The Effect of Social Networks Structure on Innovation Performance: A review and directions for research

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Abstract

Research on growth of innovations introduced to the market has gradually shifted its focus from aggregate-level diffusion to exploring how growth is influenced by a given social network structure's characteristics. In this paper, we critically review this branch of literature. We argue that the growth of an innovation in a social network is shaped by the network's structure. Borrowing from the field of industrial organization in economics, which defines itself as the study of the effect of market structure on market performance, we describe this new wave of research on growth of innovations as **the effect of social network structure on innovation performance**. Hence, social network structural characteristics should be incorporated into research on new product growth as well as into managerial marketing decisions such as targeting and new product seeding.

We review how social network structure influences innovations' market performance. Specifically, we discuss (1) a networks' global characteristics, namely average degree, degree distribution, clustering, and degree assortativity; (2) dyadic characteristics, or the relationships between pairs of individuals within the network, namely tie strength and embeddedness; (3) intrinsic individual characteristics, namely opinion leadership and susceptibility; and (4) location-based individual characteristics, or defining the individual's location in the social network, namely her degree centrality, closeness centrality, and betweenness centrality.

Overall, we find that growth is particularly effective in networks that demonstrate the "3 Cs": ***cohesion*** (strong mutual influence among its members), ***connectedness*** (high number of ties), and ***conciseness*** (low redundancy). We identify gaps in current knowledge, discuss the implications on managerial decision making, and suggest topics for future research.

Keywords: assortativity; centrality; clustering; degree; diffusion of innovations; new products; seeding; social networks

1 Introduction

Consider the following two scenarios: (1) A mobile phone service provider launches a new service and wishes to implement a seeding program that will stimulate referrals and attract new adopters. The firm needs to decide how many customers to “seed”, what types of customers to seed, and the monetary rewards each customer will receive once successfully bringing in a new customer (Hinz et al. 2011). (2) A distributor is asked by a manufacturer to introduce an innovation into a market in which consumers are organized in a certain social network structure. The distributor wishes to know whether to demand exclusivity as part of the distribution contract (Peres and Van den Bulte 2013). These two narratives exemplify managerial decisions regularly faced by marketing executives introducing new products and services. One may wonder whether and how the underlying social network in the market influences such decisions. Should seeding in a network with social hubs differ from that in a network with a flatter distribution of social ties? Should exclusivity decisions depend on the level of clustering among potential adopters?

Studying growth of innovations from a social network perspective is of growing importance due to three main catalysts: 1) social ties have become broader, with wider reach, and are easier to activate and maintain; 2) social ties are much more extensively documented, and firms have better capacities to monitor and analyze them; and 3) the increasing coexistence of consumption and social interactions in online spaces may provide firms with more means of manipulating such interactions and potentially influencing the penetration process.

To what extent are these increasing market changes reflected in academic research? Research on new product growth has traditionally focused on the aggregate level. The Bass model and its extensions (Bass 1969; Norton and Bass 1987; Jain, Mahajan, and Muller 1991; Krishnan, Bass, and Jain 1999; Dekimpe, Parker, and Sarvary 2000) focus on the change in the overall number of adopters, and are agnostic with respect to connectivity structure (Goldenberg, Libai, and Muller 2002; Peres, Mahajan, and Muller 2010). While aggregate methods proved effective for forecasting purposes, many managerial questions are of a normative nature: In both examples above, the managers need to choose between paths of actions, and need to know which of them will be optimal. In such cases, the aggregate approach is limited: The underlying social network's structure is important and should be incorporated into the decision making. Therefore research efforts have gradually shifted their focus to an individual-level perspective, and specifically, to exploring the role of the social network's structural characteristics in various performance metrics of the innovation's growth. These efforts have been enhanced by intensive research in computer science and information management.

Borrowing from the field of industrial organization in economics, which defines itself as the effect of market structure on market performance (Tirole 1988, p. 1), the new wave of research on growth of innovations can be described as **the effect of social network structure on innovation performance**. In other words this branch of research addresses the following question: Given a social network into which an innovation has been introduced, what are the effects of the social network's structure on the performance of the market penetration of this innovation? This paper seeks to provide a critical review of current knowledge regarding social networks' roles in new product growth.

Broadly speaking, the body of research we review suggests that the performance of the penetration process (as measured by various metrics) is particularly high in networks that demonstrate the "3 Cs": ***cohesion***, ***connectedness***, and ***conciseness***. A network is *cohesive* if individuals highly impact and are highly impacted by each other, and share a high level of trust due to common neighbors. A network is *connected* if the average network member has a large number of ties, if social hubs (particularly well-connected individuals) are prominent, and if network distances between individuals are small. A network is *concise* if its level of redundancy is low, i.e., individuals' social circles are sufficiently distinct from one another, such that each connection makes a meaningful contribution to the flow of information.

The main managerial theme that emerges from the literature is that understanding the structural characteristics of one's target market should be integral to managerial marketing decisions. Social interactions, which are dependent on social network structure, provide firms with measurable value (referred to as "social equity") and should therefore be considered in marketing policies, and in particular customer development and retention, as well as decisions on acquisition actions such as targeting, seeding, and referral programs.

Table 1: Paper's flow and content

Section	Content
1. Introduction	We describe the new wave of research on growth of innovations as the effect of social network structure on innovation performance; and delineate what we review in the paper.
2. Social network mechanisms and adoption of innovations 2.1 Pathways to adoption 2.2 Alternative adoption mechanisms	We suggest four behavioral mechanisms that enable social contagion. We use these mechanisms as theoretical infrastructures later in the paper.
3. The effects of Social Network Structure on growth 3.1 Innovation performance metrics 3.2 Global characteristics 3.3 Dyadic characteristics 3.4 Individual characteristics 3.5 Summarizing structural effects on growth	We discuss structural characteristics' effects on growth on three levels: global (e.g., clustering), dyadic (e.g., tie strength), and individual, relating to personal characteristics (i.e., opinion leadership and susceptibility), and location in the network (i.e., centrality).
4. The effects of Social Network Structure on marketing decisions 4.1 Targeting decisions 4.2 Developing referral programs 4.3 Optimizing seeding strategies	We review network structural characteristics' effects on managerial marketing issues in: (1) targeting decisions; (2) developing referral programs and 3) optimizing seeding strategies.
5. Directions for future research	We propose a roadmap for future research comprised of seven phases, beginning with finding a unified performance metric, and ending with exploring the role of the four pathways to adoption.

Table 1 summarizes the flow and organization of the paper. The main thrust is in Section 3, where we discuss how the performance of an innovation (measured in terms of various metrics) is influenced by social network structure, including (1) global characteristics, namely **average degree**, **degree distribution**, **clustering**, and **degree** a**ssortativity**; (2) dyadic characteristics, namely **tie strength** and **embeddedness**; (3) individual characteristics including personal characteristics, namely **opinion leadership** and **susceptibility**; and location characteristics, namely **degree centrality**, **closeness centrality**, and **betweenness centrality**.

2 Social network mechanisms and adoption of innovations

When describing how social network structure influences an innovation's growth, the underlying theory is that being part of a social network plays a role in the network members' adoption behaviors. This role is mostly attributed to social contagion, i.e., individuals are impacted by each other in their adoption decisions. Contagion is enabled through multiple social network mechanisms via which consumers gain information about the innovation, and are persuaded to adopt it. In this section we review these mechanisms, and use them as the theoretical infrastructure later in the paper to explain some of the empirical findings on social network structures' effects of social network structure on innovation's growth.

Similar to the distinction in the advertising literature, we divide the social network contagion mechanisms into informational mechanisms (how do I know about the innovation?), and persuasive mechanisms (why should I adopt the innovation?). Overall, we build on Van den Bulte and Wuyts (2007) to suggest four influence pathways relevant to our context: awareness, learning, normative pressure, and network externalities. The first two mechanisms are informational, the other two are persuasive.

2.1 Pathways to adoption

We begin with the informational pathways in which network members form a channel for information flow about new products and services. This information contributes to adoption though awareness and learning.

