What's good for me is good for us: The effect of network structure on using social psychology to motivate contributions to a social network referral tool

by

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ABSTRACT

Recent interest in practical applications of social network analysis, such as expertise finding, has sparked creation of social network referral tools. Although these tools operate largely automatically, human effort can still be required to increase the accuracy of referrals. Motivating this effort is complicated in online settings where weak incentives and reduced visibility of contributions leads to social loafing. This study examined how network characteristics interact with social psychological motivations to influence the likelihood of contributions. Experimental participants with varying levels of network constraint were presented with either individualist- or collectivist-oriented requests to update data used by a hypothetical social network referral tool. Results showed that participants in more constrained networks were less likely to make contributions, but the likelihood of contributions increased when presented with an individualist message. These findings suggest that requests can be customized according to information about network structure in order to encourage higher rates of contributions in online communities.

INTRODUCTION

Practical application of social network data is a rapidly growing area of internet use. Within this domain, social network referral tools are an emerging trend, combining information about people's social networks with information about the people in the networks. That is, these tools help reveal not only who knows who, but also who knows what. For example, QuME and AnswerGarden explored the use of network information for expertise finding [1, 2]. Similarly, SmallBlue at IBM [3] and Expert Seeker at NASA [4] represented large-scale implementations of referral systems. Finally, Referral Web introduced the concept of locating expertise by revealing chains of personal contacts between a seeker and an expert [5]. Social network referral tools are hypothesized to be particularly promising applications for facilitating collaborative projects, especially when participants need to span knowledge domains. For instance, CI-KNOW is a tool that mines the web for links, and then transforms this information into referrals for users, such as who they should approach as likely collaborators within a particular domain [6]. CI-KNOW is targeted at scientific researchers who often need to form interdisciplinary teams to address complex problems, but struggle to identify partners outside their own disciplines.

Although tools like CI-KNOW take advantage of automatic data collection to create referrals, varying amounts of human effort can still be required to increase the accuracy of referrals. As an illustration, name disambiguation (e.g., differentiating similar names in citation databases—B. Jones vs. B. A. Jones) is a challenge for computers, but is relatively easy for humans. Work by von Ahn and Dabbish [7] has identified a significant class of similar problems that are relatively intractable in terms of machine computation, but can be resolved through "human computation" (e.g., mark up of images on the web). A potential obstacle to successful human computation is that volunteers must be motivated to contribute their effort. Studies have shown that willingness to provide contributions, of any kind, can be reduced in group settings – and that these difficulties are increased in online settings. For example, an analysis of "free riding," or under contribution, on a music file sharing site showed that 70 % of users shared no files [8]. Other research shows how the incentives of online communities both promote free-riding and low levels of contributions [9, 10]. In order for social network referral tools to be successful (e.g., achieve levels of human computation to improve performance), they must be able to increase the motivation for contributions from users.

LITERATURE REVIEW

The problem of under-contribution has been well studied in social psychology as social loafing—individuals exerting less effort when working in a group than when working individually [11]. In their review of the literature on social loafing, Karau and Williams [12] developed the Collective Effort Model (CEM) as a framework for understanding social loafing. The CEM argues that social loafing is caused by a perceived disconnect between individual effort and valued outcomes when working collectively. According to the model, individual effort leads to individual and group performance. This individual and group performance results in individual and group outcomes. If these outcomes are valued and people can see how their efforts will lead to these outcomes, then social loafing decreases.

The CEM has been used to explain a variety of factors that can be manipulated to alleviate social loafing (see [12], for a review). These factors include: expected coworker performance; group cohesiveness; and achievement motivation [13, 14]. The work of Beenen and colleagues [15] is particularly relevant to this study. They used the CEM and social psychological mechanisms to describe and test system-level designs for alleviating social loafing online. In a field experiment, they tested the effects of including benefit statements in a request to members of a movie recommendation Web site to rate more movies. The benefit statements highlighted the benefits of rating movies either to the individual or to the group, or to both.

Consistent with the CEM, highlighting benefits (outcomes) should decrease social loafing and increase contribution behavior. However, in the movie rating study, there was mixed support for the CEM. Contrary to CEM predictions, highlighting benefits actually *decreased* contributions relative to a control condition. However, in cases where benefits were characterized in terms of both the individual and the group, contributions were higher than when benefits were framed in either individual or group terms. Beenen et al. identified the puzzle of why making benefits salient depressed contributions as a key focus for future research.

