ANALYZING THE EFFECTIVENESS OF MARKETING STRATEGIES IN THE PRESENCE OF WORD OF MOUTH: AGENT BASED – MODELING APPROACH

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BOĞAZİÇİ UNIVERSITY

2011

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Thesis submitted to the
Institute for Graduate Studies in the Social Sciences
in partial fulfillment of the requirements for the degree of

Master of Arts
in
Management Information Systems

by
Çiğdem Karakaya

Boğaziçi University

2011

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in the Presence of Word of Mouth:
Agent Based – Modeling Approach

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June 2011

Thesis Abstract

Çiğdem Karakaya, “Analyzing the Effectiveness of Marketing Strategies in the Presence of Word of Mouth: Agent - Based Modeling Approach”

Consumer purchasing decision making has been of great interest to researchers and practitioners for improving strategic marketing policies and gaining a competitive advantage in the market.

Traditional market models generally concentrate on single individuals rather than taking social interactions into account. However, individuals are tied to one another with invisible bonds and the influence an individual receives from others, affects her purchasing decision which is known as word of mouth (WOM) effect. In this process, some people have greater influence on other consumers’ buying decisions, which are known as opinion leaders.

A new evolving modeling approach, agent-based modeling enables researchers to build models where individual entities and their interactions are directly represented.

In this study we aim to build an agent-based simulation model for a technological product in a monopolistic artificial market. In particular we will try to assess the efficiency and profitability of different marketing strategies consisting of different price, promotion, quality levels and different number of targeted opinion leaders where consumer are subject to WOM effects . The experiments are also applied for cases where WOM is not present, to effectively evaluate WOM importance in a market.

Independent of WOM presence, increasing the price of an average quality product is found to be the most significant and increasing the promotion intensity is found to be the second most significant factor affecting the profit of the company. Also, it is found that the market environment is more sensitive to marginal cost of quality when compared to marginal cost of collaborating with an opinion leader.

Keywords: Consumer network, word of mouth, marketing strategy, agent based modeling

Tez Özeti

Çiğdem Karakaya, “Ağızdan Ağıza Pazarlama Eşliğinde Pazarlama Stratejilerinin Başarı Analizi: Ajan Tabanlı Modelleme”

Tüketicilerin satın alma kararlarına hangi faktörlerin etki ettiği ve bu faktörlerden nasıl etkilendikleri, stratejik avantaj sağlamak isteyen organizasyonların ve araştırmacıların uzun süredir çalışma konusu olmuştur.

Geleneksel market modelleri genellikle, insanların birbirleri ile etkileşimini ele almaktan çok, tek bireyler üzerine yoğunlaşır. Ancak, aslında bir toplumda insanlar birbirine görünmez bağlarla bağlıdır, ve birbirleri ile paylaştıkları bilgiler satın alma kararlarına etki eder. Buna ağızdan ağıza pazarlama denir. Bazı insanların diğerleri üzerinde ki etkisi daha fazladır. Bu insanlar toplumda fikir liderleri olarak adlandırılırlar.

Gelişmekte olan yeni bir yaklaşım, ajan-tabanlı modelleme, araştırmacıların insanlar arasındaki etkileşimi kolaylıkla modellemesini sağlamaktadır.

Bu çalışmada, monopol bir yapay markette teknolojik bir ürünün satış ve pazarlama stratejileri ajan tabanlı modelleme ile simule edilmiştir. Özellikle ürün kalitesinin, promosyon miktarının, ürün fiyatının ve pazarlama esnasında kaç tane fikir lideri ile iş birliği yapıldığının, firmanın satış rakamları ve karı üzerindeki etkisi gözlemlenmiştir. Bu faktörlerin hepsi ağızdan ağıza pazarlamanın etkin olduğu ve olmadığı her iki durum için de test edilmiştir. Böylece insanların birbiri ile paylaştığı bilgilerin firmanın satış rakamları ve karı üzerindeki etikisi de saptanabilmiştir.

Ağızdan ağıza pazarlamaya bağımlı olmaksızın, marketteki potansiyel müşterilerin ortalamasını tatmin edecek bir ürün üretip, bu ürüne yüksek fiyat koymak, firma için en karlı strateji olarak bulunmuştur. İkinci karlı strateji ise böyle bir ürün için yapılan promosyon miktarını arttırmak olarak bulunmuştur. Duyarlılık analizi ile ilgili yapılan çalışmalarda ise ürünün kalitesini arttırmanın maliyet üzerindeki etkisinin, birlikte çalışılan fikir liderlerinin sayısını arttırmaktan çok daha fazla olduğu görülmüştür.

Anahtar Kelimeler: Tüketici ağları, ağızdan ağıza pazarlama, pazarlama stratejileri, ajan tabanlı modelleme

ACKNOWLEDGMENTS

I would like to express my very sincere thanks to my master thesis supervisor, Assist. Prof. Bertan Badur, for his tremendous support and incredible guidance he has given throughout my academic work.

I am also very thankful to Assist. Prof. Dr. Hande Kımıloğlu and to Assoc. Prof. Dr. Eyüp Çetin for their contribution and participation in my thesis committee.

I would like to express my thanks to my friend Can Aytekin who have shown tremendous patience, understanding and contribution and to my friend Osman Yucel who have helped me in this period.

Finally, I owe my special thanks to my parents for their encouragement, endless belief and understanding.

CONTENTS

CHAPTER 1: INTRODUCTION

Companies and organizations seek for competitive advantage through effective marketing strategies. Research conducted by academicians and practitioners give a profound understanding of how marketing strategies can improve their sales and profit. When the market is stable, forecasting effect of marketing strategies is easier. However, under some circumstances forecasting models may not be able compensate all practical implications, for instance when a new product is introduced or its practical use is changed. An example for such a situation can be given as the trend towards digital recording and distribution of music. After being stable for a prolonged period of time, market finds its new equilibrium after a short period of time. Another example is fashion market, which shows continuous fluctuations in market share.

A key element behind the complex markets is the interactions among consumers. People tend to share their ideas and purchasing experiences between each other. They inform one another about their normative evaluations of the product by word of mouth (WOM) (Gilbert et al., 2007).

Even though marketers cannot fully control the interactions among consumers, understanding how it affects market behavior contribute to the development of new strategies. WOM effect plays an important role in the diffusion of products in a marketing environment. Meanwhile interest towards WOM marketing is increasing, interest towards modeling this complex behavior among consumers is also increasing. A new modeling technique called, Agent based modeling (ABM), enables the modeling and simulation of interactions among consumers in a market.

In this study, we use ABM to evaluate the efficiency of different marketing strategies of a firm producing a technological product in a monopolistic market. In our model, consumer preferences are influenced not only from the quality characteristics of the product but also from WOM effect disseminated from other consumers and opinion leaders. We will analyze the effect of different levels of product characteristics, price, promotion and opinion leader strategies on sales patterns and profitability of the company. We aim to contribute to consumer behavior research by conducting different simulation experiments to find how price, promotion and quality factors are affecting the profitability of the company and assess the importance of WOM in marketing strategies.

The thesis is structured as follows: Chapter 2 presents the studies conducted in the literature. Chapter 3 briefly reviews ABM, the methodology that is used in this study. Chapter 4 gives the details of our model. In Chapter 5 experimental setup of our simulation is presented. Chapter 6 presents the results of the experiments. The final chapter concludes the study and discusses the possible further improvements.

CHAPTER 2: LITERATURE SURVEY

This chapter is compromised of three sections. The first section gives information on consumer behavior in social networks. Second section describes agent based modeling and the last section presents different studies of agent based models conducted in marketing environment.

Consumer Behavior in Social Networks

Consumers are the ultimate source of revenue for companies and it is vital to understand consumers in order to gain a competitive advantage in the market. Researchers and practitioners have been delving into the study of consumer behavior for a very long time (Zhang & Zhang, 2007). After the first mention of consumer behavior concept about 80 years ago by the Austrian economist Boehm – Bawerk (Wooliscroft, Tamilia & Shapiro, 2006), a lot of studies and researches are conducted on this subject. According to Solomon (2009), an elementary marketing concept states that organizations exist to satisfy consumers' wants and needs. These wants and needs can only be satisfied by understanding the consumers that will use the product. What, when, why, where and how a consumer decides to acquire, use and dispose the product are essential questions for understanding consumer behavior (Hoyer & MacInnis, 2007). In addition to consumers' personal preferences and needs, there are psychological and sociological effects that influence the consumers' purchasing decisions. Consumers may purchase a product in order to achieve a social status or to belong to a group. They can make a purchasing decision based on their past experiences or they can communicate with their environment and learn from other consumers (Janssen & Jager, 2001).

Consumers are connected in numerous ways that were not available before. Internet plays a vital role by connecting consumers through social networking sites, blogs, wikis, recommendations sites, etc. (Hennig-Thurau et al., 2010; Wuyts et al., 2010). Individuals are tied to one another with invisible bonds. This forms criss-cross mesh of connections similar to a fishing net (Scott, 1988). Each individual receives some kind of resource from the other individual it is connected to. These connections may originate between friends, family members, people whose life standards and interests are similar, people who are physically close to each other or strangers that can reach one another through internet (Libai et al., 2010). In order to understand behaviors of individuals, it is important to understand the dynamics of the network in which they belong.

Information diffusion among the individuals in a network is an important concept for marketers. In a group of people, individuals' attitudes and opinions on an issue change as they get influenced by other members (Friedkin, 2003). The influence on an individual that originates from another individual is known to be word-of-mouth (WOM) effect. Companies are taking strategic decisions in order to benefit from the WOM power. Management consultants McKinsey & Co. estimate that two thirds of the US economy is driven by WOM effect (Dye, 2000). In their book "Connected Marketing", Kirby and Marsden (2006) asserts that recent researches has scientifically proven that, high levels of positive WOM derive business growth. Although the WOM effect has been present for a very long time, with the new developments and improvements in technology, it is much more important in influencing individuals buying decisions in recent years (Berry, 2005).

Companies spend millions to implement successful strategies to make consumers talk about their products and create an effective WOM (Solomon, Marshall & Stuart, 2008). The advertising agency JWT Worldwide states that, over 85 percent of top 1000 firms use WOM tactics today (Wasserman, 2006). Certainly, companies cannot control all the WOM created by the consumers. The motivation to talk about a product and level of satisfaction retrieved from purchasing the product may vary depending on different consumers. In addition, negative WOM can be created by unsatisfied consumers or by unsuccessful WOM strategy as it happened to McDonalds (Wasserman, 2006).

The connections between the individuals represent one individual's attention to the other. Some actors selectively pay attention to other actors, while in some cases everybody pays attention to one person's opinion, for instance a strong public figure (Lazer, 2003). This argument was first introduced by a landmark study by Lazarsfeld, Berolson and Gaudet (1944). It was found that mass media advertisements do not directly influence mass market but instead influence small amount of people who then influence other individuals through WOM. A new term "opinion leaders" is coined then. These people need not necessarily be "leaders" in the usual sense but they are leaders who have direct influence on other individuals due to being exceedingly informed, valued or merely “connected” (Watts & Dodds, 2007). They influence others’ behaviors and attitudes because others believe these people have expertise about the product (Rogers, 1983). Most of the time they become the first to buy new products and they reduce the uncertainty for other consumers (Solomon, Marshall & Stuart, 2008). The marketing policy of Windows 95 governed by Microsoft has shown the influence and power of opinion leaders (Rosen, 2000).

Marketing has been an effective tool and strategy for increasing the sales of a product (Jager, 2007). For marketing strategies, companies look for segmentation of its consumers, provision of successful goods and services for each consumer segment and also employment of right promotional tools and pricing strategies to accomplish the company’s objectives (Walker, Mullins & Larreche, 2008). Marketing mix is the strategic tool-box that marketers use in order to create a desired response from a set of predefined consumers (Solomon, Marshall & Stuart, 2008). Marketing mix, commonly known as the McCarthy’s (1960) 4Ps, consist of product, price, place and promotion. Companies spend effort to find the most efficient marketing mix in order to implement a successful marketing strategy. 4Ps of marketing are essential elements of a marketing strategy, and WOM often complements and extends the effects of promotions and has an effect on the sales of the product. Companies may be underestimating promotion effectiveness by ignoring possible WOM effects (Homan, Legon & Libai, 2004).

Marketing strategies aim at increasing the sales of a company, by the sociological and psychological influences they create on consumers as well. In addition each distinct individual is influenced in a different level and each individual has the ability to influence other people with their purchase experience. Product characteristics values are also important factors in influencing the buying decision of the consumer. Modern technologies and new marketing strategies evolve over time. The analysis of this complex environment may require different modeling methodologies besides the traditional approach.

