4-21-2011

The Role of Influentials in the Diffusion of New Products

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THE ROLE OF INFLUENTIALS IN THE DIFFUSION OF NEW PRODUCTS

by

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Business Administration

The University of Memphis

May 2011

DEDICATION

For Katayoon, Ryan, Hooshang, and Mahin.

ACKNOWLEDGEMENTS

I will be indebted for life to many wonderful people who have guided, advised, encouraged, and supported me, making it possible to complete my doctoral studies and build the foundations for my career in the academia. I am deeply grateful to my mentors whose contributions to my intellectual development go far beyond their assistance with my dissertation. I have been privileged to work with Dr. Dan Sherrell and Dr. Emin Babakus, my dissertation committee co-chairpersons, whose advice and remarkable interest in my academic progress pinpointed and helped improve my weaknesses. Their patience in reading earlier versions of this dissertation provided invaluable suggestions for developing my ideas. Special thanks go to Dr. Mehdi Amini for his invaluable friendship, mentorship, interest, and support in my academic development. His encouragement and guidance during the course of my studies played a major role in forming my research. Also, I particularly thank Dr. Jeff Thieme for his support and advice on various topics and for his important insights into constructing this dissertation.

Many thanks go to the marketing and supply chain management faculty at the University of Memphis for all that I learned from them. Moreover, I thank my colleagues in the school and the extended network of scholars and doctoral students elsewhere whose friendships and intellectual discussions have been a key factor in my success. I also thank the administrative staff at the Fogelman College of Business and Economics, especially Ms. Jacqueline Woodall, for being kind and helpful in handling the administrative tasks related to my studies.

Tremendous gratitude goes to my family for their support throughout my life and particularly during the past few years. My parents and lifelong mentors, Hooshang and

Mahin, taught me to set high goals and work hard, despite initial difficulties and challenges. They will always remain my role models as wonderful human beings who are dedicated to our family and the society. After my wife and I were blessed with our son, Ryan, who was born while we were students, my parents and in-laws, Ahmad and Shahin, gave us remarkable moral support and encouragement and helped us provide a warm environment for Ryan during his first two years while we worked on our studies. Finally, I thank Katayoon, my wonderful wife and best friend, for her love, support, patience, sacrifice, understanding, and inspiration.

ABSTRACT

Ghoreishi Nejad E., S. Mohammad. Ph.D. The University of Memphis. May 2011. The Role of Influentials in the Diffusion of New Products. Dissertation co-major professors: Emin Babakus, Ph.D. and Daniel L. Sherrell, Ph.D.

This dissertation comprises three separate essays that deal with the role of influentials in the diffusion of new products. Influentials are a small group of consumers who are likely to play an important role in the diffusion of a new product through their propensity to adopt the product early and/or their persuasive influence on others' new product adoption decisions. The literature labels these consumers as opinion leaders, social hubs, innovators, early adopters, lead users, experts, market mavens, and boundary spanners. This dissertation integrates two perspectives that researchers have mostly studied independently: market-level, which investigates the spread of a new product (e.g., total number of products sold) across markets over time as a function of aggregate-level marketing and social parameters; and individual-level, which considers how to identify influentials and their impact on the adoption behaviors of others.

The first essay reviews and integrates the literature on the role of influentials in the diffusion of new products from a marketing management perspective. The study develops a framework using the individual- and market-level research perspectives to highlight five major interrelated areas: the two theoretical bases of why influentials have a high propensity to adopt new products early and why they considerably influence others' adoption decisions, the issues concerned with how marketers can identify influentials and effectively target them, and how significant individual-level processes lead to significant market-level behavior. The study synthesizes the relevant research

findings and suggests future research directions for improving our knowledge of the role of influentials in the diffusion of new products.

The second essay explores firms' decisions regarding the selection of target consumers for seeding—providing free products to enhance the diffusion process. The study examines the profit impact of targeting five groups of potential consumers for seeding under alternative social network structures. The findings suggest that seeding programs generally increase the net present value of profits. Moreover, social hubs—the most connected consumers—offer the best seeding target under most conditions that were examined. However, under certain conditions firms can achieve comparable results through random seeding and save the resources and effort required to identify the social hubs. Finally, the interactions among several variables—the choice of seeding target, consumer social network structure, and variable seeding cost—impact the returns that seeding programs generate and the 'optimal' number of giveaways.

The third essay explores the adverse impacts of three types of consumer resistance to new products—postponement, rejection, and opposition—on firm profits. The study investigates these effects across five groups of consumers and alternative social network structures. The findings suggest that complex interactions between three groups of parameters—resistance, consumer social network, and diffusion parameters—affect the relationship between resistance and profits. Moreover, opposition reduces firm profits to a degree that is significantly greater than rejection and postponement. Finally, influential resister groups generally have stronger adverse impacts on profits than do randomly designated resisters.

PREFACE

The chapters and the appendices in this dissertation conform to the style of Journal of Marketing.

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KEY TO ABBREVIATIONS

ABMS	Agent-Based Modeling and Simulation.
NPV	Net Present Value.
NPVR	NPV Ratio—The ratio of NPV of profits in a diffusion process with treatment—seeding or resistance—over the NPV of profits of the diffusion process in the same conditions without the effect of treatment.
WOM	Word-of-Mouth.

CHAPTER 1

Introduction

Long-term survival of firms depends heavily on the market success of their new products. On average, new products account for 32% of firms' sales and 31% of their profits (Hauser et al. 2006). However, between 40% and 90% of new products fail depending on the product category and criteria used for identifying failure (Barczak et al. 2009; Gourvilee 2006). Because this failure rate stems partly from slow or inadequate diffusion of new products, marketers have long been interested in enhancing the diffusion of their new products by understanding the role of influentials in this process. The literature labels these consumers as opinion leaders, social hubs, innovators, early adopters, lead users, experts, market mavens, and boundary spanners (Goldenberg et al. 2010; Iyengar et al. 2011; Keller and Berry 2003; Rogers 2003; Rosen 2009; Weimann 1994).

This interest has significantly increased recently because of several changes in the market. First, the number of new products introduced every year has grown considerably, leading to shorter product life cycles and greater competition among marketers (Chandrasekaran and Tellis 2007; Hauser et al. 2006). Second, overwhelming amounts of unsolicited information deluge U.S. consumers, about 1,000 commercial messages daily (Steenkamp et al. 1999). Third, consumers' attention to and the interpretation of communication messages such as advertisements depend greatly on their existing beliefs, attitudes, and motivations (Chaiken et al. 1996; Rogers 2003). Therefore, consumers might not even notice messages regarding a new product, let alone be influenced to adopt it (Rogers 2003). In addition, consumers have extensive sources of information that were unavailable in the past. Furthermore, advances in the Internet, Web 2.0, and telecommunication technologies not only have significantly increased the extent and types of social interactions between consumers, but also have provided new opportunities for firms to identify and reach influentials. Indeed, firms are now able to study their consumers' adoption behavior patterns using extensive information sources such as online and Web 2.0 data, loyalty cards, product warranty registrations, and scanner and transactional data.

Believing that influentials' opinions and new product adoptions significantly affect the diffusion process, marketers continue to invest significant resources in identifying and targeting these consumers (e.g.,Green 2008; McCarthy 2007). However, their efforts have been associated with a far higher number of failed marketing campaigns than with successful ones (Watts and Peretti 2007). The question has arisen of whether the effort involved in identifying and targeting influentials is worth the high cost (Robertson et al. 1984). A recent study raised serious doubts regarding the significance of influentials' impact on the diffusion process (Watts and Dodds 2007), leading researchers and practitioners to seriously debate the impact of influentials on innovation diffusion (Van den Bulte 2010). The disparity between the widely held belief that influentials play a critical role in diffusion and the evidence challenging the significance of this role clearly point to the need for further research.

Key Research Issues

An extensive review of the literature identified several issues relating to the research in the areas of influentials and the diffusion of innovations that are likely to account for this discrepancy. These issues were subsequently organized according to their importance and study feasibility.

Definitional Issues

Researchers have used alternative labels for influentials arising from the association of adoption decisions with various traits, behaviors, and characteristics of influentials. Several best-selling books have promoted the idea that a small group of individuals shape the opinions of most consumers because they have numerous social ties with others who trust them, they tend to be early adopters of new products, and they have wide market information (Gladwell 2000; Keller and Berry 2003). However, the various terms that refer to influentials generally refer to different groups of consumers. Table 1 in Chapter 2 lists these designations and shows the potential for confusing the characteristics and behaviors among these alternative terms.

The alternative definitions of influentials have important consequences for marketers. First, because of the differences between various groups of influentials, research findings are difficult to synthesize, which slows the knowledge accumulation process. Evidence supporting certain types of behaviors as characterizing influentials may not be significant under alternative definitions based on information versus use experience. Second, research studies have been grouped according to their definition of influentials, which potentially leads to under-examination of the full range of influentials' behaviors and characteristics and fragments the research literature. Finally, because these groups have similar characteristics, chances are high of confusing the characteristics, assumptions, and behaviors of different groups, which will likely add to the existing confusions and failed marketing activities.

Resolving the definitional issues is critical with respect to clarifying the similarities and differences and eliminating the possibility of confusing these various assumptions and behaviors. Researchers have urged the importance of clarifying the differences and similarities between different groups of influentials with regard to their adoption behaviors and the mechanisms of influencing others (e.g., Goldenberg et al. 2010).

Market versus Individual-Level Perspectives

Most studies have investigated the phenomenon from one of two perspectives: the market-level behavior (macro level), which explores the spread of an innovation (e.g., the total number of products sold) across markets over time as a function of aggregate-level marketing and social parameters (Chandrasekaran and Tellis 2007); and individual-level processes (micro level), which considers identification of influentials and their effect on others' adoption behaviors. Research evidence on new product diffusion at the market level suggests that for most consumer products, innovation diffusion patterns typically start with a small group of adopters, followed by an increasing number of the relevant market segment (Chandrasekaran and Tellis 2007). There is also research evidence suggesting that some consumers significantly influence others' adoptions (Iyengar et al. 2011) and that early adopters of innovations differ along a variety of dimensions at the individual level from those consumers who adopt at later stages of commercialization (Goldenberg et al. 2002; Moore 1991).

What is missing is a detailed explanation of the processes through which the assumed influence of influentials is transferred to the rest of the market. The result of this bifurcation of research focus is some knowledge about the characteristics and behaviors of influentials and their adoption decisions as well as some knowledge of the aggregate behavior of consumers' innovation adoption decisions over time. For the most part, however, the nature and characteristics of the processes involved in the transference of influentials' impact on the diffusion of new products at the market-level behavior over time remains unexamined. Without knowledge of these processes, marketers are left to their best guess about how to proceed in effectively influencing the market to adopt their new product submissions. Synthesizing the current literature to identify the gaps between these two groups of studies is of utmost importance.

Seeding Programs

Resolving the definitional issues and synthesizing the literature at the individual and market levels lead to the next challenge: applying definitions in marketing tactics. One frequently employed tactic is seeding, or giving free products to potential consumers to enhance the diffusion process, which is a common practice in industries such as music, software, publishing, electronics, and pharmaceuticals (Heiman and Muller 1996; Jain et al. 1995; Lehmann and Esteban-Bravo 2006; Rosen 2009). The success of many well-known products such as the best-selling novel *The Da Vinci Code*, 3M's Post-it® Notes, and Microsoft Windows 95® has been associated to a certain degree with implementing this tactic to target influentials (Kirby and Marsden 2005; Paumgarten 2003; Rosen 2009). In fact, U.S. firms dramatically increased their spending on free giveaways from $1.2 billion in 2001 to about $2.1 billion in 2009, making seeding the fastest-growing consumer products' promotion category (Odell 2009).

However, marketers face several challenges in designing these programs. First, seeding is expensive, so industry leaders face a key challenge financially justifying these programs (Libai et al. 2010; Wasserman 2008). Second, the choice of the most promising potential consumers (which group to target) remains unclear. Third, firms face two dilemmas in choosing the optimal number of free products to give away (how many). On one hand, excessive seeding dramatically increases costs and decreases returns. On the other hand, targeting too few consumers is unlikely to perceptibly affect diffusion. Fourth, research has failed to explore consumers' social network structures as they affect the returns seeding programs generate, quantities of free products a company should distribute, and selections of consumers to receive them. Recent studies found that social network structure significantly affects the successful diffusions of new products (Delre et al. 2010; Rahmandad and Sterman 2008).

Considering the heavy costs involved in giving products away and the existing uncertainties regarding the impact of influentials on the diffusion outcomes, investigating these challenges is of high priority.

Influentials' Resistance to Innovations

Clarifying these issues led to the next challenge: determining influentials' negative impacts on diffusion processes. Marketing researchers have not yet explored how different groups of influentials can interfere with new product success. By primarily focusing on influentials' facilitative effects in diffusing new products, researchers have ignored the harmful effects of their resistance, for three main reasons. First, only a small group of consumers express their negative impressions of new products to firms. Therefore, until recently, negative WOM would spread in the market without being noticed by marketers (Charlett et al. 1995; Goldenberg et al. 2007). Second, sales data do not capture negative influences (Moldovan and Goldenberg 2004); therefore, collecting data about influentials' negative effects is more challenging than it is for their positive impacts. Third, research on influentials has concentrated on finding tactics that support their positive effects on the success of new products in the market rather than on preventing influentials' negative effects leading to failure.

However, negative WOM can significantly hurt the diffusion of a new product and the revenues it generates. Negative WOM is arguably more powerful than positive WOM and affects the diffusion process in ways that are different from the effects of positive WOM (Goldenberg et al. 2007). Two main reasons explain this difference. First, the marketing literature generally suggests that negative WOM has a greater impact on potential consumers' adoption decisions than does positive WOM (e.g., Harrison-Walker 2001). Disappointed consumers talk to more people than do happy consumers (Anderson 1998), and people assign more weight to negative information than they give to positive information (Hart et al. 1990; Mizerski 1982). Second, because negative WOM circulation has a non-linear and adaptive nature, negative messages from even a small percentage of consumers potentially reaches many consumers rapidly.

Despite these differences and the issue's importance, few researchers have examined the adverse impact of influentials' resistance on the diffusion process (e.g., Leonard-Barton 1985; Moldovan and Goldenberg 2004). Considering that a high percentage of products fail every year, understanding the negative roles that influentials can play in the diffusion of a new product is of high priority.

Dissertation Organization

These four issues provide the basis for the studies in this dissertation. The three essays that comprise this dissertation address the issues that were highly ranked in terms of their importance and feasibility to study. Chapter 2, the first essay, reviews and integrates the literature on the role of influentials in the diffusion of new products from a marketing management perspective. Chapter 3, the second essay, examines the profit impacts of targeting influentials through a tactic called seeding—providing free products to enhance the diffusion process. Chapter 4, the third essay, investigates the adverse impacts of influentials' resistance to new products on the diffusion process and firm profits. Chapter 5 summarizes the overall findings of the three essays. Overall, this dissertation seeks to increase our understanding of the role that different groups of influentials play in the diffusion of new products by addressing important issues that account for the impact these groups have on the diffusion process.

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CHAPTER 2

THE ROLE OF INFLUENTIALS IN THE DIFFUSION OF NEW PRODUCTS: A CONCEPTUAL FRAMEWORK AND CRITICAL REVIEW

Abstract

This study reviews and synthesizes the literature on the role of influentials in the diffusion of new products. Influentials are defined as a small group of consumers who are likely to play an important role in the diffusion of a new product through their propensity to adopt the product early and/or their persuasive influence on others' new product adoption decisions. The study develops a framework using individual- and market-level research perspectives to highlight five major interrelated areas: the two theoretical bases of why influentials have a high propensity to adopt new products early and why they significantly influence others' adoption decisions; the issues concerned with how marketers can identify and effectively target influentials; and how significant individual-level processes lead to significant market-level behavior. The study synthesizes the relevant research findings and suggests future research directions for improving our knowledge on the role of influentials in the diffusion of new products.

Introduction

Long-term survival of firms depends on the success of their new products in the market. On average, new products account for 32% of firms' sales and 31% of their profits (Hauser et al. 2006). However, between 40% and 90% of new products fail (Barczak et al. 2009; Gourvilee 2006). Since this failure rate stems in part from slow or inadequate diffusion of the new product, marketers have long attempted to increase the likelihood of new product success by identifying and targeting the most promising groups of potential adopters (Kotler and Zaltman 1976).

Attempts to better understand these groups have primarily focused on their propensity to adopt early (e.g., Hauser et al. 2006) or their ability to influence others' adoption decisions (Iyengar et al. 2011). On one hand, the interest in potential adopters who have a propensity to adopt early is not only because they are more likely to adopt the new product and generate revenue, but because their new product adoptions exposes others to the new product (Rogers 2003). On the other hand, the opinions and behaviors of consumers who are able to influence others tend to significantly increase the number of new product adopters. Both groups are likely play important roles in the diffusion of new products. The literature generally refers to these consumers as influentials and alternatively labels them opinion leaders, market mavens, social hubs, boundary spanners, innovators, early adopters, lead users, and experts (Coulter et al. 2002; Feick and Price 1987; Goldenberg et al. 2006; Goldenberg et al. 2010; Iyengar et al. 2011; Rogers 2003; Rosen 2009; Watts and Peretti 2007; Weimann 1994).

Believing that influentials' opinions and new product adoptions significantly affect the diffusion process, marketers continue to invest significant resources in identifying and targeting these consumers (e.g.,Green 2008; McCarthy 2007a). However, a far higher number of failed marketing campaigns have been associated with these efforts than successful ones (Watts and Peretti 2007). The question has arisen of whether the effort involved in identifying and targeting influentials is worth the high cost (Robertson et al. 1984, p. 412). A recent study raised serious doubts regarding the significance of influentials' impact on the diffusion process (Watts and Dodds 2007). The disparity between the widely held belief that influentials play a critical role in diffusion and the evidence challenging the significance of this role clearly points to the need for further research.

This discrepancy between belief and evidence seems related to two important characteristics of research in the areas of influentials and the diffusion of innovations. First, researchers have used alternative labels for influentials arising from the association of adoption decisions with various traits, behaviors, and characteristics of influentials. Table 1 lists these designations and shows the potential for confusing the characteristics and behaviors among these alternative terms. Researchers have urged the importance of clarifying the similarities and differences between different groups of influentials (Goldenberg et al. 2010).

Second, most studies have investigated the phenomenon from one of two perspectives: market-level behavior (macro level), which explores the spread of an innovation (e.g., the total number of products sold) across markets over time as a function of aggregate-level marketing and social parameters (Chandrasekaran and Tellis 2007); and individual-level processes (micro level), which considers identification of influentials and their effect on the adoption behavior of others. Research evidence on new product

TABLE 1
Alternative Labels and Definitions of Influentials in the Literature

Term	Source	Definition / Market Characteristic
Influentials	Iyengar (2011, p. 1)	(A key assumption in network marketing is that) some consumers' adoptions and opinions have a disproportionate influence on others' adoptions
	Watts and Dodds (2007, p. 441)	A minority of individuals who influence an exceptional number of their peers
	Van den Bulte and Joshi (2007, p. 400)	(Market consists of two segments:) Influentials who are more in touch with new developments and who affect another segment of imitators whose own adoptions do not affect the influentials
	Weimann (1994, p.xiii)	The people who influence people
Innovators and early adopters	Rogers (2003, p. 280)	The first 2.5 percent of the individuals in a system to adopt an innovation are innovators. and the next 13.5 percent to adopt the new innovation are labeled early adopters. Definitions are based on distance (number of standard deviations) from the mean time of adoption of a normal distribution of adopters
	Mahajan and Muller (1998, p. 488, 489)	Groups of consumers who not only are likely to take the risk and adopt earlier than the rest of population, but acquire competence and knowledge about the product through direct experience with it (reworded by the author)
Experts	Goldenberg et al. (2006, p.67)	People who have wide knowledge and understanding of a specific product category
Market mavens	Feick and Price (1987, p.85)	Individuals who have information about many kinds of products, places to shop, and other facets of markets, and initiate discussions with consumers and respond to requests from consumers for market information
Social hubs (Connectors)	Barabasi (2002, p.56, 58)	Nodes with an anomalously large number of links (P. 56) In a society, a few connectors know an unusually large number of people (P. 58)
Social Connectors	Goldenberg et al. (2006, p. 67)	People who have many social connections and tend to talk to many people
Boundary Spanners	Burt (1999)	Individuals who fill structural holes in social networks and carry information across the social boundaries between groups (reworded by the author)
Opinion Leaders	Katz and lazarsfeld (1955, p.3)	Individuals who were likely to influence other persons in their immediate environment
	Rogers (2003, p.300)	Individuals who lead in influencing others' opinions
	Rogers (2003, p.388)	Opinion Leadership: The degree to which an individual is able to influence other individuals' attitudes or overt behavior informally in a desired way with a relative frequency
	Coulter et al. (2002, p. 1289)	Product specialists who provide other consumers with information about a particular product class
	Rogers and Cartano (1962, p. 435)	Individuals who exert an unequal amount of influence on the decisions of others

diffusion at the market level suggests that for most consumer products, innovation diffusion patterns typically start with a small group of adopters, followed by an increasing number of adopters within the relevant market segment (Chandrasekaran and Tellis 2007). So there is support at the aggregate market level for the bell-shaped adoption curve as suggested by Rogers (2003). There is also research evidence suggesting that some consumers significantly influence others' adoptions (Iyengar et al. 2011) and that early adopters of innovations differ along a variety of dimensions at the individual level from those consumers who adopt at later stages of commercialization (Moore 1991). The result of this bifurcation of research focus is some knowledge about the characteristics and behaviors of influentials and their adoption decisions as well as some knowledge of the aggregate behavior of consumers' innovation adoption decisions over time.

A small number of studies have examined the impact of influentials on the market-level outcomes of the diffusion (Goldenberg et al. 2009). However, for the most part the nature and characteristics of the processes involved in the transference of influentials' impact on the diffusion of new products to the market-level behavior over time remains unexamined. Without knowledge of these processes, marketers are left to their best guess about how to proceed in influencing the effective adoption of their new product submissions by the market.

This study offers an integrative view of influentials' impact on the diffusion of new products by bringing together and evaluating the research on diffusion, social influence, opinion leadership, and social networks. These research streams allow us to examine both the individual attributes and social influences on the spread of an innovation in the market. This review first explores the various definitions of influentials and the consequences of these definitions for marketers. This work uses a marketing management perspective to develop a framework for organizing and reviewing five main streams of research that are relevant to the explanation of the adoption and diffusion process. This framework is displayed in Figure 1.

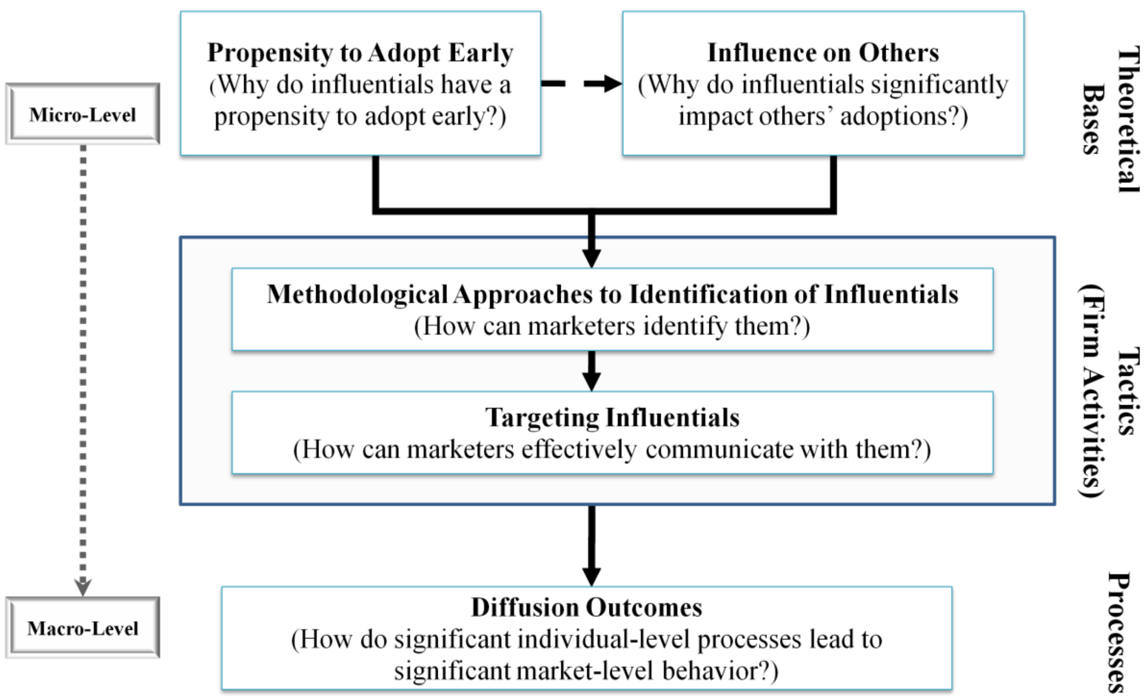

FIGURE 1

A Proposed Framework for Studying the Role of Influentials in the Diffusion Process

These five areas cover the two theoretical bases of consumer propensity to adopt a new product earlier than others and the ability to significantly influence other consumers' adoptions, which have guided research in this area; the issues concerned with how marketers can identify and effectively target influentials; and how significant individual-level processes lead to significant market-level behavior. For each area, the study reviews the literature, suggests interrelationships, and identifies gaps of knowledge in the literature which support future research directions. At this point, we turn to a consideration of how the research literature has defined Influentials.

Background

Marketing activities and social interactions among consumers facilitate the diffusion of a new product (e.g., Bass 1969; Mahajan et al. 1990a), and marketers have long attempted to increase the likelihood of new product success by finding and targeting the most promising groups of potential adopters (e.g., Iyengar et al. 2011; Lehmann and Esteban-Bravo 2006). In this regard, researchers have focused on the role of a small group of consumers, influentials, in the diffusion of a new product (e.g., Rogers 2003).

Researchers have used alternative labels for influential consumers arising from their various behaviors, assumptions, and expected impacts on the diffusion process. Table 1 lists these designations and shows the great possibility for confusing the characteristics and behaviors among these alternative terms. This paper addresses the potential for confusion by synthesizing the related literature and clarifying the similarities and differences among the alternative labels.

The various terms that refer to influential consumers generally reflect one or more of the following attributes: (a) product/market knowledge or experience (what they know), (b) strategic location in their social networks (whom they know), and (c) personification of certain values (who they are) (Weimann 1991). This study categorizes different groups of influential consumers according to these attributes, as shown in Table 2. A close inspection of Table 2 yields three key inferences. First, while alternative influential consumer groups differ significantly in their main attributes, some groups have similarities in their secondary attributes and in the roles they play in the diffusion process. These similarities increase the possibility of confusing these alternative labels. Second, these groups offer different implications for marketing. For example, while early adopters have the potential to generate revenue at early stages of diffusion, social hubs are capable of introducing the product to a large group of potential consumers. Finally, the marketing literature has frequently discussed and used the first two attributes—knowledge or experience and location in social network—to characterize influentials. The literature disregards the third trait, which relates to individual characteristics such as charisma or persuasiveness, and does not use this trait individually to characterize a specific group of influentials. However, studies find that charisma is a characteristic of persuasive individuals who act as role models for others (Conger and Kanungo 1998), and it could be used to study influentials' behaviors. The rest of this section discusses alternative influential consumer groups according to their main attributes.

Influence Based on Knowledge, Expertise, or Experience

Marketing literature identifies three groups of influentials with regard to their knowledge or expertise: experts; innovators and early adopters; and market mavens. Experts are people who are knowledgeable about a specific product category (Goldenberg et al. 2006). Innovators and early adopters (hereafter referred to as early adopters) are consumers who not only are likely to take the risk and adopt earlier than

TABLE 2
Comparison of Relevant Dimensions for Classifying Influential Consumers

Influential Consumer Group	Aspect of Influence	Distinguishing Attribute(s)	Other Dimensions/Roles	Notes
Early Adopters	Knowledge, Expertise, or Experience	Likely to adopt earlier than others	• Introduce a new product to market • Gain expertise and knowledge through experiencing the new product	• Are they identifiable *ex ante* as a segment under conventional definitions? • Is it feasible to segment consumers based on consumer innovativeness?
Market Mavens		Market information regarding different types of products and shopping places		• Appropriate for spreading news about changes in marketing mix and product assortments (e.g., retailers)
Experts		Product knowledge and expertise with the product		• Studies used various consumer knowledge conceptualizations: objective and subjective knowledge and experience • Is it feasible to identify non-formal experts?
Heavy/Light Users		Level of existing products usage	• Heavy users: Influential in the case of high risk/involvement products • Light users: Influential in the case of low risk/involvement products	• Only two empirical studies • Easily identifiable for consumer products using scanner data, loyalty cards, and product warranty registration, in addition to products such as pharmaceuticals
Social Hubs	Strategic Location in Social Network	Significantly higher than average number of social ties	• Likely to become aware earlier than others • Expand speed of diffusion and size of final market	• Appropriate target for spreading a marketing message to masses and increasing awareness
Boundary Spanners		Connecting two otherwise disconnected consumer groups	Introduce new products and ideas between groups	• Empirical studies find major impact on diffusion process • Identification is difficult, unless social network can be mapped
Opinion Leaders	A Combination of Personification, Expertise, and Location in Social Network	Highly influence other consumers' adoption of new products	High product category involvement (familiarity, interest, and knowledge), wide sources of information, high information processing skills, gregariousness, similarity with others	• Studied for a relatively long time • Differ from one product category to another • Wide range of characteristics has been discussed

others but who also acquire competence and knowledge about the product through direct experience with it (Rogers 2003; Van den Bulte and Joshi 2007). Market mavens are individuals who have vast up-to-date market information regarding different types of products and shopping places (Feick and Price 1987).

Another way to characterize influentials using their experience is by whether they are heavy or light users of existing products. Heavy users are persuasive in the case of high-involvement products because of the knowledge they gain from their extensive experience with the product. Potential consumers who are in contact with heavy users are usually already aware of the new product shortly after its release through these consumers. Light users, in contrast, are more likely to increase awareness by spreading the information to people who are not aware of the product (Godes and Mayzlin 2009; Iyengar et al. 2011).

Influence Based on Strategic Location in the Social Network

Two groups of influentials—social hubs and boundary spanners—hold strategic locations in their social networks. Social hubs, or connectors, are consumers who have a significantly higher than average number of social ties (Barabasi 2002). Boundary spanners are individuals who span structural holes in the social network and transfer information across the social boundaries between groups (Burt 1999). The influence of boundary spanners comes from holding a unique position in the social network and connecting two otherwise disconnected social groups (Burt 1997; Iyengar et al. 2011; Roch 2005). Product expertise, or having direct use experience with the product, is not a required factor for this group of influentials. Innovation-related information regarding the new product may be used as a substitute.

Influence Based on Combination of Various Characteristics

Finally, the literature generally defines opinion leaders as individuals who are able to frequently influence attitudes or behavior of other people who are in direct contact with them (Rogers 2003). First described in the two-step flow model (Katz and Lazarsfeld 1955), opinion leaders, to some degree, possess any or all of the preceding three characteristics—knowledge or experience, strategic location in social networks, and personification of certain values. The literature generally suggests that opinion leaders influence others' decisions in a limited number of domains and does not support the notion of generalized opinion leaders. Studies in marketing, communication, sociology, politics, health, fashion, and public policy have extensively investigated the importance of opinion leaders (Weimann 1994).

A Comprehensive Definition of Influentials

A close inspection of the various definitions in Table 2 yields two key dimensions that the marketing literature has focused on: propensity to adopt early (e.g., Hauser et al. 2006) and the ability to influence other consumers' adoption decisions (Iyengar et al. 2011). From a marketing management perspective, both dimensions are important in choosing a group of consumers to target. In fact, the benefit of targeting consumers who have a propensity to adopt early flows not only from their higher chances of adopting the new product, but also from the modeling influence their adoption has on other consumers' new product adoptions (Mahajan and Muller 1998; Rogers 2003).

The definition of influentials this study uses is: *a small group of consumers who are likely to play an important role in the diffusion of a new product through their propensity to adopt the product early and/or their persuasive influence on others' new* *product adoption decisions*. This definition not only encompasses both dimensions; it also focuses on a broader perspective—the impact of the individuals on diffusion of a new product, which is the firm's main criterion for attention to influentials. The following two sections describe each of the two fundamental characteristics of influentials in more detail.

Propensity to Adopt Early

To increase the probability of selling their new products, firms target their marketing activities toward consumers who have the highest propensity to adopt these products. This propensity is referred to as consumer innovativeness (Hauser et al. 2006, p. 689), which is the fundamental construct of diffusion theory (Midgley and Dowling 1978). However, no consensus exists regarding the definition of consumer innovativeness or its theoretical roots (Roehrich 2004).

Table 3 provides frequently cited definitions of this construct and highlights strengths and weaknesses of each definition. As this table indicates, definitions of consumer innovativeness differ in their theoretical underpinnings and vary in their focus from operational to individual traits. Moreover, the table reveals that innate innovativeness, a personality trait, differs from early adoption behavior. The literature suggests that innate innovativeness can be considered to be an underlying property of early adoption behavior (Hirschman 1980; Im et al. 2007; Midgley 1977).

