MASTER

Detailing the Norton-Bass model to allow product-specific forecasts incorporating the influence of online opinion leaders using Twitter

Bullens, G.

Award date:
2013

Eindhoven, December 2012

Detailing the Norton-Bass Model to Allow Product-Specific Forecasts:

Incorporating the Influence of Online Opinion Leaders using Twitter

by
G. (Geert) Bullens MSc

MSc Industrial Engineering & Management Science
Student identity number 0536829

in partial fulfilment of the requirements for the degree of

Master of Science
in Innovation Management

Supervisors:
dr. ing. J.P.M. Wouters, TU/e, ITEM
prof. dr. E.J. Nijssen, TU/e, ITEM

TUE. School of Industrial Engineering.
Series Master Theses Innovation Management

Subject headings: Innovation-diffusion, Twitter, Opinion Leaders, Online Influence, social media

Abstract

This master thesis describes the development of an extension of the Norton-Bass model in which the influence of online social networks is incorporated. By proposing this model, the Norton-Bass model is able to provide brand-specific analyses, rather than industry-specific analyses. To incorporate this influence, two additions are done to the model. Firstly, a mechanism of online influence is proposed, in which online opinion leaders act as intermediaries between advertising in the existing mechanism of external influence and word-of-mouth in the mechanism of internal influence. Secondly, online word-of-mouth is added to the existing mechanism of internal influence, as it is found to be significantly different from traditionally word-of-mouth. In order to propose these additions, a literature review is done. After the modeling stage in system dynamics has been described, different parameters that are included are studied using Twitter. Finally the model is tested and findings are reported.

Preface

Before acknowledging the people that were influential for me in this study, I first want to show my gratitude to my parents who have allowed me to add another three-and-a-half years to my academic life at Eindhoven, University of Technology. I believe that my education is now complete. Besides them, I would like to thank the rest of my family. Toine for his critical view on this study. Discussions with him have helped me overcome some naivety and improve this study. Loreen for supporting me throughout the process and for her interest in the topic. I hope I can repay your interest soon.

For getting me interested in the field of innovation-diffusion, I owe great thanks to Prof. Nijssen and Mr. Wouters for their course on 'Marketing and Innovation'. Also, their patience while I was setting up this study to achieve the goals I wanted to achieve is admirable. I would like to take the opportunity to thank Mr. Wouters for sustaining the advise throughout the years to get my thoughts written out on paper to guide them and stimulate insightful discussion during our meetings. Without prejudice to the enthusiasm of Mr. Wouters, a special thanks is in place also for Prof. Nijssen. His enthusiasm and abundance of insightful ideas have sometimes puzzled me, but have most of all lifted the level of this study.

Furthermore, I want to thank Bart and Dave for the many train travels between Tilburg and Eindhoven, the cups of coffee we had, their cooperation in many courses, and the insightful discussions we had. Also, Marco for his suggestion and help how to include opinion leaders into the model. Finally, Luc Franken at TenToday for his technical assistance during the early stages of this study.

Although I hope this thesis can contribute to the field of innovation diffusion research, I also wish it contributes to the notion that social media are not just a hype. They deserve a place in academics, they are here to stay, why wouldn't we take advantage of it.

Geert Bullens

Executive summary

Diffusion processes of innovations are becoming increasingly complex and multifaceted in recent years (Peres, Muller and Mahajan, 2010). One of the most influential contributions to diffusion research is made by Bass (1969) with the introduction of the 'Bass-model'. In the Bass model, product diffusion is contributed to word-of-mouth and advertising. Norton and Bass (1987) have proposed an extension that fits products with a multigenerational character: *The Norton-Bass model,* which is adopted in the current study. Peres et al. (2010) suggest several changes to be made to the Bass (and Norton-Bass) model in order to remain state-of-the-art that are relevant to the current study.

Research opportunity

Besides innovators in the traditional sense, the Internet also caused the group of opinion leaders, or 'influentials', to become larger and express their opinions easier (Gillin, 2007). Online social networks provide a platform acquire and exert this influence to other actors in the network. This observation feeds the discussion whether opinion leaders should get a role in the Norton-Bass model besides the role of innovator or imitator. Also, the introduction of the Internet and its online social networks might have caused the nature of word-of-mouth to change. Therefore, it is questionable whether word-of-mouth as included in the Norton-Bass model is still representative to practice. The current study is aimed to answer whether the Norton-Bass model should be extended to account for the influence of online word of mouth and the increased power of opinion leaders.

Theory and proposed extension

A literature review is performed to identify the state-of-the-art of research related to this study. This review includes an analysis on the evolution and state-of-the-art of the Norton-Bass (NB) model, word-of-mouth research, opinion leadership and an online social network application: Twitter.

Firstly, regarding opinion leaders, different models of influence are presented. Kozinets et al. (2010) explain the role of opinion leaders in an evolution of influence models. In their network coproduction model, there is no influence of marketers, but marketing messages are diffused autonomously through the network. This diffusion of information links to the model by Watts and Dodds (2007) who, in response to the two-flow influence model by Katz and Lazarsfeld (1955), propose the network influence model. In this model opinion leaders absorb mass communications directly or through other actors in the network. Their role is to diffuse this information to other actors in the model. On Twitter, this mechanism is enabled through retweeting. Although there is no formal role of opinion leaders in diffusion models, this information-diffusion role appears an appropriate one. This intermediary role of opinion leaders is adopted in the current study and is modeled as such.

Secondly, different studies were reviewed that discuss difference between online word-of-mouth is different from the word of mouth used in the Norton-Bass model. For several reasons, it appears that it is indeed significantly different. Sussan, Gould and Weisfeld-Spolter (2006) argue that advertising and interpersonal communications were previously separated in time and place, while they are now connected in one online platform. Also, Rangaswamy and Gupta (2000) find that online word-of-mouth is intensified as it is stored in searchable databases and remains available over time. Furthermore online and offline interpersonal communications differ in their continuity (Berger & Iyengar, 2012); offline conversations are typically continuous, while online conversations are merely discontinuous, which increases the quality of communications. More differences in online and offline communications can be found in key influences of WOM on consumer behavior: tie-strength, homophily, and source credibility (Brown, Broderick & Lee, 2007).