Agent Based Modeling

Agent based modeling (ABM) is a new analytical tool for social sciences and it enables one to build models where individual entities and their interactions are directly represented (Gilbert, 2008). In recent years, ABM is being utilized as an alternative research methodology in various social sciences; in economics (Tesfatsion & Judd, 2006), sociology (Macy & Willer, 2002), anthropology (Kohler & Gumerman, 2000), political science (Kollman & Page, 2006), and business (North & Macal, 2007). The modeling approach is applied in subfields of business; finance (Lebaron, 2006), organization (Myong & Harrington, 2006), supply chain management (Valluri, North & Macal, 2009) and in marketing (Gilbert et al., 2007).

In this study we use agent based modeling as our methodology. ABM is a computational simulation method that serves to the study of social sciences. “It is a form of computational social science and it enables a researcher to create, analyze and experiment with models composed of agents that interact within an environment” (Gilbert, 2008). Unlike the traditional approach in business research, which mainly focuses on collecting data through surveys, analyzing them and inferring conclusions with the aid of statistical models (Hair et al., 2009), ABM gives one the ability to create agents that have individual heterogeneity and decision rules, space them in a desired geographical or any type of space, connect them through a network for interaction and simulate them to better understand the dynamics of the social system (Gilbert, 2008). Although ABM is not a new concept, only in recent years, large amount of studies began to be published. This may be due to significant improvements in computer technology which enables modelers to analyze interacting agents, such as people or firms, and to simulate complex situations.

As human behavior is very complex, finding empirical data on consumer behavior and coping with sociological and psychological ambiguities are difficult. This makes it harder to model with traditional modeling approach. In addition, they do not always act rationally; decreasing the price of a product does not always conclude in increased sales. The study of Deffuant and Huet (2007) claims that, this bounded rational characteristic of human beings makes it harder to define strict rules in modeling.

Human beings learn from their old experiences, get influenced by their social environment, and constitute purchasing decisions based upon their current beliefs and values. Human beings also get affected by marketing strategies such as promotions and advertisements. Traditional market models generally concentrate on single individuals rather than taking social interactions into account (North et al., 2010). Another point is that, they do not comprehend the inner psychological process of consumer purchase decision, such as motivation that measures the degree of consumers' intention to buy a product.

Consumers' attitudes towards a product may change over time depending on the effects of the social network and the perceived social facts (Vag, 2007). Psychological effects of advertisements and price changes may also change individual's attitude.

This promising computational method overcomes the difficulties of conducting experiments in social sciences. In real life, it is usually impossible or unethical to create isolated social systems, and apply treatments to observe the outcomes. ABM allows us to create virtual social systems and conduct experiments repeatedly with different parameters and with randomly varying factors. Given a range of inputs, one can experiment to see how the model behaves, in other words, one can simulate the real world under variety of circumstances (Gilbert, 2008).

Agents in the model are autonomous decision making entities (Khouja, Hadzikadic & Zaffar, 2008). The study of Wooldridge and Jennings (1995) claims, an agent, from a more theoretical view of artificial intelligence, is a computer system that is either conceptualized or implemented using the concepts that are more usually applied to humans. Each individual in the model behaves according to his preferences and get influenced by a motivation function.

ABM also gives the opportunity of modeling heterogeneity which means it enables one to model any number of agents that have different attributes with differentiated values (Khouja et al., 2008). With the help of agent based modeling we analyze macro behavior emerging from micro behaviors. The study of Ma and Nakamori (2005) claims, “Simple patterns of repeated individual action can lead to extremely complex social institutions”.

The agent based simulation has some disadvantages. These disadvantages mainly derive from the shortcomings of the simulation methodology itself (Banks, 1998). First of all, the simulation case needs to be selected very cautiously. The cases which have possible analytical solutions may cause inappropriate use of simulations. One should also be aware that simulation modeling can be very time consuming and the results of the simulation can be difficult to interpret. The outputs of a simulation are mostly results of random inputs, as a result of this situation it might be hard to decide whether an outcome is caused by system interrelationships or randomness. As it is pointed out in the study of Banks (1998), it is possible to overcome these drawbacks of simulation modeling.

Another drawback of agent based simulation is the difficulty of its validation. In most cases, it is hard to acquire suitable and sufficient social science data for systematic validation (Troitzsch, 2004). The study of Merson (1998) asserts when there is no sufficient data available for validation as in abstract models, the criteria applied to evaluate theories must be applied to these models. That is, the models need to yield interpretable macro patterns from plausible micro level agent behavioral rules and interactions. The abstract agents based simulation models may be validated by this approach.

Forecasting market responsiveness to various marketing mix strategies without the presence of actual sales data is a challenging process (Luan & Sudhir, 2010). The method can be used in situations where it is hard to collect real life data (Khouja, Hadzikadic & Zaffar, 2008). ABM enables researchers to simulate real world environment and obtain possible consequences of various marketing mix decisions in the future, in situations that reliable and high quality data is not available.

ABM is an efficient tool to model consumer to consumer (C2C) interactions. The study by Ma and Nakamori (2005) defines ABM as an emerging simulation technique that promises to overcome the difficulties of modeling real world situations and managing complex human behavior. Libai et al. (2010) also stress the importance of ABM, as a simulator of "would be world" in which consumers interact with each other and aggregate outcomes of consumer interactions can be observed. ABM is an advantageous tool to use for modeling complex human behaviors aggregating from individual C2C interactions and testing their reactions to different marketing strategies. It enables one to take into account the complexity of consumer behavior in a social system such as monitoring and handling psychological effects produced by advertisements and WOM effects emerging through consumer networks. Embedding human cognition to agents makes it possible to understand the dynamics of consumers' decision making processes.

Agent based models are increasingly being used in the marketing literature. We can refer to studies Jager (2000), Janssen and Jager (1999), Baudisch (2007), Delre et al. (2007), Kuenzel and Musters (2007), Midgley, Marks and Kunchamwar (2007), Zhang and Zhang (2007) and Karakaya, Badur and Aytekin (2011) for different implementations of ABM on a variety of subjects. The study of Jager (2000) implements ABM to simulate individual decision making on communal resource usage and presents a conceptual meta-model of human behavior that integrates different theories relevant for understanding environmental behavior. Janssen and Jager (1999) uses agent ABM to model behavioral rules that dominate consumers' decision making processes and study lock – in markets and came up with two different lock-in markets, namely, a spatial lock-in and a global lock-in. The study Baudisch (2007) uses ABM to understand consumer heterogeneity in footwear consumption sector and clearly illustrates how heterogeneity among consumers may emerge from social comparison, Delre et al. (2007) investigates the consumer behavior on the take off of a new product and finds out that targeting a number of clustered consumers is effective in successful product diffusion, the study of Kuenzel and Musters (2007) implement ABM approach for the purchase of everyday food products and finds out that there are significant differences in consumers' susceptibility to informative social influence, Midgley et al. (2007) uses agent based modeling to depict complex interactions between consumers, manufacturers and retailers and explores issues of model assurance, Zhang and Zhang (2007) explores the decoy effect to understand how does adding a third product affect the preferences for two competing products and formalizes consumer motivation as a function that combines personality traits with consumer interaction. Finally the study of Karakaya et al. (2011) evaluates different marketing strategies in a monopolistic market for a technological product.

CHAPTER 3: MODEL

This chapter consists of two sections. The first section gives general information on our model. The second section gives details about modeling consumer behavior.

Model Structure

In our study we analyze the sales pattern and profitability of launching a technological product in a monopolistic market environment using ABM. The company implements different marketing strategies which consist of different promotion and price levels, different quality characteristics of the product and different number of targeted opinion leaders. It has the power to change the quality characteristic and price of the product, as well as the promotion and opinion leader strategy and to monitor WOM effect on profits. We take into account three of the 4Ps, product (quality), price and promotion in the model and ignore the place effect.

The market environment is the place where consumers and products meet. There are N heterogeneous consumers in the market and they are connected through a social network. In the consumer population there are M opinion leaders. Opinion leaders have a larger effect on the consumers compared to other people. They are randomly distributed among the population. In other words consumers have the ability to act according to their own preferences and to influence each others' purchasing decisions.

There are T discrete time steps at each experiment. At each time step the model assess whether an individual already purchased the product or not. If the individual has purchased the product, she uses the product until the last time step and does not make a purchasing decision in consecutive time steps. Otherwise the individual revises her buying decision in every time step. At the beginning of each replication, the population is initialized and the company launches its product into the market.

As the consumer population is created, Beta distributed parameters are assigned to every individual for their product preference value. Each individual also has sensitivity parameters for price, promotion and WOM which are randomly distributed. These sensitivity parameters show how receptive a consumer is to external factors. Some consumers' quality sensitivity may out weight their price sensitivity, in other words low prices may not persuade some consumers to purchase low quality products (Schwaiger & Stahmer, 2003).

After the consumer population is created, the differences between individual consumers' preferences are calculated. We set preferences as the indicator of distance between individuals assuming that individuals having similar product preferences are more likely to have similar life standards and are more likely to encounter with each other (Carley, 2003). The absolute value of the differences between individuals' preference values are used to determine whether they are connected to one another. Individuals that have a distance lower than a predetermined threshold are assumed to be connected. We assume that, consumers connected to each other have the ability to influence each other and an individual is more likely to get influenced by a person who has similar product preferences.

In this study we only take quality as the product decision and we set a single technological attribute for the specified product. The attribute is "the more, the better" type of attribute, which means that consumers are always willing to get higher levels of it, such as resolution of the screen. In another study by Karakaya et al. (2011), a very similar modeling approach is governed for a technological product that has two attributes, second attribute being preferred at any value depending on consumers' needs.

Price is the amount the consumer pay in exchange of the product. Even though it may seem that lower prices will attract larger number of consumers, with the adequate promotion strategies, the motivation and perception of the product on consumers may change and consumers may be willing to pay a higher price to own the product. They may also pay more in order to attain a social status or to belong to a group. In this study, we refer to promotion as a policy that is governed to attract more consumers, such as advertisements or campaigns.

Modeling the Consumer Behavior

The study of Zhang and Zhang (2007) is taken as a reference for the utility function. There are four components in the utility function of a consumer. These components are quality, promotion, WOM and price. The total utility of the consumer is the sum of these four components. All the parameters used for computing utility components scale from 0 to 1. The utility function for consumer i is as follows:

$$U_i = U_{i1} + U_{i2} + U_{i3} + U_{i4} \tag{1}$$

where;

U_{i1}: utility component of quality for consumer i

U_{i2}: utility component of promotion for consumer i

U_{i3}: utility component of WOM for consumer i

U_{i4}: utility component of price for consumer i

$$U_{i1} = G_i * K_i \tag{2}$$

$$G_i = \begin{cases} 1 + |P_i - A| & \text{if } A > P_i \text{ for consumer i} \\ 1 - |P_i - A| & \text{if } A < P_i \text{ for consumer i} \end{cases} \tag{3}$$

where;

K_i: quality sensitivity of consumer i

A: product characteristic value

P_i: preference value of consumer i for product

Product attributes change between 0 and 1, 0 being the lowest quality and 1 being the highest quality possible for that attribute. Cost of the product is linearly related with the quality attributes of the product, so increasing these attributes result in higher costs for the company, since higher quality technology products cost more than lower quality products. The product quality characteristic is “the more, the better” type of attribute so, every reasonable consumer will prefer higher values. However, because of the budget limitations they might choose to trade some resolution quality for lower price. For this reason the preference values are uniformly distributed between 0.5 and 1.

The second component of the utility function consists of the promotion effects. For each time step, the company has the power to define a promotion strategy.

$$U_{i2} = Pr_i * (Pro_t + \beta Pro_{t-1}) \qquad (4)$$

where;

Pr_i: promotion sensitivity of consumer i

Pro_t: promotion intensity at time t

β: smoothing constant

Consumers are modeled as having memories so that the effect created by the previous time step's promotion strategy continues to influence consumers to some extent in consecutive time steps. The effect of previous promotion intensity values decays geometrically as in exponential smoothing models. The derived promotion value gets multiplied by the promotion sensitivity value of each consumer at each time step.

