The invisible force that shapes our world

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The Invisible Force that Shapes Our World

Insights into Complex, Dynamic Social Influence Processes,

A Marketing Perspective

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The Invisible Force that Shapes Our World

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	Prof. dr. A. van Witteloostuijn

Acknowledgements

All we have to decide, is what to do with the time that is given to us.

-J.R.R. Tolkien-

With this sentence in mind, I started my first day as a PhD Candidate at the University of Groningen, on the 3rd of September 2007. Such an easy task for the four years ahead; an easy decision to make: enjoying the mountains, sailing and cycling definitely were part of the plan. In front of you lie the results of (a bit more than) four years of hard training and perseverance. Fortunately, many people supported me with my activities, all in their own way. Therefore, I say thank you to everyone who supported me: I could not have done it without you!

Writing a PhD thesis is much like climbing a mountain: when you start your hike, you need to figure out the most suitable route that will bring you to the summit. Two people gave me all the freedom to choose my own path and kept supporting me even though I sometimes decided to go off the beaten track. Therefore, I thank my promoter Peter Leeflang and my co-promoter Wander Jager. The countless conversations and (research) discussions we had, helped me developing both as a scientist and as a person! Even though this thesis is finished, I am certain that our paths will continue to cross in the future. Peter, we share our love for Switzerland (and inherently our love for the mountains), which formed a foundation for our positive collaboration and mutual understanding. Your (initial?) light skepticism towards agent-based modeling made me very much aware of potential pitfalls and encouraged me to continue the development of the models used in this thesis. Wander, we share a passion for sailing which seems strongly related to our strong interest in studying complex processes. The ship of a sailor is an instrument that helps him/her to use the wind (part of the complex weather system) in his/her advantage, without the need to understand the underlying processes in great detail. I loved our talks about the possibilities to create a similar instrument for marketers who want to sail on the 'social influence winds'. I am certain that this thesis forms an important step in that direction and I am looking forward to continue our collaboration in this field.

When I'm cycling I always prefer cycling in the wind's eye or uphill. When I look back at a cycling trip, these are the parts that make me feel satisfied; they ultimately make me stronger. While writing my PhD thesis I encountered slopes ranging from false flat to very steep; winds ranging from a light breeze to a high wind. In this light I want to thank several people for their positive contribution. First of all, the members of my dissertation committee: Arjen van Witteloostuijn (Tilburg University), Barak Libai (Arison School of Business, ICD Herzliya, Isreal) and Tammo Bijmolt (University of Groningen): thank you for taking the time to read my thesis and for the positive and valuable feedback. Also to my former colleagues Bob Fennis, Jaap Wieringa and Peter Verhoef: thank you for taking the time to read my thesis; your constructive feedback had been highly appreciated.

Furthermore I would also like to express my gratitude to the reviewers and editors of the Journal of Product Innovation Management: their feedback contributed to a highly improved Chapter 3.

Whether one goes sailing, cycling, climbing or skiing, having good equipment is the foundation for a safe and pleasant experience. Similarly, empirical data forms an important foundation for agent-based models. Therefore I want to thank everyone at Cinekid for their cooperation in collecting the empirical data used in Chapter 3. Furthermore, I also thank my (indirect) colleagues at GfK Verein, in particular Holger Dietrich, for the cooperation in collecting the data used in Chapter 5. Holger, thank you for supporting my (extensive) data request and giving all the necessary freedom to add questions to the survey. Also thanks for the research meetings we had: they were very inspiring and encouraged me to continue my research. I sincerely believe that the chapters in this thesis represent only the first steps of the journey that is still ahead of us and I am looking forward to collaborate on future research projects!

During the hike to the top of a mountain, it is easy to get wholly engrossed in the quest to reach the summit. In such cases it is extremely important to be surrounded by people who sometimes tap you on the shoulder and point at the beautiful view you already have *during* the climb. I want to thank all my friends and former colleagues of the Marketing Department in Groningen: because of you I look back at a wonderful time in Groningen. The fun times during sintekerst celebrations and the department outings will always be embedded in my memories. And, one of the advantages of my research topic, I also loved to observe the social influence processes that were visible when I co-organized the department outing and participated in the (somehow related?!) soccer pool. Jelle and Anne, thanks for all the nice moments we shared while organizing this event! I also want to thank all (former) secretaries of the Marketing Department: Hanneke, Lianne, Bea, Frederika and Jeannette, who were of great help through the years. In addition, I want to thank my fellow PhD candidates, with whom I shared many (inspiring) coffee breaks, lunches and other social events. In particular I want to mention my former office mates Matilda and Sander. Matilda, we 'shared' the office (or four offices, if I counted correctly) for three years and I enjoyed every moment of it: the serious discussions about our research, sharing the frustrations of writing a thesis, the in-office lunches and even the initial kidnapping and later adopting of 'our plant'. Also thanks for the nice dinners and other social events outside of the office! Sander, although we only shared the office for a year, I look back at a great time. The discussions about research, conferences and teaching were always valuable and amusing, but even more important: you helped me to better understand the culture in the south, which saved me a lot of frustrating moments! Also thank you (and Alec) for adopting 'the plant' after I left. Ernst: thanks, not only for sharing the experiences of moving to the south, but more importantly for the beautiful trip to New Zealand: it still is one of my most memorable holidays! Hans, thank you for the many fruitful discussions that resulted from our entirely different approaches to a similar research topic. Auke and Jacob, thanks for joining me many times on the ice-track: I always had a great time.

Although setting sail during a nice summer day is nice, it becomes even nicer if people join you. During my years in Groningen, my paranymphs Eline and Katrin have joined me on the trip. It is wonderful to be able to share the experience and make the transition from master student, to PhD candidate, to PhD at almost the same time. Eline, we already met in the early days of our bachelor studies and even though we never worked together, we stayed in touch ever since. Katrin, we met during our research master and we shared a lot of experiences during the courses we followed. It was great to share all experiences with both of you, from applying to a PhD position to the important last steps in finishing a thesis and preparing for the defense. During all my years as a member of the Marketing Department, it was a comfortable feeling that I could always count on you. Thank you for standing by my side; in the past years and during the defense! In the next years our physical paths will separate, but I am sure we will stay in touch in the future.

In the past two years I crossed some of the steepest slopes on my route to the summit. I am very grateful to my new colleagues at GfK and AiMark for their flexibility and support when I needed it. After a terrific time in Groningen, I could only hope to find such a nice group of people to work with again. Thanks for the great time so far, and I am looking forward to our future together!

Last, but not least I want to thank my family. Vincent and Sarah, you share my passions for sailing and the mountains and this resulted in countless beautiful trips that helped me relax in the sometimes stressful times. Vincent, as my brother you have always been at my side. This gave me a lot of confidence, and looking backwards, you probably even gave me the final push to accept the offer of the university to become a PhD Candidate. Mom, dad: you have always been there for me, supported me in all my decisions and always believed in me. Your unconditional love and support helped me to get through the more difficult times and you always helped me putting things into perspective. Without you I would never have reached the summit. Thank you all for your love and support!

Breda, July 2013

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Chapter 1

Introduction

1.1 Motivation and Background

Marketers face several challenges in bringing their products and services to the attention of potential consumers. The increasing number of communication channels and the rise of the Internet make it difficult and expensive to reach a large audience. Furthermore, consumers tend to lack trust in most forms of advertisement (Nielsen, 2007). Word of mouth (WoM) offers a potential solution to both challenges: Consumers trust their informal interactions with other consumers within their network (Nielsen, 2007). Furthermore, information can spread through consumer networks, thereby reaching a larger population. This raises the question: How can marketers use WoM to their advantage?

The importance of WoM already has been well established (e.g. Arndt, 1967). It is not only an important source of information (Grewal, Cline and Davies, 2003), but it also influences attitudes (e.g. Bone, 1995), purchase intentions (e.g. Charlett, Garland and Marr, 1995), and purchase decisions (e.g. Wangenheim and Bayón, 2004). Yet many companies still fail to develop marketing programs that effectively increase WoM behavior among consumers (Gremler, Gwinner and Brown, 2001). In past decades, companies simply believed that WoM was uncontrollable (Wilson, 1994), leaving them to struggle with the notion (Lovelock, 2001). In the Internet era, the threat of social media as a powerful, uncontrollable force remains a major challenge for marketing (Leeflang, Verhoef, Davis and Freundt, 2013). Recent research adds though that marketing communication can influence WoM behavior (East, Hammond and Wright, 2007). Furthermore, the successes of Google's e-mail service and Apple's iProducts—launches that relied mainly on WoM instead of traditional media campaigns—reconfirm the strength of modern WoM.

The importance of WoM makes it unsurprising that the topic has drawn a lot of attention in academic research. For a better understanding of WoM, it also is important to look beyond the field of marketing. For example, to gain insight in the social interactions involved in WoM processes, social psychology and sociology are valuable sources of information. The literature review presented in Chapter 2 integrates these disparate but related academic fields to offer useful insights regarding the current state of knowledge about WoM and identify at least three critical gaps.

First, the implementation of WoM in marketing models is often relatively simple (e.g., "How many people told you about product X?"), ignoring the actual context in which WoM takes place. The context affects the weight the consumer assigns to the received message though. This weight depends on whether the sender of the message is expected to give relevant information with respect to the purchase decision; as Wangenheim and Bayón (2004) show, source expertise is important if the purchase decision is associated with financial risk. In that case, the consumer seeks information about product attributes (informational influence). However, if the purchase decision is associated with a social risk (e.g., acceptance), consumers attach more value to the opinion of similar others. In this case, shared norms (normative influence) affect the purchase decision.

Second, most research investigates the effects of WoM on purchase intentions, rather than considering the influence of other marketing instruments (e.g., advertising) on WoM. An example of the use of WoM in relation to other marketing instruments is buzz marketing, or WoM stimulated by companies (e.g., by providing free product samples; Thomas, 2004). However, not much information is available regarding how these methods influence WoM. For example, is it possible to focus buzz marketing on a specific group of influential consumers?

Third, some consumers exert more influence on people in their surroundings than others, by advising other people about their search and purchase decisions (Flynn, Goldsmith and Eastman, 1996). The role of these influential consumers (influentials) has received attention in marketing (e.g. Engel, Kegerreis and Blackwell, 1969; King and Summers, 1970; Wiedmann, Walsh and Mitchell, 2001), because consumers who influence many others are attractive targets. These consumers often spread positive information about the product to a large group of potential consumers. However, other research questions their role (Watts and Dodds, 2007). Furthermore, other characteristics of influential consumers, such as higher levels of expertise, have been neglected. Meanwhile, Libai, Muller and Peres (2013) show that targeting influentials both accelerates the adoption of new products and expands potential market share. Therefore, the need remains to find out more about the role of influentials in consumer networks and how they influence the WoM that spreads through networks.

Based on these gaps, three areas within the WoM domain are of special interest for this thesis: the role of influential consumers (Chapter 3), the context in which WoM takes place (Chapters 4 and 5), and the role of marketing instruments in the process (Chapter 5).

1.2 WoM and Social Influence

As addressed thus far, WoM is a specific form of social influence (SI). Westbrook (1987: 261) defines WoM as “informal communications directed at other customers about the ownership, usage, or characteristics of particular goods and services or their sellers.” The term implies that the communication is verbal, whereas SI is a broader concept that encompasses non-verbal communication too. SI refers to the effect consumers have on each other’s opinions and behavior and can be either in the form of *normative* influence (the tendency to conform to the expectations of others; Burnkrant and Cousineau 1975) or *informative* influence (the tendency to accept information from others as evidence of reality; Deutsch and Gerard 1955). Wearing specific clothes or playing around with a smartphone may influence people around the influential user (e.g., they see how convenient the smartphone is, or how complicated it is to use). In this sense, it is important to recognize the challenge of investigating WoM in an isolated (i.e., only verbal) form. In a face-to-face situation, the verbal message is most likely accompanied by facial expressions and/or body language. In a digital (e.g., Internet) context, recipients also rely on non-verbal information (e.g., knowledge about the sender) to interpret the verbal message (e.g., Naylor, Lamberton and West, 2012). Therefore, this thesis investigates consumers in their social context, focusing on SI and including WoM as part of this SI.

Because WoM (rather than SI) has been the focus in marketing research, this dissertation starts with a literature review on this topic (Chapter 2), in which I discuss WoM in its social context, thereby relating it to SI (the focus of the other chapters in this dissertation).

1.3 Methodology

When investigating SI, it is important to acknowledge the complexity of the social network in which it takes place. A social network consists of a vast number of individuals who interact, ultimately resulting in large-scale (collective) behavior (Goldenberg et al. 2001). Complex systems are hard to predict, because small differences at the individual level can result in large differences on the aggregate level. A useful method for addressing this complexity relies on agent-based modeling (Schelling, 1971; Garcia, 2005). This simulation method requires to define rules for agents at the individual (e.g., choice models, interaction data) level and allows to study the results at the aggregate (e.g., market) level. In this thesis, the agent rules on the individual level are partly based on literature and partly on empirical data collected for this purpose. The balance between literature-based rules and empirical data–based rules shifts from literature to data from Chapter 3 to Chapter 5. In Chapter 3, the empirical data provide parameter inputs for the model; in Chapter 5, almost all parts of the model are based on information from empirical data. That is, empirical data strengthen the rules of agents on the individual level, which addresses a gap in the literature mentioned by Libai, Bolton, Bügel, De Ruyter, Götz, Risselada and Stephen (2010).

Whereas a choice model (and other econometric models) cannot account for the complexity caused by social interactions on the individual level, the agent-based model acknowledges these interactions, thereby revealing the consequences of interactions over time. Agent-based models also support investigations of how to *manage* complex systems, instead of just predicting their outcomes, which makes them a valuable method for investigating SI.

1.4 Research Aims and Contributions: An Outline

Considering the importance of WoM and SI and the existing gaps in current research on the topic, it is important to investigate SI further. Specifically, SI must be investigated in the context in which it takes place. Therefore, the aim of this thesis is fourfold:

1. Connect marketing with agent-based modeling methods,
2. by developing a model that supports an investigation of social influence within its complex context, and
3. that can be used to test the sensitivity of different marketing strategies to various social influences,

4. and thereby provide guidelines for further research into the relation between social influence and marketing communication strategies.

To reach the ultimate aims of this thesis, the separate chapters form distinctive steps, each with its own aims and contributions, as the overview in Table 1.1 details. The thesis aims to contribute to both marketing and agent-based modeling, as illustrated in Figure 1.1.

In Chapter 2, I discuss WoM literature by focusing on five interrelated questions: (1) about *which products* do people talk, (2) with *whom* do they talk about these products, (3) *why* do they talk about these products, (4) *what* do they talk about, and (5) how does their WoM *affect customer behavior*, on both individual and aggregated (market) levels? The aim of this chapter is to provide more insight into the complexity of the WoM process by discussing and merging prior findings. Such insights derive from an integrative discussion of literature from marketing, social psychology, and sociology, which enables a perspective on WoM in the context of SI. The chapter highlights gaps in current research on WoM and SI and therefore also provides guidelines for research, as exemplified by the other chapters in this thesis.

Figure 1.1 Overview of Studies: Field of Focus, Relations Across Chapters

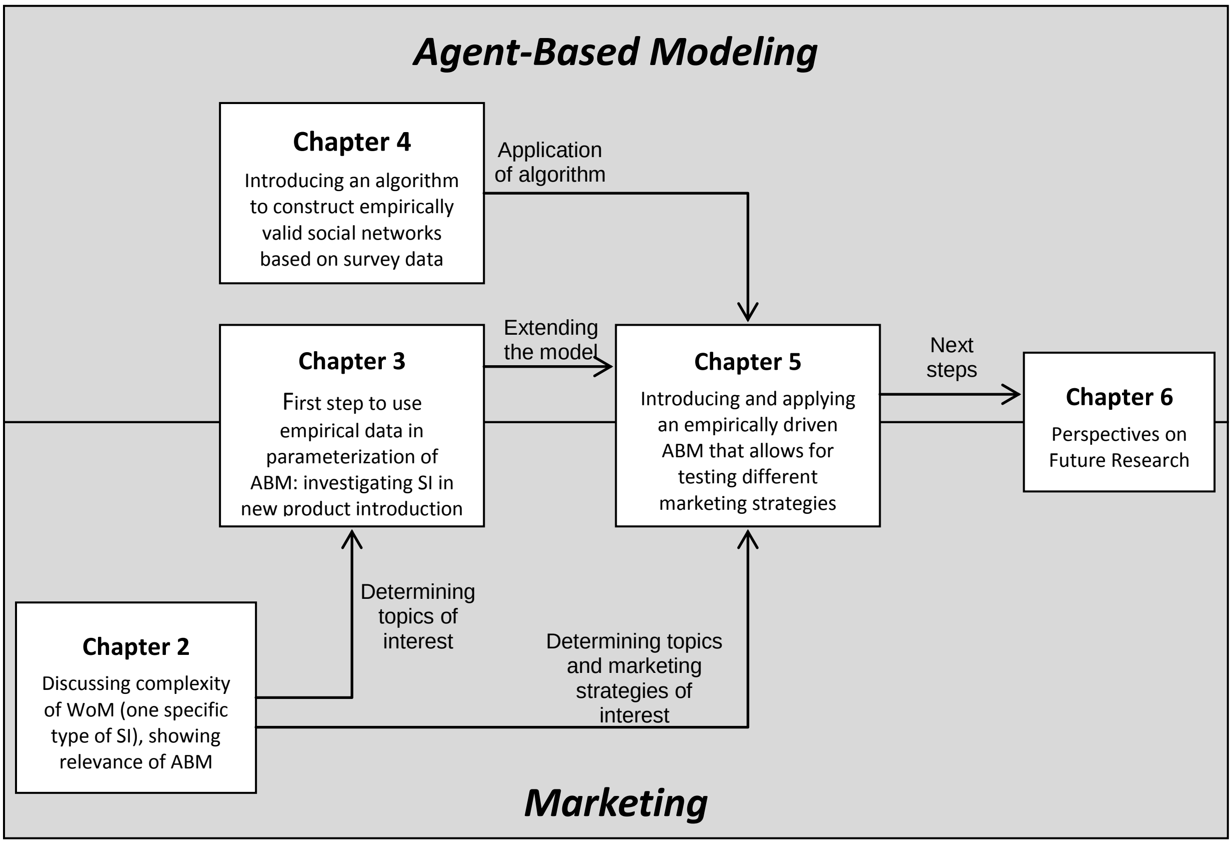


Table 1.1 Overview of Studies: Research Aims, Methodology, and Data

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Research aim	Give insight into complexity of WoM processes	Give insight into the role of (characteristics of) influentials in the diffusion process	Develop method to artificially construct a customer network based on survey data	Develop a model that can test different marketing strategies and reveal the insights that can be gained with this model
Methodology	Literature review	ABM & some basic statistics	ABM	ABM & concomitant variable latent class
Data	Literature (marketing, social psychology, sociology)	Online survey & simulation results	Artificially created	Panel data (conjoint study & survey) & simulation results

Notes: ABM = agent-based modeling.

Chapter 3 offers a first step toward developing the model mentioned as the first aim of this thesis. The agent-based model developed in this study distinguishes two forms of social influence: normative and informative. Furthermore, the model links specific agent characteristics with their position in the network. The aim of this chapter is to show in more detail how the knowledge and personal characteristics of influential consumers affect the adoption process of a new product. Therefore, the model serves to investigate how specific characteristics of influentials (i.e., knowledge, innovative behavior, and susceptibility to normative influence) affect both the speed of information and product diffusion and adoption percentages. Although empirical data are used to parameterize the model, it still relies on some important assumptions about the network structure (i.e., scale-free network structure) and the distribution of the parameters (i.e., influentials only deviate slightly from one another in their personal characteristics). Furthermore, testing of marketing strategies is limited, because little information is available about the use of different (mass) media channels.

To overcome these limitations, Chapter 4 introduces an algorithm to create a network based on cross-sectional data from a survey of unconnected respondents. This method constructs an artificial social network that captures attributes of links dealing with informational and normative influence, similarity, and expertise. The algorithm “translates” respondents into agents, which provides a means to connect other characteristics (e.g., product preferences) to the agent as well. To demonstrate the effectiveness of this algorithm, two different network structures (i.e., random network and modular network) are created. Next, the agents in these networks answer several survey questions, which are then used as input for the algorithm. The algorithm, designed to be flexible and easy to implement, succeeds in recovering the original network structures in both cases.

In Chapter 5 I introduce the most advanced agent-based model in this thesis. The chapter aims to develop a model that can test for the effect of different marketing strategies on the adoption rates of new products, taking the social interactions between customers into account. To achieve the first aim of this thesis, the model developed in this chapter extends the model developed in Chapter 3 on four important points. First, it does not assume a particular network structure but rather uses the algorithm introduced in Chapter 4 to create a network structure based on survey data. Second, using this algorithm means that the agent characteristics (e.g., sensitivity to social influence) are fully based on the empirical data. Third, the simple utility function is replaced with a choice model based on a conjoint study. Fourth, according to the survey, a distinction is made in how different agents use different media channels to retrieve information. To achieve the second aim of this thesis, the developed model tests different marketing communication strategies, applied to introduce a new product in an existing market. Specifically, different types of social influence affect awareness and the adoption rate of new products significantly; the effects also differ across traditional channels (e.g., journal advertisements, comparison sites) and between social sources (e.g., targeting central people in a network or cluster of networks). Finally, the effects depend on the product introduced (e.g., low or high market potential product).

Chapter 6 offers a discussion and summary of the conclusions of the other chapters, along with a preview of the potential uses of the model developed throughout this study. This last chapter also notes some limitations of experimental research and contemplates options for using a more interactive approach to simulation studies, in the form of gaming. The thesis ultimately concludes with suggestions for marketing research, practice, and education.

Chapter 2

Word of Mouth: Complexity of the Process[1]

2.1 Introduction

Imagine someone is in the process of buying two different products: a pack of bubblegum and a smartphone. Even though the purchase of the pack of bubblegum may be preceded by some conversation (e.g. about taste), it is unlikely that the person will have long and detailed discussions about the product. For most people, the product is not interesting enough to discuss in detail. In addition: if the first choice was not optimal, it is not much of a problem to buy a different pack of bubblegum. The involvement in the buying decision is higher for some products than for others, which affects the likelihood that someone feels the need to talk about a particular product.

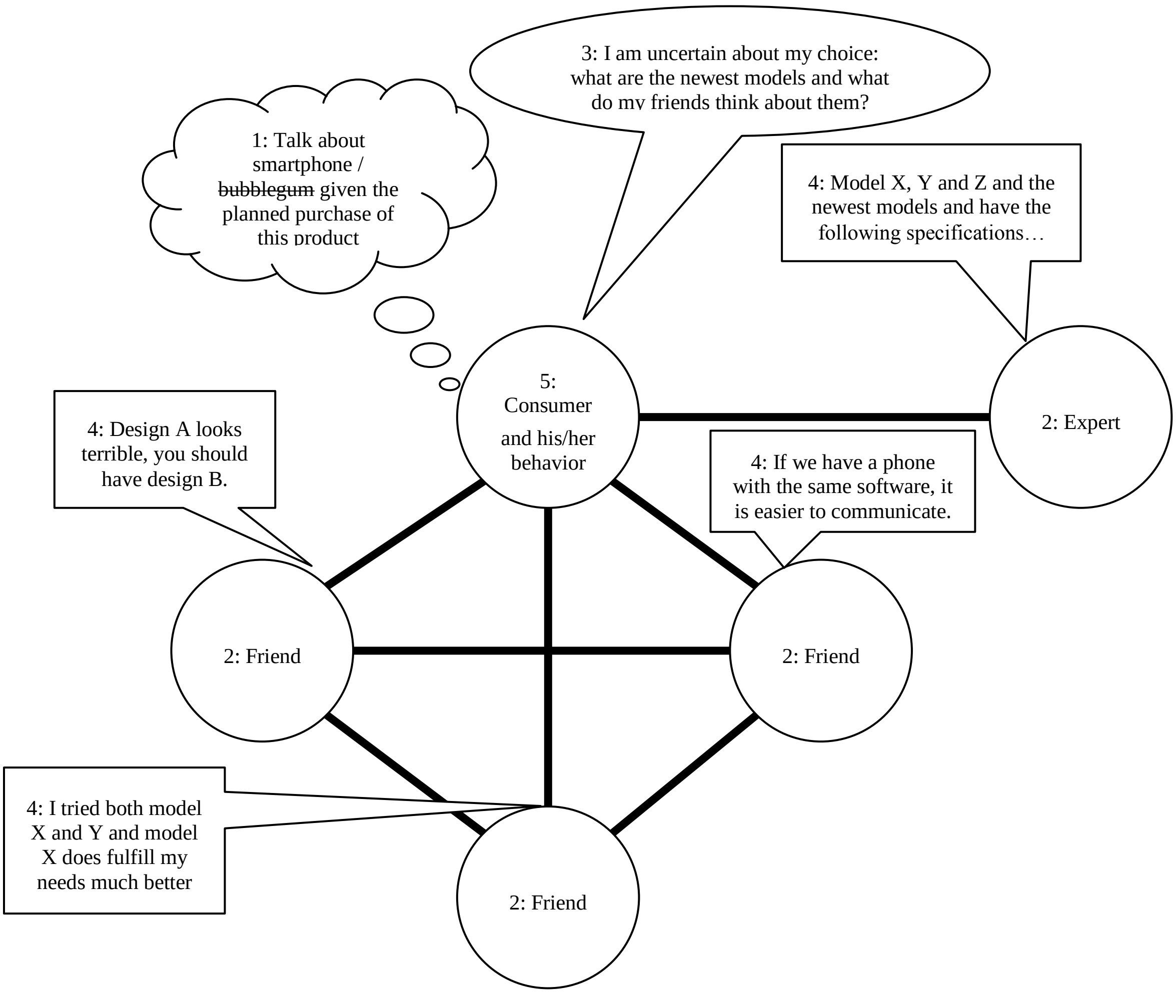
For most people the purchase of the smartphone is an entirely different story: it is preferable to make the right choice the first time, as people generally stick with this choice for at least one or two years. Smartphones are not only compared on their mostly objectively determined specifications (e.g. processor speed, memory), but also with respect to other aspects that are more difficult to determine on objective standards (e.g. design, user-friendliness). To get more information about potentially interesting smartphones, the person can decide to talk to different people. (S)he probably want information about both search attributes (characteristics that can be assessed without actual usage of the product; Ford, Smith and Swasy, 1988) and experience attributes (characteristics that require actual usage or direct contact with the product; Ford, Smith and Swasy, 1988). An expert in the field will be able to deliver information about the newest models and all their specifications (search attributes). Whereas this information can be very valuable, it may also be useful to talk to friends with similar needs in smartphone usage to hear their experiences with and thoughts about the alternative options. The expert may have a different opinion about user-friendliness (e.g. more experienced user) and the design (e.g. different taste) of the smartphones. Friends with similar needs and a similar taste are more useful sources of information on these (experience) characteristics. The ultimate decision of the person could be to buy a newer version, but the same brand of the smartphone as owned by his/her friends.

Word of mouth (WoM) has fascinated researchers for many decades. Recognized as one of the most powerful determinants of the customer decision-making process, it involves “informal communications directed at other customers about the ownership, usage, or characteristics of particular goods and services or their sellers” (Westbrook, 1987: 261). The strong impact of WoM on customer behavior also makes it an interesting topic of investigation for marketers and marketing researchers, raising the question: Is it possible to influence WoM, and if so, how?

[1] This chapter is based on Van Eck, Peter S., Wander Jager, and Peter S.H. Leeflang, Word of mouth: Complexity of the process, *working paper*, University of Groningen

To answer this question, we need to know how WoM really ‘works’. Beyond the extensive marketing studies of the effects of WoM, research into the WoM *process* takes as its foundation social psychology and sociology. Only by addressing these varied backgrounds is it possible to understand the full complexity of WoM and thereby answer five fundamental, interrelated questions in WoM research (see Figure 2.1 for an illustration of the connection between the questions): (1) about *which products* do people talk, (2) with *whom* do they talk about these products, (3) *why* do they talk about these products, (4) *what* do they talk about, and (5) how does their WoM *affect customer behavior*, on both individual and aggregated (market) levels?

Figure 2.1: Illustration of WoM, related to the five questions in WoM research



1: About which product do people talk (e.g. smartphones)

2: With whom do the talk (e.g. friends, experts)

3: Why do they talk about these products (e.g. reduce risk, get advice)

4: What do they talk about (e.g. information, norms)

5: How does their WoM affect customer behavior (e.g. opinion about experience of friend is more important than experts opinion, but the expert is more likely to inform the consumer about new options. As the consumer makes a decision based on the WoM/SI, this affects future choices of the other people in the network as well, leading to an effect on company sales and market share).

The questions appear simple. But if they all were included in a survey, the resulting responses would likely be diverse and incoherent. Moreover, WoM must be regarded in the (broad) context in which it takes place. In particular, the personal social network of a customer affects with whom people may talk (i.e., customers cannot talk with others with whom they are not connected in any way). Within a social network, people influence one another through complex social/interpersonal influences that can be conscious or unconscious, active or passive, normative or informative, and so forth. Although WoM reflects part of this social influence (mostly conscious and active), it cannot be separated from other forms, because the impact of WoM (i.e., influence on individual decision making) depends not only on *what* is said but also by *whom*.

With this chapter, we aim to provide more insight into the complexity of the WoM process by discussing and merging prior findings about this topic. We discuss answers to the five fundamental questions in WoM research, according to a wide range of literature on social networks, social influence, and WoM. Then we return to the original question: Is it possible to influence the WoM process, and if so, how? The discussion of this question offers suggestions for further research.

2.2 Products

Although WoM appears important for various offerings, including movies (Broekhuizen et al. 2011; Liu 2006; Mizerski 1982), automobiles (Swan and Oliver 1989; Thomas 2004), travel (Murphy et al. 2007), fashion (Szybillo 1975), and even industrial innovations (Czepiel 1974; Martilla 1971; Schiffman and Gaccione 1974), it is not universally important for all items (Brooks 1957). What makes WoM more important for some offerings compared with others? It is important first to recognize that WoM represents part of the broader concept of social influence. Prior literature distinguishes two types of social influence: *normative,* which refers to a tendency to conform to the expectations of others (Burnkrant and Cousineau 1975), and *informative,* or the tendency to accept information from others as evidence of reality (Deutsch and Gerard 1955). Both influences can transfer across customers through WoM.

Various characteristics of an offering affect whether social influence is important for its customers, including testability (e.g., ability to evaluate), visibility, perceived risk, and complexity (Ford and Ellis 1980; Im et al. 2007; Murray 1991). Three of these characteristics are similar to three traits that determine an innovation's rate of adoption—complexity, trialability, and observability (Rogers 2002)—so WoM likely is important for new product introductions.

Specifically, the difficulty of evaluating an offering depends on several characteristics (Christiansen and Tax 2000). Table 2.1 summarizes the most important characteristics. First, its attributes may be easy to evaluate prior to purchase, because they provide many search qualities. Most tangible goods offer many such qualities, which minimizes the need for WoM. Second, some attributes can be evaluated only after purchase, because they feature experience qualities (Christiansen and Tax 2000; Murray and Schlacter 1990). If a product, such as a restaurant meal, is dominated by experience qualities, it becomes more interesting for (potential) customers to engage in WoM behavior. Third, a product may have credence qualities, which are hard (if not impossible) to evaluate even after purchasing (Christiansen and Tax 2000; Nelson 1970), so WoM for these products (e.g., legal services) is even more attractive for customers. Many services have high credence and experience qualities; tangible products are often higher on search qualities (Christiansen and Tax 2000; Im et al. 2007). Accordingly, (informative) WoM should be more important for services than for tangible products (Murray and Schlacter 1990).

However, WoM is also important for tangible goods, especially when we consider the other three product characteristics. For example, high visibility makes WoM more important, mostly because of the potential normative influence. Greater visibility makes it obvious whether a customer has complied with the norms of the groups to which he or she belongs. High visibility products therefore can be used for group identification (e.g., Harley-Davidson) or to help customers express themselves (Apple); they also make it easier to start a conversation about the product (e.g., fashion) and even tend to prompt more WoM (Berger and Schwartz 2011). In addition, WoM is important for products that induce a high perceived risk, whether in a social context (e.g., not complying with group norms leads to social exclusion) or a technical/financial context (e.g., a nonfunctional product results in a financial loss). In both cases, WoM is important, whether to determine the fit between the product and group norms or to reveal product functionality in the experiences of other customers. Finally, high complexity makes WoM important, mostly related to informative influences. It helps customers gain a better understanding of the product, because they use other customers' evaluations to judge product functionality/quality.

Table 2.1: What makes WoM important for products?

Product Characteristics	Why Important?
Low testability	Difficult to evaluate before purchase
High visibility	Group identification, spontaneous topic
High perceived risk	Comply with group norms (social), nonfunctional product results in major loss (technical/financial)
High complexity	Get a better understanding of the product

2.3 People in Networks

Although customers frequently talk with others about market offerings, WoM is not a homogeneous source of information (Murphy et al. 2007), and customers differ in how they connect with others and respond to information (Bohlmann et al. 2010). Social networks tend to remain stable only for short periods of time, though in the long run they may become more stable for longer periods of time (Nezlek 1993). The differences stem from customer characteristics, such as their risk preference and locus of control, which affects whether they tend to talk most with their in-group (high external locus, risk avoidance) or out-group (high internal locus, risk taking) (Lam and Mizerski 2005). Near-future preferences also tend to be influenced by in-group members, but recommendations of distant others are more effective with respect to distant-future preferences (Zhao and Xie 2011). Age matters too: Children’s networks exhibit high density, whereas adults possess less integrated friendship networks (Shrum and Creek 1987). Someone can even be part of different exclusive networks (from family to forum) with very different attributes (e.g. types of influences). With regard to culture, the influences on WoM behavior are varied (Lam et al. 2009). For example, masculinity is associated with a preference to share positive WoM with in-group members. A higher individualism score instead implies a preference for spreading positive WoM to out-group members. At the individual customer level, recent research suggests a U-shaped link between susceptibility to social influence and a country’s level of collectivism–individualism (Broekhuizen et al. 2011). At the company level, U.S. companies use far fewer referral sources than comparable Japanese companies (Money et al. 1998).

Customers in most countries also confront many choices, which increases the importance of social networks as guides (Brooks 1957). Although in the past, people might have influenced only a few others in their immediate environment (Lyons and Henderson 2005), social networks have become more important as technological advances have made it easier to travel longer distances and therefore meet more people. In recent years the Internet has strongly increased this effect: Customers have the opportunity to share experiences and information with people they would otherwise never ‘meet’. An extreme example was the near bankruptcy of Dexia, a Belgian/French financial institution, after Twitter members retweeted rumors of its insolvability.

Customers’ social networks determine with whom they communicate. Whether customers talk with specific individual members in their social network depends mainly on the strength of their relations (*tie strength*), their *similarity* (homophily), and the *position* of customers in their network, which determines the role they play (see also Table 2.2). Tie strength indicates the type of relation two people have: A strong tie implies a communal relation in which people respond to others’ needs without expecting anything in return (Ryu and Feick 2007). A weak tie instead suggests an exchange relationship in which people try to maximize their own outcomes while minimizing their costs (Ryu and Feick 2007). Prior research shows that people are more likely to engage in WoM with strong ties than with weak ones (e.g., Brown and Reingen 1987; Frenzen and Nakamoto 1993). In this pre-internet era, research also shows that the amount of WoM generated in a group with mostly strong ties is also greater than the amount generated in a group with mostly weak ties (Bone 1992), likely because of the communal orientation of their relationship: People want to ‘share the pleasure’ (Ryu and Feick 2007). Because at this time people tended to have more frequent interactions with their strong ties, they also might have had better insights into their preferences and needs (Clark et al. 1986). This greater knowledge about preferences and needs should make people more comfortable about sharing experiences and even lead to more personalized advice (Feick and Higie 1992). However, the Internet likely changed many of these findings. As will be discussed in more detail in section 2.4, people have many different motives to engage in WoM on the internet (e.g. Hennig-Thurau and Walsh, 2003). This WoM can take in many different online locations, such as social networks and forums. Even the so-called social networks such as Twitter contain weak ties (Takhteyev, Gruzd and Wellman, 2012). Still within these networks a lot of WoM is generated, possibly caused by the low threshold to publish opinions and product information. In addition, the internet made it easier to find people with similar preferences and/or needs and share experiences/knowledge with these people without forming strong ties.

Some people engage in WoM to strengthen their relationships with strong ties (e.g., friends, family), though it also can initiate conversations with weak ties (e.g., acquaintances) (Cheung et al. 2007). The importance of weak ties should not be underestimated. They provide nonredundant information (Yakubovich 2005) and create important bridges within a network (Brown and Reingen 1987). In a business- to- business situation, familiar contacts have their disadvantages and can reduce the novelty of solutions (Wuyts, Verhoef, Prins, 2009). Although the strength of weak ties stems from their ability to connect socially distant locations, complex contagion (e.g., social movements) requires social affirmation, so the width of bridges is also important (Centola and Macy 2007). Spatial networks contain wide bridges, which explains how social movements often diffuse spatially (Centola and Macy 2007). The strength of weak ties appears positive, in that it aids the diffusion of information throughout a network. However, information also might be negative, in which case weak ties could hinder actual adoption (Goldenberg et al. 2007).

Related to tie strength, similarity between people, or homophily, influences with whom customers talk (Brown and Reingen 1987). According to Risselada, Verhoef and Bijmolt (2013), homophily is more important than ties strength with regard to strengthening the social influence within the relation. Similarity often depends on attributes such as age, gender, education, or lifestyle (Rogers 1983), and greater similarity tends to increase trust, understanding, and attraction, creating a stronger relationship (Ruef et al. 2003). Highly similar people also are more likely to connect (Kossinets and Watts 2009), and friendship in turn leads to increased similarity (Gibbons and Olk 2003). Therefore, measuring the influence of similar people on each other is difficult, because they already have similar needs and similar behaviors (Reingen et al. 1984). Failing to control for this effect produces skewed results (Cohen 1983). Most research focuses on influences of similar people on each other, but dissimilar people also have effects (negative modeling). For example, some people abandon products if dissimilar others adopt them (Berger and Heath 2008; Clayton et al. 2006). On the other hand, Naylor, Lamberton and West (2012) show that in an online context peoples product evaluations and purchase intentions are affected by the number of people ‘liking’ a product. Although these results indicate that similarity is not a precondition for social influence, the same study also shows that the absence of information about the people behind the ‘likes’ is better than showing information about dissimilar people.