Thirdly, Twitter is studied to identify parameters that contribute to online word of mouth. Different parameters are identified that show a relation to product diffusion, which makes them valuable to add in the conceptual model: spiking events, participation, retweets, influence, and sentiment. These parameters can either be derived directly, or need to be calculated.

Based on the findings of the literature review, two re-design proposals are done to tackle the challenge by Peres, Muller and Mahajan (2010). Based on these re-design proposals a system dynamics model is created to study the phenomena into more detail.

Re-design proposal 1:	*The mechanism of online influence is an intermediary between the mechanisms of external and internal influence, and should be modeled dependent on the number of influential tweets and the effectiveness of advertising.*

Re-design proposal 2:	*Online word-of-mouth is to be added to the existing mechanism of internal influence and is moderated by the sentiment that is expressed in it.*

Method

After the SD model is proposed, the included Twitter parameters are reviewed using data from Twitter. By doing so, more understanding is generated about the underlying forces and structure of online word of mouth using Twitter. In order to do so, a study is performed on longitudinal data from Twitter using time-series analysis. The SD model is further refined based on the findings from the review.

In the last research activity, the proposed Norton-Bass model is tested: can it predict product specific diffusion using Twitter data? Using the SD model, product diffusion is predicted for products from different categories. This is compared to actual market data gathered from retail store managers. In order to acquire this data, two surveys were held under 22 Dutch retail store managers. This study has a cross-sectional character, as no continuous data is available from retail store management.

Results

It appears that while ordinary mentions quickly rise from approximately zero to a spike at launch, influential mentions show a longer ramp-up. After launch, ordinary mentions slowly decrease to a steady level, while influential tweets quickly decrease to a minimal level near to zero. This indicates that influencers, like innovators, show a great interest to new products, but lose their interest when the product is launched. This confirms the characterization by van der Bulte and Wuyts (2007). Research using Topsy Pro Analytics reveals that there is a difference between the contents of influential mentions and non-influential mentions. Often influential mentions are retweets of either influential or non-influential mentions. A striking difference is that influential mentions often refer to launch announcements and provide previews of the product to be launched. This links to the model by Watts and Dodds (2007), where influencers use information either coming from mass communication or from other actors in the network. As they serve as diffuser of information, they are labeled as influential in their network. Another important finding is that the percentage of influential mentions in the total corpus of tweets on a product is not constant between different products. This implies that influencers show different levels of interest for different products. Thereby, influencers can stimulate product diffusion in the model if their arousal is high, which can be measured by a large amount of influential mentions relative to non-influential mentions.

Regarding the system dynamics model, the test in chapter 5 has shown that it has proper distinctive qualities for products that are well represented on Twitter. Diffusion forecasts for products that are not referred to that often appears to be unreliable. In the system dynamics model both participation and influence relate to diffusion speed. Nevertheless, the effect of participation is larger than influence, as the influence of word of mouth has longer carryover effects, while influence can exert their influence most optimally in the beginning of the diffusion process. If their influence is large enough, they can stimulate the take-off of the diffusion process, while word-of-mouth can extend the diffusion process. As there is no fixed distribution of influential and non-influential mentions, this means influencers have the power to initiate the diffusion of an innovation by provoking online word-of-mouth from advertising.

Implications

The current study was conducted to find out how the Norton-Bass model could be extended in order to incorporate the influence of online social networks. In a sequential modeling process, a model is proposed that incorporates the influence of online social networks. In this study, online word-of-mouth is added to the mechanism of internal influence. Also, an additional mechanism is proposed: the mechanism of online influence, in which online opinion leaders (influencers) have an intermediary role between mass media and word-of-mouth.

At the beginning of this study, several suggestions were made how the Bass (or Norton-Bass) model could be adjusted to remain state-of-the-art (Peres et al., 2010). The model that is developed in this study satisfies several of these suggestions. Firstly, by adding more social influences the model is now able to provide brand (or product) level analysis, rather than industry level analysis. Also by including Twitter as online social network, the model includes small-world networks, rather than an aggregate of the market. Finally, different types of social interactions are included, which are not restricted to the traditional sense of word-of-mouth. The influence of mass communication is re-defined by introducing the mechanism of online influence. Also, online word-of-mouth is added to represent more types of interpersonal communication.

The literature study revealed that opinion leaders do not have a formal role in product diffusion. Rather they have a role as diffuser of information from mass media to word-of-mouth. Therefore, in order to incorporate the role of influencers in the Norton-Bass model, an extension is proposed in which they are an intermediary between mass communications and word-of-mouth. Their influence is modeled as proposed in the network influence model by Watts and Dodds (2007). Through the inclusion of the mechanism on online influence, the Norton-Bass model now is able to distinguish products, rather than predicting the diffusion of product categories. The study shows that online influence has the largest effect on product diffusion at the beginning of the process. The findings show that large online influence causes the diffusion rate to rise faster at the beginning of the process. If influence is lower, the process takes longer to take-off.

Besides influence, another parameter that contributes to the ability of the model to distinguish products is online word-of-mouth. In the literature study it is argued that online word-of-mouth is considerably different from traditional word-of-mouth. Therefore it is included in the existing mechanism of internal influence, alongside traditional word-of-mouth. Online word-of-mouth is measured in participation, which is the times a product is mentions per week. This measure builds up fast at product launch, and slowly decreases to a constant value until a new generation is launched. While influence has its largest effect at the beginning of the process, the stimulating effects of online word-of-mouth last longer.

Table of contents

List of abbreviations

WOM	Word-of-mouth
TWOM	Traditional word-of-mouth
OWOM	Online word-of-mouth
EWOM	Electronic word-of-mouth
SD	System Dynamics
NB	Norton-Bass
GNB	Generalized Norton-Bass model

List of figures

1 Introduction

The spread of an innovation through the market from product launch to deletion is termed 'diffusion' and is described in product growth models. Originally, Rogers (2003) defined it as the process by which an innovation *"is communicated through certain channels over time among the members of a social system."* Diffusion processes of innovations are becoming increasingly complex and multifaceted in recent years (Peres, Mull and Mahajan, 2010). Therefore, they re-define diffusion of innovations as: *"the process of the market penetration of new products and services, which is driven by social influences. Such influences include all of the interdependencies among consumers that affect various market players with or without their explicit knowledge."* One of the most influential contributions to diffusion research is made by Bass (1969) with the introduction of the 'Bass-model'. In 2004 the original 'Bass model paper' is voted one of the 10 most influential in Management Science (Bass, 2004). In the Bass model, product diffusion is contributed to word-of-mouth and advertising. However, the nature of word-of-mouth seems to have changed due to the introduction of online social networks on the Internet.

