The History of Marketing Science
Chapter 4: Innovation Diffusion

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1. Introduction

Innovation diffusion has been defined as: "The process of the market penetration of new products and services, which is driven by the combined impact of the firm's marketing communications and social interactions in the market. Such interactions include all the interdependencies among consumers that affect various market players with or without their explicit knowledge."[1]

As a field in marketing innovation, diffusion began with the 1969 paper by Frank Bass, and — as the author often mentioned in private communications — was largely ignored until criticized by Bernhardt and Mackenzie in 1972, who were "skeptical about (its) immediate practical value". Refinements of the Bass model began shortly thereafter by Dodson and Muller (1978); Horsky and Simon (1983); and Peterson and Mahajan (1978); and the first review paper was published in 1979 by Mahajan and Muller, having been rewritten four times since. The 1969 paper was chosen in 2004 as one of the ten most influential papers in *Management Science*'s first 50 years (Bass 2004). As of 2022, it received over 10,000 citations.

A representative genealogy is presented in Figure 1[2], describing the main advances in the field, partitioned into research issues and methodology. The main research issues involve successive technological generations of the product; inclusion of marketing mix and their optimal allocation; international and cross-country diffusion; and the effect of competition at the brand

[1] This chapter extends the papers by Peres, Muller, and Mahajan (2010) and Muller and Peres (2019).
[2] An arrow in Figure 1, such as the one leading from Takada & Jain 1990 to Ganesh & Kumar 1996 implies that the latter relied on the former for its main issue, conceptual, theoretical, modeling, or empirical aspects. The figure is representative as one or two papers are chosen as representative(s) of a much larger body of research.

level on the diffusion of new products. In terms of methodology, early papers used the tools of differential equations, that gave way to more flexible modeling methods, both empirical and simulation, e.g., Cox hazard models, agent-based models, and recently social network analysis. In the next section we describe in detail the evolution of the field illustrated in Figure 1. We then identify promising future directions for innovation diffusion research.

2. The evolution of innovation diffusion research

2.1 Successive generations

While the basic Bass diffusion process terminates when all consumers in the specified market potential have bought the product, the reality is that old products are substituted with newer generations, and so, consumers do not stop purchasing but upgrade to a newer generation of the same base technology. The first to deal with generational substitution was Frank Bass (1987) in a paper he wrote together with one of his doctoral students, John Norton. The model therein assumed that sales are proportional to cumulative adoption, and while the first-generation growth follows a simple Bass model, the second comprises new adopters and upgraders. In this paper as well as its (1992) extension, Norton and Bass showed that the model performs best under the assumption that the growth parameters (the external and internal influence parameters p and q of the Bass model) are constant across generations, while market potential grows. These assumptions caused a lively debate on two aspects of the model: First, the fact that sales are proportional to cumulative adoption implies that the product in question is a repeat-purchase product or a service, but not a durable. Thus, later efforts such as that of Mahajan and Muller (1996) were aimed at durables, while others, such as such as that of Kim, Chang, and Shocker (2000) extended the model where it applied to services.

Second, the assumption of fixed growth parameters across generations has practical importance for forecasting, as projections regarding the growth of advanced generations of a product must often be made during the early stages of product penetration or before launch, and are thus based on using diffusion parameters from previous generations. Theoretically, this matter is important, since it deals with dependency within a sequence of diffusion processes and, more broadly, with rigidity of the social system across generations. Does the social system learn to improve its adoption skills across generations, or does it begin each diffusion process anew? If it has learning capabilities, how strong and how category-specific are they?

As Stremersch, Muller, and Peres (2009) pointed out, the literature offers contradicting answers to the question of whether diffusion accelerates across technology generations. The key finding (or assumption) of several studies across multiple product categories is that growth parameters are constant across technology generations (Kim, Chang, and Shocker 2000; Mahajan and Muller 1996; Norton and Bass 1992, 1987). Exceptions to this premise were provided by Islam and Meade (1997) and Pae and Lehmann (2003).

Contradicting the stability of growth parameters across generations, a large body of evidence suggests that the overall temporal pattern of diffusion of innovation within a generation accelerates over time (Van den Bulte and Stremersch 2004; Kohli, Lehmann, and Pae 1999). An analysis by Van den Bulte (2000) found conclusive evidence that such acceleration does indeed occur. These two findings form an intriguing paradox: It appears that, in the same economy, an acceleration of the diffusion of innovations over time should be reflected in acceleration of diffusion of technology generations that succeed one other; however, the diffusion rates of sequential technology generations remain constant.