Finally, the position of people within a network affects their WoM behavior. Weimann (1982) distinguishes horizontal (bridges between marginal members) from upward vertical (from marginal members to people located in the center of the network) information flows. People with many connections have, on average, less influence power than people who connect different clusters in the network (i.e., bridges; Katona et al. 2011), which is can be explained by the fact that it takes time to maintain relations and therefore someone with many connections has less time per connection. This results in less convincing power (Hinz, Skiera, Barrot, Becker, 2011). Yet most literature focuses on central people in networks, because they seem to be the center of the WoM process. Three key roles appear frequently in WoM-related literature: opinion leaders (e.g., Katz and Lazarsfeld 1955; King and Summers 1970; Langaard et al. 1978), innovators/early adopters (e.g., Engel et al. 1969; Midgley and Dowling 1978), and market mavens (e.g., Feick and Price 1987).

The first group of opinion leaders (OLs) includes customers who, compared with other customers, exert more influence on others' decisions (Rogers and Cartano 1962). They advise other people about search and purchase decisions (Flynn et al. 1996) and therefore can affect the outcomes of marketing strategies on the aggregate level. For example, OLs increase the speeds of the information stream and the adoption process, while also increasing maximum adoption percentages (Van Eck et al. 2011). However, OLs lack the authority and status generally associated with the term 'leader'; they simply offer a channel of advice (Brooks 1957). In addition, an OL is only relatively more influential than others, not a dominant leader followed by a passive set of followers (Myers and Robertson 1972). Other customers can influence OLs' decision making (Brooks 1957), though Venkatraman (1990) reports that OLs exhibit high involvement with a product category, which is why others perceive them as OLs (Lyons and Henderson, 2005). They also tend to exhibit a high level of innovativeness (e.g., Hirschman, 1980), are less conservative or less resistant to change (Carter and Clarke 1962), and therefore adopt new products (Baumgarten 1975)—characteristics they share with early adopters and innovators.

Such early adopters and/or innovators are often mentioned as sources of WoM. Although the concepts of opinion leaders and early adopters have different foundations (interpersonal influence and product adoption, respectively), with respect to WoM behavior, there is great similarity between the concepts (Mahajan and Muller 1998). Focusing marketing strategies only on OLs or early adopters cannot guarantee successful product adoption throughout the market though (Mahajan and Muller 1998). For example, OLs might have a bad experience with the new offering or fail to gather all relevant information (Wiedmann et al. 2001), in which case the imperfect information they share would decrease the probability that other customers buy the product (Enis 1979). In addition, OLs are part of the network they influence, so their adoption behavior depends on group norms too.

Feick and Price (1987) suggest another concept: the market maven. Unlike OLs, market mavens are not experts in a specific product category but rather have knowledge about markets in general and know how to obtain information about any product (Cheung et al. 2007). They are better informed than OLs and might be more reliable partners for marketers (Wiedmann et al. 2001). Market mavens also tend to hold more positive attitudes toward direct mail than other customers (Schneider and Rodgers 1993) and use more media sources (Abratt et al. 1995; Feick and Price 1987). Because they communicate the information that they gather frequently (Abratt et al. 1995; Higie et al. 1987), market mavens hold great interest for WoM marketers. Approximately one-third of all customers can be identified as market mavens; only 13.5% of customers are early adopters (Bagozzi 1986). Market mavens likely reach more people and thus have a greater influence on their environment. They also may be less influenced by group norms, because they are not 'leaders' and might even be outsiders in their network. However, as is true of OLs as well, it is difficult to direct marketing actions specifically to market mavens (Feick and Price 1987). Although we know that market mavens watch more television and read more magazines than other customers (Abratt et al. 1995; Feick and Price 1987), marketers still need more information about which media they use and which other information sources they rely on to be able to direct marketing efforts more precisely (Wiedmann et al. 2001). Yet even as different types of influential customers remain difficult for marketers to target, customers seem to know exactly whom to contact for which particular type of information.

Table 2.2: How does network position affect WoM?

Network (Position)	How?
Tie strength	Strong ties: more WoM, more aware of each other's preferences and needs, provision of social confirmation
	Weak ties: non-redundant information, connections with socially distant locations
Similarity	Higher trust, understanding, and attraction
Position	Opinion leader: high product involvement
	Innovator/early adopter: innovative behavior
	Market maven: knowledge about markets

2.4 Motives

People talk about products for many reasons, depending on the product and the person to whom they are talking. In general, this distinction involves three dimensions: WoM is constructive or destructive, self-focused or other-focused (Wetzer et al. 2007), and pre-purchase or post-purchase (see also Table 2.3).

In the 'Product' section, we noted one of the most obvious reasons people seek WoM, namely, as a source of information before they purchase (Brooks 1957; Burnkrant and Cousineau 1975), especially if they lack an objective standard (Cohen and Golden 1972; Venkatesan 1966). Some WoM thus starts even before the product is released, as is common in the movie industry (Liu 2006), but Apple also succeeded in creating a lot of WoM before products were introduced. Hennig-Thurau and Walsh (2003) list multiple motives for the search for information on opinion platforms: risk reduction, reduced search time, learning which products are new in the marketplace (i.e., pre-purchase), learning how to consume the product, determining social position (product social prestige), and dissonance reduction (post-purchase). High product involvement also results in WoM (Dichter, 1966), as people are enthusiastic and want to share their experience and knowledge. Other likely reasons to engage in WoM behavior include attaining status in a social group (Anderson et al. 2001) or communicating something important about themselves, in the case of self-relevant products (Chung and Darke, 2006).

If a customer identifies with a company (i.e., perceives high overlap between his or her own identity and the company's), it likely induces high commitment to the firm in the form of an enduring desire to maintain a valued relation, which results in positive WoM about that company (Brown et al. 2005).

In contrast, dissatisfying experiences with a company can lead to negative WoM, depending on the nature of the dissatisfaction, the perception of blame, and perceptions of company responsiveness (Richins 1983). Even a small group of dissatisfied customers can spread harmful information throughout a network (Goldenberg et al. 2007). If customers switch to another company, spreading negative WoM may be a way to convince themselves by convincing others (Von Wangenheim 2005). In practice, customers have multiple reasons to engage in negative WoM. If they are angry, frustrated, or irritated, negative WoM helps them blow off steam (venting, self-focused) or get revenge (destructive, other-focused) (Wetzer et al. 2007). If they feel purchase regret, negative WoM can help them bond with, entertain, or warn other customers (constructive, other-focused) (Wetzer et al. 2007). Disappointed customers also search for comfort (moral support, understanding, self-focused) and try to warn other customers (Wetzer et al. 2007). Although dissatisfaction likely results in negative WoM, satisfaction does not necessarily lead to positive WoM. Thus we can make a distinction between satisfaction (e.g., a car with functional antilock brakes fulfills utilitarian needs) and delight (a car with a panoramic sunroof fulfills hedonic wants). Delight results in more (positive) WoM, but satisfaction appears to have a lesser effect on the amount of WoM spread by customers (Chitturi et al. 2008).

Some motives to engage in WoM remain the same across cultures, such as altruism (especially toward close ties, other-focused), expressing sense of achievement, and seeking a therapeutic effect (Cheung et al. 2007). Other motives differ. Chinese customers are more likely to seek confirmation of their own judgment, advice, and connections, whereas Americans tend to seek compensation and bargaining power (Cheung et al. 2007). Along with the many reasons to share information about products, we also note motives not to engage in WoM, including a desire for uniqueness (Cheema and Kaikati 2010). Consumers who seek uniqueness avoid spreading positive WoM for publicly consumed goods, though they might offer (less persuasive) WoM about product details (Cheema and Kaikati 2010).

Table 2.3: What are the motives for WoM?

Dimension	Why?
Constructive	Warn other customers
Destructive	Get revenge
Self-focused	Blow off steam, search for comfort
Other-focused	Give advice, altruism
Pre-purchase	Learn from others, reduce risk and search time
Post-purchase	Learn how the product should be consumed, obtain status in a social group

2.5 The Topic ('The What')

What WoM is about, depends on three elements: the topic of WoM, the valance and the social influence (see Table 2.4). The *topic* of WoM pertains to ownership, usage, or characteristics of particular goods and services or their sellers. Although WoM may be brand specific, it is not necessarily: WoM can be about a specific brand or the product category in general (Libai et al. 2009).

Its *valence* can be positive, negative (i.e., similar but opposite forms of advice; East et al. 2008), or neutral (e.g., product details without judgment). Negative WoM appears more influential than positive WoM (Nam et al. 2010; Von Wangenheim 2005), probably because negative WoM requires only the availability of ties, whereas positive WoM demands a certain degree of tie strength (Weenig and Midden 1991). Customers thus are more likely to engage spontaneously in negative WoM with weak connections, to warn other customers. Positive WoM instead tends to emerge in response to requests from strong connections. In the case of web based WoM, research has shown that negative web based WoM has a stronger effect than positive versions, especially if the web based WoM pertains to experience goods rather than search goods (Park and Lee 2009). This negative effect for experience goods relates to uncertainty about actual product quality. Although negative WoM has a stronger effect, positive WoM is more common, and more people produce it (East et al. 2007), for several reasons. First, people tend to talk about their preferred brand, which also means that WoM levels tend to match market share (East et al. 2007). Second, people prefer to talk about products they love but want to avoid hated alternatives, about which they have less information anyway. They maintain strong, extensive memory encoding for information related to loved alternatives though (Gershoff et al. 2006). In an interesting finding, people who hold a minority opinion express that opinion less quickly than people who hold the majority opinion (Bassili 2003). Thus, it is difficult for a brand with a small market share to increase WoM about its product.

In other situations, negative WoM is more likely, such as when a dissatisfied customer switches to a new provider (negative frame, 'escape from the bad') (Von Wangenheim 2005). The likelihood that these customers engage in positive WoM about the new provider is lower than the chance that other people who switched because of financial benefits offered by that new provider will offer positive WoM (positive frame, 'go for the good') (Von Wangenheim 2005). Although people who produce negative WoM also tend to express positive WoM, they share negative WoM with more people (East et al. 2007). Negative WoM appears more diagnostic too (Herr et al. 1991), though it depends somewhat on whether the WoM pertains to a product (negative WoM) or prospective agent (positive WoM) (Gershoff et al. 2006).

Beyond the distinction between positive and negative WoM, the topic also relates to the social influence. We thus distinguish *informative* and *normative* influences (Deutsch and Gerard 1955): Customers might talk about the properties of a product (informative influence) or its trends or fit with group norms (normative influence). If customers learn by observing others (Im et al. 2007), the information they obtain often relates to the network structure and their position. For example, if an OL uses a product, it issues a different signal than if someone outside the network uses it. We also note a difference involving influence within the network and the spread of information (Weimann 1982). Influence spreads mostly within a cluster, such as when an OL gives advice to others. For information flows throughout a network, the role of marginal members (i.e., bridges in the network) is more important, though central people still play key roles within their own cluster. Yang, Hu, Winer, Assael and Chen (2012) find that for some customers there is a tradeoff between generating WoM and consuming it, which suggests that some people prefer to either send or receive information, but not both.

Finally, the topic of WoM relates to the person with whom the WoM gets shared. The concept of social comparison suggests three types of information a customer may want to obtain from a conversation about a product (Suls et al. 2000). First, the customer may want to know whether he or she will like the product (preference assessment), so information from similar others is most useful. Second, a customer may want to know if information about the product is correct. Depending on the social impact or use of the product, this information must come from an expert or similar expert. Third, if the customer wants a prediction about whether he or she will like the product (preference prediction), information from an experienced customer is most useful.

Table 2.4: What are the topics in WoM?

Type	What/How?
Topic	Ownership, usage, characteristics of products and sellers
Valence	Positive: more common, often on request
	Negative: stronger impact, often spontaneous
Social influence	Informative: properties of the product
	Normative: trends and fit with group norms

2.6 Impact

When WoM affects the individual customer, it also results in several influences on the more aggregated levels (social network and firm) (see also Table 2.5), and these levels have been studied extensively. At the *individual level*, WoM affects customer behavior in the form of variables such as awareness, expectations, perceptions, attitudes, judgments, intentions, and (buying) behavior (e.g., Bickart and Schindler 2001; Herr et al. 1991; John 1994; Lau and Ng 2001; Pincus and Waters 1977; Reingen 1987; Sultan et al. 1990; Ziethaml et al. 1993). The influence of WoM even might be stronger than that of formal marketing communications (e.g., Bone 1995; Herr et al. 1991), especially on actual purchase decisions (Engel et al. 1969), though impersonal sources still create awareness (Martilla 1971). Moreover, WoM has a small but significant impact on product evaluations if the customer already has experience with the product (Schumann et al. 2010). For customers, WoM offers the advantage of reducing the amount of information that must be processed before making a decision (Duhan et al. 1997), though in other cases, WoM may lead to information overload. If the customer is highly involved in the purchase, information overload results in decreased purchase intentions (Park and Lee 2008). Low involvement customers rarely experience this effect though, because they do not glean all the information from the message but rather use only the positive messages as a signal of popularity. After the purchase, WoM still might affect the satisfaction and loyalty of the customer (Von Wangenheim and Bayón 2004).

Nor does WoM affect all customers the same way, so we must consider different customer *segments*. For example, the importance of personal norms determines the importance of social influence for a particular customer (Bonfield 1974), as well as his or her initial opinions about the product (Stanley 1978). A person’s social network also affects opinions about a product. If someone is part of a congruent social network (i.e., all members have similar opinions), resistance to change is much stronger than it would be for someone who participates in a heterogeneous social network (i.e., members have a range of opinions) (Visser and Mirabile 2004). Intriguingly though, group pressure also may have the opposite effect: If someone feels that his or her individual freedom is in danger, he or she may resist group pressures (Venkatesan 1966). The impact of WoM thus depends on the initial probability of purchase, the strength of WoM expression, and whether the WoM refers to the customers’ preferred brand (East et al. 2008). Even the mode of communication could affect its impact. For example, face-to-face WoM tends to be more persuasive than printed recommendations (Herr et al. 1991), though these tendencies may have shifted since the emergence of online social networks. Naylor, Lamberton and West (2012) for example show that even ambiguous information about other people liking a brand on Facebook is enough to improve brand liking. Senders and receivers of WoM also may adopt different interpretations of a message, and their experiences with the product affect their message evaluations, even over time (Christiansen and Tax 2000). Even the level of language abstraction may affect the impact of the message (Schellekens, Verlegh and Smidts, 2010). When a sender uses abstract language in his/her positive WoM, the receiver is more likely to assume that the sender has a positive attitude towards the product and this results in higher buying intentions. With respect to negative WoM, a less abstract message has more impact. In general, customers resist negative WoM about brands they are likely to buy and reject positive WoM about brands they are unlikely to purchase (East et al. 2008). Similarly, prior impressions of a brand can reduce or eliminate WoM effects (Herr et al. 1991).

At the *firm level*, positive WoM results in greater efficiency for advertising and promotion investments (Luo and Homburg 2007), and it offers longer carryover effects and higher response elasticities than traditional marketing (Trusov et al. 2009). Furthermore, it affects customer lifetime value (Hogan et al. 2002; Lewis 2006): Negative WoM creates higher retention costs (i.e., it is more difficult to convince people to stay), higher defection rates (people hear about others' bad experiences), and thus lower profits. Positive WoM might have the opposite effect, such that it results in higher profits. Moreover, people who became customers because of WoM add twice as much long-term value to the firm, compared with marketing-obtained customers, even if the latter add more short-term value (Villanueva et al. 2008). In the movie industry, WoM offers significant explanatory power for both aggregate and weekly box office revenues, which is based mostly on the volume of WoM, not its valence (Yong 2006). Negative WoM may have negative effects on the net present value of firms though (Goldenberg et al., 2007), as well as on a firm's future idiosyncratic stock returns, long- and short-term cash flows, stock returns, and stock volatilities (Luo 2007, 2009). In addition, WoM may be perceived as a form of customer engagement behavior (Van Doorn, Lemon, Mittal, Nass, Pick, Pirner and Verhoef (2010)) It also affects firm's reputations , the attraction of new customers and the retention of existing customers.

Another interesting effect of WoM pertains to its ability to increase involvement in a product category, as a result of positive product-specific comments (Giese et al. 1996). Positive WoM about one product could increase sales for another product in the same category. A company still might try to reach more customers by increasing WoM in the category, because customers start to differentiate more among products if their involvement with the category increases (Giese et al. 1996). For a product with low initial awareness, WoM is most effective at driving sales when it is initiated by customers who are not very loyal and provided to their acquaintances (Godes and Mayzlin 2009). For example, with a new product introduction, the first entrant often has an advantage, because brand-specific WoM largely relates to this first entrant, whereas a second entrant enjoys the advantage that non–brand-specific WoM encourages its rapid dispersion in the market (Libai et al. 2009). However, the first entrant ultimately achieves a greater WoM advantage (Grewal et al. 2003), and only a vastly superior second entrant can overcome the disadvantage of its WoM effect (Horsky and Mate 1988).

Table 2.5: What is the impact of WoM?

Level	Impact on
Individual	Awareness, expectations, perceptions, attitudes, judgments, intentions, and (buying) behavior
Segment	Group pressure
Aggregate	Efficiency of advertising and promotion investments, customer lifetime value, revenues, cash flows, stock returns, and stock volatilities

2.7 Influencing the Process

The final question to answer pertains to whether it is possible to influence the WoM process. The information gathered in the previous sections suggests several ways to influencing this process, as we summarize here.

Influencing the product

Customers are unlikely to initiate WoM about every product they use, because not all products are interesting topics of conversation, nor is it always necessary to discover product quality through WoM. If the product does not encourage WoM itself, companies might work to make their offerings more interesting as topics of WoM. For example, when developing new products, firms might consider the level of originality, because product originality has a positive influence on customers' willingness to initiate WoM (Moldovan et al. 2011). However, originality only influences the amount of WoM; the valence (positive/negative) depends on product usefulness (Moldovan et al. 2011). If a company introduces an original product, its lack of usefulness still could produce significant negative WoM.

In addition, companies could consider a viral product design, which incorporates viral features to a product (Aral and Walker, 2011). They can either include an option for personalized references (e.g. sent a private message) or an automated broadcast notification (e.g. an updated status in an online social network). According to Aral and Walker (2011), the personalized references are most likely to result in an adoption and sustained product use. However, these references are used less often and therefore the automated messages ultimately result in more adoptions in the social network.

If it is not possible to change the product, a company can reconceive of its strategy to market the product. For example, the 'Intel inside' campaign in the PC processor market relied on ingredient branding, such that an otherwise invisible product became visible and therefore more attractive as a topic of conversation. Promotional giveaways (e.g., recipes) also might enhance the amount of WoM spread about a product, though giving away samples, coupons, or rebates usually does not result in more WoM (Berger and Schartz 2011).

In the absence of any objective standard, customers tend to conform with group norms (Venkatesan 1966), so companies should ensure that their products align with group norms or attempt to influence those norms. When developing a marketing communication strategy, this insight can help the firm target the right people with the right message. Companies also should take care not to force their norms on the group though, because that tactic can lead people to resist group pressure when they perceive a threat to their individual freedom (Venkatesan 1966).

Influencing the people

A frequently studied way to influence the WoM process involves influencing customers who themselves are influential. It sounds very appealing to target a small group of influential customers and encourage them to share positive WoM with other customers, which could efficiently convince everyone in the network to adopt. However, finding such influential customers is difficult, in that they do not differ demographically from other customers (Corey 1971). The impact of influential customers has been a topic of some debate as well. Watts and Dodds (2007) show that the spread of new products results from a critical mass of easily influenced individuals, instead of a few influential customers. When people with a central position in a network offer only a limited number of connections, innovation diffusion is severely hampered and becomes much more uncertain (Delre et al. 2010). Yet other research suggests that OLs can affect the speed of information and product diffusion, as well as product adoption rates (Van Eck et al. 2011). According to Vag (2007), we must realize that product preferences change over time, depending on factors such as motivations and attitudes toward messages in social networks. Measuring the actual influence of OLs on product preferences thus is difficult using simple survey data. It also is not be clear whether experts really convince others. People can make up their own minds and call on experts only to legitimize their extant decision (Leonard-Barton 1985). Furthermore, though OLs often are among the first adopters, marginal members tend to be willing to take more risks in adopting new products (Becker 1970), whereas OLs risk losing status if one of their adoptions fails. Marginal members cannot lose status, though they might gain it if they are the first adopters of a very successful new product. This distinction could help explain why central customers in a network have different effects and roles in various markets (Delre et al. 2010). As these details indicate, it is very difficult to make clear generalizations. The impact of certain messages could differ even across products in the same product category (Zhu and Zhang 2010), because OLs can specialize in two dimensions: area of interest and social economic strata (Brooks 1957). The interdependency between OLs and their groups implies that marketers should find OLs within any customer group they try to target.

A viral marketing campaign targets certain people in a social network in an attempt to reach a considerably larger audience via this social network. To make these strategies successful it is important to target the right people, such as the well-connected customers (Hinz, Skiera, Barrot and Becker, 2011)

Although targeted marketing within groups can increase profitability by approximately 20% (cf. 1% increase with group-level targeting), marketers still should avoid presenting different group members with different offers, which can easily backfire (Hartmann 2010).

Influencing the motives

Influencing motives offers another interesting route to affect WoM. Companies can alter WoM valence by dealing effectively with problems. If they fail to solve customer problems, the customer likely grows angry or disappointed and may issue negative WoM. Positive WoM instead should result from an excellent problem-solving strategy.

It is also possible to give customers other motives for talking about products, such as rewarding referral behavior. Whether and how referral behavior should be (financially) rewarded depends on the link between the sender and receiver of the information, as well as the strength of the referred brand. A weak brand and a weak relation suggests that the receiver should receive a reward for any referral behavior. However, if both the brand and the relation are strong, the reward should be divided between sender and receiver, in which case the sender senses lower social benefits and higher social and psychological costs compared with a referral without reward (Ryu and Feick 2007). Rewarding referral behavior therefore seems most beneficial if the company expects the product to be shared among weak ties. In referral programs it is important to realize that financial motives of the sender of the advice affect the way the receiver interprets this advice. The sincerity of the sender is perceived as more doubtful, resulting in a lower likelihood to follow the advice even if the sender is honest about the financial motive (Tuk, Verlegh, Smidts and Wigboldus, 2009).

Customers acquired through a referral system tend to have a higher (short term) contribution margin and higher retention rates (Smitt, Skiera, Van den Bulte, 2011). When determining the value of referral behavior (the customer referral value; Kumar, Petersen and Leone, 2010)it is important that besides the amount of referrals and the incentive paid, savings are made on acquisition and the number of people who would also have joined if the referral behavior did not take place are also taken into account.

With the anonymity of the Internet, companies also can promote their own products as ‘neutral customers’ (faking), because the motives behind messages are hidden. Customers are suspicious of such promotional information, and though it increases the likelihood that they hear about a product (Mayzlin 2006), this strategy is both ethically questionable and widely disliked by customers (Thomas 2004). Kozinets et al. (2010) outline four other communication strategies related to social media: evaluation, embracing, endorsement, and explanation. In all cases, the company asks a customer to share information through an online blog, but the orientation (communal/individual) and explicitness of the commercial intentions vary. In turn, the different strategies determine how customers evaluate the message and sender. For example, the sender’s role as an opinion leader is only partly accepted if commercial intentions are explicit. Another strategy asks ask customers to ‘buzz’ information about the product, without any commercial intentions. Self-selected agents are more likely to engage in positive WoM (Carl 2006), so this strategy is relatively easy to implement. Finally, brand communities can help companies facilitate WoM among customers, though they should work to facilitate the community only, not try to control it (Fournier and Lee 2009).

Influencing the topic

By influencing the product and motives, companies influence the topic as well. Managing communication with customers also is important, to ensure that specific customers have access to the information they want to share. For example, customers have varying needs for information (Westbrook and Fornell 1979). Some ‘objective shoppers’ want to collect neutral information from different sources and derive their own conclusions from the information. Others are personal advice seekers and prefer to obtain personal advice and specific recommendations. Companies need to recognize these varying needs and provide the right type of information to the right people. When companies receive a ‘best product’ review for example, it may seem very attractive to share this good news widely. However, a review endorsement actually can be harmful if information about the review already has achieved a high penetration rate (Chen and Xie 2005).

2.8 Predicting and Measuring WoM

Given the effect WoM has on for example firm revenues, it is attractive to measure it and use this measurement to predict future revenue. The Net Promotor Score (Reichheld, 2003), is an example of an attempt to use a very simple (single item) method to predict the growth of a firm. Several years later, Keiningham, Cooil, Andreassen and Aksoy (2007) showed that the method did not predict better than other (multiple item) methods, which is also confirmed by Van Doorn, Leeflang and Tijs (2014). The complexity of the WoM process makes it very difficult to predict outcomes. Researchers in both marketing and sociology fields have tried to deal with limitations to their methodologies. For example, it is difficult to incorporate social interactions into econometric marketing models, and data to investigate social complexity (e.g., full information about reasons for interactions in a complete social network) are impossible to obtain. However, some recent modeling techniques suggest promising opportunities to investigate WoM effects. Trusov et al. (2009) incorporate traditional marketing actions and WoM effects (direct and indirect) in a vector autoregressive (VAR) model. They reveal that an accurate model estimation must account for the effect of marketing variables on WoM and thus on customer acquisition. Spatial models also can be used to study WoM (Bronnenberg and Mela 2004), especially the influence of the environment on customers’ WoM behavior.

However, any investigation of WoM also must acknowledge the complexity of the social network used to spread WoM. A social network consists of a vast number of individuals who interact, ultimately resulting in large-scale (collective) behavior (Goldenberg et al. 2001). Complex systems are hard to predict, because small differences at the individual level can result in large differences on the aggregate level. A useful method for addressing this complexity relies on agent-based modeling (Garcia, 2005). This simulation method can define rules for agents at the individual level (e.g., use choice models and interaction data) and study the results at the aggregate (e.g., market) level. The agent rules on the individual level can be empirically validated by using existing econometric models based on empirical data at the individual level. These econometric models cannot account for the complexity caused by social interactions on the individual level: econometric models are useful to determine preferences for certain product characteristics, but if these preferences are affected by the opinions and choices (that are changing over time) of other consumers in the social network the models become extremely complicated (if not impossible) to estimate. On the other hand, agent-based models do account for these interactions, thereby showing the consequences of these interactions over time. Agent-based models therefore also support investigations of how to *manage* complex systems, instead of just predicting their outcomes.

Still, measuring the influence of WoM remains difficult. The complexity of the process means that asking simply, 'will you tell your friends about the product?' (e.g., Cheema and Kaikati 2010) is insufficient. Marketers need to know with whom the customer talks and how much influence this conversation has on purchase decisions. Furthermore, to predict referral (WoM) behavior, it is necessary to use actual (past) referral behavior, not just intentions to talk about a product (Kumar et al. 2010). Electronic surveys can be helpful for data collections in relation to referral behavior, because they meet six important criteria (De Bruyn and Lilien, 2008): They (1) allow for observations of every stage of the decision process, (2) include all referrals (even those with little or no influence), (3) include unsolicited but sent information (i.e., people are not specifically searching for the information), (4) support real-time observations (no recall bias), (5) provide a realistic context, and (6) keep the research non-obstructive and unbiased.

However, if it remains impossible to measure WoM itself, an option may be to measure its outcomes, such as purchase behavior (Manchanda, Xie and Youn 2008). Bass-type models use an 'internal influence parameter' as a proxy for WoM effect. In this case, it is important to identify processes that result in a behavior, which depend on the product category. Furthermore, outcomes may result from intended behavior (e.g., coordinated consumption in the movie industry; Broekhuizen et al. 2011) or past behavior by other customers (e.g., imitation in the smartphone market). Another possible measure of the impact of WoM compares its impact on, say, brand recall with the impact of more traditional media on the same brand recall.

2.9 Further Research Considerations

Although WoM has been studied intensively, some important limitations in WoM research must be considered in future studies. First, there is a strong need for generalization. It is important to develop an integrated method to study WoM, on the basis of research from marketing, social psychology, and sociology. Such a method would provide a better understanding of the underlying process, as well as the ultimate outcomes of WoM.

Second, it may be risky to generalize findings based on specific samples (e.g., students) to broader populations. For example, students and homemakers appear to differ in their susceptibility to social influence (Park and Lessig 1977). It is important to account for these kinds of differences in WoM research.

Third, the common use of self-reporting techniques to measure WoM suffers some risks. For example, to find opinion leaders, this technique seems workable and more practical than using sociograms (Corey 1971), but self-reported OLs also are influenced less by their contacts than are 'sociometric' OLs, that is, those whom researchers identify as OLs because of their central position in a network (Iyengar et al. 2011). Moreover, sociometric OLs are more likely to be earlier adopters, compared with self-reported OLs (Iyengar et al. 2011). Research also has shown that in self-reported network data, people indicate that they are closer to the center of the network and have more (reciprocal) ties than is actually the case (Kumbasar et al. 1994). Correspondence analysis could provide a valid group-level representation of a friendship network (Kumbasar et al. 1994). To measure susceptibility to social influence, it therefore is important to recognize that people might fail to perceive when changes in their actions reflect social influences (Vorauer and Miller 1997). They also see others as more susceptible to social influence than they are themselves (Pronin et al. 2007).

Fourth, research might observe, rather than ask people about, behaviors. Measuring WoM outcomes can be a viable solution when it is not possible to measure WoM, but observing certain types of behaviors cannot explain sufficiently the motives for that behavior. Observing that a customer buys a product already adopted by someone else in his or her network does reveal the motives for the purchase (Burnkrant and Cousineau 1975). Rather, motives have social/psychological contexts, such as establishing self-fulfilling role relationships, obtaining rewards, or avoiding punishments. Customers also could infer product quality and make the purchase simply because they perceive that they have found a good product (Burnkrant and Cousineau 1975). Other customers may not even be aware of adoptions by others in their network. Some promising results are found by Nitzan and Libai (2011), who separate effects of social influence and effects caused by the fact that similar people have similar needs. They still find that social interaction affect customer decisions. They find that the effect of a particular interaction diminishes over time. The 'similar people have similar needs' effect is expected to be persistent. It is critical to distinguish among these widely varying purchase motives. Chen et al. (2011) also show that different types of social influence (e.g., WoM and observational learning) have different impacts on behavior, even when the outcomes seem similar. Negative WoM appears more influential than positive WoM, but they find that positive observational learning is more influential than its negative form. Observing behavior thus may not provide enough information about underlying processes.

Fifth, network data are difficult and expensive to collect, but they also provide important information to help explain the behavior of people within that network (Sheingold 1973). Most existing survey methodologies do not explicate the interpersonal nature of informal communications between customers (Reingen and Kernan 1986). Transcripts of online conversations could offer an easy, cost-effective way to measure WoM, though this approach relies on the strong assumption that online conversations provide a good proxy for offline conversations (Godes and Mayzlin 2004). In chapter 4 we develop a method to create a network based on survey data that includes information about interpersonal influence, followed by an implementation of this method in chapter 5.

Sixth, the role of social leaders changes over time, because social interactions affect the roles people play in their network (Arora and Allenby 1999). Yet the role of an opinion leader often has been studied at a particular moment in time; it would be more effective to study their dynamic roles. Opinion leadership changes particularly when new product adoption results in an increase or loss of status for different people within the network.

To investigate the WoM process in more detail, the next step should be designing a model that combines behavioral, network, and survey data to understand motives underlying behavior, measured over time. Agent-based modeling may prove a valuable tool to combine and extend existing models in marketing and sociology, while also enabling otherwise impossible experiments (e.g., Van Eck et al. 2011).

Chapter 3

Opinion Leaders' Role in Innovation Diffusion: A Simulation Study[2]

3.1 Introduction

Understanding customers is one of the fundamental requirements of marketers and entails a recognition of the decision-making process that both individual customers and groups of customers undergo. In the modern digital world, understanding social influence (SI) and the role of social media (e.g., Facebook, Twitter, LinkedIn) becomes particularly important. The development and use of social media is one of the top three breakthroughs for marketing in 2008 (Sullivan, 2008). The increase in the number of potential channels for addressing people, most notably the greater number of television channels and the rise of the Internet, forces marketers to reconsider their focus on mass media efforts.

From a marketing perspective, understanding how information communicated through mass media (external influence) and then spread through SI (internal influence) affects the process of consumer adoption and thus new product diffusion has great importance. Different research methodologies attempt to investigate the role and measurement of SI. Forty years ago, Bass (1969) initiated strong interest in the role of SI (in particular Word of Mouth) for the dispersion of new products and practices by suggesting aggregate modeling. This classic line of research attempts to explain how marketing mix strategies may affect new product diffusions (Mahajan, Muller, and Wind, 2000) and shows that SI effectively encourages people to start using a product (Herr, Kardes, and Kim, 1991).

Alternative methodologies used to investigate SI include vector autoregressive (VAR[X]) modeling (Trusov, Bucklin, and Pauwels, 2009) and spatial econometrics (Bronnenberg and Mela, 2004). This study uses agent-based simulation models to investigate the role of SI in processes of diffusion. This methodology is particularly useful when the population is heterogeneous (i.e. the agent rules and characteristics can be defined on an individual level) or when the topology of the interactions between individuals is complex and heterogeneous (Garcia, 2005). This methodology also allows to incorporate insights from another stream of literature that focuses on the role of individual differences and social network structures as critical variables for explaining the process of SI (e.g. Bohlmann, Calantone and Zhao, 2010), as well as trying to identify which actors play critical roles in the SI process at various stages of the innovation diffusion process (e.g., Chatterjee and Eliashberg, 1990). In marketing practice, these investigations have initiated strategies such as viral and buzz marketing, which target particular types of consumers who are likely to encourage the diffusion of a product. For example, the

[2] This chapter is based on Van Eck, Peter S., Wander Jager, and Peter S.H. Leeflang, (2011) Opinion Leaders' Role in Innovation Diffusion: A Simulation Study, *Journal of Product Innovation Management* 28 (2), 187-203.

marketing company Buzzer (www.buzzer.nl) encourages consumers to "buzz a product" and thus relies completely on SI.

Complex dynamics underlie such social marketing interactions, which makes it difficult to predict outcomes. Consumers might interact in the regular course of their daily life, read reviews online, and employ online social networks to share their opinions about a product, or simply influence others by using the product in a visible way (Gilbert et al., 2007). To address such a multifaceted influence, multi-agent simulation models experiment with diverse SI dynamics, investigating various viral marketing strategies of product diffusion in a social network. These models address different types of heterogeneity, including different influential consumers, the various types of influence that consumers exert, and the unique network structures that may affect consumer decision making (e.g., Garcia, 2005; Janssen and Jager, 2001; Watts and Dodds, 2007). However, the empirical foundation of the assumptions on which these models are based remains limited. Although the individual agent properties and network structures both have received considerable research attention, few studies relate individual agent *properties* to their network positions. For example, consider a study by Watts and Dodds (2007): They assume a Poisson distribution of influence relations among agents and define influentials as the top 10% of this distribution. Their definition of influentials therefore relies only on the number of relations agents possess to measure their influence. Using this formulation, Watts and Dodds (2007) find a very limited effect of influentials on diffusion and suggest instead a greater influence of the critical mass, which consists of easily influenced consumers. Watts and Dodds (2007) also argue that the probability that influentials trigger a critical mass is only modestly greater than the probability that noninfluentials will do so. Whereas they acknowledge that the micro foundations for the effect of influentials require further empirical support, they still suggest that targeting influentials may not be worth the effort. Yet the concept of influential consumers should imply more than just their relatively high number of relations. To illustrate this, Goldenberg et al. (2009) indicate three factors which in particular determine the role of influential consumers: personality traits, knowledge, and connectivity. Nevertheless, these authors focus on connectivity, without investigating the potentially significant influence of personality traits or knowledge among influential consumers.

To address these research gaps, the current study investigates in more detail how the knowledge and personal characteristics of influential consumers affect the adoption process. This study posits that different types of influential consumers possess varying characteristics, which implies their varying influence on the consumers around them. The typology of influential consumers includes:

- Innovators/early adopters (e.g., Engel, Kegerreis, and Blackwell, 1969), who influence other consumers through their innovative behavior and knowledge about a specific product category.
- Market mavens (e.g., Feick and Price, 1987), who may not have knowledge about a specific product category but rather about markets in general.
- Opinion leaders (Katz and Lazarsfeld, 1955), who represent a combination of innovative behavior and market knowledge.

Both opinion leaders and early adopters reveal similar characteristics, which makes it likely that many opinion leaders are early adopters and vice versa. However, the concept of early adopters refers only to the position of the consumer in the adoption process; whereas the concept of opinion leaders refers to the influence those consumers have on others. Therefore, opinion leaders represent interesting influentials to study, and this study focuses on their influence over the adoption process.

Various studies have attempted to understand the attributes and roles of opinion leaders (Weimann et al., 2007). Besides their central position (Berelson and Steiner, 1964; Czepiel, 1974; Valente, 1996) other characteristics of opinion leaders, such as interpersonal influence and innovativeness, may significantly affect their influence.

Two main types of interpersonal influence exist: informational and normative influence (Deutsch and Gerrard, 1955). Informational influence refers to the tendency to accept information from others as evidence of reality. For example, opinion leaders directly influence other consumers by giving them advice and verbal directions about their search for, purchase of, and use of a product (Flynn, Goldsmith, and Eastman, 1994). Normative influence, on the other hand, entails the tendency to conform to the expectations of others (Burnkrant and Cousineau, 1975). Hence, normative opinion leaders exert social pressure and social support and thereby influence decision-making processes of the influenced consumers (Glock and Nicosia, 1964). Since people aim to create and maintain meaningful social relationships, they often engage in behaviors approved by others, such as adopting a product to appeal to other product adopters (Cialdini and Goldstein, 2004). The product and situation determine which type of influence is more important (Grewal, Mehta, and Kardes 2000). Privately consumed goods prioritize the informational influence, whereas for publicly consumed goods, both types of influence are critical.

Referring to the degree of innovativeness of opinion leaders, Lyons and Henderson (2005: 320) state that "Compared with consumers who seek their advice, opinion leaders frequently possess more experience or expertise with the product category, have been exposed to or acquired more information about the product, exhibit more exploratory and innovative behavior and display higher levels of involvement with the product category." Whereas Watts and Dodds (2007) suggest that the influence of such consumers is not as important as prior research has indicated, including these attributes in an agent-based model may shed greater light on the potential importance of opinion leaders. Despite extensive studies of the characteristics of opinion leaders, no research clearly combines their various characteristics.