1.1 The Norton-Bass model

Bass (1969) concentrates on the initial purchase of new consumer products, and consumer durables in particular. He notes, however, that his theory applies to the growth of initial purchases of a broad range of "distinctive new generic classes of products." Bass assumes that the rate of adoption is influenced by two means of communication: *advertising through mass media* (external influence) and *word-of-mouth* (internal influence) (Mahajan, Muller & Bass, 1990). The effect of advertising depends on the effectiveness of the medium and the number of potential adopters to advertise to. The effect of word-of-mouth depends on four parameters: the number of adoptions, the total population (the initial potential adopters), the fraction that has adopted the innovation, and the contact rate between the adopters (Sterman, 2000). Bass (1969) assumes that advertising is most effective in the beginning of the diffusion process, whereas the effect of word-of-mouth increases from zero as it is provoked by actual adoptions. Bass distinguishes two adopter groups: innovators, that are triggered by advertising and initiate the start of the diffusion process, and imitators who occupy the rest of the market and base their adoption decision on word-of-mouth.

Although the original Bass model is still influential nowadays (Bass, 2004), its applicability to modern electronic consumer durables is disputed. Typically, these products have a multi-generational character: Adopters of earlier generations become potential adopters for future generation and discard products from earlier generations. Subsequently the market expands and applications grow as technology improves (Bass, 2004). Therefore, Norton and Bass (1987) have proposed an extension that fits products with a multigenerational character: *The Norton-Bass model*. The model is best described by three assumptions. Firstly, Norton and Bass (1987) assume that the demand of a product changes over time, partly due to its power to fit a certain pre-determined need and partly because it fits needs that did not exist before it existed. Because of this the market for a product grows over time. The adopters of a product from generation *i* partly come from adopters of generation *i-1* (cannibalization of previous generations) and from an increase in the market as such. Secondly, Norton and Bass (1987) assume there is a limit to the success of a product, and that this limit is equal for different generations. Finally, they assume the parameters of internal and external influence to be equal over time. Norton and Bass adopt a specific typology to refer to products and generations. They refer to a product as such (e.g. Apple iPhone) as an 'application', while one specific generation (e.g. iPhone 5) is referred to as a 'device'.

1.2 Research opportunity

The Internet is becoming a vehicle that provides focus and strength to the opinion of innovators (Rangaswamy & Gupta, 2000). Besides innovators in the traditional sense, the Internet also caused the group of opinion leaders, or 'influentials', to become larger and express their opinions easier (Gillin, 2007). Opinion leaders have found to influential, either because of their position within social networks or by their great interest in a topic at hand (Robinson, 1976). Online social networks provide a platform acquire and exert this influence to other actors in the network. This observation feeds the discussion whether opinion leaders should get a role in the Norton-Bass model besides the role of innovator or imitator. Also, the introduction of the Internet and its online social networks might have caused the nature of word-of-mouth to change. Therefore, it is questionable whether word-of-mouth as included in the Norton-Bass model is still representative to practice. The current study is aimed to answer whether the Norton-Bass model should be extended to account for the influence of online word of mouth and the increased power of opinion leaders.

Though extensive literature is available on the origins of diffusion models and product diffusion in general, research on the influence of the Internet and online social networks in particular is still premature and covered primarily in 'future directions' (e.g. Peres, Muller & Mahajan, 2010; Van den Bulte & Wuyts, 2007; Rangaswamy & Gupta, 2000). Nevertheless, these suggestions provide a foundation for the current study.

Peres, Muller, and Mahajan (2010) identify different empirical studies that investigate the impact of online social networks on product diffusion (see Van den Bulte & Wuyts, 2007), however they also notice that there are little theoretical contributions. They argue that in order to stay state-of-the-art diffusion models should be updated to the definition of product diffusion that was provided at the beginning of this introduction. Peres et al. (2010) suggest several changes to be made to the Bass (or Norton-Bass) model in order to remain state-of-the-art that are relevant to the current study. Firstly, they suggest a transition from industry level analysis to a brand level analysis. Secondly, focus should be on local, small-world networks, rather than fully connected networks. Online social networks are an example of small-world networks. Thirdly, they suggest that interpersonal communication should be revisited and more types of social interactions should be included. These types include network externalities, the increase in value of secondary, complementary products due to the adoption of the primary product. Another type of social interactions to be included in the Bass model are social signals, which is a type of word-of-mouth that is non-suggestive but still caused by product adoption. The current study has the potential to fill this gap in existing research by providing a solution to the modeling challenge that is proposed. In this study a contribution is made by proposing an extension of the existing Norton-Bass model, in which the influence of online social networks is included. Also, in the research process, an understanding is generated of the mechanisms underlying the influence of online social networks and their relation to product diffusion.

1.3 Research assignment

The main objective of the current study is to propose an extension of the Norton-Bass model in which an understanding of the influence of online social networks is incorporated. While Bass (1969) argues this influence can be exerted by innovators and imitators, in this study it is investigated whether a third group, opinion leaders or influencers also have a role. This model should allow practitioners to make more precise representations of diffusion processes using up-to-date and freely available data from Twitter. The model allows brand level analyses rather than industry level analyses, as was proposed by Peres et al. (2010). In order to propose and test this model, the following research questions are composed:

Research question:	*How should the Norton-Bass model be extended in order to incorporate the influence of online social networks?*
Sub-question 1:	*Should the Bass model be extended to incorporate the influence of online social networks?*
Sub-question 2:	*What reasons underlie the behavior of the parameters of the mechanism of online influence and online word-of-mouth?*
Sub-question 3:	*Is the Norton-Bass model able to provide product-specific diffusion forecasts after incorporation of the mechanism of online influence and online word-of-mouth?*

1.4 Research design

A literature review is performed to identify the state-of-the-art of research related to this study. This review includes an analysis on the evolution and state-of-the-art of the Norton-Bass (NB) model, word-of-mouth research, opinion leadership and an online social network application: Twitter. Firstly, Regarding opinion leaders, different models of influence are presented. Secondly, it was argued whether online word of mouth is different from the word of mouth used in the Norton-Bass model. Thirdly, Twitter is studied to identify parameters that contribute to online word of mouth. Finally, these parameters are linked to product diffusion and two redesign propositions are composed based on the findings.