Awareness refers simply to becoming attentive to an innovation's existence. Clearly, social interactions – e.g., conversations between individuals who are familiar with the product and others who have not yet heard of it – play a role in enhancing awareness (Sheth 1971; De Bruyn and Lilien 2008). However, it seems that mass communication might be more effective in raising awareness, given its wide reach and high level of creativity. This idea is supported by Scholz et al.'s observations (2013) comparing advertising's and word-of-mouth communications' relative effects on awareness on Facebook, and showed that marketer-generated content's effect on awareness is much stronger than that of user-generated content.

Nevertheless, social interactions can provide two major contributions to awareness creation. First, they can *focus the interest of a random browser*: In many cases, consumers are exposed to information while browsing without a specific target (ill-defined exploration). Social networks have been shown to make such an exploration process more effective by directing the consumer toward products s/he is likely to enjoy (Goldenberg, Oestreicher-Singer, and Reichman 2012). Second, social networks enhance *awareness creation's effectiveness in niche markets*: For potential customers of niche products, who are difficult to reach through mass media outlets and communication channels, social interactions can be an effective way to increase their awareness (Leskovec, Adamic, and Huberman 2007).

Learning about a product is a social process through which consumers shape their beliefs regarding the performance of the product's attributes, price and additional costs they might incur, the product's legitimacy, and the risk associated with its purchase (see Acemoglu and Ozdaglar 2011 for a review on social learning processes). A key aspect of the process of learning through social interactions is the learner's relationship to the information source – namely, the source's accessibility and familiarity (Borgatti and Cross 2003). Information obtained from a member of one's close social circles tends to be echoed within those circles, inducing a stronger sense of trust (Burt 2001). In contrast, when the source of information is not familiar or easily identifiable, the consumer may be less amenable to updating his or her beliefs on the basis of that information (Choi, Gale, and Kariv 2005). Consequently, the belief updating process may be subject to biases, due to homophily among the members of one's close social circle (Golub and Jackson 2012), or it may be skewed by highly influential units (Golub and Jackson 2010).

In addition to conveying information, peers have a persuasive role on each other. We focus on two important mechanisms: normative pressure, and network externalities.

Normative pressure in the context of new product growth is the distress felt by a potential adopter when peers whose approval s/he values have adopted the product, but s/he herself has not (Van den Bulte and Wuyts 2007). Normative pressure occurs when social norms motivate an individual to act in a direction contrary to his inherent tendency (Algesheimer, Dholakia, and Herrmann 2005). Thus, normative pressure helps individuals to resolve uncertainty (Cialdini and Goldstein 2004) and to overcome their risk aversion, or their natural resistance to adopting an innovation. Indeed, normative pressure has been shown to have a significant influence on the use of social network sites (Sledgianowski and Kulviwat 2009), using the internet at work (Chang and Cheung 2001), and the use of computer equipment (Lucas and Spitler 1999). Normative pressure has been shown to come from significant people in one's social network (Sledgianowski and Kulviwat 2009). Algesheimer, Dholakia, and Herrmann (2005) showed that strong personal identification with a brand community reduces the extent to which individuals experience normative pressure from that community.

Network externalities refer to a situation in which functional utility from a product increases with the number of adopters. This phenomenon has been studied quite extensively (see Peres, Muller, and Mahajan 2010). Classic examples are the fax machine and other communication systems. Indirect network externalities exist when the utility of a product depends on the number of adopters of a complementary product (e.g., CD players and CD albums, see Stremersch et al. 2007). Influence through network externalities does not necessarily require communication. Information about the current number of users can be made available to potential adopters through the firm's marketing communication mechanisms. Generally, network externalities are believed to delay adoption in early stages of growth ("the chilling effect", Goldenberg, Libai, and Muller 2010), but accelerate it in later stages of the product life cycle. Regarding indirect network externalities, Nair, Chintagunta, and Dubé (2004) found that indirect hardware-software network effects explained 22% of the joint demand of PDA hardware and software. The chilling effect induced by network externalities becomes stronger with clustering, but is negatively correlated with network size and the average degree (Mukherjee 2014).

2.2 Alternative adoption mechanisms

The literature offers a great deal of supporting evidence for the role of social contagion in emotions (Kramer, Guillory, and Hancock 2014), political engagement (Bond et al. 2012), adoption of products and services, including pharmaceutical drugs (Manchanda, Xie, and Youn 2008; Iyengar, Van den Bulte, and Valente 2011), subscriptions to music services (Bapna and Umyarov 2015), and Facebook apps (Aral and Walker 2011). While researchers agree that social contagion exists, there is less consensus regarding its strength and reach, and its relative role in product adoption compared to other factors. Goel et al. (2016) measured the lengths of cascades in the context of content sharing online. They found that the typical cascade is short, limited to one or two degrees of separation. One reason for this phenomenon might be resistance to innovation, as suggested by Moldovan and Goldenberg (2003). Similar results were obtained in a large field study of stimulated referrals for a mobile service (Hinz et al. 2011).

A recent thread of studies finds that the role of contagion in product adoption is overestimated, as it is often confounded with other social network processes (Bollinger and Gillingham 2012). A major such confound is *homophily*, which is the tendency of individuals with similar tastes to connect to each other (McPherson, Smith-Lovin, and Cook 2001). In the presence of homophily, it becomes unclear whether adoption is indeed a result of interpersonal influences, or whether it occurs simply because the connected individuals have similar tastes (Shalizi and Thomas 2011). Aral, Muchnik, and Sundararajan (2009) used data on a mobile app's adoption among Yahoo! users to show that in the presence of homophily, social contagion is indeed overestimated, and that homophily explains over 50% of perceived behavioral contagion. Other confounding factors could be "ecological" (Manski 1993), i.e., individuals adopt at the same time because they are exposed simultaneously to an external market stimulus such as a local price promotion; or that favorable wind conditions motivate surfers to post their experiences online (Shriver, Nair, and Hofstetter 2013).

The discussion on social contagion's reach and magnitude is not only theoretical; it has practical impact on the strategic direction the firm should take. When social contagion is strong, strategies for viral marketing and seeding might be highly effective. In the presence of high levels of homophily, however, the effectiveness of seeding might be lower, and firms might want to choose other marketing strategies (Aral, Muchnik, and Sundararajan 2013).

3 The effects of social network structure on growth

In what follows, we discuss how various structural characteristics of the social network influence the growth process. We start with discussing the dependent variable, describing various metrics of innovation performance used in the literature. We then discuss the role of structural characteristics on three levels: global, dyadic, and individual.

3.1 Innovation performance metrics

Studying the effect of social network structure on innovation performance requires the definition and measurement of the dependent variable "performance". The literature does not provide a uniform definition, and offers a variety of performance metrics. The main dimensions used to define innovation performance are summarized in Table 2.

Table 2: Dimensions of innovation performance

Dimension	Definition	Papers
Magnitude	Number of network members who have eventually adopted the innovation	Ball, Mollison, and Scalia-Tomba (1997); Kempe, Kleinberg, and Tardos (2003); Jackson and Yariv (2005); Watts and Dodds (2007); Badham and Stocker (2010); Centola (2010); Hinz et al. (2011); Iyengar, Van den Bulte, and Valente (2011); Yoganarasimhan (2012); Banerjee et al. (2013); Mochalova and Nanopoulos (2014)
Threshold	Has the penetration reached a certain number of network members who have eventually adopted the innovation?	Nold (1980); Boguná and Pastor-Satorras (2002); Newman (2002); Keeling (2005)
Speed	Time to reach a certain level of penetration; peak adoption rate	Watts and Strogatz (1998); Valente and Davis (1999); Goldenberg, Libai, and Muller (2001); Keeling (2005), Centola and Macy (2007); Onnela et al. (2007); Bohlmann, Calantone, and Zhao (2010); Eck, Jager, and Leeflang (2011); Rand and Rust (2011)
Time to takeoff	Time to reach a certain inflection point	Jackson and Yariv (2005); Delre, Jager, and Janssen (2007); Choi, Kim, and Lee (2010); Mukherjee (2014)
Market share	Share of market in a competitive framework	Uchida and Shirayama (2008)
Net present value	Time-discounted sum of the number of adopters; or profits gained from those adopters over an infinite time horizon	Libai, Muller, and Peres (2005); Goldenberg, Lowengart, and Shapira (2009); Haenlein and Libai (2013); Libai, Muller, and Peres (2013); Peres (2014)

One would intuitively think that a high-performing growth process is one in which 1) many people adopt the innovation 2) it spreads to the far ends of the social network 3) within a short time 4) with low marketing efforts. This would suggest that performance is a multidimensional construct, yet typically, each study chooses one dimension and focuses on it. The diversity of performance metrics used imposes a challenge on empirically generalizing findings across papers. In this paper, we will address explicitly the performance metrics used in the studies we review, yet we strongly favor using a measure that captures more than one dimension such as NPV of the profits, or of the number of adopters; and propose that future research strive to agree on one, multidimensional metric and use it whenever possible.

