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Product Ideation in Social Networks

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Report Summary

One of the most important marketing activities a firm engages in involves product innovation. A critical stage of firms' marketing innovation processes is *ideation*, which encompasses the generation of new product-related ideas. An increasingly popular approach to marketing ideation, used by a variety of firms including Dell, Delta Air Lines, Lego, and Starbucks, involves crowdsourcing ideas from consumers using online communities or social networks. Consumers who participate in such communities are embedded in social networks where the connections between consumers allow them access to each other's ideas.

In this report, Andrew Stephen, Peter Pal Zubcsek, and Jacob Goldenberg investigate whether online crowdsourcing leads to positive or negative outcomes in terms of idea innovativeness. They propose that the structure of a consumer's network of "inspirations" (other consumers in an online community) determines whether crowdsourcing leads to more-innovative or less-innovative ideas. Members of these communities are socially networked; they are connected to some people but typically not to everyone. As in other social networks (e.g., Facebook), information—ideas—spreads over these connections, and having many connections affords one with many potential sources of inspiration.

The authors propose and test the hypothesis that the degree of interconnection among consumers will determine positive or negative outcomes in idea generation. They conduct six experiments involving ideation tasks in online communities for three products (mobile banking applications, airlines, and Facebook). Participants were randomly assigned to network positions and generated ideas over a series of rounds in which they could also see their neighbors' ideas. All ideas were judged by a separate group of consumers on innovativeness.

In all experiments, irrespective of product category or consumer type, the structure of a consumer's social network substantially impacted their ability to generate truly innovative product ideas. Having high degree—many sources of inspiration—helped consumers generate more innovative ideas, but only if those sources of inspiration were predominantly *independent* of each other.

Managerial implications

These findings suggest that denser, tightly interconnected communities—which are very typical in online communities and social networks—are counterproductive to the generation of more-innovative ideas. This implies that managers who use online communities and networks for ideation purposes should reconsider how they allow consumers to interact. "Engineering" networks that allow for many connections that are relatively independent of each other is likely to lead to optimal outcomes. However, the current practice of allowing consumers to be tightly interconnected is likely to lead to underperformance and, overall, less creative ideas.

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Introduction

One of the most important marketing activities a firm engages in involves product innovation. A critical stage of firms' marketing innovation processes is *ideation*, which encompasses the generation of new product-related ideas either for general product concepts or for specific product features (Cooper 1990; Urban and Hauser 1993). This stage is particularly important since identifying viable market opportunities as early as possible in the innovation process can lead to greater efficiency at subsequent stages (Smith and Reinertsen 1992; Dahan and Hauser 2002). Moreover, since bringing new products to market or extending or modifying existing products can be costly and risky, it is important that firms' ideation activities yield high-quality innovative ideas.

While ideation has traditionally taken place inside firms among specialist product teams, a growing trend is called "open innovation" whereby ideation involves soliciting ideas from *external* sources such as customers (Chesbrough 2003). With the rise in popularity of social media, firms have started using use online communities and social networks as platforms for "crowdsourcing" product-related ideas from consumers (Bayus 2013; Freedman 2012; Winsor 2009). For example, in February 2007 Dell launched an online community called IdeaStorm where consumers could publicly submit product ideas and comment on others consumers' ideas.[1] In March 2008 Starbucks created a similar platform called MyStarbucksIdea.[2] Other brands to take this approach include BMW, Canon, Delta Air Lines, GE, Google, Lego, McDonalds, Mountain Dew, and Pepsi.

The logic behind this approach is the belief that soliciting ideas from consumers can help firms mitigate some of the inherent risks of product development because consumers, compared to internal product development teams, are thought to have a better sense of what they want in terms of products and specific features (Boutin 2006; Ogawa and Piller 2006). In practice, however, this may not always be the case. For example, firms typically do not implement many of the ideas contributed by consumers in online product ideation communities (e.g., the respective implementation rates for Dell IdeaStorm and MyStarbucksIdea are approximately 2.84% and .16%). Obviously many factors affect the likelihood that an idea will be implemented,

[1] Between February 2007 and February 2013 18,540 ideas were submitted and 526 ideas were implemented.
[2] Between March 2008 and February 2013 151,883 ideas were submitted and 242 ideas were implemented.

however one reason for low implementation rates is the prevalence of low-innovativeness ("bad" or "mediocre") ideas from consumers that, to firms, are not worth investing in. Despite the possibility that crowdsourcing product ideas from consumers can lead to the discovery of highly innovative and marketable product concepts, in reality the majority of consumers' ideas may lack the levels of innovativeness that firms desire.

A Network Perspective on Online Product Ideation Communities

The prevalence of low-innovativeness ideas from consumers in these communities may be problematic beyond simply creating "noise" for firms who have to sift through large numbers of unviable ideas before identifying some viable prospects. An often-overlooked aspect of online product ideation is that the consumers who participate in these communities are embedded in social networks where the connections between consumers allow them to see each other's ideas. Consumers may therefore ideate *interdependently* in these settings, which may lead to undesirable outcomes. We examine interdependent ideation in networks and how individuals' positions in these networks affect their abilities to generate innovative product ideas.[3]

Similar to groups of people engaged in brainstorming tasks (cf. Osborn 1953) and to the literature on the wisdom of crowds (cf. Wolfers and Zitzewitz 2004; Surowiecki 2004), consumers in online product ideation communities can be influenced by each other and thus ideate interdependently because network connections allow them to access each other's ideas. Interestingly, prior research in related contexts such as brainstorming, collective problem solving, prediction markets, and the wisdom of crowds finds that having interdependent, socially networked agents can lead to either positive outcomes (e.g., Golub and Jackson 2010; Mason and Watts 2012; Wolfers and Zitzewitz 2004) or negative outcomes (e.g., Clemen and Winkler 1985; Easley and Kleinberg 2010; Lamm and Trommsdorff 2006; Mullen et al. 1991).

In our context it is possible that consumers will bounce good ideas off of one another and that this will lead to the generation of excellent ideas over time through a process of building on, combining, rearranging, or repurposing each others' ideas. This is consistent with extant literature on creativity showing that good ideas often result from the arrangement of concepts from existing knowledge (Dahl and Moreau 2002; Ward 1994) or from rearranging ideas that

[3] Consistent with extant literature, we consider innovative ideas to be creative/novel *and* to have the potential to be useful (Amabile 1996; Bayus 2013; Burroughs, Moreau, and Mick 2008).

already exist (Fleming and Szigety 2006; Simonton 2003). In the case of interdependent ideation, however, the concepts and ideas that an individual can draw on as “inspirations” come from both their own knowledge or experience and the ideas contributed by other community participants to whom they are exposed. Thus, allowing for interdependent ideation may be advantageous to firms because the pool of inspirations is larger.

However, since online product ideation communities can often contain many less-innovative ideas, this ideal positive situation may not be typical. Instead of collectively making each other’s ideas better, consumers embedded in these networks could end up producing less-innovative ideas. This is because these subpar ideas could serve as bad examples that participants fixate on, thus effectively contaminating an individual’s ideation. This is consistent with prior research on cognitive fixation in creativity (Marsh and Landau 1995; Smith, Ward, and Schumacher 1993). Even if others’ ideas that serve as examples or inspirations are not mediocre, their mere existence could still suppress innovativeness because fixation can result in ideas becoming more uniform. This can stifle innovation because the inspirations from which one draws lack diversity and more creative ideas tend to come from combinations of diverse concepts (Amabile 1988, 1996; Hargadon and Sutton 1997). Thus, a more plausible consequence of embedding consumers in product ideation communities is the generation of less-innovative ideas.

In light of this prediction, our objective is to understand how a consumer’s position in a product ideation network affects their ability to generate highly innovative product ideas. We define network position in terms of how many connections a consumer has to others (i.e., degree) because this determines how many potential sources of inspiration they are exposed to, and how densely interconnected their ego-networks are (i.e., clustering) because this determines how independent versus interdependent one’s neighbors are. When an individual’s neighbors are clustered their multiple sources of inspiration are interdependent, which could result in them producing less-diverse sets of ideas because they are all exposed to each other. This could lead to lower innovativeness. Conversely, when one’s inspirations are more diverse (i.e., less clustered) we expect higher innovativeness in generated ideas. We therefore hypothesize that being exposed to more sources of inspiration can diminish (enhance) an individual’s ability to produce innovative ideas when their neighbors are relatively interdependent (independent).

Theory Development

Background

The current research focuses on the effects of an individual’s social network position on their ability to generate innovative ideas in product ideation tasks. Although consumers participating in online ideation communities such as those run by Dell and Starbucks are *implicitly* embedded in social networks, *explicit* effects of network position on ideation performance has not been previously considered. Moreover, the interdependence of consumers in this setting has not been fully explored in extant research. Instead, prior research has focused on other aspects such as incentive mechanisms and rewards (e.g., Burroughs et al. 2011; Toubia 2006), creative idea typologies and ideation “templates” (Goldenberg et al. 1999a, b), how consumers can be used to screen ideas (e.g., Toubia and Florés 2007), how individual ideation performance can be fostered (Luo and Toubia 2012), online crowdsourcing more generally (Bayus 2013), and the psychological processes involved in generating creative product ideas (e.g., Dahl and Moreau 2002, 2007; Moreau and Dahl 2005).

We contribute to the literature on consumer-based product ideation by directly considering participant interdependence from a social networks perspective and, specifically, examining how one’s network position affects the innovativeness of their ideas. Although some recent product ideation research considers interdependent agents in small brainstorming teams (Girotra et al. 2010) or in large online crowdsourcing communities (Bayus 2013), research examining product ideation from a network perspective is scant. This perspective is theoretically interesting because individual performance in product ideation tasks could be affected by one’s network position since network connections allow people to see each other’s ideas. The current research helps build a better understanding of the role played by network connections in this context. Moreover, we consider how the structure of connections among one’s neighbors affects the diversity of thoughts, ideas, or—more generally—inspirations, to which one is exposed and how this, in turn, affects their own ability to generate innovative ideas.

Relation to research on brainstorming

One of the most common techniques used for ideation in a variety of contexts—including product development—is brainstorming (cf. Osborn 1953).[4] Since it is closely related to crowdsourced ideation, we turn to the literature on brainstorming to consider how being connected and exposed to others' thoughts might impact individual ideation performance. As with much of the marketing ideation literature, the performance goal for participants in a brainstorming session is usually to generate innovative ideas/concepts or to solve a particular problem. Prior research suggests that, compared to when individuals ideate alone, allowing exchanges of creative ideas in brainstorming sessions can lead to superior performance because the exchange of ideas and concepts is cognitively stimulating (Dennis and Valacich 1993; Dugosh et al. 2000; Nijstad et al. 2002; Valacich et al. 1994). Thus, socially networked product ideation could help individuals generate innovative ideas because they are more stimulated. However, since this outcome is not always observed in practice there may be other factors present that work against individual performance. In fact, much of the brainstorming literature finds that members of creative group sessions generate fewer and lower-innovativeness ideas than individuals working alone (Lamm and Trommsdorff 2006; Mullen et al. 1991). This is also true in electronic (online) brainstorming sessions, which are similar to online product ideation communities (Pinsonneault et al. 1999).