Based on the findings of the literature study, a model is proposed in which a third mechanism is added to the two existing mechanisms of internal and external influence: the mechanism of online influence. Based on the redesign propositions, different relations are proposed between the Twitter parameters from the literature study and the Norton-Bass model. These relations are implemented in a System Dynamics (SD) model, which is an extension of the Norton-Bass model.

After the SD model is proposed, the included Twitter parameters are reviewed using data from Twitter. By doing so, more understanding is generated about the underlying forces and structure of online word of mouth using Twitter. In order to do so, a study is performed on longitudinal data from Twitter using time-series analysis. The SD model is further refined based on the findings from the review.

In the last research activity, the proposed Norton-Bass model is tested: can it predict product specific diffusion using Twitter data? Using the SD model, product diffusion is predicted for products from different categories. This is compared to actual market data gathered from retail store managers. This study has a cross-sectional character, as no continuous data is available from retail store management. Furthermore, results are discussed, and implications for practice and further research are presented.

1.5 Thesis outline

The remainder of this writing is organized as follows. In chapter 2, theories and prior research of relevant concepts are discussed. This review includes an analysis on the evolution and state-of-the-art of the Norton-Bass (NB) model, word-of-mouth research, opinion leadership and an online social network application: Twitter. Based on this review, two additions to the existing Norton-Bass model are proposed: online word-of-mouth and a mechanism of online influence. In chapter 3, these additions are incorporated in a system dynamics implementation (SD) of the NB model. Also, the applicability of system dynamics in academics is discussed, and the robustness of the model is tested. Chapter 4 sheds more light on the parameters that are added to the NB model. This is done by studying these parameters using historical Twitter data. Data is made interpretable using time series analysis. Additional findings to the literature review are presented on the parameters. In chapter 5, the functioning of the SD model is tested. This is done by comparing the outcomes of the models for 17 products, to sales rankings that are collected through two surveys held under retail store managers. The chapter is concluded by an analysis on the functioning of the model and a discussion of these findings. Finally, chapter 6 reflects on the study and discusses contributions to practice and academics, together with the limitations and suggestions for future research.

2 Literature review

2.1 Introduction

The first step in the research was a literature review in which the theoretical framework of the study was set out. This chapter focuses on four topics that are relevant to the study. After the research methodology has been discussed in section 2.2, section 2.3 focuses on the evolution of the Norton-Bass (NB) model. Different extensions of the NB model are presented that can be considered to adopt in the current study. In section 2.4, the development of word-of-mouth theory is discussed. More important, the differences between traditional and online word-of-mouth are addressed. This could provide an answer to the question if online word-of-mouth can be represented in the NB model without introducing additional parameters. Section 2.5 focuses on (online) opinion leaders. The evolution of opinion leadership is discussed, and models are provided that incorporate the influence of opinion leaders. In section 2.6, literature on one specific online social network (Twitter) is presented to identify potential parameters that could be included in the conceptual model. All together, the topics covered in this literature review should be able to support an answer to the following research question:

Sub-question 1:	*Should the Bass model be extended to incorporate the influence of online social networks?*

Although sections 2.3 to 2.6 provide theoretical backgrounds to support the current study, they each only solve part of the research question provided above. Therefore, their combined findings are discussed in section 2.7. This section addresses the gap in literature that can potentially be filled by the current study. Finally, in section 2.8 sub-question 1 is answered and two re-design proposals for the Norton-Bass model are presented. These proposals should be implemented and tested in the current study.

2.2 Methodology

Several guidelines are drawn up that are used to determine whether found literature meets the academic standard required for this master thesis. For literature related to the Norton-Bass model and product diffusion, only journals, conference proceedings and recognized book sources were used. The quality is rated using two measures from the Journal Quality List (Harzing, 2012); ABDC '10 and EJL '12 ratings and number of citations are considered in determining the quality of a publication. Sources that were not available for comparison using the journal quality list (e.g. books, proceedings) were rated based on their number of citations using *Google Scholar*[1]*;* only sources with more that 100 citations were included. Both rating methods are elaborated in Appendix A.2. In the search of articles relating to diffusion theory, the following keywords were used (separately or in combination): *Bass Model, Norton-Bass model, Innovation Diffusion,*

[1] **scholar.google.com**

Diffusion Models, Opinion leaders, Influencers, Influentials, Innovators, Word of mouth, Advertising, Social Networks, Extensions, Forecasting, Author: Bass, Author: Mahajan, Author: Krishnan.

Insights on online social networks (social media) are not typically present in academic journals only. Therefore, a different rating method is applied to determine the quality of social media related literature sources. Each academic source, unless it is considered a key publication (200+ citations), should be published later than 2005. Even when a publication is considered recent, still it needs to be quoted over 50 times according to *Google Scholar*. As starting point for the literature search, articles proposed in the TU/e Innovation Management course 'New Media' were used. Using a snowballing procedure, the following search strings were identified and used in Google Scholar: *Social Media, Twitter, Facebook, Sentiment analysis, Language detection, Online word of mouth, Influencers, Influentials, Opinion leaders, Author: Haenlein, Author: Kaplan.* The ratings of the social media related articles are documented in Appendix A.3.