Researchers have used various theoretical perspectives and proposed diverse conceptual models to explain new product adoption decision processes (e.g., Gatignon and Robertson 1991) and the relationship between innate innovativeness and early adoption behavior (Hirschman 1980; Im et al. 2003; Im et al. 2007; Midgley and Dowling

1978). However, the literature offers no framework for integrating different theoretical bases with respect to why influentials are more likely to adopt a new product earlier than others (Hauser et al. 2006). As a step toward development of such a framework, Table 4 reviews and summarizes related theories and explanations. As this table indicates, the underlying theories and conceptual models fall into three groups—individual difference variables, market/segment characteristics, and social attributes. The focus here is on the question of why some consumers adopt early in the diffusion process and not the more general question of why consumers adopt new products. In this paper, the term "consumer propensity to adopt" refers to the likelihood of a consumer to adopt a new product earlier than others.

Discussion of these theories requires an acknowledgment that new product adoption is not a simple, one-stage process. Generally, potential customers go through at least two main stages before deciding to adopt or reject a new product—knowledge and persuasion (Rogers 2003). At the knowledge stage (also referred to as awareness), an individual learns about the existence of a new product and forms a general understanding of its functionality. At the persuasion stage, potential customers form a positive or negative attitude toward the new product. Studies often do not differentiate between the stages in the adoption process.

Individual Difference Variables

Investigators have typically used six individual difference variables to explain consumer propensity to adopt a new product. Four variables consider propensity to adopt to be a personality trait: novelty seeking, need for uniqueness, independence of decision making, and need for stimulation (e.g., Hirschman 1980; Steenkamp et al. 1999). The other two

TABLE 3
Various Definitions of Consumer Innovativeness in the Literature

Source	Definition / Explanation	Evaluative Comments
Rogers (2003, p. 22) Rogers and Shoemaker (1971, p. 27)	The degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a system	**Strengths:** Useful, defining innovation as "an idea, practice or object perceived as new by an individual" **Weaknesses:** Actual time of adoption is the identification measure, an operational definition
Midgley and Dowling (1978, p. 236)	The degree to which an individual is receptive to new ideas and makes innovation decisions independently of communicated experience of others"	**Strength:** Introduces independence to communication as a consistent phenomenon in innovativeness **Weakness:** Ignoring causes behind innovativeness, does not explain why consumers differ in terms of their innovativeness, focuses solely on communication side and ignores other dynamics
Roehrich (2004, p. 671)	Tendency to buy new products more often and more quickly than others	**Strength:** Includes the frequency of adopting new products, definition as being relative to others is useful for firms **Weakness:** Definition as relative to others is ambiguous and an operational definition
Hauser et al. (2006, p. 689)	The propensity of consumers to adopt new products	**Note:** Appropriate level of abstraction; general at an adequate level
Midgley and Dowling (1978) Hirchman (1980, p. 285)	Generalized, inherent, or innate innovativeness: An individual trait or predisposition to adopt early* Actualized innovativeness or innovative behavior: Adopting new products earlier than others. It has two stages: Adoptive innovativeness: Actual adoption of a new product Vicarious Innovativeness: Acquisition of information about a new product* * Reworded by the author	**Notes:** Explains a distinction between consumer innovativeness as a personality trait and actualized innovativeness. Distinguishes between the two stages of actualized innovativeness. These two are likely to tap into the two main stages of adoption decision process: knowledge and persuasion

TABLE 4
Theoretical Bases for Consumer Propensity to Adopt

Category	Theory/Conceptual Bases	References	Notes
Individual Difference Variables	Novelty Seeking	1,2,3	Important at early stages of adoption process
	Need for Uniqueness	4,5,6,7	Satisfied easily by new product adoption with little risk of hurting social relationships
	Independence of Decision Making	3,8,9,10,11	Views Innovativeness from a communications perspective A trait that is expected to be consistent across different new product adoption situations Important at later stages of adoption (i.e., persuasion)
	Need for Stimulation	12,13,14,15	Very basic (abstract) reason for many human behaviors, which can be satisfied by the adoption decision process
	Product Expertise	21, 22	Experts have better comprehension of incremental innovations, but have difficulty with understanding radical innovations
	Economic Status	23, 24, 25	Driver of early adoption, both for intra-markets and inter-markets
Market/Segment Characteristics	Chasm Framework	15, 16, 17	Technology markets consist of two separate market segments
	Two-Step Flow Model	18, 19	Opinion leaders mediate between mass media and mass consumers
Social Attributes	Social Competition	26, 28	Consumers adopt new product to gain or maintain their social status. Happens between consumers with similar social ties in social network
	Social Capital	28, 29, 30	Number of Social Ties: In touch with more people to obtain information
		31, 32, 33	Spanning Social Network Holes: Information advantage over average consumers because of having social ties to various groups

References:
1- Hirschman (1980) 2- Pearson (1970) 3- Manning et al. (1995) 4- Fromkin (1971) 5- Ruvio (2008) 6- Roehrich (2004) 7- Snyder (1980) 8- Midgley and Dowling (1978) 9- Midgley (1977) 10- Midgley and Dowling (1993) 11- Manning et al. (1995) 12- Venkatesan (1973) 13- Raju (1980) 14- Joachimsthaler and Lastovicka (1984) 15- Mittelstaedt et al. (1976) 16- Goldenberg et al. (2002) 17- Muller and Yogev (2006) 18- Katz and Lazarsfeld (1955) 19- Weimann (1994) 21- Alba and Hutchinson (1987) 22-Moreau et al. (2001) 23-Chandrasekaran and Tellis (2007) 24-Rogers (2003) 25- Van den Bulte and Stremersch (2004) 26-Burt (1987) 27- Burt (1999) 28- Van den Bulte and Wuyts 2007 29-Goldenberg et al. (2009) 30-Richmond (1977) 31-Burt 1987 32- Granovetter (1974) 33- Roch (2005)

variables are consumer product knowledge and expertise and economic status.

Novelty seeking. Novelty seeking is an internal drive, tendency, or motivation force in people to seek out new information and experiences (Hirschman 1980; Pearson 1970). Hirschman (1980) conceptualizes propensity to adopt as consumers' desire to obtain new information about innovations. She further argues that, as a personality trait, innate innovativeness is conceptually indistinguishable from innate novelty seeking. Other research finds a positive relationship between novelty seeking and awareness at early stages of diffusion (Manning et al. 1995), and that early adopters have more desire to experience novel stimuli than other consumers (Goldsmith 1984).

Need for uniqueness. Possession of a novel product, especially if it is highly visible, distinguishes one from others and, therefore, can be an easy way to satisfy consumers' need for uniqueness (Fromkin 1971). Moreover, early adoption of new products is a safe way for consumers to satisfy their need for uniqueness without hurting their social relationships (Ruvio 2008). Research has shown a positive relationship between the need for uniqueness and propensity to adopt fashion products (Workman and Caldwell 2007).

In addition, need for uniqueness affects consumer propensity to adopt a new product by influencing consumers' independence of judgment and their perceptions of being different from others (Roehrich 2004; Snyder and Fromkin 1980).

Independence of decision making. From a communication perspective, propensity to adopt is "the degree to which an individual is receptive to new ideas and makes innovation decisions independently of communicated experience of others" (Midgley and Dowling 1978, p. 236). Adopters are few in the early stages of diffusion, and they adopt the product with little or no social influence. Thus, early adopters, as those who repeatedly adopt new products early, must have little reliance on other consumers' communicated experiences in making adoption decisions (Midgley 1977; Midgley and Dowling 1978). This view is supported by other perspectives. The social characters' literature differentiates between individuals who make their decisions on the basis of their peers' opinions, labeled as other-directed actors, and those who have internalized goals, labeled as autonomous and inner-directed actors (e.g., Riesman 1950).

Middle-status conformity theory asserts that two groups of individuals are comfortable deviating from the social norms: high-status actors, who have high confidence in their social acceptance, and low-status actors, who perceive their social status to be already hurt. Middle-status actors, on the other hand, try to maintain their status by displaying acts that their peers approve of and, consequently, are highly influenced by others (e.g., Dittes and Kelley 1956; Phillips and Zuckerman 2001). Finally, empirical evidence indicates that early adopters and laggards make their decisions independent of others' adoptions, whereas reference groups— which might differ from one innovation to another—influence middle-stage adopters (Burt 1987).

Although Midgley and Dowling (1993) found empirical support for this theoretical perspective, several other empirical studies find weak or even negative correlations between independence of judgment on one hand and receptivity to new ideas, tendency toward newness, and possession of new products on the other (Roehrich 2004). This inconsistency might stem from the importance of independent judgment in the later stages of the adoption process (i.e., persuasion), whereas receptivity and tendency toward new ideas are more important at the early stages (Manning et al. 1995).

However, researchers have argued that independence in judgment cannot be empirically tested as a construct (Roehrich 2004).

In conclusion, strong theoretical bases support the role of independence of judgment in propensity to adopt. Future research must clarify the inconsistencies related to the conditions and the adoption stage in which this characteristic affects consumers' adoptions. The inconsistencies might be due to the exclusion of important control variables, such as distinguishing between stages of adoption decision or different product and innovation types.

Need for stimulation. Adoption of a new product can satisfy the need for stimulation (Venkatesan 1973). Innate consumer innovativeness, as a personality trait, might be a mediating variable between the need for stimulation, as a higher order trait, and consumer propensity to adopt (Raju 1980). This position is supported by several empirical studies (e.g., Joachimsthaler and Lastovicka 1984; Mittelstaedt et al. 1976).

Product knowledge and expertise. Expertise has five aspects: cognitive effort, cognitive structure, analysis, elaboration, and memory (Alba and Hutchinson 1987). These aspects enable an expert to analyze and comprehend complexities regarding new products more deeply and with less effort. Therefore, expert consumers plausibly respond differently to marketing messages than novices.

However, the relationship between expertise and propensity to adopt seems to be complex and is highly susceptible to the effect of innovation type. For continuous innovations, experts show higher levels of comprehension, can think of more net benefits, and are more likely to adopt early. In contrast, for radical innovations experts have lower comprehension, fewer expected net benefits, and lower preferences compared with those of non-experts (Moreau et al. 2001). This irregularity results because the characteristics and attributes of radical innovations differ significantly from those of earlier products. Since these characteristics do not fit with the already established structure in the mind of experts, experts have difficulty comprehending the benefits. Therefore, in communicating with experts regarding radical innovations, marketers must clearly relate the benefits of new products to those of the existing products (Moreau et al. 2001).

Economics. Economic factors significantly affect the adoption of new products. This impact occurs in both intra-markets, where early adopters generally have higher financial resources, and inter-markets, where new products diffuse more quickly in markets with higher economic status (e.g., Chandrasekaran and Tellis 2007; Rogers 2003; Van den Bulte and Stremersch 2004).

The average price of a new product at takeoff is 63% of that at commercialization and 30% of that at slowdown (Chandrasekaran and Tellis 2007). Therefore, consumers who adopt early pay more for new products than others who adopt later. Consumers with high financial status not only can afford to pay the higher price, but can also take the financial and performance risks associated with adopting a new product earlier than other consumers (Rogers 2003).

Market/Segment Characteristics

The chasm framework and the two-step flow model suggest that various groups of consumers have a high propensity to adopt early. This section reviews and summarizes the literature as it relates to the focus of this section.

Chasm framework and two-segment markets. According to this framework, technology markets consist of two separate markets—the early market, consisting of knowledgeable or risk-seeking consumers, and the main market, consisting of risk-averse decision makers (Moore 1991). Saddle phenomenon, or a temporary slowing of new product sales after initial takeoff, empirically supports this framework (e.g., Goldenberg et al. 2002b; Muller and Yogev 2006). Recent studies have developed two-segment market diffusion models that fit the data better than earlier one-segment models (e.g., Vakratsas and Kolsarici 2008; Van den Bulte and Joshi 2007). Several markets consist of two segments, including technology, pharmaceuticals, entertainment, teenagers (Van den Bulte and Joshi 2007).

Numerous studies consider the characteristics of early adopters. These consumers have the ability to understand and apply complex technical knowledge and also cope with the high degree of uncertainty associated with new products (Rogers 2003). They are highly interested in new ideas, follow related scientific developments, and pay more attention to commercials and professional information sources than other consumers do. Despite possible geographical distances, they also connect with others who have similar interests (Coleman et al. 1966; Fisher and Price 1992; Goldsmith et al. 2003; Mahajan et al. 1990b; Rogers 2003).

Two-step flow model. This model designates two groups of individuals: opinion leaders (i.e., influentials), who have high exposure to media and influence another group of individuals, who have less exposure (Katz and Lazarsfeld 1955). Extensive studies in marketing find that influentials have high levels of product familiarity, interest, and knowledge that researchers generally characterize as involvement with product category. Their exposure to media is heavy, and they pay more attention to product-related messages than other consumers do (e.g., Coulter et al. 2002; Katz and Lazarsfeld 1955;

Weimann 1994). They not only pay attention to specific journals but comprehend, accept, and retain information from ads in these journals more than others do (Vernette 2004).

However, not all opinion leaders have a propensity to adopt early. While some are early adopters, others only mediate between early adopters and other consumers (e.g., Schrank and Gilmore 1973). Importantly, early adopters and opinion leaders are two distinct groups of consumers. Further, as Figure 2 suggests, a subgroup of consumers possesses characteristics of both groups. All three groups are important in the diffusion process: early adopters are “non-personal influencers,” opinion leaders are “interpersonal communicators,” and the subgroup members are the “change agents” (Venkatraman 1989). In general, opinion leaders seem to be more conservative and conform more to social norms, while early adopters are more risk-seeking and conform less to social norms (Rogers 2003).

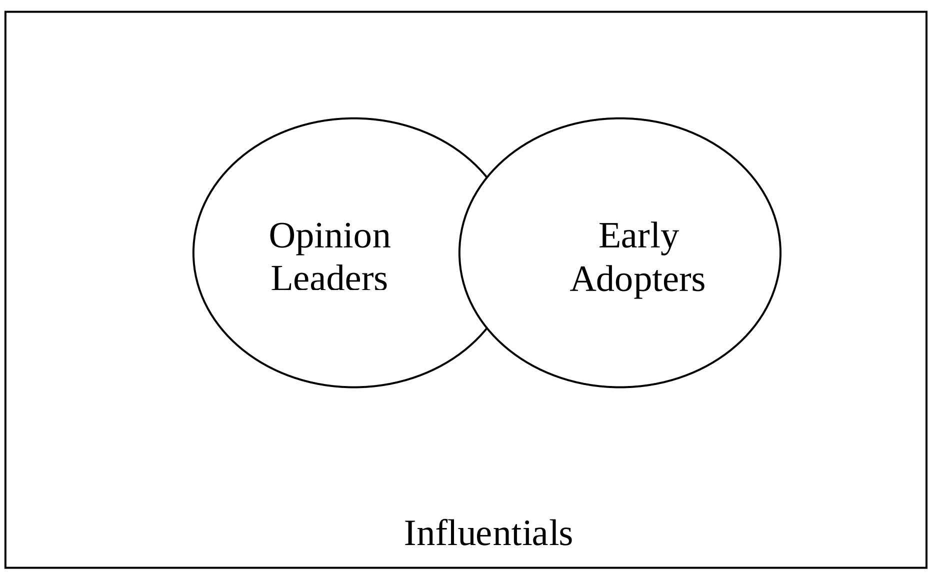

FIGURE 2
Influentials Characterized as Opinion Leaders, According to Two-Step Flow Model, or Early Adopters, According to Chasm Framework

Social attributes

Studies regarding social competition and consumer social capital suggest the social attributes of consumers contribute to a propensity to adopt new products earlier than others.

Social competition Consumers adopt new products not just to enjoy functional benefits but to create and maintain their social identity (Bourdieu 1984). Researchers have long been aware that seeking and maintaining social status is a main driver of new product adoptions (e.g., Trade 1903), and high-status consumers tend to adopt prestigious new products earlier than others to maintain their social identity. If someone of similar social status adopts a new product first, they become concerned with losing their current status and quickly adopt the product or a similar one. From a social network perspective, social competition develops among individuals who have similar social ties and belong to the same social groups (Burt 1987). Status motivation seems to be stronger in consumers who adopt the product earlier in the diffusion process than in those who adopt it at later stages (Rogers 2003).

Consumer social capital. According to the social capital literature, holding a strategic position in a social network gives a consumer advantages over others in terms of having access to information (Van den Bulte and Wuyts 2007). In relation to the focus of this paper, two positions based on social capital are the result of spanning structural holes in social networks (Burt 1999) and having large number of social ties (Ball et al. 2001).

Consumers who span structural holes in social networks—boundary spanners—have social ties with otherwise disconnected groups. Studies have found that information spreads faster within groups than between groups (e.g., Godes and Mayzlin 2004) and that individuals who bridge structural holes are likely to have information advantages over their group members (Burt 1992). Therefore, boundary spanners are likely to be the first in their group to become aware of a new product and learn about its advantages and disadvantages (Burt 1987; Granovetter 1974; Roch 2005). A recent empirical study on schoolchildren finds that early adopters have multiple ties to different social groups (Kratzer and Lettl 2009).

Consumers with large numbers of social ties—social hubs—also on average adopt earlier than others because they are in touch with more people than average consumers, giving them access to more information. Being in touch with many other consumers, they also have higher chances of spanning structural holes and acting as boundary spanners (Goldenberg et al. 2009). Even if social hubs are not early adopters themselves, they have greater chances than average consumers of becoming exposed to early adopters. Consumers who are in contact with early adopters are likely to adopt earlier than others (e.g., Coleman et al. 1966; Iyengar et al. 2011). Their propensity to adopt early does not necessarily arise from their personality traits, but rather from their strategic position in their social network (Richmond 1977).

Propensity to Adopt Early: Discussion and Future Research

Three theoretical bases explain influentials' propensity to adopt a new product earlier than others: individual difference variables, market/segment characteristics, and social attributes. The theories provide a basis for synthesizing the literature concerning the question of why influential consumers have a propensity to adopt early. As Table 5 indicates, influential consumers exhibit different adoption behaviors and also differ in terms of their propensities to adopt early. Influential consumers also vary in the ways they become aware of new products, the reasons for which they adopt new products earlier than others, and the timing for their adoption of a new product. Marketing researchers and practitioners must pay careful attention to these differences, both in their studies and in making decisions regarding the group to target.

The information in Table 5 and the synthesis of theoretical backgrounds in this section support this study's definition of influentials by suggesting that consumer propensity to adopt early is a characteristic possessed in varying degrees by consumers who are likely to affect the diffusion process.

Future research could lead to integration of these theories and development of a parsimonious theoretical model for consumers' early adoption of new products. Such research must provide explanations for why measurements of certain dimensions, such as independence of decision making, have little to no predictive validity (Roehrich 2004). As Table 5 indicates, a number of considerations relate to the development of such a framework:

- Integrating the three groups of theories to explain propensity to adopt new products.
- Providing criteria for segmenting consumers with respect to their adoption behaviors.
- Distinguishing between the knowledge and persuasion stages of the adoption process in addition to considering important control variables such as innovation type (incremental or radical), product category, and culture. Some of the conflicting results are likely to be due to exclusion of these variables.

TABLE 5
Propensity to Adopt Early: Status of Existing Literature, Gaps, and Future Research Opportunities

Influential Consumer Group	Propensity to Adopt Early			Gaps and Future Research
	Individual Difference Variables	Market-Segment Characteristics	Social Networks	
Early Market Adopters	Novelty Seeking, Favorable attitude towards change (1, 20); Independence of Decision Making (21); Technical skills/knowledge (1)	Chasm Framework (22); Higher than average socioeconomic statuses (1); Less sensitivity to price (2; 3); Higher risk tolerance (1); Product interest, attention to messages (1, 2, 4)	Connect with others who have similar interests no matter of their geographical distance (1, 5)	Need an integrative theoretical framework that is both comprehensive and parsimonious. Important aspects for consideration include: • Integrating the three groups of theories to explain propensity to adopt new products • New conceptualization of consumer innovativeness • Providing a criteria for segmenting consumers • Incorporating both adoption and rejection as potential decisions • Explaining conditions and control variables that moderate the relative importance of the three theoretical backgrounds • Differentiating between stages of adoption decision • Interactions between intrinsic and extrinsic motivations
Heavy/Light Users		Heavy Users: Likely to have product knowledge due to experience (16, 20)		
Experts	For incremental innovations: Higher levels of comprehension, can think of more net benefits. This does not hold true for radical innovations (17)			
Market Mavens		General market information, attention to coupons, retail magazines, direct mails (6; 7; 8) Early Awareness (11); Significant time and money spent on shopping, larger evoked sets (9; 10)		
Social Hubs			Information due to being in contact with many consumers (19)	
Boundary Spanners			Information due to being member of different groups (18)	
Opinion Leaders	Some are also innovators, some only mediate between innovators and others (15)	Two-step flow model (23); Conform to social norms, product familiarity, interest, knowledge, media exposure, information processing skills (12,13); Comprehension, acceptance and retention of ads (14)	Wide personal sources of information (12)	

References:
1- Rogers (2003) 2- Goldsmith et al. (2003) 3- Goldsmith and Newell (1997) 4- Mahajan et al. (1990) b 5- Fisher and Price (1992) 6- Feick and Price (1987) 7- Price and Feick (1988) 8- Higie et al. (1987) 9- Elliott and Warfield (1993) 10- Goldsmith and De Witt (2003) 11- Pornpitakpan (2004) 12- Weimann (1994) 13- Coulter et al. (2002) 14- Vernette (2004) 15 - Schrank and Gilmore (1973) 16- Iyenger et al. (2008) 17-Moreau et al. (2001) 18- Burt (1999) 19- Goldenberg et al. (2009) 20- Hirschman (1980) 21- Midgley and Dowling (1978) 22- Moore (1991) 23- Katz and Lazarsfeld (1955)

- Considering the interactions between intrinsic motivations (e.g., involvement with product category) and extrinsic motivations (e.g., others' expectations of the consumer's knowledge) of consumer propensity to adopt.

Influence on Others

Firms pay special attention to influentials for several reasons. First, modern consumers receive an overwhelming amount of unsolicited information about new products. In the U.S., consumers are exposed to about 1,000 commercial messages every day (Kotler 2003), and consumers' attention to communication messages such as advertisements and their interpretation of these messages depend primarily on their existing attitudes, beliefs, and motivations (Chaiken et al. 1996; Rogers 2003). Therefore, verbal or visual exposure to a message regarding a new product might not even lead to awareness about it, let alone persuasion to adopt it (Rogers 2003). In addition, consumers today have access to extensive sources of information that were unavailable in the past. Advances in the Internet, Web 2.0, and telecommunication technologies have not only significantly increased social interactions between consumers but have also provided new opportunities for identifying and reaching influentials. By focusing on influentials, firms seek to influence consumers' adoption decisions at both stages of knowledge and persuasion. Furthermore, marketing through WOM and social influence has a longer effect than traditional marketing activities such as advertising (Trusov et al. 2009).

This section reviews theories of social influence and social networks and offers a categorization of consumers' influence on adoption decisions of others. Table 6 shows four means of influencing that give rise to categories: contact, socialization, social norms, and social competition. As this table suggests, these mechanisms not only take place under different conditions but also differ in the theoretical underpinnings that explain how they influence potential consumers' decisions. This section applies these four mechanisms to organize the effects that influential consumers exert on others and suggests directions for future research.

Source of a Message

The influence of a message often depends on the receiver's perceptions of its source (Hovland et al. 1953; Johnson et al. 2005; Pornpitakpan 2004). The source can affect the attention given to a message, the interpretation of its content, the acceptance of the message, or the weight of the message relative to other available information. The source of a message affects both the disposition of an attitude and the confidence the receiver has in this disposition (Brinol and Petty 2005). Conceptually, the impact of the source is independent of the effects of the message contents (Kelman 1958; Wyer and Adaval 2009).

Most discussions of the different source characteristics relate to expertise, trustworthiness, and similarity (Hovland et al. 1953; Johnson et al. 2005; Weimann 1994; Wilson and Sherrell 1993). Expertise is the receiver's perception of how capable the source is to make correct assertions, and trustworthiness is the perception of how much the speaker believes in the message (Pornpitakpan 2004). Both expertise and trustworthiness affect the validity of the information (Kaufman et al. 1990). However, they influence the receiver in different ways. Expertise influences the weight the receiver attaches to the information, and trustworthiness affects the interpretation of the

TABLE 6
Social Mechanisms that Affect Consumer Adoption Decisions

Influence Mechanism	Means of Influence	Literature and Area
Contact	Consumers become aware of new products simply by being in contact with adopters. They might also get the chance to observe new product's functionality and benefits	Social Learning Theory Social Influence: Persuasion Social Networks: Contact
Socialization	Consumers discuss the product with others to develop a normative understanding of the related benefits and costs in order to reduce the risks associated with the new product adoption	Social Learning Theory Social Influence: Persuasion Social Networks: Cohesion
Social Competition	Consumers adopt new products in order to maintain or gain social statuses	Social Status Maintenance Social Networks: Structural Equivalence
Social Norms	Consumers adopt new products in order to conform to their groups	Social Influence: Normative Influence

information implications (Birnbaum and Stegner 1979). The third characteristic, similarity, refers to the degree to which the receiver perceives the source to have comparable needs and wants or to have an understanding of the receiver's needs. Similarity also indicates whether two consumers have similar views and support similar norms and values (Rogers 2003). Therefore, similarity affects the degree to which the receiver perceives the information as being relevant and applicable. Similarity to followers is the only characteristic of opinion leaders studies have supported consistently over time (Weimann 1994).

A source's expertise and similarity to the receiver affect message acceptance through the internal processes of identification and internalization (Kelman 1961). Identification occurs when the message affects the receiver because the receiver perceives self-defining relationships (similarity) with the source. Internalization occurs when the receiver adopts a message because of belief in the essence of what the message advocates mainly because of the relationship of the advocator to the content, such as a source's expertise on the subject (Kelman 1961).

Social Influence

The literature on the influence of social context on subjective beliefs and attitudes has primarily focused on influence in social groups (normative influence) and persuasive communication (Erb and Bohner 2007). These two streams of research are discussed in this section as they relate to the topic of this paper.

Normative influence. Earlier studies referred to this type of influence as conformity, often represented in the influence that a majority exerts on an individual (e.g., Sherif 1935; Asch 1956). Social identity theory argues that group membership is a fundamental concern to an individual because it determines the individual's self-definition and social identity (e.g., Tajfel 1981). Relying on the central concept of self-categorization (e.g., Turner et al. 1987), this theory argues that an individual's opinion reflects both knowledge about an issue and something about the individual's self. Conformity with a group's opinion requires adopting the group's identity and moving from individual self to collective self (Hogg 2003). Identity-defining in-groups not only provide social validity to a member's attitudes, but they also place social pressure on the individual (Crano 2001). Conversion theory explains that the majority has power because of its ability to punish and reward group members, and an individual's disagreement with the majority may lead to negative consequences. As a result, individuals who disagree are likely to experience discomfort (Moscovici 1980).

Two types of social norms—descriptive and injunctive—influence consumers' decisions. Descriptive norms refer to a consumer's perceptions of what other consumers will do in a given situation. Injunctive norms refer to what is commonly approved or disapproved within a culture (Goldstein and Cialdini 2009). Descriptive norms influence an individual by providing information about what is likely to be effective in a situation, while injunctive norms motivate behavior through informal social pressure. Marketers must pay careful attention to the interpretation of the messages they send since misalignment of these two norms can lead to undesirable outcomes. Studies find that using social norms to influence consumer decisions is most effective when descriptive and injunctive norms align in the message and situational relevance is clear to the consumers (Goldstein et al. 2008; Schultz et al. 2007).

The extent of normative influence and its impact on adoption decisions is likely to depend on the culture. Studies find that in collectivist cultures with a high degree of power distance, product diffusion is more driven by social contagion than in individualist cultures (Van den Bulte and Stremersch 2004).

Persuasive communication. The persuasion literature is dominated by two dual-process models (Erb and Bohner 2007): the elaboration likelihood model or ELM (e.g., Petty and Cacioppo 1986), and the heuristic-systematic model, or HSM (e.g., Chaiken 1980). These models distinguish between high and low processing efforts in persuasion. ELM relies on the central and peripheral routes. Under the central route, persuasion occurs as a result of a target's heavy processing of both message arguments and other related information. In the peripheral route, persuasion is based on peripheral cues (e.g., source of the message), and is the result of less effortful processing mechanisms (e.g., heuristic processing). The other model, HSM, also distinguishes between high-effort systematic processing, similar to central route in ELM, and low-effort heuristic processing. Under low-effort heuristic processing, the individual applies highly accessible simple rules (e.g., experts know more) along with relevant available cues (e.g., a communicator's academic degree).

Investigators have recently challenged the dual-process theories of persuasion. For example, the Unimodel of persuasion argues that message cues and message arguments are both evidence with no difference in the way they are processed (Kruglanski and Thompson 1999). Studies have found that the overwhelming research support for dual-processing models might be due to confounding issues in the way studies operationalized the cues (e.g., Pierro et al. 2005). According to the unimodel theory, information can reside in either the context or the contents of a message. In both cases, the receiver may perceive the information as more or less relevant to the topic. Processing complex arguments will require more cognitive resources, and therefore the relevancy of these types of arguments will be more difficult to perceive and individuals will rely more on other cues (Kruglanski and Thompson 1999).

Social Network Perspective: Contact, Socialization, and Structural Equivalence

In the social network literature, social contagion studies address the question of why adoption of a new product by a consumer triggers other consumers' adoptions (Burt 1987). Marketers often use the term social contagion to refer to how the social network structure among consumers affects information sharing and social influence regarding products or brands (Van den Bulte 2009). In line with this literature, in this paper social contagion refers to the social influence and word of mouth (WOM) among consumers regardless of whether the influencer has already adopted the new product. From a social network perspective, social contagion takes place through the social mechanisms of contact, socialization or cohesion, and structural equivalence (Burt 1987).

Contact takes place when potential consumers learn about a new product through exposure to other consumers who have adopted the product. Potential consumers might also have the opportunity to observe the new product's actual benefits and weaknesses before deciding to adopt it (Burt 1987; Van den Bulte and Wuyts 2007). From a micro-level perspective, contagion through contact can be explained by social learning theory, which holds that consumers learn from observing the behaviors of others. As consumers tend to avoid negative outcomes and seek positive ones, they imitate other consumers' new product adoptions that generated desirable outcomes and avoid those that generated negative outcomes (Bandura 1977; Rotter 1954). Social contagion through contact is more likely in the case of visible products, such as fashion, and low-involvement products with limited adoption risks. In the case of high-involvement or high-risk products, contact only creates awareness of a new product. Actual adoption decisions are usually made through socialization or cohesion.

Socialization, the second mechanism, develops because adopting a new product involves risk, and consumers try to reduce this risk by relying on feedback from others who have already adopted the product (Murray 1991). The higher the perception of risk, the more actively consumers seek information from others (Bansal and Voyer 2000). To resolve these uncertainties, potential consumers discuss the new product with others and form a normative understanding of its benefits and costs (Burt 1987; Van den Bulte and Wuyts 2007). From a persuasion literature perspective, socialization influence on the consumer is more likely to happen through the high-processing route, but it can also occur through the low-processing route (e.g., talking with a highly credible source).

The third mechanism, structural equivalence, refers to two individuals having similar social ties (Burt 1999). It is the degree of similarity between the two individuals with respect to having common neighbors and common indirect contacts (Van den Bulte and Wuyts 2007). An example is two teenagers who belong to the same social groups and are in competition to keep their status of being ahead of their peers. New product adoption through structural equivalence takes place through competition between the two individuals (Burt 1987) and relates closely to social status competition and maintenance. According to social network theory, structural equivalence promotes social contagion within groups and fosters cohesion between groups (Burt 1999).