3.2 Global characteristics

Constructing high-performing networks has been a major motivator in social network theory. For example, vis-vis speed of information flow as a metric, small-world networks – or networks that have been rewired such that several ties are replaced with random connections –are considered to engender faster information flow than are regular lattice networks, due to the shortcuts between nodes (Watts and Strogatz 1998; Newman and Watts 1999). Likewise, information flow processes in fully random networks are expected to be rapid (Erdős and Rényi 1959; Newman, Watts, and Strogatz 2002), and consequently, fully-connected networks are expected to demonstrate the quickest processes. In what follows, we discuss the roles of four specific network metrics – average degree, degree distribution, clustering, and degree assortativity – in innovations' performance in social networks.

Average degree is the average number of ties of a node in a network (Newman 2003). The impact of the number of ties on growth is straightforward: All else being equal, more ties per node lead to faster takeoff (Delre, Jager, and Janssen 2007; Mukherjee 2014), where takeoff is defined conceptually as the number of adopters from which growth rates accelerate significantly (Golder and Tellis 1997). More ties per node also lead to farther and faster penetration (Keeling 2005). Average degree is closely related to network density, defined as the ratio of overall number of network ties to number of all possible ties. Higher density is associated with faster growth (Rand and Rust 2011), as well as with higher overall net present value (NPV) of the number of adopters (Peres 2014). That is, the more *connected* the network, the higher its growth performance.

Degree distribution across nodes is important, as the average number of nodes provides only a partial look at the network's level of connectivity. For example, an average degree of 6 can be obtained either if each node has 6 ties, or if half of the nodes have 12 ties each and half are not connected at all. Two facets of degree distribution have been studied: The first is the level of heterogeneity, namely, the width of the distribution. Wider degree distributions have been shown to be associated with higher critical mass required for takeoff (Jackson and Yariv 2005), mainly due to the fact that some of the initial adopters are nodes with low connectivity, who do not promote the growth process. The second is the extent to which the distribution is right-skewed, a characteristic that reflects the proportion of highly-connected nodes, or so-called social hubs, versus nodes with less connectivity. Nodes with a small number of ties impede growth performance: Dover, Goldenberg, and Shapira (2012) observed that when degree distribution is right-skewed, adopters become more likely to join at later stages (rather than at earlier stages). The existence of nodes with high connectivity can enhance performance: Peres (2014) and Jackson and Yariv (2005) found that, controlling for overall number of ties, a higher proportion of highly-connected units is positively associated with the NPV of the number of adopters and the magnitude (i.e., overall number of adopters) respectively. Dover, Goldenberg, and Shapira (2012) studied how degree distribution impacts the shape of the adoption curve, and found that more hubs are associated with a steeper increase of the adoption curve (as they enhance the initial growth); and more relatively low-degree members are associated with a more gradual decline slope (as they join later in the process). These findings all imply that the existence of social hubs make the network more *connected* and enhances growth.

Clustering is a tendency of neighbors of the same node to be connected themselves, that is, the likelihood that if nodes *a* and *b* are connected, and *b* and *c* are connected, then *a* and *c* are also connected (Newman 2003). Clustering has the potential to influence innovation performance in two opposing ways: On the one hand, in a network with a relatively high level of clustering, each member is more likely to receive communication on the innovation from multiple network members, hence increasing awareness and concentrating peer influence and learning rate. On the other hand, clustering implies redundancy, i.e., information passed to *a* from *c* would have reached *a* anyway through *b* (because *b* and *c* are connected and therefore have access to the same information), so *c*'s efforts are "wasted". In many networks, clustering correlates with average degree, the extreme case being the fully connected network, where both clustering and average degree are maximal. However, these are two independent theoretical constructs: While degree relates to the *connectivity* in the network, clustering relates to *conciseness*, a construct that we introduce here to represent the level of significance of each tie. Higher clustering increases redundancy, renders each tie less important on average, and compromises the network's conciseness. In order to isolate clustering's impact, one should vary it on the same type of network, controlling for the other structural characteristics.

While it is hard to generalize across the various tests and metrics used for studying clustering's effect, it appears that empirical results (derived mostly from simulations) depend on the extent to which multiple communications are important to create adoption. For example, in the case of a market with network externalities, clustering might help in reaching the critical mass needed for the product to take off (Choi, Kim, and Lee 2010; Mukherjee 2014) or, in the case of competition, clustering might help one of the competitors to reach a critical level of dominance and obtain the maximum market share (Uchida and Shirayama 2008). Even without network externalities, if the threshold for adoption is high (Bohlmann, Calantone, and Zhao 2010), or if the nature of the innovation is complicated (as in the case of in health innovations that involve behavioral changes, see Centola and Macy 2007; Centola 2010), clustering can have a positive effect on the speed (time to reach a certain level of penetration, Centola and Macy 2007; Bohlmann, Calantone, and Zhao 2010) and the magnitude (Centola 2010) of growth.

When the presence of multiple influences is not critical to adoption, the lack of conciseness, that is, the redundancy created by clustering overrides the benefit of multiple influences and slows down the growth process. Peres (2014) ran extensive simulations on real and artificial networks across a wide range of network and diffusion parameters, and found that clustering has a negative influence on the NPV of number of adopters. Studies on the spread of epidemics have demonstrated how clustering negatively affects magnitude, i.e., the final size of the infected population (Ball, Mollison, and Scalia-Tomba 1997; Keeling 2005; Badham and Stocker 2010).

Degree Assortativity, or degree correlation, is a metric that combines clustering and degree distribution. Assortativity is defined as the Pearson correlation of the degrees of linked network members, and measures the extent to which nodes with similar numbers of ties are connected to each other. Put another way, this metric describes the clustering of nodes at each degree level. In networks with high assortativity, highly connected nodes will be connected to each other. Therefore, like clustering, assortativity can have opposing effects on the growth process: On the one hand, information reaches social hubs quickly, via their social hub neighbors; thus, high assortativity is expected to facilitate growth. On the other hand, assortativity can compromise the network's conciseness due to an increase in redundancy; and a more even spread of the social hubs in the network might create a more efficient process. Studies indicate that both effects are indeed observed in growth processes of innovations, and the dominance of one or the other depends on the context and market conditions. Specifically, assortativity was found to enhance growth performance with an appropriate seeding strategy (Haenlein and Libai 2013, measuring the NPV of the number of adopters), in the presence of network externalities (Uchida and Shirayama 2008, measuring the market share under competition), or when the objective metric is magnitude based, defined as passing the takeoff point of an epidemic spread (Nold 1980; Newman 2002; Boguná and Pastor-Satorras 2002). However, when externalities are not significant, or when the variable of interest is the overall reach of the growth process, redundancy dominates the initial boost provided by rapid adoption by social hubs, and the overall effect is negative (Nold 1980; Boguná and Pastor-Satorras 2002; Newman 2002; Badham and Stocker 2010).

An understanding of the connection between global structural characteristics and innovation performance can provide managers with a straightforward means of understanding how specific measurable aspects of their customer network influence relevant outcomes. To obtain such an understanding, it is necessary to compare growth processes across large sets of real and simulated networks of the *same type*, varying each metric of interest independently while controlling for the others (e.g., Peres 2014). Specifically, there is a need for large-scale *empirical* studies to validate the observations obtained thus far and to provide insight into topological influences in real-life scenarios. The objective metric should be that chosen to capture multiple growth dimensions, such as the NPV-based measures.