2.3 Evolution of the Norton-Bass model

The Norton-Bass (NB) is argued to be the pioneering multigenerational diffusion model in marketing (Jiang & Jain, 2012). However, from its original publication in 1987 by Norton and Bass different contributions have been made in addition. Jiang and Jain (2012) provide an extensive overview of contributions to the NB model over time. As starting point the NB model (Norton & Bass, 1987) assumes each generation has its own market potential and differentiation is made if adopters are new to the application, or if they have adopted previous generations. Speece and MacLachlan (1995) apply the NB model to systems for milk packaging to incorporate the influence of pricing. Mahajan and Muller (1996) have studied the optimal launch timing for successive generations and add the number of systems in use to the existing model. Jun and Park (1999) focus on the mainframe and DRAM market and build two integrated models: one where the replacement decision is based on utility maximization and one where this is neglected. Kim et al. (2000) propose a model which includes both the diffusion of multiple generations within a product category, but also products from related and complementary product categories. Danaher et al. (2001) develop a two-generation model in which periodic product renewal is modeled. They also include more marketing-mix variables. Jiang (2010) also proposes a two-generation model to represent successive software releases where updates do not require repurchases. Most recently, Jiang and Jain (2012) propose a generalized NB model (GNB) in which the substitution effects between generations are credited to adopters that have not adopted previous generations and adopters of previous generations.

2.4 Word-of-mouth

2.4.1 Traditional Word-of-Mouth

Norton and Bass (1987) refer to word-of-mouth (WOM) as interpersonal communication in the traditional sense. In a marketing context, WOM is defined as “informal communications directed at other consumer about the ownership, usage, or characteristics, of particular goods and services and / or their sellers” (Westbrook, 1987, p. 261). The valence of WOM may either be positive, negative or neutral. Positive WOM includes vivid or novel product experiences, recommendations to other, and conspicuous display. Negative WOM includes product denigration, unpleasant experiences, rumor, and complaining (Anderson, 1998). In a meta-analytic review of antecedents of WOM, de Matos and Rossi (2008) found that customer satisfaction, loyalty, (service) quality, commitment, trust, and perceived (service) value all positively correlate with WOM activity. Moreover, they found that positive WOM is primarily driven by loyalty and customer satisfaction.

2.4.2 Online Word-of-Mouth

Applied to online social networks, WOM is often referred to by a multitude of concepts. Review shows that this field is still underdeveloped and that no consensus has been reached yet on typology. The quality they all share is that they refer to a more interactive WOM than traditional word-of-mouth (TWOM). Marketing is these online environments is referred to by concepts like buzz (Rosen, 2009), electronic word-of-mouth (eWOM) (Hennig-Thurau et al., 2004), rumours (Gill, Hultink, Sääksjärvi & Wang, 2012) or Viral Marketing (Phelps et al., 2004). The definition of eWOM by Hennig-Thurau et al. (2004) provides the widest description of the phenomenon: *“eWOM communication is any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet.”* Although eWOM captures part of the definition of online WOM via social media, it does not capture the potential of social media of social relationships, a quality traditional WOM (TWOM) does have. Therefore, Hennig-Thurau, Wietz and Feldhaus (2010) propose a hybrid between the two, which they refer to as Microblogging Word of Mouth (MWOM). MWOM is focused on a microblogging application: Twitter. Although the concept of MWOM is applicable to the current study, a more general definition is provided here to allow generalization. Here, online word-of-mouth (OWOM) is proposed as: *Interactive WOM communications between potential consumers and / or sellers, which is available to a multitude of people via online social networks.* Note that OWOM can also be exerted by potential adopters, as Rosen (2009) finds customers that have not (yet) adopted can also use online social networks to express their interest in product and express their opinion about them.

Different arguments can be provided to argue that online word of mouth (OWOM) is different from traditional word of mouth (TWOM). Sussan, Gould and Weisfeld-Spolter (2006) argue that traditionally, advertising and interpersonal communications were separated by time and place. They suggest that in the new online marketing landscape, interpersonal communication becomes a new hybrid between mass media communications and traditional word of mouth (TWOM) that empowers the customer. This is in line with Mangold and Faulds (2009) who find online marketing has a hybrid form that cannot be positioned within the existing marketing paradigm.

Part of the strengthening of online word-of-mouth is that it can be archived in searchable databases, making opinions accessible to a large number of people in the future (Rangaswamy and Gupta, 2000). This intensifies online word-of-mouth effects and makes it stronger than would be the case in the physical world. In addition to the storage of opinions, Trusov, Bucklin and Pauwels (2009) find that online word-of-mouth referrals have substantially longer carryover effects.

Furthermore online and offline interpersonal communications differ in their continuity (Berger & Iyengar, 2012); offline conversations are typically continuous, while online conversations are merely discontinuous. In their study, Berger and Iyengar (2012) argue that if conversations are discontinuous, pauses allow participants to rethink and reflect their contributions to the conversation, which increases the probability that interesting discussions are held. They find evidence that therefore more innovative brands are discussed online, while more everyday brands are discussed offline. These findings show that if only TWOM is included in forecasts, more radical products are not covered completely, which is an argument to include both TWOM and OWOM in diffusion models.

More differences in online and offline communications can be found in key influences of WOM on consumer behavior: tie-strength, homophily, and source credibility (Brown, Broderick & Lee, 2007). In the offline world, homophily exists in the relationship between two actors in a dialogue. The study by Brown, Broderick and Lee (2007) shows, that online homophily is driven by shared group interests and a group mind-set and is independent of interpersonal characteristics that traditionally contribute to homophily. Furthermore, their study shows that strong individual-to-individual ties are less relevant in an online context than in an offline context. In this context, strong ties are built up with a medium (e.g. websites, social media) carrying meaning to the information seeker. This is identified as ‘website reciprocity’, being the online replacement of interpersonal tie strength. Finally, while in interpersonal communication credibility is found in trust, credibility in an online environment requires some sort of authority in that specific context. Brown, Broderick and Lee (2007) find that authority is derived from shown expertise in a certain context and is considered more valuable than personal relationships.