Influentials' Impact on Others

The four social influence mechanisms—contact, socialization, social competition, and social norms—help explain the influence of various groups of influential consumers on others' new product adoptions as organized in Table 7. Close inspection of Table 7 yields several marketing implications. First, the influence various groups have on others occurs under distinct conditions, and these groups vary in the mechanisms through which they influence potential consumers' adoptions. Furthermore, the influence of these consumers on their peers differs from their influence on other consumers. Some groups are more appropriate for increasing awareness among potential consumers who have not passed the knowledge stage, while others are more appropriate for persuading others to purchase

TABLE 7
Influence on Others: Status of Existing Literature, Gaps, and Future Research

<table>
<tr><th rowspan="2">Influential Consumer Group</th><th colspan="3">Status of Current Literature</th><th rowspan="2">Gaps and Future Research</th></tr>
<tr><th>Potential Consumers' Adoption Stage</th><th>Primary Means of Influence</th><th>Other Notes</th></tr>
<tr><td>Early Market Adopters</td><td>Primarily Knowledge[1]
Possibly Persuasion</td><td>Primarily contact
Possibly socialization
Impact other early adopters through competition</td><td>Mass market consumers perceive little similarity with those who adopt at the very early stages (1)</td><td rowspan="7">• Interactions between Variables
- What information is needed for a consumer to adopt new products given certain conditions? Who do consumers seek for these information?
- The relationship between consumers' number of social ties and the strength of each tie
• Time and Consumer Experiences
- Dynamics between different social influence mechanisms
- Changes in influentials' profiles over time
• Positive versus Negative Influentials
- Factors that increase the influence of positive versus negative influentials.
- The relative changes in the influence of positive versus negative influentials over time.</td></tr>
<tr><td>Product Usage Level</td><td>L. Users[2]: Knowledge
H. Users[2]: Persuasion</td><td>L. Users: Contact, likelihood of being in contact with unaware consumers (6)
H. Users: Socialization, product knowledge and experience (5,7,11)</td><td></td></tr>
<tr><td>Experts</td><td>Persuasion</td><td>Primarily socialization
Possibly contact</td><td>Mostly sought by other consumers in the case of incremental innovations (5, 8)</td></tr>
<tr><td>Market Mavens</td><td>Knowledge</td><td>Primarily contact
Possibly socialization</td><td>Disseminate marketplace information regarding changes in marketing mixes (2,3)</td></tr>
<tr><td>Social Hubs</td><td>Primarily Knowledge/
Possibly Persuasion</td><td>Primarily contact
Possibly socialization</td><td>Adoption by hubs exposes the product to many consumers (10)</td></tr>
<tr><td>Boundary Spanners</td><td>Primarily Knowledge/
Possibly Persuasion</td><td>Primarily contact
Possibly socialization</td><td>Act as bridges for transferring social contagion across groups (9)</td></tr>
<tr><td>Opinion Leaders</td><td>Knowledge and Persuasion</td><td>Contact, Socialization, Competition (on other opinion leaders), Social Norms</td><td>Influence others through providing information and modeling behavior (4)</td></tr>
</table>

[1] Knowledge stage, to some degree, can be compared with awareness and interest stages in AIDA
[2] L. Users: Light Users; H. Users: Heavy Users

References:
1- Rogers (2003) 2- Feick and Price (1987) 3- Price and Feick (1988) 4- Weimann (1994) 5- Iyenger et al. (2008) 6- Godes and Mayzelin (2009) 7- Robertson (1971) 8- Goldenberg et al. (2006) 9- Burt (1999) 10- Goldenberg et al. (2009) 11- Hirschman (1980)

(e.g., high-involvement products). In addition, the groups vary in terms of appropriateness for disseminating specific sets of marketing messages. Marketers must avoid confusing the similarities between these consumer groups and assuming that a single group of consumers encompasses all of these distinct characteristics. They must pay attention to the above-mentioned implications when making decisions regarding their tactics. They must first identify the objective of their tactic and identify the social contagion mechanism(s) they want to employ. This objective can be raising awareness, persuading potential consumers, or establishing social norms. The approach depends on the new product's attributes (e.g., visibility, relative advantage, perceived risks, trialability), market characteristics (e.g., size, social network, culture), and product diffusion stage (e.g., commercialization, takeoff, growth). The final decision is constrained by the feasibility and costs of alternative marketing tactics.

Generally, marketers face two key questions in WOM marketing: (1) which groups of consumers are the most appropriate for spreading the word about new offerings (e.g., know more potential consumers or are more willing to talk about a new product to others) and (2) which types of influentials do other consumers approach for advice? Studies find that consumers seek social leaders for radical innovations and seek experts for incremental innovations (Goldenberg et al. 2006; Iyengar et al. 2011). Moreover, in contrast to less innovative consumers, innovative consumers consult with experts regarding radical innovations, but to a lesser degree than they do for incremental innovations (Iyengar et al. 2011). Very little research has examined how the answers to the above questions change depending on individual characteristics, social network factors, and situational variables.

Influence on Others: Discussion and Future Research

This section has synthesized the social influence and social network literature and categorized the influence of social contexts on consumers' adoption decisions in four mechanisms: contact, socialization, social competition, and social norms. Through contact, consumers become aware of new products simply by being in touch with adopters. They might also get the chance to observe the product's functionality and benefits. Through socialization, consumers discuss the product with each other to develop a normative understanding of the related benefits and costs and reduce the risks associated with the new product adoption. Through social competition, consumers adopt new products to maintain or gain social status. Through normative influence, consumers adopt new products to conform to their social groups. WOM influences consumers' adoption decisions mostly through contact and socialization mechanisms. These mechanisms serve to organize the impact of influential consumers on others' adoption of a new product.

Synthesis of theoretical backgrounds reveals that the proposed definition of influentials is comprehensive and encompasses the characteristics of influential consumers, who can be categorized using either of two dimensions—propensity to adopt a new product early and considerable influence on others' adoptions. This review also identifies three areas of inquiry for future research. The first area concerns the interactions between variables and their impact on consumer adoption decisions. The second area is the dynamics of influentials' effect on others over time, and the third area relates to differences between positive and negative influentials.

Interaction between variables. Few studies have examined the interactions between individual characteristics such as consumer expertise, social network variables such as strategic location in the social network, and situational variables like product risks. From a theoretical perspective, research in this area requires integrating consumer behavior theories, social network theory, and diffusion theory. Surprisingly, very few studies have investigated which group of influentials have a higher potential to influence others' decisions (e.g., Goldenberg et al. 2006). The answer to the first question depends on factors such as whether consumers are concerned with functional, financial, or social risks associated with the product (Van den Bulte 2009).

Time and consumer experiences. The literature has paid little attention to the dynamics of social interactions among influentials and others over time. On one hand, as consumers participate in social interactions they adjust their attitudes and reactions toward others to cope with future social influences (Friestad and Wright 1994). On the other hand, the marketplace and consumer characteristics change over time. Understanding the impact of consumers' experiences over time on the formation of social influence is of utter importance.

Positive versus negative influentials. With the exception of a few studies (e.g., Leonard-Barton 1985), investigators have focused on positive influentials and neglected negative influentials. Future research on the nature and role of influentials might look into what consumer, market, and product characteristics increase or decrease the influence of negative influentials on others? For example, to what degree does the influence of negative and positive influentials on other consumers depend on the similarity of their personality characteristics, such as both the influential and influencee thinking positively versus negatively?

Methodological Approaches to Identification of Influentials

Developing more accurate methods for identification of influentials is a top priority for both researchers and companies such as Google (Green 2008; Iyengar et al. 2011). Identification of influentials refers to activities that locate consumers with certain characteristics, such as having the propensity to adopt early or having a high number of social ties. The vast body of literature in this area focuses on how to identify influentials. Table 8-A classifies various methods of identifying into communication-based and observation-based methods. This section discusses these two methods, including their advantages and weaknesses.

Communication-Based Methods

Communication-based methods can be self-identified or peer-identified, and focus on identification of influentials through communication with consumers.

A self-identified method surveys individuals with a measurement scale, sometimes several times on different occasions, and identifies respondents with high scores as influentials (Weimann 1994). Investigators have used this method to measure both consumers' propensity to adopt early and their self-perceptions of influence on others. Measurement scales include items such as recall of past behaviors or the

TABLE 8
Methodological Approaches to Identification and Targeting Influentials: Status of Existing Literature, Gaps, and Future Research

A: Methodological Approaches to Identification of Influentials

Status of Current Literature	Gaps and Future Research
• **Communication Based Methods** - Self-identified method - Peer-identified methods - Sociometric - Key informants' rating - Snowballing • **Observation-Based Methods** - Monitoring consumers' activities without direct communication with them - Using objective/behavioral data - Developing more complex methods for identifying influentials, usually using data mining or in online environments - Sources of data: Databases, scanner data, loyalty cards, online environment, and product warranty registration, associations/communities memberships	• Developing new measures • Comparison of various methods and measures for identifying influentials • Overcoming mis-identification of influentials: meta-analysis, replication, or using simulation modeling methods • Validity of measures over time and among different cultures • Identifying negative influentials • Investigating various consumer knowledge conceptualizations

B: Targeting Influentials

Status of Current Literature	Gaps and Future Research
• **Two Groups of Challenges:** - Reaching influentials, communicating with them, and influencing their opinion about the product - Designing marketing tactics that affect diffusion process • **Methods of Targeting:** - Mass media - Direct marketing - Online environment and Web 2.0 - Seeding tactics - Creating Influentials - Simulating Influentials • **Targeted Marketing Activities:** - Influentials are Familiar with the product and have desire to maintain statuses - Reactions: accepting, embracing, ridiculing, and apologizing	• Seeding tactics: Which group to target and what percentage? Impact of social network? • Advertising strategies: Increasing benefits vs. reducing negative features • Dynamics and time: Impact of product experiences and activities at one point of time on future behaviors • Multiple communication channels

likelihood of being asked by others for advice (e.g., Childers 1986; Flynn et al. 1996; King and Summers 1970). The main problem with self reports is that consumers generally overestimate themselves and, therefore, their self concept and actual behaviors might not overlap (Dunning 2007; Hamilton 1971).

A review of existing self-identified scales reveals several issues. First, researchers have frequently criticized opinion leadership scales, which measure self-perceptions of social influence on others, for a lack of psychometric soundness (e.g., Childers 1986; Flynn et al. 1996; Flynn et al. 1994) and for having low external validity owing to differences across different cultures (Marshall and Gitosudarmo 1995). Furthermore, consumer innovativeness scales, which purportedly measure consumer propensity to adopt early, face definitional, theoretical, and predictive capability issues. Lack of (a) consensus on the definition of consumer innovativeness and (b) an integrative theoretical framework (Tables 3 and 4) has led to development of various consumer innovativeness scales. Although these measures have different theoretical bases, scale items typically do not reflect these differences, leading to concerns regarding both construct and content validity (Roehrich 2004). Moreover consumer innovativeness scales on average predict only about 10% of actual early adoption behavior, which is very low for practical purposes (Hauser et al. 2006; Roehrich 2004). Finally, a number of studies have relied on consumer expertise and product knowledge to measure consumers' propensity to adopt and their influence on others. This review finds that researchers have paid little attention to the distinctions between various conceptualizations and measurement of consumer expertise—subjective knowledge, objective knowledge, and experience (Flynn and Goldsmith 1999). To measure consumer expertise, studies have focused on product ownership and use (e.g., Coulter et al. 2002), interest and familiarity (e.g., Coulter et al. 2002; Richins and Root-Shaffer 1988), knowledge (e.g., Flynn et al. 1996; Midgley 1976; Venkatraman 1990), brand awareness (e.g., Coulter et al. 2002; Goldsmith and Desborde 1991), and confidence in product choices (e.g., Coulter et al. 2002).

Peer-identified methods—sociometric, snowball, and key informants' rating—ask members of a group to name individuals they would seek information or advice from regarding a given topic. The sociometric method surveys all members of a society, and influentials are those who receive the highest number of ratings (Moreno 1953; Rogers 2003). The snowball method is similar to the sociometric method, but surveys only a randomly chosen group of consumers in the first round, interviews the nominated individuals in a second round, and continues until there are no further nominations. The influentials are those who receive the highest number of nominations or who pass a certain threshold value (Valente and Pumpuang 2007). Both of these methods allow for mapping the social network among consumers and conducting social network analysis. Finally, the key informants' rating or judgment method selects a subset of members who are usually knowledgeable about the society and surveys them regarding who in their judgment are influentials (Rogers 2003; Van Den Ban 1964).

Peer-identified methods can be used in marketplaces with a limited number of identifiable members, such as physicians, members of special-interest communities, associations or sports clubs, and organizational settings like industrial markets. Applying these methods to large consumer markets is very difficult. Moreover, the validity of these methods can be questionable since consumers may be unable to recall or unaware of the sources that influence them (Hamilton 1971; Weimann 1994). Finally, a recent study found a correlation of only about 30% between self-report and sociometric measures, resulting in a call for more research (Iyengar et al. 2011). This finding also brings into question the validity of a large number of studies on influentials and the validity of relationships and models these studies discuss.

In summary, despite the vast number of studies, serious concerns still exist regarding identification of influentials with communication-based methods. Future research can overcome these limitations by further developing integrative theories.

Observation-Based Methods

This category covers a wide range of methods in which investigators monitor consumers' activities without directly communicating with them. Earlier studies documented and mapped social relationships between individuals through direct observation of their behavior either by researchers or by those who were in contact with individuals, such as bartenders in gay communities (e.g., Kelly et al. 1991; Weimann 1994).

More recently, researchers have devised new methods for identification of influentials using actual behavior data. Goldenberg et al. (2009) examined data from a social networking website and found that not only do social hubs on average adopt earlier than others, they also affect the speed of diffusion and the final market penetration. Trusov et al. (2010) looked at similar data and found that activities of a small group of users, such as the number of times they logged in to the website, significantly affected other users' activities on the website. Tucker (2008) studied data from adoption of a video messaging system within an organization and found that consumers who fill structural holes in social networks and those with sources of formal influence significantly affect other employees' adoption decisions. Kiss and Bichler (2008) analyzed data from a cell phone operator company to compare different social network centrality measures for identification of influentials. Finally, Iyengar et al. (2011) assessed sociometric, self-report, and actual use data simultaneously to compare measures in terms of their prediction accuracy. Observation-based studies have benefited greatly from the recent advances in technology, allowing both researchers and firms to collect more granulated and objective data. Marketers today have access to details of consumer purchase data through scanner data, loyalty cards, and product warranty registration. Hwang and Yang (2008) proposed a data mining approach to find associations between consumers types and product genres and used it to identify the consumers with the highest propensity to adopt a new product.

Data collected through observational methods are more accurate and reliable because they are based on actual behaviors and not perceptions. However, collecting objective data can be challenging in many marketplaces, and excessive reliance on observation could lead to ignoring the dynamics in social interactions and capturing the indirect social influences.

Identification of Influentials: Discussion and Future Research

Identification of influentials has long been a challenge to both researchers and practitioners, and present methods and measurement scales have both advantages and disadvantages. The most important challenge is the predictive capability of these methods and measures to identify the appropriate influentials. Research opportunities to overcome challenges involved in identification of influentials are numerous.

New measures and theory development. Theory development will significantly improve measuring consumers' propensity to adopt. New methods and measures need to incorporate and synthesize market characteristics (e.g., economics and culture), market data, product attributes, and individual consumer characteristics. They must build on the strengths and overcome the weaknesses of existing methods and measures.

Comparison of various methods and measures. Identification of consumers who strongly influence other consumers' adoptions will benefit from applying different methods to the same group of consumers and comparing the results. Researchers must replicate this approach in diverse markets and for different product categories to investigate the extent to which the correlation between the various methods depends on product category and market characteristics such as economics and culture. Employing different measures and methods for identification is not necessarily counterproductive, and the feasibility and cost of choosing the best approach might augur for using self-identified methods in certain situations.

Misidentification of influentials. This review suggests that existing methods tend to misidentify influentials in real-world settings, and concerns regarding the validity of existing methods call into question the validity of models and relationships studied in previous research on influentials. This uncertainty arises because the validity of relationships between constructs in a model depends greatly on the validity of the scales that measure these constructs. One way to address this issue is by conducting meta-analyses to analyze whether using various methods to identify influentials leads to different conclusions regarding relationships between constructs and the prediction of diffusion outcomes. Another way is by replicating past studies in a more comprehensive manner using multiple methods and measures to identify influentials (e.g., Iyengar et al. 2011). Finally, researchers can employ other methods, such as simulation modeling, to increase insights into the phenomenon. Investigators have recommended simulation modeling as a way to advance application and theory in business and specifically in diffusion of new products (e.g., Bass 2004; Davis et al. 2007; Garcia 2005; Harrison et al. 2007).

Time and culture. The external validity of measurement scales over time and among different contexts requires further research. For example, it is not apparent whether scales can continue to provide valid data in the future (e.g., 20 years later). Influentials' characteristics change over time and among cultures, and these changes are likely to lead to changes in the criteria for identifying them.

Negative influentials. Although investigators have discussed the importance of negative influentials (e.g., Leonard-Barton 1985; Rogers 2003), the literature has paid little attention to identifying them before or after the product's release. Future research can clarify whether and how the methods for identifying positive influentials apply to the identification of negative influentials.

Targeting Influentials

Marketers face two main areas of challenge with respect to targeting and influencing influentials. As Table 8-B indicates, one group of challenges relates to reaching influentials, communicating with them, and influencing their opinions about the product. The other group relates to marketing tactics, and addresses questions such as who are the most promising consumers to target and how many of them need to be targeted to have an impact on the diffusion of a new product. Research has paid relatively little attention to either area of challenge, and the existing literature falls into a wide range of research areas.

One stream of research relies on the mass media (e.g., magazines) to reach influentials by sending messages that appeal to them, such as advertisements or reports. Originating from the two-step flow model, the general rationale behind this line of research is that because influentials pay more attention to media than others, messages sent through mass media will reach them (e.g., Katz and Lazarsfeld 1955). More recently, Vernette (2004) found that influentials and non-influentials differ with respect to the media vehicles (e.g., fashion magazines) to which they pay attention. She further concluded that firms could directly reach influentials by choosing the appropriate media for their advertisements. Unless marketers can clearly identify such media, using mass media to reach only a small group of prospects will be costly (Blackwell et al. 2005). Thus, marketers need to engage in more focused activities, such as direct mail, seminars, or more recently Web 2.0 and social media, to provide information to influential consumers (Rieken and Yavas 1986; Stern and Gould 1988).

One set of focused marketing activities is seeding, or giving free products, product demonstration, or special discounts to potential consumers with the goal of facilitating the diffusion process (Bawa and Shoemaker 2004; Heiman et al. 2001; Heiman and Muller 1996). For example, the publisher of *The Da Vinci Code* sent 10,000 free copies to readers who were likely to be influentials (Paumgarten 2003). Seeding the market by giving away free samples not only increases awareness about a new product; it also gives consumers chances to directly experience the product, reducing their uncertainties about it. Free samples increase both the likelihood of product purchase immediately after sampling and consumers' cumulative goodwill and future purchases (Heiman et al. 2001). Empirical studies find that providing free samples is an effective promotion tool that can create long-term increases in sales (Bawa and Shoemaker 2004).

Because seeding is costly, firms must pay extra attention to targeting consumers who have the highest propensity to adopt and use the product and also highly influence others. A review of the sparse literature on seeding as a marketing tactic to influence the diffusion process raises serious concerns. Jain et al. (1995) found that optimal sampling levels depend on external influences such as marketing activities, internal influence (i.e., the influence of consumers on each other), the discount rate, and the gross margin of the product. Later, Lehmann and Esteban-Bravo (2006) used an analytical model to compare different seeding tactics in a two-segment market and found that firms will benefit from seeding influentials (i.e., early adopters) only under certain conditions. From another perspective, Watts and Dodds (2007) found that influentials had only a marginal impact on diffusion outcomes, and Van den Bulte (2009) called for more research to clarify whether some consumers considerably influence others. These findings suggest further research to address important questions regarding firm decisions on using seeding as a marketing tactic.

Another stream of research focuses on communication with influentials and their reactions to marketing activities that target them. This literature highly recommends communicating with influentials through messages that appeal to them (e.g., Munson and Spivey 1981; Rieken and Yavas 1986; Stern and Gould 1988). However, stimulating influentials to promote a commercial product or brand is not an easy task, because influentials are not only familiar with the product but also want to maintain their status in their society as a credible source (Weimann 1994). Engaging in marketing activities might jeopardize their informal non-marketer status. A recent study investigated influentials' reactions to marketing activities by providing free product samples to famous bloggers and documenting their reactions through their postings on their weblogs (Kozinets et al. 2010). Bloggers had a variety of reactions, including accepting, embracing, ridiculing, and even apologizing to their readers for their roles as semi-marketers. Future research should investigate the reasons and psychological and social processes behind influentials' reactions as well as the messages that appeal to them.

Others have argued that since identifying appropriate influentials is difficult and costly, one tactic is to create them in the society (Mancuso 1969), usually by putting together a panel of consumers who are not necessarily opinion leaders but who have certain characteristics such as mobility, status, and confidence. Marketers have succeeded in applying this method for music records, electronics, and metal-working industries (Mancuso 1969). More recently TREMOR™, a word-of-mouth program developed by Procter and Gamble, has put together panels of 250,000 teenagers and 350,000 moms acting as influentials to execute WOM marketing campaigns (McCarthy 2007b; Zurek 2009).

Finally, Stern and Gould (1988) suggest simulating influentials by setting up people or by creating real-life scenes in ads that demonstrate the activities of influentials. The main challenge in the former is credibility and in the latter the limitations of advertising. An example is the hiring of good-looking young people by stores such as Banana Republic to wear the most recent products and act as a role model for customers (Blackwell et al. 2005). Another example is the Sony Ericsson T68i "Fake Tourists" campaign, in which undercover marketers acted as tourists in ten large U.S. cities, asking passersby to take pictures of them with the new camera cell phones and then engaging in conversation about the product with them (Kirby and Marsden 2005, p. xxiii).

Targeting Influentials: Discussion and Future Research

The sparse research on targeting influentials falls mostly into two main areas of investigation: reaching and communicating with influentials and designing targeting tactics that affect the diffusion process. The review of the literature identifies three neglected areas that offer opportunities for future research—Seeding tactics, dynamics and time, and multiple communication channels.

Seeding tactics. Research is meager on the effect of seeding on diffusion outcomes. Future studies might investigate the following questions: What seeding tactics significantly affect the diffusion process, given certain market conditions and product characteristics? Which group of consumers has the highest impact on the diffusion process and the outcomes? Do these groups change with product category and market characteristics? What is the optimal percentage of consumers to target to have an effect on the diffusion of a new product?

Dynamics and time. Influentials live in a dynamic environment in which new products appear regularly. Future studies must investigate how influentials' product experiences and their activities, such as recommending it to others, affect their later reactions to other products or brands. Studies also must focus on this issue in the case of multiple generations of the same product, either from the same brand or from different brands.

Multiple communication channels. To date, research has failed to address issues related to communicating with influentials through multiple channels. Examples of communication research questions include the following: Does reaching influentials in the real world differ from reaching those in the online and Web 2.0 environments? Does the impact of targeting them differ in the two environments? To what degree and under what conditions does the use of various channels to communicate with influentials increase the influence of firm activities on their decisions?

Impact on Diffusion Outcomes

In targeting influentials, one challenge marketers face is designing tactics that affect the diffusion of a new product and increase the returns it generates (e.g., market penetration, NPV of sales, or net profit). However, for two reasons, investigators have paid little attention to the impact of influentials' activities at the individual level on diffusion at the macro level (Goldenberg et al. 2009). Primarily, limitations in methodology, data collection, computational power, and modeling techniques have precluded studying this impact. Second, marketers may have assumed that the micro-level influence of influentials on others results in a significant effect on the diffusion of a new product at the macro level.

Several researchers have recently recommended studying the relationship between individual behaviors and aggregate market outcomes (e.g., Bass 2004; Garcia 2005; Hauser et al. 2006). A number of studies have shown that individual-level consumer interactions provide important insights about the diffusion process (e.g., Delre et al. 2010; Garber et al. 2004; Godes and Mayzlin 2004; Goldenberg et al. 2009; Goldenberg et al. 2007; Goldenberg et al. 2002a; Tucker 2008). One related study found that, in most cases, influentials are likely to have only a marginal effect on the overall diffusion process and called for further investigation (Watts and Dodds 2007).

This review of the literature has revealed methodological issues in earlier studies on influentials. One example comes from a well known field study that identified and trained influentials to promote safer sex in gay communities (Kelly et al. 1991). Researchers found significant reduction of risky behaviors in communities that received the intervention, but found no significant changes among community members in similar cities that did not receive the treatment. However, the results do not make clear whether the impact of intervention was due to the characteristics of subjects (being an influential) or simply the result of training members of the community. In other words, had the researchers randomly chosen and trained community members, would the change in behavior be significantly lower?

The rest of this section reviews the literature and discusses opportunities with a focus on social network structure and consumer heterogeneity, two market characteristics that may well moderate the impact of influentials on the diffusion outcomes but have received little attention.

Social Network Structure

Consumers interact with each other and exchange information during the diffusion process through their social ties (Barabasi 2002; Rogers 2003; Watts and Strogatz 1998). A social network consists of the consumers (nodes) and social ties among them (links). Social networks may present themselves in three broad structures, or topologies: random, scale-free, and small-world network structure. The bearing of consumer interactions on the diffusion process seems to depend on the structure of the social network among these individuals (Choi et al. 2010; Delre et al. 2010; Janssen and Jager 2003; Valente 1995; Watts and Peretti 2007).

For two reasons, past research has paid little attention to the role of social network structure in diffusion. First, social networks structures are not easily identifiable and are difficult to map (Alderson 2008). Second, they introduce additional complexity into modeling and estimation (Goldenberg et al. 2009). However, mapping the social network among consumers has a long history in the marketing literature. For instance, Brown and Reingen (1987) mapped a small-scale social network to investigate the effects of tie strength at both the micro and the macro levels simultaneously. A few recent studies have attempted to map large-scale social networks among consumers and have reported different network structures. For example, Goldenberg et al. (2009) concluded that social network structure among users of a social networking website approximately mapped to be scale-free, while the social network structure among consumers studied by Bampo et al. (2008) was far from being scale-free. These findings suggest that the structure of consumer social networks may vary across marketplaces depending on the nature of the product or service. This inconsistency requires further research on the structure of social networks among consumers in different markets.

The impact of social network structures on the diffusion process is complex and depends on consumer and information characteristics. Granovetter (1974) believed in "primacy of structure over motivation," arguing that the social network structure closely restricts individuals' personal experiences. Later, Frenzen and Nakamoto (1993) combined social network structures with individual consumers' decisions regarding whether to pass WOM. They found that the decisions made by consumers depended on the importance of WOM messages and these decisions had a significant impact on the spread of WOM in the social network. They demonstrated that Granoveter's assertion holds true only when information is cheap, and that motivation has primacy over structure when information is precious. More recently, Stephen and Berger (2009) demonstrated how social networks and product characteristics interact to drive WOM and wide-spread product adoptions. They also found that the network position of consumers who adopt early in the diffusion process determines the final market size and spread of a new product.

Consumer Heterogeneity

Consumer heterogeneity is one of the main drivers of diffusion (Chandrasekaran and Tellis 2007). Even though consumers are obviously heterogeneous (e.g., Shugan 2006) and heterogeneity affects diffusion (e.g., Delre et al. 2007; Rogers 2003), most research has assumed homogeneity in the marketplace (Goldenberg et al. 2009), perhaps for good reasons. On one hand, profiling an individual consumer in the diffusion context is not easy. On the other hand, introducing heterogeneity creates major complexities in modeling the dynamic interactions among individual consumers. Modeling complex dynamic interactions among consumers goes beyond the capabilities of traditional modeling methods (Garcia 2005; Goldenberg et al. 2009; North and Macal 2007; Rahmandad and Sterman 2008).

Recently, researchers have developed diffusion models that characterize the market as comprising two segments—influentials and imitators—with each segment containing homogeneous consumers (e.g., Goldenberg et al. 2002a; Lehmann and Esteban-Bravo 2006; Van den Bulte and Joshi 2007). Models also considered individual consumer profiles beyond the labels of influentials and imitators. One set of efforts focuses on incorporating consumer heterogeneity in Bass-type diffusion models, which generally depict diffusion of new products using two parameters: *p,* capturing external influence such as marketing activities, and *q,* capturing the influence of adopters on other potential adopters. Incorporating heterogeneity in these models requires randomly selecting parameters *p* and *q* on the basis of theoretical distributions (Bemmaor and Lee 2002; Karmeshu and Goswami 2001). The other set of attempts to incorporate heterogeneity into diffusion models relates to models that include individual decision making in a heterogeneous manner (Delre et al. 2010; Stephen and Berger 2009).

Impact on Diffusion Outcomes: Discussion and Future Research

Debate is ongoing as to whether influentials considerably affect the diffusion of a new product at the macro level. Until recently, studies have paid little attention to conditions under which influentials have such an impact. Social network structure and consumer heterogeneity, two under-researched market characteristics, plausibly moderate the impact of influentials on the diffusion outcomes.

The moderating role of social network structure Interactions between consumer characteristics, social network structure, and product characteristics may moderate the effect influentials have on the diffusion of a new product. For example, how do social network structure, and influential's attributes, moderate diffusion outcomes? What consumer and product types require assessment of a consumer's social network attributes for marketing tactics such as seeding to succeed?

Consumer heterogeneity Two other areas require attention to the incorporation of consumer heterogeneity in diffusion models: investigating the degree to which consumer heterogeneity moderates the impact of influentials on diffusion outcomes and overcoming the challenges in profiling individual consumers in the models. Results from addressing these two topics not only have implications for methodology, but will be helpful to practitioners in profiling their consumers and increasing prediction accuracy.

More realism in studies A number of studies have investigated the impact of influentials in the absence of marketing activities, where diffusion took place only through social influence (e.g., Goldenberg et al. 2009; Watts and Dodds 2007). However, marketing activities such as advertising can significantly change the dynamics of the diffusion process (Watts and Peretti 2007). Marketers can provide further insights by studying the impact of marketing activities and WOM simultaneously.

Conclusion

Marketing researchers and managers increasingly find use of influentials' facilitative capacities crucial to the diffusion of new products. Research on influentials has identified various consumer groups who are likely to play an important role in the diffusion process. The alternative labels for these consumers capture diverse, and in some cases contradictory, assumptions and behaviors. Therefore, these consumer groups plausibly have different impacts on diffusion outcomes. This review of the literature suggests that these alternative definitions readily combine into one cohesive definition: *Influentials are a small group of consumers who are likely to play an important role in the diffusion of a new product through their propensity to adopt the product early and/or their persuasive influence on others' new product adoption decisions*. While this definition relies on two dimensions, propensity to adopt the product early and considerable influence on new product adoption decisions, the review of theoretical backgrounds suggests that it is comprehensive and encompasses the characteristics of various influential consumers.

This work organizes and reviews key areas of research on the role and effect of influentials on the diffusion process by relying on a framework that pulls together micro- and macro-level perspectives into five major interrelated areas: propensity to adopt early, influence on others, identification of influentials, targeting influentials, and impact on diffusion outcomes. Within each area, the research findings are synthesized and the research gaps and future research opportunities are discussed.

Although many concepts presented in the proposed framework may seem familiar to researchers and managers, the merit of this study lies in bringing together the extensive body of literature in a systematic way and providing a holistic perspective of how marketers can affect the diffusion process by focusing on influentials. This framework is helpful to marketing managers in designing marketing tactics and campaigns, and it also provides a structure for evaluating and aligning their assumptions, tactics, and expected outcomes. This synthesis suggests a number of future research directions.

- Exploration of optimal seeding tactics to significantly affect diffusion outcomes (e.g., speed, extent). Knowledge is sparse regarding how to maximize the difference between diffusion outcomes and the cost of seeding.
- Investigation of the moderating role of social networks on influentials' effect on diffusion outcomes. Past research has found that the structure of consumers' social network affects WOM and diffusion process. However, little information exists about how this structure moderates the impact of influentials on diffusion outcomes and whether this moderating role bears on the definition of influentials.

- Exploration of the effect of consumer heterogeneity on influentials' impact on diffusion. While consumers are obviously heterogeneous, and heterogeneity is a main driver of diffusion, research has paid little attention to incorporating heterogeneity in diffusion models. Research might uncover methods that would not only overcome the limitations, but be feasible to validate with minimal effort.
- Development of a parsimonious theoretical model for consumer propensity to adopt by formulating a comprehensive definition for this construct, integrating the existing theories, and overcoming the limitations. This research would serve as a starting point for other areas and has immediate implications for practitioners.
- Examination of the dynamics of the evolution of influentials' profiles over time in addition to influentials' impact on others. This line of research not only increases knowledge about influentials but helps validate findings of earlier research.
- Identification of influentials in the marketplace. Serious questions have arisen recently regarding the validity of existing methods. Moreover, the tradeoff between the benefits and costs of these methods presents additional challenges to choosing them in research and business practices.
- Examination of communication with influentials regarding firm offerings and their reactions to various communication means and strategies. Not only are influentials familiar with the product, but they also have a desire to maintain their status as a credible source. Therefore, convincing influentials to engage in activities that might appear to be promoting a new product to others is not easy.

For over 60 years, marketers have investigated and discussed the importance of influentials. This study is the first to synthesize the literature on influentials' role in diffusion from a marketing management perspective. The hope is that both researchers and practitioners will benefit from the framework, the synthesis of the literature, and the future research directions this paper presents.

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CHAPTER 3

SEEDING THE MARKET TO INCREASE NEW PRODUCT PROFITS: DO INFLUENTIALS MATTER?

Abstract

This study explores firms' decisions regarding the selection of target consumers for seeding—providing free products to enhance the diffusion process. The study examines the profit impact of targeting five groups of potential consumers for seeding under alternative social network structures. The findings suggest that seeding programs generally increase the net present value of profits. Moreover, social hubs—the most connected consumers—offer the best seeding target under most conditions that were examined. However, under certain conditions firms can achieve comparable results through random seeding and save resources and effort required to identify the social hubs. Finally, the interactions among several variables—the choice of seeding target, consumer social network structure, percentage of early adopters in the market, and variable seeding cost—impact the returns that seeding programs generate and the 'optimal' number of giveaways.

