.25	> 0.05
Criticism (specific)	**0.58**	**0.18**	**< 0.05 d = 0.40**
Criticism (non-spec)	0.18	0.14	> 0.05
Directive edits	0.14	0.22	> 0.05
Directive suggestions	0.55	0.30	> 0.05
Question	0.20	0.10	> 0.05
Off topic	0.01	0.04	> 0.05

Table 3. There was significantly more specific praise and specific criticism given in the anonymous condition. Data shows the average number of each type of feedback given per feedback provider in each condition.

= 5.1967, $p<0.05$] (Table 3). Therefore, H5 is not supported.

In order to identify which types of feedback were rated most useful by students, a one-way between subjects ANOVA was conducted to compare the effect of feedback type (IV) on usefulness rating by students (DV). Feedback containing *specific criticism* [$F(1, 110) = 13.222$, $p<0.05$] and *directive suggestions* [$F(1, 110) = 24.010$, $p<0.05$] were rated significantly more useful by students (Table 4). Feedback containing *specific praise* was almost rated significantly more useful [$F(1, 110) = 3.881$, $p = 0.051$], but more data is needed to determine if there would be a significant effect at the $p<0.05$ level. We also performed t-tests comparing the mean usefulness ratings of comments with and without a certain type of feedback and found similar significant differences.

Overall, we find that H1 and H4 are supported, while H2, H3, and H5 are not supported. Feedback providers were more likely to drop out in the identifiable condition (H1 supported). There is no significant difference in overall feedback quantity or usefulness between anonymous and identifiable conditions (H2, H3 not supported). Feedback providers were more likely to give criticism, more specifically *specific-criticism*, in the anonymous condition (H4 supported). Opposite to what we expected, there was significantly more *specific praise* given in the anonymous condition (H4 not supported). However, there was no significant difference in *total praise* (specific and non-specific) between conditions.

Idea Unit Feedback Type	Comment Mean Usefulness		p-value
	With Feedback Type	Without Feedback Type	
Praise (specific)	**5.48**	**4.57**	**p = 0.051 d = 0.93 η^2 = .13**
Praise (non-specific)	4.43	4.74	> 0.05
Criticism (specific)	**5.21**	**4.27**	**p < 0.001 d = 0.84 η^2 = .21**
Criticism (non-spec)	5.00	4.55	> 0.05
Directive edits	4.63	4.57	> 0.05
Directive suggestions	**5.31**	**4.19**	**p < 0.001 d = 1.12 η^2 = .04**
Question	4.88	4.57	> 0.05
Off topic	5.69	4.59	> 0.05

Table 4. Mean usefulness as rated by students where 1=very useless and 7=very useful. Comments with specific criticism and directive edits were rated as significantly more useful.

Communal Feedback and Effect of Feedback on Students' Final Projects

All ten-student teams received sufficient to feedback make changes to their final innovation pitch. Teams collected feedback from a range of 24 to 26 responders, with an average of 17.6 responses per team and standard deviation of 3.84. All teams received 176 feedback responses in total. Furthermore, of all the feedback collected for all teams, 50% of all feedback was specific and 63% was either critical or directive.

Teams differed in how much feedback they incorporated into their final pitch, but most teams made significant changes to their pitch following the activity (Figure 4). Although, we cannot definitively conclude which changes were a result of the online feedback and which changes were a result of teams discussing amongst themselves or from another feedback source, we attempt to identify changes made in response to online feedback by matching feedback comments to edits students made. For example, one team's draft pitch was divided into three paragraphs each beginning with a rhetorical question. More than once they received specific criticism (e.g., *"...this pitch has a bit too many questions."*). In response to this feedback, their final pitch was instead subdivided by headings and the questions were eliminated.