To assess the critical assumptions that opinion leaders have more contacts, possess different attributes, exert different types of influence, and are among the earliest adopters, an empirical study is conducted in which the role of opinion leaders in the diffusion of free Internet games for children is considered. The data from this empirical study are used to infer the network position and agent attributes in an agent-based model, which is used to study experimentally how these attributes may affect the diffusion process. In particular, this study offers two main insights. First, a distinction is made between normative and informational influences and thereby investigate in greater detail how children influence one another. Second, this study notes the influence of different characteristics of opinion leaders, which suggests some insights into how (and whether) influentials affect the behavior of others.

It is assumed that opinion leaders play an important role in the diffusion of information about products (informational influence) and the products themselves (i.e., adoption behavior results in normative pressure). Therefore, this study investigates the diffusion of both information and product. An opinion leader may influence the diffusion process by increasing the speed of diffusion and/or increasing the maximum adoption percentage. Because the product that investigated in this study, free online games for children, has received considerable mass media support, it is assumed that everyone in the target audience has heard about the product, so its maximum awareness is 100%. In turn, this study can focus on the other characteristics of the innovation diffusion process, namely, the speed of information diffusion, the speed of product diffusion, and the maximum adoption percentage of the product.

Furthermore, this study investigates two factors which may affect the role of the opinion leader in the adoption process: the (more or less extensive) use of mass media by firms and the number of opinion leaders within the network. These two factors might affect how the opinion leader influences the speed of the information or product diffusion, as well as the maximum adoption percentage.

In the following sections, first the hypotheses are discussed, as well as the relevant outcomes of the empirical study. Subsequently, the simulation model is described and the experimental results are presented. The chapter concludes with a discussion and some limitations.

3.2 Hypotheses

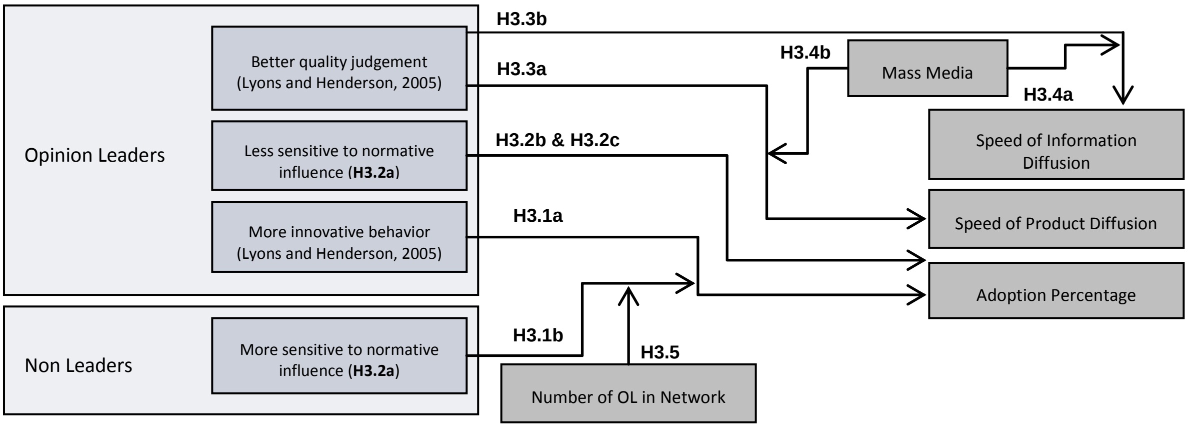
Hypothesis testing and social simulation

Before discussing the hypotheses, it is important to realize that the testing of the hypotheses is done in the setting of social simulation. Therefore the aim is not to find empirical evidence of the impact of certain variables, but rather to show what the impact of the variables can be, given a certain set of rules (section 3.4). In this chapter we use both literature and empirical data to define rules of the individual level. The hypotheses developed in this section represent the expected results of the emerging processes resulting from the individual rules. The outcome of the hypothesis testing should therefore be interpreted as guidelines for future research.

Conceptual Framework

Figure 3.1 shows the relation of the different concepts used in this study, as well as the related hypotheses. Next we discuss the influence of the specific characteristics of the opinion leaders (quality judgment, sensitivity to normative influence, and innovative behavior) on speed of information and product diffusion as well as the adoption percentage. In addition we discuss several other variables that may affect the influence of the opinion leaders' characteristics (sensitivity to normative influence of non-leaders, mass media and the number of opinion leaders in a network).

Figure 3.1: Conceptual framework of factors affecting the Opinion Leaders' influence



The Influence of the Characteristics of Opinion Leaders

Prior literature offers numerous insights about characteristics of the opinion leaders that may be responsible for their influence on the diffusion process. This, as well as their normative influence or informational influence. This study focuses on three main characteristics of opinion leaders: 1) more innovative behavior, 2) a lower sensitivity to normative influence and 3) better quality judgment.

First, the opinion leader's innovative behavior might enhance the adoption percentage rate. Because opinion leaders exert social pressure and social support (Glock and Nicosia, 1964), their normative influence makes it more likely that followers adopt the product as well. If innovative behavior of a customer is affected by the normative influence of the opinion leader, it is expected that this effect will be stronger when the normative influence is of a higher importance to followers.

> H3.1: The higher the innovative behavior by opinion leaders (a) the higher the adoption percentage in the social network, and (b) this effect is stronger if normative influence is more important to followers.

Second, opinion leaders spread information by giving advice and directions to other consumers. This active, informational influence may increase the speed of information diffusion. Furthermore, assuming the opinion leader has more experience and expertise with the product (Lyons and Henderson, 2005); a follower is likely to follow an opinion leader's advice in his or her purchase decision. Therefore, the informational influence of the opinion leader enhances the speed of information and product diffusion, as well as the level of product penetration.

Both normative and informational influence should be critical in the adoption process, though a potential difference is recognized between opinion leaders and followers with respect to which type of influence is more important. An opinion leader must both maintain his or her status by finding an appropriate level of innovativeness (Rogers, 1993) and establish the norm in the network. This explains a critical role of the opinion leader in the diffusion process, as they are more likely to adopt a product not already supported by a positive norm. Hence, opinion leaders may be less sensitive to normative influences than followers. In contrast, followers sense social pressure to adopt the product after the opinion leader has done so. This effect becomes stronger if the importance of normative influence is very low for the opinion leader, because this situation decreases the social pressure on the opinion leader (i.e. (s)he is not afraid to lose status). Therefore,

> H3.2: (a) Compared to their followers, opinion leaders are less sensitive to normative influence. A lower importance of normative influence by opinion leaders, leads (b) to a higher adoption percentage, and (c) this adoption percentage increases even more when the importance of normative influence for opinion leaders decreases.

Third, opinion leaders can evaluate products effectively through their experience, expertise, and involvement with the product category. By sharing their expert evaluations, opinion leaders “translate” marketing messages into SI, which recipients perceive as more reliable than an advertisement (Nielsen, 2007). Without the better product judgment of the opinion leader, the marketing message might remain unclear to most consumers, who are unsure if the message is reliable, in which case they are unlikely to share the information with others.

> H3.3: Opinion leaders are better at judging products than followers, which results in a faster (a) information diffusion and (b) product diffusion.

Other Factors Influencing the Role of the Opinion Leader

In comparison with mass media, SI should be more likely to activate people to act upon a received advice (Gelb and Johnson, 1995). Several authors suggest that SI has the most important influence in the consumer decision-making process (e.g., Silverman, 1997), whereas mass media may have no discernible impact on opinion leader’s influence on the behavior of other consumers or on the adoption percentage. However, high mass media usage by firms can increase the speed of information (and ultimately product) diffusion, since more people become aware of the product. If mass media are extensive, SI may become less important as a means to make people aware of the product, which would decrease the role of the opinion leader in the information diffusion process. In other words, SI is more important in a situation characterized by less extensive mass media usage and results in a stronger role for the opinion leader.

> H3.4: Less extensive use of mass media by firms leads to a stronger influence of the opinion leader's product-judgment quality on the speed of (a) information diffusion and (b) product diffusion.

In early research, Katz and Lazarsfeld (1965) and King and Summers (1970) classified 23.8–31.1% and 23–30%, respectively, of the respondents of their survey as opinion leaders. Indeed, for some products, many people act as opinion leaders. For example, virtually everyone has an opinion about movies, music, and other entertainment. Social media, such as Facebook and Twitter, also make it relatively easy to share opinions and potentially influence a great number of other people. In such situations, a high percentage of the population may be opinion leaders. However, with more complex and expensive products, such as computers and cell phones, people should be less likely to make a decision on the basis of short messages on Facebook and Twitter. A relatively smaller group of people can act as opinion leaders, because it takes time to become an expert about these product categories. For these categories, it therefore may be more accurate to define a smaller percentage of the population as opinion leaders.

Fewer opinion leaders, by definition, means fewer innovative consumers, as well as a higher average sensitivity to normative influence within the network. It is therefore expected that a lower number of opinion leaders results in a lower adoption percentage (cf. H3.1a). Furthermore, the larger number of followers increases the effect of H3.1b, because more people follow the norm established by the opinion leader particularly if normative influence is more important to these followers.

> H3.5: A smaller percentage of opinion leaders in a network enhances the influence of innovative behavior of the opinion leaders in terms of increasing the adoption percentage, particularly if normative influence is important to followers.

To test the hypotheses, both an empirical and a simulation study are conducted. The empirical study makes it possible to parameterize the model for the simulation study, as well as test H3.2a.

3.3 Empirical Study

In the empirical study, the SI behavior of children is considered, in the context of the diffusion of free Internet games. Many such games appear on both the World Wide Web and propriety online services. If children lack a past experience with the game and well-established cues to identify the quality of a game, the interpersonal exchange of information becomes especially important. The games in this study invite children to create their own television or radio programs. They are easy to use and allow users to send messages to friends to invite them to look at their creations. These young users also may talk about the games at school or invite friends to collaborate in creating a program.

To investigate the role of children as opinion leaders with regard to the adoption of an online application, an online questionnaire is used. Three popular online applications in the Netherlands are selected to obtain a large, representative sample of respondents: Kijkradio (www.kijkradio.nl), Moovl (www.moovl.nl), and Sketchstudio (www.sketchstudio.nl). Visitors to these sites can see the work of others, which makes the use of the application visible and therefore sensitive to normative influences. For example, Kijkradio has a “main radio station” broadcast on its Web site. It is an honor if a user’s news item is broadcasted on this main site, because only the best news items are selected. If a child wishes to get his or her news item broadcasted on the main station, he or she likely is sensitive to normative influences, because such child cares about what others think of the work, and wants others to see it. All the applications have several (sometimes complex) options, which implies children can learn from one another; which consequently increases the importance of informational influence.

For this research, 136 children (33.8% male, 66.2% female) between 6 and 16 years of age (mean = 10.84, standard deviation = 2.12) who already were using the application filled in an online questionnaire (see Appendix 3.1). The only way to reach these children is through an invitation on the sign-in page, because registering on these sites does not require any contact information.

To identify the opinion leaders, an item is used from the opinion leadership scale developed by King and Summers (1970) and refined by Flynn et al. (1994) (Q1, Appendix 3.1). In line with King and Summers (1970), the 29.4% who score highest on the scale are defined as opinion leaders (OL). The other 70.6% of the respondents are followers, or non-leaders (NL). The data confirm many of the characteristics of opinion leaders identified in previous research. In particular, the survey contains questions regarding the status of each user in the adoption process (Q5 and Q6, Appendix 3.1). For each respondent, the ratio is calculated of the number of friends that used the application after the focal respondent, divided by the number of friends who used the application prior to this respondent ([Q5 – Q6]/Q6). Opinion leaders know more people who adopted the product later than people who adopted the product earlier (ratio = 1.04), in contrast with followers (ratio = 0.24; t = 3.391, p = 0.001). Therefore, opinion leaders exhibit more innovative behavior than do followers. Furthermore, opinion leaders are more involved with the product; they talk about it in more situations (Q4, Appendix 3.1; OL = 2.0; NL = 1.3; t = 3.551, p = 0.001), not just when they are using the product; and they are more likely to involve others in the use of the product (Q3, Appendix 3.1), such as by inviting them to join (OL = 25.0%; NL = 6.3%; chi-square = 13.439, p = 0.001).

The data also show that opinion leaders do not know more about the product than followers (Q9, Appendix 3.1; OL = 40.0%, NL = 43.8%; chi-square = 0.485, p = 0.785), though opinion leaders can better help others in using the product (Q8, Appendix 3.1; OL = 3.4, NL = 2.1; t = 4.941, p = 0.000). This study posits that because the applications had been heavily promoted through mass media, the users are aware of them. However, the finding that opinion leaders can help others indicates that they are more capable of interpreting the information they receive (i.e., have more knowledge about the product), which might be the result of their higher involvement in and more expertise with the product category.

Data regarding the actual network structure are more difficult to obtain. First, Internet data about the interaction patterns among users are not available, because respondents can employ various means to interact, including social networks, instant messaging, and e-mail. Second, most relevant interactions involve children talking about or working together on the games, so even detailed data about who knows whom cannot reveal actual interactions. Therefore, a question is included in the survey about the sources that children used to gather information about the product (Q2, Appendix 3.1). Opinion leaders used more sources (e.g., friends, siblings) than followers (e.g., 22.5% of opinion leaders received information from siblings compared with 6.3% of followers; $t = 7.598$, $p = 0.006$), though mass media (TV and Internet) are equally important to both groups. By using more "social sources," opinion leaders likely take more central positions in the network.

The survey also contains questions about the importance of informational influence (Q8, Appendix 3.1) and normative influence (Q7, Appendix 3.1). Opinion leaders score high on both informational influence (mean = 3.39) and normative influence (mean = 3.47). Followers score high on normative influence (mean = 3.19) but considerably lower on informational influence (mean = 2.11). Combining both types of influence (i.e. calculating the ratio of normative and informative influence at the individual level), opinion leaders weight the two types of influence almost equally (mean = 0.51), whereas followers weight normative influence higher (mean = 0.60; $t = 3.861$, $p = 0.000$). Therefore, support for H3.2a is found: for opinion leaders the importance of normative influence (compared to informational influence) is lower than for followers.

In line with these results, three characteristics of opinion leaders are included in the model. First, opinion leaders are better at judging product quality; even if they do not know more about the product, they can better interpret the information they receive. Second, normative influence is less important to opinion leaders than it is for followers. Third, opinion leaders are more innovative than followers. With respect to the position of opinion leaders, the empirical study also suggests that they take more central positions in the network.

3.4 The Simulation Study

Model

An agent-based model is developed (Macy and Willer, 2002; Rahmandad and Sterman, 2008) to test the hypotheses (the model is available at www.openabm.org/model-archive/ol-model). The model distinguishes between informational and normative influence, with awareness of product quality as the informational influence. Agents (OL or NL) can decide to adopt the product on the basis of the product quality, that is, the information they receive through informational influence. However, the normative influence, which relates to the behavior of neighboring agents with whom the specific agent relates, may provide another important decision factor, such that if neighboring agents adopt a product, the agent may feel greater social pressure (i.e., normative influence) to adopt the product as well.

The simulation model is based on a model developed by Delre et al. (2007), programmed in Netlogo 4.0.2 (Wilensky, 1999). Agent *i*'s decision to adopt the product depends on the utility ($U_{i,t}$) that the agent receives from adopting the product at time t and the utility threshold ($U_{i,min}$) of this agent. Therefore, the agent will adopt the product if

$$U_{i,t} \geq U_{i,min}. \tag{3.1}$$

In the utility function, the individual preference ($y_{i,t}$) of agent i at time t (transmitted through informational influence) differs from the social influence ($x_{i,t}$) of agent i at time t (reflecting normative influence). The importance of these elements of the utility function is weighted using β_i , which results in the following utility function:

$$U_{i,t} = \beta_i x_{i,t} + (1-\beta_i) y_{i,t}. \tag{3.2}$$

Individual preference is based on the product quality (q) and the quality threshold (p_i) of agent i, as follows:

$$q \geq p_i \rightarrow y_{i,t} = 1, \text{ and}$$
$$q < p_i \rightarrow y_{i,t} = 0. \tag{3.3}$$

Unlike Delre et al. (2007), this study does not include a threshold for social pressure but rather consider social pressure as a continuum: If more neighbors adopt the product, normative influence in favor of the product increases. The normative influence agent i observes at time t is:

$$x_{i,t} = \frac{adopting\_neighbours_{i,t}}{total\_neighbours_{i,t}}. \tag{3.4}$$

Network and Parameter Settings

Bohlmann, Calantone and Zhao (2010) indicate that the choice for a specific network structure in an agent based model strongly influences the innovation diffusion process: it affects the likelihood of diffusion cascades and the speed of adoption. Part of these effects are due to the fact that the networks structure determines the location and hence the influence of innovators. Therefore it is important to justify the choice for a specific network structure. The network structure used is a Barabasi (2003) scale-free network (Wilensky, 2005). Additional agents can connect to such a type of network, with a preference for connections with agents with more connections (hubs), often referred to as "preferential attachment." This type of network follows a power law, such that many agents have only one connection, whereas a few agents have many connections. Table 3.1 provides an example of the distribution of the links in one of the simulation runs. This type of network is used in the analysis for two reasons. First, the scale-free network reflects a real-world network, as confirmed in empirical studies (e.g., Barabasi and Bonabeau, 2003). Second, the central position of opinion leaders in this type of network is more explicit than it would be in other network types that do not account for the central positions of agents (e.g., small-world networks).

Table 3.1. Degree distribution of one of the simulated networks

Number of Links	Number of Agents	Number of Links	Number of Agents
1	335	11	1
2	82	12	1
3	38	13	1
4	14	16	1
5	7	22	1
6	4	31	1
7	5	34	1
8	6	39	1
9	1		

The model contains several parameters, which describe the influence of opinion leaders in various market settings. A distinction is made between parameters that are fixed for all experiments and those that vary experimentally. The group of fixed parameters reflects the model settings used by Delre et al. (2007), as shown in Table 3.2.

Table 3.2. Fixed parameter settings

Variable	Parameter	Distribution of Value	Assumption
Utility threshold, non-leader	$U_{i,min}$	U(0, 1)	Consumers differ in their preferences
Product quality	q	0.5	Given a certain distribution of the quality threshold, product quality is too low for approximately 50% of agents
Quality threshold	p_i	U(0, 1)	Consumer differ in their preferences
Number of agents		500	
Number of runs/experiment		500	

In line with Delre et al. (2007), a uniform distributions is assumed of both the utility threshold and the quality threshold for individual agents, which introduces heterogeneity into the model. Product quality is set to 0.5, such that if agents base their adoption behavior only on product quality, approximately 50% will never adopt the product (Delre et al., 2007). However, normative influence may still affect the adoption in the latter group.

In addition to the fixed parameter settings, whose values are derived from prior literature, five additional parameters are systematically varied: (1) the innovativeness of the opinion leader, (2) the weight of normative influence, (3) the quality of the product judgment of opinion leaders, (4) the number of opinion leaders in the network, and (5) the reach of mass media.

In a reference model, values are used for these parameters from the empirical study and prior literature (a summary of these settings is shown in table 3.3). Therefore, the reference model is a relatively close representation of the results of the empirical study. In the other models the parameters 'innovativeness of the OL', 'weight of normative influence (OL & NL)', 'quality of the product judgment', 'number of OLs' and 'reach of mass media' are systematically varied. Using this reference model should allow for realistic testing of the hypotheses. The specific parameter settings used to test each hypothesis appear separately in the results section and are summarized in Table 3.4.

Table 3.3. Reference model parameter settings

Variable	Parameter	Distribution of Value	Assumption
Innovativeness of opinion leader	$U_{i,min}$	U(0, 0.8)	Opinion leaders are more innovative than non-leaders (see empirical study)
Weight of normative influence opinion leader	$\beta_{i,OL}$	N(0.51, 0.2)	Normative and informational influence are almost equally important to opinion leaders (see empirical study)
Weight of normative influence non-leader	$\beta_{i,NL}$	N(0.6, 0.2)	Normative influence is more important to non-leaders than informational influence (see empirical study)
Quality of the product judgment (opinion leaders)	NA	'Yes'	Opinion leaders have more expertise (see empirical study) and therefore are better in judging the product quality (*q*)
Number of opinion leaders in network	NA	167 (33.4%)	Based on scale of King and Summers (1970)
Reach of mass media	NA	0.01%	The applications in the empirical study are strongly supported through mass media

In the reference model, opinion leaders are more innovative than followers, which is represented by the lower utility threshold required for leaders to adopt a product. That is, the $U_{i,min}$ of opinion leaders has a uniform distribution between 0 and 0.8, so even if the immediate utility of a product is not very high (e.g., because of a lack of social pressure), the opinion leader is more likely to adopt the product than is the follower. The $U_{i,min}$ of followers is uniformly distributed between 0 and 1. Thus, the difference between the two groups of consumers is relatively small (i.e., approximately 20% higher adoption probability), because the opinion leader will avoid being too innovative: if the OL is too innovative, (s)he may adopt a product that turns out to be unsuccessful, resulting in the OL's loss of status.

The weight of the normative and informational influence of opinion leaders is based on the empirical data, measured on a five-point scale. The sum of the weights (β_i) equals 1, and is determined as follows: Assume that a respondent scores 3.23 on normative influence and 2.47 on informational influence on the selected scale. The weight of normative influence is 3.23/(3.23 + 2.47) = 0.57. For opinion leaders and followers, the weights of normative influence are 0.51 and 0.6, respectively.

The empirical study also confirms that opinion leaders have more expertise with the product category, which makes it easier for them to judge a product's quality according to the information they receive from mass media. In the model, this ability to make a good product judgment is implemented as follows: The opinion leader can judge the product using information from mass media and therefore his/her judgment will be equal to the real product quality (q = 0.5, Table 3.2). In contrast, followers cannot use mass media information, so they become aware of the product, but have less confidence in their judgment of its real quality. Instead, they use a random judgment (i.e., q has a uniform distribution between 0 and 1). Only if agents hear about the product from an opinion leader or another agent who adopted the product—that is, from reliable SI sources—do they learn the real product quality (q = 0.5).

In the empirical study, the 29.4% of respondents who score highest on the scale are defined as opinion leaders (King and Summers, 1970). In the simulation study, the number of opinion leaders is selected by defining all agents with two links or more as opinion leaders. Therefore, the network in the simulation study contains, on average, 167 opinion leaders, who represent 33.4% of the population.

Finally, in the empirical study, the product receives strong support from mass media messages. In the simulation, therefore another 1% of the population is made aware of the product during each time step (i.e., mass media reach 1% of the population in every time step). Assuming 500 agents and 1% mass media reach, in the reference model, approximately 5 agents become aware of the product through mass media during every time step.

Each experiment consists of 25 time steps, to reach the maximum adoption percentage. In the agent-based model, the experiment is repeated 500 times. Each time step also consists of three different stages: mass media, SI, and adoption. At the start of the experiments, none of the agents is aware of the product, but in the first step, mass media informs a predefined percentage (depending on experiment) of agents. Non-leaders, or followers, cannot judge product quality using this information, but they assume a quality level between 0 and 1 (uniform distribution). In contrast, opinion leaders can judge the correct product quality, and their observed product quality is 0.5.

In the SI stage, agents may hear about the product from their neighbors, but they only accept information about product quality if the neighbor is certain about the real product quality (0.5). That is, information gets shared only if the neighbor is an opinion leader and/or has experienced real product quality. The agents know who has experience with the product and/or is an opinion leader, which reflects people's tendency (1) not to talk about a product with other non-adopters and (2) to be less likely to believe others who are not capable of judging product quality (e.g., have no experience with the product).

In the third stage, the agent decides whether to adopt or not adopt the product.

Table 3.4 summarizes the parameter settings of the 11 models (including 3 reference models) needed to test the hypotheses.

Table 3.4. Parameter settings for every hypothesis

Model (hypothesis tested with model)	Innovativeness of OL	Weight of normative influence OL	Weight of normative influence NL	Quality of the product judgment (OL)	Number of OL	Reach of mm (percentage of agents reached)
	$U_{i,min}$	$\beta_{i,OL}$	$\beta_{i,NL}$			
Reference model 1	***U(0, 0.8)***	***N(0.51, 0.2)***	***N(0.6, 0.2)***	***Yes***	***167 (33.4%)***	***1.0%***
Model 2 (H3.1a)	U(0, 1)	N(0.51, 0.2)	N(0.6, 0.2)	Yes	167 (33.4%)	1.0%
Model 3 (H31b)	U(0, 0.8)	N(0.51, 0.2)	N(0.8, 0.2)	Yes	167 (33.4%)	1.0%
NA (H3.2a)[1]	NA	NA	NA	NA	NA	NA
Model 4 (H3.2b)	U(0, 0.8)	N(0.57, 0.2)	N(0.57, 0.2)	Yes	167 (33.4%)	1.0%
Model 5 (H3.2c)	U(0, 0.8)	N(0.2, 0.2)	N(0.6, 0.2)	Yes	167 (33.4%)	1.0%
Model 6 (H3.3a & H3.3b)	U(0, 0.8)	N(0.51, 0.2)	N(0.6, 0.2)	No	167 (33.4%)	1.0%
Reference model 7	***U(0, 0.8)***	***N(0.51, 0.2)***	***N(0.6, 0.2)***	***Yes***	***167 (33.4%)***	***0.1%***
Model 8 (H3.4a & H3.4b)	U(0, 0.8)	N(0.51, 0.2)	N(0.6, 0.2)	No	167 (33.4%)	0.1%
Reference model 9	***U(0, 0.8)***	***N(0.51, 0.2)***	***N(0.6, 0.2)***	***Yes***	***51 (10.2%)***	***1.0%***
Model 10 (H3.5)	U(0, 1)	N(0.51, 0.2)	N(0.6, 0.2)	Yes	51 (10.2%)	1.0%
Model 11 (H3.5)	U(0, 0.8)	N(0.51, 0.2)	N(0.8, 0.2)	Yes	51 (10.2%)	1.0%

The gray cells indicate which parameters are varied in the experiments

Note: two models are needed to test H3.5

[1] H3.2a is only tested in the empirical study

3.5 Results

To test whether the reference model (1) confirms the widespread assumption that opinion leaders have a strong and positive influence on the speed of information and product diffusion and the adoption percentage of a product, it is compared against a model that excludes opinion leaders. The weight of normative influence (β_i) in the comparison model with no opinion leaders is 0.57. In a model with opinion leaders, information diffuses significantly faster, such that only 1.75 (SD = 1.2) time steps are needed to reach maximum awareness, compared with 3.64 (SD = 1.5) time steps in the model without opinion leaders (t = 22.349, p = 0.000). The product also diffuses faster, in 4.94 (SD = 1.2) time steps versus 6.27 (SD = 2.0) time steps, to reach the maximum adoption percentage (t = 12.395, p = 0.000). The adoption percentage increases from 0.398 (SD = 0.05) to 0.491 (SD = 0.05), when opinion leaders are present in the network (t = 29.119, p = 0.000). Thus, the model confirms the expected influence of the opinion leaders in a social network. Table 3.5 shows the results of the hypotheses tests discussed next, and Table 3.6 shows a summary of the hypotheses and the conclusions. Note that all reported results are based on the average of 500 experiments with the same parameters settings. Hence, time steps can only be real numbers in the simulation model, but an average of 1.75 times steps can be reported in the results section.

Table 3.5. Results of hypotheses tests (all based on independent sample t-tests)

	Adoption percentage (standard deviation)	Speed of information diffusion Average number of steps (standard deviation)	Speed of product diffusion Average number of steps (standard deviation)
Reference model 1	*0.491 (0.05)*	*1.75 (1.15)*	*4.94 (1.2)*
Model 2 (H3.1a)	0.405 (0.04)*		
Model 3 (H3.1b)	0.458 (0.06)*		
NA (H3.2a[1])			
Model 4 (H3.2b)	0.480 (0.05)*		
Model 5 (H3.2c)	0.515 (0.04)*		
Model 6 (H3.3a & H3.3b)		4.73 (2.22)*	7.76 (2.21)*
Reference model 7		*6.74 (4.62)*	*9.79 (4.42)*
Model 8 (H3.4a & H3.4b)		11.14 (5.56)*	13.45 (4.69)*
Reference model 9	*0.488 (0.05)*		
Model 10 (H3.5)	0.407 (0.05)*		
Model 11 (H3.5)	0.454 (0.06)*		

Note: only the values relevant to test the hypotheses are presented in this table

[1] H3.2a is only tested in the empirical study

* Significant at $p \leq 0.001$

The Influence of Characteristics of the Opinion Leaders

To test H3.1a, the relevant metrics of reference model 1 are compared with the corresponding metrics of a model in which opinion leaders are set to be equally innovative as followers (model 2). That is, in the latter model, the minimum utility threshold ($U_{i,min}$) of both opinion leaders and followers has a uniform distribution between 0 and 1 (see Table 3.2). Reference model 1 results in an adoption percentage of 0.491, whereas model 2 results in an adoption percentage of 0.405. The more innovative behavior of opinion leaders in model 1 thus results in a significantly higher adoption percentage, in support of H3.1a. In light of the empirical study these results could be interpreted as follows: the online applications might appear to be quite complex and therefore many children are not immediately attracted to them. However, when the OL is innovative, (s)he is more likely to start using the online application despite its complexity. When the OL demonstrates this behavior and starts talking about the product, other children are attracted to try the online application as well.

To test whether the effect of the innovativeness of OLs on the adoption percentage is stronger if the normative influenceability of followers is further enhanced (H3.1b), an experiment is conducted in which the weight of normative influence for followers is higher ($\beta_{i,nl}$ = 0.8) than in reference model 1 ($\beta_{i,nl}$ = 0.6). This model (model 3) results in a significantly lower adoption percentage (0.458), which contradicts H3.1b. As the normative influenceability of followers increases, their likelihood to adopt the product based on the opinion leaders' behavior decreases. The following explanation is proposed for this result. The probability that a non-leader in reference model 1 adopts the product is calculated to be 20%, based on the following data and assumptions:

1. the weight for normative influence ($\beta_{i,nl}$) is 0.6
2. there are no adopters in the network, so $x_{i,t}$ is 0
3. according to equation 3.2 and equation 3.3, the utility ($U_{i,t}$) is either 0 (if the quality threshold is not reached) or 0.4 (if the quality threshold is reached)
4. given the uniform distribution of the utility threshold ($U_{i,min}$), 40% of the agents would adopt the product if the product quality threshold is reached
5. this quality threshold is reached for 50% of the agents (see Table 3.2)

Ergo, from the assumption 4 and 5 it follows that the probability that a non-leader adopts the product based both on the utility threshold and the quality threshold is (40% x 50% =) 20%.

If the normative influence becomes more important to non-leaders, the probability that agents adopt (using the calculations) becomes 10%. So, the probability that a non-leader will start adopting a product decreases by 50%. This effect is stronger than the increased probability that a non-leader will follow the opinion leader as soon as (s)he adopts the product (as suggested in the hypothesis). Hence, this study posits that H3.1b will only be confirmed under conditions of sufficiently high adoption percentages with associated normative pressure to adopt. The opinion leader evidently cannot "force" the population to reach this threshold; otherwise, the adoption percentages would approach 100%. More research is needed to investigate this process though. Strong norms can limit or stimulate the diffusion process, depending on the percentage of adopters, such that after a critical mass is reached, the direction of this effect may switch (Janssen and Jager, 2003). In the empirical study this implies that although children are familiar with the online applications, it is against the group norms to start using it and therefore many children do not start using the application. In extreme cases, the OL might even be afraid to lose his/her status if (s)he is (talking about) using the application.

Hypothesis H3.2a, on the sensitivity of the OL to normative influence, has already been tested in the empirical study described before. The outcomes confirm that the opinion leader weights normative influence and informational influence almost equally (0.51), whereas followers weight normative influence higher (0.60).

To test whether the OLs' lower sensitivity to normative influence increases the adoption percentage (H3.2b), reference model 1 is compared with a model in which the opinion leaders are equally sensitive to normative influence as non-leaders (model 4). That is, for the opinion leader and the follower, the weight of normative influence (β_i) is 0.57. In support of H3.2b, model 4 results in a slightly but significantly lower adoption percentage (0.480) compared with the reference model (0.491).

Testing whether a decrease of the OLs' sensitivity to normative influence results in an even higher adoption percentage (H3.2c) requires another experiment (model 5), in which the weight of the normative influence for the opinion leader (β_i) is lowered from 0.51 in the reference model to 0.2. Thus, normative influence, relative to informational influence, becomes unimportant to opinion leaders. As predicted in H3.2c, the lower importance given to normative influence by OLs results in a higher adoption percentage (0.515). The results of both H3.2b and H3.2c suggest that the OLs, who are less sensitive to normative influence, are more likely to adopt the online application, thereby convincing many other children to start using the application as well. This is both due to the more innovative behavior and the decreased fear to lose status (i.e. adopting the product against group norms).

To test whether OL's better product judgment results in faster information (H3.3a) and product diffusion (H3.3b), a model is used in which the opinion leader is not better at judging the product quality (model 6). Compared with reference model 1, the lack of product judgment results in a significantly slower diffusion of information about the product, such that 4.73 time steps elapse before all agents are aware of the product, compared with 1.75 in the reference model. This result supports hypothesis H3.3a. The speed of information diffusion is even lower than in the model without opinion leaders (3.64, SD = 1.49; $t = 9.094$, $p = 0.000$), as is the speed of product diffusion. In support of hypothesis H3.3b, results show that the 7.76 time steps needed to reach the maximum adoption are significantly higher than the 6.27 (SD = 2.03) time steps required by the model without opinion leaders ($t = 11.126$, $p = 0.000$), as well as the 4.94 time steps needed in the reference model. The strong effect of the lack of product judgment confirms the great importance of the opinion leader's informational influence. In the model in which the opinion leader lacks better product judgments, the opinion leader shares unreliable information. Only adopters of the product know the real quality of the product, and reliable information spreads only after the first agent adopts the product. However, this moment is delayed, because people are less likely to adopt the product based on unreliable information, in line with H3.3a and H3.3b. These results suggest that the OLs immediately recognize an online application as interesting (i.e. good quality) and therefore they start using the application and share information about it with other children who then also start using the application.

Influence of Mass Media Reach

To analyze the effect of OL's product judgment ability in a low mass media setting (H3.4a and H3.4b) a new reference model has to be established (reference model 7) with the low mass media setting assumption (note that reference model 1 assumes a high mass media setting). Reference model 7 and model 8 feature a mass media reach of 0.1% (instead of the original 1%). With 500 agents in these simulation runs, there is a 50% chance that one agent becomes aware of the product during every time step. After four steps, there is a 93.75% chance that at least one agent is aware of the product (99% in seven steps). In reference model 7, 6.74 time steps elapse before every agent is aware of the product—significantly lower than the 11.14 steps needed in model 8. That is, the better quality of product judgment of the opinion leader reduces the time steps needed to reach maximum awareness by approximately 40%. In the situation in which the mass media reach is 1% (see H3.3a), this reduction is approximately 63%. With respect to the product diffusion (H3.4b), the results are similar. In reference model 7, 9.79 times steps elapse before the maximum adoption, and significantly more time steps are needed if the opinion leader does not have better quality of product judgment (13.45). The reduction in time steps needed is 27%; this reduction is 40% in the experiment with 1% mass media reach (see H3.3b). Although the better product judgment of the opinion leader still affects the diffusion speed of both products and information, this effect is smaller if the use of mass media is less extensive, which runs counter to the predictions in H3.4a and H3.4b. This result can be explained by the fact that every agent has the same chance to be reached by mass media. The opinion leaders, who are in the minority, have a small chance (as a group) to be reached by mass media, and as long as they lack information, they cannot act as opinion leaders, which diminishes their role in the diffusion process. In the context of the empirical example it means that as long as children do not hear about the online applications they cannot use it or talk about it.

Influence of Number of Opinion Leaders

The models used to test hypothesis H3.5 include a lower number of OL. In reference model 9 and models 10 and 11 an agent is defined as an opinion leader if it has four or more neighboring agents (instead of two or more). Therefore, the models have an average of 51 opinion leaders (10.2%) instead of 167 (33.4%). In model 10 the opinion leaders are not more innovative than followers (i.e., the minimum utility threshold [$U_{i,\min}$] of opinion leaders has a uniform distribution between 0 and 1). The new reference model 9 results in an adoption percentage of 0.488, whereas model 10 results in an adoption percentage that is significantly lower, 0.407.

Also an experiment is conducted to test whether this effect is stronger if the normative influence is more important to followers (model 11). In model 11 the weight of the normative influence ($\beta_{i,nl}$) is reduced from 0.8 to 0.6. The adoption percentage becomes 0.454, which is significantly lower compared to reference model 9. This result corresponds to the results discussed with respect to H3.1. The increase in the adoption percentage because of the innovative behavior is approximately 20% in the experiments with 51 opinion leaders, similar to the 21% in the experiments with 167 opinion leaders. This implies that the number of opinion leaders within a network does not affect the influence of innovative behavior on adoption percentages. However, if normative influence becomes more important to followers, the adoption percentage decreases in both cases by approximately 7%, in contrast with the hypothesis (see Table 3.6). A smaller number of opinion leaders does not influence the effect of innovative behavior on the adoption percentage. With respect to the empirical study the results correspond to H3.1a and H3.1b: adopting the online application is against the group norms, so even the OL hesitates to adopt the application. However, it is interesting to notice that this effect is not *stronger* if the number of OLs is smaller. Despite the stronger pressure not to use the application, some children still want to play with it.