This research seeks to understand the puzzle raised by the movie rating study by including data on network characteristics of potential contributors. Specifically, within the context of contributing effort to update information used by a social network referral tool, we examined the role of network constraint on the persuasiveness of highlighting invidual vs. group benefits. For example, a possible interpretation of the Beenen et al. result is that the effectiveness of highlighting benefits is conditional on matching the content of messages according to features of recipients' networks. These network features are important because they create a context for interpreting and responding to social psychological motivations for contributions. Previous work in formal modeling has shown that network structure can modify the influence of some social psychological factors. For example, in the case of collective action, individuals with dense networks are more likely to take collective action than those with sparse networks because being densely connected provides more evidence and experience of the gains possible by working together (16).[1]

Additional work by social network analysts has shown correlations between network constraint and propensity toward conformity, obedience, risk-aversion, and group-orientation [19]. Network constraint is a structural measurement similar to density. Density is a simple proportion of how many of your ties are connected to each other compared to how many of your ties could possibly be connected to each other. Network constraint uses a similar calculation to measure what proportion of your network is dependent on one individual within your network. This calculation is summed for all individuals in your network.

Constraint measures the extent to which your network structure gives you the ability to access new resources (e.g., information, power) and leverage network connections by playing the role of broker between individuals. Past research has found that varying levels of constraint align closely with the personality framework of individual VS. collective orientation [21, 21]. That is, people in highly constrained networks (i.e., densely connected networks with little brokerage) tend to exhibit more collectivist preferences, while those in less constrained networks (i.e., sparsely connected networks with brokerage) tend to exhibit more individualistic preferences [19, 22].

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[1] Some formal models show that individuals with dense networks are more likely to have links to non-contributors which diminishes normative pressure to contribute [17, 18,]. However, this result only holds when actors gain additional information by talking to others before making a decision. Students in this study may have consulted other students before deciding whether or not to contribute, but this was not directly part of the study and seems unlikely.

CURRENT STUDY AND HYPOTHESES

Because social network structure is correlated with the group-orientation of individuals, understanding features of an individual's network structure, such as degree of constraint, may clarify the conditions under which social psychological motivations will be effective, such as the framing of benefits attributed to contributions (e.g., individual VS. collective). Specifically, a possible explanation for the contradictory result of Beenen et al. [15] is that unmeasured aspects of respondents' network structure mitigated or reversed the advantages of highlighting the benefits of contributions, at least as predicted by the CEM. For instance, assuming a random distribution of levels of constraint (e.g., even numbers of "low" vs. "high" constraint raters) in each message condition, a message highlighting only individual or group benefits would fail to resonate with a significant fraction of raters. By contrast, a message highlighting both individual and group benefits would succeed in resonating with both "low" and "high" constraint raters, but perhaps not with the same strength as a message targeted by level of constraint – and hence the apparent contradiction of the highest level of contributions from those that received no message.

Using data collected from students at the University of Michigan School of Information, we explored hypotheses about social network structure, framing of the benefits of contributions, and the resulting level of contributions. First, based on collective action models and correlations between constraint and compliance/conformity propensity, we predicted that as network constraint increases, contribution will increase (Hypothesis 1).

Second, following the CEM, we predicted that requests for contributions that highlight beneficial outcomes (either individual or collective) will increase contribution levels compared to a neutral message (Hypothesis 2).

Finally, as constraint increases, group-orientation should increase [19, 22], with a corresponding increase in the persuasiveness of framing contributions in terms of group benefits [24, 24]. Therefore, we hypothesized an interaction effect, such that at higher levels of constraint, the group framing would have greater influence on level of contributions, while at lower levels of constraint, the individualist framing would be more influential (Hypothesis 3). Support for this hypothesis, in particular, will suggest that the impact of message framing is related to matching with network characteristics.

Figure 1 illustrates our predicted results, showing a main effect in the positive direction by level of constraint (Hypothesis 1), a positive effect of individual and collective oriented messages (Hypothesis 2), and an interaction effect in the positive direction by level of constraint for the collectivist message – and in the negative direction for the individualist message (Hypothesis 3).