In the third component, we cover WOM effect.

$$U_{i3} = WOM_i * S_i \quad (5)$$

where;

WOM_i : amount of WOM consumer i receives

S_i : social sensitivity of consumer i

Each consumer has different preferences and priorities for the product and gets influenced in different levels by external factors. The satisfaction a consumer receives from consuming the product is the first component of the utility function. This component determines the level and the direction of WOM, a consumer disseminates to others. Another factor that influences the level of WOM disseminated is the WOM received in previous time steps. The amount of WOM a consumer disseminates at time t, is the weighted sum of WOM that consumer receives from others at the previous time step t-1. If the person is an opinion leader, than the influence he or she makes will be three times as powerful as a normal consumer in our experiments. The company must pay a fixed amount of money for each opinion leader it collaborates. Opinion leaders that work with the company do not disseminate negative WOM. We assume that only consumers who have purchased the product create a WOM effect. An important concept is that, consumers can disseminate negative WOM and hamper other consumers' buying stimuli.

The fourth component of the utility function consists of price.

$$U_i = - (Pri_i * price) \tag{6}$$

where;

Pri_i: price sensitivity of consumer i

price: price of the product

Price and utility has an inverse relationship. Company sets a predetermined price for each time step. This price is multiplied by the consumer's price sensitivity. Consumers with higher budget limits will be less sensitive to price and others will be influenced more by the price of the product, but in any case we assume price is an important attribute in the purchase decision so we randomly assign price sensitivity values to consumers between 0.5 and 1 instead of distributing it evenly between 0 and 1.

We use a threshold model for activating the buying decision (Granovetter, 1978). The study of Meyer and Johnson (1999) find that, consumers have a minimum threshold level that must be satisfied to purchase products, but do not have maximum limit. They also claim that, consumers do face a marginal utility decrease resulting from consumption of products that are functionally beyond their requirements. In our study we set minimum threshold level for consumption but we ignore marginal utility decrease resulting from higher functionality of products.

As it is mentioned before, human beings do not always act rationally and they may not always purchase a product even though it satisfies consumer's expectations. In order to introduce randomness to the consumer decision process, logit function is used to determine the buying decisions of consumers (Anderson, de Palma & Thisse, 1992).

$$\text{Logit (u)} = \frac{1}{1 + e^{k(u-\alpha)}} \qquad (7)$$

Logit functions are beneficial tools used in social simulations. In Equation 7, u stands for the utility of a particular consumer, k being the smoothing constant and α being the buying threshold. The logit function ranges from 0 to 1, as seen in figure 1.

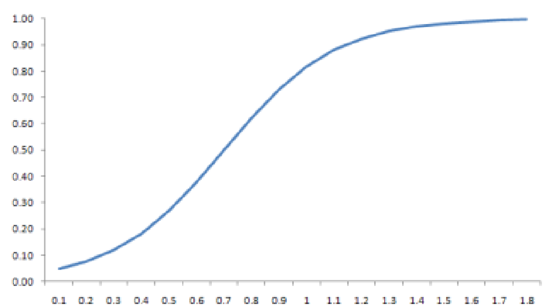

Fig. 1 – Graph of logit function

If the utility of consumer exceeds the threshold value, consumer buys the product with a probability generated by the logit function.

$$\text{if } U_i > \alpha \text{ and logit}(U_i) >= \tau_i \text{ consumer i purchases the product} \quad (8)$$

where;

α : buying threshold

τ_i : random number generated for consumer i

If a consumer buys the product, he uses the product until the last time step and he does not make another purchasing decision in the consecutive time steps. Buyers' utilities do not decay due to external factors after purchasing the product.

CHAPTER 4: EXPERIMENTAL SETUP

In this study our primary aim is to assess the efficiency and profitability of different marketing strategies through simulation experiments. Each experiment, which consists of 20 time steps, is replicated 100 times in order to reduce the variance of the outputs. In each experiment different parameter setups are governed, in order to monitor the directions and the magnitude of effects of different marketing strategies employed by the company. Experiments are executed in 3 different scenarios. Each scenario has different settings for parameters that are not in control of the company, namely for marginal costs of opinion leaders and product quality. In each scenario, experiments consisting of different decision parameters are conducted to analyze strategic decisions the company makes. In addition to assessing efficiency of marketing strategies, we make a sensitivity analysis for different strategies.

The parameters that remain the same in all our experiments are shown in Table1:

Table 1–Model Parameter Values That are Fixed in All Scenarios

Parameters	Values
Number of time steps (T)	20
Number of Consumers in the Population (N)	1000
Probability of a consumer to be an opinion leader (p)	%20
Consumer preference values of product (P)	β(5,2)
Buying threshold (α)	0.5
Exponential smoothing constant for promotion (β)	0.5
Smoothing constant for the logit function (k)	-5
Smoothing constant for WOM (π)	0.01
Marginal cost of promotion (μ)	0.2
Normal consumer WOM effect / Opinion leaders WOM effect (Ω)	1/3
Opinion leader WOM effect (ʃ)	0.6
Maximum amount of distance allowed between consumers to be connected (τ)	0.3
Smoothing constant for WOM received by a single consumer (ς)	0.02

There are four different decision variables that affect the buying decision of the consumer. Price, promotion, product quality value, number of opinion leaders the company chooses to collaborate with. The simulations are run in order to monitor the effects of different product design, price, promotion and opinion leader strategies on profit of the company. In the first scenario a total of 34 experiments are conducted. First a benchmark experiment is conducted with values of Exp1.1 as seen from Table1. Afterwards; to analyze the effects of all four decision parameters, each of the four decision parameters are tested with different values. In other words, in every experiment one decision variable is chosen to be evaluated and its value is changed within a predetermined scale. All the parameters for scenario 1 can be found in Table3. All experiments are also conducted when WOM is not in effect. For experiments that are conducted in presence of WOM, W is added as suffix and for the ones that are conducted without WOM presence, NW is added as a suffix to the name of the experiments.

For the first scenario the marginal cost setting is shown in Table2.

Table 2– Marginal Cost Setting for Scenario 1

Parameters	Values
Marginal cost of increasing product quality	0.25
Marginal cost of increasing promotion level	0.2
Marginal cost of collaborating with an opinion leader	0.5

The experimental setup for scenario 1 is shown in Table3.

Table 3– Experimental Setup for Scenario 1

Exp. No.	Quality	Promotion	price	opinion leader
1.1W -1.1NW	0.7	0.5	0.4	10
1.2W -1.2NW	0.3	0.5	0.4	10
1.3W -1.3NW	0.5	0.5	0.4	10
1.4W -1.4NW	0.9	0.5	0.4	10
1.5W -1.5NW	1	0.5	0.4	10
1.6W -1.6NW	0.7	0.1	0.4	10
1.7W -1.7NW	0.7	0.3	0.4	10
1.8W -1.8NW	0.7	0.7	0.4	10
1.9W -1.9NW	0.7	0.9	0.4	10
1.10W -1.10NW	0.7	0.5	0.2	10
1.11W -1.11NW	0.7	0.5	0.6	10
1.12W -1.12NW	0.7	0.5	0.8	10
1.13W -1.13NW	0.7	0.5	1	10
1.14W -1.14NW	0.7	0.5	0.4	0
1.15W -1.15NW	0.7	0.5	0.4	5
1.16W -1.16NW	0.7	0.5	0.4	15
1.17W -1.17NW	0.7	0.5	0.4	20

In the first scenario, we run different experiments in order to understand the effect of different decision variables controlled by the firm. The first experiment (Exp.1.1) is set as the benchmark and for the remaining experiments the different decision variable values are assigned to monitor the change in profit and in number of buyers. Through experiments Exp1.2 and Exp1.5, different product quality values are tested, to monitor how sales pattern and profit changes when the product is set as a high or low quality product. In experiments Exp1.6 to Exp1.9, effects of different promotion intensity level are monitored. In experiments Exp1.10 to Exp1.13, different price levels are set for the product and in experiments Exp1.14 to Exp1.17, different opinion leader strategies are tested. Each experimental setting is replicated for the WOM not in effect case, for scenario 1.

In the second scenario, a total of 10 experiments are conducted. In this scenario two different values are assigned for the marginal cost of opinion leaders. Both an increased and decreased value when compared to the marginal cost of opinion leader value in scenario 1. As in the first scenario, five different values are assigned for the number of opinion leaders to collaborate with.

The constant marginal cost values for scenario 2 are summarized in Table 4.

Table 4– Marginal Cost Setting for Scenario 2

Marginal cost of increasing product quality	0.25
Marginal cost of increasing promotion level	0.2

The experimental setup for scenario 2 is shown in Table 5.

Table 5– Experimental Setup for Scenario 2

Exp. No.	quality	promotion	price	opinion leader	marginal cost of O.L.
2.1W -2.1NW	0.7	0.5	0.4	0	0.3
2.2W -2.2NW	0.7	0.5	0.4	5	0.3
2.3W -2.3NW	0.7	0.5	0.4	10	0.3
2.4W -2.4NW	0.7	0.5	0.4	15	0.3
2.5W -2.5NW	0.7	0.5	0.4	20	0.3
2.6W -2.6NW	0.7	0.5	0.4	0	0.7
2.7W -2.7NW	0.7	0.5	0.4	5	0.7
2.8W -2.8NW	0.7	0.5	0.4	10	0.7
2.9W -2.9NW	0.7	0.5	0.4	15	0.7
2.10W -2.10NW	0.7	0.5	0.4	20	0.7

For the final scenario, scenario 3, a similar approach is governed. This time, instead of changing the marginal cost value of opinion leaders as in scenario 2, marginal cost of product is changed. As in the previous scenario 2 different values are assigned and a total of ten experiments are conducted.

The constant marginal cost values for scenario 3 are summarized in Table 6.

Table 6– Marginal Cost Setting for Scenario 3

Marginal cost of collaborating with an opinion leader	0.5
Marginal cost of increasing promotion level	0.2

The experimental setup for scenario 3 is shown in Table 7.

Table 7– Experimental Setup for Scenario 3

Exp. No.	quality	promotion	price	opinion leader	marginal cost of product
3.1W -3.1NW	0.3	0.5	0.4	10	0.1
3.2W -3.2NW	0.5	0.5	0.4	10	0.1
3.3W -3.3NW	0.7	0.5	0.4	10	0.1
3.4W -3.4NW	0.9	0.5	0.4	10	0.1
3.5W -3.5NW	1	0.5	0.4	10	0.1
3.6W -3.6NW	0.3	0.5	0.4	10	0.4
3.7W -3.7NW	0.5	0.5	0.4	10	0.4
3.8W -3.8NW	0.7	0.5	0.4	10	0.4
3.9W -3.9NW	0.9	0.5	0.4	10	0.4
3.10W -3.10NW	1	0.5	0.4	10	0.4

CHAPTER 5: RESULTS

In this chapter, results for three different scenarios are presented. The first section give the results for the first scenario and in its subsections give details about the decision parameter experimented is presented. Section 2 presents the results for scenario 2 and scenario 3, in which a sensitivity analysis is made. The final section gives a summary of the results.

This study is developed in Java, on a PC that has a CPU of 2.40 GHz and 4GB RAM. The average run time for an experiment is found to be one and a half minute. The code of the program is available upon request.

Effects of Different Marketing Strategies

In the first scenario, effects of different decision parameter values, on company's profit and number of buyers, are examined. The decision variables that are controlled by the firm and tested in these experiments are; product quality, promotion level, price level and number of opinion leaders to collaborate with.

Effect of Product Quality

In scenario 1, the first experiment (Exp.1.1) is set as the benchmark experiment. For the "next consecutive four experiments (Exp1.2-Exp1.5), the product quality value has been changed (increased and decreased) to monitor how profit and number of buyers change as a response to a change in product quality. In Fig. 2, number of buyers in Exp1.1W-Exp1.5W is plotted.