Table 3.6. Conclusions and overview of hypotheses

	Influence of Characteristics of the Opinion Leader	*Results*	*Methodology*
H3.1a	The more innovative behavior of the opinion leader results in a higher adoption percentage.	Supported	Agent Based Simulation
H3.1b	If the weight of normative influence becomes more important to followers, the increase in the adoption percentage caused by the more innovative behavior of opinion leaders increases.	Not supported	Agent Based Simulation
H3.2a	Opinion leaders are less sensitive to normative influence than are followers.	Supported	Empirical Study
H3.2b	If opinion leaders are less sensitive to normative influence, adoption percentages increase.	Supported	Agent Based Simulation
H3.2c	The lower the weight of normative influence of opinion leaders, the higher is the increase in the adoption percentage.	Supported	Agent Based Simulation
H3.3a	Opinion leaders are better at judging product quality, which results in a higher speed of information diffusion.	Supported	Agent Based Simulation
H3.3b	Opinion leaders are better at judging product quality, which results in a higher speed of product diffusion.	Supported	Agent Based Simulation
	Influence of Mass Media Reach		
H3.4a	Less extensive use of mass media increases the effect of the better product judgment of the opinion leader on information diffusion.	Not supported	Agent Based Simulation
H3.4b	Less extensive use of mass media increases the effect of the better product judgment of the opinion leader on product diffusion.	Not supported	Agent Based Simulation
	Influence of Number of Opinion Leaders		
H3.5	A smaller percentage of opinion leaders in a network reinforces the stronger influence of innovative behavior by the opinion leader in terms of increasing the adoption percentage if normative influence is more important to followers.	Not supported	

3.6 Conclusions and Discussion

In this study the critical role of opinion leaders in the adoption process of new products is investigated, using an agent-based simulation model based on empirical data (Table 3.6). This study contributes to the existing literature in two main ways. First, a distinction is made between the flows of normative influence and informational influence. Second, this study links agent characteristics and agent knowledge with the position of the agent in the network (e.g. agents on central positions of the network are more innovative), thereby extending work by Goldenberg et al. (2009), whose study focuses only on the connectivity of influential consumers. Thus, this study provides further insights into the dynamics that influence the diffusion process. The results of the hypotheses testing are summarized in Table 3.6. From these findings, it is deduced that 6 of the 10 hypotheses can be confirmed.

Significant differences are found between networks that contain opinion leaders and those that do not. If opinion leaders are active in a social network, information spreads faster, the product diffuses faster over the network, and the adoption percentage is significantly higher than in a network without opinion leaders. Moreover, this study investigates which opinion leader characteristics drive these effects. The speed of information and product diffusion depends on opinion leaders' capability to judge product quality. Therefore, informational influence has a dominant effect on the adoption speed of the product and the speed of information sharing. The adoption percentage depends more on the innovative behavior of opinion leaders, as well as their lower sensitivity to normative influence. Although this study hypothesized that the innovative behavior of opinion leaders is mostly emphasized by their normative influence, mixed support is found when differences between OLs and followers are taken into account. If followers become more sensitive to normative influence, the adoption percentage declines, possibly because innovative behavior has a stronger effect when informational influence increases in the network. More likely though, this effect is driven by the low adoption percentage. When the normative pressure against the adoption of the product is higher than the normative pressure in favor of the adoption, the opinion leader cannot force the network to surpass a threshold. Finally, a less extensive use of mass media further decreases the effect that opinion leaders have on the speed of both product and information diffusion, because consumers become aware of the product at a later point in time.

These findings are valuable for marketers and since they may help explaining why some products fail, as well as suggest strategies for introducing new products. The normative influence plays an important role in product diffusion in some product categories. However, it is very difficult to ensure that enough people adopt the product to make the product successful. Even if OLs are highly innovative, they may not be numerous enough to make the product a success. Mass media can reach a large audience in a short time, but if the firm can appeal to opinion leaders with a focused campaign, it may not have to engage in a large mass media campaign. Especially through online social networks, opinion leaders can reach many people and eventually exert their normative influence.

Based on the findings of the empirical study it can be concluded that OLs have an important influence on the popularity of online applications. Besides the fact that they immediately recognize a good application and therefore quickly initiate the diffusion process, they also affect the popularity of the online application. The opinion leaders in the empirical study appear to be early in the diffusion process and involve other children as well. They are able to help other children use the sometimes complex applications. Without the help of the OLs, the other children might be discouraged to use complex applications: either because they do not understand how to use the application or because they may not know who they should ask for help. Although it might seem attractive to only target the OLs in a marketing campaign, this strategy is not without risk. A focused campaign reaches an OL and therefore (s)he can initiate the diffusion process, whereas the random use of mass media in the model does not allow the OL to initiate the diffusion process. However, this campaign can only be successful if the OL actually adopts the product and starts talking about it. The simulation shows that this might not happen if the normative influence in the network is too strong: the OL might not use the application and certainly will not talk about it. By using an unpopular product, the OL might lose his/her status. So, a marketing campaign focused on OLs seems to be most successful if the importance of normative influence in the network is relatively low or if the OLs do not care that much about normative influence themselves (i.e. no fear to lose their status), even though their followers do.

Watts and Dodds (2007) suggest that influential consumers (i.e. consumers with a high number of relations) only have a very limited effect on the diffusion process. In addition, supported by empirical data, this study takes more characteristics of influential consumers (in this study opinion leaders) into account, such as innovative behavior, a lower sensitivity to normative influence and a better ability to judge product quality. Given these additional characteristics, this study finds that opinion leaders play a significant role in the adoption process and spread of information about products. Moreover, OLs exert both normative and informational influence. In contrast to Watts and Dodds (2007), the current study defines OLs as early adopters. However, this study only finds small differences between networks that contain opinion leaders and those without them (only a 9.7% higher adoption percentage is observed in networks with OLs) which suggests that other important factors may influence the diffusion process. Perhaps including the critical mass suggested by Watts and Dodds (2007). This conclusion is also supported by the finding that a product does not become popular if the normative influence in a network is too strong: in such a situation it is difficult to obtain the critical mass.

In summary, this study suggests that influential consumers (e.g. opinion leaders) are not (only) influential because of the number of relations they have: they are also more innovative, have better product judgment and are less sensitive to normative influence. These characteristics should be taken into account when investigating the role of influential consumers.

3.7 Limitations and Further Research

This research is subject to some limitations. Since the model is formalized using empirical data about free online applications for children, for the purpose of generalization the models should be tested in other settings (industries). Moreover findings may not directly be generalized to adult markets. The risk of using free Internet applications is very low, because children do not lose anything if they do not like the applications. Thus, interpersonal influence might not be very strong in this application, because the users do not need to evaluate the quality of the product extensively before "buying" it. This study posits that the results may be even stronger in different markets in which it is more difficult to judge product quality (e.g., services), because the influence of opinion leaders might increase. The weight of the normative influence also may depend on the product category, such that opinion leaders exert different influences in the online versus real world (Mak, 2008). The findings of this study thus require verification using data pertaining to different types of markets.

Future research may want to further explore the relationship between the innovativeness of a consumer and the importance of the normative influence for this consumer. More innovative people might be less sensitive to normative influence, in that they will try a new product to enjoy its characteristics, not because other consumers also (might) like to buy it.

This study also uses a relatively simple network structure. Given the important influence the network structure has on the results of the model, it is of an interest to test the model with different network structures (Bohlmann, Calantone and Zhao, 2010). This could include more complex network structures, such as dynamic networks (e.g., Macy et al., 2003). For example, research that would include tie strength in such a network could investigate the influence of both strong and weak ties.

Furthermore, the implementation of mass media in the model is not based on empirical data. It would be interesting to use empirical data to define how many agents should be informed about a new product at a certain point in time. To do this, time steps should be clearly defined in terms of days, weeks, months or years. This would result in a more realistic implementation of mass media in agent-based models.

Because this model incorporates empirical data, it would be more realistic to include a decision-making model that appears more commonly in empirical research, such as a choice model, which would replace the third stage in the described experiments. Distributions based on empirical data could also inform parameters, such as the quality threshold or the utility threshold, in additional research.

Lastly, it is suggested to investigate whether a stochastic model would be more appropriate for modeling the diffusion of (information about) a new product.

Chapter 4

Constructing Empirically Valid Social Networks: An Algorithm for Processing Survey Data[3]

4.1 Introduction

As outlined in Chapter 2 of this thesis, interactions among people represent the key process responsible for the diffusion of new ideas, products, and behavior, so it comes as no surprise that in social simulation models, this interaction is an essential component for modeling the dynamics of social systems (e.g., Garcia & Jager, 2011). Real social systems exhibit large variability in terms of the number of contacts, members' influence, and their susceptibility to social influence (also see Chapter 3). In agent-based models, such heterogeneity translates into the formalization of different types of social networks, different forms of interaction and different agent characteristics. One of the main challenges in developing agent-based models is the collection of data to empirically validate the formalization of the model. Although it is possible to collect network data (e.g. using online social networks) or data about personal preferences and characteristics (e.g. using surveys), it remains challenging to combine the personal information with the network position. The algorithm proposed in this chapter provides a solution to this challenge by constructing an empirical, realistic, simulated social network based on survey data.

Several studies confirm the relation between the position that a person takes in a social network and his or her characteristics. Many of these studies focus on opinion leadership, an important role in many social contexts. Opinion leaders take a central position, which allows them to communicate with many different people (e.g., Valente, 1996). In addition, opinion leaders tend to be more knowledgeable about new products and give unbiased opinions that convince others (e.g., Weimann, Tustin, Vuuren, & Joubert, 2007), which further affects their influence. Non–opinion leaders have different characteristics, which also affect their willingness to change their behavior in the aftermath of social interactions.

Agent-based models offer a valuable instrument for investigating social interactions in combination with personal characteristics. Some existing models investigate the effects of social network structures on the spread of information and behavior and the effects of different types of social interaction during that process. Simulation models explore different network typologies; the small-world (Watts &

[3] This chapter is based on Van Eck, Peter S., and Wander Jager, "Constructing empirically valid social networks: an algorithm for processing survey data," Working paper, University of Groningen

Strogatz, 1998) and scale-free (Barabasi & Bonabeau, 2003) versions are perhaps the most famous and widely used. However, Doreian and Conti (2012) note that the structure of a social network also depends strongly on social context and spatial structure, which suggests the need to consider other, less standardized network structures.

In relation to social influence between agents, less attention centers on information spreading or normative pressures (e.g., Delre, Jager, Bijmolt, & Janssen, 2010). In particular, despite empirically evidenced relations between agent characteristics and network positions, social simulation models fail to include this relation. Rather, agent-based models create a network and distribute agent properties randomly over it. Watts and Dodds (2007) define influential agents as those 10% of agents with the highest number of relations and thus find only limited evidence of the role of influential members in the diffusion process. In a recent simulation study, Van Eck, Jager, and Leeflang (2011 or Chapter 3) instead integrate position with other agent characteristics (e.g., innovativeness, expertise) and show that the speed and degree of diffusion increases significantly when more connected opinion leaders are also equipped with more expertise and engage in more innovative behavior. These results demonstrate the need to establish the clear link between agent characteristics and their network position.

This link should be based on empirical data, such that it demands the parameterization of the social network and interactions that take place within it. Because it is difficult to obtain detailed data from (very) large social networks, empirical social network studies often focus on small, close groups, such as those in schools (Vermeij, Van Duijn, & Baerveldt, 2009). An adaptive threshold method based on cognitive social structures (i.e., a small sample in the network reports on all relations they believe exist; Siciliano, Yenigun and Ertan, 2012) appears only suitable for networks of limited size. However, recent data refer to large networks, such as telephone, e-mail, and Internet links among people (e.g., Iyengar, Van den Bulte and Valente, 2011, Risselada, Verhoef and Bijmolt, 2013). However, even after identifying these large networks, it remains unclear which types of social influence get communicated. Nor do these networks fully capture influences outside the channels; for example, direct physical interactions may have a stronger impact on normative influence, just through the possibility of observation.

For many research questions, knowledge about the causal mechanisms of social processes in networks is highly relevant. To study processes of innovation diffusion for example, it is important to identify opinion leaders and followers to follow their process, as well as conduct experiments by targeting specific types of actors. In recent years, agent-based modeling thus has gained momentum in efforts to develop causal models of such social processes (e.g., Garcia & Jager, 2011). With this approach, the population of artificial agents connected in a social network gets created, such that experiments can be conducted to unravel the effects of social influences in these large populations. Empirical data suitable for use in the parameterization of agent-based models usually derives from representative cross-sectional samples. In terms of social influences, these data might include detailed information about the types of influence that people experience and exert, as well as the number and characteristics of people with whom they interact. Although empirical data help formalize valid representations of real social systems in agent-based models, the underlying problem of capturing empirical data about network connections remains. Therefore, many agent-based models use empirically derived distributions of agent properties, without providing a valid formalization of who is connected to whom, according to individual characteristics. That is, complete network data lack information about social processes, and data on social interactions cannot capture network data. To study these social processes in detail, the most practical option would be to create a full network that captures empirical data about social processes. Specifically, agent-based modeling could benefit from a methodology that can link agent characteristics to positions in a network, in an empirically valid way. The main challenge is using survey data from unrelated respondents to construct a simulated network of agents that captures the position and influence of people in the network. This chapter proposes a method to help construct such an empirical, realistic, simulated social network.

The method attempts to construct an artificial social network that captures the attributes of the links that reflect informational and normative influence, similarity, and expertise. To construct such a network, I propose an algorithm that parameterizes it, using cross-sectional data from a survey of unconnected respondents. The network therefore captures key features of social interaction in social networks and provides a more empirically valid social network in simulation models. This chapter introduces the algorithm and tests it with *artificial* data. In Chapter 5 I apply this algorithm to empirical data and show how it can be used to investigate the (effects of) social interactions in a social network.

In the next section, I present the general algorithm, before I detail the two most important elements of the algorithm, namely, the empirical data that can be used as input (in this chapter artificial data of this form is created to serve as an example) and the matching profiles.

4.2 The algorithm explained

The algorithm has been developed to construct a network structure that is empirically realistic and can be combined with other personal characteristics for further simulation studies. The survey data should consist of two parts: 1) a description of the relations respondents have with people in their social network, and 2) additional information relevant for the particular study (e.g. product preferences). The latter is irrelevant for the algorithm and should be incorporated in the ABM that is using the constructed social network. The algorithm itself only needs the description of the social relations.

The general structure of the algorithm is as follows: in the relevant data, respondents describe with whom they have a relation (e.g. age, gender) and what kind of relation (s)he has with the other person (e.g. the opinion of this person has a strong impact on the opinion of the respondent). While the respondents are assumed to be unconnected (i.e. they are not part of the same social network), the algorithm attempts to find another respondent that matches the description as provided by the respondent. If a match is found, the two respondents are connected. The algorithm searches for a match for all described relations, ultimately resulting in a social network.

The diagram in Figure 4.1 depicts the proposed algorithm, in which squares with rounded edges represent a certain procedure (e.g., making a selection), normal squares indicate the input/output of these procedures (e.g., list of agents), and the ovals are choices.

The starting situation involves the translation of *empirical data* in the *Agenda-Based (AB) model*. Each *respondent* is "translated" into an *agent,* so the *Reported Relations (RR)* of the respondent become *Wanted Relations (WR)* of the agent. For example, one respondent (age: 27, gender: male) might indicate that he has a relation with a 26-year-old woman (i.e., *Reported Relation* = empirical data). In the starting situation, I use this information to create an agent (age: 27, gender: male) that "wants" to be matched with another agent (age: 26, gender: female; *Wanted Relation* = ABM). Section 4.4 contains a more detailed discussion of the matching procedure. The other agent is *not* created on the basis of this information. Instead, all agents represent respondents, and the RRs do not refer to other respondents. The respondents are unconnected in the real world, because these data were collected randomly, using surveys.

Components of the first square exist in a set of unconnected agents with a specific list of profiles (i.e., agent/relation characteristics; see Table 4.1) for the agents to which they want to be connected. The process to get from this set of unconnected agents to a network of agents consists of seven steps.

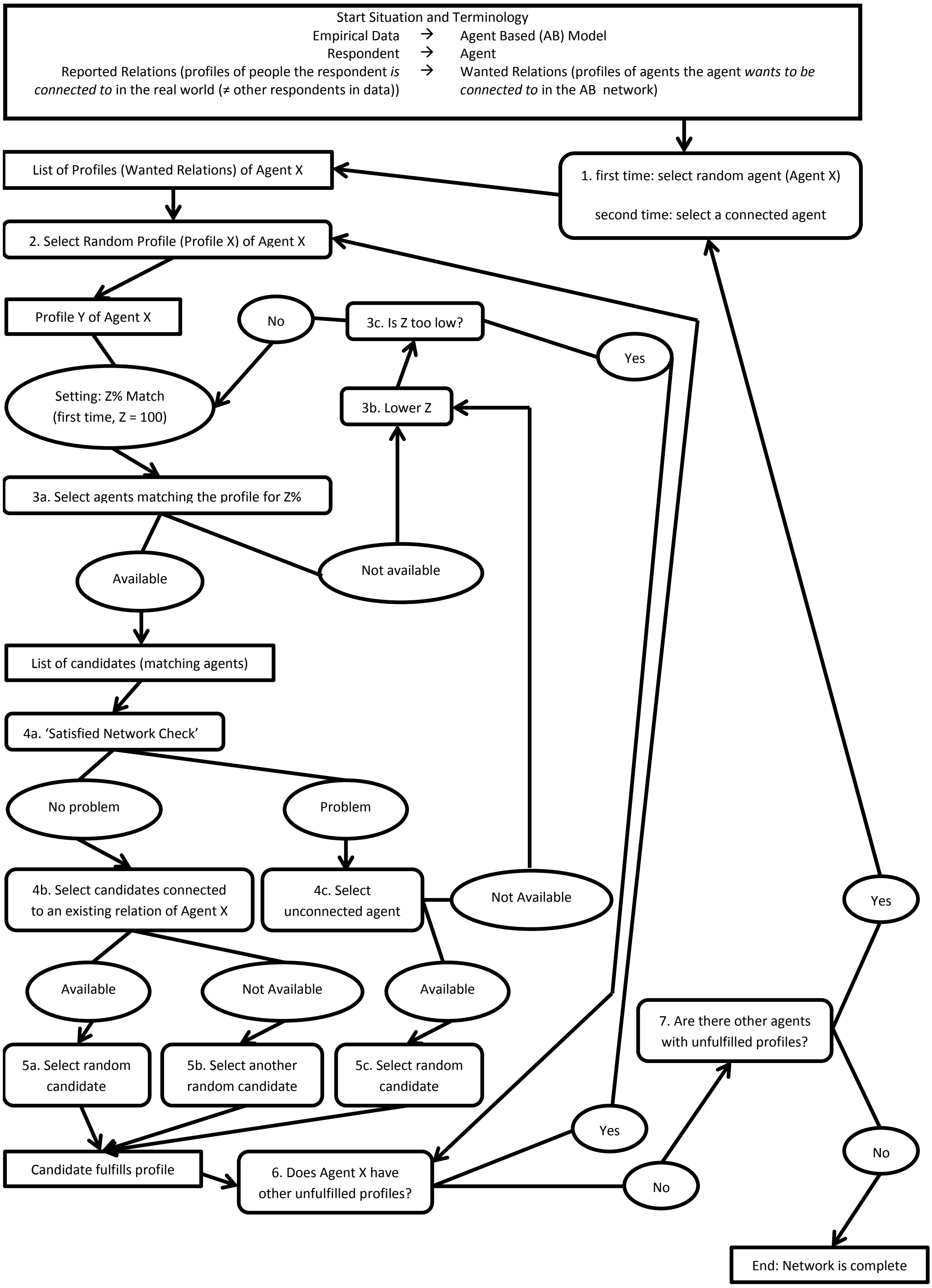
Step 1. Selecting a random/connected agent (Agent X)

The first time the algorithm initiates the procedures, it selects a *random* agent. If the first agent selected has fulfilled all its profiles (i.e., Agent X is satisfied, Step 7 is reached at least once), another *connected* agent gets selected. Selecting an agent that is already part of the network ensures that the ultimate network resulting from the algorithm is connected. If another random agent were to be selected, the algorithm may result in two (or more) unconnected networks. The result of Step 1 thus is a list of profiles (WR) of agent X.

Step 2. Selecting a profile (Profile Y) of Agent X

Agent X has a list of profiles (WR) that contain the characteristics of the agents to which Agent X wants to be related (e.g., age, gender). One of these profiles gets randomly selected: Profile Y.

Figure 4.1: Network Construction Algorithm



Step 3. Ensure a list of candidates matching Profile Y.

3a. Select agents matching the profile for Z%

In this step, the comparison of all agents with Profile Y reveals the match between any agent and Profile Y. If the match is higher than Z%, the agent is a candidate. At this point, the matching is bidirectional, because a potential candidate may not have a profile that matches Agent X. For example, assume Agent X has the following characteristics: age: 36; gender: male. Then Profile Y of Agent X is age: 35; gender: female. If a potential candidate has the characteristics [age: 35; gender: female] but the candidate lacks the profile [age: 36; gender: male, the match fails]. The next section includes a fuller discussion of the model underlying the matching procedure. The matching procedure ultimately results in a list of potential candidates that fulfill Profile Y.

3b. No agent matches the profile for Z%, lower Z

Although the preferred match is 100%, not all relations described in empirical data can be fulfilled perfectly. Therefore, the matching percentage can be lowered stepwise, until a match appears.

3c. Check if Z is acceptable

Limits on the matching percentage ensure that if the match is too low (e.g., under 50%), it does not get included in that particular relation in the network, because it disturbs the results too much. Imagine, for example, that there is empirical data on 20–29-year-old people, who appear likely to report relations with people of the same age. If one of the relations refers to someone who is 50, it might be better not to include this relation, because the connection to a 29-year-old may be very different. In that case, the profile can be skipped, continuing to Step 6.

Step 4. Refine the list of matching candidates by checking assumptions

4a. Satisfied network check

A satisfied network refers to a network in which all agents have all the relations they want (WR), so no profile needs to be fulfilled. If there are still unconnected agents in this situation, they must start a second network that does not connects to the first. To prevent this possibility, a satisfied network check determines if there are only two unfulfilled profiles left within the connected network (and there are still unconnected agents) and if they potentially fulfill each other. In this case, Step 4b gets skipped: The profile must be fulfilled with an unconnected agent.

4b. Select candidates connected to an existing relation of Agent X

In this case, people likely form clusters: Friends of friends are likely to be friends of each other (Granovetter, 1973). From this assumption, the list of candidates gets reduced to agents that connect to an agent that is already connected to Agent X.

4c. Select unconnected agents

Here, this case the list of candidates is reduced to all unconnected agents.

Step 5. Select a random candidate of the refined list

A random selection comes from the refined candidate list, which resulted from Step 4. The result of Step 5 is that Agent X is connected to one of the candidates, so Profile Y is fulfilled.

Step 6. Check whether Agent X has more unfulfilled profiles

There are two options in Step 6. First, Agent X could have more unfulfilled profiles, in which case the process returns to Step 2a. Second, Agent X could have fulfilled all its profiles, in which case the process continues.

Step 7. Check for agents in the network with unfulfilled profiles

Even if Agent X has fulfilled all profiles, other agents could still have unfulfilled profiles, in which case the process returns to Step 1. However, if all agents have fulfilled all their profiles, the network is considered complete.

Randomness

Several steps in the algorithm require random selections. The idea behind this randomness is that the algorithm does not optimize the network itself but instead potentially produces (slightly) different results, every time the algorithm applies. After running the algorithm several times, the network structures can be compared according to the level of satisfaction achieved, facilitating the selection of the best fitting network. Although this algorithm is not the most efficient, it ultimately is effective for finding an optimal solution (i.e., network in which the discrepancy between the wanted and created relations is minimal; see Section 4.4). In addition, it easy to adjust to specific research situations, such that it can deal with any type of profile (input empirical data) or assumption (Step 4), and the matching model (Step 3) is relatively easy to implement.

4.3 Empirical Data and Input Variables: An Example

The preceding algorithm contains two important steps that demand additional explanation. The empirical (input) data (i.e., what is included in the profiles) represent the topic of this section. The matching model will be discussed in the next section.

In general, the empirical data should contain information about the individual relations a respondent has with other people that are relevant to the research question (i.e., people that influence the respondent for a specific topic). The information actually needed with respect to the relation depends on the factors that affect influence within this relation. For new product introductions, similarity between people (homophily) affects the strength of the social influence (e.g., Risselada, Verhoef, & Bijmolt, 2013). In this chapter, network construction is based on (1) the type of influence being exerted between people and (2) with whom the interaction takes place. The profiles of Wanted Relations contain information about both.

Regarding the type of influence, the distinction between normative and informative influences offers a useful starting point (Cialdini and Goldstein, 2004), as applied in several agent-based modeling studies (Van Eck *et al.*, 2011; Delre *et al.*, 2010; Jager, 2007). Normative influence refers to the motive to associate with certain people (groups) and avoid social expulsion. The informative influence instead deals with exchanging experiences and opinions, so the quality of the information is important. For both influences, it is possible to distinguish outgoing and incoming forces. For example, people may have a strong susceptibility for normative influence but have virtually no normative influence on others. The measure I use in this chapter is based on Bearden, Netemeyer, and Teel’s (1989) scale. However, because the questions about social influences repeat for every connection a person reports (maximum of five), to reduce the pressure on respondents, I formulated six questions to measure the four types of influence and the general strength of incoming and outgoing influence. For this example, the questions pertain to the purchase of a new cell phone, but they also can be adjusted to other research questions.

For determining with whom an agent interacts, the first critical factor is the number of other people interacted with, which can be obtained by asking with whom they talked about a product or topic.

Next, it is important to identify potential influences; this study focuses on similarity and expertise as key variables. Similarity (homophily) enhances normative influence, and people who are more susceptible to normative influences are more likely to be influenced by similar others. Many variables serve to indicate similarity between people, but the most common rely on demographics, such as gender, age, residence, education, income, ethnicity, nationality, or language. Depending on the topic of interest, other variables may be of interest as well and can be included in similarity measurements. Examples of such variables might include general political orientation, specific attitudes about the environment, or nationality.

Expertise relates to the knowledge the other person has. The more experienced another agent is, the stronger the informative influence and resulting change will be. A very generic estimation of expertise might use education and age, which represent formal expertise and life experience, respectively. Alternatively, more specific expertise might be sought, which would require more topical definitions of expertise, such as knowledge about cars, energy, or agriculture. In this case, specific questionnaires can serve to measure expertise.

Table 4.1 lists the variables used to test an example of the network construction algorithm. Variable 4 indicates how many profiles an agent wishes to fulfill; the profiles themselves consist of the values obtained for the other questions.

Table 4.1: Variables used to test the network construction algorithm

		Example Profile
1[a]	Gender	Female
2[a]	Age	37
3[a]	Education (7 point scale)	5
4	Number of relevant[c] connections	4
5[b]	Outgoing information influence (OI) (7 point scale)	3
6[b]	Incoming informational influence (II) (7 point scale)	6
7[b]	Outgoing normative influence (ON) (7 point scale)	5
8[b]	Incoming normative influence (IN) (7 point scale)	5
9[b]	Strength outgoing social influence (in general) (OS) (7 point scale)	3
10[b]	Strength incoming social influence (in general) (IS) (7 point scale)	4

[a] Information collected about respondent *and* for all connections (based on 4).

[b] Information collected with respect to all connections (based on 4).

[c] Relevance depends on the research question (e.g., with how many people did you talk about X?)

Table 4.2 contains the scale items, which respondents evaluated on seven-point Likert scales, ranging from “complete agree” to “completely disagree.”

Table 4.2: Items to measure social influences

Incoming informative *This person provided me with technical information on cell phones.*
Outgoing informative *I provided this person technical information on cell phones.*
Incoming normative *This person told me about the fashionability of cell phones*.
Outgoing normative *I told this person about the fashionability of cell phones.*
Strength, incoming social influence (general) *This person had a strong influence on my cell phone preferences.*
Strength, outgoing social influence (general) *I had a strong influence on this person’s cell phone preference.*

4.4 Matching Model

In this section I discuss the matching model from Step 3 in more detail. Several methods can inform the matching procedure, as discussed by Gensler, Leeflang, and Skiera (2012). These authors compare several methods (e.g., covariate matching, hybrid matching) to pare treated and untreated customers and account for self-selection effects and thereby match the profiles of the agents in the model. The method applied in this chapter is a form of covariate matching, in which the similarity between two profiles reflects their scores on several parameters (e.g., Zhao, 2004). The parameters of the model depend on the empirical data used, but in general they reflect Equation 4.1, which serves to calculate the distance (i.e., mismatch) between Agent X (selected in Step 1) and Agent A (another agent who potentially could connect to Agent X). A greater distance refers to a lower match. This distance is calculated for every available agent (i.e., with unfulfilled profiles). The equation contains two components: the variable (V_k) and the weight of that variable (β_k). All the variables get rescaled, such that their values range from 0 to 1. When a particular variable is expected to be more important for the development of the connection (e.g., age is extremely important, but other variable are relevant only if age matches), the weight of that variable can be increased. For simplicity, this example assumes the weight is equal for all variables.

$$Distance_{i,j} = \sum_{k=1}^{K} \beta_k V_k \quad , \tag{4.1}$$

where:

i = Agent X.

j = Agent A ($\neq$ Agent X).

pi = Profile Y of Agent X.

pj = Profile of Agent A, set to be matched with Agent Y.

K = Number of variables (in this example, 9).

β_k = Weight of variable k (in this example, all weights are 1).

$V_1 = (0.5|gender_{pi} - gender_j|) + (0.5|gender_{pj} - gender_i|)$.

$V_2 = (0.5|age_{pi} - age_j|) + (0.5|age_{pj} - age_i|)$.

$V_3 = (0.5|eduction_{pi} - education_j|) + (0.5|education_{pj} - eduction_i|)$.

$V_4 = |OI_{pi} - II_{pj}|$ (outgoing informative).

$V_5 = |II_{pi} - OI_{pj}|$ (incoming informative).

$V_6 = |ON_{pi} - IN_{pj}|$ (outgoing normative).

$V_7 = |IN_{pi} - ON_{pj}|$ (incoming normative).

$V_8 = |OS_{pi} - IS_{pj}|$ (outgoing strength of influence).

$V_9 = |IS_{pi} - OS_{pj}|$ (incoming strength of influence).

The distances of gender, age, and education (V_1–V_3) are calculated from the perspective of both Agent X and Agent A: The age of Agent A must match the age in Profile Y of Agent X. Because both perspectives have an equal impact on *Distance* between agents, both are multiplied by 0.5. In addition, the age of Agent Y must match the age in the profile of Agent A. With respect to social influences (V_4–V_9), the outgoing and incoming influences cross: The outgoing informative influence in Profile Y of Agent X must correspond with the incoming informative influence in the profile of Agent A, because outgoing informative influence for Agent A is incoming informative influence for Agent X.

Table 4.3 presents a calculation example, in which Agent A and Agent B are potential candidates to fulfill Profile Y of Agent X.

Table 4.3: Calculation example

	Profile Y of Agent X[2]	Profile of Agent A[3]	Profile of Agent B[4]
Gender[1]	Female	Male [0.5|1-1|+0.5|0-0|=0]	Male [0.5(2-2)+0.5(1-1)=0]
Age	0.37	0.39 [0.5|0.38-0.37|+0.5|0.39-0.40|=0.1]	0.40 [0.5|0.37-0.37|+0.5|0.40-0.40|=0.0]
Education	0.5	0.7 [0.5|0.5-0.5|+0.5|0.7-0.5|=0.1]	0.5 [0.5|0.6-0.5|+0.5|0.5-0.5|=0.05]
Outgoing Informative	0.3	0.7 [|0.7-0.6|=0.1]	0.2 [|0.2-0.6|=0.4]
Incoming Informative	0.6	0.3[|0.3-0.3|=0.0]	0.3[|0.7-0.6|=0.1]
Outgoing Normative	0.5	0.4[|0.4-0.5|=0.1]	0.1[|0.1-0.5|=0.4]
Incoming Normative	0.5	0.5[|0.5-0.5|=0.0]	0.5[|0.5-0.5|=0.0]
Outgoing Strength	0.3	0.1[|0.1-0.4|=0.3]	0.4[|0.4-0.4|=0.0]
Incoming Strength	0.4	0.3[|0.3-0.3|=0.0]	0.5[|0.5-0.3|=0.2]
Distance		0.***7***	***1.15***

[1]Gender is coded as follows: 0 = male, 1 = female.

[2] Agent X is a man, age is 0.40, education level is 0.5.

[3]Agent A is a woman, age is 0.38, education level is 0.5.

[4]Agent B is a woman, age is 0.37, education level is 0.6.

Based on the calculations of the distances, Agent X connects with the agent with the lowest distance. So, in Table 4.3, Agent X connects to Agent A.

When the network is complete, the total error can be calculated (Equation 4.2) as the sum of all distances in made connections; it represents the model fit (i.e., the connection between Agent X and Agent A in the calculation example increases the total error by 0.7). A perfect fitting network has an *Error* of 0; the maximum *Error* can be determined by multiplying the maximum *Distance* by the number of relations in the network. Thus,

$$Error = \sum_{i=1}^{I} \sum_{j=1}^{J} Distance_{i,j} \ , \qquad (4.2)$$

Where

Error = summed distances between the wanted relations (WR) and the relations the agents actually have in the created network.

The Error is still difficult to interpret, as it depends on both the network size (i.e. the number of connections) and the maximum $Distance_{i,j}$ ($Distance_{MAX}$) that can result from a connection between i and j. A Standardized Error can be calculated:

$$SE = \frac{Error}{2Distance_{MAX}\,NCN}, \quad (4.3)$$

where

SE = standardized error of the network; a value between 0 and 1, where a lower number indicates a better fit.

$Distance_{MAX}$ = the maximum possible distance in a connection.

NCN = the total number of connections in the network.

Note that the *Error* is calculated twice for every connection (from the perspective of both connected agents). Therefore the *SE* needs to be divided by 2, as shown in Equation 4.3.

4.5 Experiment: Testing the Algorithm

To test the proposed algorithm, four constructed networks artificially generate survey data. The proposed method then can reconstruct the networks on the basis of the generated survey data.

Two different network structures have different sizes: a random network (250 and 1000 nodes; see Figure 4.2) and a modular network, as described by Barabasi (2003) (256 and 1024 nodes; see Figure 4.3). This last network structure is relatively easy to generate and distribute (i.e., similarity, social influence), such that respondents in clusters on the lowest level share most characteristics, and they differ from respondents in clusters on the same level. The four networks indicate the survey data: Agents completed the survey in Table 4.2 (see Section 4.3). If the proposed method works properly, it should be able to find the original network structures, based on the created survey data.

The algorithm is programmed in Netlogo 4.1.1 (Wilensky, 1999) and applied to the created survey data. For every network structure and size, the algorithm is applied 50 times. To test the performance of the model, the calculated error is saved, as is the clustering coefficient, as an indicator of the resemblance with the original network structures. The network clustering coefficient (NCC) is calculated as described by Watts and Strogatz (1998). Table 4.4 shows the number of agents, the number of connections, and the (average) number of calculations needed in every experimental setting (i.e., number of times Equation 4.1 is called for by the algorithm). Tables 4.5 and 4.6 show the average results.

According to Table 4.4, the number of calculations needed to find an optimal network structure increases if the number of agents increases and the number of connections increases. The greater number of calculations is not necessarily a problem, because it is only necessary to find the best fitting network once. This network structure then can be saved and used for additional analyses (e.g., connecting the network structure with other survey information).

Figure 4.2: Example of a random network with 50 agents

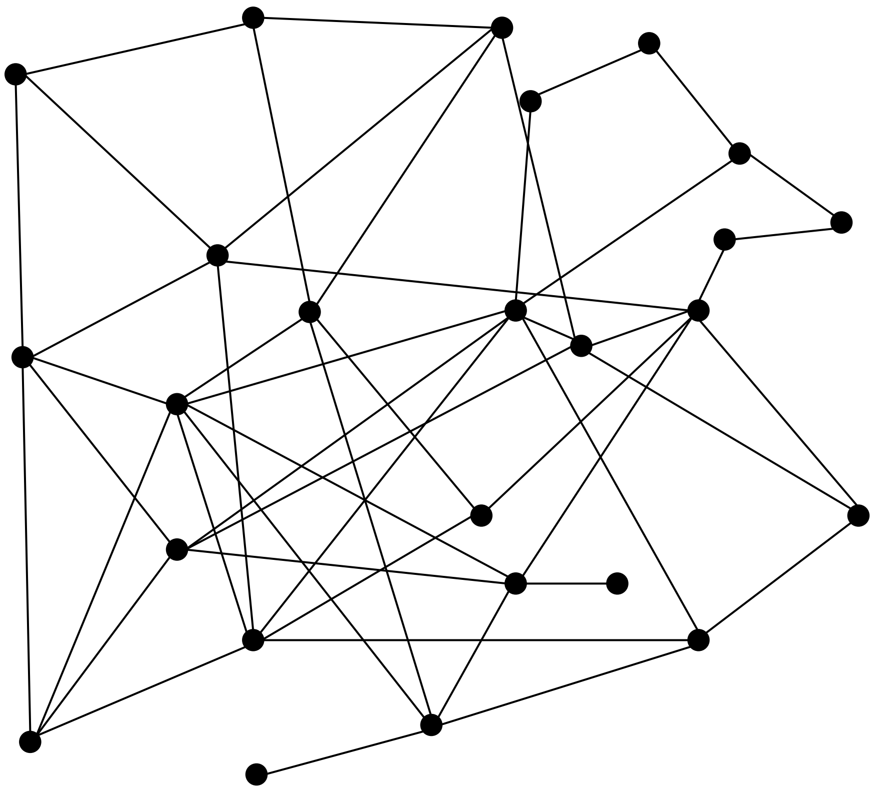
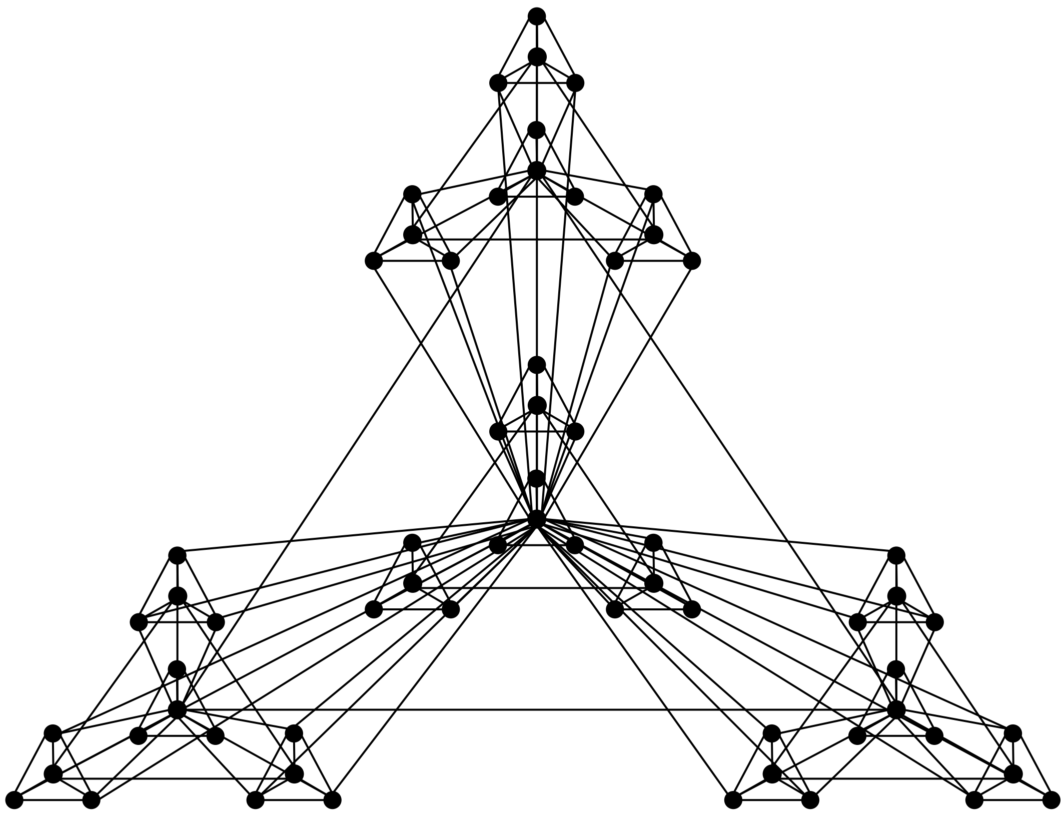


Figure 4.3: Example of a modular network with 64 agents (Source: Barabasi, 2003: 233)



The model replicates the *random* networks perfectly, every time the model runs, as shown in Table 4.5. Replicating the *modular* networks is somewhat more difficult and results in errors (6.56 and 13.85) in these two experiments. Given the number of connections in these networks (*NCN* is respectively 879 and 4095 for the networks with 256 and 1024 agents) and the maximum distance ($Distance_{MAX}$ is 9 in both networks), the standardized error is very small for both networks: 0.007 (256 agents) and 0.003 (1024 agents). The difference between the replicability of the two network structures relates to the variance in the survey data, in that most relations in the random network are unique (i.e., combination of similarity and social influence variables), due to the random distribution of their characteristics. The distribution of characteristics in the modular network structure means the relations are less unique, which increases the possibility that the "wrong" agents get connected, resulting in the small error.