Introduction

Seeding the market by giving away free products to enhance new product diffusion is commonly practiced in a variety of industries such as publishing, software, electronics, and music (Rosen 2009). For example, the publisher of *The Da Vinci Code* sent 10,000 free copies to readers who were likely to be influentials before the book was released (Paumgarten 2003). Microsoft distributed 450,000 free copies of Windows 95®, about 5% of the potential market in the US, prior to its launch in 1995 (Rosen 2009). Finally, before launching the first model of Macintosh® computer in 1984, Apple gave 100 free Mac computers to influential Americans (McKenna 1991). The success of these products has been associated to a certain degree with implementing seeding programs. In fact, U.S. firms dramatically increased their spending on free giveaways from $1.2 billion in 2001 to about $2.1 billion in 2009, making seeding and sampling the fastest-growing consumer products' promotion category (Odell 2009).

However, marketers face several challenges in designing these programs. First, seeding is expensive, so it is not easy to justify these programs (Libai 2010; Wasserman 2008). Second, the choice of the most promising potential consumers (which group to target) remains unclear. Marketing researchers have identified several groups of consumers who are likely to play important roles in the diffusion of new products. They refer to these groups as influentials and alternatively label them opinion leaders, social hubs, innovators and early adopters, market mavens, and experts (e.g., Goldenberg et al. 2010; Rogers 2003; Weimann 1994). These various terms refer to different groups of consumers who differ from each other in their main attributes and the roles they play in the diffusion process. Research is meager on the question of which group is the most profitable. In fact, marketers debate whether targeting these consumer groups worth the cost and effort of identifying and targeting them (Van den Bulte 2010). Without evidence based guidelines, marketers are left to their best guess about choosing the most promising targets in seeding programs.

Third, firms face two dilemmas in choosing the 'optimal' number of giveaways (how many?). On one hand, excessive seeding increases costs and decreases profits. On the other hand, targeting too few consumers is unlikely to perceptibly affect diffusion. Fourth, research has not explored the impact of the structure of consumer social network (hereafter referred to as social network) on the profitability of seeding programs, quantities of free products a company should distribute, and selections of consumers to receive them. Recent studies found that social network structure significantly affects the diffusion process (Choi et al. 2010; Delre et al. 2010).

This study seeks to fill in the above gaps in research by examining the impacts of seeding five different target consumer groups on the net present value (NPV) of profits. These groups are early adopters, randomly chosen consumers, social hubs, boundary spanners, and globally central consumers. The latter three groups hold key positions in a social network as identified by the most popular social network centrality measures. Furthermore, by considering three social network structures—random, scale-free, and small-world—this study explores the degree to which the social network structure impacts the profits that seeding programs generate, the choice of the most promising consumers, and the optimal number of giveaways.

A viable approach for addressing the above issues is setting up a series of experiments in which the characteristics of the market and consumers are held constant in every experiment. This is difficult to achieve consistency in the real world owing to the complexities of identifying different groups in each market and pinpointing word-of-mouth (WOM) in the marketplace (Delre et al. 2010; Hauser et al. 2006; Rogers 2003). An alternative approach is using simulation modeling which has a high degree of internal validity, is capable of studying longitudinal phenomena, and it has the potential to provide insights into a phenomenon that is difficult to examine using other methodologies (Davis et al. 2007; Harrison et al. 2007). Therefore, this study relies on Agent-Based Modeling and Simulation (ABMS), a simulation methodology that allows for longitudinal observation of the diffusion process while providing the ability to manipulate the market by simulating the consumers as agents with three essential characteristics—autonomy, interactivity, and bounded rationality (North and Macal 2007). These characteristics enable this study to capture the complex and adaptive interactions among consumers in their social networks over time, the impact of marketing activities on consumers, and alternative seeding strategy decisions. ABMS provides the ability to examine simultaneous influence of these factors on the diffusion outcomes (e.g., firm profits) over time.

Literature Review

Few studies have examined firms' decisions regarding the selection and targeting of potential consumers in a seeding program. This section organizes these sparse studies into three groups. One group has focused on the profits generated by seeding the innovators and early adopters (hereafter referred to as early adopters). Jain et al. (1995) investigated the profits generated by seeding early adopters versus choosing the seeding targets randomly regardless of their characteristics (hereafter referred to as random seeding). They found that seeding is more appropriate for products whose adoptions heavily rely on the influence of consumers on each other than it is for products whose adoptions are triggered by marketing activities. Later, Lehmann and Bravo (2006) considered a market consisting of two separate segments of early adopters and imitators and examined the impacts of targeting these two segments on profits. They found that as the influence of early adopters on others increases, so does the optimal seeding level of targeting early adopters. Moreover, when early adopters have little influence on others, firms benefit more from seeding the imitators than from seeding early adopters.

Two segment markets were first proposed by the chasm framework. According to this framework, high-technology markets consist of two markets—the early market adopters, consisting of knowledgeable or risk-seeking consumers, and the main market, consisting of risk-averse individuals (Moore 1991). Existence of the saddle phenomenon, a temporary slowing of new product sales after initial takeoff, in a wide range of products empirically supports existence of two segments (Goldenberg et al. 2002; Muller and Yogev 2006). Van den Bulte and Joshi (2007) expanded this framework and developed a two-segment diffusion model with asymmetric influence—segment-1 consumers influence others in both segments but segment-2 consumers only influence their peers in segment-2. This model fitted data better than competing models for the diffusion data of 33 different products. High-technology, pharmaceuticals, entertainment products, and teen marketing are expected to have this structure (Van den Bulte and Joshi 2007).

Another group of studies have focused on the formation of public opinion or the diffusion of a message when an initial number of members are targeted. Watts and Dodds (2007) found that the impact of targeting social hubs—the most connected individuals—

on message diffusion was only marginally higher that of targeting others under most conditions they studied and called for further investigation of the phenomenon. Focusing on the network position of consumers, Kiss and Bichler (2008) examined various network centrality metrics for identifying the best target in viral marketing programs. They found that a consumer's number of social ties serves well in identifying the best targets for spreading a message. However, the main issue with studies of this group is that they are originated from non-marketing disciplines such as sociology. Studies of this group usually measure the performance based on the final number of members who receive a message and ignore the monetary and temporal effects of adoption—adoptions in later periods have less value than those in earlier stages (Garcia 2005; Libai et al. 2010). Moreover, these studies assume that adoptions happen solely due to the influence of consumers on each other and they ignore the impact of other marketing activities such as advertising which might change the dynamics of diffusion. Finally, the extent to which the spread of a message can be generalized to diffusion of new products—a more complex phenomenon—is unclear.

In another line of research, Delre et al. (2007) demonstrated that the promotional strategy for introducing a new product significantly impacts the new product success and concluded that the optimal strategy is to target 'distant, small and cohesive group of consumers (p. 826).' Later, Delre et al. (2010) concluded that the importance of social hubs lies in their capability of informing many other consumers and not necessarily because they have higher than average influence on others.

Finally, Libai et al. (2010) demonstrated that a WOM programs generate social value—the overall change in customer equity that can be attributed to the program participants— through two mechanisms—acquisition and acceleration. Acquisition refers to the adoptions of consumers who would have not adopted the focal product otherwise. Acceleration happens when consumers who would have adopted the product anyway adopt it earlier because of the seeding program. Libai et al. (2010) also found that on average seeding social hubs generates 30% more social value than does random seeding and that the social value of seeding programs is significantly higher in competitive markets than it is under monopolistic markets. Because Libai et al. (2010) focused on the social value of seeding programs, they assumed that all consumers (including the seeds) generated the same monetary value that was discounted over time. However, seeding entails two types of costs: the variable cost of giveaways and the lost revenue –those who receive free products might have bought it at a later time.

The review of the literature reveals that research has yet to examine the profitability of targeting different potential targets with seeding programs. Believing that a small group of consumers' opinions and new product adoptions significantly affect the diffusion process, marketers continue to invest significant resources in identifying and targeting these consumers. However, a far higher number of failed marketing campaigns have been associated with these efforts than successful ones (Watts and Peretti 2007). The question has arisen of whether the effort involved in identifying and targeting these consumers is worth the high cost (Watts and Dodds 2007). The disparity between the widely held belief that a small group of consumers play a critical role in diffusion and the evidence challenging the significance of this role clearly points to the need for further research.

Purpose of Study and Research Questions

This study addresses five research questions related to the profitability of seeding programs and firms' decisions regarding the selection of potential consumers (which group to target) and the percentage of the market (how many) to target with free products:

- Do seeding programs increase firm profits?
- Does the choice of seeding target make a difference?
- What is the optimal level of seeding (as a percentage of all potential consumers in the market) to generate the best returns?
- What is the impact of consumer social network structure on seeding outcomes?
- What is the effect of variable seeding cost and the size of segment-1 (i.e., percentage of early adopters in the market) on seeding outcomes?

To fully explore the research questions, this study builds on earlier studies and conducts comprehensive simulation experiments with the following key features. First, the study focuses on the profitability of seeding programs and captures both the variable cost of giveaways and the potential lost revenue. Unlike Libai et al. (2010), this investigation assumes that the products are given for free and the consumers who receive giveaways do not generate revenue. Second, this study examines the profit impacts of targeting five different groups of consumers under three generic social network structures—random, small-world, and scale-free. Third, the study measures the performance of seeding programs using the NPV of the profits they generate. This approach captures both the monetary and the temporal aspects of adoptions. Fourth, the study considers a two-segment market comprising early adopters and main market, a characteristic likely to exist in several markets. Fifth, the investigation explores the impacts of a comprehensive set of parameters including seeding parameters, market parameters, and diffusion parameters, creating a host of market conditions. Finally, the study considers the impact of positive and negative WOM as well as marketing activities. While earlier studies have considered some of these features, this study is the first to bring them together in one comprehensive work.

Social Networks and Diffusion of New Products

Consumers interact with each other and exchange information in the diffusion process through their social ties. A social network consists of the consumers—nodes—and the social ties among them—links (Van den Bulte and Wuyts 2007). Social networks may present themselves in three broad structures: random, scale-free, or small-world (Alderson 2008). In a random network, every node is randomly connected to a small subset of nodes in the social network (Erdős and Rényi 1959). In a scale-free network, the number of links for each node follows a power law distribution, where majority of nodes have small number of links and a small percentage of nodes have significantly large numbers of links (Barabasi 2002). In a small-world network, each node is connected to a certain number of its adjacent nodes (neighbors) and a few random links to non-neighboring nodes in the network (Watts and Strogatz 1998). Figure 1 provides a graphical characterization of these three social network structures.

While small-world and random networks present little variation in terms of the number of social ties, scale-free networks present high degrees of variation in the number of social ties among members. Moreover, small-world networks demonstrate market conditions where social networks are highly-clustered (i.e., consist of subgroups in which nodes are highly connected with each other but loosely connected to others outside their subgroup) while random and scale-free networks present lowly-clustered markets (Anderson 1998; Watts and Strogatz 1998).

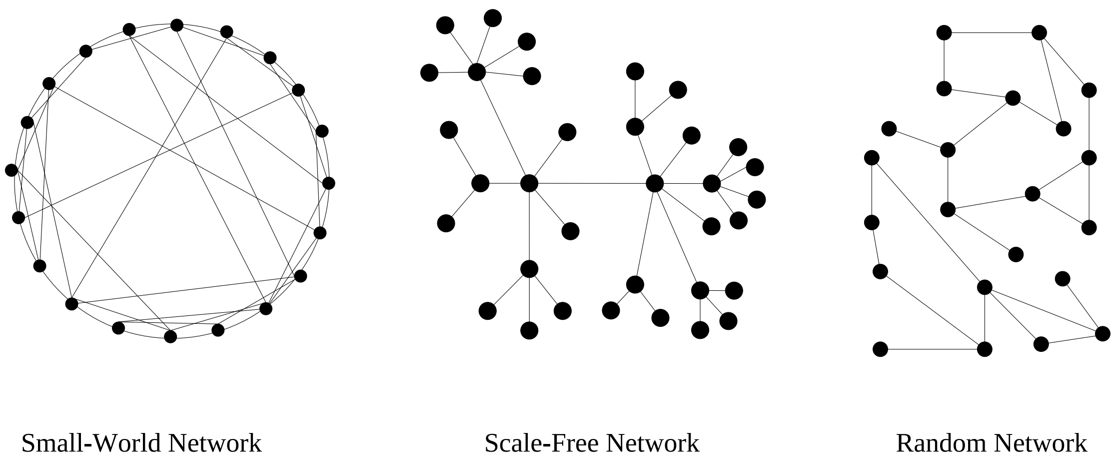


FIGURE 1
Graphical Characterization of Random, Small-World, and Scale-Free Networks

Researchers have questioned the existence of scale-free networks in real world consumer markets and argued that scale-free structures are more likely to exist in virtual environments such as online social networking websites (Watts and Dodds 2007). The reason might lie in the cost of acquiring and maintaining a relationship. When relationships have little acquisition and maintenance costs in terms of time and effort, which is the case in virtual networks, variation in terms of individuals' number of social ties will be much higher than when relationships are costly to acquire and maintain. In addition, the social network structure also depends on whether or not the product is related to individuals' social status. For products that are related to social status, people may prefer a small number of high-status people in their social networks (Janssen and Jager 2003). These findings suggest that the structure of social networks may vary across marketplaces depending on the nature of the product or service and the consumer characteristics.

Until recently, research paid little attention to the role of social network in new product diffusion for two primary reasons. First, large-scale social networks are not easily identifiable and they are difficult to map (Alderson 2008). Second, they introduce additional complexity in modeling and estimation (Goldenberg et al. 2009). A few recent studies attempted to map large-scale consumer social networks, resulting in different structures. Bampo et al. (2008) found that random and small-world networks fit the data better than scale-free network in a viral marketing campaign, while Goldenberg et al. (2009) concluded that social network structure among users of a social networking website approximately mapped to be scale-free.

Studies that investigated the impact of social network structure on the diffusion process found contradictory results. On one hand, studies find that that new products, information, and diseases diffuse slower in highly-clustered networks, and therefore they diffuse more quickly and to more consumers in scale-free and random networks than they do in a small-world networks (Delre et al. 2010; Rahmandad and Sterman 2008). On the other hand, Centola (2010) finds that behavior spreads faster in clustered networks because individuals reinforce each other's behaviors and Choi et al. (2010) finds that innovation diffusion is more likely to fail in random networks than in highly-clustered networks. So, it is not clear which type of social network structure generates the most profitable results for seeding programs.

When domain-specific details are not available, studies have used random network structures as a natural null-hypothesis in evaluating the network properties (Alderson 2008). Studying the profits seeding programs generate within three network structures—scale-free, random, and small world—covers a wide range of network characteristics and hence conditions that can occur in different markets for different product categories. Therefore, in the absence of conclusive evidence of a particular type of real-world social network structure for a given product type, this study considers random, small-world, and scale-free network structures.

Seeding Targets

This section addresses the identification of the most promising seeding targets. The marketing literature identifies several groups of consumers who play important roles in the diffusion of new products and alternatively labels them opinion leaders, social hubs, boundary spanners, and early adopters. Social network researchers, on the other hand, have developed a variety of measures (i.e., centrality measures) for the importance of a node—consumer—in social network with regards to the impact they have on communications among the members (Freeman 1979; Scott 2000).

The study brings together these two perspectives by examining the impacts of seeding five different groups of potential adopters on firm profits. These are: early adopters (Jain et al. 1995; Lehmann and Esteban-Bravo 2006; Mahajan and Muller 1998), social hubs or the most-connected consumers (Barabasi 2002; Goldenberg et al. 2009; Goldenberg et al. 2010; Watts and Dodds 2007), consumers who hold a globally central position with all other consumers in the social network (Scott 2000), boundary spanners (Burt 1992; Roch 2005; Tucker 2008), and randomly chosen targets (Libai et al. 2010;

Watts and Dodds 2007; Watts and Peretti 2007). It is important to note that some consumers might belong to more than one group, but the study chooses seeding targets based on the main characteristic that is of interest. For example, some social hubs might happen to also be early adopters, but when choosing social hubs as targets, the study focuses on consumers' number of social ties without considering whether they are early adopters. The remainder of this section describes the five seeding target groups.

Early Adopters

Marketers pay special attention to early adopters not just because they have high propensity to adopt early and generate revenue, but more importantly because they introduce the new product to other consumers (Mahajan and Muller 1998; Rogers 2003). Because early adopters are likely to be the first group to adopt the product in the diffusion process, seeding this group will shift the diffusion curve and accelerate the diffusion process. In line with earlier studies (Goldenberg et al. 2002; Moore 1991; Vakratsas and Kolsarici 2008), this study assumes that consumers in segment-1 are early adopters (i.e., have a higher propensity to adopt than those in segment-2) and interchangeably uses the terms early adopters and segment-1 consumers.

Social Hubs

Social hubs are the most connected consumers in a marketplace, or in social network terms those with the highest degrees—the total number of consumer's direct ties. Goldenberg et al. (2009) finds that social hubs not only increase the speed of diffusion, they also expand the final number of adopters. Moreover, opinion leaders among children tend to be highly connected (Kratzer and Lettl 2009). Moreover, they are likely to play an important role in bridging the chasm between adoptions of early adopters and the mainstream consumers (Goldenberg et al. 2010). The degree of a node—consumer— is calculated as (Freeman 1979; Scott 2000):

$$C_D(i) = \sum_{j=1}^{n} a\,(i,j)$$

Where $a\,(i,j)$ represents a link between nodes *i* and j, and the total number of nodes in the social network is denoted by *n*. The value of $a\,(i,j)$ is equal to 1 if and only if *i* and *j* are connected by a social tie, and is zero otherwise. Researchers have referred to this measure as 'local centrality', 'degree centrality', and 'degree of connection' (Scott 2000p. 83). Using this measure is more feasible than other network centrality measures in consumer markets, as it can be estimated using surveys without the need to map the entire social network structure and applying complex network analysis (Scott 2000).

Globally Central Consumers

Closeness centrality captures the total distances of a node from all other nodes in the social network. The distance between two nodes is the total number of links in the sequence of links that connects them, if they are connected (Scott 2000). Those who score high on this measure possess central locations and have a high potential to impact a large area of the social network in a short period of time. This work refers to these consumers as 'globally central' consumers.

Several approaches have been proposed for calculating closeness centrality, most of which fail to function in social networks that consist of disconnected sub-networks. When two nodes are not reachable from each other, the distance between them will be infinite and the measures will be undefined. Lin (1976) resolved this issue by considering the distances between the nodes that are reachable from each other and excluding unreachable nodes as follows:

$$C_c(i) = \frac{J_i/(n-1)}{\left(\sum_{j=1}^{n} d\,(i,j)\right)/J_i}$$

Where J_i denotes the number of nodes that are reachable from node i, and $d\,(i,j)$ denotes the distance between nodes *i* and *j*.

Boundary Spanners

Boundary spanners, also referred to as opinion brokers, are individuals who span structural holes in the social network and transfer information across social boundaries between groups (Burt 1992). The influence of boundary spanners comes from holding unique positions in the social network and connecting two otherwise disconnected social groups (Burt 1997; Roch 2005). The intermediary roles these consumers play makes them act as 'brokers' or 'gatekeepers' and enables them to control the information flow to other members of a social network. Kratzer and Lettl (2009) find that children who have ties to many groups tend to adopt earlier than others. In the social networks literature, betweenness centrality measures this characteristic by capturing the sum of the number of shortest paths that passes through each node as calculated using the following (Freeman 1977; Scott 2000, p. 86):

$$\frac{\sum_j^n \sum_k^n g_{jk}(i)}{g_{jl}}$$

Where *n* is the number of nodes (i.e., consumers), $g_{jk}(i)$ is the number of shortest paths between nodes *j* and *k* that pass through node i, and g_{jk} is the total number of shortest paths that connect nodes *j* and *k*. Nodes that lay on the paths between many pairs of other nodes have a high potential for controlling the spread of messages different sub-groups (Freeman 1977).

This measure is the most complex and computationally expensive among the measures this study examines (Scott 2000). Calculation of both betweenness and closeness centrality measures is only feasible when the structure of the entire network is available.

Randomly Chosen Targets

Since identifying influentials is often challenging, an alternative strategy is choosing the targets on a random basis and saving the efforts and resources. Because these targets are randomly chosen from the pool of all potential consumers in the market, they represent an average potential consumer in the market (Libai et al. 2010; Watts and Dodds 2007; Watts and Peretti 2007).

The ABMS Model

Complex adaptive systems are composed of entities that interact with each other and adapt to the changes in their environment. Simple interactions among the members of a complex adaptive system might lead to unpredictable patterns which are referred to as emergent phenomena. The market under study resembles a complex adaptive system and hence ABMS—agent-based modeling and simulation—is an appropriate choice for modeling this system (Garcia 2005; North and Macal 2007). This section explains the ABMS model including consumer adoption status, potential adopter decision making, and performance measurement.

Consumer Adoption Status

Two groups of factors influence potential consumers' decisions regarding adopting or rejecting a new product. One group relates to external factors such as marketing activities and is captured by parameter *p*. The other group relates to internal factors including WOM and social influence and is captured by parameter *q* (Bass 1969; Muller et al. 2010). This work only considers the effects of WOM between those consumers who have direct links and does not incorporate other means of social influence such as observation and the adoptions related to social status.

In line with earlier studies (e.g., Goldenberg et al. 2007), at the beginning of each period consumers can be in one of the following four pools: potential adopters (undecided), satisfied adopters, dissatisfied adopters, and rejecters. As Figure 2 shows, these groups differ in the type of WOM they initiate: satisfied adopters initiate positive WOM, dissatisfied adopters and rejecters spread negative WOM, and potential adopters do not send out WOM.

When the firm just launches the new product, time period 0, all market participants are in the pool of potential adopters. Marketing activities initiate the adoption process at the early stages of diffusion. Adopters who are satisfied with the new product will move to the pool of satisfied consumers and those adopters who are dissatisfied will move to the pool of dissatisfied consumers. Dissatisfied (satisfied) consumers will spread negative (positive) WOM to others, triggering future rejections (adoptions) of the new product. Rejecters form a separate pool and will spread negative WOM (see Figure 2). Potential adopters make a one-time decision and they do not move from one pool to another after moving out of the pool of potential adopters.

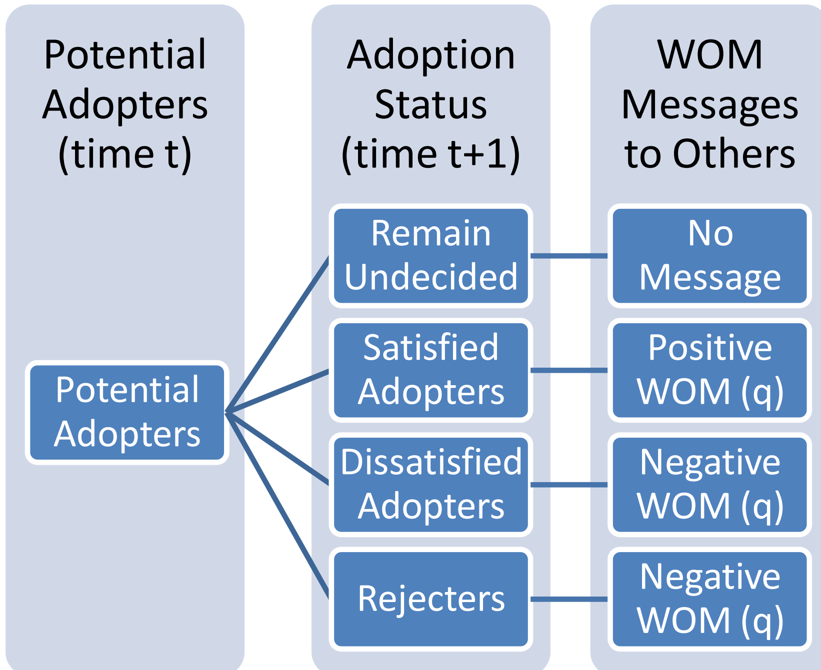


FIGURE 2
Pools of Potential Adopters, Adopters, and Rejecters, and their Engagement in WOM

Potential Adopter Decision Making

At each period, potential adopters receive WOM from others who have direct links with them and have already adopted or rejected the new product. Marketing activities and positive WOM encourage adoption of a new product and negative WOM promote rejection decision. Similar to Goldenberg et al. (2007), we assume that both dissatisfied adopters and rejecters have the same degree of negative influence and the impact of negative WOM is *m* times that of positive WOM. The value this study uses for parameter *m* will be discussed later in section "ABMS Model Parameters." The probability of an adopter becoming dissatisfied after adopting a new product is captured by parameter *d* and hence the probability of an individual becoming satisfied after adoption will be 1-*d*.

The value of parameter *d* is fixed to 5%, a conservative value in comparison to other studies (Goldenberg et al. 2007).

At every period, potential adopters might decide to adopt the product, reject it, or remain undecided. The impact of positive (negative) WOM on each potential adopter is calculated based on the total number of satisfied adopters (dissatisfied adopters and rejecters) who have direct links with the potential adopter. Considering the asymmetric influence of segment-1 on segment-2, the total numbers of adopters and rejecters who are in direct link with each consumer are calculated separately at every period as explained below.

For every potential adopter *i* in segment-1:

$S_i^{11+}(t)$: The total number of satisfied adopters in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{11-}(t)$: The total number of dissatisfied adopters and rejecters in segment-1 at period *t* who have direct links with potential adopter *i*.

For every potential adopter *i* in segment-2:

$S_i^{12+}(t)$: The total number of satisfied adopters in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{12-}(t)$: The total number of dissatisfied adopters and rejecters in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{22+}(t)$: The total number of satisfied adopters in segment-2 at period *t* who have direct links with potential adopter *i*.

$S_i^{22-}(t)$: The total number of dissatisfied adopters and rejecters in segment-2 at period *t* who have direct links with potential adopter *i*.

Given the above, the probabilities that positive or negative WOM would influence a potential adopter *i* at each period are calculated as follows (Goldenberg et al. 2007; Toubia et al. 2008). For every potential adopter *i* in segment-1:

$$p^{+}_{(i,t)} \leftarrow 1-(1-p^{1}_{i})(1-q^{11}_{i})^{S^{11+}_{i}(t)} \qquad [1]$$

$$p^{-}_{(i,t)} \leftarrow 1-(1-p^{1}_{i})(1-mq^{11}_{i})^{S^{11-}_{i}(t)} \qquad [2]$$

Where p^{1}_{i} represents the influence of external factors on potential adopter *i*, and q^{11}_{i} represents the probability that potential adopter *i* adopts at time period *t* because of interaction with another segment-1 member, and *m* is the relative impact of negative to positive WOM.

For every potential adopter *i* in segment-2:

$$p^{+}_{(i,t)} \leftarrow 1-(1-p^{2}_{i})(1-q^{12}_{i})^{S^{12+}_{i}(t)}\,(1-q^{22}_{i})^{S^{22+}_{i}(t)} \qquad [3]$$

$$p^{-}_{(i,t)} \leftarrow 1-(1-p^{2}_{i})(1-mq^{12}_{i})^{S^{12-}_{i}(t)}\,(1-mq^{22}_{i})^{S^{22-}_{i}(t)} \qquad [4]$$

Where p^{2}_{i} represents the influence of external factors on potential adopter *i*, and q^{22}_{i} and q^{12}_{i} represent the probability that potential adopter *i* adopts at time period *t* because of interaction with another segment-2 and segment-1 member respectively.

A normalization factor α_i, denoting the ratio of positive WOM influence over the total WOM (positive and negative) influence on potential adopter *i*, is calculated as follows (Goldenberg et al. 2007): $\alpha_i = \frac{p^{+}_{(i,t)}}{(p^{+}_{(i,t)} + p^{-}_{(i,t)})}$

Given the above, the probabilities of the three potential adopter decisions—remaining undecided, $p^{wait}_{(i,t)}$, adoption, $p^{adopt}_{(i,t)}$, and rejection, $p^{reject}_{(i,t)}$—are calculated as follows:

$$p_{(i,t)}^{adopt} \leftarrow (1 - p_{(i,t)}^{-})\, p_{(i,t)}^{+} + \alpha_i p_{(i,t)}^{+}\, p_{(i,t)}^{-}, \quad [5]$$

$$p_{(i,t)}^{reject} \leftarrow (1 - p_{(i,t)}^{+})\, p_{(i,t)}^{-} + (1 - \alpha_i)\, p_{(i,t)}^{+}\, p_{(i,t)}^{-}, \quad [6]$$

$$p_{(i,t)}^{undecided} \leftarrow (1 - p_{(i,t)}^{+})\, (1 - p_{(i,t)}^{-}). \quad [7]$$

The sum of the above three equations is equal to 1, therefore after calculating the above probabilities for each potential adopter, a uniform random number between 0 and 1 is generated to find the potential adopter's new status (adopt, reject, or remain undecided). For those who adopt, another uniform random number between 0 and 1 is generated and compared with parameter *d*—probability that an adopter becomes dissatisfied after adoption. Therefore, the consumer will be satisfied with the probability $(1 - d) * p_{(i,t)}^{adopt}$ and becomes dissatisfied with the probability $d * p_{(i,t)}^{adopt}$.

Performance Measurement

An effective performance measurement for comparing different seeding strategies is net present value (NPV) of the firm profits. NPV captures both the number of adopters and the discounted value of the profits over time. For comparative purposes, this work measures the performance of a seeding strategy as the ratio of the NPV of profits that two diffusion processes generate: the diffusion process where the firm applies a seeding program ($NPV_{Seeding}$), and the natural diffusion process under the same market condition without the seeding intervention ($NPV_{No\ Seeding}$). NPV-Ratio (*NPVR*) may be stated as follows:

$$NPVR = \frac{NPV_{Seeding}}{NPV_{Base(No\ Seeding)}}$$

Higher values of *NPVR* denote higher positive impacts of seeding programs on firm profits. For example, a seeding program that generates an *NPVR* of 1.25 increases the NPV of profits by 25%. Similarly, smaller values of *NPVR* indicate higher negative impacts of seeding programs on firm profits. Seeding impacts the NPV in two essential ways: On one hand, consumers who receive free products will likely influence others to adopt the product and enhance the diffusion process. On the other hand, seeding entails two types of costs: the variable cost of giveaways and the lost revenue. NPVR captures all these effects using a single measure.

In line with earlier studies (Lehmann and Esteban-Bravo 2006; Libai et al. 2010), this study assumes that seeding happens at period 0 and hence the variable cost of seeding (i.e., the total number of seeds multiplied by the unit cost) is deducted from the NPV at time period ‘0’. All NPVs are calculated using a 10% discount rate, an accepted value in the literature (e.g., Goldenberg et al. 2007). The work assumes that each adopter contributes one unit of monetary profit based on the revenue and variable costs of the product. This one unit represents the profits of a one-time purchase of a durable product. While this paper does not focus on repeat-purchased goods, Libai et al. (2010) suggest that this one unit can represent the customer’s lifetime value at the time of adoption which takes into account retention rate for a repeat-purchase product.

ABMS Model Parameters

The selected parameter values and ranges that were used in simulation experiments are organized in four subsets: diffusion, market, seeding, and fixed parameters (see Table 1). As the last column of panel B in Table 1 shows, all parameters are selected from already published empirical and theoretical studies in order to capture real-world market conditions and have the bases for validation of the results produced by this study.

Diffusion parameters: p and q

This work developed four different scenarios with parameters *p* and *q* (see Table 1, Panel A). The selective choices of *p* and *q* was necessary to avoid an exponential increase in the number of parameter combinations and hence experiments, and yet capture a wide range of market and product conditions with regards to the profitability of seeding programs. The four scenarios considered for combinations of *p* and *q* are as follows. Scenario-1 indicates a typical market condition for a generic product. The values of *p* and *q* in this scenario are in line with both the means of earlier studies' estimations for empirical data (Muller and Yogev 2006; Van den Bulte and Joshi 2007) and those used in past theoretical or simulation studies (e.g., Goldenberg et al. 2002; Lehmann and Esteban-Bravo 2006). Scenario-2 indicates a 'highly-favorable' condition where seeding will highly effect the diffusion. Scenario-3 captures a 'highly-unfavorable' condition where seeding will have less impact on the diffusion.