Three main reasons have been advanced for this (Diehl and Stroebe 1987; Pinsonneault et al. 1999). First, performance may suffer from *evaluation apprehension* in the sense that participants may be unwilling to state some of their ideas because they are afraid of being critically evaluated or judged by others (Camacho and Paulus 1995; Collaros and Anderson 1969). For example, participants may censor themselves by refraining from contributing ideas that they consider to be more "out of the box" or controversial. Second, performance may suffer due to *free riding* because some people do not work as hard in a group as they would if they had to work independently (Harkins and Szymanski 1989; Kerr and Bruun 1983; Shepperd 1993; Toubia 2006). This can mean that fewer group members actively contribute ideas. As a consequence, harder-working participants will have fewer sources of "fresh inspiration" to help them generate their own ideas. Third, the procedural sequencing of brainstorming sessions such that individuals take turns to contribute ideas can give rise to a problem called *production*

[4] See Hauser et al. (2006) for a review of research on innovation and new product development in marketing.

blocking, which is regarded as the most important cause of productivity loss in brainstorming (Lamm and Trommsforff 2006). This problem typically means that a few dominant group members take the majority of the time by sharing their own thoughts while others are forced to suppress theirs because they do not have an opportunity to share. This ultimately means that individuals draw inspiration from fewer unique sources in their group.[5]

How network structure can affect ideation

An issue not previously extensively considered in the brainstorming literature, however, is related to network structure. In organizational settings researchers have suggested that network structure can play an important role in affecting outcomes (e.g., Bavelas 1950; Burt 2002). Researchers have also proposed this in a variety of specific problem-solving contexts (e.g., Judd and Kearns 2008; Kearns et al. 2006; Mason and Watts 2012). In a standard brainstorming group all participants are exposed to everyone else.[6] From a social networks perspective this means that the network structure that connects participants and facilitates flows of information between them is fully connected, i.e., the network is maximally dense. We can also express each individual's network connectivity formally using the concepts of *degree* and *clustering*. An individual's degree is the number of other individuals to whom they are directly connected (neighbors). An individual's clustering is a measure of how interconnected their neighbors are among each other, and is equal to the total number of connections between an individual's neighbors divided by the number of connections that could possibly exist between them if everyone was connected to everyone else.

The fully connected networks typical in brainstorming groups can be efficient for rapid information (idea) diffusion, which can help good ideas spread and serve as good examples. However, in the more typical situation where there is heterogeneity across ideating consumers with respect to their underlying abilities and how innovative their ideas are, it is more likely that the ideas spreading around a network will vary considerably in their levels of innovativeness. In that case it is possible that denser network structures may hinder individual performance by making it easier for *all* types of ideas—good, bad, and everything in between—to spread. Ideas

[5] The previously mentioned concept of "cognitive fixation" (Marsh and Landau 1995) is similar to production blocking in the sense that earlier ideas in a sequence are examples that may be fixated on.
[6] This is typically the case in offline, face-to-face brainstorming groups. In online contexts this is not necessarily the case and the network structure—who works with whom—can be exogenously controlled (e.g., Judd and Kearns 2008; Kearns et al. 2006).

rapidly spreading in dense (clustered) sub-networks are particularly problematic when mediocre ideas are prevalent. Further, if consumers cognitively fixate on their neighbors' mediocre ideas then their own ideas are less likely to be innovative. Thus, one mechanism through which denser network structures (higher clustering) can reduce idea innovativeness despite multiple sources of inspiration (higher degree) is the *spreading of mediocre ideas*.

A second mechanism is related to a phenomenon in the brainstorming literature called *social convergence*. This refers to situations where groups produce ideas that fall within a limited or narrow set of categories (Paulus et al. 2002). As mentioned earlier, innovative ideas are more likely to be generated when people combine different concepts rather than similar concepts. Social convergence, however, tends to make group members' ideas more uniform. Being "on the same page" is, to some extent, probably important so that concepts are not so diverse that they are incompatible and cannot be creatively combined. However, too much uniformity (and therefore not enough diversity) may inhibit product ideation performance.[7] Idea uniformity means that participants will be exposed to fewer unique, independent sources of inspiration. This could lead to them being less innovative themselves because they have fewer unique concepts from others to spark their own ideas and to combine into new ideas through creative processes, even if the ideas to which they are exposed are reasonably innovative (Goldenberg et al. 1999a, b; Goldenberg, Lehmann, and Mazursky 2001).

We expect both mechanisms—the spreading of mediocre ideas and social convergence—to play a role in determining how innovative consumers' ideas are in online product ideation networks. Although having more sources of inspiration could help individuals produce better ideas, this depends on these two mechanisms, both of which are associated with clustering. Under higher clustering it is both easier for mediocre ideas to spread because of denser ego-networks and for individuals' ideas to socially converge because of interdependent, overlapping sources of inspiration. Thus, under higher levels of clustering the effect of increasing degree on idea innovativeness may not be positive and could be negative. For a consumer with many sources of inspiration (higher degree), how interconnected their sources are (clustering) is expected to influence the extent to which those sources are helpful to them. When their many sources of inspiration are more interdependent (higher clustering) both mechanisms are more

[7] In collaborative problem solving (e.g., Mason and Watts 2012), uniformity may help because individuals must converge to a single solution of a well-defined problem as a group.

likely to be present and performance may be hindered. This will be more pronounced at higher levels of degree because idea uniformity among interdependent sources of inspiration will be a stronger signal among more versus fewer neighbors.[8] These arguments imply a negative degree x clustering interaction effect on idea innovativeness. We expect increased clustering to reduce idea innovativeness particularly as one's degree increases. At lower levels of degree this is not expected because even high levels of clustering correspond to only a handful of interdependent pairs of neighbors and so the above-discussed mechanisms are likely to be less prominent.

Overview of Studies

Below we report six experiments. We first provide an overview of our experimental procedure because many aspects are common to all studies, and then introduce our dependent variable of idea innovativeness used in all studies. We used a web-browser-based software application developed for this research that allowed groups of people to participate together in real-time online product ideation tasks. Importantly, the software allowed us to exogenously control both the sizes and structures of the social networks in which we situated participants. The software also allowed us to randomly assign participants to network positions. Exogenously determining networks and randomly assigning participants to positions allowed us to have sufficient variation in degree and clustering for testing our theory, and mitigated concerns related to endogeneity, homophily, and selection that are important when studying "natural" networks.

Experimental procedure

First, participants were invited to take part in an ideation task in which they would develop ideas for new features for a specific product/service that would make it more useful to consumers. They were told that they would do this with other people in a real-time online environment. Participants were given an incentive to participate (either a $5 payment or class credit). The incentive was not linked to their performance. All task descriptions encouraged creativity and stated that participants were to ensure their ideas would be useful to consumers.

[8] This can be thought of as a social proof effect: uniformity among a larger set of neighbors should be a stronger and more influential example than uniformity among a smaller set of neighbors.

Second, participants were randomly assigned to a between-subjects condition (as appropriate depending on the study) and, within condition, were randomly assigned to network position with predetermined degree and clustering. All networks were undirected (i.e., if A was connected to B then A could see B's ideas and B could see A's ideas).

Third, participants completed an ideation task over multiple rounds. Each round had two parts. The first part required participants to type their idea into a box with a two-minute time limit. The second part allowed participants to view neighbors' ideas from that round with a two-minute time limit. [9] Participants were always instructed to provide their best idea in the final round. With the exception of one of the conditions in Study 4, participants were told that they were allowed to use their neighbors' ideas to improve their own ideas in subsequent rounds. Note that the use of discrete rounds is designed to mimic the asynchronous nature of popular online product ideation communities as closely as possible in an experimental setting.

Finally, after the final round had been completed, participants were asked to complete a post-task survey in which we collected data to be used as control variables in our analyses.

Dependent variable: Idea innovativeness

Our dependent variable is *idea innovativeness* (for each idea contributed in each round by each participant), which is defined as how generally innovative and creative an idea is. The submitted ideas were given to multiple independent judges who were blind to the details of the study other than the general description of the ideation task (e.g., *company X* asked people to think of innovative ideas for features that *product Y* could have that would make it more useful to customers). Each judge read an idea and first screened it for validity (i.e., that it was an idea for the product that it was supposed to be for and that it made sense). Ideas marked as invalid were not judged and were excluded from subsequent analyses.

Judges then rated valid ideas on seven five-point Likert scales (1 = strongly disagree, 5 = strongly agree) designed to measure their perceptions of how innovative the idea was in the context of the product it was for. The items are listed in Appendix A. Example items included "This idea is original," "This idea is out of the box," and "This idea is innovative." For each judge these items were averaged to form a judge-level measure of idea innovativeness. Then, across judges, these averages were averaged to form an idea-level measure of innovativeness.

[9] Neighbors were those participants to whom one was *directly* connected in the network.

Since this judge-based measurement procedure was designed to capture average consumer perception of idea innovativeness—analogous to how data from a market research survey of consumer attitudes toward a given product or attribute would be used—we were not interested in the extent to which judges' ratings for a given idea were in agreement.[10]

Study 1

Overview and procedure

This study provides an initial test of our hypothesis. Sixty-four students at a large university in the southeastern U.S. participated in this study over four separate runs/sessions for class credit. Participants in each run were randomly assigned to a position in a 16-node network. The network was designed to allow sufficient variation in degree and clustering between nodes, and to have properties similar to those found in real-world social networks (e.g., skewed degree distribution, moderate level of clustering). Degree ranged between 3 and 8 ($M = 5.13$, $SD = 1.41$), and clustering ranged between 0 and .8 ($M = .36$, $SD = .27$). We also designed the network to minimize the correlation between degree and clustering ($r = .02$). See Figure 1. (Tables and figures follow References.)

The ideation task involved generating ideas for features that a mobile banking smartphone application could have that would be innovative and useful to bank customers (see Appendix B for the task description). Participants were introduced to this task and then completed three consecutive two-part ideation rounds as described earlier. Of the 192 total ideas submitted for judges to rate on innovativeness, 177 (92.19%) were deemed to be valid and thus useable in our analysis. Each valid idea was rated by two or three independent judges ($M = 2.72$) on the seven-item innovativeness scale described earlier ($\alpha = .98$).

Results

Since the ideas submitted in the first round are independent, we use the ideas submitted in the second and third rounds for analysis, and control for the innovativeness of each participant's previous-round idea. This resulted in a panel dataset of 119 valid ideas from 61 participants

[10] Notwithstanding, across studies the typical standard deviation of judges' ratings for an idea was less than one (on a five-point scale). Inter-judge reliability was therefore not troublingly low.

(49% female) across four experimental runs.[11] The average idea length was 207.10 characters (SD = 94.14, min. = 57, max. = 473). Since the participants had not interacted prior to the first round, the network variables should not have any effects on first-round idea innovativeness, which was the case.

To examine whether a participant's network position as measured by degree and clustering affected their ability to produce innovative ideas, we estimated a mixed effects model to regress idea innovativeness on standardized degree, clustering, the two-way degree x clustering interaction, and a set of control variables. The control variables were (i) previous-round idea innovativeness (i.e., the first-order lag of the dependent variable), (ii) fixed effects for college year, (iii) a fixed effect for gender, (iv) fixed effects for run/session, (v) a fixed effect for round, (vi) the amount of time in seconds the participant took to write the idea, and (vii) a random effect for participant.