Table 4.4: Calculations needed to create a network

Network Size (type)	Number of Connections	Calculations Needed
250 (Random)	740	608863
1000 (Random)	2937	9646426
256 (Modular)	879	817543
1024 (Modular)	4095	17675056

Table 4.5: Error information

Network Size (type)	Average Error (standard deviation)	Range of Errors
250 (Random)	0.00 (0.00)	0.00 – 0.00
1000 (Random)	0.00 (0.00)	0.00 – 0.00
256 (Modular)	6.56 (5.01)	0.12 – 20.78
1024 (Modular)	13.85 (8.42)	1.82 – 34.25

To investigate whether the produced network structures are close to the actual network structure (despite the error), the NCC is calculated (Table 4.6). As expected, the produced random network structures are a perfect replication of the actual network. The produced modular network structures slightly differ from the actual network structure, though the differences are relatively small.

Table 4.6: Network clustering coefficients

Network Size (type)	NCC (standard deviation)	NCC of actual network
250 (Random)	0.010 (0.00)	0.010
1000 (Random)	0.002 (0.00)	0.002
256 (Modular)	0.282 (0.01)	0.297
1024 (Modular)	0.250 (0.00)	0.270

To test whether the calculated error indicates model fit, I also calculated the difference between the NCC of the actual network and the NCC of the 50 network structures resulting from the algorithm. The significant correlation of these differences with the calculated error is 0.482 and 0.305, respectively, for the 256-node and 1024-node networks. That is, the calculated error offers a reasonable measure to indicate the fit between the actual and the produced networks.

Although the model does not produce a perfect matching network in every run, it is only necessary to find a matching network once, because it can be saved and used again. Although the range of errors in Table 4.5 shows that the perfect match does not appear after 50 runs, the model indicates the perfect match about once in every 100 runs for the 256-node network (based on 10,000 runs). For the 1024-node network, the perfect match arose once in 15,000 runs.

4.6 Extended Experiment: Sampling a Network

The previous section showed that the model can reproduce a network based on survey data if all respondents in the network participate in the survey. However, it is not clear how the model performs for a sample with a larger network. To test the algorithm for this setting, I used a 16,384-node, created modular network to produce survey data. A random sample of 500 respondents from this survey provides the input for the model to create 50 networks.

The average error of the networks produced by the model is 1236.49 (standard deviation = 21.85), with a minimum error of 1195.20. Using equation 4.3 ($Distance_{Max}$=9, *NCN*=1973) we find an Standardized Error of 0.034, which is reasonably low.

Beyond the error of the produced networks, it is interesting to compare the network structure of the produced networks with the actual network structure. The NCC of the produced networks averages 0.0477 (SD = 0.003); the NCC of the original (large) network is 0.229. Although the best fitting network scores above average (0.0484), it is not even close to the NCC of the original network. That is, though the produced networks achieve the best fit with respect to the characteristics of the ties, the network structure itself is not very similar to the structure of the original network. There are two (not mutually exclusive) reasons for this discrepancy: (1) The assumptions about why people connect are not correct or incomplete (see the next section) or (2) the sample is biased.

A simple way to determine whether sample bias is a problem is with a split sample approach: The two samples contain 250 agents each, and the model serves to create 50 networks with both samples. If the results differ significantly, the sample must be affecting the results, so the biased sample results in an incorrect network structure. In this experiment, the NCC of the created networks differ significantly (NCC_1 = 0.08, SD_1 = 0.004; NCC_2 = 0.06, SD_2 = 0.004). Therefore, it is important to compare the network metrics of the produced networks with the expected network metrics.

4.7 Influencing Network Characteristics

Previous research offers strong evidence of the network structure (e.g., NCC in this chapter), but it also might be interesting to optimize the model, according to its fit with a particular structure, instead of using the error. To influence the network structures produced by the algorithm, it is possible to change the underlying assumptions of the algorithm, according to the matching model in Step 3 and the assumption that the priority of the distance is the same in Step 4.

The main assumptions in this algorithm thus far have been that people connect on the basis of the nine variables in Equation 4.1 and that the weights of these variables are the same (Step 3). Changing the weights affects the actual network structure, because it affects the *Distance* between the respondents and therefore their tie choices. Evolutionary modeling can serve to identify the combination of weights that leads to the best fitting network structure. Discussing this model extension is outside the scope of this chapter, but Table 4.7 shows the results of changing the weight of one variable. The NCC actually *decreases* if the weight is decreased, as expected, because in the distribution of the parameters in the original network, respondents with stronger connections were assumed to be more similar with respect to their age than respondents with weaker connections.

Table 4.7: Results of changing the weight for age

Experiment	β_2 (Age)	NCC (standard deviation)
1	0	0.037 (0.004)
2	1/3	0.041 (0.003)
3	2/3	0.044 (0.003)
4	1	0.048 (0.003)

It also is possible to include additional assumptions with respect to how people connect (Step 4). For example, people likely form clusters (Granovetter, 1973) (Step 4b). Normally the algorithm searches for the agents with the lowest distance, and from this list of candidates, it selects a connection of a connection. However, if finding the perfect match is less important than forming a cluster, it is possible to lower Z and allow for a larger distance during the first run. By increasing this allowed distance, the error of the network structure increases, as does the importance of Step 4b, as shown in Table 4.8. The assumption in Step 4b has a small effect if the allowed *Distance* is small (0.01), but this effect becomes stronger if the allowed *Distance* increases to 1.

Table 4.8: Results of increasing distance in the first run

Experiment	Step 4b Included	Allowed Distance in First Run	NCC (SD)
1	No	0.01	0.047 (0.003)
2	No	0.05	0.047 (0.003)
3	No	0.1	0.046 (0.003)
4	No	0.5	0.035 (0.003)
5	No	1	0.022 (0.002)
6	Yes	0.01	0.050 (0.003)
7	Yes	0.05	0.053 (0.003)
8	Yes	0.1	0.058 (0.003)
9	Yes	0.5	0.092 (0.004)
10	Yes	1	0.141 (0.004)

4.8 Conclusions and Discussion

The algorithm proposed in this chapter allows researchers to create a network structure using survey data. This survey data should contain information about the relations respondents have with people in a certain context (e.g., purchase decision). Which information about the relation is relevant depends on the reasons people interact. In other words, why does the relation exist—for the type of information shared, the similarity between the two persons, physical distance, or other reasons? The flexible model can be used in various research settings, should lead to improved analyses using network structures and matching survey data.

The results of the experiments show that the model can find a perfect fitting network if it exists and a close fitting network from a sample of a larger network. Furthermore, network metrics can be influenced by changing the weights of the variables or including additional assumptions about the creation of connections between agents. The unlimited combination of weight distributions makes it reasonable to use evolutionary modeling to find the combination of weights that results in an optimal network structure.

Although the results of the current model seem promising, the next important step is to use empirical data to create an optimal network structure. To determine whether this approach increases the realism of agent-based models, I compare the results of this approach with the results of a model in which empirical data provide the input only for rules and parameter distributions.

Chapter 5

Social Interaction and New Product Introductions: Reaching a Narrowly Defined Target Group[4]

5.1 Introduction

Companies introduce new products to the market on a regular basis, often without the success they hoped. The high failure rates (40–75%) can be explained partly by decisions in the product development stage (Ernst, Hoyer, & Rübsaamen, 2010). A product is likely to fail if it does not match the preferences of many customers. In addition, the marketing strategy used to introduce the new product in the market seriously affects success rates.

In the product development stage, it is important to determine what customers like in a product. A popular marketing instrument to investigate the preferences of customers for certain product characteristics is conjoint analysis (Green and Srinivasan, 1990). This method is a valuable tool to gain a better understanding of the preferences of customers; it also can simulate predicted market shares, using estimated parameters to determine respondents' buying probabilities for a choice set that includes both existing and new products. Although these insights from conjoint analysis provide a good foundation for studying the market potential of new products, the methodology ignores two important factors: the marketing strategy used to introduce the product and the social influence among customers. Both factors influence the size and composition of the evoked set that customers consider, when making a product choice.

A conjoint study assumes that customers have a certain evoked set and make decisions on the basis of their preferences for certain product characteristics. The marketing strategy can directly influence the evoked set: It makes customers aware of the product and therefore enables them to determine their preferences for it. Substantial knowledge is available about this first-order effect; considerably less is known about a second-order effect that results from social interactions among customers. If customers are aware of the product, they can share this information with others who might not be aware of the product. Furthermore, this social influence affects product preferences. If many customers in a social network adopt a certain product, it may become more attractive to other potential customers than is a less popular product. This effect results from various processes, such as increased trust in the product (i.e., "if many people are using it, it must be a good product") or normative influences (i.e.,

[4] This chapter is based on Van Eck, Peter S., Wander Jager, and Peter S.H. Leeflang, "Social Interaction and New Product Introductions: Reaching a Narrowly Defined Target Group" Working paper, University of Groningen

conforming with group norms). Social interactions strongly affect prediction results, especially because interactions exert their effects between traditional market actions and social interactions (Trusov, Bucklin, and Pauwels, 2009). Two marketing channels imaginably might have the same first-order effects (e.g., reach) but differ in their second-order (e.g., social diffusion) effects, such that people reached by one channel might be more willing to share information than those reached by another. Although first-order effects can be estimated using econometric models, social interactions among customers make the diffusion of (information about) new products a complex social phenomenon, difficult to investigate with econometric models. Agent-based models also can combine econometric models with interaction rules at the individual level, therefore offering a better understanding of the impact of social interactions in the diffusion process.

This chapter aims to develop a model that can test for the effect of different marketing strategies on the adoption rates of new products and account for social interactions across customers, with conjoint analysis as a basis. Specifically, concomitant variable latent class analysis can allow for customer heterogeneity (Kamakura, Wedel, and Agrawal, 1994). By including social interactions, this model also distinguishes between first- and second-order effects of the marketing strategy.

Therefore, this chapter makes a distinction between two types of social influence: normative and informative. Informative influence is a tendency to accept information from others as evidence of reality (Deutsch & Gerrard, 1955). Normative influence is a tendency to conform with the expectations of others (Burnkrant & Coucineau, 1975). The former informs customers about new products (i.e., makes customers aware); the second results in social pressure to (not) adopt a product (i.e., affects product preferences). Both types of influence traditionally have been defined as incoming (i.e., from the point of view of the person affected), which implies that someone could also exert both types of influence (outgoing influence).

Social interactions take place within a network of social relations. Customers differ in the number of relations they have and how sensitive they are to social influences: Do they trust the information they receive from social sources, and how strongly is their choice affected by the choices of others? The impact of a relation depends not only on the recipients' general sensitivity to social influence but also on the identity of that relation. If the other customer is very knowledgeable but has dissimilar needs, the focal customer may value the information provided but not the choices. For example, knowledgeable customers know everything about developments in the cell phone market and always buy the most advanced version; another customer may prefer a less advanced model.

The effects of these (inter)personal characteristics on adoption rates also depend on customers' network positions. If a customer in a central network position exhibits low sensitivity to normative influence, she or he may be more likely to adopt a new product first (i.e., contrary to normative influence), which sets a norm for others. If the same customer is very sensitive to normative influences, she or he might decide not to adopt the new product, decreasing the probability that related others will adopt product too. Katona, Zubcsek, and Sarvary (2011) also find a relation between network position and influence, such that people with many connections have less influence on people around them, compared with people with fewer connections. People who serve as bridges between two clusters of other consumers similarly have a stronger influence than those who do not fulfill this function.

To model these complex interactions and relations, this chapter introduces an agent-based model (ABM). Agent-based models provide useful tools for combining existing marketing models with social interactions, such as in a conjoint study (Vag, 2007). Furthermore, ABMs can test different types of targeting strategies (Delre, Jager, Bijmolt, & Jansen 2010). The agent rules in this study stem from an empirical survey (including a conjoint feature) with 500 respondents, so it ultimately serves used to answer the following research questions:

1) What relative effects do informative and normative influence have on awareness and adoption rates of a new product?
2) Do these effects differ across different marketing communication channels?
3) Do these effects differ depending on the product being introduced?

For this chapter, the answer to these questions involves a social simulation setting. The empirical data formalize agent rules at the individual level; the ABM then shows which processes emerge from these individual rules. The conclusions from the hypotheses tests using this model offer guidelines for further research that might provide empirical validation of the outcomes. Accordingly, the key contributions of this chapter are as follows:

1. I demonstrate that through the development of an empirically validated, ABM, it is possible to determine the effects of all kinds of vehicles on the adoption rate of a new product. This model specifically includes a choice model (conjoint study), information about network positions, information about (information) search behavior (in marketing communication channels), and sensitivity to informative and normative influences. Therefore, I account for relations among the personal characteristics of customers and their positions within their social networks.
2. I show that the different types of social influence affect the awareness and adoption rates of new products and that the effects depend on both marketing communication channels and the product.

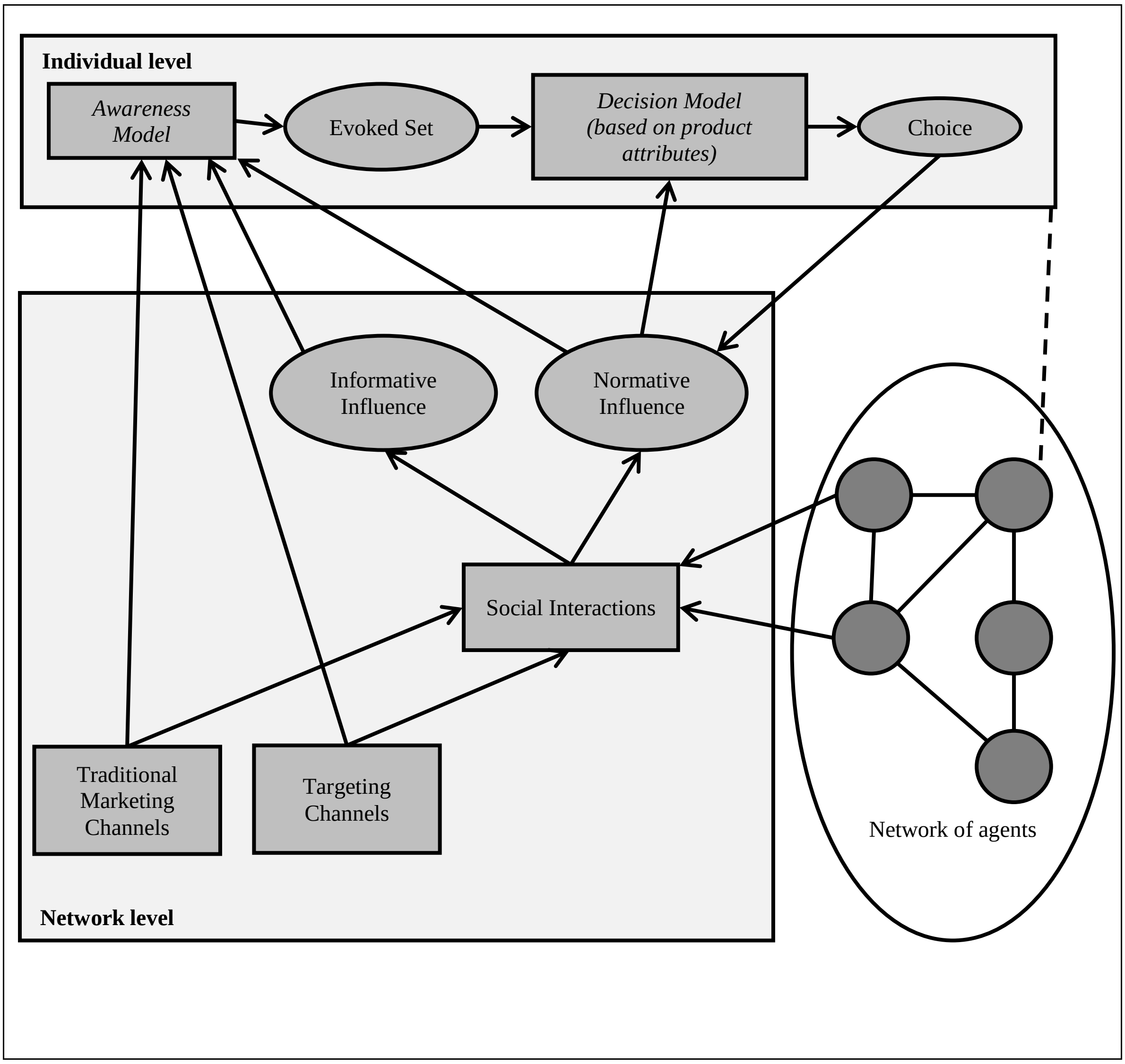
The following sections present the conceptual framework and hypotheses, followed by the methodology. After discussing the experimental design used test the hypotheses, I outline the empirical data. Finally, I present the results and conclude with a fuller discussion.

5.2 Conceptual Framework and Hypotheses

Figure 5.1 shows the relations among the most important concepts in this study. The models are discussed in detail in the next section. As shown in the right bottom corner, customers are connected in a network. With respect to the processes within networks, a distinction differentiates the network level (between customers) from the individual level (within a customer). On the network level, customers communicate (social interactions), affected by both traditional marketing channels and social marketing channels (i.e., being the original source of information). Social interactions also result in informative and/or normative influences, which affect customers at the individual level.

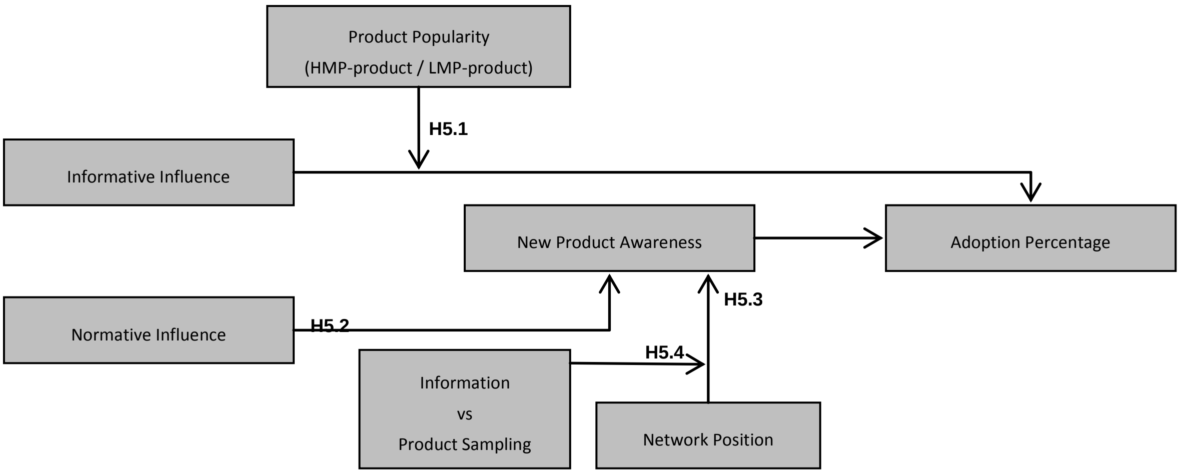
At the individual level, the process starts with a customer becoming aware of a new product. Information about new products can be communicated using traditional (mass) media channels (e.g., journal advertisements, website announcements) or channels that allow for more specific targeting of particular customers, such as social media. In addition, social interactions affect customers' awareness of new products, and such awareness ultimately results in an evoked set. From this evoked set, a customer makes a decision. The decision is potentially affected by social interactions, in the form of normative influence, and the ultimate choice affects future social interactions (e.g., sharing information, social pressure).

Figure 5.1: Process diagram of relations across models and influential factors



This study investigates the relations among informative influence, normative influence, product awareness, and adoption rates in detail. Figure 5.2 displays the conceptual framework. In addition to analyzing the results of different communication strategies (i.e., traditional or targeting channels), the investigation distinguishes product introductions of high market potential (HMP) or low market potential (LMP) products. The HMP product offers a high potential market share, whereas an LMP product is defined as one with only low potential market share. The HMP and LMP are selected based on the empirical data and are specifically defined in section 5.7. In addition, targeting strategies may have differential impacts when the product is distributed (product sampling) or when only information about the product gets distributed.

Figure 5.2: Conceptual model



5.2.1 Traditional Marketing Channels

Customers use traditional marketing communication channels to receive information about new products, including those that encompass a large audience (e.g., provider website) and those that target a smaller audience (e.g., journals). The channels used to spread information affect the percentage of people reached (first-order effect) and therefore the potential adoption rate. They also could affect the social interactions that take place after customers have been reached (second-order effect).

If customers can share the information they receive (informative influence), a higher percentage of customers is aware of the new product, which should lead to a higher adoption rate, because more customers generally consider buying the new product. An informative influence also can have an additional (indirect) positive effect on the adoption rate, because it is more personalized (Feick and Higie, 1992) and therefore more likely to reach customers who are actually interested in the product.

The increase in adoption prompted by an informative influence likely differs between HMP and LMP products: Buyers of LMP products make an unpopular decision (not many other customers are interested in their chosen product), which makes it less useful for them to use social sources to gather information. That is, they are less sensitive to informative influences than buyers of HMP products. Therefore, I expect,

> H5.1: The increased adoption percentage that results from an informative influence is greater for the launch of an HMP product, compared with an LMP product.

When a new product enters the market, an (initial) social pressure exists not to adopt, because no one else uses it. Thus, there is a (social) risk of adoption, which may be hard to overcome (Van Eck, Jager, and Leeflang, 2011). With a negative normative influence, customers are less likely to talk about the new product too. Therefore, the percentage of people aware of the new product may decrease when a negative normative influence exists in the network. Independent of the communication channel used, I hypothesize:

> H5.2: In a network with negative normative influences, the percentage of consumers aware of a new product is lower, compared with in a network without any negative normative influence.

5.2.2 Targeting Channels

Instead of using traditional market channels, companies might decide to target several customers personally. In this case, they must consider the position of the targeted customers within their social networks, because that position affects how many other customers they reach (second-order effect) and who those other customers are (i.e., are contacts likely to adopt the product?). Weimann (1982) differentiates horizontal from vertical information flows, noting that the former flows move between the bridges of networks (i.e., customers who communicate with customers outside of own cluster), whereas the latter flows within a cluster (i.e., between central customers and their contacts). Hinz, Skiera, Barrot, and Becker (2011) find that targeting central customers and bridges is a more successful strategy than random targeting, with respect to the number of people reached in a network. Because targeting either the bridges or the central customers within a network affects the informative influence spread and the awareness of the new product,

> H5.3: The network position of the targeted customers affects the percentage of people aware of the new product and thus the adoption rate of the new product.

It is interesting to investigate not only *whom* to target, using targeting channels, but also *how* to target them. This chapter features two basic strategies. The first informs customers about a new product; the second distributes the product to a select group of customers (product sampling). The product sampling method increases social pressures on the contacts of targeted customers, and it also affects awareness, because use of the product should be visible and therefore easier to talk about. Accordingly,

H5.4: Product sampling has a stronger positive effect on adoption rates than does distributing information about the new product.

5.3 Methodology

In the ABM developed in this study, agents are connected in a social network. The *construction* of this social network is based on survey data. The agent rules in the model comprise two submodels, derived from empirical data that describe searching for information and making decisions on the basis of an estimated choice model. The former *awareness model* determines the evoked set of the agent, and the latter *decision model* determines the agent's choice.

5.3.1 Constructing the Social Network

The creation of the social network relies on the method developed in Chapter 4. Respondents get connected on the basis of their (reported need for) similarity and the type of relations they report they have with other customers. Both similarity (three items) and relationship type (six items) are weighted measures, such that during network development, the combined similarity questions have as much influence as the combined relationship type questions, by adjusting the weight (β_k) of the variables in the *Distance* function (Equation 5.1). The relations include both reported relations (RR), described by the respondent in the empirical data, and actual relations (AR), resulting from the procedure used in the ABM.

Consider an example of respondent *i* (35-year-old male) who reports a relation (RR) with a 35-year-old female *j*. Within this relation, there is a strong, incoming, normative influence (from *j*) and a strong, outgoing, informative influence (toward *j*). Respondent *j* also reports a relation with the 35-year-old male *i*. Within this relation, there is a strong, outgoing, normative influence (toward *i*) and a strong, incoming, informative influence (from *i*). Respondents *i* and *j* are connected; their calculated *Distance* is 0. If the perfect match ($Distance_{ij} = 0$) does not exist, the second best match is chosen (e.g., $Distance_{ij} = 1$). If respondent *i* can connect to two (or more) respondents *j* (i.e., calculated $Distance_{ij}$ is the same for different *j*s), he prefers to connect with a respondent *j* who is already connected to one of his connections; that is, people are more likely to connect with friends of their friends (Granovetter, 1973). Therefore,

$$Distance_{ij} = \sum_{k=1}^{K} \beta_k V_k \quad (5.1)$$
,

where:

$Distance_{ij}$ = the separation between the reported relation (RR) of respondent *i* and the reported relation (RR) of respondent *j*.

β_k = weight of variable k (β_k = 1 if $k \leq 3$ and β_k = 0.5 if $k \geq 4$). These weights ensure that similarity and social influence have the same impact, despite the fact that social influence is measured with six questions and similarity with three questions.

pi = reported relation of agent *i*.

pj = reported relation of agent *j*.

K = number of variables (9).

Similarity

$V_1 = (0.5|gender_{pi} - gender_j|) + (0.5|gender_{pj} - gender_i|)$.

$V_2 = (0.5|age_{pi} - age_j|) + (0.5|age_{pj} - age_i|)$.

$V_3 = (0.5|eduction_{pi} - education_j|) + (0.5|education_{pj} - eduction_i|)$.

As these equations show, for the difference between the reported similarity characteristic (Q1 – Q3, Appendix 5.1) and the actual similarity characteristic (ABM), the values are transformed, such that the maximum is 1 and the minimum is 0. The similarity values are matched from the perspectives of both agent *i* and agent *j*: Similarities from both directions are counted equally and therefore multiplied by 0.5 to ensure a maximum value of 1.

Relationship Type

$V_4 = |OI_{pi} - II_{pj}|$ (OI = importance of outgoing informative influence).

$V_5 = |II_{pi} - OI_{pj}|$ (II = importance of incoming informative influence).

$V_6 = |ON_{pi} - IN_{pj}|$ (ON = importance of outgoing normative influence).

$V_7 = |IN_{pi} - ON_{pj}|$ (IN = importance of incoming influence).

$V_8 = |OS_{pi} - IS_{pj}|$ (OS = strength of outgoing social influence [in general]).

$V_9 = |IS_{pi} - OS_{pj}|$ (IS = strength of incoming social influence [in general]).

These equations reveal the difference between the reported relationship characteristic of agent *i* and agent *j* (Q4 – Q9, Appendix 5.1) and the actual relation characteristic (ABM). In this case, the incoming and outgoing influences cross: The outgoing normative influence for agent *i* relates to the incoming normative influence of agent *j*. The transformed values allow for a maximum of 1 and a minimum of 0.

An imperfect match instead indicates, for example, that the outgoing informative influence reported by agent *i* (OI_{pi}) is higher than the incoming informative influence reported by agent *j* (II_{pj}). To address this inequality, the following transformations can calculate values for the actual relations (AR) between agent *i* and agent *j*, as used in the ABM. The similarity measures cannot be averaged, because as they are agent, and not relation, specific.

$$gender_{AR_{ij}} = gender_j \; .$$

$$gender_{AR_{ji}} = gender_i \; .$$

$$age_{AR_{ij}} = age_j \; .$$

$$age_{AR_{ji}} = age_i \; .$$

$$education_{AR_{ij}} = education_j \; .$$

$$education_{AR_{ji}} = education_i \; .$$

$$OI_{AR_{ij}} = II_{AR_{ji}} = \frac{OI_{pi} + II_{pj}}{2} \; .$$

$$II_{AR_{ij}} = OI_{AR_{ji}} = \frac{II_{pi} + OI_{pj}}{2} \; .$$

$$ON_{AR_{ij}} = IN_{AR_{ji}} = \frac{ON_{pi} + IN_{pj}}{2} \; .$$

$$IN_{AR_{ij}} = ON_{AR_{ji}} = \frac{IN_{pi} + ON_{pj}}{2} \; .$$

$$OS_{AR_{ij}} = IS_{AR_{ji}} = \frac{OS_{pi} + IS_{pj}}{2} \; .$$

$$IS_{AR_{ij}} = OS_{AR_{ji}} = \frac{IS_{pi} + OS_{pj}}{2} \; .$$

To calculate total *Error* in the network, I add all *Distances* between the RR of agent *i* and agent *j* (Equation 5.2). The standardized error can be calculated using Equation 4.3 (Chapter 4): with Error=1,610, *NCN* (number of connections in network)=2,165 $Distance_{MAX}$=9, the SE=0.041 (an error of 0 would indicate a perfect fit).

$$Error = \sum_{i=1}^{I} \sum_{j=1}^{J} Distance_{ij} \; , \qquad (5.2)$$

where:

Error = summed distances between the reported (survey) relations (RR) and the actual relations (AR) in the created network.

5.3.2 Awareness Model

The awareness model indicates how agents receive information about a new product. In the survey, respondents selected all information sources they used to obtain information about cell phones (Q1, Appendix 5.3) but also indicated the most important source (Q2, Appendix 5.3). This information can be translated, according to the following rules, within the awareness model:

1. Agents seek information from their most important source in every time period. Because it is their most important source of information, they check the source intensively and retrieve all information available from this particular source. If the model excludes informative influences (given a specific experiment), agents using a social source must select another source and choose this other information source randomly as their main source. If they use no other information source, agents randomly select an information source, according to the overall distribution of information sources found in the empirical data.
2. If agents use other information sources, in every time period, one of these sources is randomly selected. Agents check these sources less intensively and might not be able to retrieve all available information; the probability that agent *i* retrieves information about a particular product depends on its sensitivity to incoming informative influence (II_i), calculated as follows:

$$II_i = \frac{ASII_i - 1}{4} \tag{5.3}$$

where:

II_i = general sensitivity to incoming informative influence by agent *i*.

$ASII_i = \left(\frac{Q9 + Q10 + Q11 + Q12}{4} \right)$, which is the average score on the scale of incoming informative influence for agent *i*.

Q9, Q10, Q11, and Q12 are the scores on the scale of informative influence, as found in Appendix 5.2.

To include informative influence in the model, agents may have two social information sources: (1) talking with other agents and (2) observing which products other agents adopt. The first option implies that the agent can retrieve information from another agent about all products the other agent is *aware* of, and the second implies that the agent retrieves information about products the other agent *adopts*.

Next, the agent selects one of its connections. The probability of selecting a particular connection (AR) depends on the strength of the incoming informative influence associated with this connection between agents *i* and *j* ($II_{AR_{ij}}$). A higher $II_{AR_{ij}}$ results in a higher selection probability. For example, if agent *i* has three connections, with $II_{AR_{ij}}$ values of 2, 3, and 5, the probability that it will select these connections is, respectively, 20%, 30%, and 50%.

5.3.3 Decision Model

A choice model (Equation 5.4) provides the foundation for the *decision model*. To allow for heterogeneity between customers, a conjoint study provides the input for a concomitant variable latent class analysis (Kamakura, Wedel, and Agrawal, 1994). This type of model allows for product preferences to differ across latent classes while simultaneously relating the latent classes and product preferences with additional covariates. Several variables are tested as covariates: age, gender, education, and general sensitivity to incoming and outgoing informative and normative influences.

The model estimation relies on LatentGold Choice 4.5. The concomitant variable latent class analysis supports heterogeneity among consumers in estimating the choice model.

$$P_{sim} = \frac{e^{\sum_{k=1}^{K}\sum_{v=1}^{V}\beta_{svk}x_{vkm}}}{\sum_{c=1}^{C_i} e^{\sum_{k=1}^{K}\sum_{v=1}^{V}\beta_{svk}x_{vkc}}} \tag{5.4}$$

where:

P_{ism} = probability that respondent *i*, belonging to class *s* buys product *m*,

x_{vkm} = dummy variable indicating whether value *v* of characteristic *k* of product *m* is 0 or 1 (e.g., brand name of the product),

β_{svk} = estimated parameter for respondents belonging to class *s* with respect to value *v* of characteristic *k*; note that the ABM uses the posterior mean estimates for the individual coefficients for further analyses

x_{vkc} = dummy variable indicating whether value *v* of characteristic *k* of product *c* is 0 or 1 (e.g., brand name of the product), and

C_i = number of products of which respondent *i* is aware (evoked set).

If normative influence is present in the model (given certain experiments), within the ABM, Equation 5.4 extends to Equation 5.6, such that the β parameters become specific to product *m*. Thus normative influence can affect the decisions of agents. Certain product alternatives are more attractive if connected agents adopt that product, so (1) the sum of the influences of connected agents is smaller or equal to a general level of sensitivity to incoming normative influence for agent *i* (IN_i) (Equation 5.5) and (2) the influence of a particular connection, the actual relation (*AR*) between agent *i* and agent *j*, depends on the incoming normative influence of that particular relation ($IN_{AR_{ij}}$).

$$IN_i = \frac{ASIN_i - 1}{4} \quad (5.5)$$

where:

IN_i = general sensitivity to incoming normative influence of agent i;

$ASIN_i = \left(\frac{Q1 + Q2 + Q3 + Q4 + Q5 + Q6 + Q7 + Q8}{8} \right)$, or the average score on scale of incoming normative influence of agent i; and

Q1, Q2, Q3, Q4, Q5, Q6, Q7, and Q8 are the scores on the scale for informative influence, as in Appendix 5.2.

$$P_{sim} = \frac{e^{\sum_{k=1}^{K}\sum_{v=1}^{V}\beta_{sivkm}x_{vkm}}}{\sum_{c=1}^{C_i} e^{\sum_{k=1}^{K}\sum_{v=1}^{V}\beta_{sivkc}x_{vkc}}} \quad (5.6)$$

where:

P_{sim} = probability that respondent i, belonging to class s buys product m,

x_{vkc} = dummy variable indicating whether value v of characteristic k of product c (=1, …, m, …, C_i) is 0 or 1 (e.g., brand name of the product), and

C_i = number of products of which respondent i is aware.

$$\beta_{sivkc} = \beta_{svk} + \sum_{j=1}^{J_{im}} \left(IN_{AR_{ij}} \frac{IN_i}{\sum_{l=1}^{L_i} IN_{AR_{il}}} \right),$$

where:

J_{im} = number of connections of respondent i who adopt product m (if J_{im} = 0, then $\beta_{sivkm} = \beta_{svk}$), and

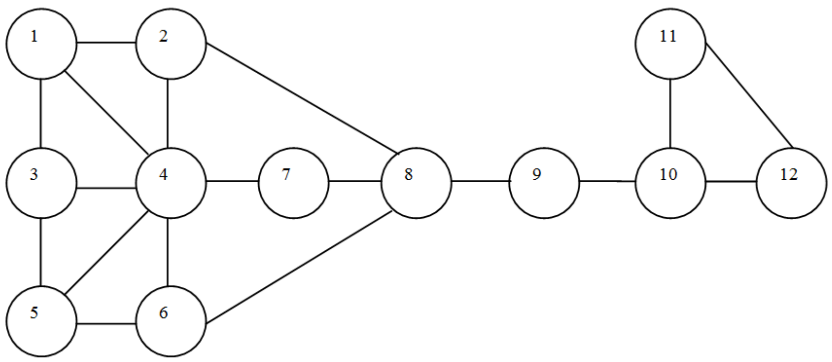
L_i = number of connections of respondent i.

5.4 Experimental Design

To test the hypotheses, several experiments use ABM; Table 5.1 summarizes the experimental design. The test of Hypothesis 5.1 involves varying the presence of informative influence in the model (present/absent), the product type (LMP/HMP), and the traditional marketing channels (8 separate/all channels together). In these experiments, normative influence is not present. For Hypothesis 5.2, informative influence remains consistently present, but the test varies the presence of normative influence (present/absent), product type (LMP/HMP), and traditional marketing channels (8 separate/all channels together) experimentally.

