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This article examines the popular marketing practice of interdependent ideation, whereby firms solicit ideas from customers through online platforms that enable customers to be exposed to or "inspired" by other customers' ideas when generating their own. Although being exposed to others' ideas means that customers are "connected" (at least implicitly) in a communication network that facilities the flow of ideas, the effect of network structure on individual innovativeness has not been considered in this context. The authors examine how, when, and why network structure—specifically, the clustering, or interconnectivity, of one's "inspirations" (other customers)—affects the innovativeness of individual customers' product/service ideas in ideation tasks. Across five experiments, the authors show that (1) higher clustering/interconnectivity negatively affects the innovativeness of a customer's ideas; (2) this effect occurs because idea inspirations are more likely to be similar or redundant when their sources (i.e., other customers to which one is connected) are clustered; (3) greater redundancy among ideas used as inspirations is what causes lower innovativeness; and (4) this effect is attenuated when customers do not rely on other customers' ideas for inspiration.

Keywords: social networks, ideation, product development, network experiments, crowdsourcing

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Lower Connectivity Is Better: The Effects of Network Structure on Redundancy of Ideas and Customer Innovativeness in Interdependent Ideation Tasks

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One of the most important marketing activities in which a firm engages is product and service innovation. A critical initial stage in any innovation process is ideation, which encompasses the generation of product or service ideas, either for general concepts or for specific features or improvements (Cooper 1990; Urban and Hauser 1993). Ideation is particularly important, because identifying potentially viable market opportunities as early as possible in the innovation process can lead to greater efficiency at subsequent stages (Dahan and Hauser 2002; Smith and Reinertsen 1992). A currently popular and fast-growing trend in marketing ideation is for *customers* to be invited to contribute product or service ideas through interactive online platforms (e.g., on social media sites or online discussion forums). This approach is sometimes referred to as the crowdsourcing of product ideas (Bayus 2013; Freedman 2012; Winsor 2009), and it has been used by companies such as Dell, Delta Air Lines, Google, LEGO,

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McDonald's, PepsiCo, and Starbucks. This fast-growing approach to ideation is a continuation of the longer-term trend of firms seeking customer input in product development (e.g., focus groups, market research). This newer approach, however, is distinct because it uses online platforms in which customers have the ability not only to suggest ideas to firms, but also to see other customers' ideas when generating their own.

Firms typically use these types of customer-based ideation for soliciting ideas that can then be fed into more conventional processes for new product development. In the customer-based ideation stage, the typical goal is to get as many highly innovative ideas as possible because it expands the set of potentially viable alternatives that can be subsequently considered internally. Thus, individual innovativeness, or a customer's ability to generate innovative ideas, is critical in this setting (this is consistent with online crowdsourcing research; e.g., Bayus 2013; Huang, Singh, and Srinivasan 2014). Although individual innovativeness is affected by many factors, an important one in this context could be the influence of other customers' ideas on a particular customer's ideas. Indeed, prior literature on creativity and innovativeness in different contexts than the one we consider has suggested that people's ideas can be influenced positively or negatively by others around them who are working on the same or similar tasks (e.g., Lamm and Trommsdorff 2006; Mason and Watts 2012; Pan, Altshuler, and Pentland 2012).

A fundamental aspect of the online product-ideation setting considered in this research is that customers express ideas in front of others, meaning that an ideating customer can access, and thus be exposed to and *potentially influenced by*, ideas previously contributed by other customers on the platform. This access to other customers' prior ideas means that ideating customers are "connected" to each other in a network in which ideas flow across ties between customers.[1] In this research, we posit that the networked, interconnected nature of the online product-ideation context plays a critical role in affecting individual customers' abilities to generate innovative ideas.

Specifically, we examine how, when, and why the connectivity structure—or network—among ideating customers affects their innovativeness. We build on prior literature in different contexts that has suggested individual creativity is reduced when ideation inputs (e.g., in our context, other customers' previous ideas) are similar, overlapping, or redundant (Lamm and Trommsdorff 2006; Pan, Altshuler, and Pentland 2012; Paulus et al. 2002; Pentland 2013). We also consider how network structure might affect the tendency for customers' ideas to become more or less redundant. We focus on the role of network clustering, which reflects the extent to which a customer's "sources of inspiration" or network "neighbors" are connected to each other, and show that neighbors' ideas are more likely to form a redundant set of inspirations for an ideating customer when the neighbors are more clustered. Clustering is defined as the density of connections between a person's direct neighbors, that is, the proportion of pairs among the person's neighbors that are directly connected to each other. Higher clustering indicates greater interconnectivity among neighbors.

We also show that a customer's ability to generate innovative ideas is stifled by this clustering-driven increase in redundancy among the ideas of network neighbors (or "social" sources of inspiration). Importantly, we find the negative effect of idea redundancy with respect to neighbors' ideas to occur only when customers rely on others' ideas as inputs into their own ideation processes. In summary, we demonstrate that the innovativeness of customers' product ideas suffers when they ideate by using others' ideas as input or for inspiration when the online network in which customers are situated is relatively highly clustered. In practice, such networks tend to have higher (as opposed to lower) levels of clustering on average. Thus, a major implication of our findings is that the typical structure used for online interdependent product-ideation tasks run by major companies such as Dell and Starbucks is suboptimal in the sense that the underlying network structure stifles customers' abilities to formulate highly innovative ideas when those customers use others' ideas for inspiration. According to our findings, firms can significantly improve the effectiveness of their ideation platforms if they control or limit the clustering of the underlying networks.

Across five experiments, we empirically test how clustering affects idea redundancy and innovativeness. A key distinction between this research and prior studies from outside marketing is that we use controlled experiments, whereby participants (who are anonymous to each other) are randomly assigned to positions in *exogenously* determined network structures that govern whose ideas they can see as they complete an ideation task in real time. This enables us to identify how clustering affects ideation without concerns related to homophily and network endogeneity that exist in related research on networks and creativity (e.g., Burt 2004, 2005; Levine and Prietula 2013; Perry-Smith and Shalley 2003).

As a preview of our results, we find that (1) higher clustering among the customers to whose ideas a particular customer is exposed negatively affects the innovativeness of that customer's ideas; (2) this effect occurs because idea inspirations are more likely to be similar or redundant when their sources are highly interconnected or clustered; (3) higher redundancy in one's set of inspirations causes lower innovativeness; and (4) this effect is attenuated when customers do not rely on others' ideas. This research contributes to the literature on interdependent or network-based ideation in a variety of fields by showing how, when, and why network clustering affects individual innovativeness, using a controlled experimental approach that is not subject to endogeneity-, simultaneity-, or homophily-related concerns associated with related research in other fields that use nonexperimental (field) network data. We also build on nonmarketing research on topics, such as brainstorming, in which redundancy has been linked to performance on innovation and problem-solving tasks but in which networks are not examined or manipulated. Finally, and most importantly, we contribute to the marketing ideation literature by showing (1) how network structure affects innovativeness and (2) that current approaches

[1]Following common practice and convention, we represent this network as a temporal "social" network. This does not imply, however, that customers who are connected to one another must know each other or be friends. Simply, the ties in this type of network at a minimum allow for ideas to be communicated between customers (i.e., a communication network).

to interdependent ideation are suboptimal. If correct, our findings suggest that firms' online interdependent product-ideation platforms should be reengineered so that the underlying networks linking ideating customers are less clustered.

BACKGROUND

Connections to other customers in communication networks allow information flows that can render individual behavior more interdependent than in situations wherein people ideate without exposure to others' ideas. Thus, we generally refer to our context as "interdependent ideation" and consider it to be distinct from settings in which people generate ideas or creatively solve problems on their own. Interdependent ideation simply means that people are situated in communication networks, and their ideas can potentially be influenced by the ideas of others around them. Importantly, interdependent ideation does not entail people working together in groups to generate ideas or solve problems collaboratively. The goal of the current research is to better understand interdependent ideation for products or services by identifying conditions under which it either enhances or diminishes the innovativeness of an individual customer's ideas. (Consistent with extant literature related to marketing outcomes, we consider innovative ideas to be creative/novel *and* to have the potential to be useful; Bayus 2013; Burroughs, Moreau, and Mick 2008.) Unfortunately, although many firms have crowdsourced product ideas by involving customers in various forms of interdependent ideation tasks, results have been mixed. For example, firms typically implement very few of the ideas submitted by customers in online interdependent ideation platforms (e.g., the success rates for ideas from Dell's IdeaStorm.com and Starbucks' MyStarbucksIdea.com are less than 3% and less than 1%, respectively). A problem faced by firms is that simply not enough of customers' ideas are sufficiently innovative to warrant serious further consideration by internal teams.

Although this underperformance could occur for a variety of reasons (e.g., customers having low task motivation and involvement, not taking the task seriously, not possessing sufficient knowledge or expertise), one possibility is that ideating interdependently could negatively affect individual innovativeness because having access to other customers' ideas could negatively affect or contaminate one's ideation processes. As we mentioned earlier, access to other customers' ideas in this setting means that ideating customers are situated in a communication network in which information in the form of ideas (or underlying concepts and themes) flows across network ties between customers who are exposed to each other's ideas. The structure of this type of network arguably determines the extent to which customers may ideate interdependently, and we are interested in how, when, and why the structure of this type of network affects individual innovativeness with respect to the product/service ideas customers generate.

Theoretical Context

Three nonmarketing literature streams offer a perspective on these questions and suggest that connections or networks can affect individual performance in complex problem-solving tasks, including tasks involving creativity. We use these literature streams as general foundations for the conceptual framework we subsequently propose.

First, the "wisdom-of-crowds" literature (e.g., Pan, Altshuler, and Pentland 2012; Pentland 2013) has documented that "crowds" can be "less wise" as they become more interdependent. In other words, connections to others can affect individual performance. However, this literature (including experimental studies; e.g., Mason, Jones, and Goldstone 2008; Mason and Watts 2012) has limited applicability in the context of creative and innovative thinking because it has typically considered problems that are well-defined and "closed-ended" (i.e., problems with usually not more than one or two objectively "correct" solutions). Conversely, in our context, the "problem" is usually ill-defined and "open-ended" (i.e., with multiple solutions, none of which are necessarily "correct," but some of which are subjectively better than others). Also, a typical wisdom-of-crowds setting considers individual, seemingly independent contributions that are aggregated to find solutions (e.g., the most common or most popular ideas). The interdependence referred to in this literature is based on the notion that each person's contribution may not be a truly independent draw from a distribution, and thus the distribution of idea popularity that is used to identify an aggregate solution is biased. Notwithstanding these key differences between the wisdom-of-crowds literature and the current research, the notion that being exposed to others can affect one's ideas (albeit on tasks very different from the type we consider) is conceptually relevant here.

Second, the "organizational sociology and networks" literature has suggested that the formal and informal social networks connecting managers or employees in organizations can affect both individual and work group performance on problem-solving tasks involving creative and innovative thinking (e.g., Bavelas 1950; Burt 2004, 2005; Levine and Prietula 2013; Perry-Smith and Shalley 2003). This literature has shown that a person's position in a network structure can be important because their connections moderate access to resources. However, as Kleinbaum (2012) points out, this literature has generally suffered from serious endogeneity concerns that make it difficult to generalize these results to other contexts (such as product ideation involving customers) and to infer a causal effect of interdependent versus independent ideation on individual innovative performance. This is because the organizational networks studied in this literature develop endogenously over time, and it is possible that, for example, a more creative manager reached a certain network position because of his or her performance and not that the creativity is a consequence of his or her network position.[2] Another concern related to this problem is that these networks have connections that carry multiple meanings, which also makes it hard to identify specific effects of network position on innovation or creativity performance. For example, a connection between two people indicates the ability to communicate (i.e., exchange

[2]For example, organizational sociology research using field (but endogenous) organization network data suggests that less-dense networks of workers are more innovative. This could be because lower density results in higher creativity, but it could also be that more-creative workers form broader sets of ties spanning across an organization, which results in lower density. In other words, it is unclear in which direction the effect goes.

information) as well as social (e.g., friendship) and/or professional (e.g., superior/subordinate) relations. Thus, the networks in this literature are naturally confounded because connections can carry meaning beyond being merely communicative.[3] We avoid these confounded networks in our experiments by connecting *anonymous* people in networks that are purely communicative, and thus the network ties in our experiments carry no social or relational connotations.

The organizational sociology literature has also often focused on how networks affect group (not individual) performance, or, when an individual unit of analysis has been used, it has often been with respect to how individuals contribute to their work groups or teams. Our context differs from this one because we are interested solely in individual innovativeness in a completely noncollaborative setting (i.e., in which people can be influenced by others but do not work or collaborate with others). Furthermore, this literature has considered tasks very different from those studied here, typically focusing on longer-term innovation and problem-solving processes in offline, intraorganizational settings involving managers or employees. We instead consider short-term (close to real-time) ideation in an online, nonorganizational setting involving customers, in which networks are temporary in that they are built for and last only for the duration of the ideation task. Thus, although the organizational sociology literature that has examined phenomena related to ours has shown that networks can matter (and has indicated some specific ways in which they matter), there are many points of distinction between that literature and the current research.

Third, the "brainstorming" literature, which is mostly in the organizational behavior and psychology literature streams, also provides a basic foundation for the current research. Brainstorming studies have shown that allowing people to generate solutions or ideas in groups versus by themselves can sometimes lead to better outcomes, but not always (e.g., Clemen and Winkler 1985; Gallupe et al. 1992; Lamm and Trommsdorff 2006; Mullen, Johnson, and Salas 1991; Pinsonneault et al. 1999). Furthermore, because much of the brainstorming research is within the social psychology paradigm, this literature has also provided some potential mechanisms for how ideating within groups can influence individual and group outcomes (e.g., the literature on production blocking, which has helped to explain why brainstorming groups sometimes underperform; Lamm and Trommsdorff 2006).