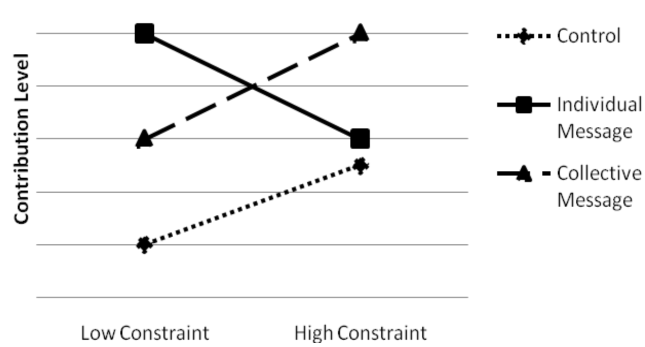

Figure 1: Predicted Results

METHODS

Social Network Data

Network data were collected from masters students enrolled at [intentionally left blank for blind review] during the 2007-08 academic year. The response rate was 51%, or 156 responses from a total of 305 students. Students received a $2 pre-incentive for participating in the study. Students were asked to fill out a survey regarding their relationships with other students at the school. Using name generator items (after [19]), respondents indicated those students who were sought out for personal discussion, social activities, advice, and as academic collaborators (see Appendix A for actual questions used). Respondents were also able to list additional students not covered by these categories. Respondents then identified connections between the friends they had already named. Unlike Burt et al. [19], respondents did not rate the strength of ties. Strength of ties between respondents and their friends was determined implicitly by the summation of the number of times respondents listed the friends. Strength of ties for connections between friends was not assessed. Figure 2 shows the resulting social network, with nodes sized by degree (number of connections with other students).

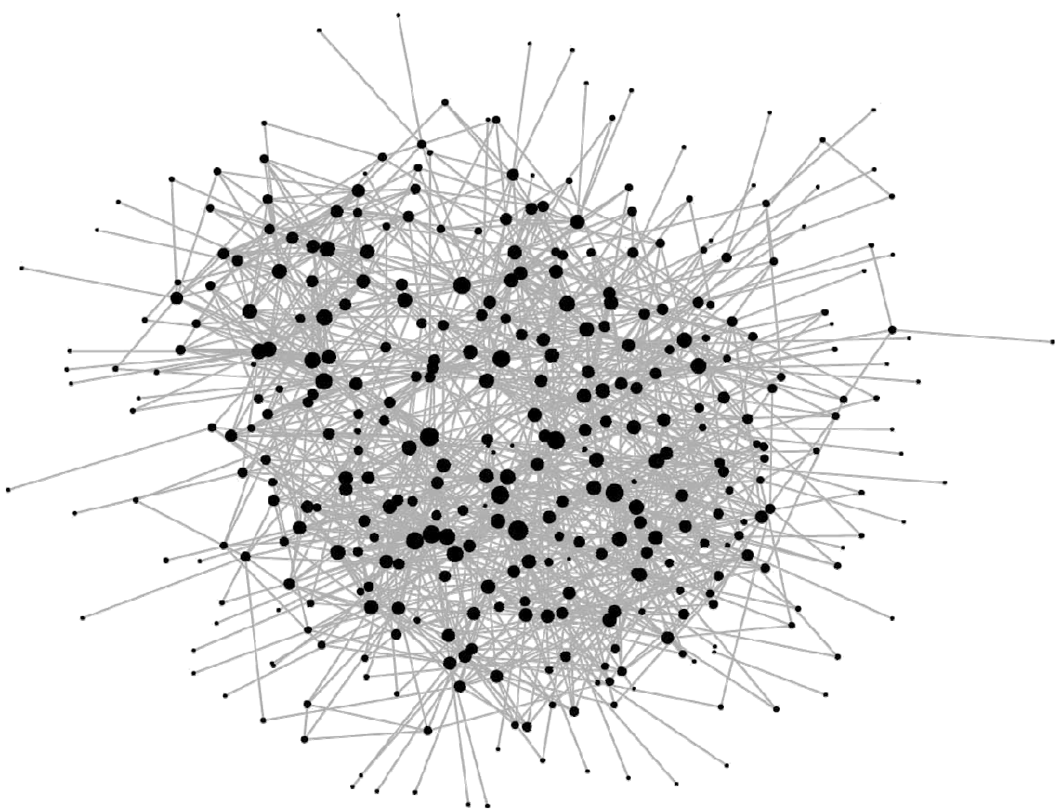

Figure 2: Student Social Network. Network statistics: diameter = 7, degree range = 1 to 27

Constraint

Network constraint is a measure for "structural holes," a concept developed by Burt [25]. Structural holes are found when a node is connected to two other nodes that are not connected to each other. Low network constraint is typically thought to correspond with more structural holes, and hence a more diverse or cosmopolitan network where individuals are not limited to just their near network neighbors when seeking resources [26]. By contrast, high network constraint is typically associated with a more parochial and homogeneous network, with correspondingly higher likelihood of conformity (as described previously).

Constraint was calculated on two levels. First, data from respondents about which other students they knew was aggregated to form a complete student network. Individual constraint was derived from this network-wide data. Second, ego networks were constructed for each respondent that responded to the survey. Data for each ego network were obtained from a respondent's survey about who he/she was connected to and whether his/her friends knew each other. Constraint was then calculated for each respondent based on his or her ego network, where an ego network is the set of individuals linked to a specific target individual. Not all respondents identified which of their friends knew each other, so these students did not have an ego constraint score.