A resolution to the paradox was suggested by Stremersch, Muller, and Peres (2009), who noted constant growth parameters across generations, yet a shorter time to takeoff for each successive generation. Takeoff is defined as the cutoff time point at the beginning of the diffusion process that distinguishes between the introduction and start of the organic growth (Golder and Tellis 1997)**.** Takeoff is an important turning point since it is a first indication that the social interactions about the product have started, and the rapid growth is about to arrive. Note, that the Bass process is agnostic about the process prior to takeoff: Its basic formulation assumes that the social interactions start right away, and since the social network is assumed to be fully connected, the left tail of the diffusion curve (representing the time to takeoff) is short. However, in real life, these processes take time to ignite and therefore, the left tail of the diffusion curve is often longer. Since these starting hurdles are not incorporated in the Bass model, two processes with different times to takeoff can have similar values of the diffusion parameters.

Stremersch, Muller, and Peres (2009) investigated whether the faster takeoff of successive generations is due to the passing of time, or to the generational effect. They defined *technology generation* as a set of products similar in customer-perceived characteristics, and *technology vintage* as the year when the first model of a specific technology generation was launched commercially. Using a discrete proportional hazard model in 12 product categories, they found that acceleration in time to takeoff is due to the passing of time, and not to generational shifts. Thus, time indeed accelerates early growth, whereas generational shifts do not.

Multi-generational diffusion raises the question of adopter segmentation. In the classic Bass formulation, there are not customer segments - the entire population is potential adopters, and as the process evolves, they gradually become adopters. However, a multi-generational process inherently involves groups of customers – those who adopted the first generation but do not adopt subsequent generations, those who will only adopt the advanced generations, those who shift between generations, etc. These aspects are studies by Jiang and Jain (2012), who developed a generalized Norton–Bass model for multi-generation diffusion which differentiates those who have already adopted the old generation from those who have not. Sood et al. 2012 suggest a competitive "Step and Wait" model in order to better assess competition and progression of technologies in different markets.

2.2 Marketing mix

The fact that the Bass model does not contain marketing mix variables, raises a conceptual conflict, since the model provides a high level of fit and forecasting power even without incorporating marketing mix. Bass, Krishnan, and Jain (1994) proposed a resolution to this conflict by introducing the Generalized Bass Model (GBM) that assumes that the marketing mix variables' effect is multiplicative (i.e., both growth parameters are affected equally), and that advertising and pricing are measured as percentage change rather than absolute values. When the percentage change in price and advertising is constant, the GBM reduces to the original Bass model. Studies that compared the performance of the GBM to that of the original Bass model concluded that both models provide a similar fit (e.g., Danaher, Hardie, and Putsis 2001). The GBM's limitations — i.e., that the marketing mix variables act only through changes, and not these variables' absolute levels — were noted later (Bass, Jain, and Krishnan 2000). The GBM's normative aspects were also recently criticized by Fruchter and Van den Bulte (2011). Peers, Fok and Franses (2012) also criticized the model for giving biased estimates when modeling seasonality despite generating good predictions. However, ignoring seasonality leads to biased parameter estimates and predictions when only part of the diffusion period is available.

A considerable number of normative studies on marketing mix influences have explored the optimal allocations under various market conditions: While work in the 1980s dealt mainly with advertising, most work from the 1990s onwards investigates the influence of price. Additional marketing mix variables such as channels, strategies, and word-of-mouth seeding campaigns began to be considered only during the 2000s.

The first major paper to tackle advertising allocations within the Bass framework was coauthored by Dan Horsky (a doctoral student of Frank Bass) and Len Simon (1983). The question they investigated was simple: If the Bass model's external coefficient *p* summarizes the firm's marketing communications effort, then shouldn't it be under the control of the firm? They found that if indeed the external coefficient is a concave function of advertising, then the optimal advertising should decline over time. The intuition is that the firm's marketing communications are needed to set things in motion, and then the social interactions take over, so firms need to invest less marketing resources as the product diffuses.