A few teams decided to re-write significant sections of their final pitch. For instance, one draft pitch that relied

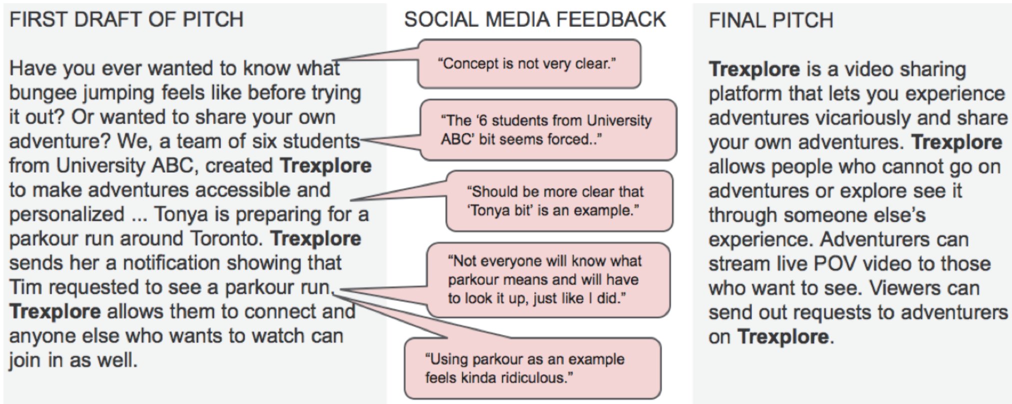

Figure 4. Example iteration of a team’s design pitch based on feedback from online social networks.

heavily on an example of how someone on a parkour run (a type of exercise) would use the app. They received specific criticisms, such as, *“Not everyone will know what parkour means and will have to look it up, just like I did. Maybe choose a different activity that more people can relate to and would understand?”* The students then completely removed the parkour example, and the new pitch included only a general example of how their app could be used for extreme sports.

Face-to-Face vs. Crowdsourced Online Feedback

In the follow-up survey, students compared their experiences collecting pitch feedback online vs. through face-to-face (F2F) interviews. All teams performed three in-person interviews in a previous assignment for their product. Students reported that online feedback from social networks produced more data, more quickly, and feedback was more honest. For example, students described that online feedback was “more about trends of people’s opinion” because they were able to easily collect a diverse range of opinions quickly. However, students also described how online feedback comments tended to be less in-depth and disliked how they could not follow up with further questions. For example, students reported that in F2F interviews, feedback providers could “understand our ideas more deeply” and “the interviewer could sense things not being said.” Overall students described how online and F2F feedback provided their own unique benefits. Although if students were put in a scenario where they were unable to seek F2F feedback, such as when they are pressed for time or have limited access to users, online social network feedback would be a viable option. We asked students how many online responses would be just as useful as one in-person interview.

Discussion

Over the years, the definition of crowds has expanded to encompass friends and extended connections from online social networking platforms. In this study, we show that student innovators are able crowdsource useful feedback through online social networks. We test two approaches to improve feedback quality in the social network context: communal feedback and enabling providers to remain anonymous. First, we qualitatively show that communal feedback—evenly distributing between teams feedback providers from the class’s collective online social networks—helps all student teams seek a sufficient amount of useful feedback to improve their work. A more equal distribution of feedback is beneficial for a classroom setting because it allows all teams to benefit from the feedback collection activity. Although some teams are essentially sharing their wealth of social capital, previous research in psychology describes how frequency and quantity of feedback is useful to a certain extent, but too much becomes overwhelming and can decrease performance (Lurie and Swaminathan 2009). This suggests that teams that would have received the most feedback may not have had the time or ability to synthesize it all given the fast-paced nature of class projects.

Second, through an experiment, we show how anonymity prompts feedback providers from social networks to provide more *specific criticism* and *specific praise*, and decreases the likelihood that feedback providers will drop out. While there have been many studies of the role of anonymity on feedback in the past, we provide a more detailed account of what *type* of feedback is more prevalent in the anonymous condition, and test additional classroom methodologies on how to collect anonymous feedback from online social networks. Previous work (Howard, Barrett, and Frick 2010; Lu and Bol 2007) describes how feedback providers give more criticism in the anonymous condition, while our study shows that only *specific criticism* is given more in anonymous contexts. This is important because our data, as well as other studies on online feedback (Greenberg, Easterday, and Gerber 2015), show that only "specific" feedback is useful because it identifies what part of the artifact needs to be improved. These results provide implications for designing tools that facilitate crowdsourcing not just critical, but primarily specific, feedback for designers (Xu, Huang, and Bailey 2014) and innovators (Greenberg, Easterday, and Gerber 2015).