How does the nature of global structural characteristics influence the dominance of the four adoption pathways? Table 3 suggests such hypothesized connections: It presents the influence of connectivity versus conciseness: Connectivity is represented through the average degree and proportion of social hubs, while conciseness is expressed here by clustering and assortativity (whose high levels reflect redundancy and therefore low conciseness).

Table 3: Hypothesized effectiveness of influence pathways under differing levels of connectivity (expressed in average degree) and conciseness (expressed in clustering and assortativity)*

Structural characteristic		**Average degree & Social hubs**	
		High	**Low**
Clustering & Assortativity	**High**	Learning	Network externalities
	Low	Normative pressure	Awareness

* High clustering and assortativity imply higher redundancy, and therefore low conciseness.

For each pair of conditions, Table 3 presents the influence pathway that is hypothesized to be dominant: When conciseness in the network is low (high clustering and high assortativity), it impedes the efficiency of social interactions. If the average degree is low and there are fewer social hubs, then the social interactions are local and information is likely to travel via mechanisms other than social interactions, therefore network externalities will be the dominant pathway. If conciseness is low (high clustering and assortativity) but the average degree and proportion of social hubs are high, then the network is characterized by strong within-cluster influence, and learning may become dominant. Under high conciseness (low redundancy), social interactions are more widespread; and when connectivity is low, the information can spread in the network in combination with the firm communications at just the right level needed to increase awareness of the innovation. Normative pressure might become dominant when clustering and assortativity are low (conciseness is high) and the network is highly connected, i.e., many ties (not necessarily strong) and low assortativity, as compared to learning that is done best within clusters.

3.3 Dyadic characteristics

Zooming in from the global structural characteristics, we now proceed to discuss dyadic characteristics. A network can be viewed as a collection of ties, where a tie is a connection between two nodes. The nature of the dyadic connections shapes the social interactions among network members, and consequently, overall growth. In what follows, we discuss two aspects of the dyadic connection that have received substantial research attention: tie strength and embeddedness.

Tie strength relates to the intensity of the connection between two network members. Although the concept appears intuitive, it is far from well defined. As Granovetter (1973, p. 1361) stated: “It is sufficient … if most of us can agree, on a rough intuitive basis, whether a given tie is strong, weak, or absent.” Note, that although tie strength is a continuous variable, Granovetter’s dichotomy of strong and weak ties is still widely used.

In the context of innovation growth, the appropriate measure of ties should address the level of influence of one individual on another. In agent-based models, it is usually operationalized as a “diffusion parameter of internal influence”, denoted q (Goldenberg, Libai, and Muller 2001, 2002). Empirical studies, which cannot use q directly, use proxies that capture certain drivers of the tie strength, such as frequency of interactions between individuals (Granovetter 1973; Onnela et al. 2007; Bakshy et al. 2012), number of different channels via which people communicate (Bond et al. 2012), or the directionality of the tie, where bidirectional ties are considered strong, and unidirectional ties weak (Shi, Rui, and Whinston 2014). Some studies suggest combined measures bundling several of these attributes together (Brown and Reingen 1987; Frenzen and Davis 1990; Aral and Walker 2014). All these metrics measure *drivers* that impact the resulting strength of the influence, assuming that these drivers correlate significantly with the strength of the tie.

How do the ties in the network influence innovation performance? To discuss this, we introduce here the concept of the network's *cohesiveness*. Cohesiveness relates to the level of network nodes' relative impact on each other. Strong ties increase cohesiveness. While this is positive at the dyadic level, one might argue that the presence of numerous strong ties in a network can impede growth at the overall network level. As strong ties are usually observed in close social circles (Onnela et al. 2007), their influence might remain local in the network, and as a result, growth will be slower (Onnela et al. 2007). Granovetter's (1973) iconic paper and the one that followed it (Granovetter 1983) claimed that weaker ties are more instrumental than stronger ties in enabling information to spread across longer distances, as weak ties serve as bridges between distant groups (Brown and Reingen 1987; Onnela et al. 2007; Zhao, Wu, and Xu 2010; Bakshy et al. 2012). Indeed, using agent-based simulations, Goldenberg, Libai, and Muller (2001) observed that weak ties' overall influence on the speed of growth is at least as strong as that of strong ties. Moreover, removal of weak ties from a network can be detrimental to the speed of the innovation's growth (Onnela et al. 2007).

Weak ties become particularly important when tie strength is coupled with other node characteristics, such as level of innovativeness. Goldenberg, Libai, and Muller (2002), for example, analyzed a dual market in which two segments of the market adopt at differing rates, and observed that when ties between the early adopters and the main market are weak, the growth process slows to create a slump in sales (saddle). Similarly, Libai, Muller, and Peres (2005) showed that when strongly-connected groups differ in their responsiveness to advertising, a sequential entry process (as opposed to simultaneous) leads to higher NPV of the number of adopters.

Two main gaps still exist in our understanding of tie strength's influence on new product growth. First, more work (and particularly experimental studies) should be done to disentangle tie strength from homophily and clustering. Homophily leads to overestimation of the impact of tie strength (since, as discussed above, it leads to overestimation of social contagion), whereas clustering leads to underestimation, due to redundancy. Second, more research is needed to determine how tie strength interacts with other node characteristics to affect growth. An interesting scenario in this regard is the case of a group with characteristics that are important to the growth process (e.g., loyalists to differing brands, exclusive customers of channels, etc.) whose members have strong ties among themselves and weak ties with other market segments. In such case, their clustering (compared to a scenario where they are equally distributed across the network) might impact the overall growth process.

Embeddedness is defined as the extent to which individuals share common peers. More precisely, this metric reflects the number of neighbors that two connected network members have in common[1]. Having common neighbors increases trust (Uzzi 1997) and adds reliability to recommendations between peers (Granovetter 1985), hence increasing the network's cohesiveness. Thus, a node pair's embeddedness is expected to be positively correlated with each node's willingness to be influenced by the other's adoption. Surprisingly, the empirical evidence

[1] Embeddedness differs from clustering: Consider two connected nodes, A and B, each with several neighbors, where their neighbors are not connected to each other, thus embeddedness and clustering are zero. If one creates a connection between one of A's neighbors and one of B's neighbors, embeddedness increases, but clustering remains at zero, as no triangles are formed.

in this regard is scarce: Some studies that discuss embeddedness conflate the concept with the individual-level notion of centrality, which refers to a node's location in the network (e.g., Grewal, Lilien, and Mallapragada 2006; see below for a discussion of centrality). In addition, most research on embeddedness has focused on the organizational setting, exploring inter-firm networks and collaborations (Gnyawali and Madhavan 2001). Aral and Walker (2014) did evaluate embeddedness and adoption in a network of individuals: In a controlled online experiment, the authors observed that embeddedness enhances peer influence with respect to adoption of a Facebook app. Clearly, more work needs to be done to gain insight into embeddedness's role in additional contexts.

Table 4: Hypothesized effectiveness of influence pathways under differing levels of tie strength and embeddedness

		Tie strength	
		Strong	**Weak**
Embeddedness	**High**	Learning Network externalities: for communication-based innovations	Learning
	Low	Normative Pressure	Awareness Network externalities: for dominant standard innovations

How do dyadic characteristics in the network influence the dominance of the four adoption pathways? Table 4 suggests such hypothesized connections. Weak ties are efficient in generating awareness. As awareness requires a wide spread of information, and not necessarily strong interpersonal influence, being connected to multiple weak ties can be effective for obtaining awareness. Learning requires a higher level of intimacy and trust, and therefore is facilitated in the presence of high embeddedness. Normative pressure has been shown to come from significant people in one's social network (Sledgianowski and Kulviwat 2009), and social groups in which the individual is a member (Algesheimer, Dholakia, and Herrmann 2005).

In a market with network externalities, the dominant mechanism appears to depend on the nature of the innovation: If the network externalities result from the need for compatibility of the innovation (such as using Microsoft Word as a word processor), then a wide spread of weak ties will facilitate growth. However, if the network externalities result from the innovation's being communication based (e.g., Facebook, Skype), and utilizes the social ties between individuals, then strong ties and embeddedness, which occur in close circles, is hypothesized to enhance growth performance.