The first paper to deal with optimal pricing in the Bass framework was by Robinson and Lakhani (1975). Price of new products is often declining due to supply-side considerations such as economies of scale, economies of scope, and learning by doing. Demand-side consideration would have the price lowest in the introductory stage of the product life cycle. Robinson and Lakhani (1975) showed that even in the presence of economies of scale and learning by doing that reduced the average costs to a tenth of the original, optimal price is still increasing because it is still worth subsidizing the first adopters. Note, that under the Bass framework, all adopters are equal in their level of willingness to accept and pay for innovations, and therefore considerations such as skimming pricing are not incorporated.

In diffusion processes, the value of the first adopters to the firm is higher than late adopters:

This stemmed not only from the time value of money, but mainly because first adopters begin the word-of-mouth process, and the viral chain that emanates from these adopters is longer the earlier they adopt. Thus, it is worth subsidizing the early adopters in terms of an advertising blitz, lower prices, or giving the product away to a select seed of individuals. The power and effect of seeding strategies, including sampling and product demonstrations, were studied by Libai, Muller, and Peres (2005), and Jain, Mahajan, and Muller (1991); and more recently of seeding programs in social networks (Hinz et al. 2011).

The value of first adopters applies to multi-generational scenarios as well: In a study on the cellular industry in Europe, Danaher, Hardie, and Putsis (2001) found an interesting nonsymmetrical interaction between generations in the response to price due to the fact that the impact of price changes for an earlier generation product on later-generation subscriptions works through two mechanisms: Via direct price response (e.g., choosing one generation over the other at the point of sale) and via the installed base of the earlier-generation product. Pricing decisions in the context of successive generations were also studied by papers such as Padmanabhan and Bass (1993), and Lehmann and Esteban-Bravo (2006).

Despite the frequent use of marketing channels in innovation marketing, the topic of diffusion through marketing channels is still under-researched. Take, for example, a typical channel model such as the one used by Mesak and Darrat (2002), where the growth process is a double diffusion model: The product has to be diffused first among retailers, and only subsequently among the final consumers. Similarly, Lehmann and Weinberg (2000) introduced technological substitution into the distribution channel: They examined the issue of sequential channels through the question of the optimal timing of the video (or DVD) release of a movie. Usually, video release pushes box office sales down to zero; thus, there is a tradeoff between an early video release, which enhances video revenues, and a later video release, which is better for box office revenues. Their empirical observation was that films are usually released to video later than optimal. The normative issue of optimal timing was investigated in the context of the entertainment industry, calculated the optimal timing of the release of a new movie (Lehmann and Weinberg 2000; Mahajan, Muller, and Kerin 1984). These issues have become very relevant today with streaming vs. cable vs. theater issues, and more broadly, in issues relating to omnichannel CRM. Omnichannel advocates seamless movement between channels, and would eschew the practice of sequential channel introduction (Neslin 2022).

In the context of technological substitution, timing issues were discussed with respect to the release of a new generation. The prevailing wisdom among practitioners is that the firm should introduce the product as soon as it is available. This rule of thumb is supported by two main studies in the field, which indicate that the firm should introduce the new generations either as soon as they are available or not at all (Wilson and Norton 1989), or at maturity of the old generation (Mahajan and Muller 1996). Inclusion of factors such as cannibalization of market potentials and competition among brands might alter these results.

2.3 International diffusion

One of the first influential papers to deal with international diffusion was coauthored by two of Frank Bass's students, Hirokazu Takada and Dipak Jain (1991). Therein, they established what became one of the major findings to date on cross-country influences, called *lead-lag effect*, namely that entry-time lag has a positive influence on the diffusion process, i.e., countries that introduce a given innovation later show a faster diffusion process (Tellis, Stremersch, and Yin, 2003; Ganesh and Kumar 1996) and a shorter time to takeoff (Van Everdingen, Fok, and Stremersch 2009). An exception to this effect is found by Elberse and Eliashberg 2003 for the film industry. The positive effect of entry time-lag is counter intuitive, since one would expect firms to introduce the new product in the "easy" markets, where it will diffuse quickly. However, while this might be true, the positive effect is caused by the spillover of word-of-mouth from the earlier to the later market. This spillover is apprently strong enough to overcome endogenous entry decisions.