Network Entrepreneur Personality Index

This study used the network entrepreneur personality index as an independent measure of individual vs. group orientation [19]. The index is a ten item version of a larger proprietary personality test. Items present respondents with an incomplete statement (e.g., "In discussions among peers, I am probably seen as:") and then asked them to choose the most appropriate completion (e.g., "an outspoken advocate" [individualist framing] OR "motivating people to my views" [group framing]). The full index is listed as Appendix B. We included this personality variable as a control on receptivity to the social psychological manipulation (i.e., framing of requests to contribute).

Contribution Data

Students who responded to the social network survey were randomly assigned to one of three groups to test the effect of different message framing on contribution behavior in relation to network structure. All participants received variants of a message asking them to complete a follow-up survey intended to collect information to improve the performance of a social network referral tool. In the control group, participants received a neutral message (neither individualist or collectivist): *"We will turn the SI social network into an expertise network. An expertise network matches people with their knowledge and abilities. We need to collect information about interests and expertise from many different people. The expertise network would be useful because it would combine social networks with expertise to help people connect."*.

In the first experimental treatment, participants received a message emphasizing the personal value of contributing information to the social network referral tool (individualist framing) through a message including these statements: *"A combined social and expertise network helps students take advantage of their network connections, Your individual input is unique and valuable, Take advantage of the opportunities around you, and see what network connections you can use to meet your goals*.".

In the second experimental treatment, participants received a message emphasizing the benefit of their contribution to the larger group (group orientation) through a message including these statements: *"A combined social and expertise network helps students connect to people who share their interests, Your input will help reach this group-wide goal, and Students can use this tool to build meaningful relationships and be more connected."*.

These messages were rooted in the values corresponding to individualism and collectivism [20] and were written based on previous field studies in targeted advertising based on individualism and collectivism [24, 24]. Individuals were contacted up to 3 times to participate in the second survey. Full message text for all 3 contacts can be found in Appendix C.

Contribution behavior was then measured in two ways. In the first approach, contributions were operationalized as a binary variable of whether students completed the follow-on survey or not. In the second approach, contributions were operationalized in terms of the word count for responses to the open-ended items in the follow-up survey. The rationale for using word count as a measure of contribution is that writing more words generally requires more effort. This measurement has been used in other studies to determine contribution level [27].

RESULTS

Network Structure and Personality

Previous findings suggest that lower network constraint is associated with more individualistic, entrepreneurial personalities [19, 22]. The test developed by Burt et al. [19] is designed to measure this personality, with higher test scores indicating a stronger network entrepreneur type. Students' constraint should therefore be negatively correlated with their network entrepreneur personality index.

Constraint for each respondent's self-identified ego network was calculated for comparison with personality test scores. This follows the procedures used by Burt et al. [19]. The entire student network was also analyzed for network-wide constraint. Table 1 shows the descriptive statistics for ego constraint, network constraint and personality test scores. All three variables generally followed a normal distribution, though both constraint measures were slightly right-skewed.

Variables	N	Min	Max	Mean	StDev
Personality Index Score	154	0	9	4.67	1.53
Constraint	154	8.1	114	24.76	16.72
Ego Constraint	96	11.5	112	31.62	16.46

Table 1. Descriptives: Personality score and constraint

Linear regression analysis between ego constraint and personality showed a very small positive correlation, but the coefficient was not significant ($r = .077$, $p = .457$). Linear regression between entire network constraint and personality also resulted in a small and insignificant correlation ($r = .026$, $p = .751$).

Social Networks and Contribution Behavior

The three groups (control, n = 50; treatment 1, n = 54; treatment 2, n = 50) were compared for similarity on age, gender, race, semesters completed, academic specialization, personality score, and network constraint. There were no significant differences, except that a higher proportion of students in the human-computer interaction (HCI) specialization ended up in the control group (39.6% in the control VS. 22.3% in the treatment groups). As a result, we controlled for HCI specialization in subsequent analyses. Table 2 shows the descriptive statistics for variables used in subsequent models.

Variables	N	Min	Max	Mean	StDev
Dependent					
Word Count	82	25	603	181	127.09
Entered Survey	154	0	1	0.53	0.5
Independent					
HCI Specialization	152	0	1	0.28	0.45
Constraint	154	8.1	114	24.7	16.72
Individual Message	154	0	1	0.35	0.48
Collective Message	154	0	1	0.32	0.47
Constraint* Individual Message	154	0	100	8.71	14.44

Table 2. Descriptives: Independent and dependent variables

After verifying that the three experimental conditions were equivalent in terms of participant characteristics (with the exception of HCI concentrators), we then conducted a linear regression analysis using word count in the open-ended responses as the dependent variable. However, analysis of outlier influence revealed a potentially problematic observation. Re-analysis without this observation was inconclusive.