However, brainstorming findings have only limited applicability to the current research. This is because communication network structure is not considered in brainstorming and therefore has never been tested. In a brainstorming setting, people are in groups of a certain size. From a communication network perspective, everyone is "connected" to everyone else in such groups, and thus there is zero variation in how people are interconnected (i.e., a brainstorming group, if represented as a network, will always be fully connected). Another point of difference between brainstorming and the current research setting is that often the outcome in brainstorming is at the group level because brainstorming is largely a collaborative activity. Our context is different from this because it involves individuals ideating in a noncollaborative manner.

In summary, although the current research is related to and draws from these research streams, the phenomenon we study is distinct and our approach is novel. In Web Appendix A, we compare and contrast these three streams with the current research. *How* (or whether) network structure affects individual innovativeness in an interdependent online product-ideation setting has indeed been hinted at in prior work, but the question is neither well examined nor clearly understood. The research mentioned in Web Appendix A indicates that network structure can be important but considers very different settings (i.e., not marketing related) and types of ideators (i.e., not customers or consumers). Also, findings from organizational sociology studies of creativity in networks are subject to endogeneity concerns that make it impossible to identify causal effects of network structure on creativity or innovativeness. Effects of network structure on innovativeness also cannot be inferred from the brainstorming literature, because in that literature, people are organized into groups in which everyone is "connected" to everyone else, and thus there is no variation in structure that allows for structure-related effects (e.g., clustering) to be identified. Finally, *when and why* network structure, particularly clustering, affects innovativeness has been largely ignored in these research streams.[4] The current research, however, addresses this gap that lies at the intersection of these three research streams by explaining how network clustering negatively influences innovativeness when people use neighbors' ideas as inputs or inspirations, because clustering makes neighbors' ideas more likely to be redundant.

Practical Context

The current research is motivated by the growing popularity of various forms of interdependent online product ideation that companies use in the earlier stages of their new product development (or improvement) processes. Although this ideation can take on many forms when implemented by marketers, the setting we consider (and base our experimental paradigm on) is intended to capture essential aspects common to many variants of interdependent online product ideation seen in practice. Specifically, we consider a customer-based product-ideation setting that has the following realistic characteristics: (1) customers generate ideas for products or services; (2) this ideation occurs in an online setting in which individuals can see other customers' previous ideas; (3) participation is noncollaborative, in that individuals do not work together to generate ideas; (4) connections between customers allow information (ideas, concepts) to be exchanged; and (5) these connections allow for possible interdependence.

A key difference, however, between what is commonly done in practice and what we do here is that we explicitly

[3]For example, in actual *social* networks, the ties between pairs of people allow information to flow (i.e., communication ties), and they have some degree of relationship strength (e.g., strangers, acquaintances, friends). How network structure/position characteristics influence individual outcomes in such networks can be interpreted in terms of communication flows, relational characteristics, or both. This makes it generally impossible to interpret observed effects of network position on individual outcomes because of the multiplicity of meanings associated with ties.

[4]We acknowledge that the organizational sociology literature conjectures a number of mechanisms, although many are not applicable to marketing, or, if they are, they reflect ideation processes that unfold over months or even years.

manipulate network structure in a manner that enables us to assess the full range of clustering. Our theory is, essentially, that innovative performance suffers at the individual level when clustering is too high. Unfortunately, in practice, clustering tends to be quite high. For example, in settings that mimic electronic brainstorming groups, everyone is "connected" to (or can see) everyone else, which means that clustering is very high. In settings that enable people who are connected to each other in existing online social networks (e.g., Facebook) to share ideas, the average clustering also tends to be high (e.g., Ugander et al. 2011). And in settings such as those used by Dell (IdeaStorm.com) and Starbucks (MyStarbucksIdea.com), which take the form of "discussion boards" where network connections are implicit according to who sees (or votes/comments on) whose ideas, the underlying networks can also be relatively highly interconnected (e.g., a mapping of the network underlying Dell's IdeaStorm.com found an average clustering of .33 [SD = .20, Mdn = .31, min = 0, max = 1]; see Web Appendix B). Thus, from a practical standpoint, this research suggests that firms should introduce a new feature to their online product- and/or service-ideation platforms that controls interconnectivity between ideating customers, and our findings can help firms optimize this interconnectivity.

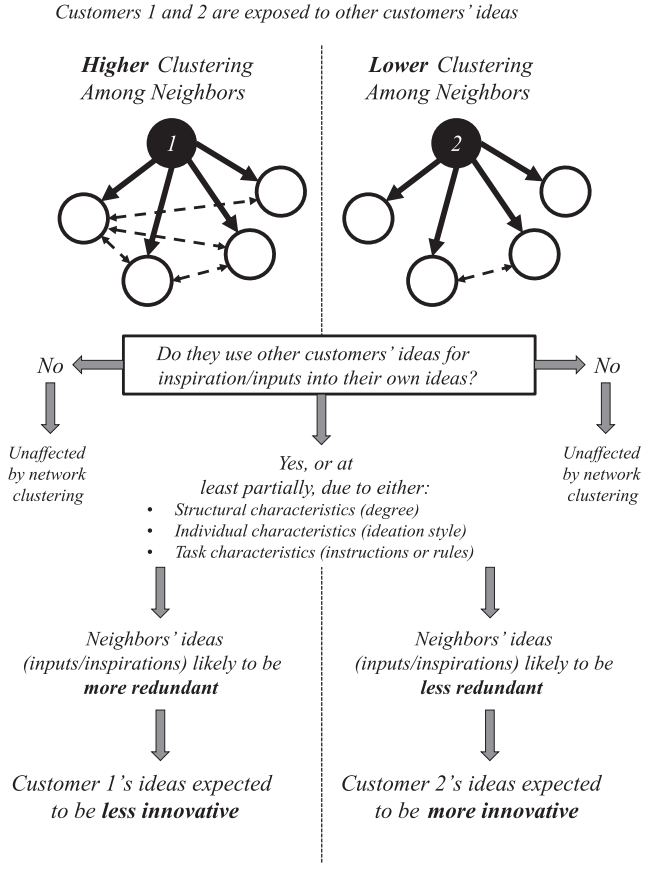
CONCEPTUAL FRAMEWORK

In this section, we formalize the arguments made earlier about how, when, and why network clustering affects the innovative performance of individual customers in interdependent online product-ideation tasks. Figure 1 summarizes our conceptual framework.

We begin by considering *how* being connected to other ideating customers in a network setting might influence an individual customer's ideas. Others' ideas could be helpful inputs to one's own idea-generating processes. Seeing what other customers have suggested, for example, could provide useful inspiration for one's own ideas, particularly given that using concepts from existing knowledge—or from others—and arranging or combining them in new ways is a common process through which innovative ideas are formed (Amabile 1988, 1996; Dahl and Moreau 2002; Fleming and Szigety 2006; Goldenberg, Mazursky, and Solomon 1999a, 1999b; Hargadon and Sutton 1997; Kohn, Paulus, and Choi 2011; Simonton 2003; Ward 1994). Thus, if a person is exposed to others' ideas in an online product-ideation task, those ideas may be inputs or inspirations that can be built on or combined in order to develop new innovative ideas. Situating customers in networks that facilitate the flows of ideas between ideators could therefore be beneficial. This has been shown to be true for collaborative problem-solving tasks (e.g., Mason and Watts 2012). Exposure to others' ideas could also be helpful because it makes an ideation task more stimulating, which is often a reason to use brainstorming groups (e.g., Dennis and Valacich 1993; Dugosh et al. 2000; Nijstad and Stroebe 2006; Nijstad, Stroebe, and Lodewijkx 2002; Paulus et al. 2013; Valacich, Dennis, and Connolly 1994).[5]

[5]More generally, the brainstorming and electronic brainstorming literature has documented various situations in which people's ideas are more innovative when they ideate in groups than when they ideate independently (e.g., Clemen and Winkler 1985; Gallupe et al. 1992; Lamm and Trommsdorff 2006; Mullen, Johnson, and Salas 1991; Pinsonneault et al. 1999).

Figure 1
SUMMARY OF CONCEPTUAL FRAMEWORK



Whether exposure to multiple sources of inspiration enhances or diminishes one's innovative performance depends on the nature of the set of ideas to which one is exposed. If people are more creative when they arrange or combine concepts from existing knowledge or other people in new ways, then for multiple sources of inspiration to be maximally beneficial, each input/inspiration ideally should be distinct from the others in the set. In our context, we expect that ideators will benefit most from other customers' ideas when those ideas are *distinct and unique* relative to each other. This means that *idea redundancy*, which we define as the extent to which neighbors' ideas are similar and not distinct, should not be high. In addition, we expect that network structure—specifically, clustering (i.e., the extent to which one's neighbors are interconnected)—plays a critical role in affecting how much neighbors' ideas are likely to exhibit redundancy. Next we explain why and when idea redundancy diminishes innovativeness, and following that, we explain the impact of clustering on idea redundancy.

There are three reasons why we expect higher idea redundancy to lead to lower individual innovativeness. First, the size of the set of neighbors' ideas that one can draw on when ideating decreases as idea redundancy increases. For example, at the top of Figure 1, we show networks in which the focal customer (dark circle) has four neighbors. If the

four ideas put forward by these others are all very different (low idea redundancy), then the focal customer has four unique inspirations to use. If the four ideas are very similar (high idea redundancy), however, the focal customer has fewer than four unique inspirations to use (perhaps only one). We argue that the latter situation provides the focal customer with an inferior set of inputs from an innovativeness perspective.[6] Second, idea redundancy, even at moderate levels, could stifle individual innovativeness because it interferes with the psychological mechanisms involved in processing others' ideas. Even a small amount of similarity among neighbors' ideas could make it more likely for an ideating customer to fixate on a more prevalent idea, theme, or concept at the expense of others. Fixation has been associated with reduced creativity in group brainstorming and creativity tasks (Kohn and Smith 2011; Marsh and Landau 1995; Smith, Ward, and Schumacher 1993).[7] Fixation can be problematic even if the concept fixated on is fairly innovative (Goldenberg, Lehmann, and Mazursky 2001). Third, the recurrence of an idea, concept, or theme among a set of neighbors' ideas could also operate as a social proof signal, which would also result in reduced innovativeness because of the production of ideas that are more consistent with or conform to existing ideas. For these reasons, we hypothesize that idea redundancy among one's neighbors' ideas negatively impacts the innovativeness of one's product ideas.

However, we expect this hypothesized negative effect to occur only when customers ideate in an interdependent manner, meaning that they pay attention to and make some use of neighbors' ideas when formulating their own. Being in an interdependent *setting* (e.g., an online network) is insufficient because people can ignore others' ideas or not use them. Ideating in an interdependent *manner* in an interdependent setting is required for idea redundancy to have an effect. We posit that the extent to which an ideating customer will do this depends on structural (network), individual, or task characteristics. With respect to structural characteristics, having a larger (smaller) set of neighbors can make ideating in an interdependent manner more (less) likely.

The number of neighbors one has (called one's degree centrality, or just degree, in network terms) is a network-structure-based constraint on how interdependent one can be. Customers with few neighbors (lower degree) will have to ideate more independently and rely nearly exclusively on their own thoughts because they do not have many sources of inspiration available to use, whereas customers with many neighbors (higher degree) do not face this constraint. With respect to individual characteristics, some people might be more inclined to pay attention to and use their neighbors' ideas than others. Customers who inherently have a more interdependent ideation "style" will thus be more likely to be affected by redundancy among their neighbors' ideas. Finally, with respect to task characteristics, redundancy among neighbors' ideas should not affect individual innovativeness if the task is designed such that ideators are encouraged to rely predominantly (or entirely) on their own thoughts or, similarly, if they are discouraged or prohibited from using other customers' ideas as inputs (e.g., based on stated rules or policies; in this situation, however, being exposed to others in an interdependent setting might still lead to better ideas by making the task more interesting or stimulating). Thus, in summary, we hypothesize that the negative effect of idea redundancy on idea innovativeness occurs only when customers ideate in an interdependent manner.

Finally, we consider the critical role of network structure—specifically, clustering. We posit that redundancy in a set of neighbors' ideas is a consequence of a social learning process related to (but not necessarily the same as) social contagion or informational cascades. When people are more interconnected, it becomes more likely that idea redundancy arises because more interconnectivity makes it easier for ideas (and underlying concepts or themes) to diffuse rapidly among people connected in a network. From a network structure perspective, idea spreading will be easier and/or faster—and thus more likely when time is short or limited, such as in a real-time product-ideation task—in *denser* networks (generally) or around people whose network neighbors exhibit higher interconnectivity (i.e., people with higher clustering). For example, in the two networks shown in Figure 1, Customer 1's neighbors are very interconnected and thus highly clustered (clustering = .67 because four out of six possible ties exist), whereas Customer 2's neighbors are not (clustering = .17 because only one of six possible ties exists). Because the network structure in Customer 1's network has higher clustering than Customer 2's, it should be easier for ideas to spread or catch on among Customer 1's neighbors than it would be among Customer 2's neighbors. This idea is supported by research that has shown that the flow of information is faster (Goldenberg et al. 2009; Watts 2002) and more efficient (Mason and Watts 2012) in more interconnected/clustered networks or parts of networks.