Cross-country effects can be a result of two types of influence mechanisms: weak ties, and signals. Weak ties come from adopters in one country who communicate with potential adopters from other countries (Wuyts et al. 2004). However, even without communicating with or imitating other individuals, potential adopters are influenced by diffusion in other countries. In other words, the level of acceptance of the innovation in one country acts as a *signal* for customers in other countries, reducing their perceptions of risk and increasing the legitimacy of using the new product. While several studies have stated explicitly that the dominant effect was due to communication (Putsis et al. 1997), others explored the effect without relating it to a specific mechanism (e.g., Dekimpe, Parker, and Sarvary, 2000b, 2000c).

Understanding cross-country influences is also valuable in the context of normative managerial decisions in multinational markets. Some studies have explored entry strategies — i.e., the question of whether a firm should enter all its markets simultaneously (a "sprinkler" strategy), or sequentially (a "waterfall" strategy). Kalish, Mahajan, and Muller (1995) suggested that the waterfall strategy is preferred when conditions in foreign markets are unfavorable (slow growth or low innovativeness), competitive pressure is low, the lead-lag effect is high, and fixed entry costs are high. Libai, Muller, and Peres (2005) extended this question to responsive budgeting strategies when firms dynamically allocate their marketing efforts as per developments in the market. Many other questions still await answers, and issues such as regulation (addressed by Stremersch and

Lemmens 2009), international competition, and the optimal marketing mix of growing international markets can be further explored.

A large number of studies in the last two decades have focused on explaining inter-country differences in new product adoption. These studies generally focused on differences in the diffusion parameters p and q (Van den Bulte and Stremersch 2004), time to takeoff (Tellis, Stremersch, and Yin 2003), and duration of the growth stage (Stremersch and Tellis 2004). The salient result of all these papers is that diffusion processes vary greatly among countries, even for the same products or within the same continent (Helsen, Jedidi, and DeSarbo 1993). In addition to measuring the differences between growth processes, these studies also investigated country-specific sources that generated these differences. These underlying factors can be divided into ***cultural*** sources and ***economic*** sources.

Cultural sources – Relate to the country's cultural characteristics and values. Takada and Jain (1991) found that the diffusion parameter q is higher in countries that are high-context and homophilous (such as Asian Pacific countries) relative to countries such as the U.S. that are low-context and heterophilous. *High-context* refers to a culture where much of the information conveyed through a communication resides in the context of the communication rather than in its explicit message; and *homophilous* implies that communication takes place among individuals who share certain characteristics. Similarly, Dekimpe, Parker, and Sarvary found — regarding cellular phones (2000b) and industrial digital telephone switches (2000c) — that population heterogeneity has a negative effect on both time to adoption and the probability of transition from non-adoption to partial or full adoption in a country. Van den Bulte and Stremersch (2004) used Hofstede's dimensions of national culture and found that the importance of word of mouth (relative to advertising) is higher in cultures that scored high on the dimensions of collectivism, power distance and masculinity.

Economic sources – The influences of many macroeconomic variables have been studied, yielding two main empirical generalizations: First, the **wealth** of the country (usually measured by gross domestic product (GDP) per capita, but also by lifestyle, health status, and urbanization) has a positive influence on diffusion (Desiraju, Nair, and Chintagunta 2004). Note that wealth is not necessarily equivalent to general welfare. For example, Van den Bulte and Stremersch (2004) found a positive relationship between the Gini index for inequality and the importance of word of mouth. A second generalization is that **access to mass media** (usually operationalized by the penetration of TV sets) has a positive influence on the diffusion parameter *p* (Stremersch and Tellis 2004; Talukdar, Sudhir, and Ainslie 2002).

2.4 Brand-level growth

The interplay between category and brand level growth raises the question of whether competition enhances or delays category growth. Generally, competition has been found to have a positive effect on diffusion parameters (e.g., Van den Bulte and Stremersch 2004; Dekimpe, Parker, and Sarvary 1998). An exception was observed by Dekimpe, Parker, and Sarvary (2000c), who showed that an existing installed base of an old technology negatively affected the growth of new technologies. Krishnan, Bass, and Kumar (2000) studied the impact of late entrants on the diffusion of incumbent brands. Using data on diffusion of minivans and cellular phones in several U.S. states, they found that the effect varied across markets. In some markets, the market potential and the internal influence parameter *q* increased with the entry of an additional brand, whereas in other markets, only one of these parameters increased. These studies do not provide explanations of the mechanisms underlying the acceleration. One potential explanation is that acceleration results from heavier marketing pressure on the target market. Kim, Bridges, and Srivastava (1999) implicitly suggested that the number of competitors constitutes a signal for the product's quality and long-term potential, which may result in acceleration. Alternatively, the positive effect may be a result of reduction in network externalities (Van den Bulte and Stremersch 2004).