Regression results are reported in Table 1 and estimated means at one standard deviation below and above mean degree and mean clustering are plotted in Figure 2. Consistent with our prediction, we find a significant negative interaction between degree and clustering (b = -.16, t = -2.04, p = .05). The main effects are not significant for both degree and clustering (p = .39 and p = .23, respectively). The nature of this negative interaction is illustrated by Figure 2 and is consistent with our hypothesis: at higher levels of degree (i.e., more sources of inspiration), mean idea innovativeness is higher when clustering is lower (est. M = 4.40) but lower when clustering is higher (est. M = 3.94; spotlight analysis simple effect of clustering at higher degree p = .037). In other words, higher-degree participants only benefitted from having more sources of inspiration when they had lower clustering.

Note that it is possible that the degree x clustering interaction is driven by low degree and restricted possibilities for variation in clustering as degree decreases. If this is the case then degree is simply a boundary condition for the clustering effect. This, however, does not appear to be the case. We re-ran our analysis excluding participants with the lowest degree (3) and again found a significant negative degree x clustering interaction (p = .024). Excluding participants with degree = 3 or 4 also did not change this result (interaction p = .037). Thus, it is unlikely that the negative degree x clustering interaction is due to the inclusion of low-degree participants.

[11] Three participants were dropped because they did not produce ideas in rounds 2 or 3 due to a software error.

Study 2

Overview and procedure

This study replicates Study 1 using two different network structures and a different participant population. Eighty members of a large U.S. online panel participated in this study over four separate runs for $5. In each run participants were randomly assigned to a position in one of two 10-node networks. Each network had 10 nodes but different structural properties. We used an Erdos-Renyi (ER) random graph and a Small-World (SW) random graph, both with mean degree = 4. The ER graph had degree between 1 and 7 (M = 4.00, SD = 1.48) and clustering between 0 and .83 (M = .47, SD = .22). The SW graph had degree between 3 and 5 (M = 4.00, SD = .63) and clustering between 0 and .67 (M = .30, SD = .22). See Figure 3.

The ideation task and procedure were identical to Study 1: generating ideas for features of a mobile banking smartphone application over three consecutive two-part rounds. Of the 240 total ideas submitted to judges for rating, 226 (94.17%) were deemed valid and were rated on our innovativeness scale (α = .96) by two or three independent judges (M = 2.82).

Results

The dataset contained 144 valid second- and third-round ideas from 72 participants (55% female; mean age = 32 years) across four experimental runs where each run had one ER and one SW network.[12] The average idea length was 149.96 characters (SD = 94.04, min. = 14, max. = 510). No network position effects were found when the first-round ideas were analyzed separately. As in the previous study, we estimated a mixed effects model to regress idea innovativeness on standardized degree, clustering, the two-way degree x clustering interaction, and a set of control variables very similar to those used previously.

Regression results are reported in Table 2 and estimated means at one standard deviation below and above mean degree and mean clustering are plotted in Figure 4. In this table we report two models, one including participants from all nodes in the networks and one excluding participants who were assigned to positions with degree = 1 (one node in the ER network has degree = 1, which could be a problem because clustering is not defined when degree = 1; when

[12] Eight participants were dropped because they did not produce ideas in rounds 2 or 3 due to either a software error or an internet connection problem.

degree = 1 we set clustering = 0 for convenience). The model excluding degree = 1 participants is reported for robustness and the substantive results are identical to those from the model including degree = 1. We base our findings on the model using participants from all nodes. Also, since the results were not different between ER and SW networks when analyzed separately we pooled participants and controlled for network type with a fixed effect.

Consistent with Study 1, the degree x clustering interaction is significant and negative ($b = -.20$, $t = -2.23$, $p = .025$). The main effect of degree is not significant ($p = .22$), though the main effect of clustering is ($b = -.19$, $t = -2.23$, $p = .03$). The nature of this negative interaction is illustrated by Figure 4. As before, at higher levels of degree mean idea innovativeness is higher when clustering is lower (est. M = 4.85) but lower when clustering is higher (est. M = 4.05; spotlight analysis simple effect of clustering at higher degree $p = .013$). We also find a positive simple effect of degree when clustering is lower ($p = .001$).

In addition to idea innovativeness, we asked judges to rate ideas on their market potential so that we could test if higher-innovativeness ideas also had higher market potential. Ten five-point Likert-scaled items measured market potential (1 = strongly disagree to 5 = strongly agree; $\alpha = .95$). Example items included "I would use an app with this feature," "This app would have many users," and "I would download this app." The correlation between idea innovativeness and market potential was .34 ($p < .001$), and the partial correlation controlling for round, network type, run, age, and gender was .32 ($p < .001$). At least in this category it appears that more innovative products are likely to be in greater demand and received more positively.

Study 3

Overview and procedure

In this study we use a different product category and test a potential moderator related to the social convergence mechanism. For network position to affect one's ability to generate innovative ideas in this interdependent setting, participants need to be able to take concepts from their neighbors' ideas and combine them with their own thoughts to create new ideas (which may or may not be innovative). For this to happen all participants' ideas need to be, to an extent, compatible. Put differently, participants need to be "on the same page" with respect to what they are thinking about, at least in general terms. When participants are not on the same page, network connections are unlikely to affect their performance because of a lack of compatibility between their ideas. Further, whether or not one's neighbors are highly clustered is unlikely to affect performance because, even if they are clustered, significant social convergence of ideas over relatively few rounds of ideation is unlikely. Accordingly, when conditions are such that participants are likely to *not* be thinking along compatible, similar lines we should not find network position effects. If this is the case it lends support to our argument that clustering can hurt performance due to social convergence because convergence is less likely when participants are not on thinking on the same page. To test this we varied how specific the ideation task was, and expected to replicate the previous studies' effects when task specificity was high, and to find no network-position effects when it was low. When task specificity is low participants are less likely to be on the same page with their thoughts.

Seventy-two members of a large U.S. online panel participated in this study over three runs for $5. In each run participants were randomly assigned to a position in one of two identical 12-node networks. In each run one network had high task specificity and the other had low task specificity (i.e., participants in the same network in the same run were all assigned to the same task specificity condition). In this network degree ranged from 2 to 7 (M = 4.17, SD = 1.40) and clustering ranged from 0 to 1 (M = .53, SD = .27). The correlation between degree and clustering was also close to zero (r = -.06, *p* = .84). See Figure 5.

The task involved generating ideas for improving the commercial air travel experience. The high task specificity condition had participants generate ideas for an airline smartphone application that would improve the travel experience. The low task specificity condition did not impose this constraint and participants were asked to develop ideas for things an airline could do to improve the travel experience. Both versions are in Appendix B. Participants were introduced to this task and then completed multiple consecutive two-part ideation rounds, however this time they completed four rounds. Of the 288 ideas, 263 (91.32%) were deemed valid and rated by two or three judges (M = 2.86) on our innovativeness scale (α = .93).

Results

The dataset contained 194 valid second-, third-, and fourth-round ideas from 67 participants (41% female; mean age = 32 years) across three runs where each run had one network in the high task specificity condition and one network in the low task specificity condition.[13] The average idea length was 175.72 characters (SD = 114.20, min. = 13, max. = 639). No network position effects were found when the first-round ideas were analyzed separately. We again estimated a mixed effects model to regress idea innovativeness on standardized degree, standardized clustering, the two-way degree x clustering interaction, and a similar set of control variables as before. An additional control variable for whether or not the participant intended to travel in the next six months (0 = no, 1 = yes) was included since, unlike mobile banking, involvement in the air travel category is potentially less common for the average person and whether or not someone is at least a semi-regular air traveler might affect their ability to generate ideas for improving air travel or the perspectives they adopt.

Regression results for high and low task specificity networks are reported in Table 3 and estimated means at one standard deviation below and above mean degree and mean clustering are plotted in Figure 6. The degree x clustering interaction is significant and negative under high task specificity ($b = -.27$, $t = -2.76$, $p = .011$; Figure 6A), but not under low task specificity as expected ($p = .96$; Figure 6B). When the task is specific we see that at higher levels of degree idea innovativeness is higher when clustering is lower (est. M = 3.64) but lower when clustering is higher (est. M = 2.95; spotlight analysis simple effect of clustering at higher degree $p < .01$).

Study 4

Overview and procedure

In this study we consider a third product category and test another moderator related to social convergence. Social convergence is less likely if participants do not fixate on neighbors' ideas, which should be the case when they are not allowed to use neighbors' ideas. Under this condition we would not expect to find network position effects. Further, since not being allowed to use neighbors' ideas makes otherwise interdependent participants effectively independent, network effects should not be present. Thus, we varied whether or not participants were allowed to use neighbors' ideas as sources of inspiration. We only expected to replicate the previous studies' effects when participants were allowed to use neighbors' ideas.

Ninety-six students at a large northeastern U.S. university participated in this study over four separate runs for class credit. In each run participants were randomly assigned to a position

[13] Five participants were dropped because they did not produce ideas in rounds 2, 3, or 4 due to a software error.

in one of two identical 12-node networks. In each run one network allowed using neighbors' ideas and one network did not. The network was the same as the one used in Study 3. The ideation task in this study asked participants to generate ideas for new features of Facebook that would make it more useful (see Appendix B). In the "allowed" condition participants were told that they were allowed to take neighbors' ideas and use them as part of their own (as in all previous and all subsequent studies in this paper). In the "not allowed" condition participants were told that they were not allowed to use neighbors' ideas as part of their own and that they should contribute only their own ideas. Participants completed three consecutive two-part ideation rounds in this study. Of the 288 ideas submitted for judges, 283 (98.27%) were valid. Each valid idea was rated by two or three judges (M = 2.91) on our innovativeness scale (α = .93). All participants and judges stated that they were current Facebook users.

Results

The dataset contained 189 valid second- and third-round ideas from 96 participants (47% female, mean age = 20 years) across four experimental runs. The average idea length was 206.84 characters (SD = 110.41, min. = 10, max. = 554). No network position effects were found when the first-round ideas were analyzed separately.

We first checked our manipulation. At the end of the ideation task participants completed a survey where we measured three items used to indicate the extent to which participants felt they used (or did not use) their neighbors' ideas in generating their own ideas during the task. The first item was a five-point Likert scale "For each idea from round 2 onwards I tried to build on previous idea(s) that other people had suggested" (1 = strongly disagree, 5 = strongly agree). The second and third items asked participants to indicate on five-point scales the extent to which their ideas were completely their own versus inspired by their neighbors' ideas separately for the second and third rounds of the task (1 = 100% my own idea and not inspired by neighbors, 5 = 100% inspired by neighbors and not at all my own idea). Participants in the allowed networks reported higher values on each of these items (M_1 = 3.42, M_2 = 2.12, M_3 = 2.16) than participants in the not allowed networks (M_1 = 2.48, M_2 = 1.30, M_3 = 1.53). All differences were significant (*p*s < .001). Thus, our manipulation operated as intended.[14]

[14] It is unlikely that participants in the not allowed condition *completely* ignored neighbors' ideas. However, they appeared to make less use of neighbors' ideas than participants in the allowed condition did.

Regression results for allowed and not allowed networks are reported in Table 4 and estimated means at one standard deviation below and above mean degree and mean clustering are plotted in Figure 7. The degree x clustering interaction is negative and significant when participants are allowed to use their neighbors' ideas for inspiration (b = -.25, t = -2.08, p = .044; see Figure 7A), as expected. We also find a marginally significant negative main effect of degree (b = -.21, t =-1.89, p = .066) but a non-significant main effect of clustering (p = .12). However, when using neighbors' ideas is not allowed, the degree x clustering interaction is not significant (p = .68; see Figure 7B). The two main effects are also not significant in this condition (ps > .30). Further, when participants were allowed to use neighbors' ideas we again see that, at higher levels of degree, mean idea innovativeness is higher when clustering is lower (est. M = 4.85) but lower when clustering is higher (est. M = 3.99; spotlight analysis simple effect of clustering at higher degree p = .05). This is not the case when using neighbors' ideas is not allowed (spotlight analysis simple effect of clustering at higher degree p = .60).