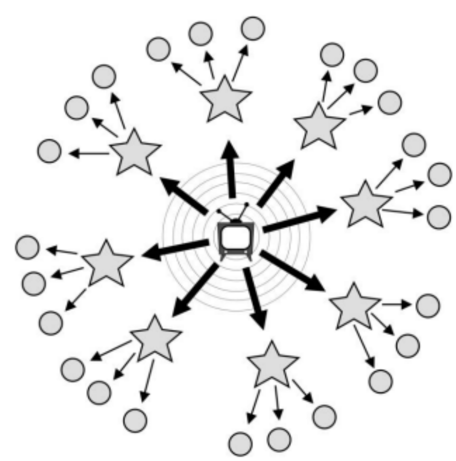
2.5 Influence of opinion leaders

In his original article, Bass (1969) refers to innovators as those that *“adopt an innovation independently of the decisions of other individuals in a social system.”* He adopters Rogers’ (2003) notion that innovators are the first two-and-a-half percent of the adopters of an innovation. Bass describes them as venturesome and daring. A third characteristic is that they interact with other innovators in the social system. The other ninety-seven-and-a-half percent of the adopters are referred to by Bass as imitators, which are influenced by the adoption timing of others in the social system. They are the ones susceptible to word-of-mouth.

While Bass only distinguishes two adopter groups, Rogers (2003) argues opinion leaders have a role in the diffusion process as well. Katz and Lazarsfeld (1955) have originally defined opinion leaders as *"the individuals who were likely to influence other persons in their immediate environment"*. This definition is still in use, more or less unchanged (Grewal, Mehta & Kardes, 2000). In a follow-up study Katz (1957) identifies three typical characteristics related to opinion leaders: (1) the personification of certain values, (2) high regarded competence, and (3) a strategic position within the social network.

Rogers (2003) argues their role in the diffusion process to be as follows: *"The behavior of opinion leaders is important in determining the rate of adoption of an innovation in a system. In fact, the S-shape of the diffusion curve occurs because once opinion leaders adopt and tell others about the innovation, the number of adopters per unit time takes off."* However, Watts and Dodds (2007) find the Bass model invariably generates S-shaped diffusion curves; no additional forces are required for it to do so. Nevertheless, they also find that though opinion leaders are absent in any formal model of diffusion does not necessarily mean they not play an important role.

Figure 2.1: Two-step flow model of influence (Watts & Dodds, 2007)



Watts and Dodds (2007) explain the function of influencers in a social network in a 'two step flow model of influence', as was originally presented by Katz and Lazarsfeld (1955) as can be seen schematically in figure 2.1. Opinion leaders (stars) act as intermediaries between mass communication and their followers in the network. Robinson (1967) criticizes the hypothesized relationship between mass communication and social networks. He finds, while leaving the original model intact, that the conversational exchange activity amongst opinion leaders deserves more attention. Watts and Dodds (2007) argue that the two-step flow model is no longer valid, as the introduction of online social networks has allowed a larger portion of people to exert power through their social networks and has allowed communication to become omni-directional rather than one-directional.

Originally, Katz and Lazarsfeld (1955) talk about opinion leaders, in an application to online social networks, they are referred to as influentials (Gillin, 2007; Watts & Dodds, 2007), or influencers (van den Bulte & Wuyts, 2007). In this study, we will adopt the latter, as this is well accepted within both academia and practice. Van den Bulte and Wuyts (2007) find influencers should show an increased interest in and be updated about new products, they have a central place in their social networks, and they need to engage in discussion about these products.

Kozinets et al. (2010) describe the evolution of WOM theory to explain the power of influential in online environments. Figure 2.2, panel A depicts the type of influence Rogers (2003) and Bass (1969) refer to. Inter-consumer communications are restricted to an exchange product- and brand-related marketing messages. Figure 2.2, panel B describes a more evolved method of influence in which influential consumers (opinion leaders) are directly addressed by marketers. These opinion leaders are specifically addressed (through marketing-mix elements) and are assumed to communicate brand-related messages unaltered and faithfully. In the most recent model, the 'Network coproduction model' (figure 2.2, panel C), marketers address consumers directly using the increased social capabilities of online social networks. Marketing messages are shared by perceived influencers in their networks. Messages do not flow unidirectional, but rather are exchanged amongst people in the network. In response to the two-step flow model by Katz and Lazarsfeld (1955), Watts and Dodds (2007) propose a network model of influence, in which influencers are defined by their position in the influence network. In the visualization in figure 2.3 mass communication feeds all actors in the network. Opinion leaders can be fed with mass communication directly or through other actors in the network. Two main differences exist with the traditional two-step flow model of influence. Firstly, influence can now flow in any direction. This allows non-influencers to exert influence, which may then be included in the communications by influencers. Secondly, while the previous model only allowed two steps of influence, here a multitude of steps is allowed. On Twitter, retweeting is the mechanism that allows actors to do so. Within this model, influencers exist by virtue of their followers. Also, when an actor is influential within a certain context, this does not dictate influence in other contexts.

Figure 2.2: Evolution of opinion leadership (Kozinets et al., 2010)

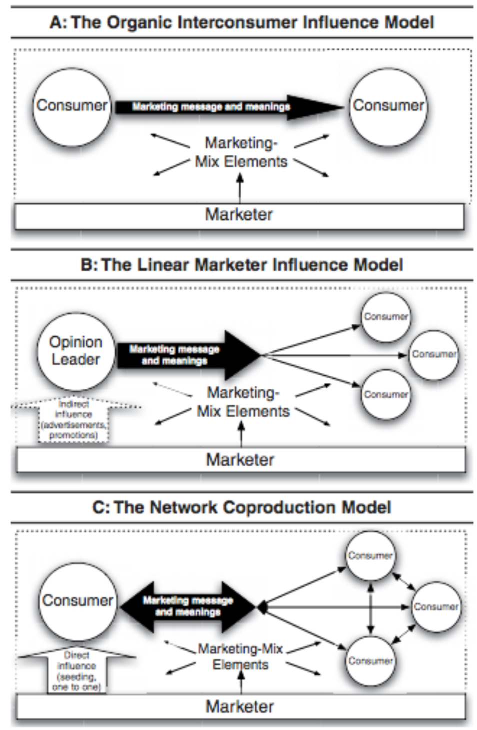
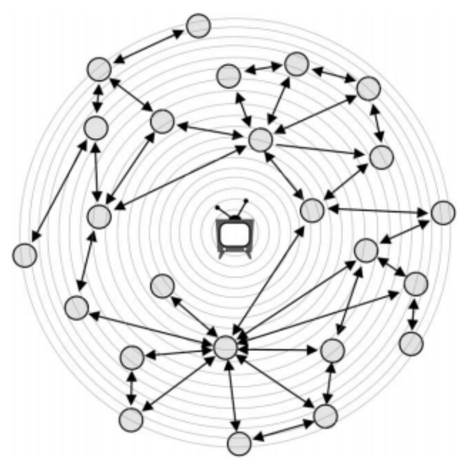