Constructing a brand-growth model requires discussing several conceptual issues. A basic question is the extent to which internal influence mechanisms operate at brand level. Some regard brand adoption as a two-stage process in which consumers first adopt the category, and then choose the brand (Givon, Mahajan, and Muller 1995; Hahn et al. 1994) based on factors other than internal communication such as promotion activities, price deals, and special offers. Despite the intuitive rationale of this approach, only rare attempts have been made to use it, partially because it requires high-quality, individual-level data.

The development of service markets and increased use of Customer Relationship Management (CRM) systems by service providers can facilitate data availability and promote the use of these types of models. Landsman and Givon (2010) used banking data to investigate the growth of financial products; and Weerahandi and Dalal (1992) used business-to-business data to study fax penetration. Liu and Gupta (2012) explored brand level diffusion in pharmaceutical markets through means of micro-level diffusion modeling. They identified how physician-oriented marketing activities, patient requests for a new drug, social contagion among physicians, and physician characteristics can predict the adaption probability of a new drug.

Although the relationships between brand-level and category-level adoption have not yet been clearly identified, the main body of literature has assumed that internal dynamics are important at the brand level, and therefore, a Bass-type model can be used to model brand choice. Mapping the communications flow in the market, one can say that a potential customer adopts the focal brand as an outcome of the combination of two alternative communication paths: ***within-brand communication*** with adopters of the focal brand; and ***cross-brand communication*** with adopters of other brands. Cross-brand communication can influence a consumer's choice of a brand in two ways: The consumer may receive negative information about the competing brands; or s/he may receive information about the category from adopters of other brands and subsequently adopt the focal brand because its marketing mix is most appealing. Two studies — Parker and Gatignon (1994) and Libai, Muller, and Peres (2009a) — examined the distinction between within- and cross-brand communication. Measuring for consumer goods and cellular services, these studies concluded that both within-brand and cross-brand influences exist. A similar communication breakdown can be conducted vis-à-vis generic and brand advertising (Bass et al. 2005).

Another conceptual issue in the modeling of brand-level diffusion relates to market potential. Some have assumed that the diffusion process operates in separate markets in which each firm draws from its own market potential; while others have assumed that both firms compete for the same market potential. The former assumption requires careful treatment and interpretation: If we assume that the market potentials of the two brands do not overlap, then the brands do not compete for the attention and wallets of the same potential consumers. On the other hand, if we assume that the market potentials of the brands do overlap, and the total market potential is the summation of the individual potentials, then this overall market potential overestimates the true potential, since the intersections should be subtracted from the overall count. Mahajan, Sharma, and Buzzell (1993) investigated the market potential issue through the Polaroid's lawsuit against Kodak, the latter having been accused of patent violation and attracting Polaroid's customers to a new brand of digital camera. By dividing the nonadopter pool into subpools according to the market potential of each brand, it was possible to filter out the effects of cannibalization vs. market expansion.

Within- and cross-brand influences occur even among brands that do not directly compete. Joshi, Reibstein, and Zhang (2009) consider a brand extension of a high-status market that comes up with a new, lower-status version of the product. According to that study, while the existing high-status market has a positive influence on the new market, the reciprocal social influence of the new, low-status market on the old market is negative. The example given is Porsche's entry into the SUV market: The target customers of the SUV Porsche were metrosexual males, who were negatively influenced by the profile of the category's existing adopters, such suburban households.

In addition to competing for market potential, firms can compete for one another's existing customers for multi-purchase products such as services, or a combination of products and services such as hardware / software in which both defection and network externalities exist either at the category level (Goldenberg, Libai and Muller 2010) or at the brand level (Binken and Stremersch 2009). Attrition and its consequences have been discussed in the CRM literature on mature markets (Neslin 2023). However, recent studies demonstrated that customer attrition can have a substantial effect on growing markets. Since most of the studies in the diffusion literature deal with durable goods, researchers have generally modeled the diffusion of services as if they were durable goods, and have not examined customer attrition. The exceptions are a few studies that attempted to incorporate churn into the diffusion framework (Libai, Muller, and Peres, 2009b; Hahn et al. 1994).