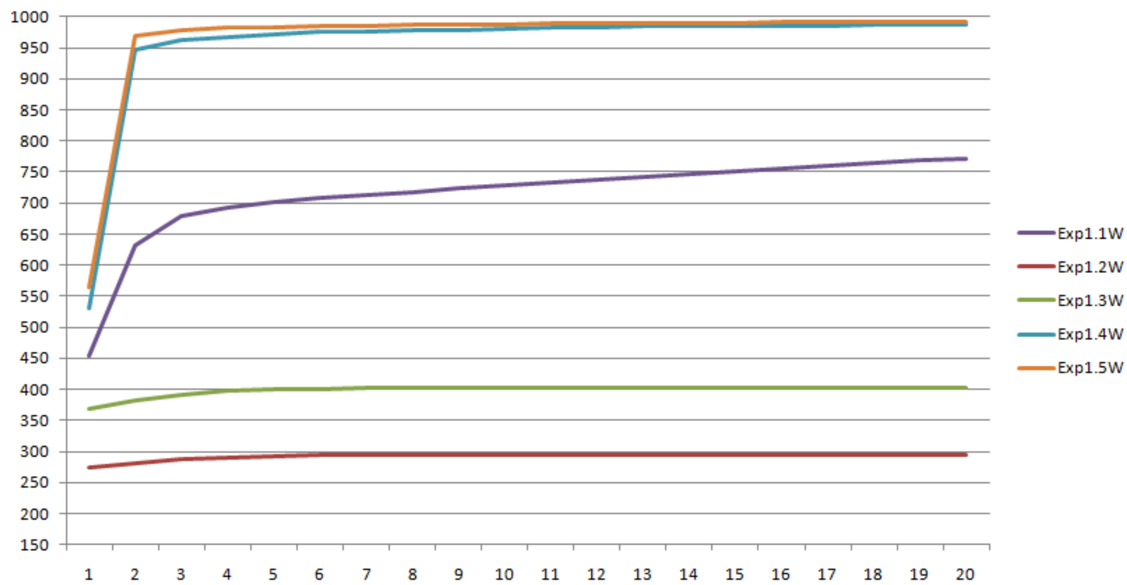

Fig. 2 – Number of buyers over time in different experimental setups for scenario 1, with WOM influence when product quality is varied

In the benchmark experiment initially 453 people purchased the product. At the second time step, roughly 200 more people purchased the product and this number continued to grow gradually until the last time step. The product quality, which is 0.7 in the benchmark experiment, is satisfying for most of the consumers in the population. This means, WOM disseminated by most of the consumers are positive. This effect continued to influence other consumers' buying decisions and number of buyers in Exp.1.1W is found to be 768 in the final time step. In Exp.1.2W and Exp.1.3W, the product quality is set 0.3 and 0.5 respectively, a value that is lower than the average quality expectations of consumers in the population. These lower quality products are not preferred by most of the population. Initially 275 and 368 people purchase the product in Exp.1.2W and Exp1.3W respectively. In the first 6-7 time steps, number of buyers shows a small increase and after 7th time step number of buyers stays constant and end up being 295 and 402 for Exp1.2 and Exp1.3 respectively. In addition to low quality product, negative

WOM disseminated hampers people buying stimuli and only a small number of people purchase the product. When the product quality is high as in Exp1.4W and Exp1.5W, initially slightly more people purchase the product when compared to the benchmark experiment, but in the second time step, a dramatic increase is seen and after third time step, almost all people in the population purchase the product.

When WOM effect is disabled in experiment settings, the number of buyers shows a different pattern in time. The results are shown in Fig 3.

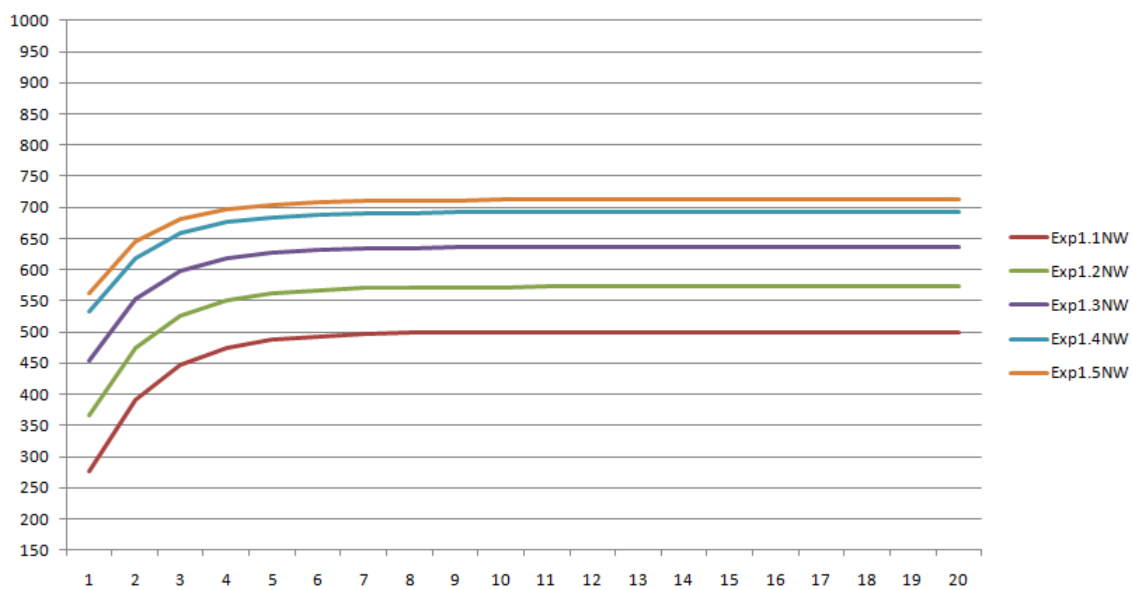

Fig. 3 - Number of buyers over time in different experimental setups for scenario 1, without WOM influence when product quality is varied

When WOM is not in effect, consumers can not share their opinions about the product with other potential consumers, and cannot influence others. Only the level of quality satisfaction, promotion intensity and the logit function enables purchasing after the initial time step. In this case all the experiments show a similar pattern: number of buyers increases in first time steps and stays constant after some time. Fig. 4 shows the number of buyers at the final time step for experiments Exp1.1 to Exp1.5, both when WOM is in and not in effect.

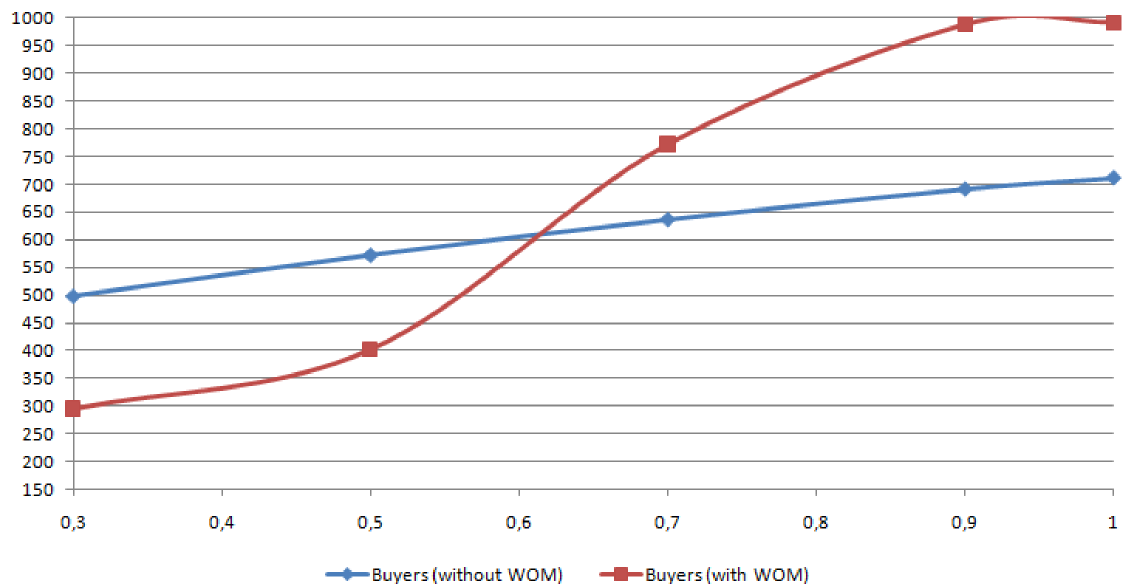

Fig 4 – Final number of buyers for different experimental setups in scenario 1

As quality values increase, number of buyers also increases in both cases (with or without WOM). But when WOM is in effect at low quality values very few people purchase the product due to negative WOM present in the environment and as quality values increase dramatic changes are observed in the number of buyers. When WOM is not in effect, slightly more people purchase the product due to the satisfaction increased from the higher quality product.

Fig. 5 shows how profit of the company varies to these different experimental setups.

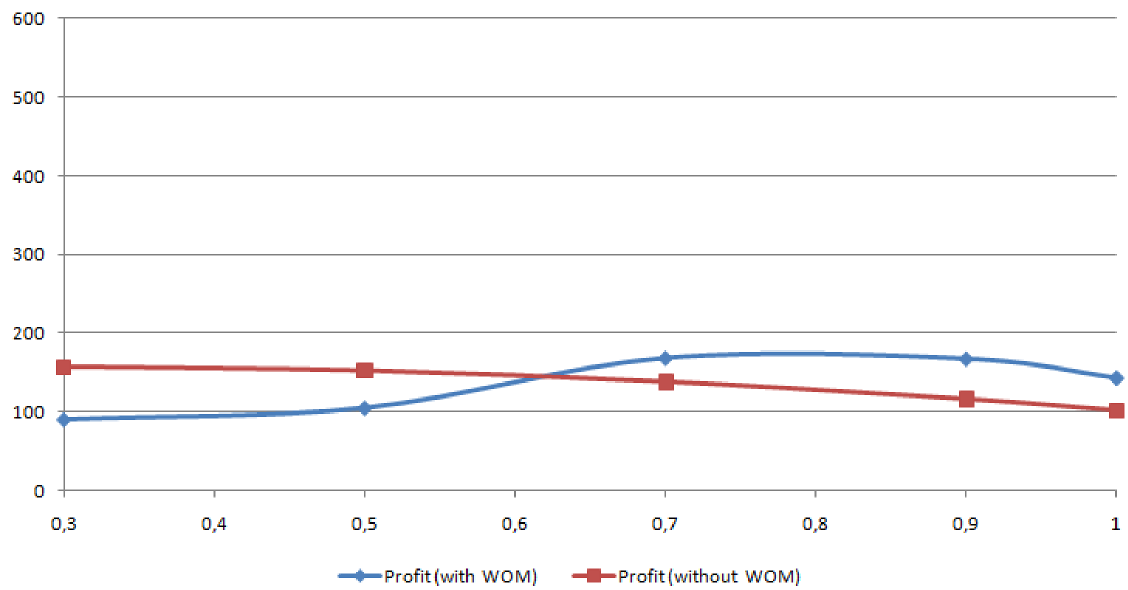

Fig. 5 – Profits for different experimental setups in scenario 1

When the product quality is set low, such as 0.3 and 0.5, number of buyers is found to be lower for cases where WOM is in effect. So the company profits more at low quality products only if people do not share their purchasing experiences with others. On the other hand if the product quality fulfills peoples' expectations, more people purchase the product if WOM is in effect and this leads to an increase in profit. But when the product's quality is really high, it costs more for the company and even the revenue is higher, the increased cost causes a decrease in the profit as it is seen when product quality is 1 at WOM in effect case in Fig. 5. As with the cases when WOM is not in effect, profit decreases as product quality increases. The reason is the same; high quality products cost more for the company and increase in number of buyers resulted from higher quality products do not compensate the extra cost which leads to a decrease in company profit.

In experiments Exp1.2 to Exp1.5, the product quality value was changed to be compared to the benchmark. In the next 4 experiments, Exp1.6-Exp1.9, the promotion intensity will be changed and these experiments will be compared to the benchmark experiment Exp1.1.

Effect of Promotion Level

Fig. 6 shows how the number of buyers changes over time with different promotion intensities when WOM is in effect.

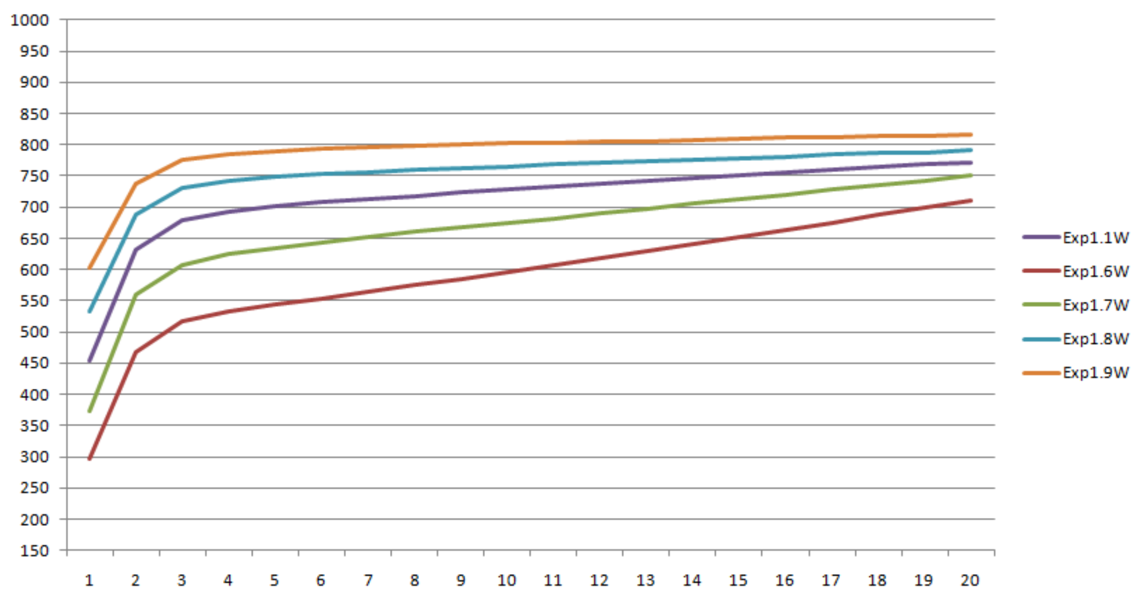

Fig. 6 - Number of buyers over time in different experimental setups for scenario 1, with WOM influence when promotion intensity is varied

From Fig. 6, it is seen that promotion intensity and number of buyers are directly related. When promotion intensity values are low, number of people that purchases product is found to be small, as it can be seen from Exp1.6W. Particularly the difference in number of buyers is very significant in the initial steps. This difference declines as time passes, which results from cumulative promotion intensity that consumers are exposed to. When the promotion intensity is high, at the beginning more number of consumers buys the product. Because the quality of the product do not change over time, there is not enough influence to affect remaining people's buying decisions. But when the promotion intensity is lower, less people buy the product in the initial time step, and there is still a big majority of people to buy the product. As time passes the cumulative promotion intensity has more chance to influence other people's buying decisions.