At the individual level, this suggests that the extent to which one's neighbors are clustered affects the redundancy of the neighbors' ideas such that a set of neighbors with higher interconnectivity (e.g., Customer 1's neighbors in Figure 1) will be more likely to have higher idea redundancy than a set of neighbors with lower interconnectivity (e.g., Customer 2's neighbors in Figure 1). Thus, we hypothesize that clustering *increases* idea redundancy. Clustering will therefore have a *negative* effect on an individual customer's innovativeness but, as discussed earlier, only when customers ideate in at least a somewhat interdependent manner.

We acknowledge that these arguments are somewhat related to organizational sociology research into how the density of intrafirm networks affects creativity (e.g., Burt 2004; Fleming, Mingo, and Chen 2007; Perry-Smith 2006; Tortoriello and Krackhardt 2010). Those studies suggest that greater employee creativity is correlated with lower network density and weaker social ties. However, field data with endogenous networks in those studies make it impossible to infer whether lower network density *causes* higher creativity. It could instead be that more (less) creative people tend to be in less-dense (more-dense) regions of the organizational networks that were studied. Furthermore, the networks in those

[6]An analogy is "production blocking" in brainstorming, in which a group's performance suffers because a minority dominates, resulting in fewer unique perspectives being considered. See Lamm and Trommsdorff (2006).

[7]In the related brainstorming literature, this mechanism is referred to as social convergence and is a major reason for the underperformance of brainstorming groups (Lamm and Trommsdorff 2006; Paulus et al. 2002).

studies are social in the sense that connections indicate social (and/or professional) long-term relations (at least months) in addition to being conduits for short-term information flows. Thus, network effects on creativity might not be due to communication (as we argue) but to social factors. It is therefore difficult to directly apply findings from the organizational sociology literature to the current research (for details, see Web Appendix C).

OVERVIEW OF STUDIES AND METHODOLOGY

In this section, we provide a general overview of the studies used to test our conceptual framework, and then describe key methodological aspects that they have in common. Using a novel methodological approach, including network-controlling software that was developed specifically for this research, we tested our hypotheses with five experimental studies. Taken together, these experiments shed light on how, when, and why ideating customers are affected by the interconnectivity of their neighbors in online product-ideation tasks. We present an overview of the five studies in Table 1. Study 1 shows the negative effect of clustering on idea innovativeness, moderated by likelihood of ideating interdependently according to the structural characteristic of degree. Study 2 replicates this effect using a different product than the one used in Study 1 and also shows that ideas spread over network connections over time. Study 3 shows that idea redundancy mediates the effect of clustering on innovativeness and that only a small amount of clustering is required for this mediation to occur. Study 4 shows that idea redundancy lowers innovativeness provided that people ideate at least somewhat interdependently according to the individual characteristic of ideation style. Finally, Study 5 shows that marketers can make the negative effect of clustering on innovativeness go away by preventing customers from ideating interdependently (i.e., task characteristic moderator).

General Methodology and Procedure

Many methodological and procedural aspects are common across these experiments, so we begin by describing the paradigm used in all experiments except for Study 4. We collected data using a custom-built, web-browser-based software application that enabled us to have people participate in real-time interdependent online product-ideation tasks in a controlled online platform. We exogenously manipulated the structures of the communication networks that connected participants, and we randomly assigned anonymous participants to positions in these communication networks. Participants who were connected could see each other's ideas but knew nothing else about their neighbors. This arrangement has two benefits. First, we could exogenously vary clustering and were therefore able to identify a causal effect of clustering (which is impossible in natural, endogenous networks because clustering may be correlated with many other properties). Second, exogenously determining network structures and randomly assigning anonymous participants to positions enabled us to avoid both endogeneity and homophily concerns, which arise when using data from naturally occurring networks (Manski 1993).

The following procedure was used in all studies in which participants interdependently ideated with others (i.e., all except Study 4). First, participants were invited to complete a task in which they would develop ideas for new, innovative features that would make a product or service more useful. They were told they would complete the task anonymously with others in real time in an online network. Participants received an incentive that did not depend on performance (five dollars for nonstudents and course credit for students).

Second, in each experimental run, participants were randomly assigned to a between-subjects condition (depending on the study) and, within condition, were randomly assigned to a position in an exogenously determined undirected communication network. Each participant had specific clustering (extent of interconnectivity among neighbors) and degree (number of neighbors). Across studies we varied network size (total number of participants per network) and other network-level properties for robustness. During each experiment, the network was fixed (connections could not be added or removed by participants or experimenters). The networks we used were designed to maximize variation in clustering and to have near-zero correlation between clustering and degree (for details, see Web Appendix D). Our objective was to use a variety of networks to ensure that results were not peculiar to a specific network type. Furthermore, to boost external validity, we used networks with features found in real communication networks.

Third, participants completed an ideation task over multiple discrete rounds. Each round had two parts. The first part required participants to type an idea into a box within a time limit. The second part showed participants their neighbors' ideas from that round. The time limits were usually two

Table 1
OVERVIEW OF STUDIES

Study	*Part(s) of Conceptualization Primarily Tested*	*Interdependent Ideation Moderator*	*Other Aspects*
1	Clustering → Innovativeness, when ideating interdependently	Structural (degree)	Replication with different networks (see Web Appendix H)
2	Clustering → Innovativeness, when ideating interdependently	Structural (degree)	Show ideas spread over time across network ties
3	Clustering → Idea redundancy → Innovativeness	—	Conservative/weak manipulation of clustering
4	Idea redundancy → Innovativeness, when ideating interdependently	Individual (interdependent ideation style)	Conservative/weak manipulation of redundancy
5	Clustering → Innovativeness, when ideating interdependently	Task (rules)	—

minutes for each part, although in one study we used three minutes (as a robustness check). These limits are similar to idea-generation times reported in brainstorming experiments (e.g., Diehl and Stroebe 1987; Gallupe et al. 1992). Participants were told that they were free to use neighbors' ideas when generating their own ideas in subsequent rounds (except in one condition in Study 5 in which this was explicitly forbidden). We used discrete rounds to mimic the "back-and-forth" nature of interdependent online product-ideation tasks in practice (e.g., in threaded discussion forums or real-time chat sessions). Also, we needed multiple discrete rounds to test our theory because we had to assess participants' ideas after they had been exposed to other participants' ideas. Using a finite number of rounds and insisting that an idea be contributed by each participant in each round meant that we could focus on idea innovativeness *per participant, per round* while holding constant the number of ideas contributed by each participant (unlike in, e.g., an unstructured brainstorming task). Thus, we could focus on idea innovativeness without having to account for variation in numbers of ideas.

Finally, after the final round, we measured some participant-level variables that we used to control for participant-level heterogeneity in innovative ability, which was important because we wanted to estimate effects of interest after controlling for participant-level factors that could be correlated with latent ability and other factors that could have been related to task involvement (which could also explain variance in innovativeness). In other words, we used a carefully considered set of controls to mitigate potential omitted-variable bias. However, excluding control variables from our statistical models did not substantially alter any of our results.

Measuring the Dependent Variable, Idea Innovativeness

To capture the innovativeness of participants' ideas, we developed a procedure for measuring idea innovativeness, the dependent variable in all studies. The procedure involved submitting each idea to multiple independent judges (two or three judges per idea) who were blind to the details of the study, had no information about the participants, and were shown only the same general description of the ideation task that participants saw. We first asked each judge to screen an idea for its validity (i.e., to confirm that it was an idea for the specified product or service and that the writing could be understood). Ideas marked as invalid were excluded, and invalidity rates in each study were low. If an idea was deemed valid, its innovativeness was assessed using a seven-item scale, with each item rated on a five-point Likert scale (1 = "strongly disagree," and 5 = "strongly agree"). Items are listed in Web Appendix E (e.g., "this idea is original"; "this idea is innovative") and are based on existing scales for idea novelty and creativity (Goldenberg, Mazursky, and Solomon 1999b; Moreau and Dahl 2005; Yang et al. 2012). Items were averaged to form judge-level measures of innovativeness for each idea, which were then averaged over judges to arrive at a single measure of each idea's innovativeness. Because this judge-based measurement procedure was designed to capture average perceptions of idea innovativeness, we were not primarily concerned with the extent to which different judges' ratings of the same idea were consistent (although, in general, they were, as discussed later in this section).

Note that this judging procedure is distinct from other creativity-judging approaches such as Amabile's (1983) Consensual Assessment Technique, in which *expert* judges are asked to "objectively" determine creativity. Our procedure was designed to measure the average intuitive, external, consumer-derived assessment of an idea's innovativeness *from the same (or similar) population of people who contributed ideas* (i.e., not experts). This is closer to what happens in practice when customers post ideas online and other customers judge those ideas by rating or voting. Furthermore, our approach is consistent with research that has found consumers to be better than expert judges at identifying "good" product ideas (Kornish and Ulrich 2014). Thus, our procedure for assessing idea innovativeness is appropriate given the practical context of this research. Nevertheless, not using expert judges may be a limitation of this research.

To validate our approach, we tested the representativeness and reliability of judges' ratings (see Web Appendix F for details). For representativeness, because each idea was assessed by a small number of judges, our concern was that a few judges' ratings would not be representative of a larger set of judges' ratings. Although using a small number of judges to rate ideas on novelty, creativity, originality, or innovativeness is very common in extant literature (e.g., Goldenberg, Mazursky, and Solomon 1999b; Moreau and Dahl 2005) and small numbers of consumer judges can make reliable predictions of idea quality (Kornish and Ulrich 2014), we validated the representativeness of judges' ratings by having a larger set of judges evaluate a random sample of ideas from Study 1. The smaller set of original judges' ratings was found to be consistent with, and therefore sufficiently representative of, the larger set of validation judges' ratings. For reliability, we checked that our procedure produced reasonable interjudge reliability. Standard interjudge reliability measures could not be used because we did not have a fixed cohort of judges who all assessed the same ideas. We did, however, do this for another randomly selected set of ideas from Study 1 and found reasonable interjudge reliability and good interjudge agreement.

STUDY 1: CLUSTERING DIMINISHES INNOVATIVENESS

Overview and Procedure

The goal of Study 1 is to test the hypothesis that clustering negatively affects idea innovativeness when customers ideate in an interdependent manner, in this instance because they have more neighbors (i.e., a structural characteristic—degree—making them more likely to use others' ideas as inputs). Sixty-four students at the University of Florida participated over four separate runs/sessions in exchange for course credit. In each run, participants were randomly assigned to a position in a 16-node network that had sufficient variation in clustering and degree between nodes (clustering: M = .36, SD = .27, min = 0, max = .80; degree: M = 5.13, SD = 1.41, min = 3, max = 8) and a near-zero degree-by-clustering correlation (r = .02). The ideation task was to generate features of a mobile-banking smartphone application that would be innovative and useful to bank customers (see Web Appendix G). Participants completed three two-part rounds, with each

part taking two minutes (i.e., two minutes to submit an idea, two minutes to look at neighbors' ideas). Of the 192 collected ideas, 177 (92.19%) were valid and thus useable in our analysis. Two or three independent judges (M = 2.72) rated each idea on the innovativeness scale (α = .98).

Results

Because the ideas submitted in the first round are independent, we used the ideas submitted in the second and third rounds for analysis and controlled for the innovativeness of each participant's previous-round idea (i.e., state dependence). This resulted in a panel data set of 119 valid ideas from 61 participants (49% female) across four experimental runs (three participants were dropped because they did not produce ideas in Rounds 2 or 3 as a result of a software error.) The average idea length was 207.10 characters (SD = 94.14, min = 57, max = 473). Also, because participants were independent in the first round, the network variables should not have affected first-round idea innovativeness, and indeed they did not. Examples of ideas are listed in Web Appendix G. Mean (SD) innovativeness in Rounds 1–3, respectively, was 2.79 (.81), 3.08 (.72), and 3.33 (.65).

Our prediction was that the effect of clustering on idea innovativeness will be negative at higher levels of degree (i.e., at which using neighbors' ideas is more likely). We first conducted a model-free analysis by estimating the correlation between clustering and innovativeness at lower (below mean) and higher (above mean) degree. Consistent with our hypothesis, when degree was lower, and thus there was a structural constraint on sources of inspiration such that ideating in an interdependent manner was less possible, there was no correlation between clustering and innovativeness (r = .006, p = .96). When degree was higher and this structural constraint was relaxed, the correlation was, as expected, negative (r = −.388, p < .01).

Next, we estimated a random-effects model in which we regressed idea innovativeness on (standardized) clustering, degree, the clustering × degree interaction, and a set of variables to control for observed participant-level heterogeneity. The variables were (1) previous-round idea innovativeness, (2) dummy variables for year in college (as a proxy for age, which we did not ask in this study but did ask in other studies), (3) a dummy variable for sex, (4) dummy variables for the experimental run, (5) a dummy variable for round, and (6) the amount of time (seconds) it took to write the idea. A participant random effect captured unobserved heterogeneity.