In addition, unlike previous studies, we also find that anonymous feedback providers are more likely to provide *specific praise*—describing a specific part of the artifact positively and why. Having more *specific praise* in the anonymous condition is surprising because theories of participant response bias (Dell et al. 2012) and social capital (Jung et al. 2013; Resnick 2002) support the idea that identifiable feedback providers would feel less license to be critical and more likely to offer praise. This unexpected result could be an effect of the communal feedback approach. This method increases the social distance between feedback seeker and provider by maintaining anonymity on both sides as communal feedback has the student asking for feedback on randomly selected artifacts from all the class teams, and not necessarily their own. The social distance created could reduce evaluation anxiety and participant response bias. In this case, anonymity caused responders to give more specific feedback overall, both positive and negative, which were rated as more useful by students.

Furthermore, it is important to investigate the long-term effects of repeatedly turning to social networking platforms to collect feedback. Friendsourcing has its costs (Rzeszotarski and Morris 2014), and student innovators may becomes less willing to spend social capital on their work, or those in their social networks may begin to be less willing to help. There are also different psychological costs to performing innovation online where people are made aware of the projects' shortcomings (Harburg et al. 2015). It important to understand the balance between seeking large amounts of quick, honest feedback from social networks and the detriments of sharing early stage work publicly. In the future, it would be useful to study how providing feedback influences one's opinion of the innovator and when the benefits of crowdsourced pitch feedback outweigh the costs.

Limitations

A small number of feedback providers did not comply with the survey's request for identifying information by putting in gibberish in the name box, making them effectively anonymous though exposed to the identifiable treatment. This data was permitted in the identifiable condition following the intention-to-treat experimental practices. There was also a lower dropout rate among feedback providers assigned to the anonymous condition. This may indicate some selection bias in the results of the main study. However, this is also part of the predicted effects of anonymity on feedback providers. Regardless, because there was a higher dropout rate in the identifiable condition, any bias created would seem to strengthen the conclusions of this study.

Conclusions

When in an educational setting and limited by time, money, and experience, student innovators can find an accessible and responsive source of motivated feedback providers from online social networks. Study data show that anonymous feedback in a communal setting leads to more a more equal distribution of feedback among peers and more specific criticism and specific praise. Together, these techniques can be used to increase the usefulness of crowdsourced pitch feedback from online social networks, particularly in the classroom setting.

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References

Cho, Kwangsu, Christian D. Schunn, and Davida Charney. 2006. "Commenting on Writing: Typology and Perceived Helpfulness of Comments from Novice Peer Reviewers and Subject Matter Experts." *Written Communication* 23 (3): 260–94.

Dell, Nicola, Vidya Vaidyanathan, Indrani Medhi, Edward Cutrell, and William Thies. 2012. "Yours Is Better!: Participant Response Bias in HCI." In *Proceedings of the ACM Conference on Human Factors in Computing Systems*, 1321–30. ACM.

Dow, Steven, Elizabeth Gerber, and Audris Wong. 2013. "A Pilot Study of Using Crowds in the Classroom." In *Proceedings of the ACM Conference on Human Factors in Computing Systems*, 227–36. ACM.

Dow, Steven P., Julie Fortuna, Dan Schwartz, Beth Altringer, Daniel L. Schwartz, and Scott R. Klemmer. 2012. "Prototyping Dynamics: Sharing Multiple Designs Improves Exploration, Group Rapport, and Results." In *Design Thinking Research*, 47–70. Springer.

Dow, Steven P., Alana Glassco, Jonathan Kass, Melissa Schwarz, Daniel L. Schwartz, and Scott R. Klemmer.

2010. “Parallel Prototyping Leads to Better Design Results, More Divergence, and Increased Self-Efficacy.” *ACM Transactions on Computer-Human Interaction (TOCHI)* 17 (4): 18.