2.5 Evolution of methodologies

In terms of methodology, early papers used almost exclusively models of differential equations. While elegant and simple, differential equations gave way to more flexible modeling methods, both empirical and simulation: Cox (proportional) hazard models and agent-based models. There are two ways to integrate hazard modeling into innovation diffusion: The first is to reinterpret the Bass model as a hazard model by noting that the conditional probability of adoption given that the consumer has not adopted (the hazard rate) is linear in the number of previous adopters. A detailed explanation of this equivalence and how the marketing mix variables are added to the hazard model is given in Bass, Jain, and Krishnan (2000). The second way is to use the hazard model for discrete events in the product life cycle such as takeoff or saddles (Golder and Tellis 1997, 2004; Goldenberg, Libai, and Muller 2002).

Golder and Tellis (1997) applied a proportional hazard model to data that included 31 successful innovative product categories in the U.S. between 1898 (automobiles) and 1990 (direct broadcast satellite media). They found that the average time to takeoff for categories introduced after World War II was six years, and that average penetration at takeoff was 1.7% of market potential. Yet, this is not always the situation, as Dover, Goldenberg and Shapira (2012) showed, under heavily right-skewed degree distribution conditions (such as scale-free networks), the majority of adopters (in some cases, up to 75%) join the process after the sales peak. This strong asymmetry is a result of the unique interaction between the dissemination process and the degree distribution of its underlying network.

Later studies investigated factors that influence time to takeoff. Factors that have been found to accelerate takeoff include price reduction, product category (entertainment products take off faster than do white goods), and cultural dimensions such as a low level of uncertainty avoidance

(Tellis, Stremersch, and Yin 2003). Sign-up bonus as a strategy for adaptation across heterogeneous population was found to have mixed effects depending on whether it is limited or permanent in time and the age group it is targeted toward (Yang and Ching, 2014). Toubia, Goldenberg and Garcia (2014) showed how capturing social interactions through an individual-level hazard rate in a way that the resulting aggregate penetration process is available in closed form and nests extant diffusion models. This approach was also applied to the mixed influence model (Bass model) and asymmetric influence model successfully.

While a hazard model does provide several advantages including the ability to handle data right-censoring, it is still an aggregate approach, while increasingly the data are on the disaggregate level, such as data from social networks. One well known approach for describing individual adoption decisions and tying them to aggregate outcomes is agent-based modeling. As Rand and Rust (2011) note, if one looks at new products, the patterns of growth in the market that result from the interaction of many consumers might be much more complex than the adoption rules of these individuals. The advantage of the agent-based approach is that the modeling is conducted at the individual level, and does not require knowledge of or assumptions regarding the macro-dynamics.

Agent-based models describe the market as a collection of individual units (*agents*) interacting with each other through connections (*links*). The adoption behavior of each individual unit is determined by a decision rule. Neural networks, cellular automata, and small-world models are examples of agent-based modeling techniques. A typical agent-based model is the cellular automata of Goldenberg, Libai, and Muller (2001) where the individual consumer is an agent that receives a value of “0” if it has not yet adopted the product, and “1” if it has. Potential adopters adopt due to a combination of both external and internal influences in a pattern similar to that of the Bass framework. In the last two decades, agent-based models are increasingly being used in the marketing literature, particularly to examine issues related to new product growth (Delre et al. 2010; Garber et al. 2004). For more on agent-based modeling, its validation and verification, see Rand and Rust (2011).

Using agent based models has turned research attention to the importance of the underlying network structure. While aggregate level modeling had been agnostic with respect to the underlying social network's structure, agent-based model must represent the ties in the underlying social system. Therefore, research efforts have gradually shifted their focus to exploring the role of the social network's structural characteristics in various performance metrics of the innovation's growth. Borrowing from the field of industrial organization in economics, which defines itself as the effect of market structure on market performance, 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? Muller and Peres (2019) provide a comprehensive review of the research literature on this question.

In general, network characteristics can be divided into four classes[3]:

[3] Average degree is the average number of ties of a node, while Degree Distribution is the distribution of the degree across nodes where the measure often used is the extent to which the distribution is right-skewed. Clustering is a tendency of neighbors of the same node to be connected themselves. Degree Assortativity measures the extent to which nodes with similar numbers of ties are connected to each other. Tie Strength relates to the intensity of the connection between two network members, while Embeddedness is defined as the extent to which network members share common peers. Opinion Leaders are network members who are effective in persuading or influencing others, while Susceptibility is its mirror image, defined as responsiveness to communications. Degree Centrality relates to the number of ties a node has compared to other nodes in the network, while Closeness Centrality measures how close a node is to each of the other nodes in the network, and lastly, Betweenness Centrality measures the extent to which a node is an important intermediary between other members' connections in the social network.