We report regression results in Table 2. There was a significant negative interaction between clustering and degree (b = −.16, t = −2.04, p = .046), and the nature of this interaction is consistent with our prediction: clustering negatively affects idea innovativeness as degree increases. (With covariates removed, this interaction effect is the same: b = −.17, t = −2.02, p = .048.) To illustrate, on the basis of estimated means from the model, at higher degree (1 SD above its mean), mean idea innovativeness is higher when clustering is lower (1 SD below its mean; estimated M = 4.40) and lower when clustering is higher (1 SD above its mean; estimated M = 3.94). In a spotlight analysis, the simple effect of clustering at higher degree is negative (p = .037). On the other hand, the simple effect of clustering at lower degree is not significant (p = .36). Also, the simple effects of degree at higher and lower levels of clustering were, respectively, marginally negative (p = .08) and nonsignificant (p = .22). As a robustness check, we reran the analysis excluding participants with the lowest degree (3) or the two lowest degrees (3 and 4) to rule out the possibility that the clustering × degree interaction was driven by low degree and the resulting reduced possibilities for variation in clustering. The interaction was negative when participants with degree = 3 were excluded (p = .024) and when participants with degree = 3 or 4 were excluded (p = .037). Finally, we centered clustering at its maximum (.80) and minimum levels (0) and estimated degree simple effects. Degree has a negative effect on innovativeness at maximum clustering (b = −.31, t = −1.93, p = .059), but not at minimum clustering (b = .15, t = 1.51, p = .14). Thus, having higher degree does not hurt one's innovativeness if one has low clustering, and being connected to others is therefore not necessarily problematic.

Finally, we replicated this study and its results using the same task but with two different types of networks to rule out the possibility that these results are artifacts of the specific network structure used. We report the results in Table 2 and provide full details in Web Appendix H.

STUDY 2: IDEA CONCEPTS SPREAD OVER NETWORK CONNECTIONS

Overview and Procedure

The goal of Study 2 is twofold: to replicate Study 1's findings in a different category and to empirically show that concepts on which ideas are based spread between connected participants over network connections between successive rounds. Showing that ideas spread over network connections over time is critical for our theory because, as discussed earlier, our explanation for how clustering increases redundancy among neighbors' ideas is based on the assumption that ideas spread over network connections in a social contagion–like manner. Thirty-six students at the University of Pittsburgh participated in this study over three separate runs in exchange for course credit. The task involved generating innovative ideas for new features of Facebook that would make the popular online social network more useful to people. All participants were active Facebook users. In each run, participants were randomly assigned to a position in a 12-node network with properties similar to the first network in Study 1 (clustering: M = .53, SD = .27, min = 0, max = 1; degree: M = 4.17, SD = 1.40, min = 2, max = 7; clustering-by-degree correlation: r = −.06, p = .84). Except for the product being Facebook instead of a mobile-banking application, the procedure was identical to that of the previous study. Of the 108 collected ideas, 100 (92.59%) were valid and were rated by two or three independent judges (M = 2.84) for innovativeness (α = .92).

Results

Replication of the effect of clustering on innovativeness. The data set contained 66 valid second- and third-round ideas from 34 participants (36% female) across three runs (two participants were dropped because they did not produce ideas in Rounds 2 or 3 as a result of a software error.)

Table 2
EFFECTS OF CLUSTERING AND DEGREE ON INNOVATIVENESS (STUDY 1)

	Estimate (SE)		
		Replication[a]	
Effect	*Main*	*Including Nodes with Degree = 1*	*Excluding Nodes with Degree = 1*
Intercept	4.11 (.57)***	4.60 (.38)***	4.50 (.39)***
Clustering	−.08 (.06)	−.20 (.09)**	−.23 (.09)**
Degree	−.06 (.07)	.09 (.08)	.07 (.07)
Clustering × Degree	−.16 (.07)**	−.21 (.09)**	−.24 (.10)**
Lagged idea innovativeness	.08 (.07)	−.15 (.07)**	−.11 (.07)
Age	—	−.02 (.01)**	−.02 (.01)**
College year (baseline = postsenior)			
1	−.66 (.59)	—	—
2	−1.01 (.48)**	—	—
3	−.79 (.47)*	—	—
4	−.69 (.47)	—	—
Sex = female (baseline = male)	−.11 (.12)	−.01 (.07)	.003 (.07)
Run/session (baseline = 4)			
1	.12 (.18)	−.19 (.17)	−.21 (.17)
2	.08 (.16)	−.52 (.17)***	−.48 (.17)***
3	−.15 (.16)	−.62 (.18)***	−.57 (.18)***
Round = 2 (baseline = 3/final)	−.28 (.12)**	−.19 (.08)**	−.19 (.08)**
Ideation time	−.001 (.002)	.002 (.002)	.002 (.002)
Network type[a]	—	−.03 (.14)	−.06 (.14)
Participant random effect	.37 (.15)**	.15 (.06)**	.14 (.06)**

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]See Web Appendix H.
Notes: Model fits (McFadden R^2): .09, .13, .12. Main: 177 valid first-, second-, and third-round ideas from 61 participants; replication: 226 valid first-, second-, and third-round ideas from 72 participants.

The average idea length was 164.82 characters (SD = 103.96, min = 31, max = 462), and we found no network position effects when we analyzed the first-round ideas separately. We list examples of submitted ideas in Web Appendix G. Mean (SD) innovativeness in Rounds 1–3, respectively, was 2.65 (.65), 2.80 (.62), and 2.70 (.56). Our prediction was the same as in Study 1: clustering has a negative effect on innovativeness when degree is higher. We again first conducted a model-free analysis by estimating the correlation between clustering and innovativeness at lower (below mean) and higher (above mean) degree and found a significant negative correlation at higher degree ($r = -.41$, $p = .05$) but not at lower degree ($r = -.10$, $p = .50$). Next, we ran the same regression analysis as in Study 1 (see Table 3), and, as expected, the clustering × degree interaction was negative ($b = -.40$, $t = -3.19$, $p < .01$; with covariates removed, this interaction effect was the same: $b = -.35$, $t = -2.67$, $p = .012$). In a spotlight analysis, the simple effect of clustering at higher degree was negative ($p < .01$), but the simple effect of clustering at lower degree was not significant ($p = .59$). The simple effects of degree at higher and lower levels of clustering were, respectively, negative ($p < .01$) and nonsignificant ($p = .88$). Finally, when clustering was centered at its maximum (1) and minimum levels (0), degree had a negative effect at clustering = 1 ($p < .01$) and a positive effect at clustering = 0 ($p = .02$).

Idea-spreading analysis. To demonstrate that ideas spread across network connections, we developed a method for assessing how similar participants' ideas were across successive rounds (but not the same round) and compared these similarity assessments for connected versus random participant pairs. The logic is that if ideas spread across connections over time, we should find greater similarity among connected pairs' ideas than among random pairs'

Table 3
EFFECTS OF CLUSTERING AND DEGREE ON INNOVATIVENESS (STUDY 2)

Effect	*Estimate (SE)*
Intercept	1.64 (.67)**
Clustering	−.37 (.13)***
Degree	−.40 (.12)***
Clustering × Degree	−.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)***

**$p < .05$.
***$p < .01$.
Notes: Model fit (McFadden R^2): .15. Data are from 100 valid first-, second-, and third-round ideas from 34 participants.

ideas (only between rounds because of the way our task was designed). Quantifying the similarity of two ideas, however, is challenging because two ideas can be conceptually or thematically very similar without being identical. Thus, we developed a natural-language-processing procedure to quantify the similarity of pairs of ideas at the concept level.

We subjected the text of all valid ideas from all three rounds to the following procedure (for full details, see Web Appendix I). First, we identified "noun chunks" (the concepts in contributed ideas) in each entry using the Natural Language Toolkit software (Bird, Loper, and Klein 2009). This process extracted noun chunks from each idea by identifying nonoverlapping linguistic groups (noun phrases), which resulted in a set of concepts present in each idea. Second, the sets of concepts were manually cleaned to remove duplicates, fix typographical errors, convert plurals to singulars, convert abbreviations (e.g., "app") to long forms (e.g., "application"), delete nonsensical terms, and check that each original idea matched its concept set. We also removed concepts that were part of the task description (e.g., "Facebook"). This resulted in a set of unique concepts that were mapped to participants in each network in each round.

For each concept, we then looked at all pairs of participants in the same network for whom the same concept occurred in different rounds.[8] This enabled us to compute the empirical probability that a pair of participants who had one or more common concepts in different rounds were in fact directly connected to each other. We defined this probability as P(connected | common) = q. The higher q, the more likely that participants ideated interdependently and ideas spread. We compared probability with the probability of two *randomly* selected nodes being connected, which was equal to the density of the network (d = .38). If ideation was independent and ideas spread, pairs with common concepts would occur only by chance, and q = d. Accordingly, q > d is evidence of concepts spreading across connections (for a proof, see Web Appendix J). Across runs and concepts, q = .53, which is significantly greater than d = .38 ($\chi^2(1) = 15.11$, $p < .001$). Thus, concepts likely spread across connections between rounds in a manner akin to social contagion. Because our networks are exogenous and participants anonymous, it is highly unlikely that idea spreading observed here could be due to homophily.

STUDY 3: REDUNDANCY MEDIATES THE CLUSTERING EFFECT ON INNOVATIVENESS

Overview and Procedure

The goal of Study 3 is to test the hypothesis that the negative effect of clustering on idea innovativeness is mediated by idea redundancy. Sixty students at the University of Pittsburgh (62% female, mean age = 20 years) participated in this study over five runs in exchange for course credit. Participants in each run were randomly assigned to one of two between-subjects conditions: no clustering versus clustering. Within each condition, participants were then randomly assigned to a position in a six-node network. In both conditions, each participant had three neighbors (i.e., degree = 3).[9] In the no-clustering condition, the network was structured so that each participant's neighbors were not interconnected (clustering = 0). In the clustering condition, the network was structured so that each participant had the minimum possible nonzero level of clustering (.33; one of the three pairs of their neighbors was connected).

The remainder of the procedure was similar to that of the previous studies, and the Facebook ideation task from Study 2 was used. The main differences were for the sake of robustness: in this study, participants went through five two-part ideation rounds instead of three, and each part lasted three minutes instead of two. The same idea-judging procedure used in Studies 1 and 2 was used in this study. Of the 300 collected ideas, 285 (95%) were valid and were rated by an average of 2.67 independent judges on the innovativeness scale ($\alpha = .94$). Mean (SD) innovativeness in Rounds 1–5, respectively, was 2.68 (.81), 2.64 (.84), 2.71 (.65), 2.93 (.73), and 2.86 (.90). Note that we designed this study to provide a conservative test of our predictions by holding degree constant at 3 (which is low, and at which level we would not expect a particularly strong clustering effect) and by having only a minimal amount of clustering in the clustering condition.

To measure idea redundancy, in the posttask survey, participants indicated agreement or disagreement with two items on a five-point Likert scale (1 = "strongly disagree," and 5 = "strongly agree"): "There was a lot of redundancy among my group members' ideas," and "There was a lot of overlap in the ideas submitted in my group." These items were positively correlated (r = .58, $p < .001$), and we averaged them to form a measure of neighbor-related perceived idea redundancy. In addition, participants responded, using the same five-point scale, to two items that measured their attention to their neighbors' ideas (r = .72, $p < .001$; "I paid close attention to my group members' ideas," and "I carefully read my group members' ideas"). We measured attention to rule out the possibility that clustering also affects attention paid to neighbors' ideas in general (as an indicator of involvement in the interdependent ideation task), which might suggest a potential alternative process for the effect of clustering on idea innovativeness. In a regression, we found no effect of clustering on attention ($p = .29$).

Results

As in the previous studies, we first looked for model-free evidence in support of our hypotheses. First, the mean for idea redundancy in the clustering condition was higher than in the no-clustering condition ($M_{clustering} = 3.32$, SD = .76 vs. $M_{no\ clustering} = 3.03$, SD = .96; $p = .01$), as suggested by our theory. Second, idea innovativeness was lower in the clustering condition (M = 2.68, SD = .85) than in the no-clustering condition (M = 2.82, SD = .69), also consistent with our hypothesis (although a comparison of means test was not significant; $p = .16$). Third, as we expected, there

[8]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).

[9]We expected that three neighbors would be a large enough number to make it likely that participants would ideate in at least a somewhat interdependent manner (per Studies 1 and 2), but small enough to make this a conservative test.

was a negative correlation between idea redundancy and idea innovativeness (r = −.16, p = .015). Finally, we formally tested our mediation hypothesis using a conditional indirect effects analysis (Hayes 2013). As in the previous studies, we controlled for age, sex, experimental run, round, and ideation time as potential sources of heterogeneity. Clustering had a significant negative indirect effect on innovativeness, mediated by idea redundancy (indirect effect = −.04, SE = .025, 95% confidence interval [CI] = [−.11, −.01]; with covariates removed, this indirect effect is the same: effect = −.04, 95% CI = [−.10, −.01]). There was no direct effect of clustering on innovativeness when we controlled for redundancy (p = .95); clustering had a positive effect on idea redundancy (b = .30, t = 2.55, p = .01); and idea redundancy had a negative effect on innovativeness (b = −.13, t = −2.05, p = .04). These results are consistent with our conceptualization; specifically, they support the hypothesis that neighbor interconnectivity reduces individual innovative performance because clustering increases the likelihood of neighbors' ideas being more redundant. Importantly, we found this using a weak clustering manipulation (i.e., the minimum amount of nonzero clustering for degree = 3) and with only a few neighbors. This is, therefore, a conservative test, and we expect that with higher clustering and degree, the effect of clustering through redundancy would be more negative.