Figure 2.3: Network model of influence (Watts & Dodds, 2007)



2.6 Identification of parameters

In line with other social media studies (e.g. Bollen et al., 2011; Curtis, 2012; Esch et al., 2006; Jansen et al., 2009; Kwak et al., 2010) Twitter[2] has been selected to examine OWOM and online influencers in further detail. Twitter is an online blogging application which is categorized as *microblogging*. Jansen, Zhang, Sobel and Chowdury (2009) describe microblogs as *"short comments usually delivered to a network of associates"*. On Twitter, the length of a message is restricted to 140 characters, and the network of associates is formed by other users that follow what a user is *Twittering*. Because of the popularity of Twitter, a microblog is often referred to as a *tweet,* and has been adopted in common speech like *Xerox* for copying and *Google* for online searching (Jansen et al., 2009).

Three reasons are provided why Twitter is introduced to the study. Firstly, Twitter allows capturing 1% of the total message stream (which results in 39 messages per second). Secondly, in contrast to other applications like Facebook[3], Twitter data is publicly available. Thirdly, historical Twitter data is also available through online applications like *Topsy Pro Analytics*[4] and *PeopleBrowsr*[5].

Different parameters are identified that show a relation to product diffusion, which makes them valuable to add in the conceptual model: spiking events, participation, retweets, influence, and sentiment. These parameters can either be derived directly, or need to be calculated. In the remainder of this section, each parameter is explained and its relation to product diffusion is enlightened.

2.6.1 Participation

Participation is measured by the raw count of unique tweets on a topic per time unit. It is assumed to have a positive effect on the adoption from buzz, as it has proven to be highly predictive for sales in a different (movie) context (Asur & Huberman, 2010). Also, Pang and Lee (2008) find that the number of times a brand is mentioned is highly predictive for product sales after launch. In a movie-context, Mishne and Glance (2006) found differences in the correlation between participation and sales pre-release (*.484)* and post-release (*.601)*.

2.6.2 Spiking events

Over time, the level of participation varies from low values to sudden peaks. Thelwall, Buckley and Paltoglou (2011) identify these peaks as spikes, which are caused by a large increase in certain keyword usage during a short period of time. Two different causes are found for spikes to emerge: internal and external spiking events. Internal events are appear within the corpus[6] of tweets and are caused by viral activity: a few single tweets are retweeted so often that they cover a

[2] www.Twitter.com
[3] www.facebook.com
[4] pro.topsy.com
[5] www.peoplebrowsr.com
[6] A corpus: a collection of tweets (on a topic)

disproportional large portion of the corpus. External spiking events are caused by events that occur independently of the tweets in the corpus. Examples include product launches and news events.

2.6.3 Retweets

Retweets are tweets that are forwarded by someone's followers to their followees. The quality of a tweet is reflected in the number of retweets it gets. For a retweet to be effective, it should at least be retweeted 6 times and maximally 11 times (Kwak et al., 2010). Retweet paths that are longer than 11 steps lose their impact, as paths beyond 11 times take too long to be established. Literature does not provide any reason to assume a direct relationship between the diffusion rate and the number of retweets. However, Kwak et al. (2010) do find that it adds a quality dimension over other measures. Therefore it is assume there is a positive relationship between online influence and retweets; a sort of extra *boost* over original tweets.

2.6.4 Sentiment

Jansen et al. (2009) have found that 20% of the tweets that mention a brand are subjective (contain sentiment). From these, 50% were positive and 33% were critical towards the brand. In the Norton-Bass model, sentiment is not included (Norton & Bass, 1987). Pang and Lee (2008) find that the effect of negative sentiment is larger than the effect of positive sentiment. Similarly, Lucking-Reiley et al. (2007) find that negative evaluations have a negative on selling price: a move from 2 to 3 negative online product evaluations cuts price by 11%. Park and Lee (2009) quantify these impacts. They find that the effect of negative sentiment (*3.6, $p < .001$*) is significantly larger than the effect of positive sentiment (*3.3, $p < .001$*). Thelwall, Buckley and Paltoglou (2011) research the relationships between pre- and post-spike sentiment, and find that negative sentiment increases after a spike, while positive sentiment remains constant independently of the spike.

2.6.5 Influence

Online influence can be derived from a combination of different parameters. The number of followers a poster[7] contributes to the influence that poster has. Kwak et al. (2010) find that retweet-counts also add to the influence of a communication. Besides these raw counts that can be used to calculate influence, different online applications offer composed measures to represent influence.

One measure that is suggested by Twitter is provided by *Topsy Pro Analytics*[8]. Topsy follows the findings by Kwak et al. (2010) that the likelihood that a poster gets attention is a combination of the number of retweets he gets and the number of followers he has (Topsy, 2012c). Additional, Topsy calculates the centrality of each poster, which is defined as: "the likelihood of a person receiving attention form any random point on the graph." Iyengar, Bulte and Valente (2011) argue that centrality is positively related to opinion leadership. The influence measure by Topsy (2012c) is transitive, which implies that your influence increases when more attention from other

---

[7] poster = a Twitter user that share a tweet (Thelwall et al., 2011)
[8] pro.topsy.com (Twitter certified data reseller)

influential posters is received. Additionally, a decay factor ensures that when a poster is inactive for a period, his influence decreases. Though these composed influence parameters are widely used in practice, a shortcoming of these measures is that their underlying parameters cannot be accessed for further research.

2.7 Discussion

In this chapter, research on four topics is presented. Together, the studies that are presented provide an argument to positively answer the question whether the Norton-Bass model should be extended to incorporate the influence of online opinion leaders. Though the topics were rather well covered in literature, integration appears to be missing. Combining these opportunities results in two redesign opportunities, which are discussed below.