When WOM is not in effect, the promotion has less chance to affect consumers since people will not be able to talk about the product or the promotion to others. Fig. 7 shows how number of buyers changes when WOM is not in effect.

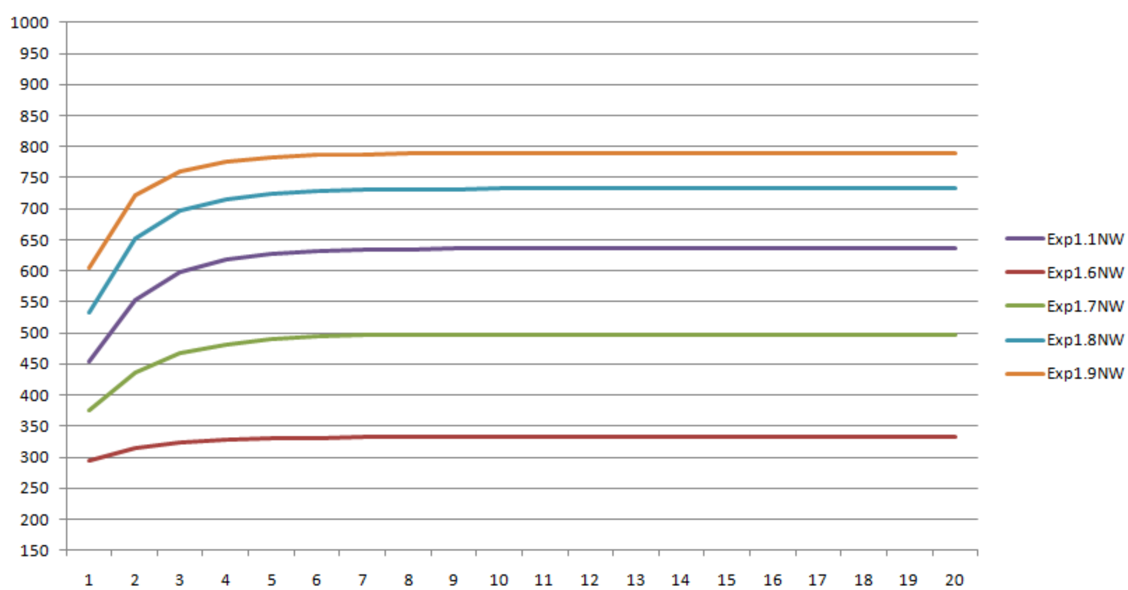

Fig. 7 - Number of buyers over time in different experimental setups for scenario 1, with WOM influence when promotion intensity is varied

When WOM is not in effect the number of buyers shows only in small increase after the initial time step and stays constant after the first few time steps. In this setting, lower promotion intensity result in lower number of buyers.

In Fig. 8, the final number of buyers for each promotion intensity level is plotted.

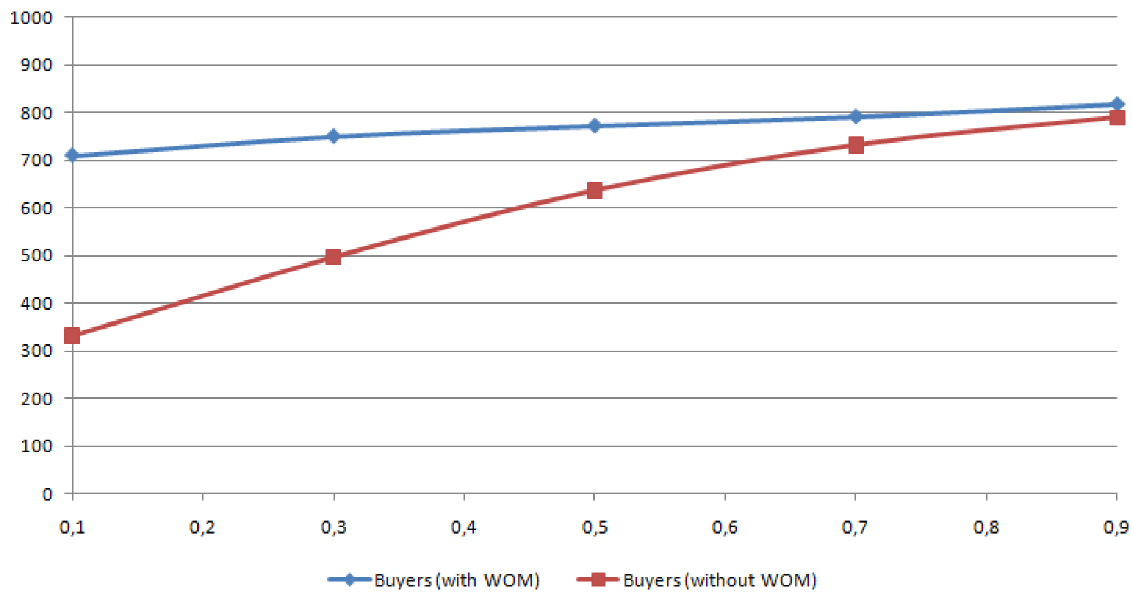

Fig. 8 - Final number of buyers for experiments Exp1.6-Exp1.9, when promotion level is varied

When WOM is in effect the difference in promotion intensity values do not lead to significant changes in the final number of buyers. But in WOM not in effect experiments, when the promotion is low, few people buy the product compared to the WOM in effect case. When we look at Exp1.9, we see that in both WOM in effect and not in effect cases, the final numbers of buyers are very close to each other. This finding indicates that high promotion intensity has the power to activate people's buying decisions, even WOM is not in effect, large number of people buys the product.

Fig. 9 shows the profits with respect to different promotion values.

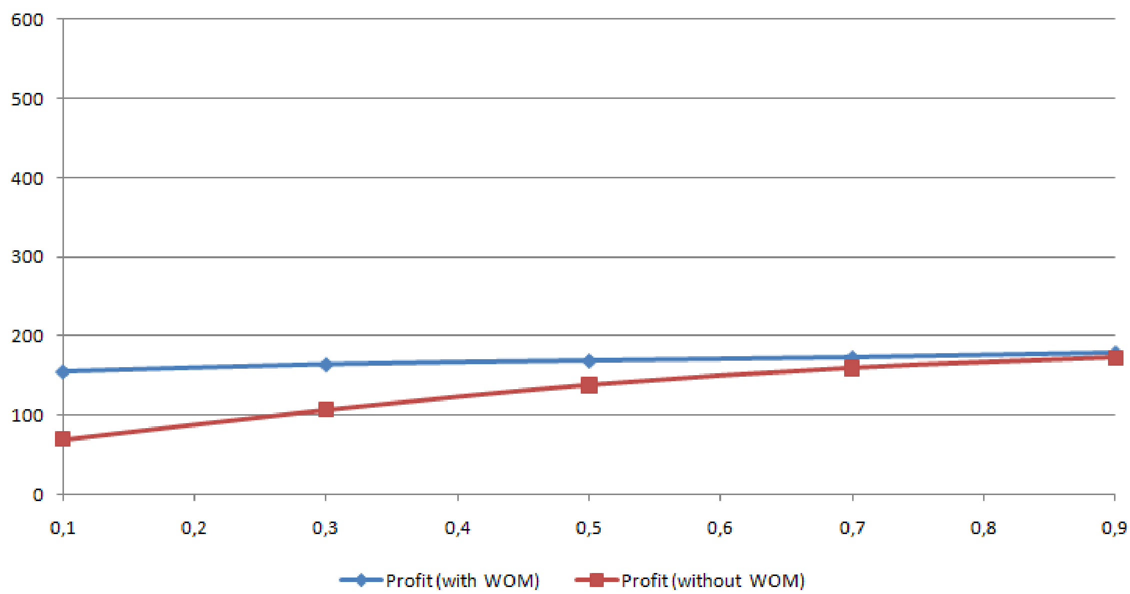

Fig. 9 – Profits for different experiments for Exp1.6-Exp1.9, when promotion level is varied

When promotion intensity value is low, more people buy the product in WOM in effect case, which leads to higher profit, but when the promotion intensity is high, WOM in effect and not in effect case profits are approximately the same. This can be explained by the fact that, when WOM is not present in the environment, the company has to obtain a more aggressive promotion strategy in order to reach more people and thus make more people purchase the product. So only when the promotion intensity level is very high, approximately the same amount of people purchases the product when compared to WOM in effect case. Similar number of buyers lead to similar profits for the company.

Effect of Price Level

In the next four experiments (Exp1.10-Exp1.13), the effect of price level on profit and number of buyers are analyzed. Fig. 10 shows the number of buyers for each price level under the WOM influence.

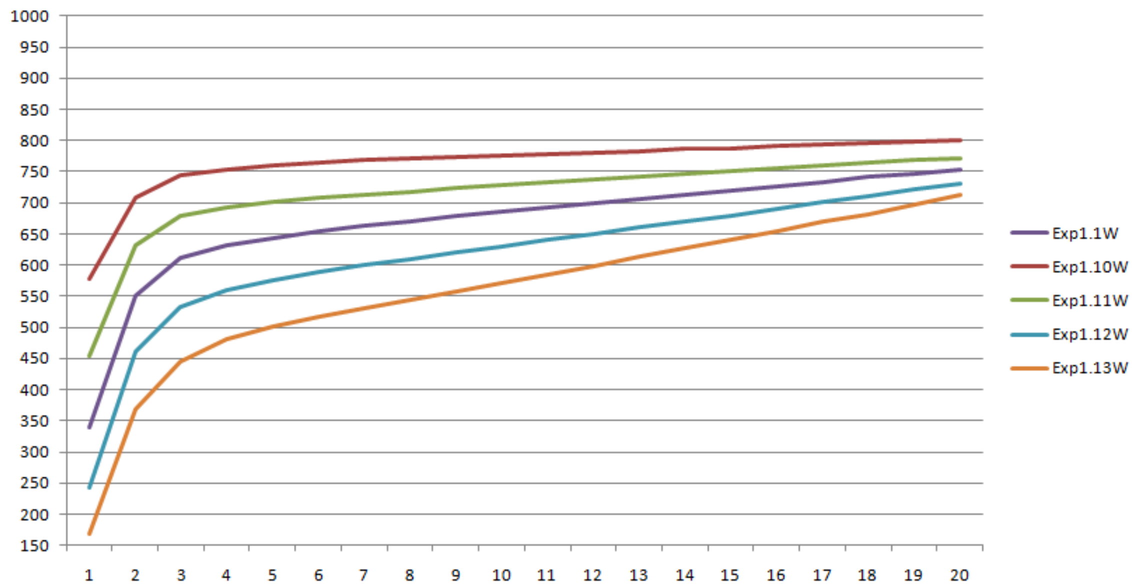

Fig. 10 - Number of buyers over time in different experimental setups for scenario 1, with WOM influence when product price is varied

Fig. 10 indicates that when price level is low more people purchase the product. As price level increases, number of buyers decreases. Price and number of buyers are inversely related.

Fig. 11 shows buyers pattern when WOM is not in effect.