To estimate the values of parameters *p* and *q* in scenarios 2 and 3, the work builds on earlier studies. Jain et al. (1995) found that seeding is more effective when marketing activities weakly affect consumers (i.e., low values of *p*) but consumers highly influence each other (i.e., high values of *q)*. Thus, seeding provides consumers with the chances of experiencing the product and hopefully influencing others. On the other hand, seeding is less effective when marketing activities highly influence consumers (i.e., high values of *p*) and consumers do not highly influence each other (i.e., low levels of *q*). This logic was used to come up with parameters *p* and *q* under the highly-unfavorable and highly-favorable scenarios. Constant values were deducted/ added from/to the values of *p* and *q* in scenario-1—typical market condition. As a result, not only the values of parameters *p*

TABLE 1
ABMS Scenarios and Simulation Parameters

A. Diffusion Parameters p and q: the Four Scenarios

Scenario	Market Conditions	p^1	q^{11}	q^{12}	p^2	q^{22}
Scenario-1	Typical market conditions	0.05	0.62	0.18	0.005	0.31
Scenario-2	Highly favorable market conditions for the profitability of seeding	0.01	0.92	0.35	0.001	0.51
Scenario-3	Highly unfavorable conditions for the profitability of seeding	0.09	0.32	0.01	0.009	0.11
Scenario-4	High Influence of Segment-1 on Segment-2	0.05	0.62	0.54	0.005	0.31

B. Other Model Parameters

Parameter Group	Parameter	Parameter Value or Range	Selection Sources
Market Structure	Social Network Structure	Random, Scale Free, Small World	Alderson (2008); Bampo et al. (2008); Barabassi (2003); Goldenberg (2009); Watts and Storgatts (1998)
	Consumers' Average Number of Social Ties	4, 14, 24	Goldenberg (2007); Libai (2010)
	Size of Segment 1	5%, 10%, 20%	Goldenberg et al. (2002); Lehmann and Bravo (2006); Muller and Yogev (2006)
Seeding Strategy	Seeding Target	Random, Segment 1, Social Hubs, Boundary Spanners, Globally Central	Freeman (1977, 1979); Jain et al. (1995); Lehmann and Bravo (2006); Libai et al. (2010); Lin (1976); Mahajan and Muller (1998); Rosen (2009); Scott (2001); Watts and Dodds (2007);
	Seeding Percentage	1%, 3%, 5% and 1%-12% Increments of 1%	Delre (2007); Jain et al. (1995); Libai (2010); Rosen (2009)
	Cost of Seeding (Giveaway)	0.2, 0.6, 1.0	Jain et al. (1995); Lehmann and Bravo (2006)
Fixed Variables	Market Size	3000	Goldenberg (2007)
	Discount Rate	10%	Goldenberg (2007); Libai (2010)
	Relative impact of neg. WOM to pos. WOM	2	Goldenberg et al. (2007), Libai et al (2010)
	Profit generated by unit sales	1	Goldenberg et al. (2007), Libai et al (2010)
	Probability of Dissatisfaction Adopters	5%	Lowest value considered in Goldenberg et al. (2007)
	Simulation Termination Condition	95% of the market has decided	Goldenberg (2007)

and q that were used in the three scenarios correspond with the estimations for empirical data, the three scenarios also cover a wide range of market conditions from highly unfavorable to highly favorable with regards to the profitability of seeding programs.

The final scenario, scenario-4, represents market conditions where consumers in segment-1 highly influence those in segment-2 (i.e., $q^{11}>q^{12}>q^{22}$). This condition likely exists in markets such as fashion products or business electronics (Coulter et al. 2002; Lehmann and Esteban-Bravo 2006). With the exception of the parameter q^{12}, influence of segment-1 consumers on others, all the other parameters p and q in this scenario are similar to those in scenario-1—typical market conditions (see scenario 4 in Table 1, Panel A).

For comparison purposes to other studies, panels A and B in Table 1 present these parameters at the aggregate market level, rather than at the individual level. To identify the values for parameters p and q at the individual level, this work relies on the methods suggested by earlier studies for calculating individual-level parameters from aggregate-level parameters (Goldenberg et al. 2002; Toubia et al. 2008). The value of parameter p will be the same at both individual level and aggregate level. The values of aggregate-level parameters q—q^{11}, q^{22}, q^{12}— are transformed to individual-level parameter values q_j—q_i^{11}, q_i^{12}, q_i^{22}—by dividing each parameter by the respective average number of links per individual (Goldenberg et al. 2002; Toubia et al. 2008). Therefore, the individual-level values used for parameters p and q generate aggregate results that are comparable to those of the previous studies focusing on aggregate level models.

Market Structure Parameters

Market Structure Parameters consist of social network structure, average number of links per consumer, and size of segment-1. A few studies attempted to investigate these parameters leading to different estimations (e.g., Bampo et al. 2008; Goldenberg et al. 2009; Libai et al. 2010; Muller and Yogev 2006). These differences depend on the type of products as well as the consumers and the communication environment characteristics. This study examines the effects of the three generic social network structures among consumers—random, scale-free, and small-world—on seeding returns. Moreover, the work considers three values for the average number of links (i.e., 4, 14, 24) and three different values for the relative size of segment-1 (5%, 10%, 20%) which cover the ranges used in most studies as indicated in Table 1, Panel B.

Seeding Parameters

The two main decisions for firms in a seeding program are choosing the seeding targets (which group to target?) and seeding size (how many?). The work examines five target groups—random, early adopters, social hubs, globally central, boundary spanners (see section 'Seeding Target'). Studies 1 through 3 examine three seeding sizes (1%, 3%, and 5% of all potential consumers). Study 4 is a sensitivity analysis to study the impact of seeding sizes 1% to 12% with increments of 1% —values that are in line with earlier studies (Delre et al. 2007; Jain et al. 1995; Libai et al. 2010). Finally, the work examines three levels of seeding costs: 20%, 60%, and 100% of profit. The ranges are in line with other studies (Jain et al. 1995; Lehmann and Esteban-Bravo 2006), and they characterize products with low variable costs (e.g., software programs) and goods with higher variable costs—with up to 100% markup.

Fixed Parameters

Panel B in Table 1 presents the fixed parameters. This section discusses the relative impact of negative WOM over positive WOM. Other fixed parameters are explained throughout the paper.

Negative WOM adversely impacts the diffusion process and firms' profits. This work considers both negative and positive WOM among consumers to mimic more realistic market conditions. The marketing literature generally suggests that negative WOM has a greater impact on potential adopters than does positive WOM (Harrison-Walker 2001). Not only do consumers assign more weight to negative information than positive ones (Hart et al. 1990; Mizerski 1982), but also dissatisfied consumers talk to more people than satisfied ones (Anderson 1998). Therefore, the relative power of negative to positive WOM is fixed to 2 (Goldenberg et al. 2007).

The ABMS Computational Experimental Design

The ABMS computational experimental design included four studies as depicted in Table 2. As this figure shows, these studies address the research questions under different market conditions with regards to parameters *p* and *q* (See Panel A in Table 1). Each study executes a full factorial design of the market structure and seeding parameters (see Table 1, Panel B). To provide insights into the 'optimal' seeding size, study 4 conducts further sensitivity analysis.

Similar to other studies, the work fixed the number of potential consumers in the market to 3,000, and stopped each simulation experiment once 95% of the market made their decisions—adoption or rejection (e.g., Goldenberg et al. 2007). Each simulation experiment needed to be replicated multiple times to capture the variations that might be due to stochastic effects of the simulation model.

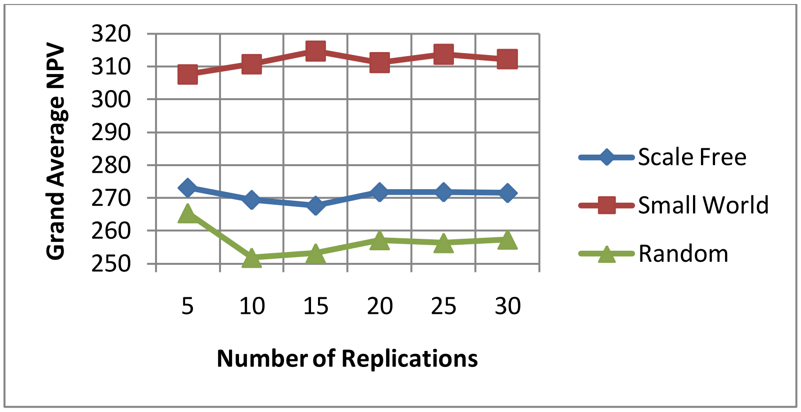
TABLE 2
ABMS Experimental Design

Study	Market Conditions with Regards to Parameters *p* and *q*	Study Purpose – Research Questions
Study 1	Scenario-1 'Typical' Market Conditions	- Do seeding programs increase the profits of the diffusion of new products? - Does the choice of the target in seeding make a difference? - Does the social network structure make a difference?
Study 2	Study 2-A: Scenario-2 'Highly Favorable' Market Conditions'	
	Study 2-B: Scenario-3 'Highly Unfavorable' Market Conditions'	
Study 3	Scenario-4 High Influence of Early Adopters on others	- Does the choice of the target in seeding make a difference? - What is the effect of the size of segment-1 on the profits generated by seeding programs?
Study 4	Scenario-1'Typical' Market Conditions	- What is the effect of seeding variables—seeding size and cost of seeding—on the profits generated by seeding programs?

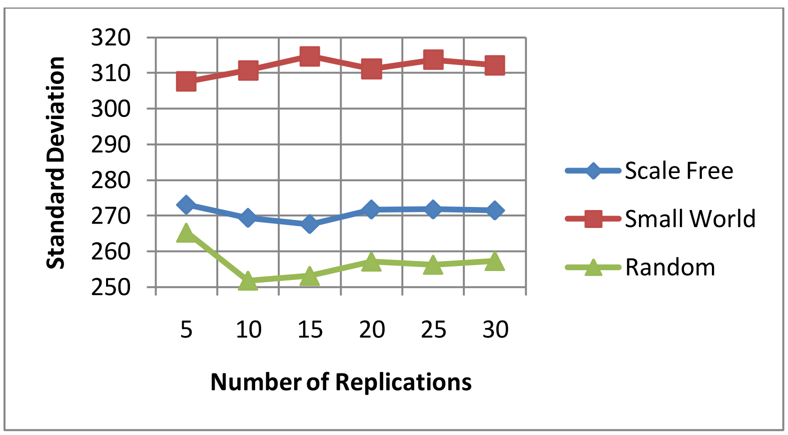
To determine the required number of replications at which the average NPV is stable, or in the simulation terminology where system arrives at a steady state, we chose the values of parameters *p* and *q* under scenario-1 and executed the simulation under the three network structures. For every combination of market structure variables—social network structure, average number of links, and size of segment-1—the work ran the base cases—no seeding—for each generated market structure. It then replicated each experiment 5 to 30 times with increments of 5 and averaged the value of NPV for the replications and captured both the mean and standard deviation of the grand NPV (See Figure 3). As this figure shows, the beginning of steady state status is approximately around 15 replications. Therefore, a conservative estimate of steady state is 20 replications.

Relying on this analysis, for every selected combination of market structure variables—social network structure, average number of links, and size of segment-1—the simulation program generated 20 social networks each including 3000 potential consumers. Each replication was executed using a new random seed (generating new random number stream), leading to 20 replications for every combination of parameters. However, in order to have comparable results for alternative seeding strategies, it is important to capture the performance of all seeding programs under the same market conditions. To maintain this condition, the simulation program generated 20 replications for every combination of market parameters using different random seed numbers and then executed all combinations of seeding strategy parameters under each of these 20 replications (see Panel B in Table 1).

The experiments generated a total of 540 randomly-generated social network structures, 180 different networks of each social network structure—random, small-world, and scale-free. Considering all replications and the factorial combinations of all parameters and the experiments for capturing the performance of base cases, 29,160 simulation runs were executed for each of the studies 1 through 4. In addition, for sensitivity analysis of the impact of seeding, a total of 97,200 simulation runs were executed. In summary, considering all scenarios and sensitivity analysis, the simulation experiments generated 213,840 simulation runs.



A. The Overall Grand Average NPV Generated for Network Structures



B. Standard Deviation of the NPV Generated by Network Structures

FIGURE 3
Steady State Analysis for Choosing the Number of Replications

The ABMS simulation algorithms were implemented using Java programming language and Repast agent-based modeling toolkit, developed by Argonne National Laboratory (http://repast.sourceforge.net). These programs were executed on a standard Dell desktop computer (Xeon, CPU 3.2 GHz, and 2.00 GB of Ram) under Microsoft Windows XP Professional operating system. All necessary computational simulation experiments were conducted in the same environment.

The rest of this chapter discusses the analysis, the results, and the implications that studies 1 through 4 present. Table 3 summarizes these findings.

Study 1: 'Typical' Market Conditions

This study examines the profit impact of seeding under a typical market condition (See Table 2). Moreover, the study seeks to examine the impact of social network structure on seeding profitability and choice of best seeding target.

Results

Impact of seeding. In an effort to address the question of whether seeding programs increase the profits generated by new products, a 6 (the five seeding targets plus the no seeding case) × 3 (social network structures) between-subjects ANOVA was conducted. The results show that the main effect of seeding target is significant ($F_{(5, 29142)}$ =1926.44, p<.001). As Panels A and C in Table 4 indicate, seeding all the five targets increased NPV of profits (M=1.05 to 1.69).

Alternative seeding targets, seeding size, and social network structures. In order to compare the effects of alternative seeding targets on the firm profits, the no-seeding cases were excluded and a 5 (seeding targets) × 3 (social network structure) × 3 (seeding size) between-subjects ANOVA was conducted. The results show that seeding target ($F_{(4, 24255)}$=1157.71, p<.001), network structure ($F_{(2, 24255)}$=4415.18, p<.001), and seeding percentage ($F_{(2, 24255)}$=494.04, p<.001), all had significant main effects on *NPVR*. Moreover, the results show a significant interaction effect between seeding target and social network structure ($F_{(8, 24255)}$=431.96, p<.001). As Table 4 and Panel A in Figure 4 indicate, social hubs in scale-free network promise the highest profits. Moreover, seeding

TABLE 3
Summary of the Findings

Insight Number(s)*	Insights Summary
1	On average, seeding programs significantly increase the profits under most market conditions that were examined.
2, 13	Consumer social network structure impacts the profits generated by seeding programs. Scale-free networks showed to generate the most profitable results from seeding programs followed by random and small-world networks respectively.
3, 4, 6	The choice of seeding target significantly impacts the NPV of profits. Consumers' number of social ties is a valuable measure for identifying the best seeding target under most conditions that were examined. The more complex measures—closeness and betweenness centrality—are slightly less effective. Even slight variation in consumers' number of social ties will favor social hubs as the best seeding target.
11	In scale-free networks, the profits generated by seeding only 1% of social hubs is comparable to that of targeting optimal seeding size, even if this 1% are chosen randomly from the top 10% of the most connected consumers.
4, 12, 14	Firms can consider random seeding as an option and save the resources and efforts required to identify the social hubs when identifying them is difficult. While targeting social hubs generates higher returns than does random seeding, on average random seeding generates about half the profits generated by targeting social hubs. Scale-free social network structure and high variable seeding cost favor targeting social hubs and small-world social network structure and low seeding costs favor random seeding. When variable cost of seeding is low, the 'optimal size of random seeding is between 10% to 12%.
2, 3, 5, 6, 9, 10, 15	The variables that tend to cause high variation in the profit impact of seeding programs and the optimal size of seeding are the social network structures, variable cost of seeding, the percentage of early adopters of a specific product in the market, external marketing influence (parameter *p*), influence of adopters on others (parameter *q*) that exist in different markets and for different products. Moreover, firms' decisions regarding the choice of target groups and percentage of market to provide with free products also significantly affect the profits that seeding programs generate.
4, 7, 8	Early adopters of a specific product are often not the best seeding targets for generating the highest profits. Although seeding early adopters does increase the profits because of the WOM they generate, but the lost revenue balances these profits as those who receive free products might have bought it at a later time. The revenue and cash flow early adopters generate is crucial to firms at early stages of diffusion. Random seeding generally results in higher profits than seeding early adopters. Targeting early adopters generates highest profits when early adopters highly influence others and the social network structure is small-world, or when they highly influence others, social network structure is random, and 10% or more of the market are early adopters. Under all other conditions, seeding early adopters is only recommended when other marketing activities are less likely to be effective on them or when other targets are unlikely to use the new product (e.g., because of its complexity) but early adopters will likely use the product and expose others to it.

* After each study several insights emerged. These insights are summarized in this table.

is most profitable in scale-free networks followed by random and small-world networks and targeting social hubs generate the highest average profits. However, in small-world networks, random seeding generates profits that are close to those generated by targeting social hubs and random seeding, on average, generates better results than seeding early adopters.

The partial η^2 for seeding target and social network structure and for the interaction between them ranged from .13 to .26. The relatively low partial η^2 for seeding percentage (.039) is further investigated in study 4. The other two-way and the three-way interaction effects were also significant, but the practical significance of these results are questionable because of small magnitude of partial η^2, ranging from .002 to .007 (See Table 5, Panel A).

Study 1: Summary and Discussion

This study provides several important insights (see Table 3for a summary of all findings):

Insight 1. On average, seeding programs significantly increase the NPV of profits under all social networks when the market conditions are 'typical'.

Insight 2. Consumer social network structure impacts the profits that seeding programs generate. Scale-free networks showed to generate the most profitable results from seeding programs (M=1.47) followed by random (M=1.19) and small-world (M=1.10) networks respectively. However, as expected, the effect of social network structure is significantly higher for social hubs, globally-central consumers, and boundary spanners comparing to early adopters or randomly chosen consumers. Because firms' investments in identifying and targeting the best targets depends on the returns they expect, a basic understanding of

TABLE 4
Comparison of Seeding Targets - Different Social Network Structures

A. Social Network Structure and Seeding Target

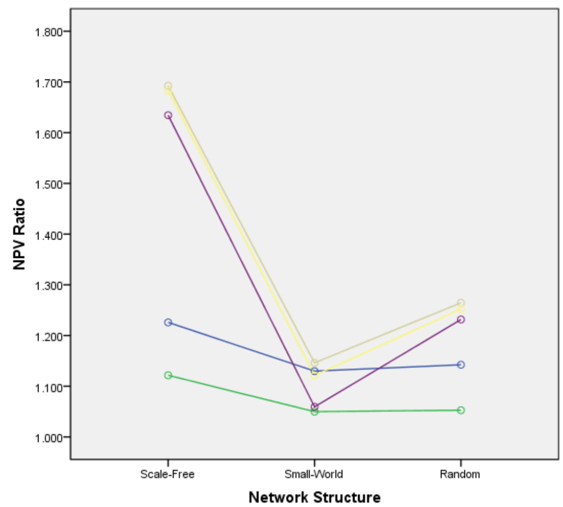
Seeding Target	Network Structure	'Typical' Mean	'Highly Favorable' Mean	'Highly Unfavorable' Mean
Random	**Scale-Free**	1.226	1.735	1.006
	Small-World	1.130	1.789	.995
	Random	1.142	1.841	.998
Segment-1	**Scale-Free**	1.122	1.705	.868
	Small-World	1.050	1.777	.861
	Random	1.053	1.799	.861
Social Hubs	**Scale-Free**	1.693	2.564	1.272
	Small-World	1.146	1.829	1.004
	Random	1.265	2.158	1.060
Globally Central	**Scale-Free**	1.634	2.476	1.234
	Small-World	1.059	1.534	.966
	Random	1.232	2.083	1.041
Boundary Spanners	**Scale-Free**	1.683	2.540	1.264
	Small-World	1.121	1.784	.990
	Random	1.252	2.134	1.051

B. Social Network Structure

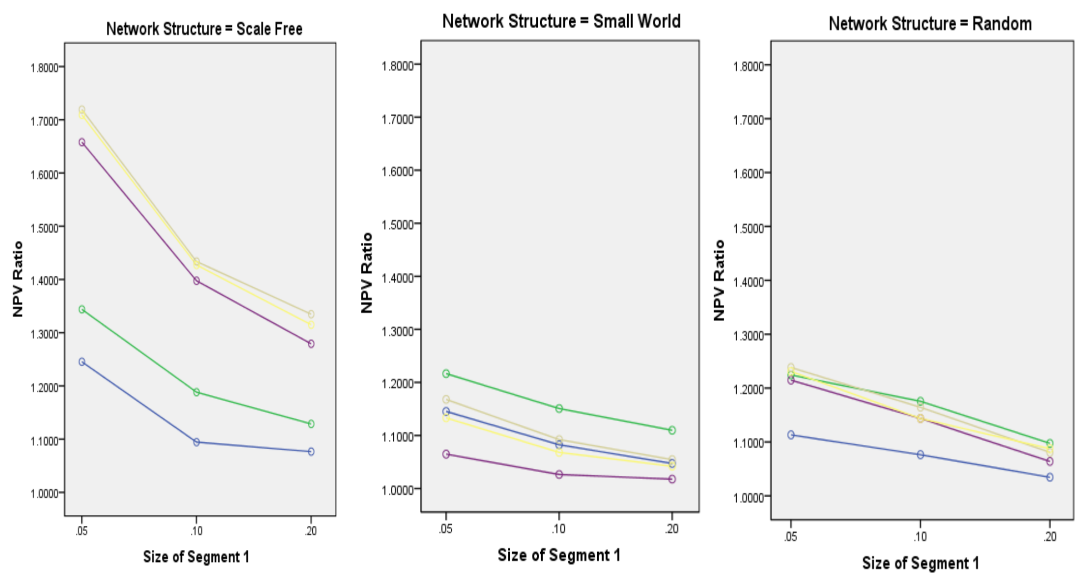
Social Network Structure	NPVR		
	'Typical'	'Highly Favorable'	'Highly Unfavorable'
	Mean	Mean	Mean
Scale-Free	1.471	2.204	1.129
Small-World	1.101	1.743	.963
Random	1.189	2.003	1.002

C. Seeding Target

Social Network Structure	NPVR		
	'Typical'	'Highly Favorable'	'Highly Unfavorable'
	Mean	Mean	Mean
Random	1.166	1.788	1.000
Segment-1	1.075	1.760	.864
Social Hubs	1.368	2.184	1.112
Globally Central	1.308	2.031	1.080
Boundary Spanners	1.352	2.153	1.102



A. The Mean Overall NPVR for The 'Typical' Market Conditions



B. Different Sizes of Segment 1 (High Influence of Segment-1 on Segment-2)

FIGURE 4

NPVR Generated by Different Seeding Targets under Different Network Structures

TABLE 5

ANOVA Model Tables for the Effects of Network Structure, Seeding Target, and Seeding Size (Tables A-C) / Segment-1 Size (Table D)

A. 'Typical' Market Condition – Scenario 1

Source	Sum of Squares	DF	Mean Square	F	p-Value	Partial η^2
NW. Structure	606.322	2	303.161	4415.179	.000	.267
Seeding Target	317.970	4	79.493	1157.714	.000	.160
Seeding Size	67.845	2	33.922	494.040	.000	.039
NW. Structure * Seeding Target	237.279	8	29.660	431.960	.000	.125
NW. Structure * Seeding Size	3.750	4	.938	13.654	.000	.002
Seeding Target * Seeding Size	10.911	8	1.364	19.864	.000	.007
NW. Structure * Seeding Target * Seeding Size	3.500	16	.219	3.186	.000	.002

B. 'Highly Favorable' Market Condition – Scenario 2

Source	Sum of Squares	DF	Mean Square	F	p-Value	Partial η^2
NW. Structure	866.179	2	433.090	364.590	.000	.029
Seeding Target	772.673	4	193.168	162.616	.000	.026
Seeding Size	1018.157	2	509.079	428.560	.000	.034
NW. Structure * Seeding Target	777.069	8	97.134	81.770	.000	.026

C. 'Highly Unfavorable' Market Condition – Scenario 3

Source	Sum of Squares	DF	Mean Square	F	p-Value	Partial η^2
NW. Structure	121.588	2	60.794	8219.464	.000	.404
Seeding Target	208.969	4	52.242	7063.251	.000	.538
Seeding Size	5.245	2	2.623	354.575	.000	.028
NW. Structure * Seeding Target	72.389	8	9.049	1223.396	.000	.288

D. High Influence of Segment-1 on Segment-2 Consumers – Scenario 4

Source	Sum of Squares	DF	Mean Square	F	p-Value	Partial η2
NW. Structure	318.622	2	159.311	2478.962	.000	.170
Seeding Target	70.391	4	17.598	273.829	.000	.043
Seg.1 Size	131.440	2	65.720	1022.640	.000	.078
NWStructure * Seeding Target	128.602	8	16.075	250.138	.000	.076
NWStructure * Seg.1 Size	41.491	4	10.373	161.406	.000	.026
Seeding Target * Seg.1 Size	6.545	8	.818	12.731	.000	.004
NWStructure * Seeding Target * Seg.1 Size	8.396	16	.525	8.165	.000	.005

the social network structure is a necessary first step. Future research must develop methods for estimating the social network structure in large markets.

Insight 3. The choice of seeding target significantly impacts the NPV of profits. Consumers' number of social ties is a valuable measure for identifying the best seeding target under most conditions that were examined (M=1.368). The more complex measures—closeness and betweenness centrality—are slightly less effective (M=1.308, 1.352 respectively). Hence, rather than trying to map the entire social networks, firms can rely on finding the most connected consumers as the best seeding targets.

Insight 4. On average, random seeding generates about 47% of the NPVR generated by seeding social hubs. This ratio highly depends on the social network structure. Random seeding does a very good job under small-world networks, generating 89% of profits generated by targeting social hubs. This might seem obvious because of the little variation in consumers' number of social ties. However, this finding has two implications. First, under small-world networks, there is a high variation in consumers' betweenness centrality measure. Yet, consumers' number of social ties identifies the best seeding targets. Second, the modest variation in consumers' number of social ties will favor the most connected consumers as the best seeding target. Therefore, when identification of social hubs is easily attainable, firms must identify the most connected consumers. However, when identification of social hubs is difficult and firms expect little variation in consumers' number of social ties, random seeding can achieve acceptable results. Moreover, random seeding generally results in higher profits than targeting early adopters.

Study 2: 'Highly favorable' and 'Highly unfavorable' Market Conditions

Study 2 examines whether findings of Study 1 hold true under other combinations of parameters *p*—marketing activities—and *q*—WOM influence—that capture 'highly favorable' and 'highly unfavorable' market conditions for the profit impacts of seeding (see Panel A in Table 1).

Results

Impact of seeding. Similar to study 1, two separate 6 (5 seeding targets+ no-seeding) × 3 (social network structure) × 3 (seeding size) between-subjects ANOVAs on NPVR was conducted for the 'highly favorable' and the 'highly unfavorable' conditions. The effect of seeding target was significant for both 'highly favorable' ($F_{(5, 29142)} = 161.62$, $p<.001$) and 'highly unfavorable' ($F_{(5, 29142)}=7063.25$, $p<.001$) conditions. As Panels A and C in Table 4 indicate, under the 'highly favorable' condition seeding all the 5 targets increased NPVR (M= 1.76 to 2.18). Under the 'highly unfavorable' condition, however, seeding early adopters reduced NPV of profits (M= .865) and random seeding didn't significantly impact the NPVR (M=.999). Under this condition, seeding the other three groups increased the NPVR (M = 1.08 to 1.11).

Alternative seeding targets, seeding size, and social network structures. In order to compare alternative seeding strategies, the no-seeding scenarios were excluded and two separate 5 (seeding targets) × 3 (social network structure) × 3 (seeding size) between-subjects ANOVAs were conducted separately for the 'highly favorable' and the 'highly unfavorable' conditions. All main effects were significant in both 'highly favorable' and 'highly unfavorable' scenarios. The results of both analyses are discussed separately.

Study 2-A: 'Highly Favorable' Market Condition

The results indicate that seeding target ($F_{(4, 24255)}$=162.61, p<.001), network structure ($F_{(2, 24255)}$=364.59, p<.001), and seeding percentage ($F_{(2, 24255)}$=509.07, p<.001), all had significant main effects on NPVR (see Table 5, Panel B). The results also show a significant interaction effect between seeding target and social network structure ($F_{(8, 24255)}$=81.77, p<.001). This study supports the findings of study 1 (See Panel A in Table 4). Seeding all 5 targets generated positive NPVR under all social network structures. The partial η^2 for the main effects and the interaction between social network structure and seeding target ranged from .026 to .034, values that are acceptable for practical purposes but lower than those in study 1 (See Table 5, Panel B).

Study 2-B: 'Highly Unfavorable' Market Condition

The results indicate that seeding target ($F_{(4, 24255)}$=7063.25, p<.001), network structure ($F_{(2, 24255)}$=8219.46, p<.001), and seeding percentage ($F_{(2, 24255)}$=354.57, p<.001), all had significant main effects on NPVR (see Table 5, Panel C). The results also show a significant interaction effect between seeding target and social network structure ($F_{(8, 24255)}$=1223.40, p<.001). As Panel A in Table 4 indicates, seeding social hubs generated the highest NPVR under all social network structures (M= 1.00 to 1.27). On average, random seeding does not increase the NPV of profits and seeding early adopters reduces it. Under small-world networks, seeding social hubs and random seeding generate comparable results (M_{random}=0.995, $M_{social\ hubs=}$1.004). The partial η^2 for seeding target, network structure, and the interaction between them ranged from .288 to .538 (See Table 5, Panel C). Study 4 further examines the effect of seeding percentage.

Study 2: Summary and Discussion

This study supports the findings of study 1 with regards to the impact of different seeding targets and social network structures on firm profits. The study also provided the following insights:

Insight 5. The values of parameters *p*s and *q*s significantly impact the profits that seeding programs generate. Under a 'highly unfavorable' condition, seeding might reduce firm profits.

Insight 6. The social hubs remain the best seeding target under both 'highly favorable' and 'highly unfavorable' market conditions. Moreover, even under a 'highly unfavorable' market condition, seeding social hubs will likely increase NPV of profits.

Study 3: Early Adopters Highly Influence Others

The analysis so far shows that early adopters are not the most promising seeding target (i.e., segment-1 consumers). One can argue that early adopters highly influence others in markets such as fashion products or business electronics (e.g., Coulter 2002, Lehman 2006). To address this concern, this study focuses on scenario 4 (Table 1, Panel A), in which early adopters highly influence others (i.e., $q^1>q^{12}>q^2$).

Results

Alternative seeding targets, social network structures, and size of segment-1. A 5 (seeding targets) × 3 (social network structure) × 3 (size of segment-1) between-subjects ANOVA was conducted. As Panel D in Table 5 indicates, seeding target ($F_{(4, 24255)}$=273.83, p<.001), network structure ($F_{(2, 24255)}$=2478.96, p<.001), and size of segment-1 ($F_{(2, 24255)}$=1022.64, p<.001) all had significant main effects on NPVR.

Moreover, there was a significant interaction between seeding target and social network structure ($F_{(8,\ 24255)}$=25.14, p<.001) and between network structure and size of segment-1 ($F_{(2,\ 24255)}$= 161.41, p<.001).

As in earlier studies, under a scale-free network structure, social hubs remain the best target (See Figure 4, Panel B), but seeding early adopters (M=1.22) performs better than random seeding (M=1.139). Under a small-world network, early adopters generate best results (M=1.159), followed by social hubs (M=1.105). This is because there is little variation in consumers' number of social ties, but early adopters have a high impact on those in segment-2. Under a random network, however, the choice of best target depends on the size of segment-1. When segment-1 is small (5%), the best target is social hubs (M=1.238). As the size of segment-1 increases, early adopters become the best target (M=1.176, 1.097). However, under these conditions, the difference between seeding the two groups are relatively small ($M_{difference}$ =.011 to M=.017).

Surprisingly, the analysis shows that the size of segment-1 negatively impacts performance of seeding programs (i.e., NPVR) due to two reasons. First, as the size of segment-1 increases, the overall NPV of profits will increase because there are more consumers who have a higher propensity to adopt early ($p^1 > p^2$). This leads to a larger denominator in the NPVR formula (i.e., NPVR $= \frac{NPV_{Seeding}}{NPV_{Base(No\ Seeding)}}$). Second, as discussed earlier, seeding will be more likely to be effective when the value of p is small. Because this study assumes $p^1 > p^2$, segment-2 consumers' new product adoptions are more likely to accelerate as the result of seeding than do those of early adopters. As the size of segment-1 increases, the size of segment-2 decreases, and therefore there will be less consumers whose adoptions are likely to accelerate as the result of seeding, leading to further decreases in NPVR. One might argue that as the size of segment-1 increases, there are more consumers in this segment to be influenced by the targeting early adopters, leading to an increase in the NPVR. However, the analysis showed that this increase is less than the decrease in NPVR caused by the two above reasons.

The partial η^2 for the three variables and the interaction between social network structure and seeding target ranged from .043 to .170. The other two-way and the three-way interaction effects were also significant, however the practical significance of these results are questionable because of small magnitude of partial η^2, ranging from .004 to .026 (See Table 5, Panel D).

Study 3: Summary and Discussion

The analysis shows that while there are conditions where seeding early adopters will be more profitable than seeding social hubs, these scenarios are limited to market conditions where there is little variation in consumers' number of social ties.

Insight 7. The revenue and cash flow generation by early adopters is crucial to firms at the early stages of diffusion. Not only products are more expensive at introduction than they are at later stages (Chandrasekaran and Tellis 2007), the time value of money is also higher for early adoptions. Therefore, seeding early adopters must be considered only when other marketing activities are less likely to be effective on them. Seeding early adopters is also recommended when other targets are unlikely to use the new product because of its complexity or other reasons, but the firm believes that early adopters will use the product and expose others to it.

Insight 8. In a market where early adopters strongly influence others, three different cases can happen with regards to the most promising seeding target (See Figure 4, Panel B).

First, if the social network structure is scale-free (i.e., high-variation in consumer number of social ties), social hubs remains the best target. Second, if the social network structure is small-world (i.e., high clustering and little variation in consumers' number of social ties), early adopters are the most promising target. Finally, if the social network is random, the best target depends on the size of segment-1. Small sizes of segment-1 will favor social hubs, while moderate or large sizes of segment-1 will favor early adopters as the most promising seeding targets.

Insight 9. As the size of segment-1 increases, the effectiveness of seeding programs decreases. Under typical conditions (i.e., scenario 1), this statement holds true for all seeding targets.

Study 4: 'Optimal' Seeding Size

To provide further insights into the 'optimal' seeding size, study 4 examines the effects on NPVR of seeding 1 to 12 percent of the market with increments of 1 percent in a 'typical market' condition (i.e., scenario 1). The study examines two targets: social hubs, because studies 1-3 identified them as the most promising targets, and random seeding, as it entails little or no effort and cost in the identification of targets. Table 6 summarizes the 'optimal' size of seeding and NPVR that each 'optimal' seeding generates under different social network structures, sizes of segment-1, and variable costs of seeding and Figure 5 shows the effect of seeding size on NPVR for different targets under different social network structures and variable costs. The insights Table 6 and Figure 5 provide are discussed in the summary and discussion section.