Study 5

Overview and procedure

The purpose of this study is to provide general support for the premise that, under interdependent ideation, ideas (or concepts on which ideas are based) can *and in fact do* spread between connected participants. Thus, we attempt to find evidence of the idea-spreading mechanism described earlier. To do this we employ semi-automated natural language processing methods that allow us to directly examine participants' ideas and the extent to which they are similar. Thirty-six students at a large northeastern U.S. university participated in this study over three separate runs for class credit. In each run participants were randomly assigned to a position in a 12-node network that was the same as the one used in Studies 3 and 4. The "allowed" condition of the Facebook task from Study 4 was used here. Participants completed three consecutive two-part ideation rounds. Of the 108 ideas submitted to judges, 100 (92.59%) were deemed valid. Each valid idea was rated by two or three independent judges (M = 2.84) on our innovativeness scale (α = .92). All participants and judges were Facebook users.

Results

The dataset contained 66 valid second- and third-round ideas from 34 participants (36% female) across three runs.[15] The average idea length was 164.82 characters (SD = 103.96, min. = 31, max. = 462). No network position effects were found when the first-round ideas were analyzed separately. Regression results are reported in Table 5 and estimated means at one standard deviation below and above mean degree and mean clustering are plotted in Figure 8. As with all previous studies, the degree x clustering interaction is negative and significant (b = -.40, t = -3.19, p < .01; see Figure 8). The main effects of degree (b = -.40, t = -3.39, p < .01) and clustering (b = -.37, t = -2.92, p < .01) are also significant. Once again, at higher levels of degree idea innovativeness is higher when clustering is lower (est. M = 3.16) but lower when clustering is higher (est. M = 1.63; spotlight analysis simple effect of clustering at higher degree p < .01).

Idea similarity analysis using semi-automated natural language processing

Next we examined participants' ideas with respect to how similar or dissimilar they were among connected participants in each run of this task. The purpose of this analysis was to establish that our effect is due to interdependent ideation among connected participants and not other factors (e.g., chance). We subjected the raw text of all valid ideas submitted by participants across all three rounds to the following procedures (see Appendix C for a detailed explanation of the steps involved in these procedures).

First, we employed natural language processing techniques to extract "noun chunks" from each idea using the "chunk" package in the *Natural Language Toolkit* software (Bird et al. 2012). This algorithm parses noun chunks from each idea to identify non-overlapping linguistic groups (noun phrases), resulting in a set of concepts summarizing each idea's key components.

Second, we manually cleaned and checked the set of concepts corresponding to each idea. For each set we removed duplicate concepts, fixed typographical errors, converted plurals to singulars, converted abbreviations (e.g., "app") to their long forms (e.g., "application"), deleted nonsensical terms, and checked that each original idea matched its concept set. We also removed the noun "Facebook" from all concept sets since it was redundant, and removed any concepts that were part of the task description itself.

[15] Two participants were dropped because they did not produce ideas in rounds 2 or 3 due to a software error.

Each participant (node) in each network had a concept set associated with it. We analyzed these concepts for each network. For each different concept, we looked at all pairs of nodes for whom the same idea concept occurred in common but appeared first in different rounds.[16] Across all pairs of nodes we computed the probability that two nodes with the same idea concept from different rounds in common were, in fact, connected to each other in the network; i.e., P(connected | common) = q. The higher q is the more likely it is that participants ideated interdependently, as expected. This was compared to the probability of any two randomly selected nodes being connected, which is equal to the density of the network (d = .3788). If ideation was fully independent then dyads with idea concepts in common would occur only by chance, and q would equal the network density (see Appendix D for details). Pooling across runs and idea concepts $q = .5283$, which is significantly greater than $d = .3788$ ($\chi^2(1) = 15.11$, $p < .001$). Thus, it appears likely that, based on an examination of participants' actual ideas and whether they were sufficiently similar among connected dyads, participants operated interdependently and idea concepts spread between rounds.[17]

Study 6

Overview and procedure

The previous studies suggest that the negative effect of clustering on idea innovativeness at higher levels of degree when participants ideate interdependently is associated with social convergence (Studies 3 and 4) and the general spreading of idea concepts among connected participants (Study 5). This final study introduces another moderator to show that our finding is associated with the spreading of *mediocre* (or bad, low-innovativeness) ideas. To test this we gave participants an example idea before they began the ideation task and varied whether this example idea was bad, average, or good in terms of innovativeness.[18]

One hundred and forty-four students at a large northeastern U.S. university participated in this study over four separate runs for class credit. In each run participants were randomly

[16] The nature of our sequential ideation procedure means that interdependence should be observed across rounds (e.g., for connected nodes A and B, node A's concept in round 1 appears at node B in round 2 or round 3).
[17] In natural social networks interdependence could be due to homophily or contagion/spreading. Since our networks are exogenously formed and participants are randomly assigned to nodes homophily is unlikely.
[18] Giving example ideas can lead to fixation or lower creativity (e.g., Dahl and Moreau 2002). This, however, implies an intercept effect and should not interact with network position variables.

assigned to a position in one of three identical 12-node networks. The network was the same as the one used in Studies 3-5. In each run one of the networks had participants who saw a bad example, one of the networks had participants who saw an average example, and one of the networks had participants who saw a good example. Participants were not told how innovative the idea was. The examples came from participants in Study 5.[19] The same Facebook ideation task was used with three two-part ideation rounds. Of the 432 ideas submitted to judges, 412 (95.33%) were valid and useable. Each valid idea was rated by two or three judges (M = 2.84) on our innovativeness scale (α = .93). All participants and judges were Facebook users.

We expected that priming participants in the same network with a single idea would result in them starting in a similar place in terms of idea innovativeness. If participants' thought processes are interdependent and higher clustering results in lower innovativeness due to fewer unique sources of inspiration and the spread of bad ideas we should see our previous pattern of results replicated in the bad-example condition. However, in the average- and good-example conditions we do not necessarily expect network position to affect innovativeness because providing an average or good example may be sufficient inspiration for participants such that they rely less on their neighbors' ideas for inspiration.

Results

The dataset contained 282 valid second- and third-round ideas from 141 participants (57% female, mean age = 20 years) across four experimental runs.[20] The average idea length was 187.04 characters (SD = 101.56, min. = 11, max. = 459). No network position effects were found when the first-round ideas were analyzed separately. Regression results for each example idea are reported in Table 6 and estimated means at one standard deviation below and above mean degree and mean clustering are plotted in Figure 9. Consistent with the previous studies, we find a significant negative degree x clustering interaction but only when participants are primed with a bad example ($b = -.37$, $t = -3.08$, $p < .01$; Figure 9A). We also find significant negative main effects of degree ($b = -.34$, $t = -3.15$, $p < .01$) and clustering ($b = -.30$, $t = -2.66$, $p = .01$). All these effects become non-significant when participants are primed with average or good

[19] Based on Z-scores from Study 5, the innovativeness scores were: bad Z = -1.45, average Z = -.07, and good Z = 1.42. Also, idea lengths were similar: bad 170 characters/32 words, average 173 characters/30 words, good 202 characters/36 words.
[20] Three participants were dropped because they did not produce ideas in rounds 2 or 3 due to a software error.

examples (average: ps > .15, good: ps > .80). In the bad-example condition, we again see that, at higher levels of degree, idea innovativeness is higher when clustering is lower (est. M = 3.00) but lower when clustering is higher (est. M = 1.67; spotlight analysis simple effect of clustering at higher degree $p < .01$).

Discussion

Summary of findings

Marketers are increasingly interested in crowdsourced product innovation, which often involves the participation of consumers in online product ideation communities. These communities are social networks where the connections allow participants to access each other's ideas, which in turn allows for *interdependent ideation*. Although having multiple sources of inspiration is often thought to be beneficial to individuals attempting to generate innovative ideas, this may not always be the case. Having multiple *unique* sources of inspiration could be helpful; however, if one's sources of inspiration are to some extent redundant they may not help as much. This is particularly likely to be the case when the ideas others have suggested are not themselves highly innovative.

We demonstrated with six studies that the structure of the social network that connects ideating consumers and, in particular, the size (degree) and density (clustering) of an individual's ego-network, affects their ability to generate innovative product ideas. When an individual's ego-network is dense their sources of inspiration—other consumers—are likely to be more interdependent and idea uniformity as a result of social convergence is more likely. The likelihood of idea concepts spreading, particularly mediocre ones, is also more likely. We showed that this results in lower idea innovativeness for three different products, among different participant populations, and using different types of networks in terms of size and structure. We consistently found that having multiple sources of inspiration in a networked ideation setting is only productive at the individual level when those sources are relatively independent of one another (i.e., lower clustering). Table 7 summarizes our studies and findings.

Our main finding of a negative degree x clustering interaction was consistent across all six studies despite variations in product category, participant population, and task design. To further establish the robustness of this finding we pooled data from all studies and performed a meta analysis.[21] We estimated a similar regression model to those reported for each study but dropped control variables that did not match between studies and added study fixed effects (we also converted the college year control variable in Study 1 to age to be consistent with the other studies using typical ages corresponding to each college year). Results from this model are reported in the first column of Table 8. The degree x clustering interaction is negative and significant ($p < .001$). For robustness we tested different fixed effects using either product category or network size instead of study and the results were unchanged.

Our statistical analyses each considered how degree and clustering affect *average* levels of idea innovativeness. This is appropriate given that in online product ideation communities firms would like to understand how to increase the innovativeness of each idea (i.e., maximizing individual performance). However, firms may also want to increase the probability that any submitted idea has a level of innovativeness above a certain threshold. For example, on the 1-5 scale used in our studies firms may want to maximize the probability that any submitted idea scores above the midpoint (3) because this means the idea is likely to be more "good" than "bad" and worth looking at more closely. We tested whether degree and clustering affect this "above threshold" outcome using a logistic regression with the same set of covariates used in the linear regression meta analysis model where the dependent variable was 1 if idea innovativeness > 3 and 0 otherwise. Results are reported in Table 8, and we see that the degree x clustering interaction is again negative and significant ($p < .001$). Note that we also performed this "above threshold" analysis for each study separately and found negative and significant degree x clustering interactions in Studies 1, 2, 4, and 6 (all $p < .05$). In Studies 3 and 5 this effect was negative but not significant ($p = .19$ and $p = .26$ respectively).

Implications for theory and practice

Our findings appear to be the result of two related mechanisms that are both more likely to be activated under higher clustering when participants ideate interdependently. First, more densely interconnected people are more likely to produce similar ideas, thus reducing the uniqueness of their ideas as sources of inspiration to others connected to them. In other words, clustering can lead to the *social convergence* of concepts upon which ideas are based, which

[10] For Studies 3 (task specificity), 4 (using neighbors' ideas allowed), and 6 (example idea) we excluded data from conditions where the degree x clustering effect was not found.

inhibits the creativity of others observing those ideas by narrowing the scope of their inspirations. Research on creativity has demonstrated that innovative ideas often come from the combination of different (but compatible) concepts, not highly similar concepts (Goldenberg et al. 1999a, b). A related problem is found in research on creative brainstorming groups (Paulus et al. 2002). Our main finding went away when we inhibited the potential for social convergence by making it less likely that participants' ideas would be related or "on the same page" (Study 3). This was also the case when we told participants that they could not use their neighbors' ideas for inspiration, which also made social convergence less probable (Study 4).