STUDY 4: REDUNDANCY LOWERS INNOVATIVENESS

Overview and Procedure

Study 3 showed a negative effect of participant-perceived redundancy on idea innovativeness, consistent with our conceptualization. The goal of Study 4 is to examine the negative effect of idea redundancy on innovativeness in greater detail by manipulating redundancy and by showing that the effect is stronger when customers ideate in a more interdependent manner. Instead of using the structural characteristic moderator (degree) from earlier studies, here we use a measured individual characteristic, interdependent ideation style (IIS). Seventy members of Amazon Mechanical Turk (46% female, mean age = 30 years) participated in this study in exchange for a small payment (an additional 17 participants were excluded for failing to correctly recall degree in a comprehension check). We used the Facebook task from Studies 2 and 3, and all participants reported being active Facebook users. Participants *did not* ideate in real time with other people, but their instructions led them to believe they were doing so. They did, however, complete a task similar to that of Study 3, although with only two rounds that each had two parts, with each part two minutes long.

Participants were led to believe that they were in a network with four other people (i.e., degree = 4). We randomly assigned them to one of two between-subjects conditions: no redundancy versus redundancy. We manipulated idea redundancy by showing participants ideas that we told them had been generated by their neighbors in the first round (ideas were presented in randomized order within condition). In the no-redundancy condition, the first-round ideas that participants saw from their supposed neighbors were distinct (i.e., four different ideas). In the redundancy condition, two of the four neighbors' ideas were similar (i.e., participants really saw only three different ideas). Both conditions had the same three ideas for improving Facebook, based on real ideas collected in Study 2: (1) add a "dislike" button, (2) allow users to see who "unfriends" them, and (3) make Facebook more like Pinterest. The fourth idea in the no-redundancy condition was different from the other three (allow users to follow sports teams and get score updates), but in the redundancy condition it was the same as the first idea (add a "dislike" button), with slightly different wording. Thus, the redundancy condition had the minimal amount of idea similarity possible for degree = 4. After viewing their supposed neighbors' first-round ideas, participants wrote their own second-round ideas, which we expected would be less innovative for participants in the redundancy condition.

Finally, after the ideation task, we checked the idea-redundancy manipulation using the same two response items that measures idea redundancy in Study 3 (r = .46, p < .001). We also assessed the extent to which participants believed they had used an IIS, using seven items (e.g., "My ideas came from combining concepts that came up in others' ideas"; "I built my ideas by combining some aspects of group members' ideas with my previous ideas"; "I linked concepts that came up in others' ideas to form new ideas": see Web Appendix K) that participants rated on a five-point Likert scale (1 = "strongly disagree," and 5 = "strongly agree"; α = .95). We expected the negative effect of idea redundancy on idea innovativeness to be stronger for higher-IIS participants because idea redundancy should hurt innovativeness only if one actually ideates in an interdependent manner.

Results

Manipulation check. We tested whether redundancy participants perceived greater idea redundancy than no-redundancy participants. We regressed perceived idea redundancy on a dummy variable for condition (0 = no redundancy, 1 = redundancy) and found a positive effect (b = .93, t = 5.02, p < .001). Thus, the manipulation operated as intended.

Effect of idea redundancy on innovativeness. Idea innovativeness was measured as it was in previous studies, that is, on the innovativeness scale (α = .94) as rated by two or three independent judges (M = 2.98). Of the 140 collected ideas, 137 (97.86%) were valid. The average idea length was 145.41 characters (SD = 102.58, min = 8, max = 465), and no redundancy effect was found when the first-round ideas were analyzed separately. Mean (SD) innovativeness in Rounds 1 and 2, respectively, was 2.88 (.72) and 2.89 (.68). As an initial test, we used a model-free analysis to compare mean innovativeness between the conditions and found lower innovativeness when there was redundancy (M = 2.66, SD = .69) versus when there was no redundancy (M = 3.09, SD = .61; p < .01). Also, the difference in innovativeness was larger when IIS was above the scale midpoint (2.47 vs. 3.23, p = .001), but there was no significant difference when IIS was below the midpoint (2.92 vs. 3.07, p = .55).

Next, we formally tested our hypothesis that idea innovativeness suffers in the second round after the participant is exposed to some (albeit minimal) redundancy in neighbors' first-round ideas. We regressed second-round idea innovativeness on the redundancy dummy variable and control variables to account for observed participant-level heterogeneity (first-round idea innovativeness, age, sex, and ideation time in

seconds). We report regression results in Table 4. Redundancy negatively affected idea innovativeness (b = −.46, t = −2.83, p = .006; estimated $M_{no\ redundancy}$ = 3.09, estimated $M_{redundancy}$ = 2.63; with covariates removed, this effect is the same: b = −.46, t = −2.92, p = .005). We then ran a spotlight analysis to estimate the simple effect of idea redundancy on innovativeness at three levels of IIS. At lower IIS (1 SD below the mean), the effect of redundancy on innovativeness was not significant (p = .44). However, at both moderate (mean) and higher IIS (1 SD above the mean), the simple effect was negative (moderate: b = −.45, t = −2.66, p = .01; higher: b = −.71, t = −3.00, p = .004). A floodlight analysis found that the negative effect of idea redundancy is significant (at p = .05) when IIS ≥ 2.60 (on a 1–5 scale), that is, at moderate IIS and higher.

STUDY 5: MODERATING THE CLUSTERING EFFECT USING TASK RULES

Overview and Procedure

Studies 1–4 provide robust support for the hypothesized relationships in our conceptual framework. The goal of Study 5 is to test another factor that might affect the extent to which customers ideate in an interdependent manner, as a moderator of the negative effect of clustering on idea innovativeness that was shown previously. In previous studies, we considered structural and individual characteristics as factors that made interdependent ideation more or less likely. Here, we consider how the ideation task's rules can be altered to make ideating interdependently less likely, which should mitigate the negative effect of clustering on innovativeness. The purpose of this investigation is to show that it is possible to prevent high clustering from stifling creativity through a simple adjustment of task rules, which has practical value in settings whose highly clustered structure cannot be changed. Theoretically, when ideating customers are less likely to fixate on neighbors' ideas, they may be less susceptible to the effects of redundancy in settings with higher clustering. Thus, establishing a task rule that discourages fixation should be effective at mitigating the negative effect of clustering on innovativeness. Here, we use a simple rule: participants are *not* allowed to use neighbors' ideas when formulating their own.

Ninety-six students at the University of Pittsburgh participated in this study over four separate runs in exchange for course credit. The procedure was very similar to that of Study 2 and involved generating ideas for improving Facebook. All participants reported being active Facebook users. In each run, participants were randomly assigned to one of two between-subjects conditions and then, within condition, were randomly assigned to a position in a 12-node network (the same network used in Study 2). The between-subjects factor manipulated the ideation style participants were allowed to use: interdependent ("allowed") or independent ("not allowed"). In the interdependent condition, as in the previous studies, participants were told they could take neighbors' ideas and use them as part of their own. In the independent, or "not allowed," condition, participants were explicitly told that they could not use neighbors' ideas as inputs into their own and that they should contribute only their own ideas. Participants completed three two-part ideation rounds in this study. Of the 288 collected ideas, 283 (98.27%) were valid and were rated by two or three judges (M = 2.91) for innovativeness (α = .93).

Table 4
EFFECT OF IDEA REDUNDANCY ON INNOVATIVENESS (STUDY 4)

Effect	*Estimate (SE)*
Intercept	2.97 (.85)***
Redundancy (1) vs. no redundancy (0)	−.46 (.16)***
Lagged idea innovativeness	.18 (.11)
Age	−.01 (.01)
Sex = female (baseline = male)	−.04 (.17)
Ideation time	−.000 (.007)

***p < .01.

Notes: Model fit (R^2): .17. Data are from 137 valid first- and second-round ideas from 70 participants.

Results

The data set 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. Mean (SD) innovativeness in Rounds 1–3, respectively, was 2.83 (.67), 2.92 (.60), and 2.95 (.69).

Manipulation check. At the end of the ideation task, we measured with three items the extent to which participants felt they used (or did not use) their neighbors' ideas in generating their own ideas during the task. Participants rated each item on a five-point Likert scale. The first item was "For each idea from round 2 onwards I tried to build on previous idea(s) that other people had suggested" (1 = "strongly disagree," and 5 = "strongly agree"). The second and third items asked participants (separately for the second and third rounds of the task) to indicate the extent to which their ideas had been completely their own versus inspired by their neighbors' ideas (1 = "100% my own idea and not inspired by neighbors," and 5 = "100% inspired by neighbors and not at all my own idea"). As expected, participants in the allowed condition 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 condition (M_1 = 2.48, M_2 = 1.30, M_3 = 1.53); all differences were significant (ps < .001).[10]

Effect of clustering on innovativeness. We first ran a model-free analysis and found that in the not-allowed condition, there was no correlation between clustering and innovativeness either at higher degree (r = −.17, p = .35) or lower degree (r = .01, p = .96). Next, we estimated a regression model (see Table 5). There was a significant three-way condition × clustering × degree interaction (b = −.31, t = −1.72, p < .09).[11] When the by-condition effects were estimated, the clustering × degree interaction

[10]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.

[11]Because our predicted effect is directional—the clustering × degree interaction occurs only in the allowed condition—a one-tailed test is acceptable (one-tailed p < .05).

Table 5
EFFECTS OF CLUSTERING AND DEGREE ON INNOVATIVENESS ACCORDING TO WHETHER USING NEIGHBORS' IDEAS IS OR IS NOT ALLOWED (STUDY 5)

	Estimate (SE)	
Effect	*Using Others' Ideas Allowed*	*Using Others' Ideas Not Allowed*
Intercept	4.44 (1.87)**	4.50 (1.38)***
Clustering	−.19 (.12)	.10 (.12)
Degree	−.21 (.12)*	.14 (.12)
Clustering × Degree	−.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)***

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Model fits (McFadden R^2): .07, .08. Combined degree × clustering × condition: b = −.31, t = 1.72, $p < .09$, p (one-tailed) < .05; pseudo-R^2 = .04. Data are from 283 valid first-, second-, and third-round ideas from 96 participants.

in the allowed condition was negative (b = −.25, t = −2.08, $p = .044$; with covariates removed, this interaction effect is the same, although only marginally significant: b = −.23, t = .−1.86, $p = .067$), consistent with the results of the previous studies. However, the clustering × degree interaction was not significant in the not-allowed condition ($p = .68$). In a spotlight analysis, in the allowed condition, the simple effect of clustering was negative at higher degree ($p = .06$) but was not significant at lower degree ($p = .31$). Also, in the allowed condition, the simple effect of degree at higher and lower levels of clustering was, respectively, negative ($p = .05$) and nonsignificant ($p = .44$). Finally, in the allowed condition, the simple effect of degree at maximum (1) and minimum (0) levels of clustering showed that degree had a negative effect on innovativeness at maximum clustering ($p = .05$) and a positive effect at minimum clustering ($p = .06$).

DISCUSSION

We present a summary of the findings from each of our studies in Table 6. Despite different networks, task designs, products/services, participant populations, and ways of operationalizing ideating in an interdependent manner (i.e., interdependence driven by structural, individual, or task characteristics), our main finding of a negative effect of clustering on idea innovativeness when customers ideate interdependently was consistent across all studies in which this effect was tested. To demonstrate the robustness of the negative clustering × degree interaction specifically, we pooled data from Studies 1 (including the replication), 2, and 5 and performed a meta-analysis.[12] These studies include 786 valid ideas from 263 participants. We estimated a regression model similar to those reported in these studies, with fixed effects to control for study (for consistency with the other studies, we also converted Study 1's control variable of college year to age, using typical ages corresponding to each college year). We report full results in Web Appendix L; the clustering × degree interaction was negative (b = −.16, t = −3.67, $p < .001$; with covariates removed, this interaction effect is qualitatively the same: b = −.10, t = −2.29, $p = .02$). We also replaced the fixed effect for study with other relevant controls—product (mobile banking or Facebook) and network size—and achieved consistent results.

A final general point worth noting is that all of our analyses considered how the mean level of idea innovativeness was affected by clustering. This is appropriate given that when firms involve customers in their interdependent online ideation processes, managers primarily want to maximize the innovativeness of *each idea* (i.e., maximize individual innovative performance). In practice, managers hope that this leads to more ideas falling above a certain threshold of innovativeness, which implies that they want to increase the probability of an idea having an innovativeness score above a minimum acceptable level. For example, on our 1–5 innovativeness scale, a manager might want more ideas that score above the midpoint (3), because this threshold delineates between "good" (>3) and "bad" (≤3) ideas. We tested this alternative "above threshold" outcome with a logistic regression, using the same set of covariates used in the linear regression meta-analysis model, with a dependent variable equal to 1 if idea innovativeness > 3 and 0 otherwise (for results, see Web Appendix L). We found that the clustering × degree interaction was again negative and significant (b = −.47, t = −3.08, $p = .002$).[13]

[12]For Study 5, we included only the "allowed" condition, where the degree × clustering effect was significant.

[13]We did this analysis separately for each study and found the clustering × degree interaction to be significantly negative in Studies 1 and 5 (all $p < .05$) and not significant but still negative in Study 2 ($p = .26$).

Table 6
SUMMARY OF FINDINGS

Study	Product Context	Network Size per Run	Manipulation	Main Findings
1	Smartphone banking application	16	N.A.	• At higher levels of degree (interdependent ideation more likely), idea innovativeness is higher when clustering is lower
1 (replication)	Smartphone banking application	10	N.A.	• Replicated Study 1 with different network types[a] • Positive correlation between idea innovativeness and market potential
2	Facebook	12	N.A.	• Replicated Study 1 • Evidence that ideas spread across network connections
3	Facebook	6	Clustering vs. no clustering	• Clustering leads to higher idea redundancy among neighbors, which in turn lowers idea innovativeness
4	Facebook	N.A.	Redundant vs. not redundant	• Lower idea innovativeness when some idea redundancy among neighbors • Stronger effect when an interdependent ideation style is used
5	Facebook	12	Using others' ideas allowed: yes vs. no	• Effect only when interdependent ideation is allowed

[a]See Web Appendix H.
Notes: N.A. = not applicable.