3.4 Individual characteristics

Zooming in further to the node level, we note that not all members of a social network are equal: Some contribute more to the growth process than do others. This can be due to their personal characteristics: being highly persuasive; having a high need to communicate; or being highly susceptible to influence. Also, their contribution can stem from occupying a strategic location in the network. In the upcoming section, we discuss the effect of personal characteristics and location characteristics on growth performance, and also possible dependencies and interactions between the two.

A key question to ask when discussing an individual's contribution to the social network is how such a contribution should be measured. When a customer engages in social interactions about a brand, the firm gains the value derived from these interactions (Chevalier and Mayzlin 2006; Godes and Mayzlin 2009; Kumar et al. 2010; Libai, Muller, and Peres 2009a; 2009b; 2013). This *social value* does not originate from the direct payments each customer individually adds to the firm's revenues, but rather from the customer's interaction with other prospective customers, coupled with their payments if they adopt the innovation (Ofek, Libai, and Muller 2018). Due to the social network's complexity and redundancy, quantifying the contribution is far from trivial. Mostly, studies on social networks have taken a unsophisticated approach with respect to this measurement, using measures such as the strength of interpersonal impact (Nair, Manchanda, and Bhatia 2010), and (using simulation) the overall speed, number of adopters, and length of cascade created by individuals with certain characteristics (e.g., Valente and Davis 1999; Eck, Jager, and Leeflang 2011).

We strongly suggest that research aim to expand upon these performance metrics. Broadly speaking, measuring the social value of a social network member requires predicting the overall NPV of the growth process with and without her contribution. This measure captures this individual's entire span of influence, including higher degrees of separation, and redundancies are taken care of, as the network neighbors could have been influenced by someone else, or could have adopted the product anyway at a later date (Libai, Muller, and Peres 2013; Meyners et al. 2017). While this has been done using simulations, the challenge still remains as to how to approximate such a measure empirically.

3.4.1 Personal characteristics

Influentials, or opinion leaders, are individuals who are effective in persuading or influencing other individuals. These individuals are considered important drivers of the growth process, a perception that stems from the work of Katz and Lazarsfeld (1955), who described social influence as a two-stage process, in which opinion leaders are influenced by the media, and then spread their influence to the entire population. Since Katz and Lazarsfeld (1955), opinion leaders have garnered substantial research attention. Studies have shown the contribution of opinion leaders to various aspects of innovation growth, such as opinion leaders' impact on non-opinion leaders (Nair, Manchanda, and Bhatia 2010); and the impact of their presence on the adoption hazard (Aral and Walker 2012), overall magnitude (Iyengar, Van den Bulte, and Valente 2011), and speed (Eck, Jager, and Leeflang 2011). Seeding the process with opinion leaders was found to speed up growth (Valente and Davis 1999). Interestingly, there is evidence that opinion leaders' influence is not always positive: Opinion leaders can have a negative influence on others' propensities to adopt in cases in which the former disseminates negative word of mouth on the product (Leonard-Barton 1985).

Opinion leaders' characteristics have been researched extensively. Their key characteristics can be defined along three axes: ***who one is***, ***what one knows***, ***and whom one knows***. The first axis entails opinion leaders' individual characteristics such as personality traits, socio-demographic backgrounds, and lifestyles. Opinion leaders were found to be highly individualized, i.e., they perceive themselves as being differentiated from others and are willing to act differently (Chan and Misra 1990; Van Eck, Jager, and Leeflang 2011). Relative to the overall population, they have stronger personal influence skills (Weimann 1991). Evidence suggests that most opinion leaders are also early adopters (Coulter, Feick, and Price 2002); however, not all early adopters are opinion leaders. Demographically, opinion leaders have a higher social status (Weimann 1991). As for their lifestyles, studies have found that opinion leaders have accumulated life experience, i.e., they have undergone career and personal changes; they are active in the community, lead active leisure lives (read, listen to music, surf the web, spend time with friends and family, see Aral and Walker 2012), and are highly exposed to media (see Keller and Berry 2003 for a comprehensive review).

The second axis of characteristics entails ***what one knows***, namely individuals' competence, such as their knowledge, expertise, or ability to provide information or guidance on particular issues. Research has found that the influential power of opinion leaders can come from domain expertise. Opinion leaders can be considered leaders in their professional communities (Nair, Manchanda, and Bhatia 2010); have a high level of involvement and familiarity with the products they assist in promoting (Chan and Misra 1990; Coulter, Feick, and Price 2002; Van Eck, Jager, and Leeflang 2011); and they view these products as reflecting part(s) of their identities (Grewal, Mehta, and Kardes 2000).

The axis of opinion leaders' characteristics entails ***whom one knows***, that is, the individual's structural position in a network. While research on this aspect is sparse, evidence suggests that opinion leaders, on average, occupy a more central place in the social network (Van Eck, Jager, and Leeflang 2011). Note that the first characteristic type, namely who one is, carries over across various contexts. However, what one knows, and whom one knows, are domain specific, and an opinion leader in one domain (such as whether to adopt an innovative medical treatment in a physicians' social network), might not be an opinion leader in other domains (such as adopting a new technological app in the neighborhood parents' social network).

Opinion leaders' role can be further studied in more complex contexts, for example, under competition (e.g., how a firm can overcome the influence of opinion leaders who have adopted competing brands); under a complicated distribution chain structure; and with respect to other marketing mix variables such as price and advertising. Also, as we discuss in the next section, many research questions remain open regarding the interaction between opinion leadership and location in the network.

The capacity to influence others in the network might be related to market mavenism. Market mavens are individuals who are highly familiar with market alternatives, shopping outlets, prices, and available promotions, and are active in initiating discussion about such topics with other individuals. They are gatherers and transmitters of information, and their knowledge is broad, rather than product specific (Feick and Price 1987). While market mavenism, similar to opinion leadership, is domain specific, market mavens share some overall personal traits. For example, they are motivated by a need to share information, a desire to help others, and sense of pleasure associated with informing others about products (Walsh, Gwinner, and Swanson 2004). Various aspects of market mavens' influence have been studied, including psychological influence (Clark and Goldsmith 2006), level of innovativeness (Goldsmith, Flynn, and Goldsmith 2003), decision making (Williams and Slama 1995), and communication patterns (Slama and Williams 1990).

Although research on this topic is sparse, it appears that market mavens differ from opinion leaders: Where opinion leaders have expertise in specific knowledge domains, market mavens' expertise lies in evaluating information in the network. They collect, filter, and transmit pieces of information; and connect information seekers and information providers. For example, a highly accomplished pediatrician might be an opinion leader on childhood diseases, but an administrator of a parents' Facebook group would know who is considered the best pediatrician in New Jersey, or what the new trends are in child vaccinations. What is market mavens' role in the growth of an innovation? The answer to this question remains open.

Susceptibility is defined as responsiveness to communications, and is expected to be associated with more rapid adoption. While little is known about susceptibility's drivers and outcomes, it is usually regarded as having two dimensions: informative, and normative (Bearden, Netemeyer, and Teel 1989). The informative dimension relates to the tendency of susceptible people to seek information from their peers prior to making decisions. The normative dimension is the tendency to seek peers' social approval. Aral and Walker (2012) found that compared to influentials, who tend to cluster together, susceptible individuals are distributed more evenly across the network. Susceptibility is negatively correlated to opinion leadership (Iyengar, Van den Bulte, and Valente 2011) and to innovativeness (Clark and Goldsmith 2006).

The results on personal characteristics suggest that innovation growth is benefitted by the presence of both opinion leaders and susceptibles; that is, a cohesive network, where members impact and are impacted by each other, will show higher-performance growth.

3.4.2 Location characteristics

A node's location in the social network affects its contribution to growth of innovations. The ***centrality*** of a node is a measure of its location's "importance" in the network. Studies on the growth of innovations typically focus on the following three node location types: degree centrality, closeness centrality, and betweenness centrality.

Degree centrality relates to the number of ties a node has compared to other nodes in the network (nodes with a larger degree have higher degree centrality). At the aggregate level, networks with many high-degree nodes are more connected. At the individual level, a node's degree centrality in the network is positively correlated with its ability to spread content and ideas throughout the network. Yoganarasimhan (2012) found that a YouTube member's number of first- and second-degree connections has a positive impact on the popularity of videos s/he posts. Susarla, Oh, and Tan (2012) and Banerjee et al. (2013) obtained similar results.