Finally, to test Hypotheses 5.3 and 5.4, both normative and informative influence remain constantly present in the network, whereas product type (LMP/HMP) and distribution (information/product) vary, as do the four potential positions of targeted customers, such that the targeting focuses on customers (1) randomly within the network, (2) who form bridges across clusters (high betweenness centrality serves as an indicator of the number of shortest paths moving through a specific customer in a network), (3) who have central positions within a cluster (high degree centrality indicates the number of connections a specific agent has), and (4) who have central positions within a network (high closeness centrality, or the number of steps by which a specific customer is separated from any other customer in the network). Figure 5.3 depicts an example network, to demonstrate the differences across centrality measures. Option 1 can result in targeting any customer, Option 2 targets customer 9, Option 3 focuses on customer 7, and Option 4 results in targeting customer 9. In all targeting scenarios, the product is launched by a cell phone company, which distributes information about the new product to 1.6% of agents. By using a low percentage, this study creates a realistic scenario, in that higher percentages are less feasible for a company that uses a personalized targeting strategy. Lower percentages likely would not trigger any effect at all.

Figure 5.3: Network example: Visualizing centrality measures



Customer 9 functions as a bridge (scores high on *betweenness centrality*)
Customer 4 has a central position within a cluster (customers 1-7) (scores high on *degree centrality*)
Customer 7 has a central position in the network (scoring high on *closeness centrality*)

Table 5.1: Summary of experimental designs

H5.1: The increased adoption percentage that results from an informative influence is greater for the launch of an HMP product compared with an LMP product.		
Experimental design	2 × (1) × 2 × 9	
Variables experimentally varied:	Informative influence active in model:	Yes/no
	Normative influence active in model:	No
	New product type:	HMP/LMPproduct
	Traditional marketing channel offering information about the new product:	Shop/salesperson/site manufacturer/site provider/comparison site/folder/journal/other/ all sources
H5.2: In a network with negative normative influence, the percentage of consumers aware of a new product is lower, compared with a network without negative normative influence.		
Experimental design	(1) × 2 × 2 × 9	
Variables experimentally varied:	Informative influence active in model:	Yes
	Normative influence active in model:	Yes/no
	New product type:	HMP/LMP
	Traditional marketing channel offering information about the new product:	Shop/salesperson/site manufacturer/site provider/comparison site/folder / journal/other/ all sources
H5.3: The network position of the targeted customers affects the resulting percentage of people aware of the new product and thus the adoption rate of the new product. H5.4: Product sampling has a stronger positive effect on the percentage of customers aware of the new product and thus its adoption rate than does distributing information about the new product.		
Experimental design	(1) × (1) × 2 × 2 × 4	
Variables experimentally varied:	Informative influence active in model:	Yes
	Normative influence active in model:	Yes
	Distributing:	Information/product
	New product type:	HMP/LMP
	Position of targeted customers:	Random/high betweenness centrality[1]/high degree centrality[2]/high closeness centrality[3]

[1] Indicator of the number of shortest paths going through a specific agent in a network, normalized by network size.

[2] Indicator of the number of connections a specific agent has, normalized by network size.

[3] Indicator of the number of steps by which a specific agent is separated from any other agent in the network, normalized by network size.

5.5 Simulation Procedure

5.5.1 Situation at t = 0

To test the hypotheses, several experiments were performed, using the proposed ABM as a basis. The model features a market with five competing products; all agents are aware of all five products, so their evoked set consists of five products at t = 0. The agents make a random choice, after which the decision model (depending on the experiment, Equation 5.4 or Equation 5.6) allows them to select a product they prefer. The random choice is needed first, because every agent has a cell phone to start, but then in the decision model, they could decide not to buy any cell phone (i.e., they stick with their random choice).

5.5.2 Running the Experiments

The experiments include three distinct time periods: before new product introduction, the moment of the new product introduction, and after new product introduction.

Ad 1. At time t = 0, all agents are aware of all products available in the market, so the awareness model has no influence. For the decision model, there are two possible scenarios: without or with normative influence. In experiments without normative influence, the decision model (Equation 5.2) immediately results in a stable market situation, such that agents select a cell phone they prefer or stay with their random first choice if they do not like the available options. If normative influence is present in the network (Equation 5.4), the choices made by the agents depend on the choices of other agents in the network. The decision model repeats until the market is stable, as occurs when none of the agents have changed their decision in five consecutive time periods.

Ad 2. A stable situation changes with the introduction of a new product in the market. Which product gets introduced (LMP/HMP) and how (marketing strategy) represent the experimentally varied constructs, as summarized in Table 5.1.

Ad 3. After the product introduction, the simulation runs until a new stable market arises. Agents consecutively pursue new information (through the awareness model) and use it to make a decision (through the decision model). The market is stable if none of the agents receive new information or change their decision in five consecutive time periods.

All experiments repeat 50 times; the results presented in the results section reflect the average across these 50 repetitions.

5.6 Empirical Data

Five hundred members of an Internet panel maintained by GfK Germany completed an electronic survey about a cell phone purchase decision. These respondents had just bought a cell phone (past six months) or planned to buy one in the near future (within three months), so they were aware of the decision process. The survey contained:

- Conjoint study.
- Survey in which customers specified information about their social network and their SI behavior.
- Survey about customers’ sensitivity to informative and normative influences and their information searching behavior.

5.6.1 Data from the Conjoint Study

All respondents evaluated 15 different choice sets. Within each choice set, the respondent has to choose from three cell phones and a "none" option. The cell phones were described using the nine characteristics described in Table 5.2. The study differentiated postpaid from prepaid contracts: Postpaid contracts apply a monthly fee, which is considerably lower than the onetime fee involved with a prepaid contract. The 355 respondents who currently had a postpaid contract answered the postpaid choice sets, while 145 respondents who had prepaid contracts answered the prepaid choice sets. In this sense, price was the only variable that differed between the two groups of respondents. The conjoint study then provided the input for the decision model; the product characteristics of the HMP and LMP products also reflected the results of the conjoint study.

5.6.2 Network Information

Respondents answered several questions about their network position (see Appendix 5.1 for the full list of survey questions), including the number of other customers with whom they talked about cell phones. For the first five relations, they reported how similar they were (age, gender, and education) and what kind of influence each relation had. These items supported the distinction between normative and informative influence and between (for both types of influence) incoming and outgoing influence.

5.6.3 Additional Information

To combine the information about the network position of customers and their sensitivity to social influence, the respondents also answered 12 additional questions about their (general) sensitivity to normative and informative influences (see Appendix 5.2). For the investigation of the relation between traditional marketing channels and social interactions in a network, the respondents reported which information sources they used to collect information about cell phones (see Appendix 5.3).

Table 5.2: Cell phone characteristics used in the conjoint study

Characteristic		Value		
Attribute Number	Information	Number	Information	
1	Design type	1	Bar	
		2	Clam	
		3	Slider	
		4	PDA with keyboard	
		5	PDA with touch screen	
2	Brand	1	Sony Ericsson	
		2	Motorola	
		3	Nokia	
		4	Sagem	
		5	Samsung	
		6	LG	
		7	Blackberry	
3	Camera	1	None	
		2	1.3 Megapixel	
		3	2.0 Megapixel	
		4	3.2 Megapixel	
		5	5.0 Megapixel	
4	Music features	1	None	
		2	Radio	
		3	MP3 player	
		4	Radio + MP3 player	
5	E-mail functionality	1	None	
		2	Client without push function	
		3	Client with push function	
6	Organizer	1	None	
		2	Synchronization with PC not possible	
		3	Synchronization with PC possible	
7	WLAN	1	No	
		2	Yes	
8	GPS	1	No	
		2	Yes	
			Postpaid	Prepaid
9	Price	1	9.99	49.99
		2	79.99	119.99
		3	149.99	189.99
		4	219.99	329.99

5.7 Empirical Results

The estimations of two separate models—one for the 145 prepaid users and one for 355 postpaid users—both resulted in three latent classes. For the postpaid users model, outgoing normative and outgoing informative influences significantly improved model fit. In the prepaid users model, only incoming normative influence improved model fit.

The R-square values of the models were calculated by comparing the prediction error with a null model in which the predicted probability of selecting an alternative was based on the overall observed marginal distribution of that alternative. As shown in Tables 5.3 and 5.4, the improvement, compared with the null model, was relatively low (prepaid 40.7%; postpaid 30.9%).

Because the parameters of the choice model were estimated at the individual level, they were included in the ABM at the individual level too. Table 5.3 shows the Average Weight of Evidence (AWE) scores of the 1 to 5 class solutions of both the postpaid and prepaid model. This selection criteria is proposed by Banfield and Raftery (1993) and implemented in Latent GOLD Choice (Vermunt and Magidson, 2005). This criteria suggests a 3-class solution for the prepaid model and a 3-class or 4-class solution for the postpaid model. Given the small improvement for the 4-class solution, the 3-class solution is selected for both the postpaid and prepaid model.

Table 5.3: Average Weight of Evidence (AWE) scores of prepaid models and postpaid models

	Prepaid model	Post model
1-class solution	5432	13157
2-class solution	4901	11749
3-class solution	4673	11479
4-class solution	4777	11434
5-class solution	4882	11509

Tables 5.3 and 5.4 show the parameter estimates of the choice model for prepaid and postpaid users, respectively. The parameters for product characteristics that did not differ significantly from 0 were set to 0, prompting a model re-estimation. The parameter estimates in Tables 5.3 and 5.4 represented the ultimate results of this estimation process. As shown in Table 5.4, several parameters did not differ for prepaid users and thus were excluded: music features, e-mail functionality, and GPS. For Class 3, three variables needed to be excluded, because the parameters estimated for the different categories did not differ significantly within the class, namely, design type, brand, and the "none" option. The none option referred to a preference not to buy any phone from the offered set. From the model for postpaid users (Table 5.5), only one variable had to be excluded for Class 3 (e-mail functionality).

The results of the estimated choice model specified which HMP and LMP product to select. The initial market consisted of five products, so the introduced HMP or LMP product represented the sixth product on the market. For this market, the HMP product (preferred by 47.4% of respondents) contained a *PDA with touchscreen*, Sony Ericsson, 5 megapixel camera, *no music feature*, e-mail client with push function, organizer with synchronization option, WLAN, and GPS, offered at a price of €9.99. The LMP product (preferred by 7.4% of the respondents) instead offered the following attributes: *clam phone*, Sony Ericsson, 5 megapixel camera, *radio & MP3 player*, e-mail client with push function, organizer with synchronization option, WLAN, and GPS, offered at a price of €9.99. Neither product was particularly realistic with respect to their characteristics, but they represented two fundamentally different offerings, namely, a quite popular product and a product preferred by just a few people in the market.

Table 5.4: Parameter estimates of decision model based on latent class analysis for 145 prepaid users

	Latent Classes					
Characteristic	Class 1 (estimates)	SE	Class 2 (estimates)	SE	Class 3 (estimates)	SE
Design type						
Bar	-0.01	0.09	0.02	0.19	0	Na
Clam	-0.62	0.11	0.09	0.19	0	Na
Slider	0.13	0.1	0.32	0.24	0	Na
PDA with keyboard	0.04	0.09	-0.86	0.27	0	Na
PDA with touch screen	0.46	0.08	0.43	0.17	0	Na
Brand						Na
Sony Ericsson	0.26	0.11	-0.09	0.26	0	Na
Motorola	-0.17	0.11	-0.14	0.24	0	Na
Nokia	0.18	0.11	0.77	0.19	0	Na
Sagem	-0.34	0.12	-0.17	0.25	0	Na
Samsung	-0.17	0.12	0.43	0.22	0	Na
LG	0.01	0.11	-0.17	0.25	0	Na
Blackberry	0.23	0.11	-0.64	0.33	0	Na
Camera						
None	-0.28	0.08	-0.28	0.08	-0.28	0.08
1.3 Megapixel	-0.21	0.08	-0.21	0.08	-0.21	0.08
2.0 Megapixel	0.06	0.07	0.06	0.07	0.06	0.07
3.2 Megapixel	0.15	0.07	0.15	0.07	0.15	0.07
5.0 Megapixel	0.29	0.07	0.29	0.07	0.29	0.07
Music Features						
None	0	Na	0	Na	0	Na
Radio	0	Na	0	Na	0	Na
MP3 Player	0	Na	0	Na	0	Na
Radio + M3 Player	0	Na	0	Na	0	Na
E-mail functionality		Na		Na		Na
None	0	Na	0	Na	0	Na
Client without push function	0	Na	0	Na	0	Na
Client with push function	0	Na	0	Na	0	Na
Organizer						
None	-0.13	0.05	-0.13	0.05	-0.13	0.05
Synchronization with PC not possible	-0.1	0.05	-0.1	0.05	-0.1	0.05
Synchronization with PC possible	0.23	0.05	0.23	0.05	0.23	0.05
WLAN						
No	-0.08	0.03	-0.08	0.03	-0.08	0.03
Yes	0.08	0.03	0.08	0.03	0.08	0.03
GPS						
No	0	Na	0	Na	0	Na
Yes	0	Na	0	Na	0	Na
Price						
49.99	0.23	0.08	1.31	0.17	2.59	0.15
119.99	0.21	0.07	0.05	0.2	0.26	0.13
189.99	-0.21	0.08	-0.07	0.24	-1.07	0.18
329.99	-0.23	0.08	-1.29	0.31	-1.78	0.22
None						
0	0.13	0.05	-1.58	0.08	0	Na
1	-0.13	0.05	1.58	0.08	0	Na
R-square	0.4071		Prediction error	0.3545		

Notes: Parameters differ significant at 0.05 within each class and within each characteristic. If parameters for classes differ between classes, this difference is also significant at 0.05.

Table 5.5: Parameter estimates of decision model based on latent class analysis for 355 postpaid users

	Latent Classes					
Characteristic	Class 1 (estimates)	SE	Class 2 (estimates)	SE	Class 3 (estimates)	SE
Design type						
Bar	0.09	0.11	-0.15	0.06	-0.39	0.18
Clam	-0.45	0.11	-0.48	0.06	0.17	0.18
Slider	-0.01	0.1	-0.03	0.05	0.67	0.2
PDA with keyboard	-0.09	0.1	0.14	0.05	-0.07	0.18
PDA with touch screen	0.46	0.09	0.51	0.05	-0.37	0.19
Brand						
Sony Ericsson	0.19	0.12	0.26	0.06	0.45	0.26
Motorola	-0.61	0.16	-0.11	0.07	-0.47	0.24
Nokia	0.67	0.1	0.04	0.07	0.18	0.21
Sagem	-0.75	0.16	-0.44	0.07	-0.31	0.21
Samsung	0.12	0.12	0.15	0.07	0	0.25
LG	-0.31	0.14	-0.11	0.07	0.24	0.22
Blackberry	0.69	0.14	0.2	0.08	-0.09	0.23
Camera						
None	-0.22	0.05	-0.22	0.05	-0.22	0.05
1.3 Megapixel	-0.18	0.05	-0.18	0.05	-0.18	0.05
2.0 Megapixel	-0.03	0.04	-0.03	0.04	-0.03	0.04
3.2 Megapixel	0.14	0.04	0.14	0.04	0.14	0.04
5.0 Megapixel	0.3	0.04	0.3	0.04	0.3	0.04
Music Features						
None	-0.12	0.04	-0.12	0.04	-0.12	0.04
Radio	-0.17	0.04	-0.17	0.04	-0.17	0.04
MP3 Player	0.1	0.04	0.1	0.04	0.1	0.04
Radio + M3 Player	0.19	0.04	0.19	0.04	0.19	0.04
E-mail functionality						
None	-0.1	0.08	-0.21	0.04	0	Na
Client without push function	0.16	0.07	0.07	0.04	0	Na
Client with push function	-0.07	0.09	0.13	0.04	0	Na
Organizer						
None	-0.05	0.03	-0.05	0.03	-0.05	0.03
Synchronization with PC not possible	-0.09	0.03	-0.09	0.03	-0.09	0.03
Synchronization with PC possible	0.14	0.03	0.14	0.03	0.14	0.03
WLAN						
No	-0.1	0.02	-0.1	0.02	-0.1	0.02
Yes	0.1	0.02	0.1	0.02	0.1	0.02
GPS						
No	-0.11	0.02	-0.11	0.02	-0.11	0.02
Yes	0.11	0.02	0.11	0.02	0.11	0.02
Price						
9.99	0.88	0.07	0.22	0.05	3.38	0.3
79.99	0.04	0.09	0.17	0.04	0.71	0.28
149.99	-0.47	0.11	-0.04	0.05	-1.15	0.37
219.99	-0.44	0.1	-0.35	0.05	-2.94	0.72
None						
0	-1.36	0.04	0.23	0.03	-0.93	0.14
1	1.36	0.04	-0.23	0.03	0.93	0.14
R-square	0.3093		Prediction error	0.3731		

Notes: Parameters differ significant at 0.05 within each class and within each characteristic. If parameters for classes differ between classes, this difference is also significant at 0.05.

5.8 Simulation Results

The parameters show in Table 5.4 and Table 5.5 are saved for every individual (depending on their class membership) and included in the simulation model. So, the latent class analysis is used to introduce heterogeneity in the individual agent preferences for certain product characteristics. In the ABM these preference are combined with 1) the additional information from the survey with respect to the sensitivity to normative influence and informative influence and preference preferences for information sources, and 2) the network structure that is constructed in section 5.3.

Table 5.6 shows the awareness and adoption rates for the experiments in which traditional marketing channels served to launch the new product (Hypotheses 5.1 and 5.2).

Table 5.6: Overview of awareness rates, adoption rates, and market shares for traditional marketing channels

Source	Percentage Awareness in Network				Percentage Adoption in Network			
	No II & no NI	Only II	Only NI	II & NI	No II & no NI	Only II	Only NI	II & NI
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HMP product								
Salesperson	43.8	50.9	43.7	49.4	19.1	23.8	8.0	11.0
	(0.3)	(0.7)	(0.3)	(0.8)	(0.2)	(0.6)	(0.4)	(1.0)
Shop	24.2	37.5	24.2	34.9	12.2	19.8	3.9	5.6
	(0.3)	(1.2)	(0.4)	(1.5)	(0.2)	(0.9)	(0.3)	(0.9)
Site manufacturer	49.1	55.0	49.2	53.1	23.8	27.5	10.3	11.4
	(0.3)	(0.7)	(0.2)	(0.8)	(0.2)	(0.5)	(0.6)	(1.3)
Site provider	48.0	54.5	48.0	53.0	25.1	29.1	11.0	12.9
	(0.3)	(1.0)	(0.3)	(1.1)	(0.2)	(0.7)	(0.8)	(1.2)
Comparison site	53.7	59.1	53.7	57.9	27.8	31.2	13.9	16.4
	(0.3)	(0.7)	(0.3)	(0.8)	(0.2)	(0.4)	(0.8)	(1.8)
Folder	21.8	33.0	21.6	31.5	10.2	16.8	2.5	5.0
	(0.5)	(1.3)	(0.7)	(1.2)	(0.4)	(0.8)	(0.4)	(1.0)
Journal	21.2	32.4	21.2	29.5	11.1	17.5	3.4	4.8
	(0.8)	(1.0)	(0.8)	(2.2)	(0.5)	(0.7)	(0.3)	(1.0)
Other source	10.8	27.9	10.6	27.1	4.9	14.8	2.2	6.0
	(1.1)	(1.8)	(1.3)	(1.9)	(0.6)	(0.7)	(0.3)	(0.9)
All sources	100.0	99.9	100.0	99.9	47.4	47.4	38.8	38.9
	(0.0)	(0.1)	(0.0)	(0.1)	(0.0)	(0.1)	(4.1)	(4.2)
LMP product								
Salesperson	43.7	48.7	43.7	47.8	3.8	4.4	2.4	2.4
	(0.3)	(0.8)	(0.4)	(0.7)	(0.0)	(0.1)	(0.3)	(0.2)
Shop	24.2	34.3	24.2	33.6	1.4	2.3	0.6	0.8
	(0.3)	(1.3)	(0.4)	(1.5)	(0.0)	(0.1)	(0.1)	(0.2)
Site manufacturer	49.1	52.4	49.2	52.1	2.2	2.4	0.7	1.0
	(0.2)	(0.7)	(0.3)	(0.6)	(0.1)	(0.1)	(0.2)	(0.2)
Site provider	48.0	51.8	47.9	51.2	3.4	3.6	1.7	1.5
	(0.3)	(0.7)	(0.3)	(0.8)	(0.0)	(0.1)	(0.2)	(0.3)
Comparison site	53.7	57.1	53.7	56.8	2.6	3.2	1.0	1.5
	(0.3)	(0.7)	(0.3)	(0.8)	(0.0)	(0.1)	(0.2)	(0.2)
Folder	21.7	31.2	21.6	30.4	1.1	1.7	0.4	0.6
	(0.6)	(1.3)	(0.7)	(1.3)	(0.1)	(0.2)	(0.2)	(0.2)
Journal	21.4	29.1	21.4	28.0	1.3	1.9	0.1	0.5
	(0.8)	(1.4)	(0.8)	(1.7)	(0.1)	(0.1)	(0.1)	(0.2)
Other source	11.1	24.8	10.9	23.9	0.6	1.2	0.3	0.5
	(1.1)	(1.9)	(1.1)	(2.9)	(0.1)	(0.3)	(0.1)	(0.2)
All sources	100.0	99.8	100.0	99.4	7.4	7.4	4.0	4.1
	(0.0)	(0.2)	(0.0)	(0.2)	(0.0)	(0.0)	(0.4)	(0.4)

Notes: For all values, the mean (standard deviation) is based on 50 repetitions of the experiment. II = informative influence; NI = normative influence, HMP = high market potential, and LMP = low market potential.

The HMP product has a potential market share of 47.4% (column 6, all sources), assuming no informative or normative influence. However, with normative influence, the percentage drops to 38.9% (column 9, all sources). Similarly, the potential market share of the LMP product declines from 7.4% (column 6, all sources) to 4.1% (column 9, all sources) when normative influence enters the model. This evidence affirms the importance of considering normative influence in models of new product introductions: A model that ignored this type of influence would produce overly optimistic adoption predictions.

The experiments that do not include informative or normative influence (column 2 in Table 5.6), give a clear indication of the reach of certain communication channels. Comparison sites reach about

54% of the market directly; journals reach 21%. Informative influence increases these percentages (column 3), but normative influence does not have a direct impact on awareness (column 4). The combined effects of informative and normative influence is positive (column 5), but the resulting awareness is slightly lower than that which occurs with only informative influence. Some agents selected “check which cell phones others have” as their main source of information, so if a new cell phone is not adopted by anyone in the agent’s network, it is unlikely that the agent becomes aware of the product.

Compared with a situation without normative influence, informative influence has a positive effect on adoption rates (column 7 in Table 5.6), whereas normative influence has a negative influence (column 8). The combination of normative and informative influence results in a lower adoption rate compared with a situation without these influences (column 9). This result can be explained mainly by the popularity of the product class and resulting adoption rate. Even the HMP product is preferred by less than 50% of the market, so normative influence remains negative in almost all simulation runs. That is, the norm in the network is *not* to adopt. Furthermore, the people who do not prefer the HMP product may have a preference for another product that is too strong to overcome with just normative influences. Overall, the conclusions based on the outcomes in Table 5.6 do not differ between the HMP and LMP products.

Hypothesis 5.1 predicted that the adoption percentage increases that result from informative influences should be greater for a new HMP product launch. To test this hypothesis, it is necessary to calculate the percentage increase in adoption rates between the experiments without and with informative influences, by matching the experimental results. A t-test indicated whether the increases in percentages differed significantly between product types (Table 5.7). The overall difference (not distinguishing among information sources) was significant and more positive for HMP products, as expected. This pattern held for all but two information sources: shop and comparison sites. For these two information sources, the LMP product seemingly profited the most from the inclusion of informative influences in the model. This result cannot be explained by the sources of information that buyers of the LMP product used but rather by the sources of information used by the people to whom they were connected. Buyers of the LMP product thus appeared more connected to people who used shops and comparison sites as a source of information, compared with buyers of the HMP product.

As Table 5.6 indicates, informative influence had a positive influence on the awareness percentage. However, Hypothesis 5.2 predicted that in a network with negative normative influence, the percentage of aware customers would be lower than in a network without negative normative influence. Tables 5.7 (HMP product) and 5.8 (LMP product) present the results of the comparison between models with only informative influences and those with both informative and normative influence. In support of Hypothesis 5.2, awareness decreased significantly in nearly every case (cf. the other channel). However, the differences were smaller for the LMP product, which may be because informative influence also had a weaker positive influence in this market.

Table 5.7: Comparison of adoption rates due to informative influence for HMP and LMP products

Source	Percentage Increase in Adoption Rate		t-Value (Comparison Test)
	Popular Mean (standard deviation)	Unpopular Mean (standard deviation)	
Salesperson	24.5 (2.9)	15.1 (2.7)	16.705***
Shop	62.3 (8.2)	67.4 (11.2)	2.635**
Site manufacturer	15.6 (2.5)	8.3 (4.9)	9.394***
Site provider	16.0 (2.9)	4.4 (2.9)	20.317***
Comparison site	12.3 (1.7)	21.5 (3.1)	18.451***
Folder	65.3 (8.2)	56.3 (23.2)	2.609*
Journal	58.3 (9.5)	46.2 (19.5)	3.930***
Other source	205.0 (46.7)	116.5 (78.5)	6.852***
Overall	57.4 (62.2)	42.0 (46.5)	3.981***

* Significant at 0.05.
** Significant at 0.01.
*** Significant at 0.001.

Table 5.8: Comparison of no normative influence and normative influences for HMP products

Source	Percentage of Aware Agents in the Network		t-Value	Percentage Change Compared with No NI
	No NI (with II) Mean (standard deviation)	NI (with II) Mean (standard deviation)		
Salesperson	50.9 (0.7)	49.4 (0.8)	9.094*	-2.9
Shop	37.5 (1.2)	34.9 (1.5)	9.475*	-6.9
Site manufacturer	55.0 (0.7)	53.1 (0.8)	13.296*	-3.5
Site provider	54.5 (1.0)	53.0 (1.1)	7.129*	-2.6
Comparison site	59.1 (0.7)	57.9 (0.8)	8.651*	-2.0
Folder	33.0 (1.4)	31.5 (1.2)	5.960*	-4.5
Journal	32.4 (1.0)	29.5 (2.2)	8.792*	-9.0
Other	27.9 (1.8)	27.1 (1.9)	1.899 ns	-2.9

* Significant at 0.001.
Notes: NI = normative influence, II = informative influence.

Table 5.9: Comparison of no normative influence and normative influences for LMP products

Source	Percentage of Aware Agents in the Network		t-Value	Percentage Change Compared with No NI
	No NI (with II) Mean (standard deviation)	NI (with II) Mean (standard deviation)		
Salesperson	48.7 (0.8)	47.8 (0.7)	5.469***	-1.8
Shop	34.3 (1.3)	33.6 (1.5)	2.525*	-2.0
Site manufacturer	52.4 (0.7)	52.1 (0.6)	2.613*	-0.6
Site provider	51.8 (0.7)	51.2 (0.8)	4.187***	-1.2
Comparison site	57.1 (0.7)	56.8 (0.8)	1.991*	-0.5
Folder	31.2 (1.3)	30.4 (1.3)	3.151**	-2.6
Journal	29.1 (1.4)	28.0 (1.7)	3.321**	-3.8
Other	24.8 (1.9)	23.4 (2.9)	1.979 ns	-5.6

* Significant at 0.05.
** Significant at 0.01.
*** Significant at 0.001.
Notes: NI = normative influence, II = informative influence.

To test Hypotheses 5.3 and 5.4, several experiments focused on the relation of awareness rates and adoption rates with targeting channels. The results appear in Table 5.10.

Table 5.10: Results for targeting channels (normative influence and informative influence both present)

	Distributing Information to 1.6% of the Network		Product Sampling to 1.6% of the Network		
	Percentage Aware	Percentage Adoptions	Percentage Aware	Percentage Adoption	t-Test Comparison of Percentage Awareness
HMP product					
Random	6.5	1.2	6.4	1.0	0.060
	(6.4)	(1.1)	(6.9)	(1.6)	
Betweenness centrality	5.3	1.1	6.6	1.9	1.019
	(6.0)	(1.0)	(7.4)	(1.5)	
Degree centrality	22.1	4.3	23.4	5.5	3.144*
	(2.2)	(0.7)	(1.9)	(0.8)	
Closeness centrality	22.8	5.1	22.8	4.8	0.065
	(2.4)	(1.0)	(2.5)	(0.9)	
LPM product					
Random	4.3	0.1	5.7	0.6	1.387
	(4.6)	(0.1)	(6.0)	(0.4)	
Betweenness centrality	4.1	0.0	5.3	0.5	1.073
	(4.8)	(0.1)	(5.9)	(0.2)	
Degree centrality	21.1	0.6	22.2	1.2	2.661*
	(2.3)	(0.1)	(1.7)	(0.2)	
Closeness centrality	21.1	0.6	21.1	0.6	0.030
	(2.0)	(0.1)	(2.0)	(0.2)	

* Significant at 0.01.
Notes: HMP = high market potential, LMP = low market potential.

Hypothesis 5.3 stated that the network position of the targeted customers would affect awareness of the new product. A one-way analysis of variance (ANOVA) tested whether the differences between the results in Table 5.10 were significant. In support of Hypothesis 5.3, awareness was significantly affected by the network position of the targeted group in all four combinations: information/HMP product ($F = 207.260$), information/LMP product ($F = 355.633$), product/HMP product ($F = 163.662$), and product/LMP product ($F = 224.452$). Across the board, agents scoring high on degree or closeness centrality offered the best group to target if the goal was to increase awareness.

As expected, there also was a strong correlation between awareness and adoption rates ($r = 0.6$). For the HMP product, targeting the group that scored highest on closeness centrality with information resulted in a significantly higher adoption rate ($t = 4.722$, $p = 0.000$) than targeting the group with the highest degree centrality. In contrast, for product targeting methods, focusing on the group that scored higher on degree centrality resulted in significantly higher adoption rates ($t = 4.188$, $p = 0.000$). Agents connected to the central agent in the network (high closeness centrality) thus appeared more sensitive to informative influence and less affected by the adoption behavior of other agents, such that they were more interested in the information that the other agents had to offer. Furthermore, agents connected to the central agent within a cluster (high degree centrality) were more sensitive to normative influence: The adoption behavior of the central agent affected the adoption behavior of surrounding agents, whereas the distribution of information about the new product did not have this effect.

According to Hypothesis 5.4, distributing the product, rather than distributing information about it, should increase awareness. The results of the t-test that compared awareness percentages appear in Table 5.10. Although the results were insignificant for most network positions, they offered partial support of Hypothesis 5.4, because a significant increase in awareness occurred when the targeted agents scored high on degree centrality. Distributing the product increased awareness percentages only when central customers within a cluster received those products (as opposed to central customers within a network). This finding held for both LMP and HMP products.

5.9 Conclusions and Discussion

This chapter has presented a model to test different marketing strategies, taking social interactions among customers into account. Specifically, I investigate how informative and normative influences affect the awareness and adoption rates of new products in the market and how these effects depend on the different marketing communication channels used and the product being introduced. This study accordingly demonstrates that combining existing marketing models in an empirically validated agent-based model supports detailed analyses of different marketing strategies and product innovations.

In particular, the increase in adoption percentages achieved through informative influence is greater for HMP than for LMP products. This finding persists in most traditional marketing channels, but two exceptions exist: For shops and comparison sites, the increase is highest for the introduction of an LMP product. Therefore, buyers of the LMP product are more strongly connected to people who use shops and comparison sites as sources of information, compared with buyers of the HMP product. This result affirms the importance of combining information about network position, social influence, information-seeking behavior, and adoption behavior, because the effect of traditional marketing channels on adoption differs, according to the available networks of customers.

Furthermore, the normative influence in a network creates a lower percentage of aware consumers within that network, because some customers use this normative influence as their main source of information. If no customers in the network of a specific customer adopts a product, they will not gain awareness of the product. Including different types of social influence in marketing models thus significantly and strongly affects their outcomes. If normative influence is not included in the model, the informative effect likely gets overestimated.

For the targeting setting, the greatest increase in awareness occurs when targeted people take a central position within a cluster or network. Targeting bridges in a network seems to have an impact similar to that of targeting random people. In addition, differential influences emerge from distributing the product (sampling) versus distributing information about the product on adoption rates. If information is distributed, the best strategy is to target central people in the network (high closeness centrality); the distribution of the product has the strongest impact if it targets central people within a cluster (high degree centrality).

5.10 Limitations and Further Research

As mentioned in the empirical results section, the choice model could perform better. The relatively low improvement, compared with null models, partly reflects the high percentage of cases in which respondents chose the "none" option in the choice sets (prepaid 42%, postpaid 46%), such that predicting choices based on the distribution of these choices was relatively reliable—even a model that predicts that everyone picks "none" is good—which makes improvements more difficult. An option might be to include phone characteristics that are more attractive to consumers, such as focusing on smartphones only. Some phone characteristics do not significantly affect choices (see Tables 5.2 and 5.3); that is, not all characteristics were evaluated as important by customers. Finally, the number of respondents might have an effect, especially in the study of 145 prepaid customers.

A second limitation entails the inclusion of different types of social influence in the ABM. Informative influence is neutral, in that customers share all product characteristics, without any value assumptions. It would be interesting to allow agents to let one negative or positive characteristic affect the interpretation of other characteristics as well, which would integrate both positive and negative informative influences in the model. Normative influence similarly could be positive or negative (e.g., product adopted enthusiastically or rejected). Furthermore, it would be interesting to allow agents to share information about only a few characteristics (e.g., the camera on the phone), because in reality customers are unlikely to know every detail about all the products of which they are aware. Finally, agents usually need to request information, but if a customer reads about an exciting new product, she or he might enthusiastically and actively share this information, in which case her or his contacts do not have to make information requests, because the agent starts the conversation.

In further investigations, it would be interesting to address various other targeting strategies. Whereas this study focused on targeting based on customers' position in a network, recent research suggests that companies might try targeting people on the basis of their profitability (i.e., revenue leaders; Haenlein and Libai, 2013). An alternative option might be to target customers with particular product interests, especially if customers with similar interests appear together in a cluster.

Chapter 6

Conclusions and a Future Outlook[5]

6.1 Summary

When Google introduced its webmail service Gmail in April 2004 (increasing the storage capacity available through e-mail significantly), the company decided not to rely on traditional marketing. Only a few opinion leaders, selected because of their significant activity on Google's blog, were invited to start using Gmail. Eventually these users were permitted to invite several other people to open an account. By this time, news of the new webmail service had spread widely, and people started offering to pay for one of the (normally free) invitations. Without a single marketing investment, Gmail became one of the largest webmail providers in the world.

6.1.1 Word of Mouth: Process Complexity

Social media may help companies increase sales of their products. Communication taking place through social media results from complex social influence processes. Chapter 2 introduced the complexity of social influence, and WoM in particular, with five interrelated questions: (1) about *which products* do people talk, (2) with *whom* do they talk about these products, (3) *why* do they talk about these products, (4) *what* do they talk about, and (5) how does their talk *affect customer behavior*, on both the individual and aggregated (market) level? The answers to these questions offer valuable information about how to manage word of mouth among customers. They may seem reasonably simple to answer, but their interrelationships make answering these questions quite complex. For example, a consumer might discuss the design of a new cell phone with a close friend and the technical features with an acquaintance. Whether either discussion actually influences the person, and which influence is stronger, varies in each relationship though. Without recognizing the complexity of this system, it is impossible to manage WoM to aid product sales.

Whereas Chapter 2 introduces the complexity of social influences, Chapters 3–5 investigate the process step by step, using an agent-based modeling (ABM) approach. This methodology is suitable for exploring the dynamics of complex social systems and has gained momentum in many disciplines (e.g., Gilbert & Troitzsch, 2005). In ABMs, agents (e.g., virtual customers) are connected in a network and follow simple rules, programmed on the individual level. It is possible to use such models to investigate agents' individual choices, variables on the aggregate level (e.g., market share), and

[5] This chapter is partly based on a chapter that appeared as Wander Jager and Peter van Eck (2011), "Nintendo in the Board Room: A Preamble on Gaming in Marketing," in: Wieringa, J.E., P.C. Verhoef, J.C. Hoekstra (Eds.) *Liber Amicorum in honor of Peter S.H. Leeflang*, University of Groningen.

developments over time. Furthermore it is possible to conduct experiments specific to certain parts of the model or certain scenarios in more detail.

6.1.2 Opinion Leaders' Roles in Innovation Diffusion: A Simulation Study

Increasing marketing literature applies agent-based models to study social complexities in markets (e.g., Garcia & Jager, 2011; Gilbert et al., 2007; Libai, Muller, & Peres, 2013). Chapter 3 presented an ABM to investigate a new product introduction, based on the model discussed by Delre et al. (2007). In particular, I incorporated empirical data about the characteristics of opinion leaders and their network positions to investigate their influence in diffusion processes. Opinion leaders increase the speed of the spread of information and the diffusion of the product, as well as the ultimate adoption percentage. With the ABM, my coauthors and I also could separate out the effects of different characteristics of opinion leaders, which revealed that informative influence exerted a dominant effect on adoption speed and the speed of information sharing. Adoption percentage instead depends on the innovative behavior of opinion leaders and their lower sensitivity to normative influence.

6.1.3 Constructing Empirically Valid Social Networks: An Algorithm for Processing Survey Data

Chapter 3 represented a first attempt to use empirical data to validate an ABM. This model used a relatively simple (though well-known) scale-free network and relied on (literature-based) assumptions about characteristics, such as the relation between innovative behavior and sensitivity to social influence. This kind of relation may differ among customers within the same network. Chapter 4 proposes a method to eliminate these limitations.

Researchers face a challenge in their efforts to collect data about large-scale networks. The existence of online social networks, such as Facebook, offers an opportunity to investigate the personal networks of customers. However, it remains difficult to collect data about actual influences within these networks. Beyond ethical and legal concerns in collecting data about the conversations, their impact would be hard to deduce from these data. The method in Chapter 4 suggests a means to use survey data to create an artificial network structure. The survey needs to contain information about the network position of the respondent and the type of relations he or she has with the other people in the network. In addition, the survey can contain all kinds of information relevant to the research question. Ultimately, the method creates a network of agents that captures the properties of a real network and provides a means to connect these agents with other important characteristics such as product preferences and their sensitivity to social influence. At this stage, no assumptions are needed with respect to the relation between the network position and other personal characteristics.