Given marketing practitioners' growing interest in involving customers in interdependent ideation processes in online social platforms, and the fact that customers in this setting are connected to (and therefore potentially influenced by) each other, understanding how and why communication network structure affects individual innovative performance is important. Research on related but different contexts such as wisdom of crowds, organizational sociology, and brainstorming offers some guidance, but those literature streams have considered situations that are distinct from the marketing ideation setting considered here. They also have sometimes failed to consider either effects of network structure on performance or individual-level behavioral outcomes, and they generally have not explained why network structure affects a person's innovative performance. Thus, despite extant literature outside of marketing touching on this phenomenon, the effect of network structure, particularly clustering, on real-time interdependent product ideation has not been previously studied. Across our five experiments, we find that clustering plays a key role in affecting individual innovativeness, and we show that this occurs because highly clustered neighbors are more likely to have higher idea redundancy.

Notably, we found that idea redundancy does not need to be very high for it to drive the negative effect of clustering on innovativeness when customers ideate in an interdependent manner. Moreover, clustering itself does not have to be very high for idea redundancy to be affected. For example, even a minimal amount of clustering triggered increased idea redundancy among neighbors' ideas in Study 3. Furthermore, a minimal amount of redundancy negatively affected innovativeness in Study 4. As we discussed earlier, it is likely that idea redundancy is problematic even at small levels because it leads people to fixate on redundant themes or concepts and thus spend more time considering those than exploring the broader set of inspirations from neighbors. Results from Study 5 seem to support this idea: when we prohibited participants from using neighbors' ideas (thus reducing the likelihood of fixation), clustering did not stifle innovativeness. Fixation is problematic for two reasons. First, it causes participants to spend less time considering other inspirations, which makes it harder (in a fixed amount of time) to be creative by combining and building on others' ideas. Second, it might cause participants to devote more cognitive resources to trying to identify distinctions between two otherwise redundant concepts, which would reduce the resources available for generating new innovative ideas. Simply put, idea redundancy hurts innovativeness because it is cognitively burdensome and interferes with the psychological mechanisms involved in how people process information when ideating.

It is important to note that the negative consequences of networks found here are due to the interconnectivity of the networks and not simply a result of participants' exposure to others' ideas. Thus, we do not suggest that isolating people is a viable approach for remedying these effects. In fact, allowing people to ideate interdependently could be beneficial because it makes the task more stimulating, and, if this is the case, under the right conditions it might be good to have *more* network connections (higher degree). Our data support this suggestion. For example, in the meta-analysis, the simple effect of degree when clustering is centered at 0 is positive ($b = .28$, $t = 3.62$, $p < .001$). Conversely, the simple effect of degree when clustering is centered at 1 is negative ($b = -.35$, $t = -3.24$, $p = .001$).

Practically, the fact that clustering can negatively affect innovativeness is important because the status quo in online ideation platforms is high clustering, as discussed earlier. A likely reason why firms do not get more highly innovative ideas through these platforms is that ideating customers are suboptimally interconnected. Instead of allowing everyone to see everyone else's ideas, firms should reduce interconnectivity among ideating customers by preventing highly clustered cliques from forming. This could be achieved

by engineering networks such that average clustering is low (to reduce idea redundancy) but degree is moderate or high (to encourage ideating in an interdependent manner and to make the task more stimulating). Controlling interconnectivity in online networks is possible by limiting whom one is exposed to (e.g., what Facebook's "EdgeRank" algorithm does when determining which friends' posts one sees). In summary, our findings suggest that firms' current practice of interdependent customer ideation is suboptimal, and reducing network clustering will help firms increase the average level of idea innovativeness in their online ideation platforms.

We conclude by acknowledging some limitations of our research. First, although the networks used were realistic, they were smaller than many found in practice. Network sizes were limited for pragmatic reasons associated with experiment logistics. However, further research may attempt to study larger networks in field settings. We note, however, that most large real-world social networks can be (and perhaps should be) decomposed into small subnetworks (such as the networks we used). Second, our studies were not incentive compatible in that participants were not paid based on performance. Incentive mechanisms for ideation have been studied previously (e.g., Burroughs et al. 2011; Toubia 2006). However, because many commercial marketing applications of interdependent online ideation do not offer economic incentives to participating customers, we avoided adding this extra layer of complexity. Third, our dependent variable was consumer-judged innovativeness, which may not always be a good indicator of an idea's market success potential. Future studies may consider alternative dependent variables. We do note, however, that in the replication of Study 1 (see Web Appendix H), we measured the perceived market potential of each idea and found it to be significantly positively correlated with idea innovativeness. Finally, we did not consider customer expertise in our theory or empirical applications, beyond attempting to control for it as a source of heterogeneity. It is an open question whether these tasks are better suited to more or less experienced customers, and further research could consider this as well as related possibilities, such as training ideation participants or giving them frameworks or templates to make the task easier. In conclusion, the current research provides a new perspective on how network structure affects customer innovativeness in interdependent online ideation. We hope this research spurs more work on this complex topic.

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WEB APPENDIX

LOWER CONNECTIVITY IS BETTER: THE EFFECTS OF NETWORK STRUCTURE ON REDUNDANCY OF IDEAS AND CUSTOMER INNOVATIVENESS IN INTERDEPENDENT IDEATION TASKS

Andrew T. Stephen

Peter Pal Zubcsek

Jacob Goldenberg

A. THE CURRENT RESEARCH VERSUS RELATED LITERATURE

				Current research
	Wisdom of crowds	**Organizational sociology**	**Organizational brainstorming**	**Interdependent product ideation**
What types of "problems" are "solved"?	Well defined, usually with a small number of correct answers	Ill defined, open ended, complex	Ill defined, open ended, complex	**Ill defined, open ended, complex**
How are solutions identified?	Looking across people for their collective wisdom (i.e., aggregation)	Soliciting an idea from participants in parallel	Gathering spontaneously contributed ideas from group members	**Gathering spontaneously contributed ideas from connected customers**
Context?	Various (e.g., economics, financial markets)	Organizations	Various (e.g., organizations, marketing)	**Marketing**
Who participates?	Anyone	Employees and managers	Employees, managers, experts	**Customers**
Online or offline setting?	Online or offline	Online or offline, but mostly offline in existing intra-firm networks	Online or offline in relatively small groups	**Online platforms with connected customers**
Do people actively collaborate?	No	Typically yes	Typically yes	**No**
Are people situated in network structures?	Possibly but networks are endogenous, existing, inferred or self-reported	Yes but networks are endogenous, existing, inferred or self-reported	No because everyone is connected to everyone else in the group	**Yes and the networks are exogenous and predetermined**
Primary methodology?	Non-experimental	Non-experimental	Experimental and non-experimental	**Experimental**

B. NETWORK ANALYSIS OF CONSUMER INTERACTIONS ON IDEASTORM.COM

As a demonstration of the importance of taking a network perspective in studying interdependent ideation for products in online settings (such as discussion forums), we collected data from Dell's ideation platform, IdeaStorm.com, and used this to map the underlying network of interactions between ideating consumers on this platform. The IdeaStorm.com platform is similar to other mainstream interdependent online product ideation platforms (e.g., MyStarbucksIdea.com), and the experimental paradigm used in most of our studies was modeled on these platforms in the sense that, over time, participants are exposed to other participants' previous ideas. We do not provide a detailed description of IdeaStorm.com here; see Bayus (2012) and Huang et al. (2014).

For the purposes of the following analysis, the process for contributing ideas on IdeaStorm.com is as follows. Any user registered to the platform is allowed to post an idea at any point in time. These ideas can be about almost anything related to Dell's products and services, but often ideas are solicited on particular topics. For example, in Figure B1 we show a screenshot for a product ideation task in which consumers were invited to submit ideas for designing and marketing a laptop for children. Each submitted idea is displayed on IdeaStorm.com, and other users can view these ideas (they can also add comments below each idea, and vote "up" or "down" each idea).

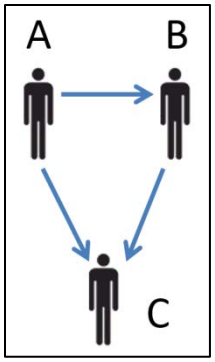
Figure B1: Example Task



The ability to view, comment on, and/or vote for other consumers' ideas means that there is a communication network between consumers on this platform. In this case the network is implicit in the sense that it is not an explicit network in the style of, for example, Facebook, where individuals form observable ties with others. Instead, in this case, we infer that a tie exists between two platform users based on commenting and/or voting actions taken in relation to their posted ideas (note that simply viewing someone's idea should also imply a connection, but viewing data could not be collected).

Specifically, suppose that user A contributes an idea. If user B either comments or votes on that idea, we assume this means that user B was exposed to user A's idea. Such interactions may be represented in a directed network, and in this example there would be a directed tie from user A to user B. Then, suppose that user B posts an idea, and another user—C—visits the platform and views both A's and B's ideas and comments and/or votes on them. This would add two more directed ties: one from A to C, and another from B to C. This small, three-node network is shown in Figure B2 (below).

Figure B2: Network Construction



To summarize, in Figure B2, user B was exposed to user A's idea, and user C was exposed to user A's idea and user B's idea. In other words, user C saw ideas contributed by both A and B, B saw an idea contributed by A, and A saw no one else's ideas. Note that the three-node network in Figure B2 is a directed graph, meaning that information (ideas) can flow in one direction but not necessarily the other between pairs of people. This is different to the networks used in our studies, where the graphs were undirected, thus meaning that for a connected pair of participants, they could see each other's ideas (this was done for simplification reasons).

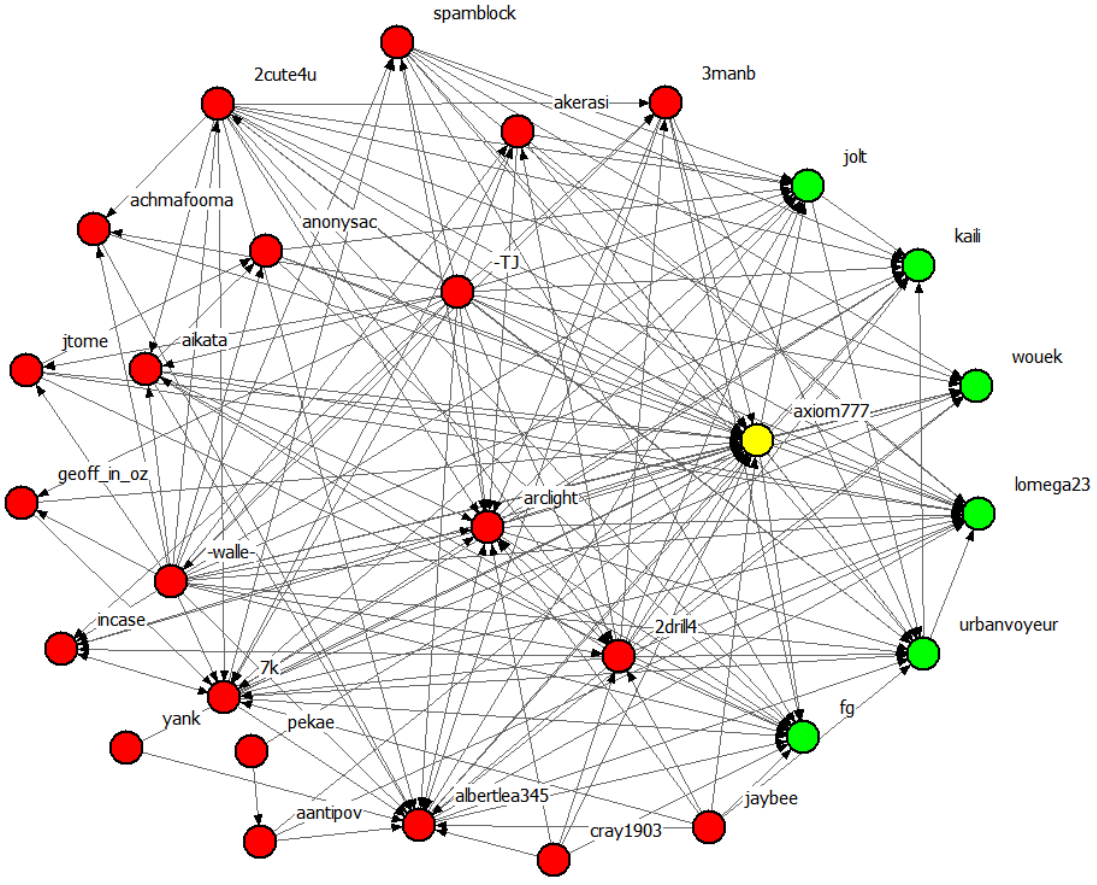
Using the data collected from IdeaStorm.com and this approach to mapping implicit network ties, we first created a node for each registered IdeaStorm.com user who had contributed at least one idea between January 1, 2008 and October 26, 2011.[1] Next, we collected all the comments and votes for all 9,424 unique ideas available on IdeaStorm.com at the time of data collection. We knew, for each idea's comments and votes, who made the comment or vote. Using this we created directed links from the idea contributors to everyone who commented or voted on their ideas per the above illustration of network tie formation. This procedure resulted in a network with 5,749 nodes (individual consumers) and 44,269 directed communication

[1] The latter date corresponds to the time of collecting the data. In line with the findings of Huang et al. (2014), we ignored all idea contributors who abandoned the website before 2008. IdeaStorm launched on February 16, 2007.

relationships. Thus, the density of connections in the network is approximately 0.00134 (i.e., this is a typical sparse communication network).