Easterday, Matthew W., Daniel Rees Lewis, Colin Fitzpatrick, and Elizabeth M. Gerber. 2014. “Computer Supported Novice Group Critique.” In *Proceedings of the ACM Conference on Designing Interactive Systems*.

Ellison, Nicole B., Charles Steinfield, and Cliff Lampe. 2011. “Connection Strategies: Social Capital Implications of Facebook-Enabled Communication Practices.” *New Media & Society*.

Ellison, N., J. Vitak, R. Gray, and C. Lampe. 2014. “Cultivating Social Resources on Social Network Sites: Facebook Relationship Maintenance Behaviors and Their Role in Social Capital Processes.” *Journal of Computer-Mediated Communication* 19 (4): 855–70.

Erving Goffman. 2012. “The Presentation of Self in Everyday Life.” In *Contemporary Sociological Theory*, 46. John Wiley & Sons.

Fergusson, Dean, Shawn D. Aaron, Gordon Guyatt, and Paul Hébert. 2002. “Post-Randomisation Exclusions: The Intention to Treat Principle and Excluding Patients from Analysis.” *BMJ* 325 (7365): 652–54.

Gray, Rebecca, Nicole B. Ellison, Jessica Vitak, and Cliff Lampe. 2013. “Who Wants to Know?: Question-Asking and Answering Practices among Facebook Users.” In *Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1213–24.

Greenberg, Michael D., Matthew Easterday, and Elizabeth M. Gerber. 2015. “Critiki: A Scaffolded Approach to Gathering Design Feedback from Paid Crowdworkers.” In *ACM Conference on Creativity and Cognition*.

Harburg, Emily, Julie Hui, Michael Greenberg, and Elizabeth Gerber. 2015. “The Effects of Crowdfunding on Entrepreneurial Self-Efficacy.” In *Proc. of the Conference on Computer Supported Cooperative Work and Social Computing*. ACM.

Heider, Fritz. 1958. *The Psychology of Interpersonal Relations*. Psychology Press.

Holland, Paul W., and Samuel Leinhardt. 1974. “The Statistical Analysis of Local Structure in Social Networks.” Working Paper 44. National Bureau of Economic Research. http://www.nber.org/papers/w0044.

Howard, Craig, Andrew Barrett, and Theodore Frick. 2010. “Anonymity to Promote Peer Feedback: Pre-Service Teachers’ Comments in Asynchronous Computer-Mediated Communication.” *Journal of Educational Computing Research* 43 (1): 89–112.

Hui, Julie S., Elizabeth M. Gerber, and Steven P. Dow. 2014. “Crowd-Based Design Activities: Helping Students Connect with Users Online.” In *Proceedings of the 2014 Conference on Designing Interactive Systems*, 875–84. DIS ’14. New York, NY, USA: ACM.

Jung, Yumi, Rebecca Gray, Cliff Lampe, and Nicole Ellison. 2013. “Favors from Facebook Friends: Unpacking Dimensions of Social Capital.” In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 11–20. CHI ’13. New York, NY, USA: ACM.

Lampe, Cliff, Donghee Yvette Wohn, Jessica Vitak, Nicole B. Ellison, and Rick Wash. 2011. “Student Use of Facebook for Organizing Collaborative Classroom Activities.” *International Journal of Computer-Supported Collaborative Learning* 6 (3): 329–47.

Lurie, Nicholas H., and Jayashankar M. Swaminathan. 2009. “Is Timely Information Always Better? The Effect of Feedback Frequency on Decision Making.” *Organizational Behavior and Human Decision Processes* 108 (2): 315–29.

Lu, Ruiling, and Linda Bol. 2007. “A Comparison of Anonymous versus Identifiable E-Peer Review on College Student Writing Performance and the Extent of Critical Feedback.” *Journal of Interactive Online Learning* 6 (2): 100–115.

Luther, Kurt, Amy Pavel, Wei Wu, Jari-lee Tolentino, Maneesh Agrawala, Björn Hartmann, and Steven P. Dow. 2014. “CrowdCrit: Crowdsourcing and Aggregating Visual Design Critique.” In *Proceedings of the Companion Publication of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 21–24. ACM.