Study 4: Summary and Discussion

The study supports the findings of earlier studies and provides the following insights:

Insight 10. Social network structure, size of segment-1, and seeding cost impact the 'optimal' size of seeding, the NPV of profits, and the relationship between seeding size and profits. These impact depends on the seeding target (See Figure 5).

Insight 11. In scale-free networks, seeding only 1% of social hubs generates profits that are comparable to the 'optimal' profits. (M_{ratio}=.85 when variable cost is high, and M_{ratio}=.71 when variable cost is low). To examine whether this is because of targeting a few nodes that have significantly high number of social ties, another experiment was conducted in which the seeding targets were randomly chosen from a pool of the top 10% most connected consumers. This experiment generated results that were comparable to the earlier study, although the NPVRs were slightly lower. This finding supports practitioners' rule of thumb of seeding 1% of the market (Rosen 2009) under certain conditions.

Insight 12. When the variable cost of seeding is low, the 'optimal' seeding size for random seeding is more than 10% of the market for all the cases reported in Table 6, suggesting heavy seeding for these cases. Seeding beyond 12% of the market might further increase firm returns, but these sizes are considered impractical (Delre et al. 2007). Interestingly, when seeding cost is low and the social network is small-world, random seeding promises the best results.

Insight 13. For all cases shown in Table 6, scale free networks generate the highest NPVR, followed by random and scale-free networks. The results support Insight 2.

TABLE 6
The Optimal Size of Seeding and the NPV Ratio of the Profits
'Typical' Market Condition – Scenario 1

S/NW Structure	Size of Seg. 1	Variable Seeding Cost	Social Hubs: 'Optimal' Seeding Size*	Social Hubs: NPVR	Random Seeding: 'Optimal' Seeding Size*	Random Seeding: NPVR
Scale Free	0.05	0.2	6-9%	2.191	12%	1.728
		0.6	5,6%	2.075	9,10%	1.528
		1	3-5%	1.982	5%	1.437
	0.1	0.2	6,7%	1.772	12%	1.408
		0.6	6%	1.683	7%	1.283
		1	3,4%	1.61	7%	1.182
	0.2	0.2	6%	1.605	11,12%	1.289
		0.6	5,6%	1.53	9%	1.178
		1	3,5%	1.472	3-5%	1.126
Random	0.05	0.2	10-12%	1.732	12%	1.555
		0.6	8,9%	1.553	8-12%	1.351
		1	8%	1.417	6, 8%	1.206
	0.1	0.2	11,12%	1.591	12%	1.442
		0.6	7,8%	1.436	7-12%	1.269
		1	7%	1.329	5,7,8%	1.154
	0.2	0.2	11,12%	1.379	10-12%	1.279
		0.6	6,8%	1.255	6-9%	1.159
		1	5,6%	1.171	6, 7%	1.08
Small World	0.05	0.2	9-11%	1.52	11,12%	1.557
		0.6	7-9%	1.362	9-12%	1.356
		1	5-7%	1.234	6,7%	1.212
	0.1	0.2	8,9%	1.371	11,12%	1.4
		0.6	8%	1.255	8-11%	1.24
		1	7,8%	1.138	4-8%	1.128
	0.2	0.2	7-11%	1.207	8-12%	1.214
		0.6	8%	1.114	7,8%	1.111
		1	2-5%	1.048	2-5%	1.039

* When the difference in NPVR is less than or equal to .001, all seeding sizes are reported.

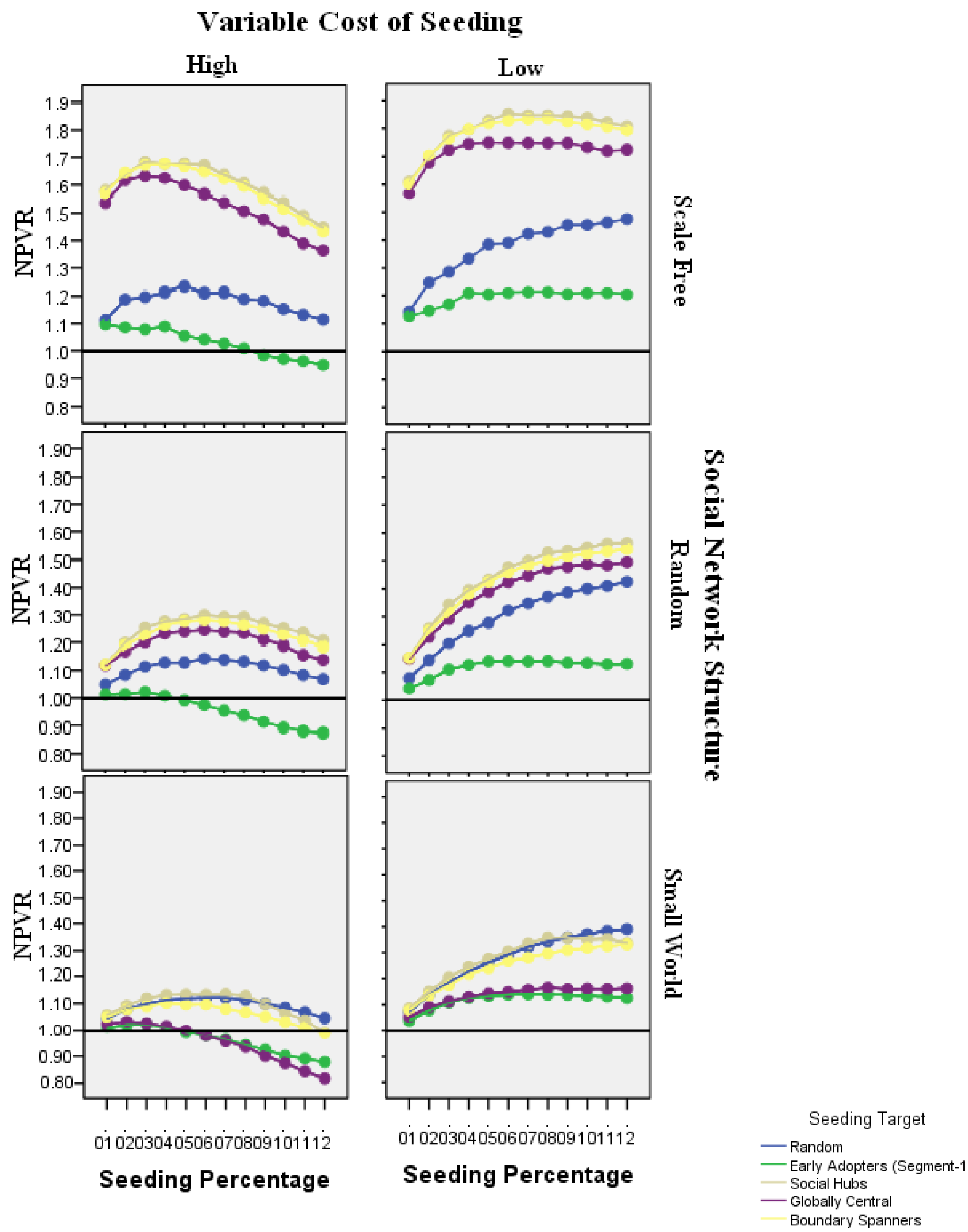


FIGURE 5
Impact of Seeding Size on NPVR:
Alternative Seeding Targets, Social Network Structures, and Seeding Costs

Insight 14. The ratio of the NPVR that the 'optimal' random seeding generates over that of targeting social hubs for every case reported in Table 6 is between .27 and 1.08. A combination of scale-free social network structure and high variable seeding cost generate the lowest ratios (i.e., favor targeting social hubs) and small-world social network structure and low seeding costs generate the highest ratios (i.e., favor random seeding).

Insight 15. Size of segment-1 negatively impacts the NPVR and the 'optimal' seeding size under all cases reported in Table 6. The findings support Insight 9.

Conclusion

This study examined profits seeding programs generate and the profit impact of firms' decisions regarding the selection of potential consumers to target with these programs. Four specific studies explored the research questions providing the following key findings:

The utility of seeding programs. Under majority of the conditions that were examined, seeding programs have the potential to significantly increase the firm profits. Even under a highly unfavorable market condition, a well-planned seeding program can increase firm returns. However, the results show that the profits seeding programs generate are the result of complex interactions among several factors. These are the structure of social network, size of segment 1, variable cost of giveaways, the seeding target, and seeding size, the impacts of external factors such as marketing activities (p) and internal factors such as the influence of adopters on others (q). These findings suggest that designing an “optimal” seeding program is a complex task and requires careful analysis of the market and product conditions.

The importance of influentials. Social hubs offer the best seeding target among the five targets that were examined under all three social network structures. In most conditions that were studied, targeting social hubs increases the NPV of profits. Consumers’ number of social ties identifies the most promising seeding targets better than do the popular but more complex social network centrality measures of closeness centrality and betweenness centrality. Using these two complex measures requires the mapping of the entire social networks, a task that seems infeasible in many consumer markets.

This finding is also important due to the fact that it addresses the debate on the importance of influentials in the diffusion process. Given that the firm is able to identify influentials, this study shows that targeting at least one group of influentials (i.e., social hubs) with free products generates returns that are significantly higher than the profits generated by targeting randomly chosen consumers. Moreover, it supports the literature that emphasize the importance of social hubs (Goldenberg et al. 2009; Goldenberg et al. 2010).

Impact of social network structure. The NPV of profits generated by seeding programs, regardless of the seeding target, depends on the social network structure. This effect is higher for seeding targets that are identified using network centrality measures—social hubs, globally central consumers, and boundary spanners—relative to other targets—random or early adopters. Therefore, the high variation in the success of seeding programs is to some degree due to different social network structures in different markets and for different products. Having a general understanding of the social network structure is essential in the design of a successful seeding program. The advances in telecommunication technology, the Internet, and Web 2.0 have potentially provided marketers with new means to map social network structure.

Random Seeding. On average, random seeding—choosing the targets randomly—generates about 47% of the NPV of profits generated by targeting social hubs. However, this ratio highly depends on the variable cost of seeding and the social network structure: in small-world network (i.e., where there is high clustering and little variation in consumers' number of social ties), this ratio can be as high as 89%. Moreover, under this structure and when seeding entails little variable cost, randomly targeting a large percentage of the market will be the most promising seeding strategy. Therefore, under certain conditions, firms must consider random seeding and thus save the resources and efforts required to identify the social hubs.

Methodological approach. This study introduces a new agent-based modeling and simulation approach for the estimation of the profits alternative seeding strategies generate prior to execution. The most desirable condition is when firms are able to estimate the parameters perfectly and map the social network. Under these conditions, this approach will provide estimations with high accuracy. However, the study also provides general conclusions for cases where firms are only able to partially estimate the parameters and the social network structure.

Limitations and Future Directions

This work does not attempt to over-simplify seeding decisions and acknowledges several limitations as well as future research directions. First, the study investigates the research questions with the assumption that the firm is able to identify and target these groups. The feasibility and the cost of identifying and targeting influentials are beyond the scope of this study. Second, the dependent variable used in this study is the ratio of NPV of profits over NPV of profits under natural diffusion without seeding intervention. This dependent variable captures both dimensions of the number of adopters and the time-value of adoptions. However, it does not capture aspects such as the experiential benefits of seeding or the affective impacts of communication strategies on consumers. Third, the study assumes that social ties are bi-directional and consumers are homogeneous within their segments in terms of parameters *p*s and *q*s. It will be interesting to investigate how the findings might change if these assumptions are altered. Fourth, the study only captures WOM communications from adopters and rejecters to undecided consumers through social ties. It does not capture WOM initiated from someone who has not adopted the product nor does it capture other means of social influence such as social status or the observation of others using a new product. Fifth, this study examines targeting only one group of consumers at the time of product launch. It will be interesting to examine more complex seeding strategies such as targeting more than one group Sixth, it will be interesting to study seeding programs for products that consumers purchase on a regular bases—consumable or soft goods—or for multiple generations of a single product. Finally, future research must develop new methods for estimating the social network structure in real-world consumer markets. The advances in Web 2.0, and telecommunication technologies allow for the mapping of social networks. Yet, there is need for methods that are feasible for estimating social network in real-world markets.

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CHAPTER 4

THE ADVERSE IMPACTS OF INFLUENTIALS' RESISTANCE TO NEW PRODUCTS ON FIRM PROFITS

Abstract

This study explores the adverse impacts of three types of consumer resistance to new products—postponement, rejection, and opposition—on firm profits. The issue is investigated across five groups of consumers—early adopters, social hubs, boundary spanners, globally central consumers, and randomly designated resisters— and three social network structures—random, scale free, and small world. The findings suggest that complex interactions between three groups of parameters—resistance parameters, diffusion parameters, and consumer social network structure—affect the relationship between resistance and profits. Opposition negatively influences firm profits to a degree that is stronger than that of rejection and postponement. Moreover, influential resister groups generally have stronger adverse influences on profits than do randomly designated resisters. Finally, resistance type, consumer social network structure, and the two drivers of diffusion—external versus internal influences—impact the relationship between resistance and firm profits.

Introduction

Firms introduce tens of thousands of new products to the market every year. Although most of these products are developed after extensive marketing research, between 40% and 90% of them fail depending on the product category and the criteria used for product failure (Barczak et al. 2009; Gourvilee 2006). Consumer resistance to new products (hereafter referred to as resistance) is one of the main reasons for these failures (Ram and Sheth 1989). Although resistance by a single consumer hardly impacts the diffusion process, resistance by a few consumers can potentially hinder the diffusion process or even influence a large group of consumers to resist the new product (Erez et al. 2006; Moldovan and Goldenberg 2004).

However, marketers are unclear about how individual consumer resistances aggregate to adversely affect firm profits at the market level due to several gaps of knowledge in the literature. First, resistance covers a continuum of decisions from postponing the adoption to actively opposing the new product and spreading negative information about it (Kleijnen et al. 2009; Szmigin and Foxall 1998). The degree to which these various decisions hurt firm profits remains unexplored. Second, studies identify several groups of consumers—opinion leaders, social hubs, boundary spanners, early adopters, just to name a few—who play important roles in the diffusion of new products and broadly refer to them as influentials (Goldenberg et al. 2009; Iyengar et al. 2008; Rogers 2003; Weimann 1994). The literature has primarily focused on the facilitative roles these groups play in the diffusion process and failed to examine the adverse effects they have on this process if they resist new products. Third, research has yet to study the impact of the structure of consumer social networks (hereafter referred to as social network) on the transference of individuals' resistance to market-level lost profits. The few studies that examined the effects this structure has on the diffusion process, focused on the positive effect consumer adoptions has on this process (Choi et al. 2010; Delre et al. 2010). Fourth, two types of influences drive diffusion of new products: external influence of marketing activities and internal influence or social influence (Bass 1969; Muller et al. 2010). The impact of these two types of influences on the relationship between resistance and profits is unclear. Fifth, the relationship between the percentage of all consumers in the market who resist the product (hereafter referred to as resister group size) and firm profits is yet to be explored. Both marketing scholars and practitioners need a more detailed understanding of how individual decisions aggregate to form market-level outcomes such as firm profits (Muller et al. 2010). Without this knowledge, marketers continue to regard the adverse effects of resistance on firm profits as a black box.

This study seeks to fill in the above gaps by examining the adverse impacts of three types of resistance on firm profits. These are postponement or delaying adoption decisions, rejection or developing strong reluctance towards adoption (Rogers 2003), and opposition or rejecting the product and actively engaging in activities against the product such as spreading negative word-of-mouth (WOM) about it. These influences are investigated across five groups of consumers—early adopters, social hubs, boundary spanners, globally central consumers, and randomly designated resisters, hereafter referred to as resister groups—and three social network structures—random, scale free, and small world. The study also examines the degree to which the drivers of diffusion—external and internal influences—affect the above relationships.

A viable approach for addressing the above issues is setting up a series of experiments in which the characteristics of the market and consumers are held constant in every experiment. This consistency seems unfeasible in the real world owing to the complexities of identifying different groups in each market and pinpointing WOM in the marketplace (Delre et al. 2010; Hauser et al. 2006). An alternative approach is using simulation modeling which has a high degree of internal validity, is capable of studying longitudinal phenomena, and has the potential to provide insights into a phenomenon that is difficult to examine using other methodologies (Davis et al. 2007; Harrison et al. 2007). Therefore, this study relies on Agent-Based Modeling and Simulation (ABMS), a simulation methodology that allows for longitudinal observation of the diffusion process while providing the ability to manipulate the market by simulating the consumers as agents with three essential characteristics—autonomy, interactivity, and bounded rationality (North and Macal 2007). These characteristic enable this study to capture the complex and adaptive interactions among consumers in their social networks over time and the influence of marketing activities on consumers. ABMS provides the ability to examine simultaneous influence of these factors on the diffusion outcomes (e.g., firm profits) over time.

Resistance to New Products

Drivers of Resistance

Consumers resist new products due to a wide range of reasons. Those who are happy with their current states prefer to maintain their status quo rather than pursuing changes (Chernev 2004; Oreg 2003; Sheth 1981). Adopting many new products such as software programs requires that consumers learn new skills and change the behaviors they are already accustomed to. They are reluctant to give up a product for which they have already spent their time and resources to adopt, and invest in adopting a new one and learning how to use it. Consumers generally view giving up the products they currently own as losses and adopting new product as gains. Thus, they tend to overestimate the value of existing products and underestimate the value and advantages of the new ones (Gourvilee 2006; Kahneman and Tversky 1979). Consumers hardly have the time and skills to evaluate a new product and when overloaded with information, people tend to stick to what they are familiar with and resist changes (Herbig and Day 1992). Even experts often resist radical innovations because they have difficulty fitting these products' attributes with the already-established structures in their minds (Moreau et al. 2001). Finally, new product adoption usually entails different types of risks—physical, economic, functional, and social. Consumers often resist new products, at least for some time, to reduce these risks (Ram and Sheth 1989).

Furthermore, consumers might resist a new product when they find it in conflict with their existing beliefs, values, traditions, and norms (Ram and Sheth 1989). For example, a large group of men resist adopting makeup and other skin-care products since using these products by men is in conflict with their beliefs and social norms. Those men who lean towards adopting these products often face social risks associated with the negative image of using such products by men. This effect is so powerful that even though the demand for these products is booming, some companies ship makeup to their male customers in discreet packages such as old cigar boxes (Stein 2010). Negative image can also cause resistance when consumers rely on extrinsic cues such as country of origin to make their decisions. For example, it took a great deal of effort for Indian manufacturers of industrial machine tools to overcome consumers' skepticism about tools that were made in India (Ram and Sheth 1989).

Finally, consumers' relationships with brands or firms can serve as basis for resistance to new products. A brand's loyalists frequently reject new products introduced by competitors (Fournier 1998a). For example, Apple fans are reluctant to adopt new PCs regardless of the advantages that these PCs might have over an Apple computer. Moreover, dissatisfied customers resist new products from the company in order to retaliate for the damages they perceive the firm caused them (Grégoire et al. 2009). Some buyers base their decisions solely on hating a rival product such as those who buy Apple computers just because they hate PCs (Fournier 1998a).

The Three Types of Resistance

Resistance to innovations has been broadly defined as "the resistance offered by consumers to an innovation" (Ram and Sheth 1989, p. 6) and an 'avoidance behavior' (Fournier 1998b). More recently, Reinders (2010) categorized resistance into passive and active resistance. Consumers who passively resist a new product simply ignore it and do not deliberately consider the product because of their inclination towards maintaining their existing habits. This type of resistance can also include 'not trying' the innovation and lack of awareness about it (Kleijnen et al. 2009). Active resistance, however, is a deliberate decision after consumers have evaluated the new product. Researchers suggest that resistance is a response that is grounded on conscious choices and hence, it is not simply the 'obverse' of adoption (Kleijnen et al. 2009; Ram 1987; Szmigin and Foxall 1998). Studies find that the parameters that explain rejection decisions differ from those explaining adoptions and also consumers might resist innovations even when conditions that predict adoption exist (Garcia and Atkin 2002; Gatignon and Robertson 1989). Since establishing boundaries around passive resistance behaviors is difficult, this study focuses on active resistance and throughout the paper the term resistance refers to active resistance.

As Table 1 shows, resistance covers a range of decisions and behaviors that can be categorized into three distinct types—postponement, rejection, and opposition (Szmigin and Foxall 1998). Consumers postpone their adoption decisions to a later point in time when they find the new product acceptable and even attractive, but they perceive high levels of risks, mainly economic, associated with the adoption or when the adoption requires changes in their existing usage patterns (Kleijnen et al. 2009). Rejection entails that consumers become reluctant to adopt a new product after evaluating it. Consumers reject a new product when they perceive social and functional risks in adoption or when adopting the product requires major changes in their behaviors or mindsets (Kleijnen et al. 2009; Szmigin and Foxall 1998). They might also reject a new product because they are loyal to a competing brand or firm. Finally, Opposition entails rejecting a new product and actively engaging in activities against its success such as spreading negative WOM about it. People oppose a new product when they find it conflicting with their values, traditions, and norms. They might also oppose a new product when they associate social, functional, and physical risks or a negative image with the adoption (Kleijnen et al. 2009). Finally, they might oppose a new product in order to retaliate against the manufacturer due to their past negative experience with the firm or brand (Grégoire et al. 2009).

TABLE 1
Resistance Types and Their Drivers*

Resistance Type	Description	Main Drivers (antecedents)
Postponement	Postponing adoption decision to a later point in time, although potential adopters might find the product acceptable in general This study assumes that postponers delay decisions until 16% of the market has adopted the product.	- Risks, mainly economic (affordability) - Conflict with existing usage patterns - Situational factors
Rejection	Becoming strongly reluctant to adopt a new product after evaluating it.	- Risks: Social, functional, and economic - Perceived negative image (e.g., appropriate for kids, product origins)
Opposition	Rejecting a new product and actively engaging in activities against its success. Opposers spread negative WOM, engage in online activities and send complaint letters to the firm.	- Risks: Functional, physical, and social - Perceived negative image - Conflict with existing norms and traditions

* This table summarizes the findings of Kleijnen et al. (2009) and Szmigin and Foxall (1998).

Resistance to new products must not be confused with boycotts, although they have similarities in behaviors and antecedents. Boycott is a group effort, usually initiated and promoted by an organization such as an NGO, aiming to make a difference by enforcing a firm to adjust its products or policies (Garrett 1987; Klein et al. 2004).

Influentials, Resistance, and Diffusion of New Products

The literature identifies different groups of consumers (e.g., opinion leaders, social hubs, boundary spanners) who play important roles in the diffusion of new products and generally labels them influentials. Researchers have mainly focused on identifying influentials and the influence they have on those around them and have failed to examine the effects these groups might have on the diffusion process (Goldenberg et al. 2009; Goldenberg et al. 2010). A few recent studies examined the effects influentials have on the diffusion process at the market level (e.g., Goldenberg et al. 2009; Iyengar et al. 2008; Tucker 2008). Previous studies primarily focused on influentials' facilitative effects in diffusing new products, but ignored their adverse capacities if they resist new products. This shortcoming could be due to three main reasons. First, research has mostly focused on strategies that positively impact the diffusion process than seeking to reduce the negative effects that lead to new product failure. Second, a small number of consumers express their negative impressions to firms so marketers might not notice the negative WOM that is spreading in the market (Charlett et al. 1995). Finally, sales data does not capture negative influences (Moldovan and Goldenberg 2004) so collecting data on the adverse effects of influentials' resistance on diffusion process is more challenging than it is for their adoptions. Although researchers have long called for research on resistance, the literature is still meager on this topic (Gatignon and Robertson 1989; Kleijnen et al. 2009; Reinders 2010; Sheth 1981).

Few studies have examined the impact of resistance on the diffusion process. Leonard-Barton (1985) found that experts can positively or negatively affect dentists' opinions towards a controversial dental technology. She also found that even in the case of a successful product, about 20% of the market deliberately rejected the product based on the negative WOM they had received and without even trying it. Moldovan and Goldenberg (2004) demonstrated that opinion leaders' resistance to new product critically hurts the product’s growth and it hampers the effects of advertising and positive WOM. Later, Erez et al. (2006) found that in a market where WOM is the sole driver of the diffusion process, new products might fail as the rejection by a small group of consumers has the potential to block the innovation from reaching majority of consumers. Finally, Goldenberg et al. (2007) found that for every 1% increase in consumer dissatisfaction rate, the net present value (NPV) of firm profits drops by 1.8%.

In addition, according to the chasm framework, high technology markets consist of two markets—the early market adopters, consisting of knowledgeable or risk-seeking consumers, and the main market, consisting of risk-averse individuals (Moore 1991). The saddle phenomenon—a temporary slowing of new product sales after initial takeoff—empirically supports existence of two segments and it also indicates that early adopters have modest impact on the main-market consumers adoptions (Goldenberg et al. 2002; Muller and Yogev 2006). The question arises as how decisions to resist a new product by early adopters—those who have a high propensity to adopt early but weakly impact the main market consumers—compare with resistance by those who considerably influence others in terms of the adverse impacts they have on firm profits.

Research has yet to explore the degree to which the three types of resistance that can be associated with different groups of consumers affect the diffusion process and firm profits. Studying this effect is important as marketing managers might target a specific group of consumers not because such targeting is expected to yield positive returns but since those consumers may severely damage the diffusion process if they resist the new product. Moreover, following a recent study, marketers debate on the extent to which influentials affect diffusion process (Van den Bulte 2010; Watts and

Dodds 2007). The gaps of knowledge in the available research literature regarding the impact of resistance on firm profits and the high failure rate among new products clearly points out for future research.

Purpose of Study and Research Questions

This study addresses five questions related to the adverse impacts of resistance on the diffusion of new products:

- What are the effects of different resistance types on diffusion outcomes such as firm profits?
- Do consumer characteristics determine the degree to which their resistance reduces profits?
- What is the effect of social network structure on the relationship between resistance and profits?
- What are the effects of the two diffusion drivers—external influence of marketing and internal influence or social influence—on the relationship between resistance and profits?
- What is the impact of the resister group size and percentage of early adopters in the market on firm profits?

To fully explore the research questions, this study conducts comprehensive simulation experiments with the following unique features. First, the study examines the adverse impacts of three distinct types of resistance that can be associated with five resister groups under three generic social network structures. Second, resistance adversely affects the number of adopters and the timing of adoptions. The study captures both the monetary and the temporal effects of resistance by examining the effects they have on the NPV of profits. Third, the study examines the influences of a comprehensive set of parameters including resistance parameters, market parameters, and diffusion parameters. Finally, the study considers a two-segment market comprising early adopters and main market, a feature likely to exist in several markets including high technology, pharmaceuticals, entertainment, and teens (Van den Bulte and Joshi 2007).

Social Network Structure and Diffusion of New Products

Consumers interact with each other and exchange information in the diffusion process through their social ties. A social network consists of the consumers—nodes—and the social ties among them—links (Van den Bulte and Wuyts 2007). As Figure 1 shows, social networks may present themselves in three broad structures: random, scale-free, or small-world (Alderson 2008). In a random network, every node is randomly connected to a small subset of nodes in the social network (Erdős and Rényi 1959). In a scale-free network, the number of links for each node follows a power law distribution, where majority of nodes have small number of links and a small percentage of nodes have significantly large numbers of links (Barabasi 2002). In a small-world network, each node is connected to a certain number of its adjacent nodes (neighbors) and a few random links to non-neighboring nodes in the network (Watts and Strogatz 1998). While small-world and random networks present little variation in terms of the number of social ties, scale-free networks present high degrees of variation in the number of social ties among members. Moreover, small-world networks demonstrate market conditions where social networks are highly-clustered (i.e., consist of subgroups in which nodes are highly connected with each other but loosely connected to others outside their subgroup) while

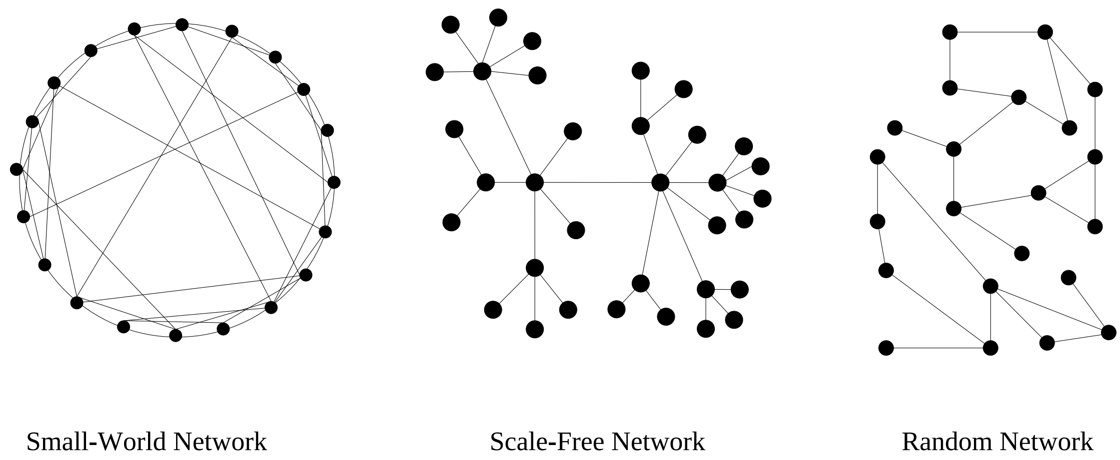


FIGURE 1
Graphical Characterization of Random, Small-World, and Scale-Free Networks

random and scale-free networks present lowly-clustered markets (Anderson 1998; Watts and Strogatz 1998).

Large-scale social networks are generally difficult to map and they introduce additional complexity in modeling and estimation (Alderson 2008; Goldenberg et al. 2009). A few recent studies attempted to map large-scale consumer social networks, resulting in different structures. Bampo et al. (2008) found that random and small-world networks fit the data better than scale-free network in a viral marketing campaign, while Goldenberg et al. (2009) concluded that the social network structure among users of a social networking website closely mapped to be scale-free. Researchers suggest that the structure of social networks varies across markets depending on the nature of the product or service, the communication environment (e.g., online versus real world), and the consumer characteristics (Janssen and Jager 2003; Watts and Dodds 2007).

Moreover, studies that investigated the impact of social network structure on the diffusion process found contradictory results. One group of studies find that that diffusion is slower in highly-clustered networks, and therefore new products and diseases diffuse more quickly and to more consumers in scale-free and random networks than they do in small-world networks (Delre et al. 2010; Rahmandad and Sterman 2008). Another group finds that diffusion is faster in clustered networks because individuals reinforce each other's behaviors and hence new products are less likely to fail in highly-clustered networks (Centola 2010; Choi et al. 2010).

To date research has failed to examine the role of social network structure on the transference of individuals' resistance to market-level lost profits. While the networks observed in the real-world are rarely random (Barabasi 2009), when domain-specific details are not available, studies have used random network structures as a natural null-hypothesis in evaluating the network properties (Alderson 2008). To cover diverse network characteristics and hence potential conditions in different markets for different types of product, this study examines the research questions within three network structures—scale-free, random, and small world.

Resister Groups

Marketers have identified several groups of consumers who play important roles in the diffusion process. Social network researchers, on the other hand, have developed a variety of centrality measures for the importance of a node—consumer—in social network with regards to the impact they have on communications among others. The most popular centrality measures are degree centrality, closeness centrality, and betweenness centrality (Scott 2000; Van den Bulte and Wuyts 2007). This study brings together the two perspectives and examines the adverse influences of five groups' resistance decisions on the diffusion process. These are: early adopters (Rogers 2003;

Vakratsas and Kolsarici 2008), social hubs or the most-connected consumers (Barabasi 2002; Goldenberg et al. 2010), boundary spanners (Burt 1992; Roch 2005; Tucker 2008), those holding a globally central position with all others in the social network (Scott 2000), and a group of randomly designated resisters (Watts and Dodds 2007). It is important to note that while some consumers might belong to more than one group, the study chooses each group based on their main attribute. For example, some social hub might also be early adopters, but the study chooses social hubs based on consumers' number of ties regardless of whether they are early adopters.

Early Adopters

Marketers pay special attention to early adopters not just because they have high propensity to adopt early, but more importantly as they introduce the new product to other consumers (Mahajan and Muller 1998; Rogers 2003). This group's resistance is expected to significantly cut firm profits as their adoptions generate considerable revenue during early stages of diffusion. Moreover, although early adopters might slightly influence others who view them as deviants, their resistance delays others' exposure to the product. In line with earlier studies (Goldenberg et al. 2002; Moore 1991; Vakratsas and Kolsarici 2008), this study assumes that consumers in segment 1 are early adopters (i.e., have a higher propensity to adopt than those in segment 2) and interchangeably uses the terms early adopters and segment 1 consumers.