To illustrate the level of interconnectivity of this network and to demonstrate it is relatively high (despite the network itself being sparse), in Figure B3 we provide a graph of the information flows around one IdeaStorm.com user "axiom777" (yellow node). The red nodes indicate users who contributed at least one idea that axiom777 saw (commented and/or voted on), and the green nodes correspond to users who saw (commented and/or voted on) at least one of the ideas that axiom777 contributed.

Figure B3: Communication Network around User "Axiom777"



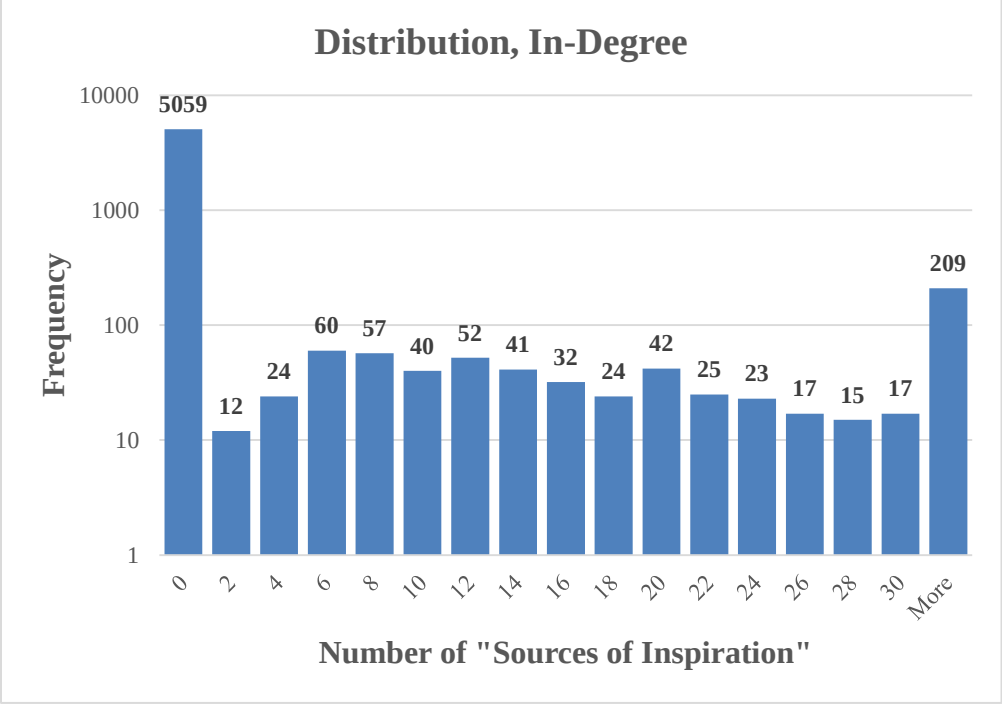
From Figure B3 it is easy to see that the relationships around axiom777 form a non-trivial network. In particular, if we focus on the red nodes, which are axiom777's "sources of inspiration" in this particular ideation task, we can see high levels of interconnectivity—clustering—among them. In other words, a high proportion of axiom777's sources of inspiration (red nodes) were each other's sources of inspiration in the sense that they saw each other's ideas. This is consistent with our arguments that the networks (explicit or implicit) in online ideation platforms such as IdeaStorm.com tend to be dense and highly clustered.

We next quantified the level of clustering, averaged over all nodes, in this network. Because this is a directed graph (i.e., information flows do not have to go in both directions in dyads), some care was required in defining clustering (as well as degree). Since we are interested in how the ideas from others seen by individuals may affect subsequent ideation, for each node in the network we calculated the number of incoming links, which is the number of other users' whose ideas the user on that node saw (commented and/or voted on). For each node, this is the size of that user's set of neighbors who served as potential sources of inspiration. This measures degree (or, more precisely, in-degree). For clustering, for each node, we calculated the interconnectivity among the nodes that formed the set of neighbors who served as potential sources of inspiration. Consistent with our studies, this was the proportion of connected pairs out of all possible pairs of nodes. Based on these definitions of degree and clustering, in the three-node network in Figure B2 above, the degree values for nodes A, B, and C are 0, 1, and 2. And the clustering values for nodes A, B, and C are 0, 0, and 0.5 (note that ignoring the directed links would mean that clustering coefficients for A, B, and C in Figure B2 would instead be 1, 1, and

1; clustering defined as inward clustering, as it is here, is therefore typically a lower-bound value for actual clustering in social networks).

On the IdeaStorm.com network, the mean in-degree was 7.70 (SD = 69.72, median = 0, min. = 0, max. = 2729; see histogram in Figure B4), which means that the average ideating customer (contributor) on this platform had 7.70 other customers as sources of inspiration. We note that while this metric is much lower than the typical count of "friends" in massive online social networks such as Facebook, this number is in line with the larger values used for degree in the networks used in our experiments.

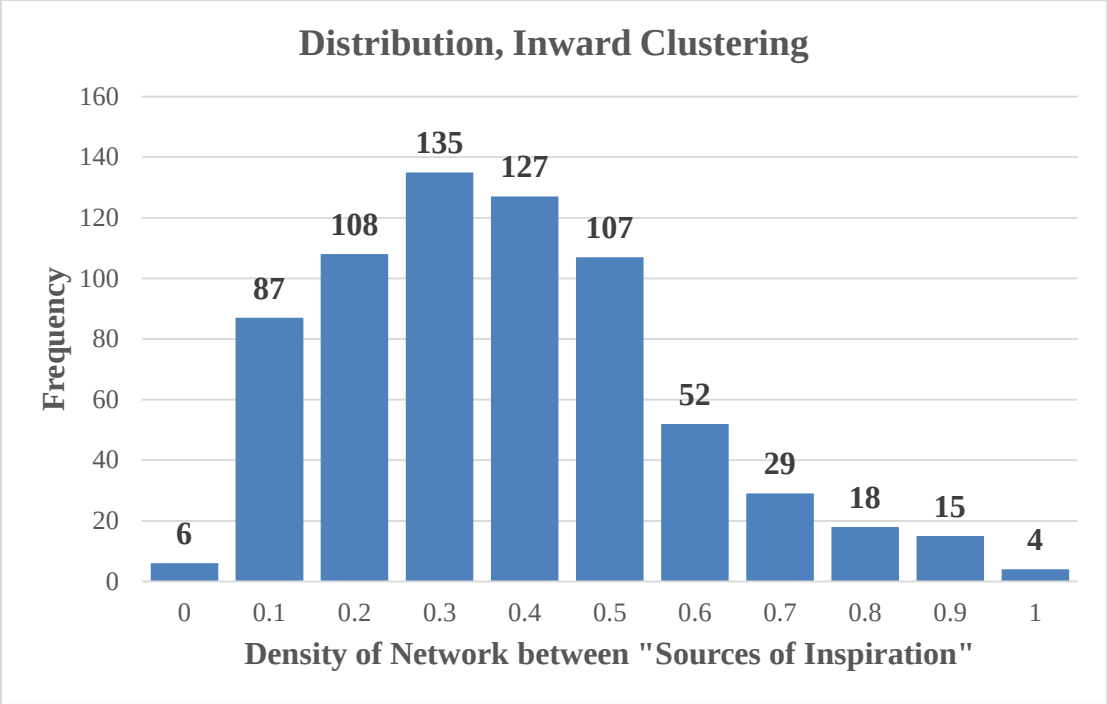
Figure B4: Histogram of the In-Degree Distribution



For clustering on the IdeaStorm.com network, the mean (inward) clustering coefficient across nodes was .33 (SD = .20, median = .31, min. = 0, max. = 1; see histogram in Figure B5).

We note that this is vastly higher than the clustering that would be expected in a random network with the same number of nodes and the same density as this network (.00134; difference $p <$ .001), indicating that the mean level of clustering is non-trivial and not due to random chance. Put simply, this statistic indicates that the interconnectivity of a typical node's sources of inspiration in the IdeaStorm.com network is relatively high and non-random; i.e., ideators are generally highly interdependent on this platform.

Figure B5: Histogram of the Inward Clustering Distribution



To conclude, the purpose of this analysis of real-world data extracted from Dell's IdeaStorm.com interdependent ideation platform was twofold. First, to show how consumers contributing ideas on these types of platforms can be represented in a communication network where they are exposed to others' ideas and inspiration or influence flows over network ties. Second, to quantify the level of interconnectivity among ideators' sources of inspiration (i.e.,

clustering) and show that it is non-trivial, relatively high, and indicative of interdependence among ideating consumers. Our empirical analysis showed both of these key points, and supports our claims of the ecological validity of the central phenomena in the current research and the approach taken across our experimental studies.

C. ORGANIZATIONAL SOCIOLOGY LITERATURE VERSUS CURRENT RESEARCH

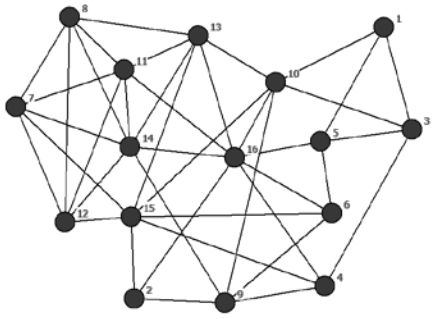
Paper	**Data**		**DV (creativity / innovativeness)**	**Network Source**	**Redundancy Metric**	**All selection issues resolved?**	**Endogeneity issues resolved?**			
	Ideas	**Network**					**Network formation (nodes do NOT choose ties)?**	**No common unobserved shock?**	**Position cannot appreciably improve skills over time?**	**Tie strength NOT correlated with redundancy metric?**
Our work	***Primary (experiments)***	***Perfectly observed (experiments)***	***Innovativeness scale (2-3 raters per idea)***	***Exogenous (6 different networks tested)***	***Clustering coefficient (triadic closure)***	***Yes***	***Yes (exogenous networks)***	***Yes (random assignment to nodes + econometric control)***	***Yes (3-5 rounds, 10-15 minutes)***	***Yes (random assignment to nodes; anonymous participation)***
Burt (2004)	Primary (surveys)	Inferred (surveys)	Two senior managers evaluate potential of idea	Self-reported	Local constraint (triadic closure and hierarchical C4 closure)	No (self-reporting)	No	No	No	No
Fleming et al. (2007)	Secondary (patent collaboration)	Inferred (patent collaboration)	Number of (patent) subcategory combinations	Inferred from joint successes (9 networks pooled)	Clustering coefficient[2]	No (successes only / failures unobserved)	No	Yes (econometric control)	Yes (econometric control)	No
Perry-Smith (2006)	N/A	Inferred (surveys)	Expert ratings of people, not ideas	Self-reported (2 networks)	Local constraint and betweenness centrality	No (self-reporting)	No	No	No	No
Tortoriello and Krackhardt (2010)	Secondary (patent data)	Inferred (surveys)	Number of patent applications	Self-reported	Simmelian ties (yes/no triadic closure)	No (self-reporting)	No	No	No	No

[2] The term used in the paper is “cohesion”.

D. NETWORKS USED IN STUDIES AND ALGORITHM TO GENERATE NETWORKS

Study 1

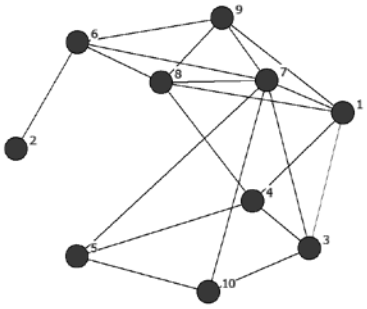
Number of nodes = 16
Degree range (M, SD) = 3 to 8 (5.13, 1.41)
Clustering range (M, SD) = 0 to .80 (.36, .27)



Study 1 (Replication)

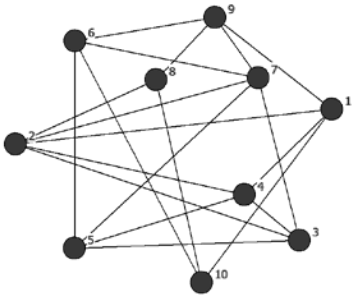
(i) Erdos-Renyi (ER)

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



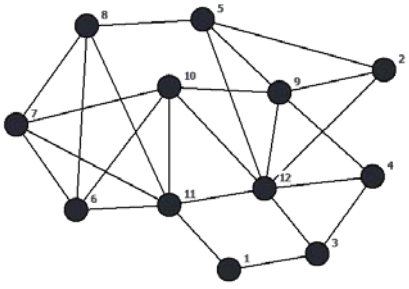
(ii) Small-World (SW)

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



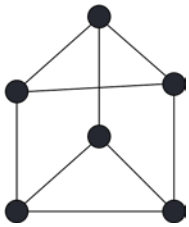
Studies 2 and 5

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



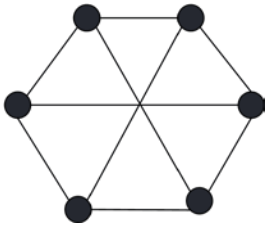
Study 3

(i) Clustering



Number of nodes = 6
Degree (M, SD) = (3.00, .00)
Clustering (M, SD) = (.33, .00)

(ii) No clustering



Number of nodes = 6
Degree (M, SD) = (3.00, .00)
Clustering (M, SD) = (.00, .00)

Algorithm Used to Generate Networks in Studies 1, 2, and 5

Computer code used is available upon request from the authors. Below we list the steps in the algorithm ("pseudo-code").