Second, as clustering increases it becomes easier for ideas to spread among connected neighbors. This means that ideas among densely interconnected consumers could become very similar, which also reduces the diversity of ideas that individuals can draw on for inspiration. This is related to the production-blocking problem in the brainstorming literature (Lamm and Trommsforff 2006). We found evidence of idea similarity and the spreading of ideas between rounds (Study 5). More critically, we saw that our main finding occurred when participants were primed with a mediocre or "bad" idea example but not when they were primed with a better one (Study 6). Priming with better ideas (average or good) did not result in clustering having a positive effect on outcomes, but it did cancel-out the negative effect. This could be because higher clustering still means that social convergence is more likely to occur, thus limiting the number of unique sources of inspiration available (even if those sources are not bad). Further, this mechanism may also amplify the importance of the social convergence mechanism because social convergence is even more likely when ideas (or concepts) can spread easily.

Overall, our studies show that having densely connected ideating agents—which is typical in crowdsourcing, brainstorming, and online product ideation communities—can lower performance. Theoretically, this is an important finding for the growing literature on innovation and ideation. It appears that when consumers can ideate interdependently careful attention must be paid to how they are connected. Degree and clustering jointly impact the average levels of innovativeness of ideas produced from these types of communities. Thus, firms could increase the expected innovativeness of submitted ideas by embedding consumers in sparser networks where everyone is not exposed to everyone else and, specifically, clustering is minimized.

While our theory predicted a negative degree x clustering interaction and our focus was on individual performance in ideation tasks, it is interesting to consider other situations where it may be possible to see the opposite effect; i.e., when increased clustering helps higher-degree consumers. This may be possible in situations where the goal is not individual-based but rather group-based (e.g., in collaborative problem-solving tasks). Social convergence may be a helpful mechanism in tasks that require individuals to form a consensus or adopt a common perspective in order to be productive. More broadly, in ideation settings where group cohesion is required for successful task performance, increased clustering may help consumers focus. While interesting, we leave exploration of these more collaborative and group-focused settings for future research.

Practically, our results have direct implications for how online product ideation communities are structured and organized. The typical online product ideation community (e.g., Dell's Ideastorm.com) is organized like a standard online forum where everyone can see what everyone else contributes. This implies relatively high levels of degree and clustering, which is a potentially lethal combination based on our findings. Our results suggest that it may be better to remove some connections to reduce clustering. Further, one way to mitigate the negative effect of clustering at higher levels of degree while still having specific ideation tasks and allowing interdependent ideation (and idea spreading) is to seed consumers with non-mediocre examples upon which to build their ideas. This may not, however, prevent problems associated with social convergence and cognitive fixation.

The current research is not without limitations. While the network structures used were realistic in that their properties were in line with those typically observed in real-world social networks, our networks were not as large as those found in real-world online ideation communities. We limited network sizes for pragmatic reasons associated with participant recruitment, the fact that we needed groups to participate at the same time for each run, and software reliability. Another limitation of our studies is that they were not incentive compatible (e.g., payment based on performance). Prior ideation research has demonstrated the importance of incentive mechanisms (e.g., Burroughs et al. 2011; Toubia 2006), however typical online ideation communities do not provide explicit incentives, let alone incentives tied to performance. Future research may consider network-based interdependent ideation and incentives together. The current research also did not examine whether our findings are limited to relatively inexperienced consumers or if they would also be found among "expert" consumers in a category. It would be interesting for future research to study ideation in networks where consumers have varying levels of expertise because more-experienced consumers may help seed networks with better ideas initially and may help prevent less-experienced consumers socially converging to low-innovativeness concepts. Overall, the current research represents a first step in understanding how groups of socially networked consumers ideate interdependently.

Appendix A: Items Used to Measure Idea Innovativeness

The following scale items were used in all studies to measure idea innovativeness on five-point Likert scales (1 = strongly disagree, 5 = strongly agree):

- This idea is original
- This idea is novel
- This idea is unconventional
- This idea is out of the box
- This idea is creative
- A [*product name*] with this feature will be innovative
- A [*product name*] with this feature will be original

Appendix B: Product Ideation Task Descriptions

Mobile banking smartphone application features (Study 1, Study 2)

A large retail/commercial bank is developing a new mobile banking application for smartphones. They want help thinking of features that this app should have. You will be asked to give your idea for an app feature. Try to be creative and original. Your goal is to think of features this app should have that the eventual users of the app would find useful and would like.

Airline improvements (Study 3)

High task specificity condition

This task is about helping develop ideas for one of the world's largest airlines. They want to get ideas for how to make the commercial airline travel experience better for travelers like yourself. What real-world improvements do you think would make the travel experience better? To make this task more structured, we want to you focus on improvements on a particular aspect of the overall air travel experience. A number of airlines now have smartphone apps (e.g., for iPhone). Please focus yourself in this task on thinking of useful features that the airline's smartphone app could have that would help make the airline travel experience better for passengers.

Low task specificity condition:

This task is about helping develop ideas for one of the world's largest airlines. They want to get ideas for how to make the commercial airline travel experience better for travelers like yourself. What real-world improvements do you think would make the travel experience better?

Facebook (Study 4, Study 5, Study 6)

Facebook is seeking input from users like yourself to help them develop new features for their popular social networking platform. In this task you will develop ideas for Facebook. Specifically, your task is to develop ideas for making the Facebook user experience better and more useful for users like yourself. What real-world improvements do you think would make the Facebook user experience better? To make this task more specific we want to you focus on coming up with ideas for specific features/functions that Facebook could introduce. What are some useful features that Facebook does not have right now that you think it should have because it would improve the user experience and functionality?

Appendix C: Procedures for Extracting Concepts from Ideas

The following table describes the sequence of steps that were performed on every contributed idea from Study 5 to prepare them for similarity analysis (i.e., to extract idea concepts). To illustrate each step we provide, in the third column of the table the output of that step on the following example idea:

> *Draw off of websites like Linkedin and create a platform on Facebook dedicated to networking and uploading resumes, cover letters, etc. Companies look at Facebook anyway in their decision process so this would be convenient for both potential employees and companies.*

Step	Details	Output for Example Idea
1 Get noun-chunks using NLTK	Download idea from the experiment software and run a Python script invoking the NLTK algorithm to identify noun-chunks	draw, websites, linkedin, a platform, facebook, networking, resumes, letters, etc., companies, facebook, decision, process, both potential employees, companies
2 Fix typographic errors and remove nonsensical terms	Use Microsoft Word's spell checker to identify and fix errors. Since we relied on a spell checker's output for this, the process also replaced non-word abbreviations with the corresponding full expressions (e.g., substituting "facebook" for "fb"). Mistyped concepts that did not correspond to a noun (e.g., 'esp' for 'especially') were removed. Inappropriate and nonsensical terms and redundant abbreviations (e.g., "etc") were also removed.	draw, websites, linkedin, a platform, facebook, networking, resumes, letters, companies, facebook, decision, process, both potential employees, companies
3 Remove punctuation	All punctuation marks were removed from the concepts. When multiple concepts were separated by a punctuation mark (e.g., a forward slash), the concepts were split from each other. The only occurrence of "i.e." was also removed.	draw, websites, linkedin, a platform, facebook, networking, resumes, letters, companies, facebook, decision, process, both potential employees, companies
4 Remove articles	The articles "the," "a," and "an" were removed from all concepts.	draw, websites, linkedin, platform, facebook, networking, resumes, letters, companies, facebook, decision,

Step	Details	Output for Example Idea
		process, both potential employees, companies
5 Put nouns in singular form	All nouns were put into singular form. Since much of this was done after performing a computer search, in the process we also removed some verbs in simple present form (ending in "s"). Concepts that are only used in plural form (e.g., "news," "people," and "docs" from "Google Docs") remained in plural form.	draw, website, linkedin, platform, facebook, networking, resume, letter, company, facebook, decision, process, both potential employee, company
6 Split complex expressions	For each concept spanning multiple words, these words were split into separate concepts.	draw, website, linkedin, platform, facebook, networking, resume, letter, company, facebook, decision, process, both, potential, employee, company
7 Resolve further abbreviations	All abbreviations that occurred both in short and long form in the runs analyzed were resolved. In practical terms, this meant that "app" was converted to "application" (no other abbreviations were also present in their full form).	draw, website, linkedin, platform, facebook, networking, resume, letter, company, facebook, decision, process, both, potential, employee, company
8 Re-run the NLTK script	The Python script invoking the NLTK algorithm was run again to remove non-noun chunks that remained after the previous cleaning steps.	draw, linkedin, platform, facebook, resume, letter, company, decision, process, employee, company
9 Remove Duplicates	Duplicate concepts were removed.	draw, linkedin, platform, facebook, resume, letter, company, decision, process, employee
10 Remove concepts that were in the task instructions	Concepts "task," "idea," "feature," "function," "experience," "user," "improvement," "people," and "facebook" were removed	draw, linkedin, platform, resume, letter, company, decision, process, employee

Appendix D: Explanation of Idea Similarity Analysis Probabilities

The idea similarity analysis in Study 5 uses the probability of a pair of nodes being connected conditional on them having an idea concept in common; i.e., q = P(connected | common). This is computed empirically by looking at all pairs of participants (pooled across runs) who had common idea concepts between rounds (not in the same round) and computing the proportion of them who were in fact connected in the network. Also, d = network density = P(connected). We now establish conditions for comparing q and d using Bayes theorem.

According to Bayes theorem:

1. $P(connected|common) = \frac{P(common|connected)P(connected)}{P(common)}$

Substituting into equation 1 and rearranging:

2. $\frac{q}{d} = \frac{P(common|connected)}{P(common)}$

If ideation is *independent* then any pair of participants having common ideas between rounds and being connected are independent events; i.e., P(common | connected) = P(common), which results in equation 2 reducing to $q/d = 1$. If ideation is *interdependent* then it must be that P(common | connected) > P(common | not connected); i.e., the probability of having common idea concepts is higher among connected participants than not-connected participants. It must also be the case that having common ideas and not being connected are independent events; i.e., P(common | not connected) = P(common). Thus, P(common | connected) > P(common). This results in $q/d > 1$ under interdependent ideation where idea concepts spread between connected participants.