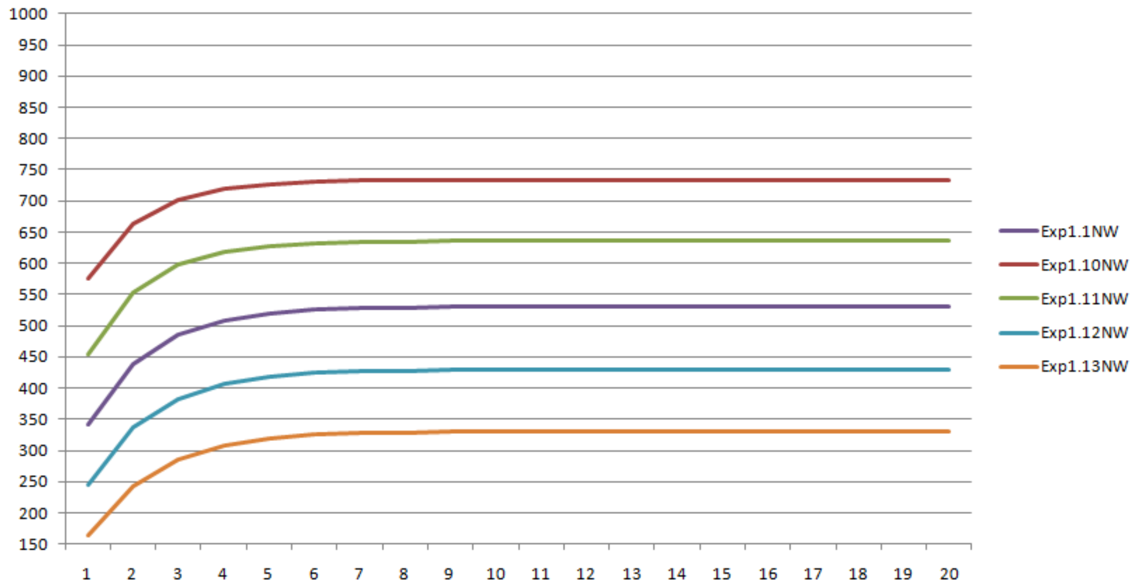

Fig. 11 - Number of buyers over time in different experimental setups for scenario 1, without WOM influence when product price is varied

When WOM is not in effect, less people purchase the product when compared to WOM in effect cases. As in most of the other experiments where WOM is not in effect, number of buyers stays constant after the few time steps.

Fig. 12 plots the final number of buyers for all price levels.

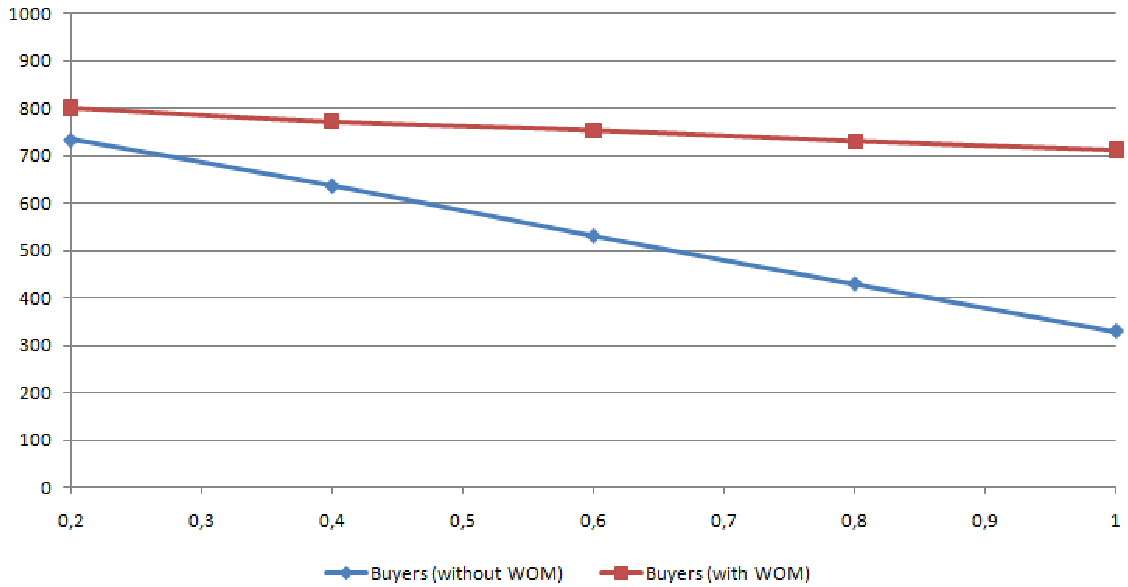

Fig. 12 - Final number of buyers for experiments Exp1.10 – Exp1.13, when price level is varied

Increased price level results in decreased number of buyers. When WOM is in effect, positive WOM stimulates people to purchase the product, so final number of buyers is higher when WOM is in effect.

Fig. 13 shows how profit changes to price level changes.

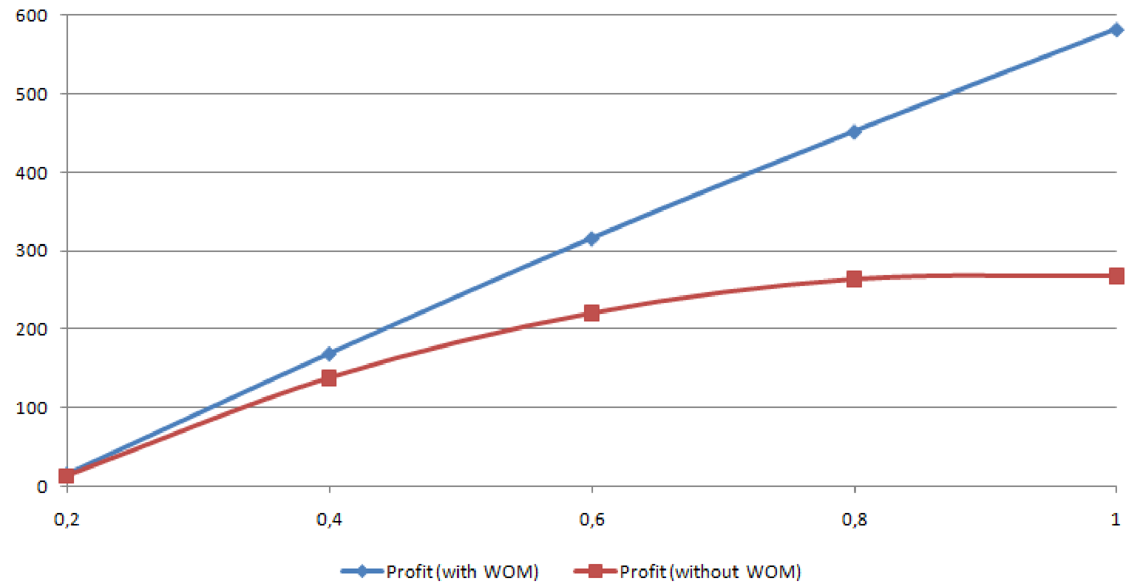

Fig. 13 - Profits for experiments Exp1.10 – Exp1.13, when promotion level is varied

When the price level is low, company profit varies small amount, independent of WOM. As the price level increases, profit of the company also increases. But because less people buy the product in WOM not in effect case, company profit is less than in effect case. Also the final number of buyers is approximately the same for levels 0.8 and 1, which leads nearly the same profits for both levels.

<u>Effect of Opinion Leaders</u>

Experiments Exp1.14-Exp1.17, are the last four experiments in scenario1. In these experiments different values for opinion leader strategy are set and results are compared to the benchmark.

Fig. 14 shows the purchasing pattern of consumers over time steps for each different opinion leader strategy.

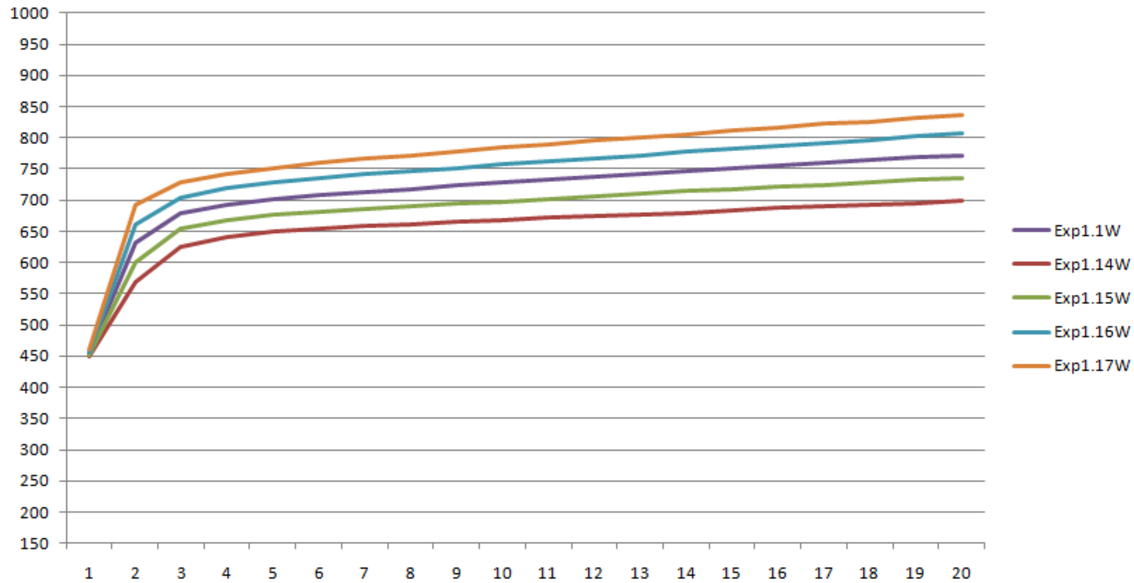

Fig. 14 - Number of buyers over time in different experimental setups for scenario 1, with WOM influence when number of opinion leaders is varied

Number of opinion leaders to collaborate with is set 10 in the benchmark experiment, Exp1.1. As this number is increased, more people buy the product and as it is decreased less people buy. The number of buyers in the initial time step is approximately the same for all the experiments. The difference starts to emerge after the first time step. The reason is that, opinion leaders influence people through WOM and WOM starts to show its effect after the first time step.

Fig. 15 gives the same information as the previous figure, but this time WOM effect is not present in the environment.

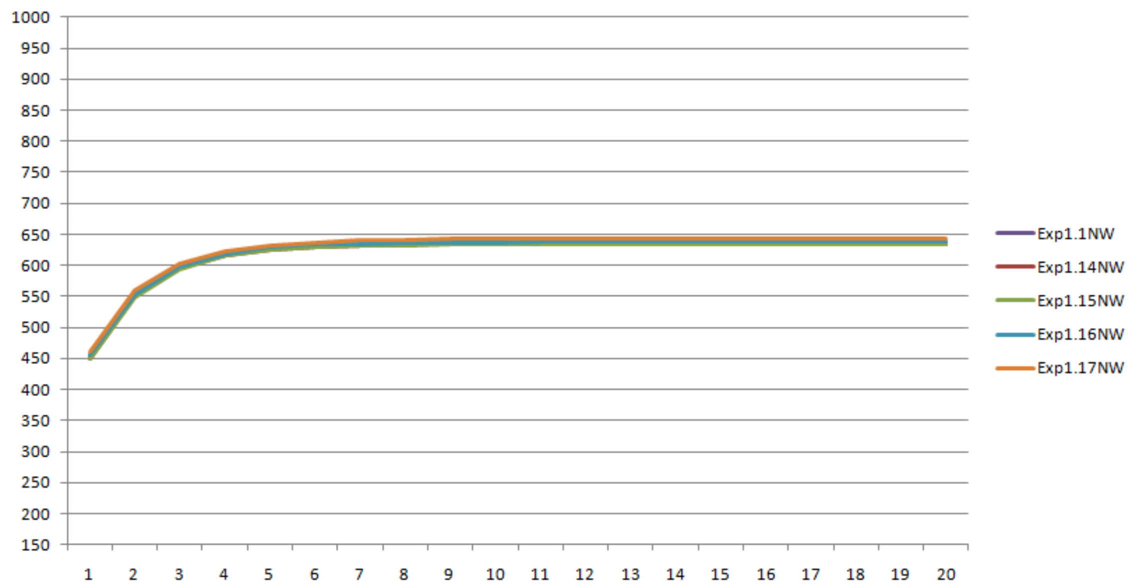

Fig. 15 – Number of buyers over time in different experimental setups for scenario 1, without WOM influence when number of opinion leaders is varied

When WOM is not in effect, all the experiments give approximately the same buying patterns. Opinion leaders influence people positively and stimulate their buying decisions. When WOM is not in effect, they cannot influence people so they remain ineffective. Only difference is originated from the randomness that is naturally present in the system.