Social hubs, mentioned above, are nodes with considerably high degree centrality. Different researchers define social hubs differently, e.g., as the top 10% of network members in terms of degree (Watts and Dodds 2007), or as nodes whose degree is at least 3 standard deviations above (Goldenberg et al. 2009) or 10 times that of the network mean (Goldenberg, Lowengart, and Shapira 2009). Most studies indicate that social hubs contribute positively to growth. For example, hubs have a positive impact on total market size (Goldenberg et al. 2009). A single social hub can contribute several tens of percentage points to NPV, and adoption speeds among hubs are about double or triple those in the remainder of the market (Goldenberg, Lowengart, and Shapira 2009). Libai, Muller, and Peres (2013) found that compared to random seeding, seeding with social hubs adds 20%-30% to NPV; and Hinz et al. (2011) found that seeding social hubs increases awareness and belief updating by 39%-100% (see also Mochalova and Nanopoulos 2014). A counter example is suggested by Watts and Dodds (2007), who showed, using simulations, that in a social network where susceptibility of nodes is inversely proportional to number of ties, social hubs will not have a positive effect on the length of adoption cascades.

What is the source of social hubs' effect on growth? One possibility is that social hubs adopt early, as they are exposed to information about the product relatively early on (Goldenberg et al. 2009; Iyengar, Van den Bulte, and Valente 2011). This might explain the findings of Watts and Dodds (2007), who simulated social hubs as having low susceptibility, which translates into late adoption, that is, these individuals need a higher number of adopting neighbors to adopt themselves. Hubs might also accelerate adoption among individuals who would have adopted even in the absence of hubs, but later (Libai, Muller, and Peres 2013). In other words, not only are social hubs early adopters, but they also induce others' earlier adoption.

Closeness centrality measures how close a node is to each of the other nodes in the network. Network members with higher closeness centrality are assumed to be better connected, i.e., have easier access to information and to sources of influence. Only a few studies have explored the link between a node's closeness centrality and its contribution to growth, and results generally indicate a rather weak connection with respect to the individual's social influence

(Kimura et al. 2009) and magnitude (Kempe, Kleinberg, and Tardos 2003; Banerjee et al. 2013; Mochalova and Nanopoulos 2014). The impact of closeness centrality on innovation performance needs to be further studied. First, it is necessary to validate and generalize the results obtained thus far. In addition, contexts other than seeding should be examined. To what extent is a network node's social value (in the spirit of Libai, Muller, and Peres 2013) dependent upon its closeness centrality? How vulnerable is the growth process to removal of nodes with high closeness centrality? Finally, the interactions between closeness centrality and other location and impact variables should be studied.

Betweenness centrality measures the extent to which a node is an important intermediary between other members' connections in the social network. In other words, it reflects the number of shortest paths connecting any pair of nodes that pass through a particular node. Nodes whose betweenness centrality is very high, as they connect communities, or clusters that otherwise would have been disconnected from each other, are termed ***brokers***, or ***bridges***[2]. Burt (1999) drew an interesting distinction between opinion leaders and opinion brokers: While opinion leaders' influence is manifested in strong ties, opinion brokers' influence is exercised through weak ties, as they connect different clustered groups.

Empirical studies measuring betweenness centrality have tended to focus on the organizational context (e.g., Grewal, Lilien, and Mallapragada 2006). The few studies focusing on betweenness centrality's role in innovation growth focused on seeding, and indicate that seeding nodes with high betweenness centrality has a positive impact on the magnitude of growth (Hinz et al. 2011; Banerjee et al. 2013; Mochalova and Nanopoulos 2014).

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[2] In large social networks, connection between groups rarely depends on a single individual. Thus very few "pure" brokers are often identified as nodes with high betweenness centrality, even if they are the only connectors between groups (Hinz et al. 2011). Moreover, even the measure of betweenness as a count of the shortest paths evolved into more inclusive measures that give weights also to indirect longer paths (Newman 2005).

Yoganarasimhan (2012), however, found that a node's local betweenness has a negative impact on the extent to which content (specifically, a YouTube video) seeded by that node ultimately propagates across the network. As the author explained, a node with higher betweenness embodies two opposing properties: network dominance, and low path diversity, where the latter reflects the fact that information has fewer distinct paths through which to flow to various parts of the network. Similar to our discussion on clustering and assortativity, while low path diversity renders the network more concise, it also potentially renders it less connected, and the resulting growth performance depends upon their balance.

A more refined approach to measuring centrality is to look at the network as a set of concentric shells, where the inner shells, representing the core of the network, are comprised of nodes that have both high degree and closeness centrality. The decomposition into shells is executed by an iterative filtering process where at each stage, the lower-degree nodes are eliminated. The nodes surviving a high number of iterations in this "k-shell decomposition" process can be considered the core of the network, which has been shown to contain the most effective spreaders of information (Kitsak et al. 2010).

Location and personal individual characteristics are not independent of each other. Opinion leadership has been shown to correlate with closeness centrality (Van Eck, Jager, and Leeflang 2011) and to some extent, with degree centrality (Iyengar, Van den Bulte, and Valente 2011). Susceptibility, on the other hand, is negatively correlated with degree centrality (Aral and Walker 2012; Bapna and Umyarov 2015). Thus, opinion leaders have higher overall centrality, while susceptibles have lower centrality. Disentangling the reciprocal influence and assessing the relative role of personal versus location characteristics is a challenge for future research. For example, if opinion leaders have been shown to positively impact growth, then we should find a way to decouple the component of interpersonal influence from that of high centrality. A way to conduct this assessment is via simulations that independently vary opinion leadership and network position, and measure the effects. Cho, Hwang, and Lee (2012) have been one of the few to run such simulations, and found in the context of seeding that opinion leaders with high degree centrality are the best seeds for obtaining fast growth, whereas those with high closeness centrality are the best at generating the maximum cumulative number of adopters.

One may wonder which of the pathways is more dominant on susceptibles versus on opinion leaders, and what the effect is of central versus peripheral network location. Table 5 suggests that susceptible individuals might be mostly influenced by normative pressure and learning, pathways that require social interaction in close circles. Opinion leaders, however, need to become aware of the innovation, but then might form their own opinions based on influences that are not necessarily related to social interactions. Also, it can by hypothesized that one of their considerations in adopting is to maximize their scope of influence, therefore they will derive a higher utility from innovations with network externalities (e.g., opinion leaders who are artists will derive a high utility from arts and crafts website Etsy as, in addition to its functional utility, it will enable them to influence others). Network location interacts to amplify influence: The more central the network member is, the stronger will be the adoption pathway. For example, an opinion leader with high closeness or degree centrality will have more access to information and therefore his impact of awareness and network externalities will be stronger than that for a peripheral individual. For a peripheral susceptible individual, overall level of social interactions is lower, and therefore the effect of learning and normative pressure will be weaker than that for central individuals.