1. *Global characteristics* such as average degree, degree distribution, clustering, and degree assortativity.
2. *Dyadic characteristics* such as tie strength and embeddedness.
3. *Individual characteristics* such as opinion leadership and susceptibility.
4. *Location characteristics* such as degree centrality, closeness centrality, and betweenness centrality.

Table 1: The effects of network characteristics on innovation performance*

Class	Characteristic	Effect	Representative paper(s)
Global	Average Degree	+ +	Delre et al (2007); Mukherjee (2014); Rand & Rust (2011)
	Degree Distribution	+	Peres (2014); Jackson & Yariv (2005)
	Clustering	±	Centola (2010); Bohlmann et al (2010); Peres (2014)
	Degree Assortativity	±	Haenlein & Libai (2013); Boguná & Pastor-Satorras (2002); Newman (2002)
Dyadic	Tie Strength	±	Goldenberg et al (2002); Onnela et al (2007); Landsman & Nitzan (2020)
	Embeddedness	+	Aral & Walker (2014); Kim & Rao (2022)
Individual	Opinion Leadership	+ +	Moldovan et al (2017); Iyengar et al (2011); Van Eck et al (2011)
	Susceptibility	+	Aral & Walker (2012)
Location	Degree Centrality	+ +	Yoganarasimhan (2012); Susarla et al (2012); Banerjee et al. (2013); Gelper, van der Lans & van Bruggen (2021)
	Closeness Centrality	+	Banerjee et al (2013); Mochalova et al (2013)
	Betweenness Centrality	+	Hinz et al. 2011; Mochalova et al (2013)

* Performance is usually measured in terms of the extent and speed of adoption. ++ and + indicate strong and weaker evidence respectively; A ± sign indicates the existence of evidence in both directions.

To see the difficulties in finding an unambiguous effect of network structure on innovation performance, consider the effect of clustering: The effect of clustering on diffusion depends 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 (Mukherjee 2014). Even without network externalities, if the threshold for adoption is high, or if the nature of the innovation is complicated, as in the case of in health innovations that involve behavioral changes, clustering can have a positive effect on the speed of adoption (Bohlmann, Calantone, and Zhao 2010) and the magnitude of growth (Centola 2010). On the other hand, when single communication is sufficient for social contagion, extensive simulations on real and artificial networks across a wide range of network and diffusion parameters found that clustering has a negative influence on the net present value of number of adopters (Peres 2014). Likewise, studies on the spread of epidemics have demonstrated how clustering negatively affects the final size of the infected population (Badham and Stocker 2010).

3. What's next?

Overall economic outcomes of diffusion processes are usually measured at the aggregate level. However, firms' marketing activities often take place at the individual level and are increasingly aimed at influencing the internal dynamics of the market such as influential programs and buzz campaigns. Maximizing or even just measuring their effectiveness requires a transition from aggregate-level to individual-level perspective both in practice as well as in research. This transition appears to be the main driver in current diffusion research.

The structure of the social network is the first factor taken into account when modeling individual-level decisions, since it directly influences the speed and spatial pattern of diffusion, and in turn, the firm's marketing decisions If, for example, the social system is comprised of isolated "islands" that hardly communicate with one other, the firm should launch the product separately in each such island in order to create global diffusion; whereas for other network structures, the firm might be better off enhancing internal communications.

A notable recent marketing phenomenon is firms' attempts to impact their customers' word-of-mouth processes via word-of-mouth agent campaigns, referral reward programs, influencer marketing, and viral marketing campaigns. In a world where social media is a means of mass communication, opinion leaders are now playing the role of word-to-mouth agents in campaigns in order to increase diffusion speed and efficiently reach large numbers of adopters. Cho, Hwang and Lee (2012) found that when looking for the right opinion leader for a campaign, many factors should be taken into account such as the leader's sociality and distance centrality while the product category should also be considered. The complex nature of word-of-mouth dynamics, including difficulties in following the spread of the effect of word of mouth and the lack of established ways to measure the effect, makes the financial justification for word-of-mouth programs a pressing issue, especially since such initiatives interact with traditional marketing efforts. Goel et al (2016) show how in Twitter, popular events regularly grow via both broadcast and viral mechanisms, as well as essentially all conceivable combinations of the two.