We then performed a logistic regression using the binary variable for contribution behavior (whether or not a participant completed the follow-up survey) and excluded the same outlier. The results from the logistic regression are similar to the results from the linear regression without the outlier, but the logistic regression yields significant results.

Demographic variables (race, age, gender, semesters completed) had little to no affect on the logistic regression. Additionally, because one of the researchers is part of the student network, her relationships with other students were controlled for, and made no difference in the outcomes. Finally, tests of other network statistics (degree, betweenness, closeness) did not have any predictive value for contribution level (either as measured by word count or follow-up survey completion).

Unlike linear regression, coefficients in logistic regressions do not have a simple “all else constant” interpretation. However, large positive beta coefficients correspond with odds ratios much higher than one, i.e., a strong increase in the odds of completing the follow-up survey. Large negative beta coefficients correspond with odds ratios much lower than one, i.e., a large decrease in the odds of completing the follow-up survey.

The results of the logistic regression analysis are shown in Table 3. A loose interpretation of the odds ratio for each variable is as follows. First, constraint had a small and significant negative relationship with contribution behavior, contradicting Hypothesis 1. In particular, for each unit increase in constraint, the odds of completing the survey decreased by roughly 10%. Second, those who received an individual message were .023 times less likely to contribute as subjects who did not receive the individual message, contradicting Hypothesis 2. Similar results held for the group message, though not at the .05 significance level. Third, the interaction between constraint and individual message was positive. For those with high constraint who received an individual message, the odds of completing the survey increased by roughly 14%. The interaction between constraint and group message was also positive, but much smaller and insignificant. Therefore, Hypothesis 3 was not supported.

Variables	Beta	S.E.	Wald	Sig.	Odds Ratio
HCI	1.002	0.43	5.53	**0.019**	**2.724**
Individual Message	-3.75	1.29	8.45	**0.004**	**0.023**
Collective Message	-2.37	1.34	3.10	**0.078**	**0.094**
Constraint	-0.09	0.04	4. 80	**0.029**	**0.912**
Constraint* Individual Message	0.133	0.05	6.80	**0.009**	**1.142**
Constraint* Collective Message	0.047	0.06	.72	**0.395**	**1.049**
Constant	2.667	1.07	6.16	**0.013**	**14.398**

Table 3. Logistic Regression. The adequacy of the model was assessed using the Hosmer & Lemeshow test for goodness-of-fit (chi-squared = 2.936, signif. = .938) and classification tables, which showed that the model correctly predicted 68.9% of cases (compared to constant only prediction rate of 53.6%).

To clarify the results, we used the logistic regression to predict probability of contributions for actual case studies from our data. In Table 4, the first set of numbers shows that as constraint increased, probability of contribution decreased, holding the message constant. The second set shows that, holding constraint constant, an individual message decreased the probability of contribution. The last set shows that as constraint increased and an individual message was given, the probability of contribution increased.

Hypotheses	Constraint	Message	Probability	Result
As network constraint increases, contributions will increase	8.1	Control	0.988	**As network constraint increases, contributions decrease**
	30.81	Control	0.405	
Individual & group messages will increase contributions compared to a neutral message	21.22	Control	0.838	**Individual messages decrease contributions compared to a neutral message**
	21.14	Indiv.	0.378	
Interaction: as network constraint increases, group messages will have a greater effect on contributions and individual messages a lesser effect	21.14	Indiv.	0.378	**Interaction: as network constraint increases, individual message have a greater effect on contributions**
	31.02	Indiv	0.606	

Table 4. Case study results

Figure 3 shows the results in terms of the effect of network constraint on contribution behavior given the different framing of messages (individual vs. group). Subjects were divided into three equal groups to create the three levels of constraint (low, medium, high). For each group and message, the proportion of contributers was then calculated.