Fig. 16 plots the final number of buyers in each experiment settings.

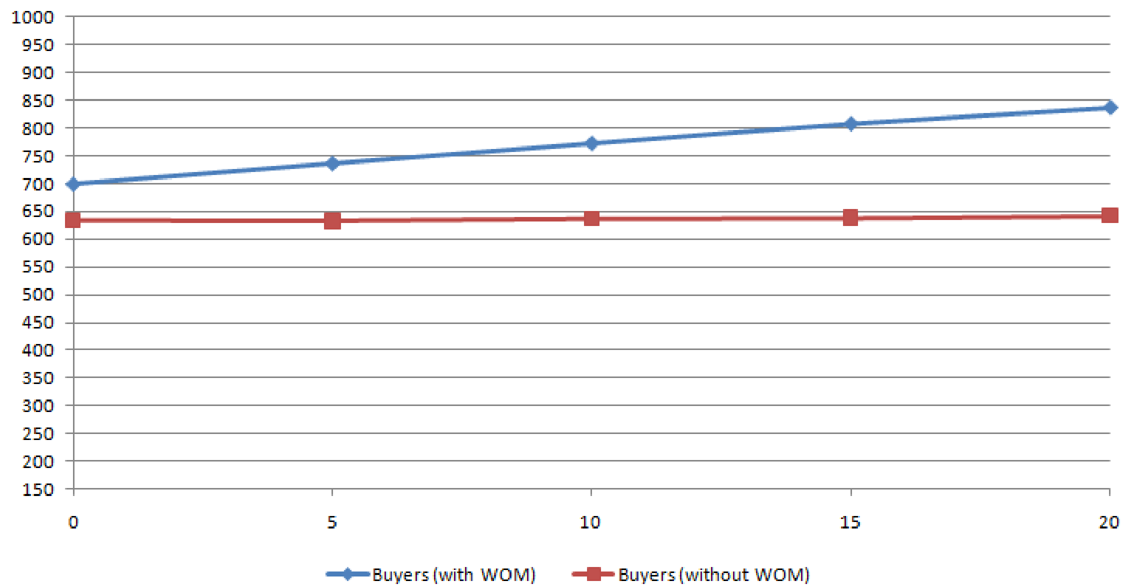

Fig. 16 – Final number of buyers for experiments Exp1.14 – Exp1.17, when number of opinion leaders is varied

As it is seen from Fig. 16, when WOM is not in effect, the final number of buyers stays almost the same independent of collaborated opinion leaders. The only differences steam from the randomness in the model. But when WOM is in effect, number of buyers is increasing as number of opinion leaders collaborated increases.

Fig. 17 shows how profit is changed with respect to different opinion leader strategies.

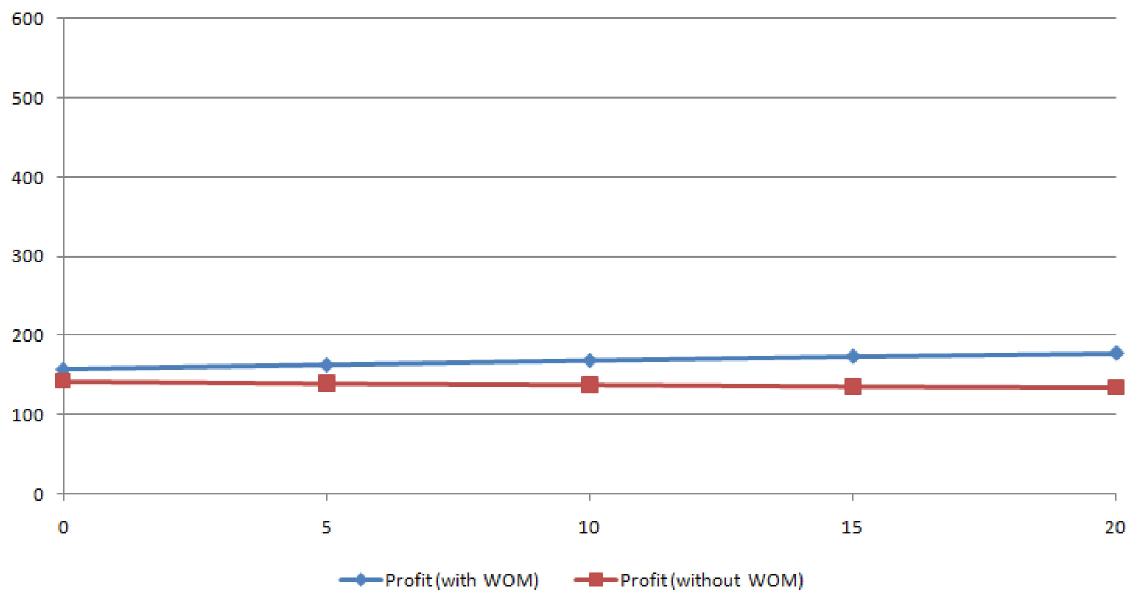

Fig. 17 – Profits for experiments Exp1.14 – Exp1.17, when number of opinion leaders is varied

Profit does not show big differences even when WOM is in or not in effect. Due to the small increase in the number of buyers when WOM is in effect, profit also shows a small increase as it is seen from Fig. 17.

Sensitivity Analysis for the Cost Parameters

In scenario 2, marginal cost of collaborating with an opinion leader is changed and new experiments are conducted to monitor the effects of this new setup. In the experiments Exp2.1 to Exp2.5, the marginal cost is set to be 0.3 and five different opinion leader strategies are tested. In experiments Exp2.6-2.10, the marginal cost is increased to 0.7. The purchasing patterns of consumers are independent of the marginal cost, so purchasing patterns of experiments Exp2.1 to Exp2.10 are approximately the same with the purchasing patterns of experiments Exp1.1 and Exp1.14 to Exp1.17.

Fig. 18 compares profit of the company where marginal cost of collaborating with an opinion leader is 0.3, 0.5 and 0.7.

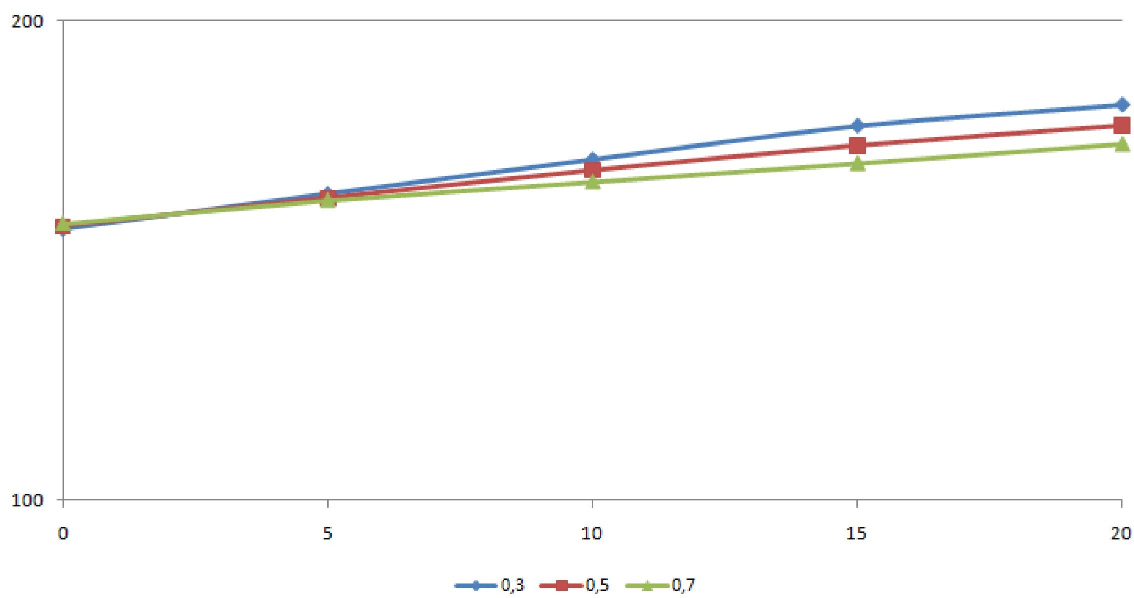

Fig. 18 – Profits for different opinion leader marginal costs in scenario 2

When marginal cost is high, profit decrease and when marginal cost is low, profit increases as it is expected. Through experiments in scenario 2, we found out that profit is not sensitive to marginal cost change of opinion leaders.

In scenario 3, marginal cost of improving product quality is changed. In experiments Exp3.1-Exp3.5, the marginal cost is increased to 0.4 and in experiments Exp3.6-3.10 it is decreased to 0.1, from the initial marginal cost value 0.25. All these experiments are compared to the results of Exp1.1 to Exp1.5. As in scenario 2, marginal cost of product quality do not change the purchasing patterns of consumers and we can refer to Fig. 2 to see how number of buyers change over time in scenario 3.

Fig. 19 plots profit of the company for each different experiment in scenario 3, also experiments Exp1.1 to Exp1.5 are included to be compared.

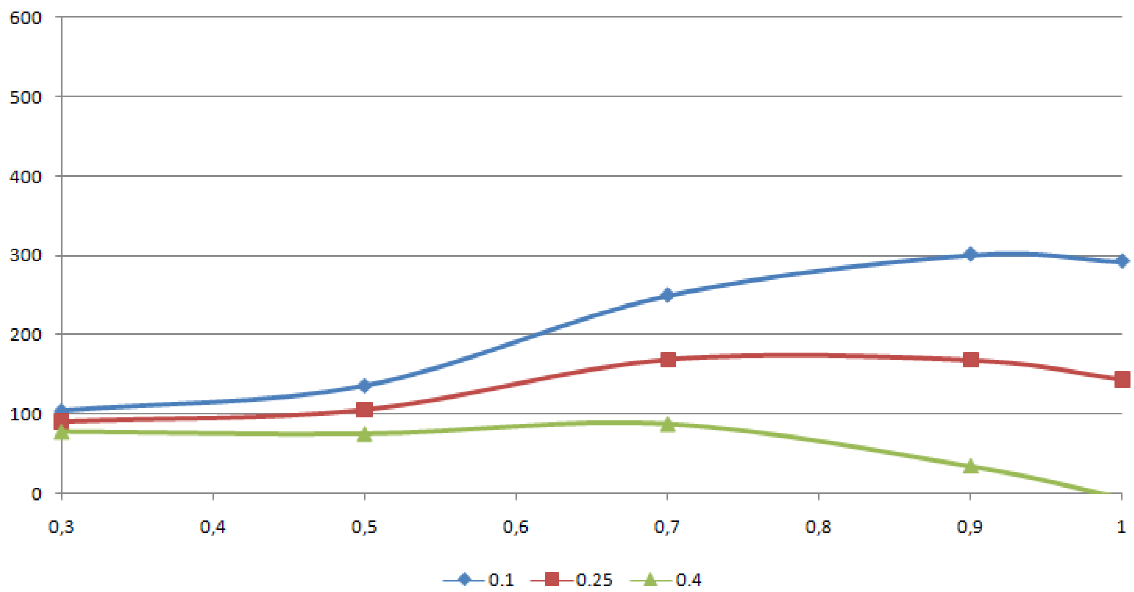

Fig. 19 - Profits for different product quality marginal costs in scenario 3

As it is expected, when marginal cost of product quality is increased, profit decreases. When marginal cost equals 0.3 the difference between profits is not very significant. As the cost increases the difference in profits is also increased. When we compare these results to the results of scenario 2, we find out that, product quality cost has more influence on profits.

Summary of Results

In this study, three different scenarios and fifty four different experiments are conducted, in order to efficiently analyze effects of different marketing strategies that consist of different quality, promotion, price and opinion leader values. In addition, by changing the marginal costs for quality and opinion leaders, a sensitivity analysis is performed. For every experiment, number of buyers and profit of the company is obtained. In scenario 1, experiments are also run for cases when WOM is not in effect and the results are also obtained to monitor WOM influence on consumers' decisions.

In scenario 1, when WOM is in effect, increasing the price of an average quality product is found to be the most profitable strategy (582.547). When a product satisfies a consumer, no matter the price, a lot of people purchase the product. The second most profitable strategy is to increase the promotion intensity (178.723). The increase in revenue because of more number of buyers is more than the cost it creates so for an average quality product, making more promotions increase the awareness of people in the population and thus leads to an increase in profit. Increasing number of opinion leaders to collaborate with also increases the profit in approximately the same amount with promotion intensity increase (178.166). As a final statement; producing a product that is at market expectations is better than producing one above the market expectations. The increase in revenue when a higher quality product is produced is less than the additional cost, a higher quality product generates. And when product quality is too low, under the presence of WOM, too few people buy the product and it leads to a decrease in profit (90.8985).