6.1.4 Social Interaction and New Product Introductions: How to Reach a Narrowly Defined Target Group

Chapter 5 investigates the impact of different marketing strategies (using traditional and social media channels) to introduce a new product. The proposed method for creating the network is applied, in combination with concomitant variable latent class analysis, to determine preferences for products at the individual level. The ABM developed in Chapter 5 thus demonstrates that combining existing marketing models in an empirically validated ABM supports detailed analyses of different marketing strategies and product innovations. The marketing strategies include the use of different traditional and social media channels. Two product innovations, with varying levels of market potential, are investigated: HMP and LMP.

With respect to the use of traditional marketing channels, this study shows that informative influence in a network has a stronger effect on increasing adoption percentages if it pertains to an HMP product, rather than an LMP product. However, considering the relation among network positions, product preferences, and information search behavior, two traditional marketing channels represent an exception to this rule.

Informative influence has a positive influence on *adoption* percentages, whereas normative influence has a negative impact on *awareness* percentages, because some people use normative influence as their main source of information and do not become aware of the product until someone in their network adopts it. Therefore, ignoring normative influence in a model results in the overestimation of the effects of informative influence.

When channels serve to target specific customers, targeting those people in a central position within the cluster or network results in the greatest increase in awareness. Targeting bridges (i.e., people who connect different clusters within a social network) has approximately the same impact as targeting random people. However, a distinction can be made between targeting customers with information or with the product itself (sampling). In the former case, targeting central people within the network (high closeness centrality) has the highest impact; in the latter case, targeting central people within a cluster (high degree centrality) is the best option.

6.2 Key Findings

The chapters in this thesis emphasize the complexity of the processes of social influence. Research often tends to focus on either informative influence (WoM) or assumes a *positive* normative influence (social contagion); my thesis shows that ignoring either one of these influences results in an incorrect estimation of the effects. For example, despite the neutral rule used to implement normative influence, its effects are negative for all simulations of the new product introductions investigated in this thesis. In general, normative and informative influences have distinct but interrelated effects. Whereas informative influence relates mostly to making customers aware of new products, normative influence has a stronger relation with the decision to buy the product. The relation between increased awareness (through normative influence) and increased adoption rates is obvious; I also note the less obvious (negative) effect that normative influence has on awareness.

Chapter 3 shows that characteristics of certain people within a network affect both the speed of adoption and the adoption rates. Chapter 4 presents a method to relate people's characteristics to their position in the social network. This method has an advantage, in that it can link personal characteristics to the position of the person in a social network, without making assumptions about their relation. Therefore, it (empirically) includes consumer heterogeneity, in both personal characteristics and relations with others in the social network. Even if the general assumptions in the model are valid (e.g., opinion leaders have more central positions and are more innovative), the algorithm still provides insights into dealing with other (less explicit) assumptions: Are opinion leaders in the *most* central positions or just close to the center? Are they much more or only slightly more innovative?

Applying this method in Chapter 5 emphasizes the complexity of the processes in such a network. For example, the relative increase in adoption percentages as a result of using a certain media channel is product specific. Specifically, certain channels appear better at increasing the adoption percentage of the LMP product relative to the HMP product. This finding cannot be explained by looking at the people reached by the media channels. Rather, it suggests that the people who are connected to others reached by the media have higher interest in the LMP product.

6.3 Further Research: The Next Steps

The ABM in Chapter 5 applied to a situation in which a new (HMP or LMP) product had been introduced in a market with existing, competitive products. The model applied to this specific situation, as tested with several specific marketing strategies (e.g., traditional marketing channels, more specific targeting strategies), but this chapter offered only a first example of the potential for analyses through this (type of) ABM. This section therefore describes five next steps that would be possible without (strongly) adjusting the ABM before moving on to several potential model extensions.

6.3.1 Applying the Current ABM

First, Chapter 5 focused on a limited set of marketing strategies. The different channels, used independently, have different effects for two types of products. It would be interesting to combine different marketing channels, whether by using several traditional media channels or combining (one of) them with a specific targeting strategy. For example, a mass marketing instrument could be used to create awareness of a product, while targeted social media strategies (i.e. narrow casting) could support influential people in adopting the product and reinforcing a positive norm regarding the product. Such an experiment could help determine an optimal marketing strategy, as well as grant insights into the potential interaction effect between traditional marketing channels and targeted campaigns.

Second, Chapter 5 focuses on the introduction of one product (HMP or LMP). The introduction of a new product often prompts introductions of similar products by competitors or the product is introduced in an existing market, so it would be interesting to investigate the overall processes in these markets. Existing research has demonstrated that the first entrant has an advantage with respect to SI effects (e.g., Horsky and Mate 1988; Grewal et al. 2003; Libai et al. 2009). However, the role of normative influence has not been taken into consideration. In addition, it would be interesting to investigate whether a specific marketing strategy can overcome the disadvantages of the second entrant.

Third, instead of looking at the ultimate outcomes (awareness percentage and adoption percentage), it would be interesting to consider how outcomes develop over time. Some products might reach their maximum adoption percentage at a very early stage; others may take longer to reach a maximum. Investigating this topic could help marketers evaluate their ongoing campaigns and determine whether they should change their strategy or continue what they are doing.

Fourth, it is interesting to extend the targeting strategies. The implemented strategies focus on location within the network, but it also is possible to target people on the basis of their product interest or potential value for the company (e.g., Haenlein and Libai, 2013)—though the latter would require the collection of more empirical data. When developing targeting strategies, it is important to recall that even though some people are interesting to target, it does not mean they are easy to reach. The Internet provides opportunities to target specific people though; an online product forum could be a good place to start to find people interested in a specific product.

Fifth, the current ABM assumes that agents either share all information about a new product or no information at all. It is interesting to investigate what happens if incomplete information about products gets shared. If the sharing of certain characteristics aids the acceptance of a new product, this analysis could provide valuable insights into which characteristics to communicate when a new product is being introduced.

Sixth, regression methods would be useful to investigate the outcomes of the simulation runs (e.g., Andrews, Currim, & Leeflang, 2011; Dykstra et al., 2013). In their framework for ABM research, Rand and Rust (2011) propose this type of analysis to investigate the relations across different variables. Especially if many variables appear in the ABM, the use of regression technique offers a better overview of the effects and provides more insight into the importance of the different variables. However, before applying regression techniques, it is important to look at the underlying data: An ABM could predict that (given a particular model parameterization) a product introduction leads to either a great success (say 25% adoption) or an extreme failure (say 3% adoption). In this case, it might be an indicator of a very turbulent market in which small differences in the initiation stage of the ABM result in different outcomes. It would be wrong to conclude that the product gains 14%

market share (given the parameterization of the model). Such a situation may be hard to address in regression analysis, especially if the cause of the effects is unknown (i.e., not registered).

6.3.2 Extending the ABM

The ABM developed in Chapter 5 provides an interesting instrument to investigate different research questions. There are also several extensions and next steps that would improve the model.

First, most parameters applied in the ABM are constant over time. Some parameters of a specific agent differ depending on the adoption behavior and knowledge of agents in the environment, so it would be interesting to extend the model in this respect. For example, if a new product consists of an important innovation (e.g., smartphone with touchscreen), it could affect the preferences of some agents (e.g., physical keyboard becomes less important). A new product also might be attractive shortly after its introduction, purely based on its newness. This attraction could decrease over time, stressing the importance of early product success.

Second, in the current ABM, product information is shared objectively: The preferences of agents do not affect the information they share, and they are fully capable of sharing all details. To make the model more realistic, it should include certain forms of bias, such as with respect to the content of information shared (e.g., if the processor speed of a smartphone is very important for a particular person, it becomes the most important piece of information for this person to share as well). Another bias could relate to the level of detail (e.g., someone might just want to know that the memory available is sufficient). Yet another bias could relate to the reliability of the information (e.g., someone who dislikes small screens is more negative about other characteristics of a smartphone with a small screen).

Third, the validation of the current ABM relies on empirical data at the individual level. It remains unclear whether the aggregate outcomes of these rules represent a real market. The current model advances the investigation of the processes that emerge from programmed rules, validating the outcomes at the aggregate level also would make the results easier to interpret (i.e., more comparable to the real world, which should increase market acceptance of the technique). However, validation on the aggregate level (model outcomes) is a hazardous process. It is particularly difficult to gather the needed information, especially in markets with a wide variety of products (e.g., smartphones), which makes it virtually impossible to find the market shares of all products for example. Even if this information is available, determining the validity of an ABM may not be easy. Consider a turbulent market in which brands A, B, and C introduce three almost identical new products. Assume that social influence is of critical importance in consumers' product choices. For some reason, the product introduction by brand A succeeds, but product introductions by brands B and C fail. The ABM shows that the product introduction of brand A succeeds in one-third of the runs but fails in two-thirds of them. The ABM seems wrong in most of the runs but is likely perfectly valid, given the information provided in the example (i.e., if the right people randomly made their initial choice). In most cases it is hard to determine the likelihood of a scenario that happened in the real world, compared with that of scenarios that could have happened. Determining the true validity of an ABM on the aggregate level thus remains an important challenge.

Fourth, whereas the current ABM only focuses on customers and their interactions, an interesting extension would include companies in the model, similar to so-called structural models that model demand and supply simultaneously (e.g., Chintagunta, Erdem, Rossi and Wedel, 2006). For example, research could account for companies that (on the basis of the market situation) adjust their strategy after a competitive product introduction by lowering their prices, reacting with their own product introduction, starting a new marketing communication campaign, or canceling a current campaign. This extension offers valuable insights into the effectiveness of marketing strategies in a competitive environment and therefore aids in the development of effective, adaptable marketing strategies.

6.4 Future Outlook: Nintendo in the Boardroom?

In the previous section, I suggested including competitors (and their strategies) in the ABM. Whereas empirically validated ABMs clearly provide a relevant perspective for identifying social complexities in many markets, their application for experimentally testing the effect of marketing strategies ultimately becomes problematic. Suppose there is an empirically validated ABM of a particular market, in which multiple firms compete for market share. Assume that one firm, say X, is interested in testing the effect of a pricing strategy in combination with an advertisement. Order effects likely exert an influence, such that an advertisement followed by a price cut would have a different effect than the two tactics when they appear simultaneously or in reverse order. In the simplest case, three different marketing strategies thus are possible, and other firms respond to the strategy adopted by firm X. Again taking a simple position, say that five other firms also have three possibilities to respond, so in this case, there would be 3 (firm X) $\times$ 3^5(other firms) = 729 experimental conditions. Testing more marketing strategies and including responses to marketing strategies by the competition would result in an exponential explosion in the size of the experimental design. We accordingly come to the conclusion that traditional experimental designs ultimately are not feasible for identifying promising marketing strategies.

An interesting question is whether gaming provides a perspective for dealing with this enormous complexity. The essential difference between gaming and experimental designs is that in games, players respond to developments as they emerge (whereas in experiments, the responses have been developed beforehand and organized into an experimental design). A gaming situation thus allows for much more freedom in terms of the marketing actions that brand X might employ, as well as in the possible responses of competitors. However, experimental control is lacking, so what can we really learn from such games?

6.4.1 Gaming as a Marketing Tool

Gaming (using simulations) is being applied in many professional environments, such as flight simulators, which may be used for fun but also help train professional pilots to respond to calamities that are rare but serious in a real flight situation. Similar gaming simulations also can help test the effectiveness of the organization of firefighting departments, the optimal crowd streams in cities and stadiums, or improved traffic flows.

In marketing, early developments include Unilever's simulation game for testing strategic decisions and new product development in a competitive environment. With this game, users gain experience with different types of marketing strategies, which often prompts discussions of marketing strategies.

Accordingly, I consider three fields in which games could be or currently are applied: fundamental research, marketing practice, and education. A clear distinction among the three is not possible; the same game could, in principle, be applied to all three fields. However, because the main goals of the games would differ across these three fields, I try to pinpoint some key challenges and possible applications for each field separately.

6.4.2 Gaming in Research

Experimental designs in simulations run into problems related to the exponential growth of experimental conditions. To study which marketing strategies are most effective, given a certain type of marketing, a better option might be to focus on a more aggregated level, referring to the managerial marketing style. A managerial marketing style is a more generic means to interact with a market, as described in open systems theory (Johnson, Kast, and Rosenzweig 1964; Katz and Kahn 1978). According to this approach, the long-term survival of an organization depends on its ability to adapt its activities to environmental changes—especially the timing and speed of its responses to environmental developments (Thompson 1967; Katz and Kahn 1978). It is possible to distinguish between customer-related and competitor-related responsiveness, such that in a marketing game, it may be possible to test experimentally the market conditions in which more adaptive or faster marketing response strategies outperform more conservative strategies. Such games also could test if customer or competitor orientations perform better or worse in certain market conditions. To test the efficacy of different marketing styles, real people could interact with the marketing game, which would indicate their marketing style and its relation to performance. Finally, it would be possible to measure the extent to which participants can develop a correct mental representation of the simulation model structure, which would be a proxy for their "gut feeling" about the market. More practical marketing experience likely would translate into a better representation.

Another approach, offering more possibilities to control for marketing styles, would be to define the strategies of marketing agents with a predefined style. In this case, large series of experiments can test broader designs, considering various marketing styles and market conditions. Alternatively, research might seek to make marketing styles flexible, using a genetic algorithm approach to select and propagate marketing styles for artificial agents that perform optimally in certain markets. Then the poorly performing strategies get removed from the simulation and replaced by (slightly adapted) more successful strategies; over generations of simulations, it would be possible to evolve effective marketing styles. For such research, a key question would be if a certain type of (complex) market always results in the dominance of a certain marketing style, or if the optimal result also might consist of a heterogeneous population of strategies in markets. Such results might offer empirical data about marketing styles and firm performance in different markets.

6.4.3 Gaming in Marketing Practice

In marketing practice, the games should closely match the market in which the firm operates. Whereas different generic frameworks already attempt to model various markets (e.g., Jager, 2007; Garcia & Jager, 2011), the challenge for a practical application is the parameterization of models using empirical data. One possibility would be to use conjoint analysis to develop a valid population of artificial agents representing different types of customers.

A valid simulation model creates a possibility for firms to play market games and explore their own strategies. It might be possible, for example, to test different strategies for adapting marketing for an existing product or for introducing a new product. Various strategies then can be tested and compared; perhaps most important, it would become possible to explore the effects of and potential countermeasures against competitors' responses, which represent the least predictable factor in the market. Marketing experts can explore different scenarios and play the market game for those that seem most realistic. Not only would they gain more knowledge about the efficacy of certain marketing strategies, but they might also reveal the unexpected consequences of certain competitive actions, as well as viable strategies for counteracting them. Awareness of consequences may result in faster recognition of marketing effects once the marketing strategy is enforced in practice; faster responses may provide a competitive advantage. Learning in advance about possible consequences thus may result in a more adaptive marketing strategy in practice, which should result in better performance.

6.4.4 Gaming in Education

Practical experience may be the best way to learn, but it also is hard to obtain. For example, dealing with an emergency situation while flying a plane is such a (thankfully) rare occurrence that learning from practice is not an option. Nor would learning from real-world mistakes be practical or ethical for pilots in training. Marketers might not deal with such life-or-death situations, but poor decisions can result in serious damage and perhaps even the bankruptcy of a firm. Giving students an environment in which they can make important marketing decisions and serious mistakes without devastating consequences thus should provide a rich, effectively learning environment. Instead of learning marketing principles in a more abstract sense, studying books and case studies, they would confronted the outcomes of their own choices. Especially if things go wrong, such choices should stimulate them to reflect on their own decision-making processes, which will increase the relevancy of the marketing principles they have already learned. Playing market games also could speed up the learning process and allow young marketers to develop experience and their “gut feeling” more quickly. Then when actual experiences reflect their prior experiences with gaming, it reinforces the practical learning experiences.

For example, the LINKS learning game (Chapman, 2010) provides a gaming environment in which students interact, through a web-based simulation tool, with a market in which anywhere from two to eight firms compete. Students make decisions about product costs, product reconfigurations, patenting, market prices, marketing spending, marketing communication positioning, promotional programs, the introduction or expiration of a product, levels of service, and sales volume forecasting. However, this model does not incorporate a population of heterogeneous and interacting customers, which seems essential for training marketers who will make decisions in markets with different segments of customers, such that the exchange of information and normative influences (fashions) likely have a role. Incorporating such customer behavioral principles into market games to make the experiences more valid and realistic, and further enhance the learning experience of students, thus represents a remaining challenge for research.

6.4.5 Final Words

Gaming offers a challenging new perspective on studying, teaching, and managing complex markets. For a viable application of gaming in marketing, the simulation tool must be based on a sound theoretical framework that can capture relevant processes of social interactions; the researchers also must collect empirical data that can parameterize the simulated customer population. The next challenge is developing interfaces that allow for easy interactions with the simulation tool. A gaming situation requires players to have a clear view of the current behavior of customers in the market, the actions of competing firms, and the possibilities for managing the system. Therefore, the interface should center around a “view center” of the market’s behavior and a “control center” for managing the product. The view center might be equipped with different tools for exploring the state of the market, such as sales graphs, profit data, and properties of the customer base. It is also possible to export these data to support standard analyses for decision making. For example, a cluster analysis might reveal the key attributes of the current customer base and the customers of competitors. That is, standard marketing research tools can be used in a game setting. In the control center, various possibilities emerge in relation to product development, pricing, promotion, and placement (see Jager, 2007). In practical settings, as new products are being developed, detailed information on factors such as production costs and research and development must be included as well.

Finally, the fun factor should be addressed. Colleagues should compete for market share and profit, demonstrate high involvement in the game, and enjoy playing with it. Gaming, if supported by valid simulation tools, can combine learning with fun, which seems to be a great combination for success.

References

Abratt, R., D. N., and C. Nezer (1995), Role of the Market Maven in Retailing - a General Marketplace Influencer, *Journal of Business and Psychology,* **10** (Fall), 31-55.

Anderson, C., John, O. P., Keltner, D. and A. M. Kring (2001), Who Attains Social Status? Effects of Personality and Physical Attractiveness in Social Groups, *Journal of Personality & Social Psychology,* **81** (1), 116-132.

Andrews, R.L., Currim, I.S., and P.S.H. Leeflang (2011), A Comparison of Sales Response Predictions From Demand Models Applied to Store-Level versus Panel Data, *Journal of Business & Economic Statistics*, 29(2), 319-326.

Aral, S. and D. Walker (2011), Creating Social Contagion Through Viral Product Design: A Randomized Trial of Peer Influence in Networks, *Management Science,* **57** (9), 1623-1639.

Arndt, J. (1967). Word-of-Mouth Advertising and Informal Communication. in: *Risk Taking and Information Handling in Consumer Behavior B2 - Risk Taking and Information Handling in Consumer Behavior*. D. F. Cox. Boston, Harvard Business School Press.

Arora, N. and G. M. Allenby (1999), Measuring the Influence of Individual Preference Structures in Group Decision Making, *Journal of Marketing Research,* **36** (Nov), 476-87.

Bagozzi, R. P. (1986), *Principles of Marketing Management.* Chicago, IL: Science Research Association.

Banfield, J. D. and A. E. Raftery (1993), Model-Based Gaussian and Non-Gaussian Clustering, *Biometrics*, 49, 803-821.

Barabasi, A. L. (2003). *Linked*. Penguin Group, New York, NY.

Barabasi, A.L., and E. Bonabeau. (2003). Scale-Free Networks. *Scientific American* 288, 60-69.

Bass, F. M. (1969). A New Product Growth for Model Consumer Durables. *Management Science* 15, 215-227.

Bassili, J. N. (2003), The Minority Slowness Effect: Subtle Inhibitions in the Expression of Views Not Shared by Others, *Journal of Personality & Social Psychology,* **84** (2), 261-276.

Baumgarten, S. A. (1975), The Innovative Communicator in the Diffusion Process, *Journal of Marketing Research (JMR),* **12** (1), 12-18.

Bearden, W.O., Netemeyer, R.G., Teel, J.E. (1989). Measurement of consumer susceptibility to interpersonal influence. *Journal of Consumer Research* 15 (March), 473-481.

Becker, M. H. (1970), Sociometric Location and Innovativeness: Reformulation and Extension of the Diffusion Model, *American Sociological Review,* **35** (2), 267-282.

Berelson, B. and G. A. Steiner. (1964). *Human Behavior and Inventory of Scientific Findings*. New York: Harcourt, Brace & World, Inc.

Berger, J. and C. Heath (2008), Who Drives Divergence? Identity Signaling, Outgroup Dissimilarity, and the Abandonment of Cultural Tastes, *Journal of Personality & Social Psychology*, **95** (3), 593-607.

Berger, J. and E.M. Schwartz (2011), What Drive Immediate and Ongoing Word of Mouth?, *Journal of Marketing Research*, **48** (5), 869-880.

Bickart, B. and R. M. Schindler (2001), Internet Forums as Influential Sources of Consumer Information, *Journal of Interactive Marketing (John Wiley & Sons),* **15** (Summer2001), 31-40.

Bohlmann, J. D., Roger J. Calantone, and Zhao Meng (2010), The Effects of Market Network Heterogeneity on Innovation Diffusion: An Agent-Based Modeling Approach, *Journal of Product Innovation Management*, **27** (5), 741-760.

Bone, P. F. (1992), Determinants of Word-of-Mouth Communications during Product Consumption, *Advances in Consumer Research,* **19** 579-583.

Bone, P. F. (1995), Word-of-Mouth Effects on Short-Term and Long-Term Product Judgments, *Journal of Business Research,* **32** (Mar), 213-223.

Bonfield, E. H. (1974), Attitude, Social Influence, Personal Norm, and Intention Interactions as Related to Brand Purchase Behavior, *Journal of Marketing Research (JMR),* **11** (4), 379-389.

Broekhuizen, T. L. J., Delre, S. A., and A. Torres (2011), Simulating the Cinema Market: How Cross-Cultural Differences in Social Influence Explain Box Office Distributions, *Journal of Product Innovation Management*, **28** (2), 204-217.

Brooks Jr., R. C. (1957), "Word-of-Mouth" Advertising in Selling New Products, *Journal of Marketing*, **22** (2), 154-61.

Bronnenberg, B. J., and C. F. Mela (2004), Market Roll-Out and Retailer Adoption for New Brands, *Marketing Science*, **23** (4), 500-518.

Brown, J. J. and P. H. Reingen (1987), Social Ties and Word-of-Mouth Referral Behavior, *Journal of Consumer Research,* **14** (3) 350-362.

Brown, T. J., Barry, T. E., Dacin, P. A. and R. F. Gunst (2005), Spreading the Word: Investigating Antecedents of Consumers' Positive Word-of-Mouth Intentions and Behaviors in a Retailing Context, *Journal of the Academy of Marketing Science,* **33** (Spring), 123-138.

Burnkrant, R. E. and A. Cousineau (1975), Informational and Normative Social Influence on Buyer Behavior, *Journal of Consumer Research,* **2** (3), 206-215.

Carl, W. J. (2006), What's all the Buzz about? *Management Communication Quarterly,* **19** (4), 601-634.

Carter, R. E., Jr., and P. Clarke (1962), Public Affairs Opinion Leaders among Education Television Viewers, *American Sociological Review*, **27** (6), 792-799.

Centola, D. and M. Macy (2007), Complex Contagions and the Weakness of Long Ties, *American Journal of Sociology,* **113** (3), 702-34.

Chapman, R.G. (2010). *LINKS Marketing Principles Simulation.* LINKS Simulations. http://www.links-simulations.com/MP/manualMP.pdf

Charlett, D., R. Garland and N. Marr (1995). How Damaging is Negative Word-of-Mouth. *Marketing Bulletin* 6: 42-50.

Chatterjee, R., and J. Eliashberg. (1990). The Innovation Diffusion Process in the Heterogeneous Population: A Micromodelling Approach. *Management Science* 36, 1057-1079.

Cheema, A. and A. M. Kaikati (2010), The Effect of Need for Uniqueness on Word of Mouth, *Journal of Marketing Research (JMR),* **47** (3), 553-563.

Chen, Y., Q. Wang and J. Xie (2011), Online Social Interactions: A Natural Experiment on Word of Mouth Versus Observational Learning, *Journal of Marketing Research,* **48** (2), 238-254.

Chen, Y. and J. Xie (2005), Third-Party Product Review and Firm Marketing Strategy, *Marketing Science,* **24** (Spring), 218-240.

Cheung, M., M. M. Anitsal, and I. Anitsal (2007), Revisiting Word-of-Mouth Communications: A Cross-National Exploration, *Journal of Marketing Theory & Practice*, **15** (Summer), 235-249.

Chintagunta, P., Erdem, T., Rossi, P.E. and M. Wedel (2006), Structural Modeling in Marketing: Review and Assessment, *Marketing Science*, 25(6), 604-616.

Chitturi, R., Rajagopal R., and V. Mahajan (2008), Delight by Design: The Role of Hedonic Versus Utilitarian Benefits, *Journal of Marketing,* **72** (3), 48-63.

Christiansen, T. and S. S. Tax (2000), Measuring Word of Mouth: The Questions of Who and when? *Journal of Marketing Communications,* **6** (3), 185-199.

Chung, C. M. Y. and P. R. Darke (2006), The Consumer as Advocate: Self-Relevance, Culture, and Word-of-Mouth, *Marketing Letters,* **17** (Dec), 269-279.

Cialdini, R.B., and N.J. Goldstein. (2004). Social Influence: Compliance and Conformity. *Annual Review of Psychology*, 55 (1), 591-621.

Clark, M. S., M. C. Powell, and J. Mills (1986), Keeping Track of Needs in Communal and Exchange Relationships, *Journal of Personality and Social Psychology,* **51** (Aug), 333-338.

Clayton, J. H., A. K. James, and J. S. C. Nicholas (2006), Positive and Negative Opinion Modeling: The Influence of another's Similarity and Dissimilarity, *Journal of Personality & Social Psychology,* **90** (3), 440-52.

Cohen, J. (1983), Peer Influence on College Aspirations with Initial Aspiration Controlled, *American Sociological Review,* **48** (5), 728-734.

Cohen, J. B. and E. Golden (1972), Information Social Influence and Product Evaluation, *Journal of Applied Psychology,* **56** (1), 54-59.

Corey, L. G. (1971), People Who Claim to be Opinion Leaders: Identifying their Characteristics by Self-Report, *Journal of Marketing,* **35** (4), 48-53.

Czepiel, J. A. (1974), Word-of-Mouth Processes in the Diffusion of a Major Technological Innovation, *Journal of Marketing Research (JMR),* **11** (2), 172-180.

De Bruyn, A. and G. L. Lilien (2008), A Multi-Stage Model of Word-of-Mouth Influence through Viral Marketing, *International Journal of Research in Marketing,* **25** (3), 151-163.

Delre, S.A., W. Jager, T.H.A. Bijmolt, and M.A. Janssen. (2007). Targeting and Timing Promotional Activities: An Agent-Based Model for the Takeoff of New Products. *Journal of Business Research*, 60 (8), 826-835.

Delre, S. A., Jager, W., Bijmolt, T. H. A., M. A. Janssen (2010), Will it Spread Or Not? the Effects of Social Influences and Network Topology on Innovation Diffusion, *Journal of Product Innovation Management,* **27** (2), 267-282.

Deutsch, M. and H. B. Gerard (1955), A Study of Normative and Informational Social Influence upon Individual Judgment, *Journal of Abnormal and Social Psychology,* **51** (3), 629-636.

Dichter, E. (1966), How Word-of-Mouth Advertising Works, *Harvard Business Review,* 44 (6), 147-157.

Doreian, P., Conti, N. (2012). Social context, spatial structure and social network structure. *Social Networks* 34, 32-46.

Duhan, D. F., Johnson, S. D., Wilcox, J. B. and G. D. Harrell (1997), Influences on Consumer use of Word-of-Mouth Recommendation Sources, *Journal of the Academy of Marketing Science,* **25** (Fall), 283-295.

East, R., K. Hammond and W. Lomax (2008), Measuring the Impact of Positive and Negative Word of Mouth on Brand Purchase Probability, *International Journal of Research in Marketing,* **25** 215-24.

East, R., K. Hammond and M. Wright (2007), The Relative Incidence of Positive and Negative Word of Mouth: A Multi-Category Study, *International Journal of Research in Marketing,* **24** (2), 175-184.

Engel, J. F., R. J. Kegerreis and R. D. Blackwell (1969), Word-of-Mouth Communication by the Innovator, *Journal of Marketing,* **33** (3), 15-19.

Enis, B. M. (1979), *Personal Selling: Foundations, Process, and Management.* Santa Monica, CA: Goodyear Publishing Company.

Ernst, H., W. D. Hoyer, and C. Rübsaamen (2010), “Sales, Marketing, and Research-and-Development Cooperation Across New Product Development Stages: Implications for Success,” *Journal of Marketing* 74 (5), 80-92.

Feick, L. and R. A. Higie (1992), The Effects of Preference Heterogeneity and Source Characteristics on Ad Processing and Judgments about Endorsers, *Journal of Advertising,* **21** (Jun), 9-24.

Feick, L. F. and L. L. Price (1987), The Market Maven - A Diffuser of Marketplace Information, *Journal of Marketing,* **51** (Jan), 83-97.

Flynn, L. R., R. E. Goldsmith, and J. K. Eastman. (1994). The King and Summers Opinion Leadership Scale: Revision and Refinement. *Journal of Business Research* 31(1), 55-64.

Flynn, L. R., R. E. Goldsmith, and J. K. Eastman (1996), Opinion Leaders and Opinion Seekers: Two New Measurement Scales, *Journal of the Academy of Marketing Science*, **24** (Spring), 137-147.

Ford, J. D. and E. A. Ellis (1980), A Reexamination of Group Influence on Member Brand Preference, *Journal of Marketing Research (JMR)*, **17** (1), 125-132.

Ford, G.T., Smith, D.B. and J.L. Swasy (1988), An Empirical Test of Search, Experience and Credence Attributes Framework, *Advances in Consumer Research*, 15, 239-244.

Fournier, Susan and Lara Lee (2009), Getting Brand Communities Right, *Harvard Business Review*, **87** (4), 105-111.

Frenzen, J. and K. Nakamoto (1993), Structure, Cooperation, and the Flow of Market Information, *Journal of Consumer Research*, **20** (3), 360-375.

Garcia, R. (2005), Uses of Agent-Based Modeling in Innovation/New Product Development Research, *Journal of Product Innovation Management*, **22** (Sep), 380-398.

Garcia, R., Jager, W. (2011). From the Special Issue Editors: Agent-Based Modeling of Innovation diffusion. Journal of Product Innovation Management 28, 148-151.

Gelb, B., and M. Johnson. (1995). Word-of-Mouth Communication: Causes and Consequences. *Journal of Health Care Marketing* 15(3), 54-58.

Gensler, S., Leeflang, P.S.H., Skiera, B. (2012), Comparing methods to separate treatment from self-selection effects in an online banking setting. *Journal of Business Research*, doi:10.1016/j.jbusres.2012.02.025.

Gershoff, A. D., A. Mukherjee, and A. Mukhopadhyay (2006), "I Love it" Or "I Hate it"? the Positivity Effect in Stated Preferences for Agent Evaluation, *Marketing Letters*, **17** (Apr), 103-117.

Gibbons, D. and P. M. Olk (2003), Individual and Structural Origins of Friendship and Social Position among Professionals, *Journal of Personality & Social Psychology*, **84** (2), 340-351.

Giese, J. L., E. R. Spangenberg, and A. E. Crowley (1996), Effects of Product-Specific Word-of-Mouth Communication on Product Category Involvement, *Marketing Letters*, **7** (2), 187-199.

Gilbert, N., W. Jager, G. Deffuant, and I. Adjali. (2007). Introduction to the Special Issues: Complexities in Markets. *Journal of Business Research* 60(8), 813-815.

Gilbert, N, Troitzsch, K.G., (2005). *Simulation for the Social Scientist*. Buckingham: Open University Press.

Glock, C. Y., and F. M. Nicosia. (1964). Uses of Sociology in Studying ‘Consumption’ Behavior. *Journal of Marketing* 28(3), 51-54.

Godes, D. and D. Mayzlin (2004), Using Online Conversations to Study Word-of-Mouth Communication, *Marketing Science*, **23** (Fall), 545-560.

Godes, D. and D. Mayzlin (2009), Firm-Created Word-of-Mouth Communication: Evidence from a Field Test, *Marketing Science*, **28** (4), 721-739.

Goldenberg, J., S. Han, D.R. Lehmann, and J.W. Hong. (2009). The Role of Hubs in the Adoption Process. *Journal of Marketing* 73(2), 1-13.

Goldenberg, Jacob, Libai, B., Moldovan, S. and E. Muller (2007), The NPV of Bad News, *International Journal of Research in Marketing,* **24** (4) 186-200.

Goldenberg, J., B. Libai and E. Muller (2001), Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth, *Marketing Letters,* **12** (8), 211-223.

Granovetter, M.S. (1973), The strength of Weak Ties. *American Journal of Sociology* 78 (6), 1360-1380.

Green, P. E., V. Srinivasan (1990). Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice, *Journal of Marketing* 54 (4), 3-19.

Gremler, D. D., K. P. Gwinner and S. W. Brown (2001). Generating positive word-of-mouth communication through customer-employee relationships. *International Journal of Service Industry Management* 12(1): 44.

Grewal, R., T. W. Cline, and A. Davies (2003), Early-Entrant Advantage, Word-of-Mouth Communication, Brand Similarity, and the Consumer Decision-Making Process, *Journal of Consumer Psychology,* **13** (3), 187-197.

Grewal, R., R. Mehta, and F. R. Kardes. (2000). The Role of the Social-Identity Function of Attitudes in Consumer Innovativeness and Opinion Leadership. *Journal of Economic Psychology* 21(3), 233-252.

Haenlein, M. and B. Libai (2013). Targeting Revenue Leaders for a New Product. *Journal of Marketing*, doi: 10.1509/jm.11.0428.

Hartmann, W. R. (2010), Demand Estimation with Social Interactions and the Implications for Targeted Marketing, *Marketing Science,* **29** (July), 585-601.

Hennig-Thurau, T. and G. Walsh (2003), Electronic Word-of-Mouth: Motives for and Consequences of Reading Customer Articulations on the Internet, *International Journal of Electronic Commerce,* **8** (Winter), 51-74.

Herr, P. M., F. R. Kardes, and J. Kim (1991), Effects of Word-of-Mouth and Product-Attribute Information of Persuasion: An Accessibility-Diagnosticity Perspective, *Journal of Consumer Research,* **17** (4), 454-462.

Higie, R. A., L. F. Feick, and L. L. Price (1987), Types and Amount of Word-of-Mouth Communications about Retailers, *Journal of Retailing,* **63** (Fall), 260-278.

Hinz, O., B. Skiera, C. Barrot, and J.U. Becker (2011), Seeding Strategies for Viral Marketing: An Empirical Comparison, *Journal of Marketing*, 75 (November), 55-71.

Hirschman, E. C. (1980), Innovativeness, Novelty Seeking, and Consumer Creativity, *Journal of Consumer Research,* **7** (3), 283-295.

Hogan, J. E., K. N. Lemon, and R. T. Rust (2002), Customer Equity Management: Charting New Directions for the Future of Marketing, *Journal of Service Research,* **5** (1), 4-12.

Horsky, D. and K. Mate (1988), Dynamic Advertising Strategies of Competing Durable Good Producers, *Marketing Science*, **7** (Fall), 356-367.

Im, S., C. H. Mason, and M. B. Houston (2007), Does Innate Consumer Innovativeness Relate to New Product/Service Adoption Behavior? the Intervening Role of Social Learning Via Vicarious Innovativeness, *Journal of the Academy of Marketing Science*, **35** (March), 63-75.

Iyengar, R., C. van den Bulte, T.W. Valente (2011), Opinion Leadership and Social Contagion in New Product Diffusion, *Marketing Science*, **30** (2), 195-212.

Jager, W. (2007), The four p's in social simulation, a perspective on how marketing could benefit from the use of social simulation. *Journal of Business Research* 60 (8), 868-875.

Janssen, M.A. and W. Jager. (2001). Fashions, Habits and Changing Preferences: Simulation of Psychological Factors Affecting Market Dynamics. *Journal of Economic Psychology* 22, 745-772.

Janssen, M.A. and W. Jager. (2003). Self Organisation of Market Dynamics: Consumer Psychology and Social Networks. *Artificial Life* 9 (4), 343-356.

John, Joby (1994), Referent Opinion and Health Care Satisfaction, *Journal of Health Care Marketing*, **14** (Summer), 24-30.

Johnson, R.A., Kast, F.E., Rosenzweig, J.E. (1964). Systems Theory and Management. *Management Science, 10, 2* . pp. 367-384

Kamakura, W.A., M. Wedel, and J. Agrawal (1994), “Concomitant variable latent class models for conjoint analysis”, *International Journal of Research in Marketing*, 11, 451-461.

Katona, Z., P.P. Zubcsek, M. Sarvary (2011), Network Effects and Personal Influences: The Diffusion of an Online Social Network, *Journal of Marketing Research*, **48** (3), 425-443.

Katz, D., & Kahn, R. L. (1978). *The social psychology of organizations, 2nd Ed*. New York, NY: John Wiley and Sons.

Katz, E. and P. F. Lazarsfeld (1955), *Personal Influence.* Glencoe: The Free Press.

Keiningham, T.L., Cooil, B., Andreassen, T.W. and L. Aksoy, (2007), A Longitudinal Examination of Net Promoter and Firm Revenue Growth, *Journal of Marketing*, 71(3), 39-51.

King, C. W. and J. O. Summers (1970), Overlap of Opinion Leadership Across Consumer Product Categories, *Journal of Marketing Research (JMR),* **7** (1), 43-50.

Kossinets, G. and D. J. Watts (2009), Origins of Homophily in an Evolving Social Network, *American Journal of Sociology,* **115** (2), 405-450.

Kozinets, R. V., De Valck, K., Wojnicki, A. C. and S. J. S. Wilner (2010), Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities, *Journal of Marketing,* **74** (2), 71-89.

Kumar, V., J. A. Petersen, and Robert P. Leone (2010), Driving Profitability by Encouraging Customer Referrals: Who, when, and how, *Journal of Marketing*, **74** (9), 1-17.

Kumbasar, E., K. Romney, and W. H. Batchelder (1994), Systematic Biases in Social Perception, *American Journal of Sociology,* **100** (2), 477-505.