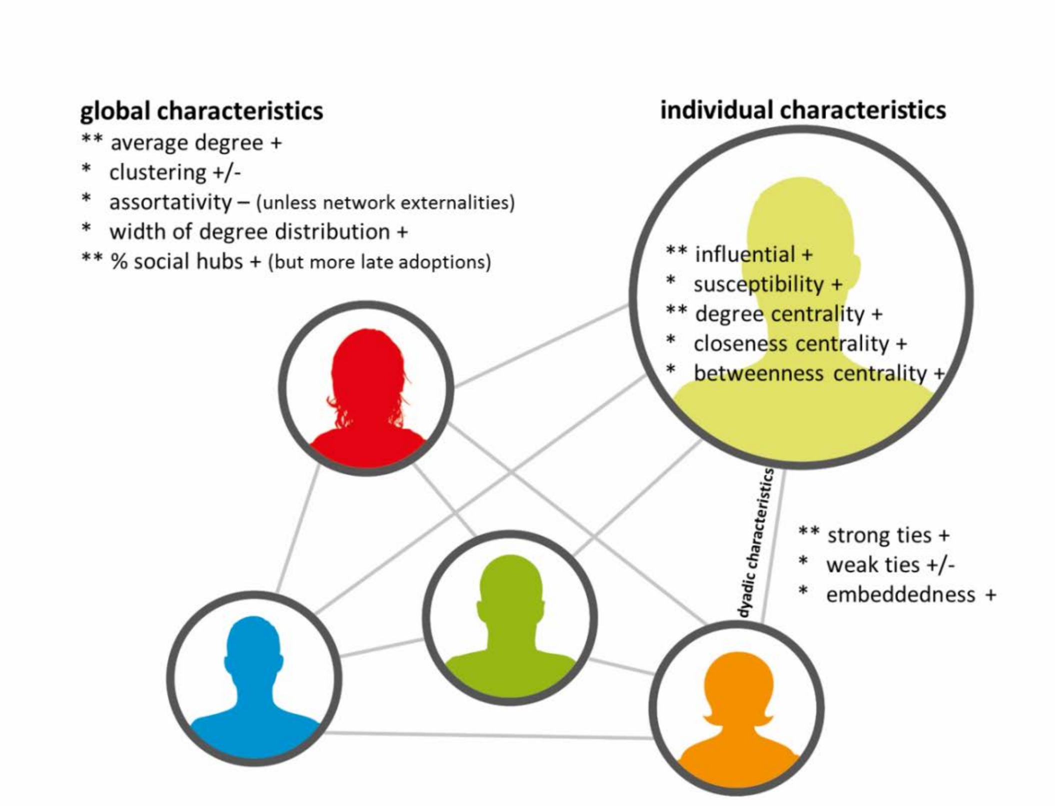
Table 5: Hypothesized effectiveness of influence pathways for opinion leaders vs susceptibles in central vs peripheral locations (the + symbol indicates the magnitude of the effect)

Location	Personal characteristic	
	Opinion leader	**Susceptible**
Central	Awareness, Network externalities ++	Normative pressure, Learning ++
Peripheral	Awareness, Network externalities +	Normative pressure, Learning +

3.5. Summarizing structural effects on growth

Figure 1 summarizes the effects of the three levels of social network structure metrics – global, dyadic, and individual characteristics – on an innovation's growth performance.

Figure 1: Summary findings on structural characteristics' influence on innovation growth



*Note: ** and * indicate strong and weaker evidence respectively; the sign indicates the direction of the effect. A +/- sign indicates evidence in both directions.*

The figure reflects effect strength and direction. Note that the dependent variable—that is, the goodness of the growth process—is defined differently by various researchers: It can be defined as cascade length, the NPV of the penetration process, or the final number of adopters.

Aggregating the dyadic and individual characteristics and joining them to the global characteristics, one may ask what networks would lead to high-performance growth. The figure implies that according to the literature, a high-performance growth process is observed in networks that are *cohesive*, *connected*, and *concise*: properties that we refer to collectively as "the 3 Cs". A network is *cohesive* if individuals highly impact and are highly impacted by each other: This is manifested in a dominant role of influentials on one hand, and high susceptibility on the other hand. A network with high embeddedness will be more cohesive, as common neighbors enhance trust, communality, and therefore, mutual impact. A network is *connected* if it exhibits a high average degree, strong presence of social hubs, and high connectivity among its parts, expressing high average closeness centrality. A network is *concise* if it has low redundancy, i.e., each tie provides a meaningful contribution to the network; this is usually manifested in low clustering, low assortativity, and the existence of nodes with high betweenness centrality.

4 The effects of social network structure on marketing decisions

Managerial decisions in marketing typically do not consider the structural aspects of the underlying social network. However, as the customer's personal social network is a component of the value she offers, incorporating network information has the potential to improve managerial decisions. In this section we discuss these managerial opportunities in terms of 1) targeting, 2) developing referral programs, and 3) optimizing seeding strategies.

4.1 Targeting decisions

Targeting a new market for an innovation involves considerations around the fit of the product to the target audience, the potential size of the target market, and the costs of serving this market. While research regarding the actual contribution of such information is still in its infancy, the results definitely point to network information's value: Hill, Provost, and Volinsky (2006) showed that when a direct marketing campaign targeted a market segment consisting of potential adopters whose neighbors had already adopted a new telecom service, resultant adoption rates of that service were 3-5 times that of those obtained in baseline groups selected by the best practices of the firm's marketing team. Haenlein and Libai (2013) showed that high-revenue customers of telecommunication services show high assortativity, as they tend to connect to other high-revenue customers. Therefore, targeting the network neighbors of customers in the high-revenue tiers might be an effective strategy.

The main practical challenge with implementing these types of insights is that they require access to customers' network connections. Obtaining this is not always feasible, especially if the firm's market share is small, and most network neighbors are served by competitors. Moreover, in many cases, desirable segments might be hard to access and approach.

4.2 Developing referral programs

Referral programs are plans through which firms reward existing customers for bringing in new customers. Recent studies have documented that, as compared to marketing induced, customers acquired through referral programs tend to churn less, bring in more customers through their own contagion activities (though not in a free trial case), and in general are more valuable in the long term (Villanueva, Yoo, and Hanssens 2008; Trusov, Bucklin, and Pauwels 2009; Aral and Walker 2011; Schmitt, Skiera, and Van den Bulte 2011; Armelini, Barrot, and

Becker 2015; Datta, Foubert, and Van Heerde 2015; Van den Bulte, Bayer, Skiera, and Schmitt 2018). Structural characteristics were studied in only one of these studies: A referrer's degree influenced the number of adopters acquired (Aral and Walker 2011). This is thus an area of research with some low-hanging fruit.

Similar questions can be asked with respect to customer attrition: When a customer churns, the firm might lose not only the revenue stream from that customer, but also the potential revenue stream associated with his or her network neighbors. It has been also shown that customers are affected by their peers' attrition (Nitzan and Libai 2011; Haenlein 2013). Hence, attrition of a customer might suggest special handling of her network neighbors.

4.3 Optimizing seeding strategies

The most intensive discussion on social network structure and managerial decisions has been on seeding. Seeding strategies target the best subsets of individuals with whom to initiate the penetration process. A set of models, termed "influence maximization models", was proposed for choosing the optimal initial seed. In a given network, an exhaustive way of finding this optimal seed is to go over all combinations of possible seed members, simulate all possible growth paths emanating from each seed, then choosing the seed with the optimal outcome. In their seminal paper, Kempe, Kleinberg, and Tardos (2003) showed that this task is NP complete, and proposed an approximation algorithm that outperforms random seeding, and is better than choosing a seed based on degree or other structural characteristics.

Looking for such characteristics, some studies have suggested that seeding social hubs enhances awareness and belief updating (Hinz et al. 2011) and leads to faster growth (Valente and Davis 1999) and higher NPV (Libai, Muller, and Peres 3013). Trusov, Bodapati, and Bucklin (2010) suggested a procedure for online social networks where the login activity of each member is monitored. Individuals whose login activity causes changes in their neighbors' login activity (namely, their login/posting stimulates others to log in) are identified as being influential in the network, and should be targeted first. Seeding nodes with high betweenness centrality was found to increase growth magnitude (Hinz et al 2011; Banerjee et al. 2013; Mochalova and Nanopoulos 2014). Recently, it was suggested that multiplicity, types, and duration of connections and relationships in a network affects targeting and seeding strategies (Ansari, Koenigsberg, and Stahl 2011; Chen, van der Lans, and Phan 2017).

In contrast to this careful selection of seed members, a growing number of studies assume that as most networks are characterized by a low degree of separation, influential nodes will be reached in any case. Thus, Libai, Muller, and Peres (2005) showed that in a multinational market, a seeding strategy that spreads marketing efforts performs better than does seeding elite countries that show a higher propensity to adopt. Similarly, Bakshy et al. (2011) showed that random seeding of a large number of network members can be more cost effective than investing in a small group of selected individuals.

Seeding's effectiveness in the presence of homophily was questioned by Aral, Muchnik, and Sundararajan (2013) using simulations on a real-life telecom user network. They found that seeding is effective for a small percentage of the population, as the gain from adoption by a large percentage is lower than that from their natural adoption (sans seeding).