When WOM is not in effect, increasing the price of the product is still the best strategy for a higher profit (267.9007). The second most profitable strategy is to increase promotion intensity (172.5835). Increasing the number of opinion leaders to collaborate with only decreases the profit, because when WOM is not in effect, opinion leaders remain ineffective (134.4962). The final finding in scenario 1 is that, because negative WOM cannot be disseminated in this case, producing a product that is just below the market expectations is better than producing one at the market expectations. Decrease in cost because of producing a low quality product is higher than the revenue a higher quality product generates (157.3188).

In Scenario 2 and Scenario 3, a sensitivity analysis is made and it is found that increasing the marginal cost of product quality has bigger influence in the profit of the company when compared to marginal cost opinion leaders. In other words, company is more volatile towards the marginal cost of increasing quality of the product quality.

Table 8, summarizes the results of all the experiments conducted in this study.

Table 8 – Results of All Experiments

Exp. No	Buyers	Profit	Exp. No	Buyers	Profit
1.1W	772	168.807	1.1NW	637	138.2408
1.2 W	295	90.8985	1.2 NW	499	157.3188
1.3 W	402	105.650	1.3 NW	573	152.5272
1.4 W	988	167.828	1.4 NW	692	116.14
1.5 W	992	143.784	1.5 NW	712	101.7675
1.6 W	710	154.824	1.6 NW	332	69.902
1.7 W	750	163.908	1.7 NW	497	106.9562
1.8 W	791	172.981	1.8 NW	732	159.623
1.9 W	817	178.723	1.9 NW	790	172.5835
1.10 W	801	14.9257	1.10 NW	734	13.26975
1.11 W	754	315.758	1.11 NW	531	220.575
1.12 W	731	452.118	1.12 NW	430	263.7375
1.13 W	712	582.547	1.13 NW	330	267.9007
1.14 W	699	157.195	1.14 NW	634	142.7458
1.15 W	736	163.060	1.15 NW	633	140.0342
1.16 W	807	173.993	1.16 NW	638	135.9995
1.17 W	836	178.166	1.17 NW	642	134.4962
2.1	696	156.554			
2.2	735	163.952			
2.3	774	171.119			
2.4	812	178.154			
2.5	838	182.555			
2.6	701	157.787			
2.7	738	162.632			
2.8	771	166.467			
2.9	804	170.304			
2.10	837	174.312			
3.1	295	104.075			
3.2	402	135.715			
3.3	772	249.666			
3.4	987	301.08			
3.5	992	292.509			
3.6	296	77.8752			
3.7	401	75.124			
3.8	771	87.528			
3.9	988	34.4304			
3.10	993	-5.1			

CHAPTER 5: CONCLUSION

In this study we evaluated the influences of different marketing strategies in a monopolistic market and investigated the level of influences of product, price, promotion and opinion leader strategies on profit of the company, using agent based modeling methodology. We also aimed to find how product sales patterns evolve over time and profitability of the company changes when WOM is in and not in effect.

Regardless of WOM effect, increasing cost of a product, which satisfies the average quality expectation of population, is found to be the most profitable strategy. Increasing promotion intensity is found to be the second most profitable strategy in both WOM in effect and not in effect case. When WOM is in effect, producing a low quality product result in very low profit when compared to WOM not in effect case, which means that negative WOM can hamper other people's buying stimuli. Opinion leaders strategy is only effective when WOM is in effect.

When a sensitivity analysis is made to investigate the effects of costs on profit and number of buyers, the marginal cost of product quality is found to have a larger influence when compared to the marginal cost opinion leaders.

As further studies, the model can be extended to include more than one company and product in order to simulate a competitive marketing environment. The optimal time for launching a new product can be investigated and different social network models for consumer interactions can be analyzed.

REFERENCES

Anderson, S. P., A. de Palma and J.-F. Thisse, (1992). Discrete Choice Theory of Product Differentiation, the MIT Press, Cambridge, Massachusetts.

Banks, J. (1998). Principles of Simulation, "Handbook of Simulation - Principles, Methodology, Advances, Applications, and Practice" in J Banks (ed.), chapter 1, Wiley- Interscience

Baudisch, A. F. (2007). "Consumer heterogeneity evolving from social group dynamics: Latent class analyses of German footwear consumption 1980 – 1991", *Journal of Business Research*, 60 (8), 836-847.

Berry, J. (2005). "Identifying Reaching and Motivating key influencers", conference paper presented at the Word of Mouth Marketing Association Summit, 29-30 March Chicago.

Carley, K. M. (2003). "Dynamic Network Analysis", Workshop on Dynamic Social Network Modeling and Analysis, National Research Council of the National Academies, 7-9 November, 133-145.

Delre, S. A., Jager, W., Bijmolt, T.H.A. and Janssen, M. A. (2007). "Targeting and timing promotional activities: An agent-based model for the takeoff of new products", *Journal of Business Research*, 60 (8), 826-835.

Deffuant, G. and Huet, S. (2007). "Propagation effects of filtering incongruent information", *Journal of Business Research*, 60 (8), 816-825.

Dye, R. (2000). "The buzz on buzz", *Harvard Business Review*, 78(6), 139-146.

Friedkin, N. E. (2003). "Social Influence Network Theory: Toward a Science of Strategic Modification of Interpersonal Influence Systems", Workshop on Dynamic Social Network Modeling and Analysis, National Research Council of the National Academies, 7-9 November, 89-100.

Gilbert, N. (2008). Agent-Based Models, SAGE Publications, UK.

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

Granovetter, M. (1978). “Threshold Models of Collective Behavior”, *The American Journal of Sociology*, 83 (614), 1420-1443

Hair, J. F., Black, W. C., Babin, B. J. and Anderson, R. E. (2009). Multivariate Data Analysis, Prantice Hall.

Hennig-Thurau, T., Malthouse, E., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A. and Skiera, B. (2010). ‘‘The Impact of New Media on Customer Relationships,’’ *Journal of Service Research*, 13 (3), 311-33.

Homan, J. E., Legon, K. N. and Libai, B. (2004). “Quantifying the Ripple: Word of Mouth and Advertising Effectiveness, *Journal of Advertising Research*, 271-280.

Hoyer, W. D. and MacInnis (2007). Consumer Behavior, Houghton, Boston.

Jager, W. (2000). “Modeling Consumer Behavior”, Rijksuniversiteit Groningen

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 (1999). “An integrated approach to simulating behavioural processes: A case study of the lock-in of consumption patterns”, *Journal of Artificial Societies and Social Simulation*, 2(2).

Janssen, M. A. and Jager, W. (2001). “Fashions, habits and changing preferences: simulation of psychological factors affecting market dynamics”, *Journal of Economic Preferences*, 22(6), 745-772.

Karakaya, C., Badur, B. and Aytekin, C. (2011). “Analyzing the Effectiveness of Marketing Strategies in the Presence of Word of Mouth: Agent-Based Modeling Approach”, *Journal of Marketing Research and Case Studies,* 2011.

Khouja, M., Hadzikadic, M. and Zaffar, M. A. (2008). “An agent based modeling approach for determining optimal price-rebate schemes”, *Simulation Modeling Practice and Theory*, 16 (1), 111-126.

Kirby, J. and Marsden P. (2006). Connected Marketing: The Viral, Buzz and Word of Mouth Revolution, Butterworth-Heinemann.

Kohler, T. A. and Gumerman, G. G. (2000). Dynamics in Human and Primate Societies: Agent-Based Modeling of Social and Spatial Processes (eds), Oxford University Press, USA

Kollman, K. and Page, S. E. (2006). "Computational Methods and Models of Politics," Handbook of Computational Economics, in: L Tesfatsion & KL Judd (ed.), edition 1, 2, 1433-1463.

Kuenzel, J. and Musters, P. (2007). “Social interaction and low involvement products”, *Journal of Business Research*, 60 (8), 876-883.

Lazarsfeld, P., Berolson, B. and Gaudet, H. (1944). The People’s Choice, Columbia University Press, New York.

Lazer, D. (2003). “Information and Innovation in a Networked World”, Workshop on Dynamic Social Network Modeling and Analysis, National Research Council of the National Academies, 7-9 November, 101-118.

LeBaron, B. (2006). "Agent-based Computational Finance," Handbook of Computational Economics, in: L Tesfatsion & KL Judd (ed.), edition 1, 2, 1187-1233.

Libai, B., Bolton, R., Bügel M. S., Ruyter, K., Götz, O., Risselada, H. et al. (2010). Customer-to-Customer Interactions: Broadening the Scope of Word of Mouth Research, *Journal of Service Research*, 13(3), 267-282.

Luan, Y. J. and Sudhir, K. (2010). “Forecasting marketing mix responsiveness for new products”, *American Marketing Association*, 47, 444-457

Ma, T. and Nakamori, Y. (2005). “Agent-based modeling on technological innovation as an evolutionary process”, *European Journal of Operational Research*, 166 (3), 741-755.

Macy, M. and Willer, R. (2002). “From factors to actors: Computational sociology and agent based modeling”, *Annual Review of Sociology*, 28, 7229-7236

McCarthy, E. J. (1960). Basic Marketing: A Managerial Approach, Homewood, USA.

Merton, R. K. (1968). Social theory and social structure (Enl. Ed.), New York: Free Press

Meyer, R. and Johnson, E. J. (1999). "*Emprical generalizations in the modeling of consumer choice*", Marketing Science, 14(3), G180-G189.

Midgley, D., Marks, R. and Kunchamwar D. (2007). "Building and assurance of agent-based models: An example and challenge to the field", *Journal of Business Research*, 60 (8), 884-893.

Myong-Hun, C. and Harrington, J. (2006). "Agent-Based Models of Organizations," Handbook of Computational Economics, in: LTesfatsion & KL Judd (ed.), edition 1, 1273-1337.

North M.J., Macal, C. M. (2007). Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation, Oxford University Press, USA

North M.J., Macal, C. M., Aubin, J. Thimmapuram, P., Bragen, M., Hahn, J. et al. (2010). "Multiscale agent-based consumer market modeling", *Wiley Interscience,* 15(5), 37-47.

Rosen, E. (2000). The Anatomy of Buzz, DoubleDay Business, New York.

Rogers, E. M. (1983). Diffusion of Innovations, Free Press, USA.

Schwaiger, A. and Stahmer B. (2003). "SimMarket: Multiagent-Based Customer Simulation and Decision Support for Category Management", *Lecture Notes in Computer Science*, 2831, 74-84.

Scott, J. (1988). Social Network Analysis. *SAGE Journals*, 22 (1), 109-127.

Solomon, M. R. (2009). Consumer Behavior: Buying, Having and Being, Prentice Hall, USA.

Solomon, M.R., Marshall, G.W. and Stuart, E.W. (2008). Marketing: Real People, Real Choices, Prentice Hall, New Jersey.

Tesfatsion, L. and Judd, K.L. (2006). Agent-Based Computational Economics: A Constructive Approach to Economic Theory, in Tesfatsion L & Judd KL (ed.), *Handbook of computational economics,* North Holland Publications, The Netherlands

Troitzsch, K. G. (2004). Validating Simulation Models, 18th European Simulation Multiconference, SCS Europe.

Vag, A. (2007), "Simulating changing consumer preferences: A dynamic conjoint model", *Journal of Business Research*, 60 (8), 904-911

Valluri, A., North, M. J. and Macal, C. M. (2009), "Reinforcement learning in supply chains", *International Journal of Neural Systems*, 19(5), p331-344.

Walker, O. C., Mullins, J. W. and Larreche, J. C. (2008), Marketing Strateg: A Decision Focused Approach, MacGraw-Hill, New York.

Wasserman, T. (2006), "Word Games", *Brandweek*, 24.

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

Wooldridge, M. and Jennings, N. (1995), "Intelligent Agents: Theory and practice", *Knowledge Engineering Review*, 10 (2), 115-152.

Wooliscroft, B., Tamilia, R. D., and Shapiro, S. J. (2006) A twenty-first century guide to Aldersonian marketing thought, Springer, New York.

Wuyts, S., Stremersch, S., Van den Bulte, C. and Franses, P. H. (2004), ''Vertical Marketing Systems for Complex Products: A Triadic Perspective,'' *Journal of Marketing Research*, 41(4), 479-487.

Zhang, T. and Zhang D. (2007), "Agent Based simulation of consumer purchase decision-making and the decoy effect", *Journal of Business Research,* 60 (8), 912-922.