Marlow, Jennifer, and Laura Dabbish. 2014. “From Rookie to All-Star: Professional Development in a Graphic Design Social Networking Site.” In *Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing*, 922–33. ACM.

Oeldorf-Hirsch, Anne, Brent Hecht, Meredith Ringel Morris, Jaime Teevan, and Darren Gergle. 2014. “To Search or to Ask: The Routing of Information Needs between Traditional Search Engines and Social Networks.” In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 16–27. ACM.

Paulhus, Delroy L. 1991. “Measurement and Control of Response Bias.” In *Measures of Personality and Social Psychological Attitudes*, edited by J. P. Robinson, P. R. Shaver, and L. S. Wrightsman, 17–59. Measures of Social Psychological Attitudes, Vol. 1. San Diego, CA, US: Academic Press.

Putnam, Robert D. 2001. *Bowling Alone: The Collapse and Revival of American Community*. Simon & Schuster.

Rains, Stephen A. 2007. “The Anonymity Effect: The Influence of Anonymity on Perceptions of Sources and Information on Health Websites.” *Journal of Applied Communication Research* 35 (2): 197–214.

Reinecke, Katharina, Tom Yeh, Luke Miratrix, Rahmatri Mardiko, Yuechen Zhao, Jenny Liu, and Krzysztof Z. Gajos. 2013. “Predicting Users’ First Impressions of Website Aesthetics with a Quantification of Perceived Visual Complexity and Colorfulness.” In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2049–58. CHI ’13. New York, NY, USA: ACM.

Ren, Yuqing, F. Maxwell Harper, Sara Drenner, Loren Terveen, Sara Kiesler, John Riedl, and Robert E. Kraut. 2012. “Building Member Attachment in Online Communities: Applying Theories of Group Identity and Interpersonal Bonds.” *MIS Q.* 36 (3): 841–64.

Resnick, P. 2002. “Beyond Bowling Together: Sociotechnical Capital.” In *Human-Computer Interaction in the New Millennium*, edited by John M. Carroll. New York, New York : Boston, MA: ACM Press ; Addison-Wesley.

Ringel Morris, Meredith, Kori Inkpen, and Gina Venolia. 2014. "Remote Shopping Advice: Enhancing In-Store Shopping with Social Technologies." In *Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing*.

Rzeszotarski, Jeffrey M., and Meredith Ringel Morris. 2014. "Estimating the Social Costs of Friendsourcing." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2735–44. CHI '14. New York, NY, USA: ACM.

Tohidi, Maryam, William Buxton, Ronald Baecker, and Abigail Sellen. 2006a. "Getting the Right Design and the Design Right." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1243–52. CHI '06. New York, NY, USA: ACM.

———. 2006b. "User Sketches: A Quick, Inexpensive, and Effective Way to Elicit More Reflective User Feedback." In *Proceedings of the 4th Nordic Conference on Human-Computer Interaction: Changing Roles*, 105–14. NordiCHI '06. New York, NY, USA: ACM.

Williams, Dmitri. 2006. "On and off the'Net: Scales for Social Capital in an Online Era." *Journal of Computer-Mediated Communication* 11 (2): 593–628.

Xu, Anbang, and Brian Bailey. 2012. "What Do You Think?: A Case Study of Benefit, Expectation, and Interaction in a Large Online Critique Community." In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, 295–304. CSCW '12. New York, NY, USA: ACM.

Xu, Anbang, Shih-Wen Huang, and Brian Bailey. 2014. "Voyant: Generating Structured Feedback on Visual Designs Using a Crowd of Non-Experts." In *Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing*. Baltimore, MD.

Xu, Anbang, Huaming Rao, Steven P. Dow, and Brian P. Bailey. 2015. "A Classroom Study of Using Crowd Feedback in the Iterative Design Process." In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 1637–48. ACM.

Zhao, Yong. 1998. "The Effects of Anonymity on Computer-Mediated Peer Review." *International Journal of Educational Telecommunications* 4 (4): 311–45.