Table 6 summarizes some of the insights gained from the literature. It aligns the strategies along two dimensions – the network's conciseness, determined by its level of redundancy (e.g., clustering and assortativity); and its level of heterogeneity across network members. Heterogeneity can be reflected in degree, opinion leadership, or any individual characteristic important to the growth process. When redundancy is high and heterogeneity is low, seeding is less effective, as information tends to remain within clusters of individuals. Thus, to reach sufficient spread, it is necessary to identify the clusters and then seed individuals in each segment. This can result in seeding a large number of individuals distributed over multiple areas of the network, which might prove less cost effective.

Table 6: Hypothetical effects of structural characteristics and heterogeneity on the effectiveness of seeding and referral programs

Structural Characteristic		Heterogeneity in individual structural characteristics	
		High	**Low**
Clustering, & Assortativity	**High**	Seeding along identified characteristics is effective	Seeding is less effective
	Low	Seeding hubs & influentials is effective	Random seeding Referral programs

If redundancy and heterogeneity are high, seeding high-impact groups might be effective. To see this, consider the case of redundancy due to high assortativity: In such a case, high-impact individuals are connected to each other, and therefore, seeding within the high-impact group might help in efficiently spreading the innovation across the high-impact network members. Moreover, high assortativity can help the firm seed based on attributes that are easy to identify such as per-user revenue or lifetime value; while relying on assortativity to benefit from other attributes that are more difficult to identify, such as how influential these individuals are.

When redundancy is low, random seeding and referrals (i.e., acquisition through the existing customer base) are likely to be preferable under low heterogeneity, as network members are similar in their contributions, whereas seeding social hubs and influentials might be more effective under high heterogeneity. While this of course depends upon costs as well, in terms of benefits, the higher is heterogeneity in terms of degree and impact, the more beneficial it is for the firm to make the effort and seed within these groups.

5. Directions for future research

The first scenario in the introduction to this paper describes a new service launched by a mobile provider that wishes to implement a referral program. How and in what fashion do we need to extend our current cumulative knowledge in order to suggest an answer to such issues that marketing managers face?

Research so far has provided many insights into the relationship between structural characteristics and innovation performance. However, most papers reviewed here focus on a single structural characteristic, use a single type of network, and measure a single performance metric. We argue that in order to provide meaningful generalizations, research needs to move toward standardization and integration. Standardization means reaching agreement on an accepted performance measure and set of structural characteristics to be measured. Integration means testing the impact of multiple factors, measuring their relative effects and synergies, and moving toward a broader range of marketing decisions. In what follows, we propose a roadmap for future research in order to achieve these goals. Our proposed roadmap is comprised of seven stages:

1. *A unified performance metric* – As indicated in Table 1, current research uses a variety of metrics to describe growth performance, yet generalization across scenarios and papers requires standardization of the performance metric. As discussed above, we suggest using the NPV of either the number of adopters, or the adoption profits. NPV's value stems from capturing the number of adopters, the speed of growth, and the cost effectiveness of the process. Hence, we view it as the most appropriate performance measure of an innovation's growth.

2. *A unified set of structural characteristics* – Network research has proposed numerous characteristics through which a social network's structure can be described. In the aforementioned, we suggested a set of structural characteristics that have been shown to be important for innovation growth, and that are fairly independent of each other. These characteristics include: (1) global characteristics: average degree, degree distribution, clustering, and degree assortativity; (2) dyadic characteristics: tie strength and embeddedness; (3) individual characteristics including personal characteristics: opinion leadership and susceptibility; and location characteristics, namely degree centrality, closeness centrality, and betweenness centrality. We propose refining this core set of structural characteristics for the innovation at hand, and determining their relative importance to innovation growth. To do so, we propose using simulations to run large-scale full-factorial experiments on networks, varying independently the various structural characteristics and determining the relative impact of each on growth performance.

3. ***Group the characteristics into the 3 Cs* –** Our review of the literature suggests that the structural characteristics can be grouped into three classes: *cohesive*, *connected*, and *concise*. *Cohesive* describes influentials' dominant role, high susceptibility, and high embeddedness. C*onnected* means high average degree, strong presence of social hubs, and high connectivity among the network's parts, manifested in high average closeness centrality. C*oncise* means low redundancy, i.e., low clustering, low assortativity, and the existence of nodes with high betweenness centrality. We propose further exploring this classification in the spirit suggested in Fig. 1 and in terms of each of the *C*'s role in innovation growth. This can be done by running large-scale full-factorial experiments, varying each structural characteristic independently, and testing the resulting NPV. Each group's relative importance, synergies, or super-additivity can be tested using regressions or other statistical techniques, to determine *each C*'s relative role, the weight of each attribute within each *C*, and synergies, if any.

4. *Conduct empirical studies coupled with simulations* – Empirical studies are always limited in context and mostly deal with a single network, with information sometimes available on a limited set of characteristics. To enable fitting empirical studies into this framework, we suggest, in addition to using NPV as a performance metric, conducting a supplementary set of simulations to test the robustness of the results across various social network structures. For example, consider a study on the relationships between opinion leaders' incentives and innovation performance. One would ask whether the effect would be higher for networks with higher clustering/average degree; or, how is the impact moderated as a function of the node's degree/closeness/betweenness centrality? While some of these questions can be directly answered from the data, others can be answered by such supplementary simulations.

5. *Progress from diagnostic to normative questions* – For marketers, understanding innovation growth matters both for diagnostic purposes (identifying patterns and flows) and for normative decisions. While research so far has focused mostly on diagnostics, marketers are often interested in normative aspects: How does social network structure influence the desired managerial decision? As we described above, decisions related to targeting, referral programs, and seeding programs are typically discussed with respect to social networks. However, social network considerations are also highly relevant to established practices of advertising and pricing where much of advertising and some of the retailing are done online, and thus the network structure of current and potential customer matters greatly. Thus we suggest that research move toward asking normative questions related to the allocation of marketing resources, various customer management strategies (e.g., customer acquisition and development), and marketing mix decisions under various network conditions. This can be done either theoretically using simulations, or empirically using natural experiments. Many of today's commerce platforms such as WeChat and AliExpress have a social network component, and are therefore conducive to performing natural experiments on the relationship between social network structure and various decisions.

6. *Measuring market potential* – Measuring market potential is crucial to properly managing innovation growth. While the aggregate Bass model provides the means to estimate market potential, it is not clear how to do so under an individual-level social network model. One would think that the concept of "market" has now been replaced with "social network", but the two are not interchangeable. While Facebook or WeChat, for example, are representative of social networks, they do not necessarily describe specific target markets. In our view, a social network describes the underlying social system's entities and connections, and it may contain many target markets, depending on the nature and purpose of the innovation. How we can define the boundaries of the target market and estimate the potential within such a structure, is an open challenge for marketing researcher.

7. *Studying the role of the four pathways* – In this paper, we presented the four pathways of adoption: *awareness*, *learning*, *normative pressure*, and *network externalities*. In Tables 3, 4, and 5, we suggested a set of hypotheses as to the way these pathways interact with social networks' structural characteristics. In order to enhance our understanding of the mechanisms behind social structure's effects on innovation performance, these relationships should be studied. As in other situations where behavioral mechanisms are examined, these relationships are best suited for lab experiments.

Note that with respect to modeling methods, our course of action fits well with the classification of Chen, van der Lans, and Trusov (2017), who classified the methods researchers use to study innovation growth in social networks into four modeling approaches: 1) integrating network measures directly into the model (e.g., Stephen, Zubcsek, and Goldenberg 2016; Ansari et al. 2018); 2) statistical models, where consumers' actions and choices are modeled as a stochastic spatial process (e.g., Wang, Aribarg, and Atchadé 2013); 3) structural economic models that take into account the interactions among consumers and their effects on their adoption decisions (e.g., Bollinger, and Gillingham 2012); 4) agent-based models that simulate data on a social network, and model consumers' interactions in order to achieve aggregate market behavior (e.g., Peres and Van den Bulte 2014). The methods we propose using for our proposed roadmap involve modeling approaches nos. 1 and 4 above: The simulations would be run using agent-based models (approach no. 4), and the estimation of network characteristics' and other market parameters' relative roles will obtained by integrating these characteristics directly into the model (approach no. 1).

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