Social Hubs

Social hubs are the most connected consumers in a market or in social network terms those who score high on degree centrality measure—the total number of consumer's direct ties (see Appendix 1). Kratzer & Lettl (2009) find that opinion leaders among children tend to be highly connected and Goldenberg et al. (2009) find that social hubs not only increase the speed of diffusion, they also expand the final number of adopters. They also tend to bridge the chasm between adoptions of early adopters and the main-market consumers (Goldenberg et al. 2010). Therefore, the resistance exerted by social hubs slows the diffusion and enhances the spread of negative WOM. For practical purposes, identifying social hubs in consumer markets is more feasible than the two groups discussed below, as marketers can estimate one's number of social ties using surveys without mapping the entire social network (Scott 2000).

Boundary Spanners

Boundary spanners, also referred to as opinion brokers, span structural holes in the social network and transfer information across social boundaries between groups or clusters (Burt 1992). Their influence comes from holding unique positions in a social network and connecting otherwise disconnected social groups (Burt 1997; Roch 2005). The intermediary roles they play makes them act as 'brokers' or 'gatekeepers' and enables them to control the flow of information between different sub-groups (Burt 1992; Freeman 1977). Kratzer and Lettl (2009) found that children who have ties to different groups tend to adopt earlier than others. Resistance by these consumers will likely hinder the diffusion process between clusters and in the case of opposition, spread negative WOM to different groups. Betweenness centrality measures captures this characteristic based on the sum of the number of shortest paths that passes through each node (see Appendix A). Identification of globally central consumers and boundary spanners using the measures presented in this study are only feasible when the map of the entire network is available.

Globally Central Consumers

'Globally central consumers' are those who possess central locations in their social networks with regards to all other consumers. They can potentially enhance the diffusion of the new product to a large area of the social network in a short period of time. Therefore, resistance by this group will likely hinder spread of the diffusion globally and their oppositions will quickly spread negative WOM around the market. Closeness centrality measure captures this characteristic by calculating the total distances of a node from all other nodes in the social network (see Appendix A).

Randomly Designated Resisters

For comparison purposes, the study also examines the adverse effects of a group of randomly designated resisters on firm profits. Because these resisters are randomly chosen from the pool of all potential consumers in the market, they represent an average potential consumer in the market and the adverse effects of their resistance on firm profits represent that of average consumers.

The ABMS Model

Complex adaptive systems are composed of entities that interact with each other and adapt to the changes in their environment. Simple interactions among the members of a complex adaptive system might lead to unpredictable patterns which are referred to as emergent phenomena. The market under study resembles a complex adaptive system and hence ABMS—agent-based modeling and simulation—is an appropriate choice for modeling this system (Garcia 2005; North and Macal 2007). This section explains the

ABMS model including consumer adoption status and decision making, and the performance measurement.

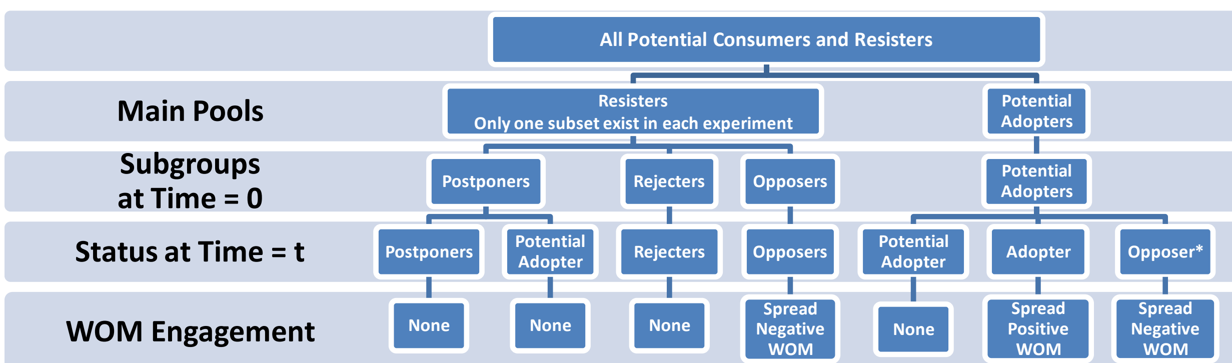
Consumer Adoption Status and Decision Making

External influence or marketing activities captured by parameter p and internal influence or social influence captured by parameter q impact consumers' adoptions (Muller et al. 2010). In line with other studies (e.g., Garber et al. 2004; Goldenberg et al. 2007), this work only considers WOM between adopters (or resisters) and those potential adopters who have direct links with them and does not consider other means of social influence such as observation and adoptions related to social status. The literature on the topic of resistance does not discuss the degree to which postponers, rejecters, and opposers engage in negative WOM about the product. These studies suggest that the opposers actively engage in negative WOM, but they neither talk about postponers and rejecters' engagements in WOM nor they measure or quantify the degree to which opposers engage in such activities (Kleijnen et al. 2009; Szmigin and Foxall 1998).

Due to the lack of evidence about different groups' engagement in negative WOM, this study assumes that while postponers and rejecters avoid engaging in WOM, opposers spread negative WOM. This assumption is conservative because postponers and rejecters might express their opinions to others and moreover, the study does not incorporate the 'active' characteristic of opposers' engagement in negative WOM. However, the study fixed the effect of negative WOM on consumers to two times that of positive WOM (Goldenberg et al. 2007). Previous studies generally suggest that negative WOM has a greater influence on potential adopters than does positive WOM (Harrison-

Walker 2001) as consumers assign more weight to negative information than positive ones (Hart et al. 1990; Mizerski 1982).

Considering new product diffusion process, at the beginning of each period consumers can be in one of the following pools: potential adopters (undecided), adopters, and resisters (see Figure 2). Members of different pools differ in the type of WOM they initiate: adopters initiate positive WOM, opposers spread negative WOM, and others—undecided consumers, postponers, and rejecters—do not engage in WOM. Since each experiment considers one resistance type, the resister pool consists of only one sub-group at a time. Therefore, the experiments that investigate opposition maintain both positive and negative WOM and the experiments that focus on postponement and rejection only focus on positive WOM.



*Potential Adopters May Move to the pool of opposers only in studies that examine opposition.

FIGURE 2
Pools of Potential Consumers and Resistors and their WOM Engagement

When the firm launches the new product, time period 0, all market participants are in the pool of potential adopters. Marketing activities initiate the adoption process at early stages of diffusion and adopters move to the pool of adopters. Adopters (opposers) will spread positive (negative) WOM to others, triggering future adoptions of (resistance to) the product (see Figure 2). With the exception of postponers, potential adopters make a one-time decision and they do not move to other pools after moving out of the pool of potential adopters.

The study assumes that all resisters make their decisions at period 0—when the product is launched. At period 0 of every experiment, based on a certain criteria (e.g., number of social ties) a certain percentage of all potential adopters in the market is randomly selected and assigned to the designated resister pool. Although resistance can potentially occur at different diffusion stages (i.e., periods), fixing the timing of resistance allows for comparing different resistance types. This timing only impacts the growth in experiments that focus on opposition and it does not affect those examining rejections or postponements as these groups do not spread negative WOM. Moreover, potential consumers are frequently aware of new products before they become available and many people dislike a product or decide to postpone their decisions right after exposure to it.

This study's approach is different from that of Moldovan and Goldenberg (2004) who assumed two groups of leaders—opinion leaders and resistant leaders. The two groups were influenced to the same degree by parameters p and q but they differed in their decisions: opposition leaders' decisions entailed resistance (i.e., opposition) and opinion leaders' choice was to adopt. The bases for one group of resistant leaders is that some consumers consistently resist new products because of their personalities (Oreg 2003). However, studies find that the basis for resistance differ from those for adoption (Gatignon and Robertson 1989) and potential consumers might resist new products due to various reasons. Potential consumers differ in terms of their expertise, interests, socio-economic status, and backgrounds and new products also differ in terms of their attributes. Resistance also depends on the innovation type as experts might resist radical innovations more than an average consumer does because the new products' attributes do not fit with their mindsets (Moreau et al. 2001). Thus initial resisters to a new product cover a range of potential consumers that is larger than those who consistently resist new products. Moreover, adoption decisions generally entail more time and greater degrees of risks than resistance (Ram and Sheth 1989). Thus, parameters p and q might not influence adoption and rejection decisions to the same extent.

This study assumes that postponers delay their decisions to a point in time at which 16% of the market has adopted the product and at this time they move to the pool of potential adopters. At this point a fair size of the market has adopted the product, the price has dropped significantly, and the product generally takes off (Chandrasekaran and Tellis 2007). Studies find that consumers postpone their decisions when the adoption entails economic risks or conflicts with existing usage patterns, therefore the above assumption is fair (Kleijnen et al. 2009).

At every period, potential adopters receive WOM from others who have direct links with them and have already adopted or rejected the new product. Marketing activities and positive WOM encourage adoption of a new product and negative WOM, if present, promote rejection decision. To address the research questions, the study adopts a two-segment diffusion model with asymmetric influence—segment 1 consumers influence others in both segments but segment 2 consumers only influence their peers in segment 2. This model fitted data better than competing models for the diffusion data of 33 different products (Van den Bulte and Joshi 2007). Appendix 2 discusses further details of consumer decision making.

Performance Measurement

An effective performance measurement for comparing the adverse effects of different resister groups is NPV. NPV captures both the number of adopters and the discounted value of profits over time. This work measures the negative impacts of resistance as the ratio of the NPV of profits that two diffusion processes generate: the diffusion process in a market where resisters exist ($NPV_{resistance}$), and the one under the same conditions without resistance ($NPV_{No\ Resistance}$). NPV Ratio (*NPVR*) may be stated as follows:

$$NPVR = \frac{NPV_{resistance}}{NPV_{No\ Resistance}}$$

Lower values of *NPVR* denote stronger adverse impacts of resistance on profits. For instance, a diffusion process with an *NPVR* of 0.80 generates profits that are 20% less than that in the same conditions if no one resists the product. Resisters reduce NPV in two ways. On one hand, they impede the diffusion process and in the case of opposition, spread negative WOM. On the other hand, opposers and rejecters do not generate revenue and postponers generate it at a later point in time. Using a single measure, NPVR captures all these effects.

All NPVs are calculated using a 10% discount rate, an accepted value in the literature (e.g., Goldenberg et al. 2007). The study assumes that each adopter contributes one unit of monetary profit based on the revenue and variable costs of the product, representing the profits of a one-time purchase of a durable product. While this study does not focus on repeat-purchased goods, Libai et al. (2010) suggest that this one unit can represent a customer's lifetime value at the time of adoption, taking into account retention rate for a repeat-purchase product.

ABMS Model Parameters

As Table 2 shows, parameters that were used in simulation experiments are organized in four subsets: diffusion, market, resistance, and fixed parameters. The parameter values and ranges are selected from already published empirical and theoretical studies in order to capture real-world market conditions and have the basis for validation of the results produced by this study. The fixed parameters are explained throughout the paper and will not be discussed here.

Diffusion Parameters: p and q

This study developed five different product-market conditions with regards to parameters p and q, hereafter referred to as pq combination (see Table 2, Panel A). The selective choices of p and q was necessary to avoid an exponential increase in the number of parameter combinations and hence experiments, and yet capture diverse market and product conditions. Combination 1 indicates a "typical" product-market condition for a generic product. Combinations 2-5 capture conditions where parameters p and/or q strongly/weakly drive the diffusion. The values of p and q are chosen in line with both

TABLE 2
ABMS Scenarios and Simulation Parameters

A. Diffusion Parameters: *pq* Combination

pq Combination	Diffusion Drivers	p^1	q^{11}	p^2	q^{22}	q^{12}
'Typical'	Average Product: Moderately by marketing activities and WOM	0.051	0.51	0.0051	0.25	0.17
High-High	Highly by both marketing activities and WOM	0.13	.99	0.013	0.6	0.3
High-Low	Highly by marketing activities / Slightly by WOM	0.13	0.17	0.013	0.1	0.05
Low-High	Slightly by marketing activities/ Highly by WOM	0.004	0.99	0.0004	0.6	0.3
Low-Low	Slightly by both WOM and marketing activities	0.004	0.17	0.0004	0.1	0.05

p^1, p^2: Marketing activities' influence on adoption by segment 1/segment 2 consumers.
q^{11}: Influence of segment1 consumers on each other.
q^{12}, q^{22}: Influence of segment 1/segment 2 consumers on segment 2 members.
The above ranges are chosen from the following studies: Goldenberg et al. (2002), Lehmann and Esteban-Bravo (2006), Muller and Yogev (2006), Van den Bulte and Joshi (2007).

B. Other Model Parameters

Parameter Group	Parameter	Parameter Value or Range	Selection Sources
Market	Social Network Structure	Random, Scale Free, Small World	Alderson (2008); Bampo et al. (2008); Barabassi (2003); Goldenberg (2009); Watts and Storgatts (1998)
	Consumers' Average Number of Social Ties	Fixed at 14 (4 and 24 were also tested)	Goldenberg (2007); Libai (2010)
	Size of Segment 1	5%, 10%, 20%	Goldenberg et al. (2002); Lehmann and Bravo (2006); Muller and Yogev (2006)
Resistance	Resistance Type	Postponement, Rejection, and Opposition	Kleijnen et al. (2009), Szmigin and Foxall (1998)
	Resister Group	Random, Early Adopters, Social Hubs, Globally Central, Boundary Spanners	Freeman (1977, 1979); Lehmann and Bravo (2006); Libai et al. (2010); Mahajan and Muller (1998); Rosen (2009); Scott (2001); Watts and Dodds (2007)
	Resister Group Size	1%, 3%, 5% and in sensitivity analysis: .5%-20% Increments of .5% up to 4% and 1%	Indirectly from Delre (2007); Libai (2010); Rosen (2009)
Fixed Variables	Market Size	3000	Goldenberg (2007)
	Discount Rate	10%	Goldenberg (2007); Libai (2010)
	Neg./pos. WOM impacts	2	Goldenberg et al. (2007)
	Profit of unit sales	1	Goldenberg et al. (2007), Libai et al (2010)
	Simulation Termination Condition	95% of the market has decided	Goldenberg (2007)

the earlier studies' estimations for empirical data (Muller and Yogev 2006; Van den Bulte and Joshi 2007) and the values used in past theoretical or simulation studies (e.g., Goldenberg et al. 2002; Lehmann and Esteban-Bravo 2006). The "typical" condition captures an average product and the "high" and "low" values for parameters p and q were chosen by avoiding the outliers in the estimations of empirical data by the above-mentioned studies.

For comparison purposes to other studies, panel A in Table 2 present these parameters at the aggregate market level. To identify the values for parameters p and q at the individual level, the study adopts the methods earlier studies suggest for calculating individual-level parameters from aggregate-level ones (Goldenberg et al. 2002; Toubia et al. 2008). The value of parameter p will be the same at both individual and aggregate levels. The values of aggregate-level parameters q—q^{11}, q^{22}, q^{12}— are transformed to individual-level parameter values q_i—q_i^{11}, q_i^{12}, q_i^{22}—by dividing each parameter by the respective average number of links per individual. Therefore, the individual-level values used for parameters p and q generate aggregate results that are comparable to those of the previous studies that focused on aggregate-level models.

Market Parameters

As Panel B in Table 2 shows, market parameters consist of social network structure, average number of links per consumer, and size of segment 1. This study considers the three generic social network structures among consumers—random, scale-free, and small-world—and three different values for the relative size of segment 1 (5%, 10%, 20%) covering the ranges used in most past studies. The conversion of aggregate-level values of q to individual-level ones uses the average number of social ties, hence the study fixed this value to 14. However, the average number of social ties of 4 and 24 were examined and the conclusions remained the same.

Resistance Parameters

Resistance parameters consist of resistance type, resister group, and resister group size. The study examines three resistance types—postponement, rejection, and opposition, see Table 1—that can be associated with five resister groups—randomly designated, early adopters, social hubs, globally central, and boundary spanners. The main study examined resister group sizes of 1%, 3%, and 5% of all potential consumers. A sensitivity analysis examined sizes of .5% to 4% with increments of .5% and 4% to 20% with increments of 1%.

The ABMS Computational Experiments, Analysis, and Results

The ABMS computational experimental design included a main study executing a full factorial design of the market, resistance, and diffusion parameters (see Table 2). To provide insights into the effect of resister group size, a sensitivity analysis further examines this parameter. In line with other studies (e.g., Goldenberg et al. 2007), the number of potential consumers in the market was fixed to 3,000, and each simulation experiment was stopped once 95% of the market made their decisions. Each simulation experiment was replicated 20 times to capture variations that might be due to stochastic effects of the simulation runs. Appendix 3 provides further details about the computational experiments. The remaining parts of this paper discuss the analysis, results, and implications. Table 3 summarizes the findings.

TABLE 3
Synopsis of the Findings

Parameter	Findings
Complexity of phenomenon	The degree to which resistance reduces firm profits depends on complex interactions between several parameters (see Figure 3). These are resistance type, resisters group, social network structure, *pq* combination, and the resister group size. The challenges marketers face in predicting the success of new products is partially due to their failure in considering and evaluating these parameters.
Resistance Type	Opposition reduces firm profits to a degree that is significantly stronger than rejection and postponement. Opposition by only 0.5% of the market potentially cuts the profits between 11% to 75% . The adverse effects of rejection are marginally greater than postponement. This parameter is the most critical parameter among the ones this study considered.
pq Combination	Postponement and rejection significantly affect NPVR* when *pq* combination is "low-low" and they slightly affect it when pq combination is "high-high." Opposition, however, strongly impacts NPVR when *pq* combination is "low-high" and slightly affects it when *pq* combination is "high-low." Diffusion processes that rely on internal influences (i.e., WOM) are highly vulnerable to resistance comparing to those relying on external influences (e.g., advertising). This parameter is the second critical parameter among the ones this study investigates.
Social Network Structure	Scale-free networks have the strongest impact on NPVR followed by random and small-world networks. Under scale-free networks, the social network resister groups have a stronger negative impact on NPVR than early adopters and randomly designated resisters. However, under random and small-world networks, early adopters are generally the group with highest negative effect.
Resister Group	Influential resister groups overall have stronger adverse impacts on profits than do randomly designated resisters. On average, influentials potentially reduce NPVR less than twice as randomly designated resisters do for most of the cases when social network is random or small-world, and this impact factor is greater than 2 for most cases under scale-free networks. However, the influentials impact factor might be less than one under certain conditions (See Figure 4). Finally, social network significantly affect the influentials' impact factor for the three social network resister groups and imperceptibly impact that for early adopters. The influentials' impact factor falls as the intensity of resistance increases, dropping from postponement to rejection to opposition.
The Most Critical Group	Overall, under scale-free networks, the social network resisters are the critical group. Under this structure, for every 1% increase in the size of three social network resister groups, the overall NPVR drops by about 2.1% for rejections and about 1.3% for postponements, compared to 1.3% and .5% for randomly designated resisters, respectively. However, under small-world and random networks, early adopters are the most critical group. The marginal effects of their postponements and rejections on NPVR are higher when resister group size is larger than 5%, compared to when resister group size is smaller than 5%. Overall, for every 1% increase in this resister group size, the NPVR drops by about 2.4% for rejections and 1.9% for postponements compared to 1.3% and .5% for randomly designated resisters, respectively.
Resister Group Size	The relationship between resister group size and NPVR is roughly linear for postponements and rejections while the relationship resembles an inverse exponential function for opposition.
S/NW structure and group size	Social network structure significantly impacts the relationship between resister group size and NPVR for the three social network resisters. It weakly affects that of early adopters and randomly designated resisters.
Importance of Parameters	Resistance type by far has the highest effect on profits, followed by *pq* combination and social network structure. Moreover, the resister group size has stronger impact on profits than does the group who resists. The effect of size of segment 1 is questionable.

* NPVR: Net present value ratio

Analysis and Results

To address the research questions, a 3 (resistance type) × 5 (resister group) × 3 (social network structure) × 5 (*pq* combination) × 3 (resister group size) × (size of segment 1) between-subjects ANOVA was conducted. Table 4 shows all main and interaction effects with a partial η^2 of at least 0.01, although the significance of results which show small partial η^2 are questionable for practical purposes. As Table 4 shows, resistance type ($F_{(2,38731)}$= 182960.05, p<0.001), resister group ($F_{(4, 38731)}$= 1261.11, p<0.001), network structure ($F_{(2, 38731)}$=15138.48, p<0.001), *pq* combination ($F_{(2, 38731)}$= 10483.49, p<0.001), and resister group size ($F_{(2,38731)}$= 7311.41, p<0.001) all had significant main effects on NPVR. The practical significance of segment 1 size ($F_{(2, 38731)}$=282.36, p<0.001) is questionable due to small magnitude of partial η^2 (.014).

As Figure 3 shows, opposition (M=.365) significantly reduces firm profits to a degree that is greater than rejection (M=.889) and postponement (M=.923). Moreover, post-hoc tests show that randomly designated resisters (M=.785) impact NPVR less than other four groups (M=.704 to .719). Furthermore, scale-free networks significantly impact NPVR (M=.628) followed by random (M=.745) and small-world (M=.805) networks. Finally, a *pq* combination of “low-high” (M=.611) has the strongest effects on NPVR followed by “low-low” (M=.675), “typical case” (M=.730), “high-high” (M=.741), and “high-low” (M=.872). The results also show significant two-way, three-way, and four-way interaction effects between these parameters (see Table 4). The important insights resulted from this study are discussed below.

TABLE 4
ANOVA Model for the effects of Resistance Type, Resister Group, Social Network Structure, Resister Group Size, and Size of Segment 1

Source	Sum of Squares	DF	Mean Square	F	P-Value	Partial η2
Resistance Type	2643.63	2	1321.81	182960.05	.000	.904
Resister Group	36.44	4	9.11	1261.11	.000	.115
NW. Structure	218.74	2	109.37	15138.48	.000	.439
pq Combination	302.96	4	75.74	10483.49	.000	.520
Resister Group Size	105.64	2	52.82	7311.41	.000	.274
Segment1 Size	4.08	2	2.04	282.36	.000	.014
Resistance Type * NW. Structure	54.59	4	13.65	1888.94	.000	.163
Resistance Type * Resister Group Size	11.71	4	2.93	405.24	.000	.040
Resistance Type * Resister Group	4.54	8	.57	78.62	.000	.016
Resistance Type * pq Combination	383.61	8	47.95	6637.26	.000	.578
Resister Group * NW. Structure	66.83	8	8.35	1156.26	.000	.193
Resister Group * pq Combination	9.75	16	.61	84.34	.000	.034
NW. Structure * pq Combination	46.59	8	5.82	806.15	.000	.143
pq Combination * Resister Group Size	5.00	8	.63	86.52	.000	.018
Resistance Type * NW. Structure * pq Combination	24.28	16	1.52	210.05	.000	.080
Resistance Type * NW. Structure * Resister Group Size	12.61	8	1.58	218.13	.000	.043
Resistance Type * Resister Group * NW. Structure	8.41	16	.53	72.78	.000	.029
Resistance Type * pq Combination * Resister Group Size	13.28	16	.83	114.87	.000	.045
Resistance Type * Resister Group * pq Combination	10.45	32	.33	45.22	.000	.036
Resistance Type * Resister Group * Resister Group Size	3.11	16	.19	26.94	.000	.011
Resister Group * NW. Structure * pq Combination	16.84	32	.53	72.84	.000	.057
Resistance Type * NW. Structure * pq Combination * Resister Group Size	2.74	32	.09	11.85	.000	.010
Resistance Type * Resister Group * NW. Structure * pq Combination	14.58	64	.23	31.54	.000	.050
Error	279.82	38731	.01			
Total	25639.31	40500				

This table demonstrates the main and interaction effects that showed a partial eta-square of more than .01.

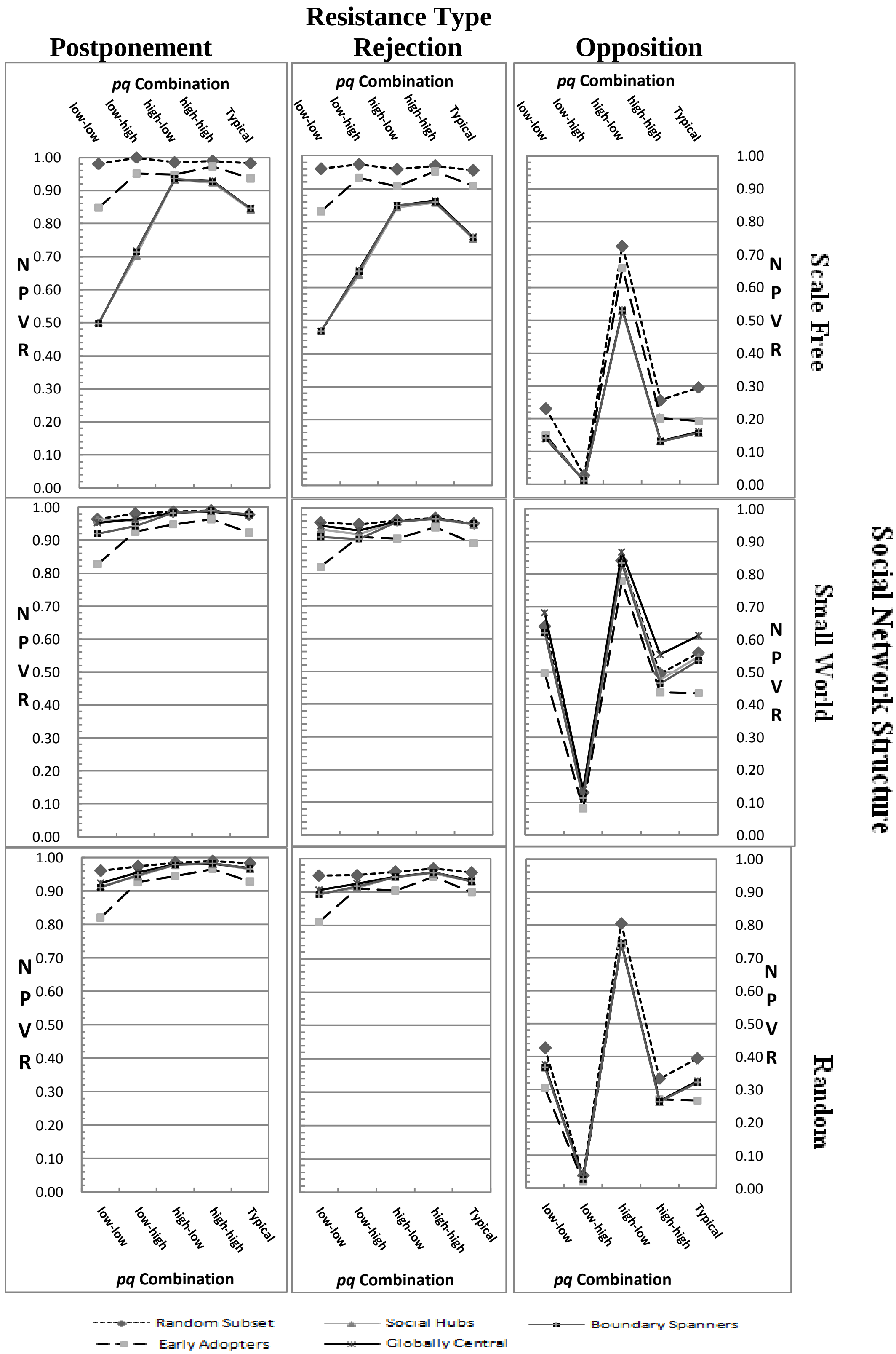


FIGURE 3
NPVR Generated by Different Consumers Resistances under Different Conditions

Complexity of phenomenon. The degree to which resistance adversely affects firm profits depends on complex interactions between several parameters (see Figure 3), including resistance type, resisters' characteristics, social network structure, *pq* combination, and the resister group size. The challenges marketers face in predicting the success of new products is partially due to the fact that they fail to consider or are unable to evaluate the effects of these parameters.

Resistance type. As Figure 3 and Table 4 show, opposition by all resister groups effectively reduces firm profits (M=.365) to a degree that is greater than rejection (M=.889) and postponement (M=.923) decisions. Opposition by a small group of consumers—overall 3% of the market—significantly reduces the NPVR (M=0.012 to 0.867). A follow-up study further examines this effect. Rejection reduces profits only marginally more than does postponement.

Social network structure. Scale-free networks have the strongest effect on NPVR (M=.628) followed by random (M=.745) and small-world (M=.805) networks. Moreover, social network structure impacts the relationship between resister groups and NPVR (see Figure 3). Under scale-free networks, social hubs, globally central consumers, and boundary spanners, hereafter referred to as the social network resister groups cut NPVR (M= .497 to .936) significantly more than early adopters and randomly designated resisters do (M= .847 to .999). However, under random and small-world networks, early adopters are generally the critical group, reducing NPVR ($M_{Small\text{-}world}$=.082 to .964 and M_{Random}= .021 to .966) more than other resister groups do ($M_{Small\text{-}world}$=.113 to .99 and

M_{Random}=.28 to .989). In summary, social network structure plays a critical role in understanding the adverse effects of resistance on profits.

Resister Group. For every experiment, the study compared the adverse effects of each group on NPVR with that of randomly designated resisters under the same combination of parameters using ($\frac{1-NPVR_{Influential\ Resister\ Group}}{1-NPVR_{Randomly\ Designated\ Resisters}}$), referred to as influentials' impact factor in this discussion. Higher ratios indicate greater adverse impacts of a resister group on NPVR relative to randomly designated resisters. For example, a ratio of 2 means that the resister group cuts NPVR twice as much as randomly designated resisters. Figure 4 shows this ratio for the four groups. The maximum ratio in Figure 4 was fixed to 15 because graphically presenting the four outliers cases (M_{ratio}>100, M_{ratio}=48.7) obscures the interpretation of graphs.

A close inspection of Figures 3 and 4 shows that the four resister groups generally reduce NPVR more than do randomly designated resisters. Social hubs' opposition strongly influence influentials' impact factor under scale-free networks and a *pq* combination of "low-high" (M=297.36). However, globally central consumers' postponements generate a low ratio (M=.83) under a small-world network and a *pq* combination of "high-low." The few outliers with significantly high ratios occur due to the minute negative impact of randomly designated resisters on NPVR under conditions that lead to small denominators in influentials' impact factor. Overall, scale-free networks have the strongest effect on influentials' impact factor ($M_{With\ Outliers}$ =20.34, $M_{Outliers\ Removed}$=5.50) followed by random (M=1.76) and small-world networks (M=1.54). Social network structure affects influentials' impact factors for the three social network resister groups but its impact on influentials' impact factor is weak for early adopters.

After removing the outliers, under scale-free networks, the three social network resister groups generate high ratios (M_{ratio}= 6.45 to 6.55) compared to early adopters (M_{ratio}=

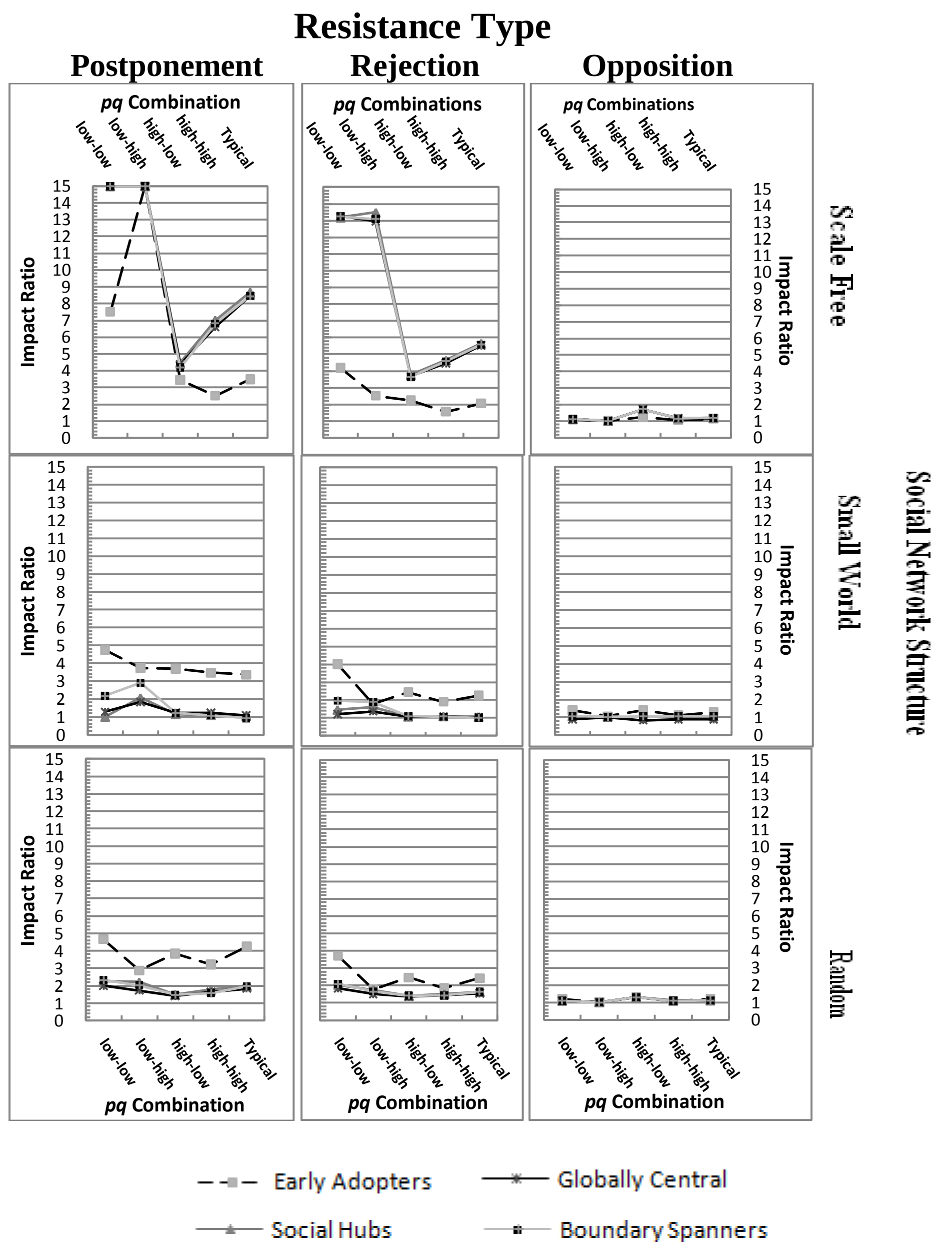


FIGURE 4
The Ratio of Influentials' Resistance Impact on NPVR Over That of a Randomly Designated Subset of Consumers

2.51). Under random networks, however, early adopters (M_{ratio}=2.46) generate high ratios compared to the social resister groups (M_{ratio}=1.46 to 1.58). Under small-world networks, early adopters generate high ratios (M_{ratio}=2.51), followed by boundary spanners (M=1.37), social hubs (M=1.19), and globally central consumers (M=1.12). Under this network, boundary spanners overall generate ratios that are significantly greater than the other two social network groups, but this ratio is significantly less than that of early adopters. Overall, social network resister groups are comparable in terms of their ratios under scale-free networks ($M_{Relative\ Difference}$=.000 to .06) and become less similar under random networks ($M_{Relative\ Difference}$=.002 to .22) and small-world networks ($M_{Relative\ Difference}$=.02 to .54). The average ratio is less than 2 for 76.6% of cases under random networks, 81.6% of cases under small-world networks, and 35% of cases under scale-free networks.