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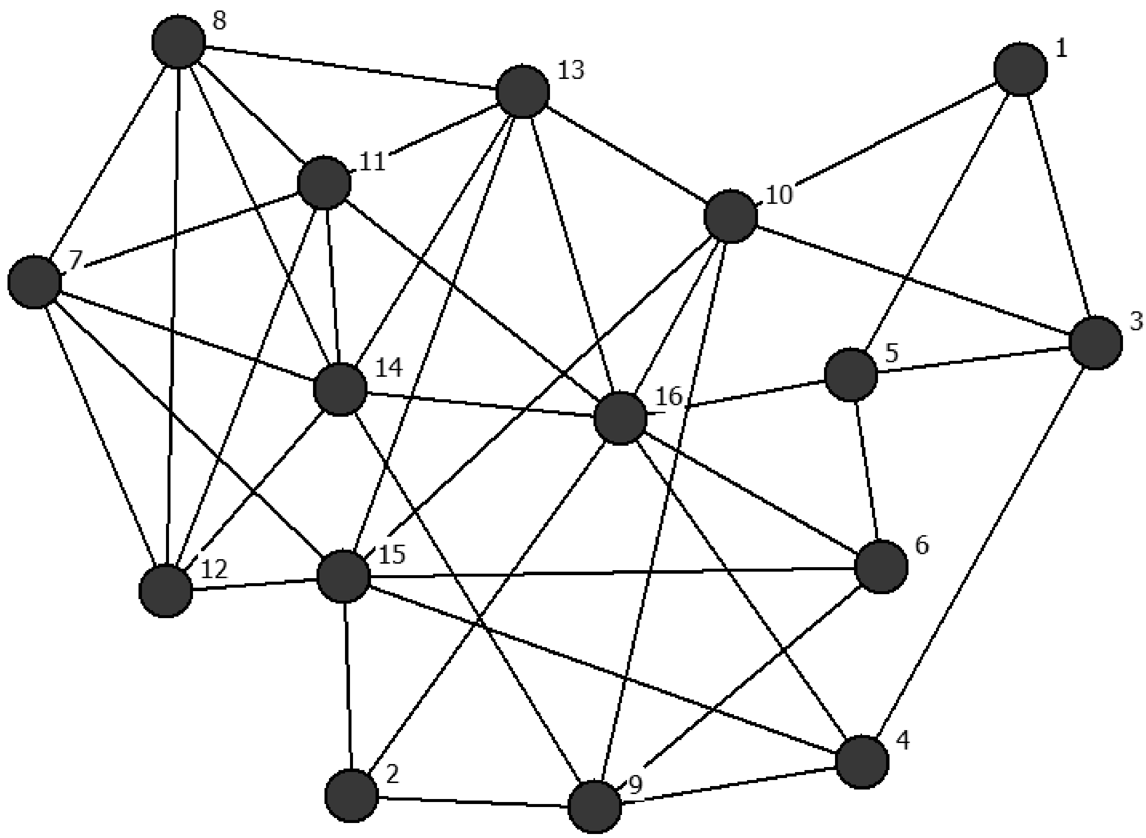
Figure 1: Network Used in Study 1



Number of nodes = 16
Degree range (M, SD) = 3 to 8 (5.13, 1.41)
Clustering range (M, SD) = 0 to .80 (.36, .27)

Figure 2: Estimated Means from Study 1 Mobile Banking

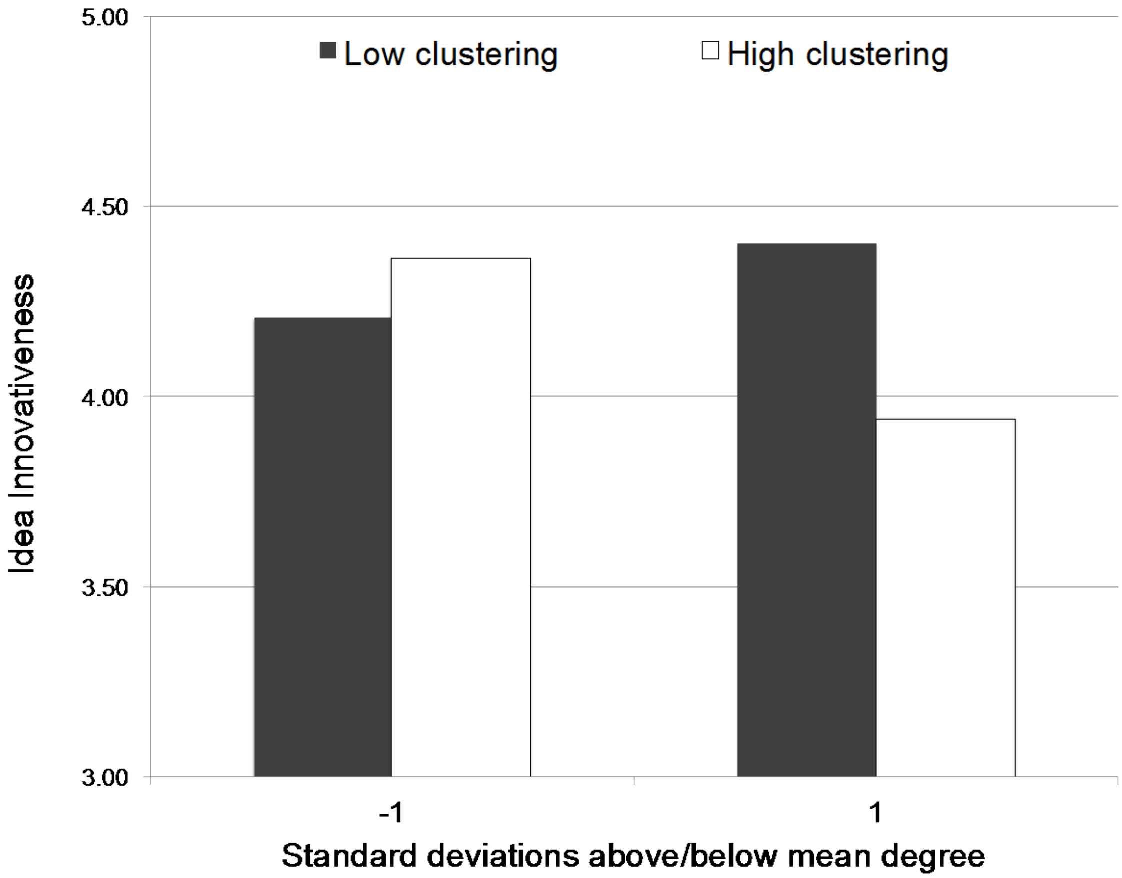
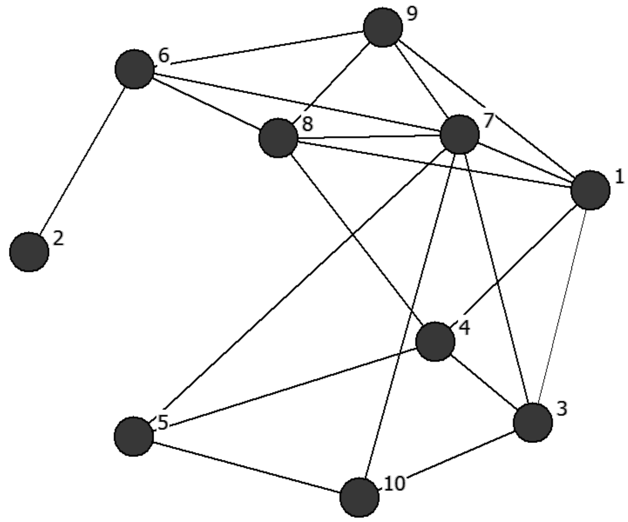


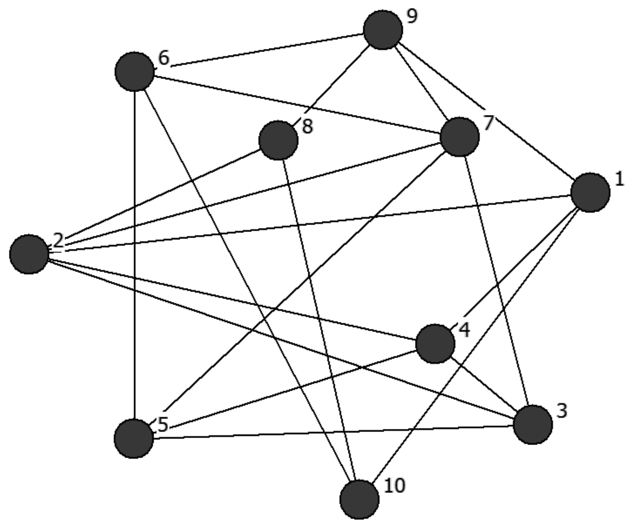
Figure 3: Networks Used in Study 2

Erdos-Renyi (ER)



Number of nodes = 10
Degree range (M, SD) = 1 to 7 (4.00, 1.48)
Clustering range (M, SD) = 0 to .83 (.47, .22)

Small-World (SW)



Number of nodes = 10
Degree range (M, SD) = 3 to 5 (4.00, .63)
Clustering range (M, SD) = 0 to .67 (.30, .22)