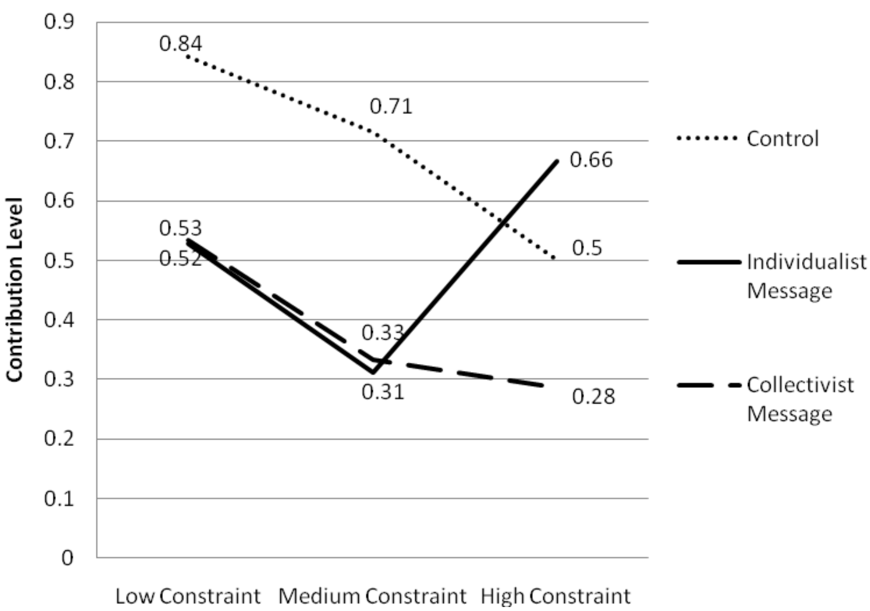

Figure 3. Effects of constraint on contribution, by message

The low constraint group had network constraint between 8.1 and 17.51, medium between 17. 53 and 25.25, and high between 25.67 and 114.43. The high group included 4 subjects with constraint of 100 and higher. Because these scores were extremely greater than average, we excluded these data points from the graphical analysis, and the results stayed the same.

DISCUSSION

This paper was motivated by contradictory findings with respect to predictions of the CEM and contributions in online settings, such as Beenen et al. [15]. We speculated that unmeasured characteristics of potential contributors, particularly network constraint, may modify the impact of social psychological motivators, possibly in ways that mitigate or reverse effects associated with the CEM. Results of an experimental exploration of the relationship between network structure and contributions were mixed. Specifically, the predicted relationship between level of constraint and persuasiveness of message framing (i.e., individual vs. group) was not supported. In particular, we didn't find evidence for the matching of framing and constraint suggested by prior research on social network characteristics and social psychological factors. However, the results did show a different and unexpected matching, where participants with high network constraint were more responsive to individualist framing of requests for contributions.

Below we present two possible explanations of the findings. In the first explanation we argue that individual and collective messages differentially activate intrinsic motivation as a function of network constraint. In the second explanation, we argue that individual and collective messages differentially offer information about effort and outcome expectations, again as a function of network constraint.

Constraint and Contribution

Our findings are consistent with a view that when presented with a network referral tool, those with low network constraint may have stronger intrinsic motivation to contribute than those with high constraint, because networks have relatively higher value and interest with decreasing constraint. That is, according to social network theorists, people with lower constraint are network entrepreneurs who use their networks to move independently and inspire change [19]. Their network is a valuable asset that gives them access to resources and brokerage opportunities. Intrinsic motivation is manifest when someone is motivated by the task itself, or related feelings about the task, rather than an external reward [28]. Participation in a network referral tool closely mirrors the preferences of low constraint individuals for networking behavior and feelings about network utility, making them more likely to be intrinsically motivated to contribute.

Motivational Effects of Messages

Introducing individual and collective messages may have decreased contribution because the messages affected intrinsic motivation by framing contributions in terms of extrinsic rewards. Past research has shown that giving people extrinsic rewards interferes with their intrinsic motivations [30, 30]. Similar to the work by Beenan et al. [15], highlighting individual or collective outcomes of contribution could have been seen as a presentation of external rewards for contributions. Thus, the message re-framed the contribution task in the context of external rewards that may have weakened or even replaced internal motivations.

The results are consistent with this explanation to the extent that, except for high constraint people who received an individualist message, all other message recipients contributed at lower rates than in the control (no message) condition. We can speculate that the individual framing of the request message, for high constraint participants, offered sufficient extrinsic motivation to overcome otherwise low levels of intrinsic motivation to contribute to improving the social network referral tool.

Informational Effects of Messages

Alternatively, the individual and collective messages may have been informational rather than motivational. The Collective Effort Model suggests that social loafing is reduced when people see how their effort leads to desired outcomes. The individual and collective messages act as information about what efforts will lead to what outcomes (e.g. by contributing to this network referral tool, you can take advantage of network opportunities). As described above, those with low constraint already have networks that give them access to resources and opportunities [19]. Therefore, messages about the benefits of the network referral tool highlight opportunities that may already be available to low constraint individuals (e.g. access to resources, networking opportunities). Because they perceive sufficient opportunities without the addition of the referral tool, low constraint individuals may see little reason to contribute information that will improve the performance of the referral application.