Using agent-based modeling, along with empirical verification via actual social networks, researchers are beginning to investigate approaches to quantifying the effects of word-of-mouth seeding programs. One potential means of quantifying the value of a member in such a program is to observe and measure that individual's ripple effect, i.e., the number of others that s/he affects directly, as well as and second- and third-degree "infections". Thus far, little has been done in terms of empirically measuring the effects of such programs in general, and as regards social networks in particular.

An additional network-related issue that we believe merits more research attention is network externalities. One of the surprising findings in the empirical literature thereon is the lack of empirical evidence on individuals' adoption threshold levels. For adoption to occur in the presence of network externalities, a potential adopter has to overcome two barriers: First, the consumer has to be convinced via the communication process that the product provides good value and fit. Second, s/he must be assured that the number of other adopters is such that the network product will indeed supply its potential value, i.e., it surpasses the consumer's individual threshold level. The shape of the thresholds' distributions within a population is of utmost importance to the speed of diffusion. Given that social threshold modeling is already well grounded in the sociological literature on collective action, one would imagine that the issue of threshold distribution is by now well established. Unfortunately, this is not the case, and empirical evidence in that sense is missing.

As for technological substitution, while models for the diffusion of technology generations have been around for a while, major questions remain unanswered. The first question relates to the substitution process: According to traditional approaches, the new generation eventually replaces the older generation; however, this is no longer the case. For many products, old and new generations coexist for a long time. In the mobile phone industry, the number of users of analog phones continued to increase long after digital technologies became available. Use of older handset types in emerging economies challenges manufacturers to cope simultaneously with multiple technology generations. The current models of technological substitution are restrictive in their treatment of the coexistence of multiple generations. They also provide little insight into other substitution issues such as leapfrog behavior, and the differences between adopter groups (e.g., new customers joining the category vs. upgraders). Moreover, generational shift at the brand level has not yet been tackled.

Current demographic changes are affecting cross-country influences and raising new challenges for global marketers. Diffusion of innovations in emerging economies is of increasing managerial interest, especially in industries such as telecommunications, where market potential in the developed world is about to approach its limit, while emerging economies present rapidly growing potential markets for innovations.

As competitive structures become complex, brand-level decision making becomes important in optimizing managerial decision making. Consider the scope of competition: Is there a single market potential from which all brands draw, or is it a reasonable working hypothesis that each brand has its own market potential? Since having a distinct market from which to draw customers implies that competitive pressures are relatively low, it would seem that when competition is intense, the common market potential hypothesis is more reasonable. Second is the question of the influence of competition along the distribution chain. In the mobile phone industry, for example, while competing service providers distribute the same handset model, third parties offer customers real-time auto-selection of the network with the best rate, so that customers use the services of multiple service providers. Extending the basic diffusion model to include both multiple layers and competition would improve descriptive and normative investigations of this matter.

The third is the still-open issue of brand choice as a one- or a two-stage process. If brand choice is a two-stage process in which consumer interactions are dominant in category choice, and special offers and advertising are dominant in choosing the brand, then straightforward application of a standard diffusion model on brand-level data is problematic. Although some insights into the brand choice process will derive from behavioral studies, diffusion modeling can combine choice and individual-level decisions and estimate their relative importance at each stage. Insights from such combined models might be striking in terms of marketing mix decisions.

The fourth issue deals with the nature of consumer interactions under competition. For example, the launch of the iPhone by Apple that relied heavily on word-of-mouth communication lifted not only iPhone, but the entire smart phone industry. While the distinction between consumer interactions at the category level and the brand level has received scant attention so far, it is crucial for managing the growth process.

Current network analysis research uses a variety of metrics to describe growth performance, yet generalization across scenarios and research projects requires standardization of the performance metric. We suggest using the net present value (namely, the discounted sum) of either the number of adopters, or the adoption profits (see for example Kumar, Petersen and Leone 2010; Libai Muller and Peres 2013). The net present value captures 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. Network research has also proposed numerous characteristics through which a social network's structure can be described. What is still missing is a refinement of 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.

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