Figure 4: Estimated Means from Study 2 Mobile Banking

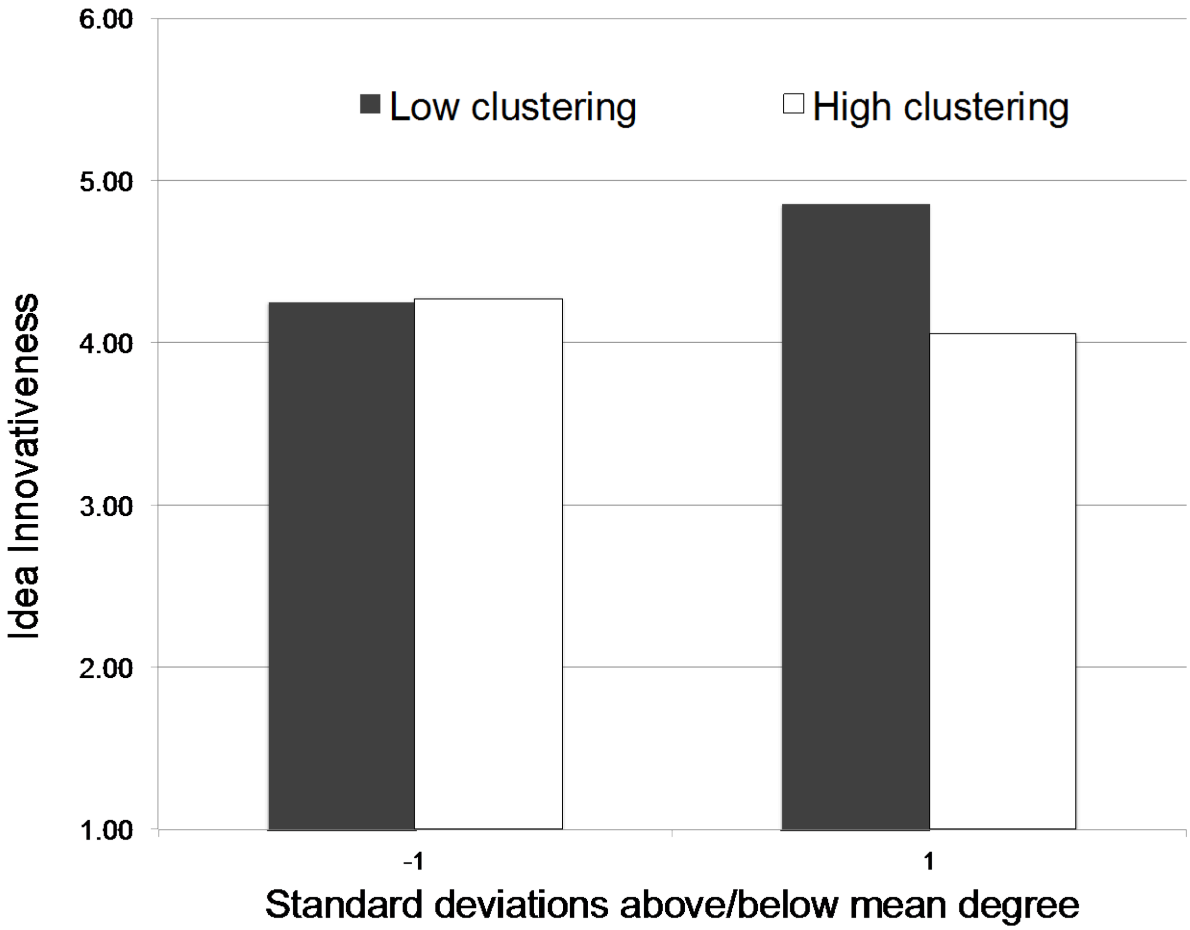
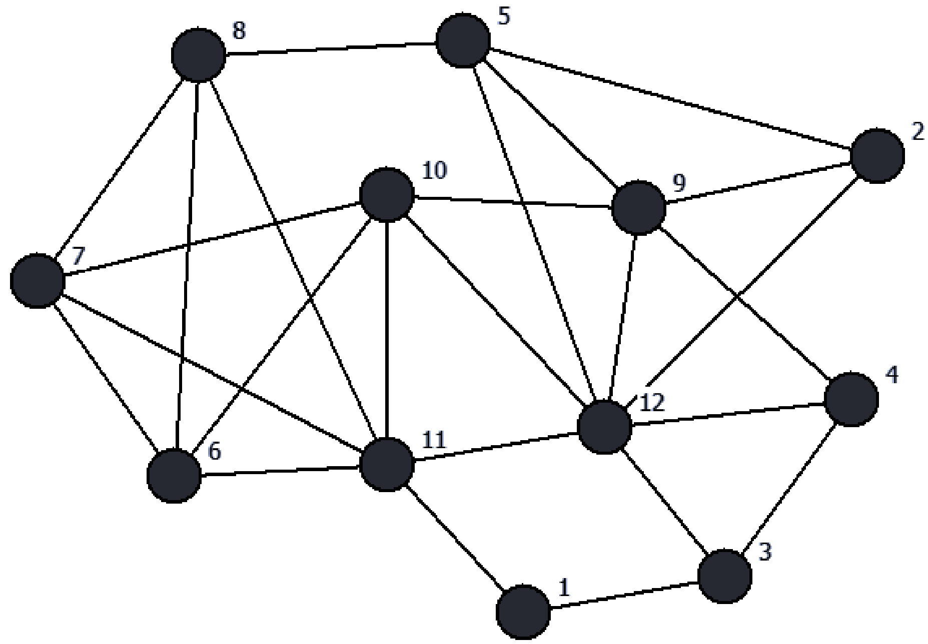
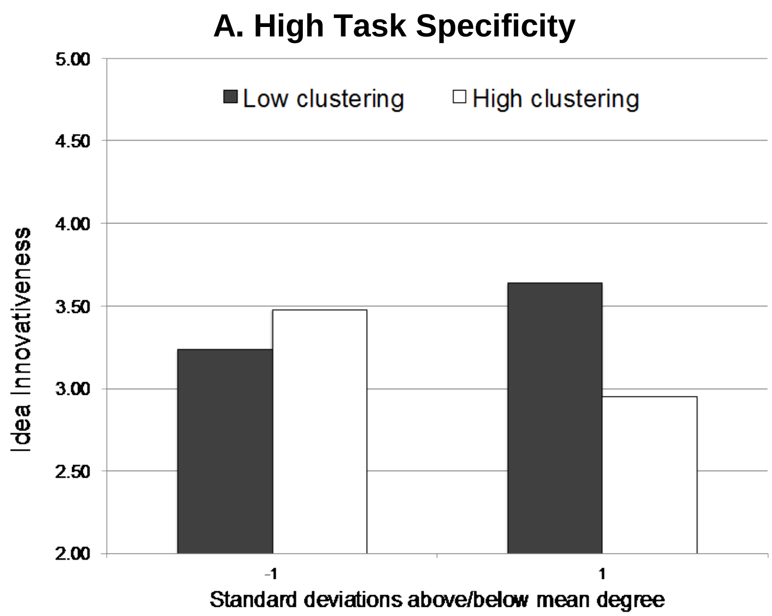


Figure 5: Network Used in Studies 3 to 6



Number of nodes = 12
Degree range (M, SD) = 2 to 7 (4.17, 1.40)
Clustering range (M, SD) = 0 to 1 (.53, .27)