On the other hand, those with high constraint have more limited networks in terms of resources, social capital, brokerage, information acquisition, and the like [19, 26]. Messages about individual network outcomes from the tool inform high constraint people that the tool will give them opportunities they do not already have. Thus, high constraint individuals may contribute more when given an individual-oriented message, but the group-oriented message may not have the same salience.

This informational view of the messages is similar to previous findings about expected coworker performance and social loafing. When people expect coworkers to work hard, then they are more likely to engage in social loafing, but when they expect coworkers to work less, they exert even more effort as compensation [14]. Amount of effort is determined by incoming information about whether valued outcomes will occur with or without increased effort.

One limitation of the informational and motivational views is that they both fall somewhat short of explaining the consistent negative effects of the collective-oriented message. However, these findings were small and statistically insignificant. The collective-oriented message manipulation may not have been strong enough to bear out any conclusive results.

Another possible limitation of the study overall is the lack of correlation between the network entrepreneur index for personality and constraint. We cannot be completely certain that constraint was related to individualist/collectivist orientation the way network analysts have predicted. However, the design of the index as a truncated version of a larger test [19] is problematic, which may make the index a poor measurement tool to begin with.

DESIGN IMPLICATIONS & CONCLUSION

Whether the findings are best explained by motivational or informational cues, the implications for design are similar, both for social network referral tools in particular and more broadly for online contributions (such as to support human computation).

First, social network structure—specifically, network constraint—appears to play some role in shaping decisions to contribute. Therefore, the design of systems that depend on contributions may need to take this into account. Specifically, because people with lower network constraint appear more likely to contribute, designers may want to consider how to increase experience with brokering and other advantages of low constraint networks by increasing the ratio of low constraint networks in their target population. For example, it may be helpful to use social networking mechanisms, such as hobbies or interests, to diversify individual networks beyond existing acquaintanceship, friendship, or workflow networks. Early work on computer-mediated communication, for instance, speculated that electronic mailing lists served a similar function [31]. That is, a worker might join a list ostensibly dedicated to cooking, but in the course of exchanging recipes ties are built to other workers in ways that might otherwise be impossible – and that may produce advantages consistent with the cooking list functioning as a low constraint network.

Second, specific messages meant to motivate contributions must be used with caution. Giving people a reason for doing something may do more harm than good. Resources can be used more effectively in creating a useful tool or program for the community, and then simply introducing it to people and relying on them to tap their own motivations to contribute.

Finally, although tailored messages must be used carefully, they can still be motivators for contribution. However, more research is required to determine when these messages are effective and in what direction. In the case examined in this study, we speculate that features of the network referral tool interacted with the structure of participant's networks to produce unexpected consequences in terms of contributions. It may be that in the context of more generic contributions, the interaction of network structure and contribution behavior – as a function of social psychological factors – will be more consistent with our original predictions.

APPENDIX A

1. From time to time, people discuss important matters with other people, people they trust. If you look back over the last six months, who are the students at SI with whom you discussed matters important to you? (list up to 4 people).
2. Consider the students with whom you like to spend your free time. Over the last six months, who are the students at SI you have been with most often for informal social activities such as going out to lunch, drinks, films, visiting one another's homes, and so on? (list up to 4 people)
3. Of all the students at SI, who have contributed most to your academic and professional growth within SI? (list up to 4 people)
4. Imagine that you are graduating from SI next month. Which SI students would you most likely discuss and evaluate your job options with? (list up to 4 people)
5. Who do you consider to be part of your SI friendship network that you have not already listed? (list up to 4 people)

APPENDIX B

Network Entrepreneur Personality Index.

Instructions: Check the box next to each item that better describes you. Select only one box per question. If you disagree with both phrases, select the one with which you disagree less. Select phrases that describe how you actually operate, rather than how you should or would like to operate. There are no right or wrong answers.

1. When evaluating opportunities, I am likely to look…
    a. For a chance to be in a position of authority
    b. For the long-run implications
2. My strength lies in the fact that I have a knack for…
    a. Being easygoing
    b. Getting a point across clearly
3. In discussions among peers, I am probably seen as…
    a. An outspoken advocate
    b. Motivating people to my views
4. In evaluating my aims in my career, I probably put more emphasis on…
    a. My ability to create an aura of excitement
    b. Being in control of my own destiny
5. I believe that people get into more trouble by…
    a. Being unwilling to compromise
    b. Not letting others know what they really think
6. In a leadership role, I think my strength would lie in the fact that I…
    a. Won people over to my views
    b. Kept everyone informed
7. As a member of a project team, I…
    a. Seek the advice of colleagues
    b. Closely follow the original mandate of the group
8. Others are likely to notice that I…
    a. Let well enough alone
    b. Let people know what I think of them
9. In an emergency, I…
    a. Take the safe approach
    b. Am quite willing to help

10. I look to the future with…
    a. Unshakable resolve
    b. A willingness to let others give me a hand

Answers that correspond with higher network entrepreneur score: 1A, 2B, 3A, 4A, 5B, 6B, 7A, 8B, 9B, 10A

APPENDIX C

Control, individual, and group messages used for contribution level data collection. Each message has 3 iterations, the first for the initial email, the second and third for subsequent reminder emails.