Input: Size of network N, Desired degrees $D_1 \geq D_2 \geq ... \geq D_N$, with $1 < D_i < N$,
Degree-clustering correlation threshold *t*

Output: **A**, an N×N matrix that describes the adjacency relationships in the output network.

Procedure:

1. Reset matrix **A** to all zeroes.
2. Draw $(D_1 + D_2 + \cdots + D_N)/2$ edges randomly to the network, updating entries of **A**.
3. Calculate the degrees of the random network by totaling the values in each row of **A**.
4. Verify if the (sorted) degree distribution is the same as the input degrees. If not, start over from Step 1.
5. Calculate the clustering coefficients in the network. (Since $D_i > 2$, it is always defined.)
6. Verify that the maximum clustering is sufficiently large and the minimum clustering is 0. If it isn't, start over from Step 1.
7. Calculate the degree-clustering correlation. If it isn't smaller than *t*, start from Step 1.
8. Output **A** as the random network instance meets all our requirements.

On average, the code based on this algorithm outputs a viable network in about 100,000 cycles, which takes less than 1 second on a typical machine.

E. ITEMS USED TO MEASURE IDEA INNOVATIVENESS

The following scale items were used 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

F. RESULTS FROM IDEA-JUDGING VALIDATION STUDY

Representativeness

The validation procedure for representativeness was as follows. First, we randomly sampled 16 ideas (out of 177 valid ideas) from Study 1A and used a different set of 50 judges from the same population as the original judges. These judges completed the same idea-judging task that original judges had completed for judging idea innovativeness. Second, after completing this task, we told the 50 validation judges the mean innovativeness score from the original judges for the idea they had just rated and asked if they thought the score was "in the right direction and in the ballpark" (0 = no, 1 = yes) as a general measure of their agreement.

We tested for evidence of the original judges' ratings being representative and consistent with the larger number of validation judges' ratings in a number of ways. First, across ideas, the mean percentage of validation judges who were in general agreement with the original judges' idea innovative score was 83.92% (SD = 8.36%, min. = 68.00%, max. = 97.96%, median = 83.33%). This is an indication that the validation judges concurred with the original judges.

Second, the correlation between the average ratings from the original and validation judges was positive ($r = .79$, $p < .001$), which is another indication of consistency between the original and validation judges' ratings.

Third, we used a bootstrapping procedure to test whether sampling three judges from a larger set of judges was appropriate in terms of representativeness. For each idea, we randomly sampled three validation judges (out of the 50 judges) and computed the mean idea innovativeness for their ratings. This was done 50,000 times per idea, which produced a distribution of mean innovativeness ratings for each idea based on *only three* randomly sampled validation judges. We then checked if the 95% credible interval for each idea's rating distribution included the mean innovativeness rating from the original judges. Results are summarized in the table below, and show that the original judges' rating was *always* inside the 95% credible interval generated by the bootstrapping procedure on validation judges' ratings.

Thus, we are confident in the validity of the judging procedure used in our studies with respect to the representativeness of a few judges' idea ratings.

Sample Idea Number	Mean Innovativeness Ratings		Percent of Validation Judges Agreeing With Original Judges	Bootstrapping with 50,000 random samples of 3 judges from validation set			
	Original Judges	Validation Judges		Mean	95% Credible interval		Original Rating Inside Interval?
					2.5%	97.5%	
1	4.50	3.72	83.33%	3.72	2.67	4.52	Yes
2	4.10	3.75	97.96%	3.75	2.95	4.43	Yes
3	3.00	3.03	97.87%	3.03	2.29	3.76	Yes
4	2.33	1.83	82.22%	1.83	1.10	2.86	Yes
5	3.00	3.08	83.33%	3.08	2.10	4.10	Yes
6	3.10	2.69	79.59%	2.68	1.71	3.67	Yes
7	3.00	3.38	89.80%	3.38	2.62	4.10	Yes
8	3.95	3.97	87.76%	3.96	2.90	4.81	Yes
9	3.86	3.59	87.76%	3.59	2.62	4.48	Yes
10	3.57	3.10	78.00%	3.10	1.90	4.19	Yes
11	4.00	3.72	91.84%	3.72	2.67	4.52	Yes
12	2.90	3.33	68.00%	3.34	2.48	4.24	Yes
13	3.71	3.20	82.00%	3.20	2.29	4.14	Yes
14	2.48	2.01	85.71%	2.01	1.29	2.90	Yes
15	4.14	3.40	75.56%	3.40	2.14	4.38	Yes
16	1.93	2.79	72.00%	2.79	1.43	4.19	Yes

Reliability and Agreement

This validation study checked that, when a cohort of judges was asked to rate multiple ideas, there was reasonable inter-judge reliability. We randomly selected 20 ideas Study 1A and asked 20 judges who were not original judges, were not in the set of judges for the representativeness validation study, but who were from the same population as these other sets of judges to evaluate *all* of these 20 ideas, one at a time (presented in random order), on our innovativeness scale. This procedure allowed us to assess inter-judge reliability using standard measures.

First, we found that inter-judge reliability was very high (α = .95) using all 20 judges for the single-item innovativeness index (after averaging the separate items). Reliabilities for the separate items ranged between .86 and .94.

Second, we accommodated for the fact that approximately three people originally judged each idea. Similar to the representativeness validation study, we employed a bootstrapping procedure. Specifically, we randomly sampled three judges from our set of 20 judges and computed inter-judge reliability for that random subset of judges. This was done 50,000 times. The mean (SD) reliability was .73 (.12), and the median was .75.

Third, as an additional check we assessed inter-judge agreement with r_{WG}. For the single-item innovativeness index (after averaging the separate items), the mean (SD) agreement was .71 (.10), and the median was .73.

Thus, we are confident in the validity of the judging procedure used in our studies with respect to the inter-judge reliability of a few judges' idea ratings.

G. TASK DESCRIPTIONS AND EXAMPLES OF SUBMITTED IDEAS

Mobile banking smartphone application features (Study 1)

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.

Example ideas:

Innovativeness Range	**Idea (score)**
> 1 and ≤ 2	• View bank balance (1.33) • Red letters/numbers for the withdrawal of money (1.86). • Send an email to your phone every time you deposit or withdrawal to keep up with your balance (1.95)
> 2 and ≤ 3	• Report transactions that weren't made by the customer...identity theft protection (2.19) • The app should have the function of allowing someone to transfer funds to other individuals from either the same bank or other banks (2.38) • Let people see pictures of checks that have been deposited either from the user or from people the user has written checks to (2.90)
> 3 and ≤ 4	• The app can have a visual representation of what you spend your money on (3.10) • An app that let's you use your phone to pay without having to pull a credit or debit card out of your pocket would be really neat (3.71) • The app should include live chat section where users can chat with a representative from the particular bank in texting format to ask any questions they have if they don't have the time to sit through a phone call and wait for a representative to become available (4.00)
> 4 and ≤ 5	• Finger print password (4.05) • An app that gives you one financial advice tip per day based on your age and current saving/spending habits. you could rate it as "helpful" or "not helpful" and over time it would adapt to give you more and more relevant advice (4.11) • Bill pay feature with the ability to use the phone itself as your banking card (5.00)

Facebook Features (Studies 2, 3, 4, 5)

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? You should try to be as creative and original as possible.

Example ideas:

Innovativeness Range	**Idea (score)**
> 1 and ≤ 2	• Add email (1.64) • Stop changing the format of Facebook every six months or so (1.62) • Link to twitter, because Facebook is terrible (2.00)
> 2 and ≤ 3	• Create a Facebook planner or calendar (2.03) • A way to see a list of comments you've posted on other people's walls (2.19) • Add a dislike button (2.81)
> 3 and ≤ 4	• Group video chatting for up to 30 people (3.10) • Facebook can act like a dating website, it can match up single females and males based on their hobbies, favorite books/movies, and about me sections. This can either be part of the homepage or a separate application (3.57) • Have some sort of translation device built into Facebook (3.86)
> 4 and ≤ 5	• Divide Facebook into two segments where one is social and the other is business. That way you can still integrate all your friends and coworkers into your profile (4.24) • A feature is needed to hide a continuously embarrassing friend/relative who posts nonsense, rants, or offensive comments on your posts or wall all the time, however to make them think they are actually posting. This is good for a drunken relative whose feelings you don't want to hurt by outright blocking or unfriending them (4.33) • Personalize Facebook to make it more of a unique experience. When click on or mouse goes over about info (musicians, artists, likes), have the ability to listen or view their work (4.86)

H. STUDY 1 REPLICATION

We replicated Study 1's results by re-running Study 1 using different network structures and a different participant population. The purpose was to affirm that the findings above were not artifacts of the specific network structure or participant population used. Eighty members of a large U.S. online panel participated in this study for $5 over four separate runs. In each run participants were randomly assigned to one of two 10-node networks, and then to a position one of those networks. The two networks were based on common structural properties found in real-world social networks (Erdos-Renyi [ER] and Small-World [SW] networks). 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). The ideation task and procedure were otherwise identical to that described above. Of the 240 collected ideas, 226 (94.17%) were valid and rated on the innovativeness scale (α = .96) by two or three judges (M = 2.82). 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.[3] 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. Mean (SD) innovativeness in rounds 1 to 3, respectively were 3.18 (.88), 3.28 (.64), and 3.46 (.70).

Regression results are reported in Table 2. For this study we include two analyses, one with participants from all network nodes, and another excluding degree = 1 participants (only in the ER network) because clustering is not defined for them (when degree = 1 we set clustering = 0, consistent with our conceptualization of clustering in this context). Results were consistent across models and here we report results from the analysis that used all participants. Since the results were not different between ER and SW networks when analyzed separately, we pooled participants and controlled for network type with a dummy variable. As before, we found a significant negative clustering × degree interaction (b = -.20, t = -2.23, p = .025),[4] and again we see that mean idea innovativeness is higher (lower) when clustering is lower (higher), particularly as degree increases.

Finally, judges in this study were also asked to rate ideas on "market potential" to indicate levels of consumer demand, using a ten-item scale (1 = strongly disagree to 5 = strongly agree; α = .95; example items: "I would use an app with this feature," "this app would have many users," and "I would download this app"). This is similar to scales used to measure idea usefulness in prior research (e.g., Goldenberg et al. 1999b). We found a significant positive correlation between market potential and idea innovativeness (r = .34, p < .001). The partial correlation after controlling for round, network type, run, age, and sex was also positive ($r_{partial}$ = .32, p < .001). Thus, idea innovativeness is also likely to be a positive indicator of customer-based evaluations of market potential or product demand.

[3] 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.

[4] With covariates removed this interaction effect is the same: b = -.18, t = -2.15, p = .035.

I. PROCEDURES FOR EXTRACTING CONCEPTS FROM IDEAS IN STUDY 2

The following table describes the steps that were performed on every contributed idea from Study 2 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 this 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, 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

Step	Details	Output for Example Idea
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

J. EXPLANATION OF IDEA SPREADING ANALYSIS PROBABILITIES

The idea spreading analysis in Study 2 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.

K. ITEMS USED TO MEASURE INTERDEPENDENT IDEATION STYLE (IIS)

The following scale items were used in Study 4 to measure IIS on five-point Likert scales (1 = strongly disagree, 5 = strongly agree):

- I tried to see connections between group members' and my ideas.
- I looked for "common ground" between group members' and my ideas.
- My ideas came from combining concepts that came up in others' ideas.
- I linked concepts that came up in others' ideas to form new ideas.
- I integrated or combined concepts and ideas from previous rounds (mine and others').
- I built my ideas by combining some aspects of group members' ideas with my previous ideas.
- Creating my ideas involved blending parts of group members' previous ideas and my previous ideas.

L. META ANALYSIS OF RESULTS ACROSS STUDIES 1, 2, AND 5

Effect	**Estimate (std. error)**	
	Linear Regression	**Logistic Regression (Innov. > 3)**
Intercept	3.32 (.23)***	.36 (.67)
Clustering	-.11 (.04)**	-.37 (.14)***
Degree	-.06 (.04)	-.24 (.14)*
Clustering × Degree	-.16 (.05)***	-.47 (.15)***
Lagged Idea Innovativeness	-.004 (.04)	.24 (.23)
Age	-.009 (.006)	-.01 (.02)
Sex = female (baseline = male)	-.03 (.05)	-.05 (.17)
Run/session (baseline = 4)		
1	-.18 (.09)*	-.55 (.35)
2	-.29 (.10)***	-.90 (.35)**
3	-.25 (.10)**	-.75 (.35)**
Round (baseline = 3)		
2	-.15 (.06)***	-.54 (.21)**
Ideation time	.001 (.001)	.003 (.004)
Study (baseline = 5)		
1	.30 (.10)***	.74 (.34)*
1 replication	.61 (.12)***	1.47 (.43)***
2	-.14 (.11)	-.46 (.39)
Participant random effect	.08 (.04)***	.41 (.29)

$p < .10$, ** $p < .05$, *** $p < .01$. Model fits (McFadden's Pseudo-R^2): .10, .12.

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