Figure 6: Estimated Means from Study 3 Air Travel



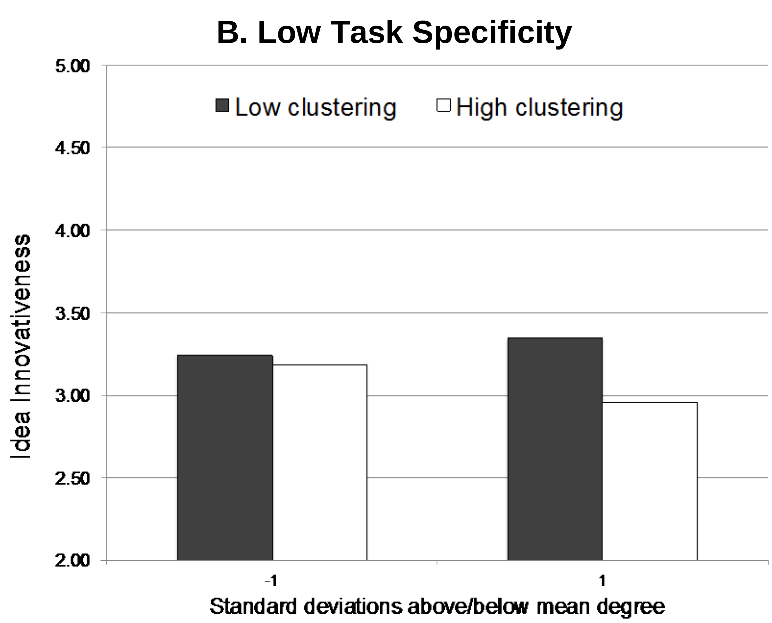


Figure 7: Estimated Means from Study 4 Facebook

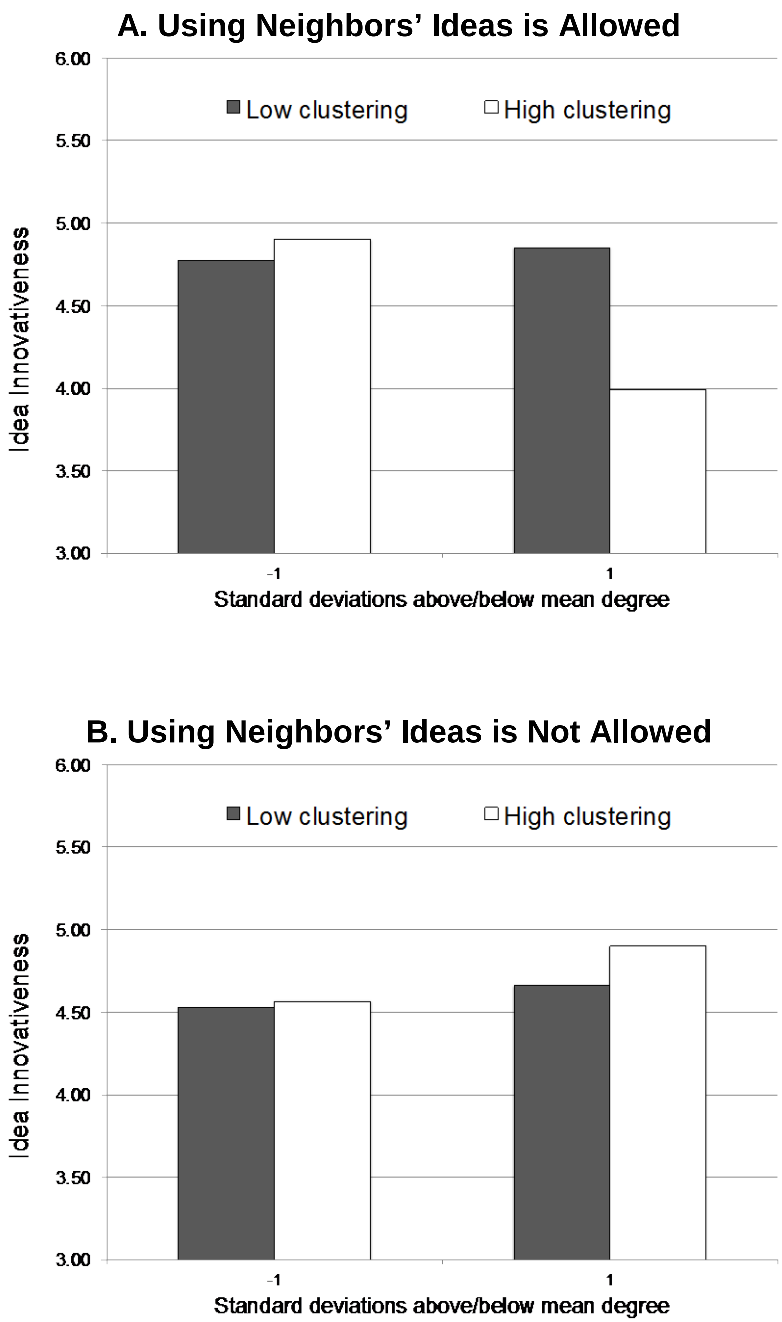


Figure 8: Estimated Means from Study 5 Facebook

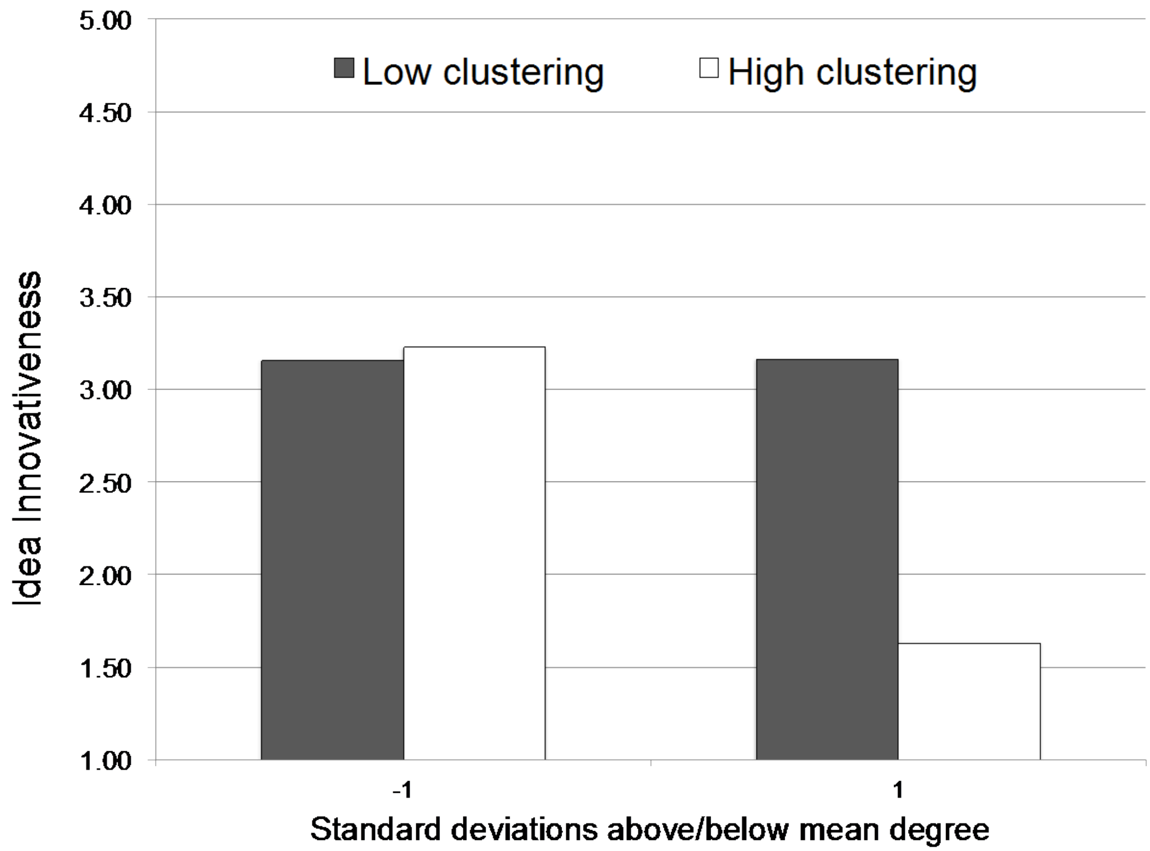


Figure 9: Estimated Means from Study 6 Facebook

A. Bad Example **B. Average Example** **C. Good Example**

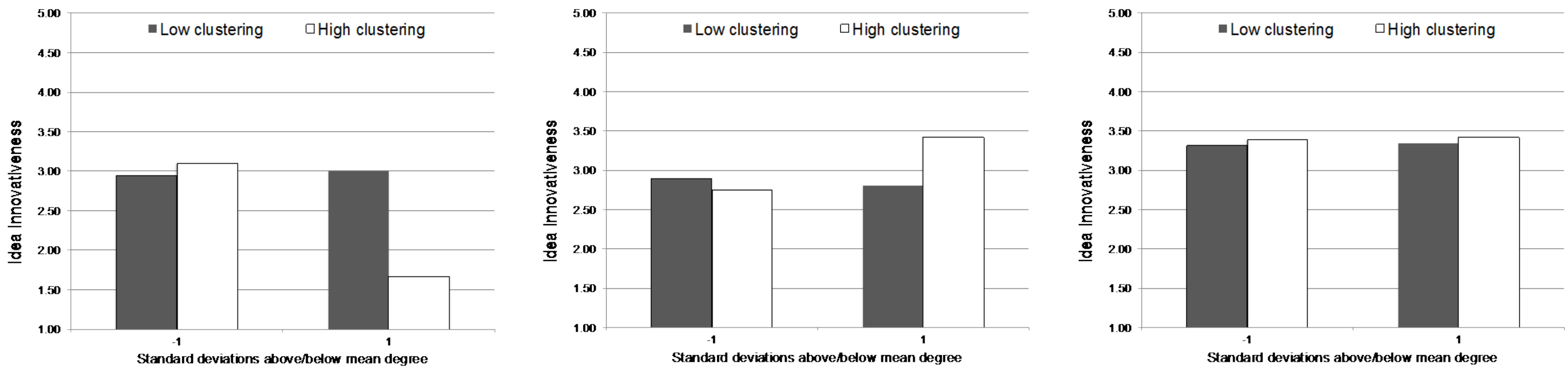


Table 1: Regression Results from Study 1 Mobile Banking

Effect	Estimate (std. error)
Intercept	4.11 (.57)***
Degree	-.06 (.07)
Clustering	-.08 (.06)
Degree x Clustering	-.16 (.07)**
Lagged Idea Innovativeness	.08 (.07)
College Year (baseline = post-senior)	
1	-.66 (.59)
2	-1.01 (.48)**
3	-.79 (.47)*
4	-.69 (.47)
Sex = female (baseline = male)	-.11 (.12)
Run/session (baseline = 4)	
1	.12 (.18)
2	.08 (.16)
3	-.15 (.16)
Round = 2 (baseline = 3/final)	-.28 (.12)**
Ideation time	-.001 (.002)
Participant random effect	.37 (.15)**

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2: Regression Results from Study 2 Mobile Banking

Effect	Estimate (std. error)	
	Including Nodes With Degree = 1	Excluding Nodes With Degree = 1
Intercept	4.60 (.38)***	4.50 (.39)***
Degree	.09 (.08)	.07 (.07)
Clustering	-.20 (.09)**	-.23 (.09)**
Degree x Clustering	-.21 (.09)**	-.24 (.10)**
Lagged Idea Innovativeness	-.15 (.07)**	-.11 (.07)
Age	-.02 (.01)**	-.02 (.01)**
Sex = female (baseline = male)	-.01 (.07)	.003 (.07)
Run/session (baseline = 4)		
1	-.19 (.17)	-.21 (.17)
2	-.52 (.17)***	-.48 (.17)***
3	-.62 (.18)***	-.57 (.18)***
Round = 2 (baseline = 3/final)	-.19 (.08)**	-.19 (.08)**
Ideation time	.002 (.002)	.002 (.002)
Network type = ER (baseline = SW)	-.03 (.14)	-.06 (.14)
Participant random effect	.15 (.06)**	.14 (.06)**

* *p* < .10, ** *p* < .05, *** *p* < .01.

Table 3: Regression Results from Study 3 Air Travel

Effect	Estimate (std. error) High Task Specificity	Estimate (std. error) Low Task Specificity
Intercept	2.46 (.49)***	2.83 (.50)***
Degree	-.11 (.10)	.10 (.11)
Clustering	-.09 (.09)	-.07 (.13)
Degree x Clustering	-.27 (.10)***	-.01 (.12)
Lagged Idea Innovativeness	-.03 (.08)	-.13 (.11)
Age		
Sex = female (baseline = male)	.18 (.07)**	-.05 (.07)
Run/session (baseline = 3)		
1	-.14 (.13)	-.20 (.14)
2	-.11 (.14)	.13 (.14)
Round (baseline = 4/final)		
2	-.26 (.12)**	-.18 (.14)
3	-.04 (.12)	-.25 (.13)*
Ideation time	.004 (.002)**	.004 (.002)
Traveling soon (baseline = not traveling soon)	.44 (.15)***	.24 (.19)
Participant random effect	.23 (.03)***	.27 (.04)***

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4: Regression Results from Study 4 Facebook

Effect	**Estimate (std. error)**	
	Using Others' Ideas Allowed	**Using Others' Ideas Not Allowed**
Intercept	4.44 (1.87)**	4.50 (1.38)***
Degree	-.21 (.12)*	.14 (.12)
Clustering	-.19 (.12)	.10 (.12)
Degree x Clustering	-.26 (.13)**	.07 (.12)
Lagged Idea Innovativeness	-.08 (.12)	.09 (.09)
Age	-.05 (.09)	-.11 (.06)*
Sex = female (baseline = male)	-.10 (.07)	.08 (.07)
Run/session (baseline = 4)		
1	-.15 (.18)	.03 (.19)
2	-.45 (.19)**	.09 (.18)
3	-.28 (.18)	.27 (.18)
Round = 2 (baseline = 3/final)	-.11 (.13)	.06 (.12)
Ideation time	-.001 (.003)	.003 (.002)
Participant random effect	.38 (.06)***	.34 (.05)***

$p < .10$, ** $p < .05$, *** $p < .01$.

Table 5: Regression Results from Study 5 Facebook

Effect	Estimate (std. error)
Intercept	1.64 (.67)**
Degree	-.40 (.12)***
Clustering	-.37 (.13)***
Degree x Clustering	-.40 (.13)***
Lagged Idea Innovativeness	-.18 (.11)
Age	.09 (.04)**
Sex = female (baseline = male)	.09 (.07)
Run/session (baseline = 3)	
1	-.09 (.17)
2	-.24 (.17)
Round = 2 (baseline = 3/final)	.06 (.13)
Ideation time	-.002 (.002)
Participant random effect	.26 (.05)***

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6: Regression Results from Study 6 Facebook

Effect	Estimate (std. error) Bad Example	Average Example	Good Example
Intercept	2.22 (1.10)**	3.29 (1.44)**	4.45 (1.86)**
Degree	-.34 (.11)***	.14 (.12)	.02 (.15)
Clustering	-.30 (.11)**	.12 (.12)	.04 (.15)
Degree x Clustering	-.37 (.12)***	.19 (.13)	-.001 (.16)
Lagged Idea Innovativeness	.23 (.08)***	.09 (.10)	-.09 (.12)
Age	-.02 (.06)	-.06 (.06)	-.05 (.09)
Sex = female (baseline = male)	-.01 (.07)	-.03 (.07)	.24 (.10)**
Run/session (baseline = 4)			
1	.20 (.17)	-.09 (.18)	-.48 (.23)**
2	.18 (.17)	.05 (.18)	-.01 (.22)
3	.14 (.18)	.28 (.19)	-.64 (.25)**
Round = 2 (baseline = 3/final)	.35 (.12)***	-.24 (.13)*	.03 (.16)
Ideation time	.002 (.002)	.006 (.002)**	-.001 (.003)
Participant random effect	.30 (.04)***	.39 (.06)***	.56 (.08)***

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 7: Summary of Studies and Findings

Study	Context	Study Design: Manip.	Nodes per Network	Number of Runs/ Sessions	Networks per Run/ Session	Number of Rounds per Run	Deg. x Clu. Effect	Main Findings
1	Smartphone banking app	n/a	16	4	1	3	-.16	• At higher levels of degree, idea innovativeness is higher (lower) when clustering is lower (higher)
2	Smartphone banking app	n/a	10	4	2	3	-.20	• Replicated S1 with different network types (ER, SW) • Positive correlation between idea innovativeness and market potential
3	Airline experience	Task specificity: high vs. low	12	4	2	4	-.27 (high) -.01 (low)	• Replicated S1, S2 in different category • Effect only when high task specificity
4	Facebook features	Using others' ideas allowed: yes vs. no	12	4	2	3	-.26 (yes) .07 (no)	• Replicated S1, S2, S3 in different category • Effect only when interdependent ideation allowed
5	Facebook features	n/a	12	3	1	3	-.40	• Replicated S1, S2, S3, S4 • Evidence of ideas spreading
6	Facebook features	Example idea: bad, average, good	12	4	3	3	-.37 (bad) .19 (avg.) -.00 (good)	• Replicated S1, S2, S3, S4, S5 • Effect only when bad example idea given prior to task

Table 8: Meta Analysis Regression Results

Effect	Estimate (std. error)	
	Linear Regression	Logistic Regression (Innov. > 3)
Intercept	3.50 (.24)***	.98 (.78)
Degree	-.08 (.04)**	-.30 (.12)**
Clustering	-.10 (.04)***	-.38 (.11)***
Degree x Clustering	-.18 (.04)***	-.56 (.14)***
Lagged Idea Innovativeness	-.03 (.03)	.32 (.19)*
Age	-.007 (.005)	-.01 (.02)
Sex = female (baseline = male)	-.002 (.04)	.04 (.12)
Run/session (baseline = 4)		
1	-.22 (.10)**	-.59 (.33)*
2	-.28 (.09)***	-.86 (.33)***
3	-.26 (.10)***	-.71 (.32)**
Round (baseline = 4)		
2	-.19 (.12)*	-.64 (.48)
3	-.08 (.11)	-.32 (.49)
Ideation time	.0014 (.0009)*	.005 (.003)
Study (baseline = 6)		
1	.14 (.10)	.05 (.33)
2	.42 (.12)***	.78 (.39)**
3	.25 (.13)*	.41 (.42)
4	-.15 (.11)	-.64 (.34)*
5	-.29 (.12)**	-1.06 (.39)***
Participant random effect	.11 (.03)***	.36 (.23)

p < .10, ** *p* < .05, *** *p* < .01.