Control Message 1

Subject: SI Social Network - Next Step

Body: [FirstName],

Thanks for completing the SI social network survey last semester. For the second part of this research, we will turn the SI social network into an expertise network. An expertise network matches people with their knowledge and abilities.

We need to collect information about interests and expertise from many different people. The expertise network would be useful because it would combine social networks with expertise to help people connect.

Follow this link to tell about your interests and expertise.

[LINK]

All of the information you provide will be kept confidential. If, at the end of this study, we have enough information to create a usable network, you may choose to make your information identifiable.

Thanks!

Control Message 2

Subject: Reminder: SI Social Network

Body: [FirstName]

We still need information about SI students to create the expertise network. By providing this information, you will help make a better network referral tool.

Visit http://www.surveymonkey.com/s.aspx to finish the survey about your interests and expertise.

Thanks!

Control Message 3

Subject: SI Social Network - Last Chance

Body: [FirstName],

This is the last chance to provide information for the SI expertise network.

Visit http://www.surveymonkey.com/s.aspx to finish the survey about your interests and expertise.

Thanks!

Individual Message 1

Subject: SI Social Network - Next Step: The Network Advantage

Body: [FirstName],

Thanks for completing the SI social network survey last semester. For the second part of this research, we will turn the SI social network into an expertise network. An expertise network matches people with their knowledge and abilities.

A combined social and expertise network helps students take advantage of their network connections. A student who needs a graphic designer for a project could use the network to find one. Plus, if the student does not know the other person directly, the network will show the student which of her friends knows the other person, so she can be introduced.

We need to collect information about interests and expertise from many different people. Your individual input is unique and valuable. Your contribution will help make a robust network tool that you can use to take advantage of the opportunities around you. You can see how your expertise is unique, find others who have the knowledge you need, and see what network connections you can use to meet your goals.

Follow this link to tell about your interests and expertise.

http://www.surveymonkey.com/s.aspx

All of the information you provide will be kept confidential. If, at the end of this study, we have enough information to create a usable network, you may choose to make your information identifiable.

Thanks!

Individual Message 2

Subject: Reminder: SI Social Network - Give Your Input

Body: [FirstName]

We still need information about SI students to create the expertise network. By providing this information, you will help make a better network referral tool. This tool helps you take advantage of the opportunities around you and meet your academic and career goals.

Visit http://www.surveymonkey.com/s.aspx to finish the survey about your interests and expertise.

Thanks!

Individual Message 3

Subject: SI Network Advantage - Last Chance

Body: [FirstName]

This is the last chance to provide your unique input for the SI expertise network.

To give your opinions, visit http://www.surveymonkey.com/s.aspx.

Thanks!

Group Message 1

Subject: SI Social Network - Next Step: Connecting Students

Body: [FirstName],

Thanks for completing the SI social network survey last semester. For the second part of this research, we will turn the SI social network into an expertise network. An expertise network matches people with their knowledge and abilities.

A combined social and expertise network helps students connect to people who share their interests. A student who is interested in graphic design could use the network to find others interested in graphic design. If the student does not know the other person directly, the network will show which of her friends knows the other person, so she can be introduced.

We need to collect information about interests and expertise from many different people. Your input will help reach this group-wide goal. Your contribution combined with other students' contributions will make a robust network tool for all SI students to benefit from. Students can use this tool to build meaningful relationships and be more connected.

Follow this link to tell about your interests and expertise.

[LINK]

All of the information you provide will be kept confidential. If, at the end of this study, we have enough information to create a usable network, you may choose to make your information identifiable.

Thanks!

Group Message 2

Subject: Reminder: SI Social Network - Be Part of the Network

Body: [FirstName]

We still need information about SI students to create the expertise network. By providing this information, you will help make a better network referral tool. This tool helps students at SI get connected, find others who share their interests, and develop stronger relationships.

Visit [LINK] to finish the survey about your interests and expertise.

Thanks!

Group Message 3

Subject: SI Network Connections - Last Chance

Body: [FirstName],

This is the last chance to be help build an SI expertise network for students to make meaningful connections.

To connect to the network, visit [LINK].

Thanks!

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