Lam, D., A. Lee and R. Mizerski (2009), The Effects of Cultural Values in Word-of-Mouth Communication, *Journal of International Marketing*, **17** (3), 55-70.

Lam, Desmond and Dick Mizerski (2005), The Effects of Locus of Control on Word-of-Mouth Communication, *Journal of Marketing Communications,* **11** (3), 215-228.

Langaard, E., M. Crousillat, and R. Weisz (1978), Exposure to Cultural Activities and Opinion Leadership, *Advances in Consumer Research,* **5** (1), 606-610.

Lau, G. T. and S. Ng (2001), Individual and Situational Factors Influencing Negative Word-of-Mouth Behaviour, *Canadian Journal of Administrative Sciences-Revue Canadienne Des Sciences De L Administration,* **18** (September), 163-78.

Leeflang, P.S.H., Verhoef, P.C., David, C. and T. Freundt, (2013), Challenges and Solutions for Marketing in a Digital Era, *working paper, University of Groningen*.

Leonard-Barton, Dorothy (1985), Experts as Negative Opinion Leaders in the Diffusion of a Technological Innovation, *Journal of Consumer Research,* **11** (4), 914-926.

Lewis, M. (2006), Customer Acquisition Promotions and Customer Asset Value, *Journal of Marketing Research,* **43** (May), 195-203.

Libai, B., Bolton, R., Bügel, M.S., De Ruyter, K., Götz, O., Risselada, H. and A.T. Stephen, (2010), Customer-to-Customer Interactions: Broadening the Scope of Word of Mouth Research, *Journal of Service Research*, 13, 267-282.

Libai, B., E. Muller, and R. Peres (2009), The Role of within-Brand and Cross-Brand Communications in Competitive Growth, *Journal of Marketing,* **73** (3), 19-34.

Libai, B., E. Muller, and R. Peres (2013), Decomposing the Value of Word-of-Mouth Seeding Programs: Acceleration Versus Expansion, *Journal of Marketing Research,* **50** (April), 161-176.

Liu, Y. (2006), Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue, *Journal of Marketing,* **70** (3), 74-89.

Lovelock, C. H. (2001). *Service Marketing: People, Technology, Strategy*. Upper Saddle River, NJ, Prentice Hall.

Luo, X. (2007), Consumer Negative Voice and Firm-Idiosyncratic Stock Returns, *Journal of Marketing,* **71** (3), 75-88.

Luo, X. (2009), Quantifying the Long-Term Impact of Negative Word of Mouth on Cash Flows and Stock Prices, *Marketing Science,* **28** (1), 148-165.

Luo, X. and C. Homburg (2007), Neglected Outcomes of Customer Satisfaction, *Journal of Marketing,* **71** (2), 133-149.

Lyons, Barbara and Kenneth Henderson (2005), Opinion Leadership in a Computer-Mediated Environment, *Journal of Consumer Behaviour,* **4** (5), 319-329.

Macy, M.W., J. Kitts, A. Flache, and S. Benard. (2003). Polarization in Dynamic Networks: A Hopfield model of Emergent Structure. In *Dynamic Social Network Modelling and Analysis:*

Workshop Summary and Papers. Eds. Ronald Breiger, Kathleen Carley, and Philippa Pattison. Washington: The National Academies Press, 162-173.

Macy, M.W. and R. Willer. (2002). From Factors to Actors: Computational Sociology and Agent-Based Modeling. *Annual Review of Sociology* 28(1), 143-166.

Mahajan, V. and E. Muller (1998), When is it Worthwhile Targeting the Majority Instead of the Innovators in a New Product Launch? *Journal of Marketing Research,* **35** (November), 488-495.

Mahajan V., E. Muller, and J. Wind, eds. (2000). *New Product Diffusion Models*. Boston, MA: Kluwer Academic Publishers.

Mak, V. (2008). The Emergence of Opinion Leaders in Social Networks, July 5. Available at http://ssrn.com/abstract=1157285.

Manchanda, P., Y, Xie and N. Youn (2008), The Role of Targeted Communication and Contagion in Product Adoption, *Marketing Science,* **27** (6), 961-976.

Martilla, J. A. (1971), Word-of-Mouth Communication in the Industrial Adoption Process, *Journal of Marketing Research (JMR),* **8** (2) 173-178.

Mayzlin, Dina (2006), Promotional Chat on the Internet, *Marketing Science,* **25** (Spring), 155-163.

Midgley, D. F. and G. R. Dowling (1978), Innovativeness - Concept and its Measurement, *Journal of Consumer Research,* **4** (4), 229-242.

Mizerski, R. W. (1982), An Attribution Explanation of the Disproportionate Influence of Unfavorable Information, *Journal of Consumer Research,* **9** (3), 301-310.

Moldovan, S., J. Goldenberg, A. Chattopadhyay (2011), The Different Roles of Product Originality and Usefulness in Generating Word-of-Mouth, *International Journal of Marketing*, **28** (2), 109-119

Money, R. B., Mary C. Gilly, and John L. Graham (1998), Explorations of National Culture and Word-of-Mouth Referral Behavior in the Purchase of Industrial Services in the United States and Japan, *Journal of Marketing,* **62** (4), 76-87.

Murphy, Laurie, Gianna Mascardo, and Pierre Benckendorff (2007), Exploring Word-of-Mouth Influences on Travel Decisions: Friends and Relatives Vs. Other Travellers, *International Journal of Consumer Studies,* **31** (5), 517-527.

Murray, K. B. (1991), A Test of Services Marketing Theory - Consumer Information Acquisition Activities, *Journal of Marketing,* **55** (January), 10-25.

Murray, Keith B. and John L. Schlacter (1990), The Impact of Services Versus Goods on Consumers' Assessment of Perceived Risk and Variability, *Journal of the Academy of Marketing Science,* **18** (Winter), 51-65.

Myers, J. H. and T. S. Robertson (1972), Dimensions of Opinion Leadership, *Journal of Marketing Research (JMR),* **9** (1), 41-46.

Nam, Sungjoon, Puneet Manchanda, and Pradeep K. Chintagunta (2010), The Effect of Signal Quality and Contiguous Word of Mouth on Customer Acquisition for a Video-on-Demand Service, *Marketing Science*, **29** (July), 690-700.

Naylor, R.B., C.P. Lamberton and P.M. West (2012), Beyond the "Like" Button: The Impact of Mere Virtual Presence on Brand Evaluations and Purchase Intentions in Social Media Settings, *Journal of Marketing*, 76 (November), 105-120.

Nelson, P. (1970), Information and Consumer Behavior, *Journal of Political Economy,* **78** (2), 311-329.

Nezlek, John B. (1993), The Stability of Social Interaction, *Journal of Personality & Social Psychology,* **65** (5), 930-941.

Nielsen. (2007). *Word-of-Mouth the Most Powerful Selling Tool: Nielsen Global Survey*. Available at http://asiapacific.acnielsen.com/news/20071002.shtml (visited 22 September 2009).

Nitzan, I. and B. Libai (2011), Social Effects on Customer Retention, *Journal of Marketing*, 75 (November), 24-38.

Park, C. W. and V. P. Lessig (1977), Students and Housewives: Differences in Susceptibility to Reference Group Influence, *Journal of Consumer Research,* **4** (2), 102-210.

Park, C. and T. M. Lee (2009), Information Direction, Website Reputation and eWOM Effect: A Moderating Role of Product Type, *Journal of Business Research*, **62** (1), 61-67.

Park, D.-H. and J. Lee (2008), EWOM Overload and its Effect on Consumer Behavioral Intention Depending on Consumer Involvement, *Electronic Commerce Research & Applications,* **7** (12), 386-398.

Pincus, S. and L. K. Waters (1977), Informational Social Influence and Product Quality Judgments, *Journal of Applied Psychology*, **62** (5), 615-619.

Pronin, E., S. Molouki, and J. Berger (2007), Alone in a Crowd of Sheep: Asymmetric Perceptions of Conformity and their Roots in an Introspection Illusion, *Journal of Personality & Social Psychology,* **92** (4), 585-595.

Rahmandad, H. and J. Sterman. (2008). Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models. *Management Science* 54(5), 998-1014.

Rand, W., and R.T. Rust (2011), Agent-based modeling in marketing: Guidelines for rigor, *International Journal of Research in Marketing*, 28, 181-193.

Reichheld, F.F. (2003), The One Number You Need to Grow, *Harvard Business Review*, 81 (December), 46-54.

Reingen, P. H. (1987), A Word-of-Mouth Network, *Advances in Consumer Research,* **14** (1), 213-217.

Reingen, P. H., Foster, B. L., Brown, J. J. and S. B. Seidman (1984), Brand Congruence in Interpersonal Relations: A Social Network Analysis, *Journal of Consumer Research,* **11** (3), 771-783.

Reingen, Peter H. and Jerome B. Kernan (1986), Analysis of Referral Networks in Marketing: Methods and Illustration, *Journal of Marketing Research (JMR)*, **23** (4), 370-378.

Richins, M. L. (1983), Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study, *Journal of Marketing,* **47** (Winter), 68-78.

Risselada, H., Verhoef, P.C., Bijmolt, T.H.A. (2013), Dynamic Effects of Social Influence and Direct Marketing on the Adoption of High-Technology Products, *working paper*, University of Groningen.

Rogers, E. M. (1983), *Diffusion of Innovations.* New York: Free Press.

Rogers, E.M. (1993). *Diffusion of Innovations*. 4th ed. New York: The Free Press.

Rogers, E.M. (2002), Diffusion of Preventive Innovations, *Addictive Behaviors **27**, 989-993.*

Rogers, E. M. and D. G. Cartano (1962), Methods of Measuring Opinion Leadership, *Public Opinion Quarterly,* **26** (Fall), 435-441.

Ruef, M., H. E. Aldrich, and N. M. Carter (2003), The Structure of Founding Teams: Homophily, Strong Ties, and Isolation among US Entrepreneur, *American Sociological Review,* **68** (Apr), 195-222.

Ryu, G. and L. Feick (2007), A Penny for Your Thoughts: Referral Reward Programs and Referral Likelihood, *Journal of Marketing,* **71** (1), 84-94.

Schellekens, G.A.C., Verlegh, P.W.J., and A. Smidts (2010), Language Abstraction in Word of Mouth, *Journal of Consumer Research*, 37, 207-223.

Schelling, T.C., (1971), Dynamic Models of Segregation, *Journal of Mathematical Sociology*, 1, 143-186.

Schiffman, L. G. and V. Gaccione (1974), Opinion Leaders in Institutional Markets, *Journal of Marketing,* **38** (2), 49-53.

Schmitt, P., Skiera, B. and C. van den Bulte (2011), Referral Programs and Customer Value, *Journal of Marketing*, 75, 46-59.

Schneider, K. C. and W. C. Rodgers (1993), Generalized Marketplace Influencers' (Market Mavens') Attitudes Toward Direct Mail as a Source of Information, *Journal of Direct Marketing,* **7** (9), 20-28.

Schumann, J.H., F. v. Wangenheim, A. Stringfellow, Z. Yang, V. Blazevic, S. Praxmarer, G. Shainesh, M. Komor, R.M. Shannon and F.R. Jiménez (2010), Cross-Cultural Differences in the Effect of Received Word-of-Mouth Referral in Relational Service Exchange, *Journal of International Marketing*, **18** (3), 62-80.

Sheingold, C. A. (1973), Social Networks and Voting: The Resurrection of a Research Agenda, *American Sociological Review,* **38** (6), 712-720.

Shrum, W. and N. H. Creek Jr. (1987), Social Structure During the High School Years: Onset of the Degrouping Process, *American Sociological Review,* **52** (5), 218-223.

Siciliano, M.D., Yenigun, D., Ertan, G. (2012), Estimating network structure via random sampling: Cognitive social structures and the adaptive threshold method. *Social Networks* 34, 585-600.

Silverman, G. (1997). How to Harness the Awesome Power of Word of Mouth. *Direct Marketing* 60(7), 32.

Stanley, T. J. (1978), Are Highly Credible Sources Persuasive?, *Journal of Consumer Research*, **5** (1), 66-67.

Sullivan, E.A. (2008). We Were Right. *Marketing News* 42(20), 16-17.

Suls, J., R. Martin and L. Wheeler (2000), Three Kinds of Opinion Comparison: The Triadic Model, *Personality & Social Psychology Review (Lawrence Erlbaum Associates),* **4** (3), 219-237.

Sultan, F., J. U. Farley, and D. R. Lehmann (1990), A Meta-Analysis of Applications of Diffusion-Models, *Journal of Marketing Research,* **27** (Feb), 70-77.

Swan, J. E. and R. L. Oliver (1989), Postpurchase Communications by Consumers, *Journal of Retailing,* **65** (Winter), 516-533.

Szybillo, G. J. (1975), A Situational Influence on the Relationship of a Consumer Attribute to New-Product Attractiveness, *Journal of Applied Psychology,* **60** (5), 652-655.

Takhteyev, Y., A. Gruzd, B. Wellman (2012), Geography of Twitter networks, *Social Networks*, 34, 73-81.

Thomas Jr., Greg M. (2004), Building the Buzz in the Hive Mind, *Journal of Consumer Behaviour,* **4** (1), 64-72.

Thompson, J.D., (1967). Organizations in action: Social science bases of administrative theory. New York: McGraw-Hill.

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site, *Journal of Marketing,* **73** (5), 90-102.

Tuk, M.A., Verlegh, P.W.J., Smidts, A., and D.H.J. Wigboldus, (2009), Sales and sincerity: The role of relational framing in word-of-mouth marketing, *Journal of consumer Psychology*, 19, 38-47.

Vag, A. (2007), Simulating Changing Consumer Preferences: A Dynamic Conjoint Model, *Journal of Business Research,* **60** (Aug), 904-11.

Valente, T.W. (1996). Social Network Thresholds in the Diffusion of Innovations. *Social Networks*, 18, 69-86.

Van Door, J., Leeflang, P.S.H. and Tijs, M. (2014), Satisfaction as a Predictor of Future Performance: A Replication, *International Journal of Research in Marketing, forthcoming*.

Van Doorn, J., Lemon K.N., Mittal, V., Nass, S., Pick, D., Pirner, D, and P.C. Verhoef, Customer Engagement Behavior: Theoretical Foundations and Research Directions, *Journal of Service Research,* 13 (3), 253-266.

Van Eck, P. S., Jager, W., and P. S. H. Leeflang (2011), Opinion Leaders' Role in Innovation Diffusion: A Simulation Study, *Journal of Product Innovation Management* **28** (2), 187-203.

Venkatesan, M. (1966), Experimental Study of Consumer Behavior Conformity and Independence, *Journal of Marketing Research,* **3** (4), 384-387.

Venkatraman, M. P. (1990), Opinion Leadership, Enduring Involvement and Characteristics of Opinion Leaders - A Moderating Or Mediating Relationship, *Advances in Consumer Research,* **17** (1), 60-67.

Vermeij, L., van Duijn, M.A., Baerveldt, C. (2009), Ethnic Segregation in Context: Social Discrimination among Native Dutch Pupils and their Ethnic Minority Classmates. *Social Networks* 31, 230-239.

Vermunt, J. K. and J. Madigson (2005), Technical Guide for Latent GOLD Choice 4.0: Basic and Advanced. Bolmont Massachusetts: Statistical Innovations Inc.

Villanueva, J., S. Yoo, and D. M. Hanssens (2008), The Impact of Marketing-Induced Versus Word-of-Mouth Customer Acquisition on Customer Equity Growth, *Journal of Marketing Research (JMR),* **45** (1), 48-59.

Visser, P. S. and R. R. Mirabile (2004), Attitudes in the Social Context: The Impact of Social Network Composition on Individual-Level Attitude Strength, *Journal of Personality & Social Psychology,* **87** (6), 779-795.

Von Wangenheim, F. (2005), Postswitching Negative Word of Mouth, *Journal of Service Research,* **8** (Aug), 67-78.

Von Wangenheim, Florian and Tomás Bayón (2004), Satisfaction, Loyalty and Word of Mouth within the Customer Base of a Utility Provider: Differences between Stayers, Switchers and Referral Switchers, *Journal of Consumer Behaviour,* **3** (3), 211-220.

Vorauer, Jacquie D. and Dale T. Miller (1997), Failure to Recognize the Effect of Implicit Social Influence on the Presentation of Self, *Journal of Personality & Social Psychology,* **73** (2), 281-295.

Wangenheim, F. V. and T. Bayón (2004). The effect of word of mouth on services switching: Measurement and Moderating Variables. *European Journal of Marketing* 38(9/10): 1173-1185.

Watts, Duncan J. and Peter S. Dodds (2007), Influentials, Networks, and Public Opinion Formation, *Journal of Consumer Research,* **34** (4), 441-458.

Watts, D.J., Strogatz, S.H. (1998). Collective Dynamics of ‘‘Small-World’’ Networks. *Nature* 393, 440–442.

Weenig, M. W. H. and C. J. H. Midden (1991), Communication Network Influences on Information Diffusion and Persuasion, *Journal of Personality & Social Psychology,* **61** (5), 734-742.

Weimann, G. (1982), On the Importance of Marginality: One More Step Into the Two-Stop Flow of Communication, *American Sociological Review,* **47** (6), 764-773.

Weimann, G., D.H. Tustin, D. Vuuren, and J.P.R. Joubert. (2007). Looking for Opinion Leaders: Traditional vs. Modern Measures in Traditional Societies. *International Journal of Public Opinion Research* 19(2): 173-190.

Westbrook, R. A. (1987), Product/ Consumption-Based Affective Responses and Postpurchase Processes, *Journal of Marketing Research (JMR),* **24** (3), 258-270.

Westbrook, R. A. and C. Fornell (1979), Patterns of Information Source Usage among Durable Goods Buyers, *Journal of Marketing Research (JMR),* **16** (3), 303-312.

Wetzer, I. M., M. Zeelenberg, and R. Pieters (2007), "Never Eat in that Restaurant, I did!": Exploring Why People Engage in Negative Word-of-Mouth Communication, *Psychology & Marketing,* **24** (Aug), 661-680.

Wiedmann, K.P., G. Walsh, and V.W. Mitchell (2001), The Mannmaven: An Agent for Diffusing Market Information, *Journal of Marketing Communications,* **7** (4), 195-212.

Wilensky, U. (1999). NetLogo. http://ccl.northwestern.edu/netlogo/ models/PreferentialAttachment. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Wilensky, U. (2005). NetLogo Preferential Attachment model. http://ccl.northwestern.edu/netlogo/ models/PreferentialAttachment. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Wilson, J. R. (1994). *Word-of-mouth Marketing*. New York, John Wiley & Sons.

Wuyts, S., Verhoef, P.C., and R. Prins (2009), Partner selection in B2B information service markets, *International Journal of Research in Marketing*, 26, 41-51.

Yakubovich, V. (2005), Weak Ties, Information, and Influence: How Workers Find Jobs in a Local Russian Labor Market, *American Sociological Review,* **70** (3), 408-421.

Yang, S., M. Hu, R.S. Winer, H. Assael and X. Chen (2012), An Empirical Study of Word-of-Mouth Generation and Consumption, *Marketing Science,* 31 (6), 952-963.

Yong, L. (2006), Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue, *Journal of Marketing,* **70** (3), 74-89.

Zhao, Z. (2004). Using matching to estimate treatment effects: Data requirements, matching metrics, and Monte Carlo evidence. *Review of Econometric Statistics* 86 (1), 91-107.

Zhao, M. and J. Xie (2011), Effects of Social and Temporal Distance on Consumers' Responses to Peer Recommendations, *Journal of Marketing Research,* **48** (3), 486-496.

Zhu, F. and X. Zhang (2010), Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics, *Journal of Marketing,* **74** (2), 133-148.

Ziethaml, V. A., L. L. Berry, and A. Parasuraman (1993), The Nature and Determinants of Customer Expectations of Service, *Journal of the Academy of Marketing Science*, **21** (Winter), 1-12.

Appendices

Appendix 3.1: Questionnaire

Q1. How many friends did you tell about the game?

a) 0
b) 1
c) 2
d) 3
e) 4 or more

Q2. Who told you about the game? (more answers possible)

a) Friends
b) Siblings
c) Parents
d) Teachers
e) Someone else
f) Internet / TV

Q3. The first time I made something with the game:

a) I did it alone
b) A friend asked me
c) I asked a friend

Q4. If I talk about the game with friends, I do so: (more answers possible)

a) while I am at school
b) using the internet
c) using the telephone
d) while playing after school
e) somewhere else

Q5. How many of your friends made something with the game?

a) 0
b) 1
c) 2
d) 3
e) 4 or more

Q6. How many of them made something earlier than you did?

a) 0
b) 1
c) 2
d) 3
e) 4 or more

Q7. It is important that others like what I make with the game.

a) Never
b) Not often
c) Sometimes
d) Often
e) Always

Q8. I help friends with the game.

a) Never
b) Not often
c) Sometimes
d) Often
e) Always

Q9. If I talk about the game with friends, …:

a) I know more
b) I know as much as my friends
c) My friends know more

Appendix 5.1: Survey Questions Regarding the Social Network

Q0 Condidering the people you know; with whom (family/friends) did you talk about mobile phones in the past three months?
Mention the names of these people (max. 5)

The additional questions are repeated for all mentioned names
Q1 What is the highest educational level of … finished (6 degrees)
Q2 What is the gender of …
Q3 What is the age of …

Can you indicate to which degree you agree with the following statements (repeated for all mentioned names)
Outgoing informative influence
Q4 I informed … about technical features of cell phones
Totally disagree 1 2 3 4 5 6 7 totally agree

Incoming informative influence
Q5 … informed me about technical features of cell phones
Totally disagree 1 2 3 4 5 6 7 totally agree

Outgoing normative influence
Q6 I informed … about trends in the cell phone market
Totally disagree 1 2 3 4 5 6 7 totally agree

Incoming normative influence
Q7 … informed me about trends in the cell phone market
Totally disagree 1 2 3 4 5 6 7 totally agree

Strength of outgoing influence (in general)
Q8 I have a strong influence on the cell phone preference of …
Totally disagree 1 2 3 4 5 6 7 totally agree

Strength of incoming influence (in general)
Q9 … has a strong influence on my cell phone preference
Totally disagree 1 2 3 4 5 6 7 totally agree

Appendix 5.2: Survey Questions Regarding Social Influence

Normative Influence

Q1: I rarely purchase the newest products and brands until I am sure my friends approve them.
Totally agree 1 2 3 4 5 totally disagree

Q2: It is important that others like the products and brands I buy.
Totally agree 1 2 3 4 5 totally disagree

Q3: When buying products, I generally purchase those brands that I think others will approve of.
Totally agree 1 2 3 4 5 totally disagree

Q4: If other people can see me using a product, I often purchase the brand they expect me to buy.
Totally agree 1 2 3 4 5 totally disagree

Q5: I like to know what brands and products make good impressions on others.
Totally agree 1 2 3 4 5 totally disagree

Q6: I achieve a sense of belonging by purchasing the same products and brands that others purchase.
Totally agree 1 2 3 4 5 totally disagree

Q7: If I want to be like someone, I often try to buy the same brands that they buy.
Totally agree 1 2 3 4 5 totally disagree

Q8: I often identify with other people by purchasing the same products and brands they purchase.
Totally agree 1 2 3 4 5 totally disagree

Informative Influence

Q9: To make sure I buy the right product or brand, I often observe what others are buying and using.
Totally agree 1 2 3 4 5 totally disagree

Q10: If I have little experience with a product, I often ask my friends about the product.
Totally agree 1 2 3 4 5 totally disagree

Q11: I often consult other people to help choose the best alternative available from a product class.
Totally agree 1 2 3 4 5 totally disagree

Q12: I frequently gather information from friends or family about a product before I buy.
Totally agree 1 2 3 4 5 totally disagree

Appendix 5.3: Survey Questions Regarding Information Sources

Q1 Please indicate which of the following sources you used when searching for a new cell phone. (more than one answer possible)

a. acquaintances / friends / family
b. I checked which cell phones other people have
c. Salesperson (e.g. getting advice / checked cell phones)
d. Shop (e.g. taken information brochure)
e. The site of the manufacturer
f. The site of the provider
g. A comparison site
h. Folders (from providers / shops)
i. Journals (cell phone related)
j. Other

Q2 Which of the sources you used, do you consider the most important source of information?

Samenvatting (Summary in Dutch)

In april 2004 introduceert Google haar webmail dienst Gmail, een introductie die niet ondersteund werd door enige vorm van traditionele marketing. Met een significante vergroting van de opslagcapaciteit (van enkele MB's naar één GB) en een introductie op 1 april (Google heeft een rijke historie 'introducties' op deze datum), plantte Google het zaadje voor een grote geruchtenstroom op internet. Slechts een aantal opinieleiders, geselecteerd naar aanleiding van hun veelbetekenende activiteiten op Google's blog, werden uitgenodigd om de dienst te gebruiken. Tegen de tijd dat deze eerste gebruikers de mogelijkheid kregen om een aantal andere mensen uit te nodigen, waren mensen zelfs bereid om te betalen voor zo'n (normaal gesproken gratis) uitnodiging. Zonder enige investering in marketing activiteiten groeide Gmail uit tot één van de grootste webmail providers ter wereld.

Hoewel Gmail een mooi voorbeeld vormt van een succesvolle productintroductie, slagen de meeste nieuwe producten er niet in om een rendabel marktaandeel te behalen. Een belangrijke factor die hierin een rol speelt is de sociale invloed die consumenten op elkaar uitoefenen. Deze sociale invloed bestaat niet alleen uit het verspreiden van product informatie (informatieve invloed), maar kan ook leiden tot het vaststellen van normen (normatieve invloed): hoor je bijvoorbeeld nog wel bij de groep als je een product aanschaft? Dit proefschrift geeft inzicht in de rol die deze sociale invloeden spelen bij de introductie van nieuwe producten en verschaft methodologische handvaten om onderzoek op dit gebied, zowel voor de wetenschap als de praktijk, een vervolg te geven.

Mond-tot-mondreclame: een complex proces

Mits op de juiste manier ingezet, kunnen bedrijven de verkoopcijfers van hun producten verhogen met behulp van sociale media. De communicatie die plaatsvindt via sociale media is het resultaat van complexe sociale beïnvloedingsprocessen, wat het moeilijk maakt voor bedrijven om die communicatie te beïnvloeden. De resultaten van campagnes die gericht zijn op sociale media zijn dan ook moeilijk te voorspellen.

De enorme impact die sociale invloed heeft, wordt al decennia lang onderkend en dit heeft dan ook geleid tot een rijke stroom aan wetenschappelijk onderzoek in onder andere marketing, sociologie en sociale psychologie. Op basis van de hierdoor ontstane inzichten wordt in hoofdstuk 2 het complexe proces van sociale invloed, mond-tot-mondreclame in het bijzonder, beschreven aan de hand van vijf onderling sterk samenhangende vragen: 1) over *welke producten* praten mensen, 2) met *wie* praten ze over die producten, 3) *waarom* praten ze over deze producten, 4) *waar* praten ze over, en 5) hoe *beïnvloedt* dat *het gedrag van de consument* op individueel en geaggregeerd (markt) niveau?

Het lijkt eenvoudig om deze vragen te beantwoorden, maar de samenhang tussen de vragen maakt dit erg complex. Zo is het mogelijk dat iemand het ontwerp van een mobiele telefoon bespreekt met een goede vriend (sterke relatie), maar de technische details met een bekende (minder sterke relatie). Of deze gesprekken invloed hebben op de productkeuze en hoe sterk deze invloed is verschilt van relatie tot relatie. Alleen door stil te staan bij de eerder genoemde vragen, daarbij de complexiteit van het proces in ogenschouw nemende, is het mogelijk om een strategie te ontwikkelen die het proces beïnvloedt.

Om een complex proces als sociale beïnvloeding te kunnen onderzoeken is het belangrijk een methode te gebruiken die dergelijke processen inzichtelijk kan maken. In dit proefschrift wordt gebruik gemaakt van agent-gebaseerd modellen (ABM). Dit is een simulatietechniek waarbij agenten (virtuele consumenten), aan elkaar verbonden in een netwerk, eenvoudige regels volgen die op individueel niveau geprogrammeerd zijn. Binnen zo'n model is het mogelijk om een agent door de tijd heen op individueel niveau te volgen: welke keuzes maakt de agent, aan welke invloeden wordt de agent blootgesteld, etc.? Tegelijkertijd is het mogelijk om informatie op een geaggregeerd niveau waar te namen: wat is het markaandeel, wat is het algemene beeld dat agenten hebben van een bepaald product, etc.? Ook biedt de techniek de mogelijkheid om te experimenteren met verschillende scenario's en de uitkomsten hiervan in detail te onderzoeken.

De rol van opinieleiders in het diffusieproces

In het begin van de tweede helft van de vorige eeuw werd in wetenschappelijk literatuur aandacht besteed aan een bijzonder type consument: de opinieleider. De opinieleider is een consument die bovengemiddeld veel invloed heeft op consumenten in zijn/haar omgeving, wat het aantrekkelijk maakt om marketing activiteiten op deze personen te concentreren. In het begin van *deze* eeuw werd een discussie gestart, waarbij vraagtekens worden gezet bij de daadwerkelijke invloed van de opinieleiders. Hoofdstuk 3 levert een bijdrage aan deze discussie, door de rol van opinieleiders met behulp van een ABM te onderzoeken.

De bovengemiddelde invloed van opinieleiders komt voort uit een aantal eigenschappen die de opinieleider onderscheidt van andere consumenten: ze hebben een centrale positie in hun sociale netwerk (veel contacten), ze vertonen innovatief gedrag, ze zijn minder gevoelig voor normatieve invloed en zijn beter in staat de kwaliteit van nieuwe producten te beoordelen. In de ontstane discussie over de rol van opinieleiders ligt de focus op mensen met een centrale positie in hun sociale netwerk. In hoofdstuk 3 wordt daarom ingegaan op de andere eigenschappen die een bijdrage leveren aan de invloed van opinieleiders.

Uit experimenten met het, op basis van empirische data opgestelde, ABM blijkt dat opinieleiders de snelheid van de diffusie van informatie over nieuwe producten positief beïnvloeden. Met betrekking tot de diffusie van het product zelf, beïnvloeden opinieleiders zowel de snelheid als ook het uiteindelijke adoptiepercentage. De snelheid van deze diffusieprocessen blijkt vooral te worden beïnvloed door de informatieve invloed die opinieleiders hebben, wat gerelateerd is aan hun vermogen om de kwaliteit van nieuwe producten goed in te schatten. Het innovatieve gedrag (waar meer normatieve invloed uit voortkomt) van opinieleiders is de drijfveer achter de hogere adoptiepercentages.

Het construeren van empirisch valide sociale netwerken

Eén van de grootste uitdagingen bij het opstellen van een ABM is het opstellen van regels die empirisch valide zijn. In onderzoek naar sociale invloeden is hierbij een onderscheid te maken tussen de regels die de individuele agent volgt en de manier waarop deze agent in verbinding staat met andere agenten in het netwerk. Voor het opstellen van individuele regels zijn vragenlijsten een waardevol instrument. Vervolgens wordt echter vaak gekozen voor een 'standaard netwerk vorm' (*random*, *scale-free* en *small-world* netwerken zijn bekende vormen) waarbinnen de agenten met elkaar in verbinding staan. Voor deze methode wordt vaak gekozen, omdat het combineren van de vragenlijst met empirische netwerkdata (bijvoorbeeld op basis van online sociale netwerken of telefoondata) erg moeilijk te realiseren is. In hoofdstuk 4 wordt een methode ontwikkeld die het mogelijk maakt om een netwerk te construeren op basis van een vragenlijst. Met behulp van deze methode is het mogelijk om een relatie te leggen tussen de positie die iemand heeft binnen een netwerk en de sociale invloed die zo'n persoon heeft of waar deze persoon aan blootgesteld wordt, zonder aannames te hoeven maken over de relatie tussen deze twee factoren.

De voorgestelde methode maakt gebruik van een vragenlijst die, naast de voor het vervolg onderzoek relevante vragen, ook een sectie bevat waarin de respondent gevraagd wordt om relaties met mensen te beschrijven die invloed hebben op het gedrag of de mening van de respondent. Zo'n relatie kan bijvoorbeeld beschreven worden aan de hand van de mate van gelijkheid tussen de personen (leeftijd, geslacht, opleiding), het type invloed dat uitgewisseld wordt (normatief, informatief) en de impact die deze invloed heeft. Aangenomen wordt dat de respondenten van het onderzoek geen onderdeel zijn van hetzelfde sociale netwerk: de beschreven relaties worden gebruikt om vergelijkbare respondenten te zoeken. Het algoritme legt vervolgens een link tussen deze personen, wat uiteindelijk resulteert in één gesimuleerd sociaal netwerk. Dit sociale netwerk kan vervolgens gelinkt worden aan de andere relevante informatie (zoals product voorkeuren) en voor vervolganalyses gebruikt worden. In Hoofdstuk 5 wordt dit algoritme met dat doel geïmplementeerd.

De rol van sociale invloed bij de introductie van nieuwe producten

Het ABM dat in hoofdstuk 5 wordt geïntroduceerd combineert een netwerkstructuur op basis van het algoritme in hoofdstuk 4, met een *concomitant variable latent class* model (om heterogeniteit in product preferenties te introduceren) en empirische data over voorkeuren van informatiebronnen met betrekking tot de aanschaf van een nieuwe mobiele telefoon. Onder deze informatiebronnen bevinden zich zowel traditionele media (tijdschriften, websites, etc.) als sociale media kanalen (vrienden, familie, etc.). Het ABM wordt gebruikt om verschillende marketing strategieën te testen, waarbij in het bijzonder wordt gekeken naar de relatie tussen deze strategieën en de sociale invloeden binnen het netwerk. De strategieën worden getest met de introductie van twee verschillende producten: een product dat een laag potentieel marktaandeel (LPM) heeft en een product dat een hoog potentieel marktaandeel (HPM) heeft.

Als de marketing strategie bestaat uit het inzetten van traditionele media, blijkt informatieve invloed een belangrijker bijdrage te leveren tot een hoger adoptiepercentage voor het HPM-product, in vergelijking tot het LPM-product. Door een samenhang tussen de positie van bereikte agenten binnen het netwerk, productvoorkeuren en voorkeuren voor bepaalde informatiebronnen, blijkt dat twee informatiebronnen een uitzondering vormen op deze regel.

Waar informatieve invloed een positief effect heeft op de adoptiepercentages, heeft normatieve invloed een negatieve invloed op het percentage agenten dat op de hoogte is van het nieuwe product. Dit heeft te maken met het feit dat enkele agenten, om met nieuwe producten in aanraking te komen, op normatieve invloed vertrouwen: deze agenten zullen derhalve pas op de hoogte raken van een product op het moment dat een agent in hun omgeving het product aanschaft. Dit toont aan dat het negeren van normatieve invloed zal leiden tot het overschatten van de effecten van informatieve invloed.

Het is ook mogelijk om een marketing strategie te hanteren die op specifieke agenten is gericht. Het hoogste percentage agenten dat op de hoogte is van het product wordt bereikt door de strategie op agenten te richten die een centrale positie hebben binnen (een cluster van) het netwerk. Het focussen op ‘bruggen’ (agenten die twee clusters binnen een netwerk verbinden) heeft hetzelfde effect als het focussen op willekeurige agenten binnen het netwerk. Daarnaast kan nog onderscheid gemaakt worden tussen het verspreiden van informatie over het product of het verspreiden van het product zelf. In het eerste geval kan de strategie zich het beste richten op agenten die een centrale positie hebben in het netwerk, terwijl in het tweede geval de strategie meer effect heeft als het is gericht op agenten die zich op een centrale positie in *een cluster* van een netwerk bevinden.

Belangrijkste bevindingen

Dit proefschrift benadrukt de complexiteit van sociale beïnvloedingsprocessen, waarbij informatieve invloed en normatieve invloed nadrukkelijk worden onderscheiden. Binnen veel onderzoek op het gebied van sociale beïnvloeding wordt een focus gelegd op informatieve invloed (mond-tot-mondreclame), of wordt uitgegaan van een positieve normatieve invloed (sociale aansteking). In de verschillende hoofdstukken van dit proefschrift wordt aangetoond dat het negeren van één van de twee invloeden zal leiden tot een verkeerde inschatting van de effecten ervan. Zo tonen de resultaten dat, hoewel normatieve invloed in dit proefschrift neutraal is geïmplementeerd in de modellen, het in alle simulaties een negatief effect blijkt te hebben. Informatieve invloed blijkt vooral een rol te spelen bij het vergroten van de bekendheid van het nieuwe product, terwijl normatieve invloed vooral het adoptiepercentage beïnvloedt. Verrassender is het resultaat dat normatieve invloed de bekendheid van het nieuwe product negatief kan beïnvloeden.

In hoofdstuk 3 wordt aangetoond dat eigenschappen van bepaalde agenten de snelheid van de verspreiding van (informatie over) een nieuwe product en het adoptiepercentage van dit product kunnen beïnvloeden. In hoofdstuk 4 wordt een methode ontwikkeld die dergelijke persoonlijke eigenschappen kunnen verbinden aan de positie van deze persoon in het netwerk. Deze methode geeft de mogelijkheid om de relatie tussen persoonlijke eigenschappen en de netwerkpositie in meer detail te onderzoeken, zonder aannames te hoeven doen over de onderlinge relatie.

Het toepassen van de geïntroduceerde methode in hoofdstuk 5, benadrukt wederom de complexiteit van de processen in zo'n sociaal netwerk. Zo blijkt bijvoorbeeld dat de impact van informatieve invloed afhankelijk is van zowel het gebruikte marketing kanaal als het product dat is geïntroduceerd. De verschillen die we waarnemen kunnen niet verklaard worden door te kijken naar de agenten die bereikt zijn via een specifiek mediakanaal. De resultaten suggereren dat deze verschillen samenhangen met de productvoorkeuren van de agenten in de omgeving van de bereikte agenten.

Alles bij elkaar genomen toont dit proefschrift aan dat sociale invloed een belangrijke impact heeft op consumentengedrag en om die reden niet genegeerd moet worden in onderzoek naar dit gedrag. Gelijktijdig wordt ook aangetoond hoe complex deze beïnvloedingsprocessen zijn. In dit proefschrift worden instrumenten geïntroduceerd die een bijdrage kunnen leveren aan onderzoek op dit gebied: zowel in de wetenschap als in het bedrijfsleven.