Finally, influentials' impact factor drops as the intensity of resistance increases from postponement (M=5.35) to rejection (M=3.36) to opposition (M=1.13), mainly because randomly designated resisters' postponements and rejections weakly impact NPVR. All five resister groups are comparable in terms of the effects their oppositions have on NPVR. While this seems counter intuitive, it shows the critical impact opposition has on NPVR and highlights the importance of paying attention to opposition by all consumers rather than focusing on a specific group.

pq combination. pq combination influences the relationship between resistance and NPVR and this effect is comparable for postponement and resistance (see Figure 3). Regardless of the social network structure, postponement and rejection show strong impact on NPVR when *pq* combination is "low-low" (M=.83 and .81) and weak effect when *pq* combination is “high-high” (M=.97 and .94). Opposition, however, shows strong effect on NPVR when *pq* combination is “low-high” (M=.054) and weak impact when *pq* combination is “high-low” (M=.73). *pq* combination affects the relationship between resistance type, resister group, and social network structure on one hand, and NPVR on the other hand (see Figure 3).

A comparison of “low-high” and “high-low” cases reveals that a *pq* combination of “low-high” generally has stronger negative impact on NPVRs than combinations of “high-low”. Thus, resistance has a stronger impact on diffusion processes that are driven by internal influences (i.e., WOM) compared to those relying on external influences (e.g., advertising).

Segment 1 Size. For all resister groups, size of segment 1 positively impacts NPVR, but this effect is insignificant and it is questionable due to small magnitude of partial η^2 (.014). The observed impact is because as segment 1 size increases, there are more consumers with high propensities to adopt early ($p^1 > p^2$), leading to higher overall NPV of profits. This increases both the enumerator and denominator in the ratio of $\frac{NPV_{Resistance}}{NPV_{Base\ Case}}$ and hence increasing NPVR.

Resister group size. Another experiment performed a sensitivity analysis on the effect of resister group size on NPVR. The experiment studied resister group sizes of 0.5% to 4% of the market with increments of 0.5%, and 4% to 20% with increments of 1%. The *pq* combination was fixed to ‘typical’ and segment 1 size was fixed to 20% of the market. Figure 5 shows the effects of resister group size, resister group, resistance type, and social network structure on NPVR.

A careful inspection of Figure 5 reveals that resistance type significantly influences the relationship between the resister group size and NPVR. For postponement and rejection the relationship is roughly linear while it resembles an inverse exponential function for opposition. Opposition by only 0.5% of the market cuts the NPVR to between .247—when social hubs oppose under scale-free networks—and .888—when randomly designated individuals oppose in under small-world network. Overall, the relationship between opposition and firm profits is weakly affected by the characteristics of group who is opposing the new product.

Social network structure significantly affects the relationship between resister group size and NPVR for the three social network resister groups, but it weakly impacts that of early adopters and randomly designated resisters. The three social network resister groups show comparable patterns in terms of the negative effects they have on NPVR. Further analysis shows that overall, under scale-free networks, for every 1% increase in the size of these three groups (i.e., 1% of the market), the overall NPVR drops by about 2.1% for rejections and 1.3% for postponements, compared to 1.3% and .5% for randomly designated resisters respectively. However, under small-world and random networks, early adopters have the strongest effect on NPVR. Overall, for every 1% increase in this resister group size, the NPVR drops by about 2.4% for rejections and 1.9% for postponements compared to 1.3% and .5% for randomly designated resisters respectively. Overall, early adopters' postponements and rejections moderately impact NPVR when resister group size is less than about 5% and this effect increases thereafter.

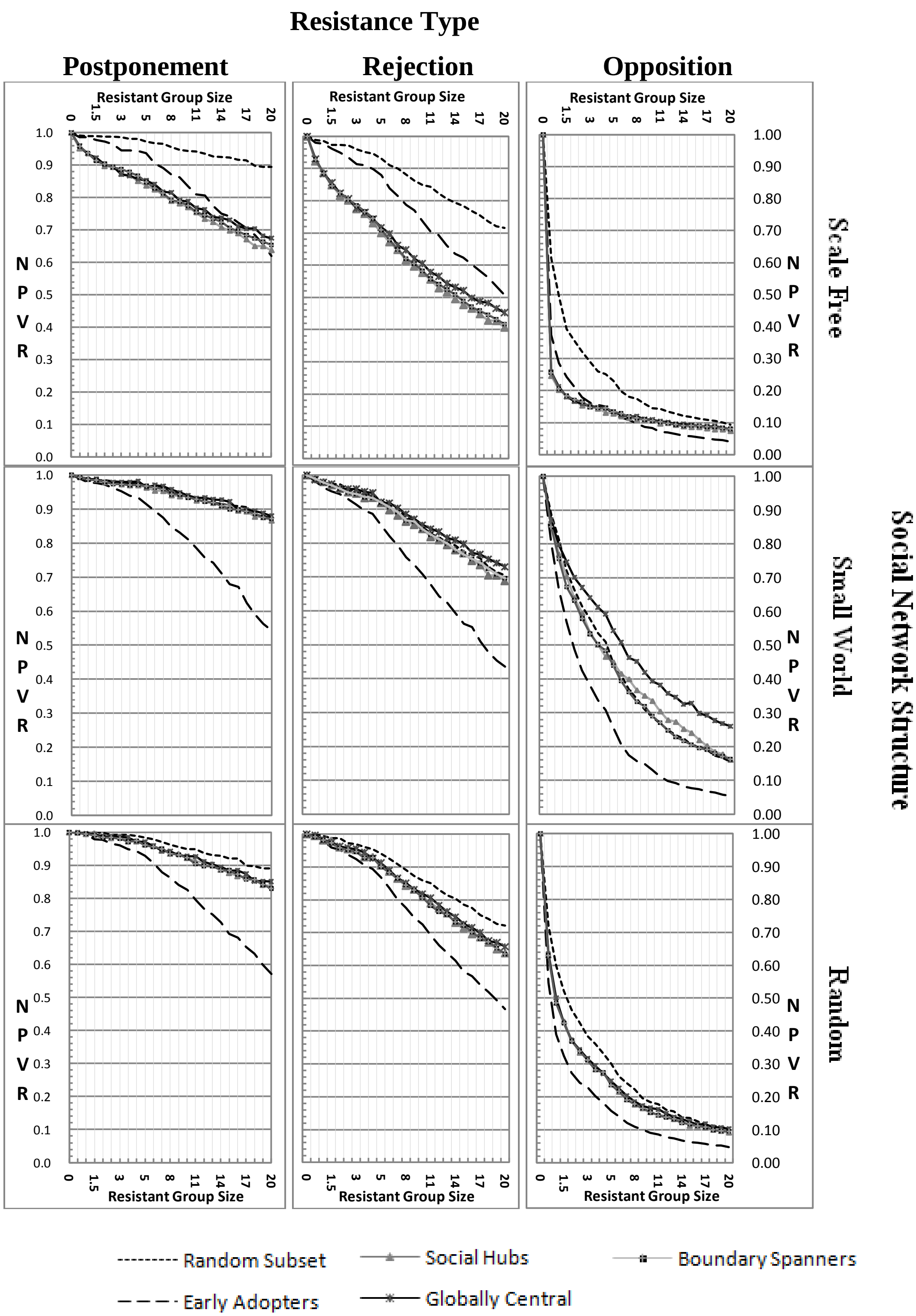


FIGURE 5
The NPVR as a Function of Different Resistance Type, Resister Group and Social Network Structures

Relative importance of parameters. A careful examination of partial η^2 shows that the resistance type (partial η^2=.904) has the strongest impact on firm profits followed by *pq* combination (partial η^2=.520), social network structure (partial η^2=.439), resister group size (partial η^2=.274), resister groups (partial η^2=.115), and segment 1 size (partial η^2=.014). Moreover, the interaction between resistance type and *pq* combination shows a partial η^2 of .578.

Discussion and Implications

Summary of findings

This study investigated how and under what conditions the resistance by a minority of consumers negatively impacts firm profits. Extensive Agent-Based simulation experiments demonstrate that the relationship between resistance and firm profits depends on complex interactions between three sets of parameters—resistance, diffusion, and consumer social network structure.

First, resistance type—postponement, rejection, and opposition—has the strongest impact on firm profits among the parameters that were examined. Opposition reduces profits to a degree that is significantly greater than rejection and postponement. Under certain conditions, opposition by only 0.5% of the market has the potential to reduce the profits by 75%. Opposers initiate negative WOM that can potentially reduce profits to a degree that is significantly larger than past studies find for negative WOM (e.g., Goldenberg et al. 2007). Moreover, even though postponers and rejecters do not engage in negative WOM, they block the spread of positive WOM and diffusion process. This finding is interesting because unlike viral campaigns that solely rely on WOM (e.g., Bampo et al. 2008; Kiss and Bichler 2008), in this study advertising creates seeds at different areas of the social network which undermines the effect of blocking diffusion process by a few consumers.

Second, the study examines the degree to which influentials affect the diffusion process (Van den Bulte 2010; Watts and Dodds 2007) from a novel perspective; the negative impacts they have on profits if they resist the product. To evaluate this influence, the study captured the ratio of the adverse effects each resister groups has on NPV with that of a group of randomly designated resisters. Overall, the results indicate that the four resister groups reduce profits to a degree that is more than that of randomly designated individuals, but the ratio depends on interactions between other parameters. The ratio is significantly large (e.g., >100) in the case of postponement under scale-free networks and it is less than 1 in some cases such as when globally central consumers oppose under small-world networks. The average ratio is less than 2 for 76.6% of cases under random networks, 81.6% of cases under small-world networks, and 35% of cases under scale-free networks. Early adopters show consistent ratios under different social networks while the ratio for the social network resister groups depends on the social network structure. These results are also consistent with previous studies' findings that social hubs significantly influence the diffusion process (Goldenberg et al. 2009; Kiss and Bichler 2008).

Third, the study is the first to investigate the effect of social network structure on the relationship between resistance and profits. Past studies have found conflicting results regarding whether new products diffuse faster under scale-free networks or small-world networks (Centola 2010; Choi et al. 2010; Delre et al. 2010; Rahmandad and Sterman 2008). The present study examines this question from a novel perspective of how resistance adversely affects profits under these networks. The findings indicate that all three resistance types under scale-free networks cut profits to a degree that it is greater than that in random and small-world networks. However, this effect is significant for the three social network resister groups and it is moderate for randomly designated resisters only when they postpone or resist, and it is generally weak for early adopters. Moreover, the study finds that random and small-world networks differ moderately in terms of the overall impact they have on the relationship between resistance and profits. The two network structures differ more in the case of opposition rather than rejection or postponement.

Fourth, *pq* combination has a strong effect on firm profits and it also affects the relationship between other variables and firm profits. Therefore, the effect various resister groups have on the diffusion process depends on the degree to which advertising and/or social influence drive the diffusion. For example, several studies find that boundary spanners play crucial roles in the diffusion process especially when the network is clustered (Burt 1992; Tucker 2008). This study shows that they significantly affect profits in case they resist the product when parameter p is low and in other cases, this effect is similar to that of other social network resister groups. Furthermore, under random and small-world networks, early adopters have the strongest negative impact on the diffusion process. This finding also raises concerns about the degree to which we can generalize the findings of studies that focused on viral campaigns where diffusion solely relies on WOM (e.g., Bampo et al. 2008; Kiss and Bichler 2008; Watts and Dodds 2007) to cases where the firm employs some type of advertising.

Implications for Marketing Practice

The findings of this study have five key implications for marketing practice. First, since opposition impacts profits significantly greater than other resistance types, firms can effectively control the damages of resistance by trying to convert the opposers to rejecters or postponers. They can achieve this by focusing their persuasion attempts on reducing the negative features rather than seeking to increase the perceptions of benefits of their offerings. Researchers suggest that marketing activities must focus on addressing the underlying reasons why consumers resist new products (Knowles and Riner 2007). Generally, people oppose new products when they find the products in conflict with norms or when they perceive negative images, functional risks, and physical risks with the adoptions (Kleijnen et al. 2009). Addressing these concerns will help in controlling the adverse effects of resistance by converting the opposers to rejecters, even though the potential consumers might not be convinced to adopt. For example when religious concerns drive opposition, a religious leader's opinion can turn many opposers to rejecters or postponers. Another approach is making the products more compatible with existing ones. This will not only reduce resistance (Gourvilee 2006), it can also reduce people's perceptions about the degree to which the product conflicts with norms.

Second, firms need to carefully consider the degree to which advertising and/or social influence drives the diffusion before designing marketing tactics. The study finds that resistance has the strongest impact on profits when the diffusion primarily relies on social influence than when it relies on advertising. Thus, although WOM programs seem promising when the diffusion process relies on social influence, such campaigns might act as a double edge sword when consumers will likely resist. Such programs might not succeed because resisters block the diffusion through the social network or as they might spread negative WOM about it. Therefore, firms need to balance their investments in different types of marketing activities when expecting resistance.

Third, the findings have implications for choosing the most promising targets for marketing activities (Kotler and Zaltman 1976). By considering that different groups may react both negatively and positively to new products, marketers can use the study findings to plan more effective marketing tactics. For instance, a marketing manager might target a specific group of influentials not because this targeting is expected to yield positive returns but as those groups may severely damage the diffusion process if they resist the product. The findings indicate that negative effects of the three social network resister groups on profits depends on the social network structure while early adopters show a consistent effect under different social network structures. Thus, firms can evaluate the revenue loss if early adopters resist their products regardless of the social network structure, but they need a general understanding of the social network structure for evaluating the revenue loss if the social network groups resist. Moreover, resister group size has a stronger adverse effect on profits that does the resister group. In the case of opposition, there is minor difference between influentials and randomly designated resisters. Thus, when identifying and targeting the four influential groups is difficult, firms can focus on programs that attempt to limit the number of resisters.

Finally, the study presents an agent-based modeling and simulation approach that firms can employ to evaluate different potential scenarios regarding consumer resistance to their products prior to product release. While there is no claim of a new diffusion model, past diffusion models have never been applied to evaluating different resistance scenarios that can occur in the market. Even in the cases where firms are only able to partially estimate some parameters such as the social network structure, the approach will still be helpful.

Limitations and Future Research

This study investigated a complex phenomenon in an under-researched area. There are several limitations as well as the future research directions that the findings raise. The study relies on several assumptions and limitations that are in line with majority of the relevant research (e.g., Garber et al. 2004; Goldenberg et al. 2007; Goldenberg et al. 2002; Moldovan and Goldenberg 2004). The study only captures WOM communications from adopters and rejecters to undecided consumers through social ties. It does not capture WOM initiated from someone who has not adopted the product nor does it capture other means of social influence such as social status or the observation of others using a new product. Moreover, the study assumes that the influence is the same among all ties, the ties are bi-directional, and consumers are homogeneous within their segments in terms of parameters *p*s and *q*s. Furthermore, this research assumed that resistance happens in the first period of diffusion process at the time of product introduction. Finally, the study made conservative assumptions regarding resisters' engagement in negative WOM. Future research is needed to investigate how relaxing these assumptions affect the findings.

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CHAPTER 5

Conclusion

This dissertation addressed the role of influentials in the diffusion of new products. Three separate essays explored the topic providing the following key novel contributions:

First, the dissertation brought together the extensive body of literature in a systematic way, providing a holistic perspective of how marketers can affect the diffusion process by focusing on influentials, identifying the gaps of research, and suggesting future research directions. The framework presented in essay one is also helpful to marketing managers in designing marketing tactics and campaigns. It provides a structure for evaluating and aligning their assumptions, tactics, and expected outcomes.

Second, essays two and three provided novel insights into both the positive and the negative roles influentials play in the diffusion of new products. A comparison of the findings shows that under certain conditions some influential groups are worth targeting, not necessarily because their adoptions significantly increases firm profits, but because they critically impact profits if they resist the product. This highlights the importance of considering two distinct perspectives in the marketing of new products: the facilitative activities aiming to enhance the diffusion process versus damage control activities that focus on reducing the adverse impacts of resistance.

Third, essays two and three demonstrate that under most conditions, influentials have the potential to impact firm profits to a degree that is significantly more than that of a randomly designated group of potential consumers. However, the extent of this differential impact depends on complex interactions between other variables. The studies also indicate that under certain conditions, firms can focus on a group of randomly chosen consumers and thus save the resources and efforts required to identify the influentials. Moreover, the studies show that consumers' number of social ties identifies influential consumers as targets for seeding programs better than do the more complex social network centrality measures of closeness centrality and betweenness centrality.

Fourth, social network structure highly impacts the relationship between influentials' adoptions and/or resistances on one hand and firm profits on the other hand. This effect is greater for the influential groups who are identified using network centrality measures—social hubs, globally central consumers, and boundary spanners—relative to other groups—randomly designated or early adopters. Overall, scale free networks have the strongest impact on this relationship followed by random and small world networks.

Finally, the studies present an agent-based modeling and simulation approach that firms can employ to evaluate different potential scenarios regarding consumer positive and negative reactions to their products prior to product release. While the author does not claim to have developed a new diffusion model, the approach provided by this dissertation, especially in evaluating the adverse impacts of consumer resistance, is novel. The most desirable condition for applying this approach is when firms are able to estimate the parameters perfectly and map the entire social network. Under these conditions, this approach will provide estimations with high degrees of accuracy. However, the approach also provides general conclusions for conditions where firms are only able to partially estimate the parameters and the social network structure.

The hope is that both researchers and managers will benefit from the framework, the synthesis of the literature, the findings, the methodology used, and the future research directions this dissertation presents.

APPENDIX A
Identifying the Social Network Resister Groups

The three social network resister groups are social hubs, globally central consumers, and boundary spanners. This appendix explains the methods for identifying these groups in a social network. The simulation program identifies these groups using the most popular centrality measures in the social network literature—closeness centrality, closeness centrality, and betweenness centrality (Scott 2000; Van den Bulte and Wuyts 2007).

Social Hubs

Social hubs—the most-connected members of a social network—are those who score high on a measure called the degree of a node—consumer—which is calculated as (Freeman 1979; Scott 2000):

$$C_D(i) = \sum_{j=1}^{n} a\ (i, j)$$

Where $a\ (i, j)$ represents a link between nodes *i* and *j*, and the total number of nodes in the social network is denoted by *n*. The value of $a\ (i, j)$ is equal to 1 if and only if *i* and *j* are connected by a social tie, and is zero otherwise. Researchers have referred to this measure as 'local centrality', 'degree centrality', and 'degree of connection' (Scott 2000p. 83). Number of social ties can be estimated using surveys without the need to map the entire social network structure and applying complex network analysis (Scott 2000). Therefore, using this measure is more feasible in consumer markets than the other two network centrality measures this study employs.

Globally Central Consumers

Closeness centrality measure identifies consumers who possess central locations in their network with regards to all other consumers. The measure calculates the total distances of a node from all other nodes in the social network. The distance between two nodes is the total number of links in the sequence of links that connects them, if they are connected (Scott 2000).

Several approaches have been proposed for calculating closeness centrality, most of which fail to function in social networks that consist of disconnected sub-networks. When two nodes are not reachable from each other, the distance between them will be infinite and the measures will be undefined. Lin (1976) resolved this issue by considering the distances between the nodes that are reachable from each other and excluding unreachable nodes as follows:

$$C_c(i) = \frac{J_i / (n-1)}{\left(\sum_{j=1}^{n} d\,(i,j)\right) / J_i}$$

Where J_i denotes the number of nodes that are reachable from node i, and $d\ (i,j)$ denotes the distance between nodes i and j.

Boundary Spanners

In the social networks literature, betweenness centrality measures the characteristics of boundary spanners by capturing the sum of the number of shortest paths that passes through each node as calculated using the following (Freeman 1977; Scott 2000, p. 86):

$$\frac{\sum_{j}^{n} \sum_{k}^{n} g_{jk}(i)}{g_{jl}}$$

Where n is the number of nodes (i.e., consumers), $g_{jk}(i)$ is the number of shortest paths between nodes j and k that pass through node i, and g_{jk} is the total number of shortest paths that connect nodes j and k. Nodes that lay on the paths between many pairs of other nodes have a high potential for controlling the spread of messages among all others (Freeman 1977). This measure is the most complex and computationally expensive among the measures this study examines (Scott 2000). Calculation of both betweenness and closeness centrality measures are only feasible when the structure of the entire network is available.

APPENDIX B

Consumer Adoption Process

This appendix explains the consumer adoption process used in essay 3, chapter 4. This essay assumes that postponers and rejecters do not engage in WOM, and only opposers spread negative WOM (see the section "The ABMS Model" in essay 3, chapter 4). Therefore, postponement and rejection employ different algorithms than opposition. Also, please note that each study only examines one type of resistance—postponement, rejection, and opposition. This appendix first explains consumer decision making for the experiments that focus on postponement and rejection and then explains that for opposition.

Postponement and Rejection

At every period, potential adopters might decide to adopt the product or remain undecided. Only positive WOM spreads in the market as postponers and rejecters do not engage in WOM. The impact of positive WOM on each potential adopter is calculated based on the total number of adopters who have direct links with the potential adopter. Considering the asymmetric influence of segment-1 on segment-2, the total number of adopters and who are in direct link with each consumer is calculated at every period as explained below.

For every potential adopter *i* in segment-1:

> $S_i^{11+}(t)$: The total number of adopters in segment-1 at period *t* who have direct links with potential adopter *i*.

For every potential adopter *i* in segment-2:

> $S_i^{12+}(t)$: The total number of adopters in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{22+}(t)$: The total number of adopters in segment-2 at period *t* who have direct links with potential adopter *i*.

The levels of positive influence received by potential adopter *i* via WOM and marketing efforts at period *t* are calculated as follows (Toubia et al. 2008):

$$p_{(i,t)}^{+} \leftarrow 1-(1-p_i^1)(1-q_i^{11})^{S_i^{11+}(t)} \quad [1]$$

Where p_i^1 represents the influence of external influence (i.e., marketing activities) on potential adopter *i*, and q_i^{11} represents the probability that potential adopter *i* adopts at time period *t* as the result of interaction with another segment-1 member who has already adopted the product.

For every potential adopter *i* in segment-2:

$$p_{(i,t)}^{+} \leftarrow 1-(1-p_i^2)(1-q_i^{12})^{S_i^{12+}(t)}\,(1-q_i^{22})^{S_i^{22+}(t)} \quad [2]$$

Where p_i^2 represents the influence of external influence (i.e., marketing activities) on potential adopter *i*, and q_i^{22} and q_i^{12} represent the probability that potential adopter *i* adopts at time period *t* as the result of interaction with another segment-2 and segment-1 member respectively.

Given the above, the probabilities of the two potential adopter decisions—remaining undecided, $p_{(i,t)}^{wait}$ and adoption, $p_{(i,t)}^{adopt}$—are calculated as follows:

$$p_{(i,t)}^{adopt} \leftarrow p_{(i,t)}^{+}\ , \quad [3]$$

$$p_{(i,t)}^{undecided} \leftarrow (1 - p_{(i,t)}^{+}). \quad [4]$$

The sum of the above two equations is equal to 1. After calculating the above probabilities for each potential adopter, a uniform random number between 0 and 1 is generated to find the potential adopter’s new status (adopt or remain undecided).

Opposition

At every period, potential adopters might decide to adopt the product, oppose it, or remain undecided. The influence of positive (negative) WOM on each potential adopter is calculated based on the total number of adopters (opposers) who have direct links with the potential adopter. Considering the asymmetric influence of segment-1 on segment-2, the total numbers of adopters and opposers who are in direct link with each consumer are calculated separately at every period as explained below.

For every potential adopter *i* in segment-1:

$S_i^{11+}(t)$: The total number of adopters in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{11-}(t)$: The total number of opposers in segment-1 at period *t* who have direct links with potential adopter *i*.

For every potential adopter *i* in segment-2:

$S_i^{12+}(t)$: The total number of adopters in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{12-}(t)$: The total number of opposers in segment-1 at period *t* who have direct links with potential adopter *i*.

$S_i^{22+}(t)$: The total number of adopters in segment-2 at period *t* who have direct links with potential adopter *i*.

$S_i^{22-}(t)$: The total number of opposers in segment-2 at period *t* who have direct links with potential adopter *i*.

To capture the levels of positive and negative influence received by potential adopter *i* via WOM and marketing activities at period *t,* the study brings together and expands the earlier works (Goldenberg et al. 2007; Toubia et al. 2008) and calculates these influences as follows:

$$p_{(i,t)}^{+} \leftarrow 1 - (1 - p_i^1)(1 - q_i^{11})^{S_i^{11+}(t)} \qquad [5]$$

$$p^{-}_{(i,t)} \leftarrow 1-(1-p_i^1)(1-mq_i^{11})^{S_i^{11-}(t)} \quad [6]$$

Where p_i^1 represents the influence of external influence (i.e., marketing activities) on potential adopter *i*, and q_i^{11} represents the probability that potential adopter *i* adopts at time period *t* because of interaction with another segment-1 member, and *m* is the relative impact of negative to positive WOM.

For every potential adopter *i* in segment-2:

$$p^{+}_{(i,t)} \leftarrow 1-(1-p_i^2)(1-q_i^{12})^{S_i^{12+}(t)}\,(1-q_i^{22})^{S_i^{22+}(t)} \quad [7]$$

$$p^{-}_{(i,t)} \leftarrow 1-(1-p_i^2)(1-mq_i^{12})^{S_i^{12-}(t)}\,(1-mq_i^{22})^{S_i^{22-}(t)} \quad [8]$$

Where p_i^2 represents the influence of external factors on potential adopter *i*, and q_i^{22} and q_i^{12} represent the probability that potential adopter *i* adopts at time period *t* as the result of interaction with another segment-2 and segment-1 member respectively. A normalization factor α_i, denoting the ratio of positive WOM influence over the total WOM (positive and negative) influence on potential adopter *i*, is calculated as follows (Goldenberg et al. 2007): $\alpha_i = \frac{p^{+}_{(i,t)}}{(p^{+}_{(i,t)} + p^{-}_{(i,t)})}$

Given the above, the probabilities of the three potential adopter decisions—remaining undecided, $p^{wait}_{(i,t)}$, adoption, $p^{adopt}_{(i,t)}$, and oppose, $p^{oppose}_{(i,t)}$—are calculated as follows:

$$p^{adopt}_{(i,t)} \leftarrow (1 - p^{-}_{(i,t)})\, p^{+}_{(i,t)} + \alpha_i p^{+}_{(i,t)}\, p^{-}_{(i,t)}, \quad [9]$$

$$p^{oppose}_{(i,t)} \leftarrow (1 - p^{+}_{(i,t)})\, p^{-}_{(i,t)} + (1 - \alpha_i)\, p^{+}_{(i,t)}\, p^{-}_{(i,t)}, \quad [10]$$

$$p^{undecided}_{(i,t)} \leftarrow (1 - p^{+}_{(i,t)})\,(1 - p^{-}_{(i,t)}). \quad [11]$$

The sum of the above three equations is equal to 1. After calculating the above probabilities for each potential adopter, a uniform random number between 0 and 1 is generated to find the potential adopter's new status (adopt, oppose, or remain undecided).

APPENDIX C

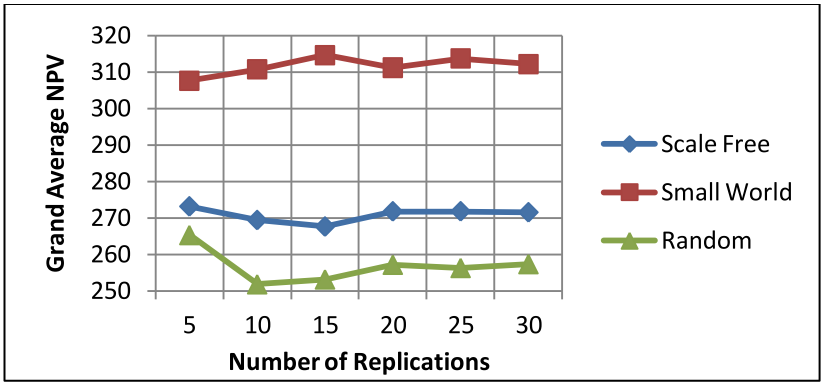
The ABMS Computational Experimental Design

To determine the required number of replications at which the average NPV is stable, or in the simulation terminology where system arrives at a steady state, we chose the values of parameters *p* and *q* under “Typical” *pq* combination and executed the simulation under the three network structures. For every combination of market variables—social network structure, average number of links, and size of segment-1—the ABMS platform executed the base cases—no resistance—for each generated market. It then replicated each experiment 5 to 30 times with increments of 5 and averaged the value of NPV for the replications and captured both the mean and standard deviation of the grand NPV (see Figure C-1). As this figure shows, the beginning of steady state status is approximately around 15 replications. Thus, a conservative estimate of steady state is 20 replications.

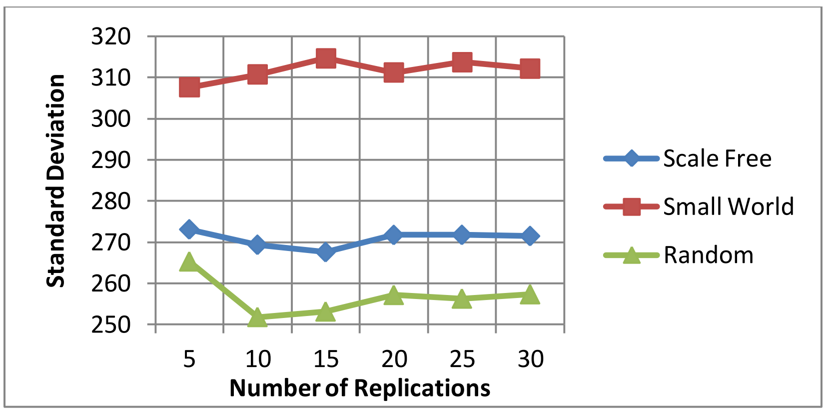
Relying on this analysis, for every selected combination of market variables—social network structure, average number of links, and size of segment-1—the simulation program randomly generated 20 social networks each including 3000 potential consumers. Each replication was executed using a new random seed (generating new random number stream), leading to 20 replications for every combination of parameters. However, in order to have comparable results for alternative resistance scenarios, it is important to capture the performance of all resistance programs under the same market conditions. To maintain this condition, the ABMS platform generated 20 replications for every combination of market parameters using different random seeds and then executed all combinations of resistance parameters under each of these 20 replications (see Table 2 in Essay 3, Chapter 4).

The experiments generated a total of 180 randomly-generated social network structures, 60 different networks of each social network structure—random, small-world, and scale-free. Considering all replications and the factorial combinations of all parameters and the experiments for capturing the performance of base cases, 41,400 simulation runs were executed for the main study. In addition, for sensitivity analysis of the effect of resister group size, a total of 324,000 simulation runs were executed. In summary, considering all scenarios and sensitivity analysis, the simulation experiments generated 365,400 simulation runs.

The ABMS simulation platform was implemented using Java programming language and Repast agent-based modeling toolkit, developed by Argonne National Laboratory (http://repast.sourceforge.net). The ABMS platform was executed on a standard Dell desktop computer (Xeon, CPU 3.2 GHz, and 2.00 GB of Ram) under Microsoft Windows XP Professional operating system. All necessary computational simulation experiments were conducted in the same environment.(Scott 2000)



A. The Overall Grand Average NPV Generated for Social Network Structures



B. Standard Deviation of the NPV Generated for Social Network Structures

FIGURE C-1
Steady State Analysis for Choosing the Number of Replications

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