At the beginning of this chapter different extensions on the Norton-Bass model are presented. Each version is a specific application of the traditional NB model. Also, each model has been tested in a single context, which questions the generalizability of these models. An exception is the recently published study by Jiang and Jain (2012). Their Generalized NB model distinguished between adopters and non-adopters of previous generations. However, unfortunately for the current study, the distinction of these two groups is hard to make using Twitter data. For the reasons presented above, the current study adopts the traditional NB model Norton & Bass, 1987) as starting point of the extension.

Opinion leaders do not have a role yet in formal models like the Norton-Bass model, as no formal role in the diffusion of innovations has been identified (Watts & Dodds, 2007). Nevertheless, they do have a role in the diffusion of information. Watts and Dodds (2007) and Kozinets et al. (2010) provide models in which the influence of online influencers is modeled. Watts and Dodds (2007) argue that communications between actors in a social network are no longer one-directional, but now have become multi-directional. Also, word-of-mouth is no longer communicated in two steps, but longer communication paths are possible. Regarding Twitter, these paths are established by retweets. The role of influencers in product diffusion is an intermediary role between the advertising and the mechanism of internal influence. Topsy Pro Analytics provides a measure that is similar to the concept of opinion leadership, but in an online environment. Therefore, their measure is included in a mechanism that introduces the influence of online influencers to the Norton-Bass model. This mechanism is proposed in the following re-design proposal:

Re-design proposal 1:	*The mechanism of online influence is an intermediary between the mechanisms of external and internal influence, and should be modeled dependent on the number of influential tweets and the effectiveness of advertising.*

In section 2.4, different studies are presented that show differences exist between online and offline word-of-mouth. Therefore, it is argued here that online word-of-mouth is not represented in the Norton-Bass model. Though different studies are presented that show relationships between participation and product diffusion, and sentiment and product diffusion, these were not addressed together in a study. Here, it is suggested that sentiment moderates the effect of participation on product diffusion. Furthermore, it is suggested that OWOM should be added to the existing mechanism of internal influence, as it is different but also shows a positive relation to product diffusion. Therefore, the following re-design proposal is done:

Re-design proposal 2:	*Online word-of-mouth is to be added to the existing mechanism of internal influence and is moderated by the sentiment that is expressed in it.*

3 Building the model

3.1 Introduction

In the previous chapter it is discussed that in order to incorporate the influence on online opinion leaders an extension of the existing Norton-Bass model is desirable. This resulted in two redesign proposals, which are implemented in the current chapter. Before focusing on the redesign of the Norton-Bass model, section 3.2 first focuses on the modeling approach. In the current study, system dynamics (SD) is chosen as modeling language. This visual mathematical modeling language relies on systems thinking, which is the "mental effort to uncover endogenous sources of system behavior" (Richardson, 2011). SD is a modeling approach which has different advantages over other mathematical models, such as likelihood models in which the Norton-Bass model is originally modeled (Bass, 1969). Nevertheless, critique exists on the usage of system dynamics. This critique typically comes from academics, while most arguments in favor of SD are aimed at practice. In section 3.2 the use of SD in the current study is justified.

In section 3.3 the mechanism of online influence, in which redesign proposal 1 is included is explained. Section 3.4 focuses on the specification of the influence of online influencers and online word-of-mouth, which are both included in the SD model that is presented in section 3.5. The sensitivity of this model is tested in section 3.6, which concludes the development of the model.

3.2 Modeling approach: System Dynamics

3.2.1 Advocates of system dynamics

In the current study, different mechanisms are added to the Norton-Bass model that have been studied separately in prior studies. Using system dynamics (SD), their combined effect on product diffusion is studied. SD primarily serves the purpose of understanding the behavior and underlying structure of a phenomenon. These range from business cycles, HIV/AIDS epidemics, and the diffusion of new products. Lane (2000) describes three main characteristics of SD: (1) the use of causal feedback loops, (2) computer simulation is used to compensate limited human capability, and (3) the involvement of mental models, which consist of objective and subjective decision making variables. SD offers means to compare both types.

Regarding the current study, SD allows to create a more comprehensible representation of the likelihood function that is proposed by Norton and Bass (1987). Executives involved in both radical and incremental innovations indicate that one of the reasons diffusion models are not often used in practice is the mathematical sophistication of those models (Kahn, 2002). Sterman (2000) argues SD offers a flexible modeling approach that is able to incorporate last minute changes in trends and turning points in cycles. Other, less flexible, methods do not allow this, which causes forecasts to lag behind reality. Moreover, Lyneis (2000) finds SD is flexible enough to adapt the model even during product launch. By doing so during the first two weeks after launch, forecast error can be reduced to 8% (instead of 47% on average) (Fisher, Raman & Sheen

McClelland, 2000). Also, Lyneis (2000) finds that SD provides a means of understanding the reasons for events to occur during launch, which feeds the on going learning within a company. Finally, SD allows simulating different scenarios as input for company decisions and policy design.

Lane (2000) argues that when different mechanisms are combined, which appeared unterpretable in isolation, some mechanisms can become predominant. This causes results to become counter-intuitive and inexplicable. SD allows researchers to simulate this behavior computationally to find an explanation.

3.2.2 Critique on system dynamics

The main source of academic literature on SD is found in journals related to systems research and more specific in *System Dynamics Review*. Nevertheless, in some of these articles the appropriateness of SD is questioned. Critics argue that SD is 'simple' (Jackson & Keys, 1984), 'machine-like' (Flood & Jackson, 1991), and 'deterministic' (Jackson, 1994). Lane (2000) reviews different arguments why this is and provides a reflection on them.

Firstly, within SD systems, everything has a cause that can be identified within the model. Therefore, there is no place for exogenous forces. This argument includes a straw-man fallacy, as it neglects the power of boundaries in SD models. These boundaries allow modelers to understand the behavior of the model and adjust the boundaries when inexplicable behavior occurs. Secondly, SD would be too deterministic by neglecting the autonomy in human decision-making. In his original article on SD, Forrester (1961) already argues decision-making is strongly conditioned by one's environment. This view is shared by Rogers (2003) and Bass (1969), who see the market as an aggregation of groups of individuals. Regarding systems thinking, Phillips (1987) argues for the appropriateness of this notion through an example: if a theatre hall is filled with students, the behavior of one student cannot be predicted through a SD model. However, the filling of the hall as such can be predicted as there is a structure underlying this phenomenon. This structure can be modeled using SD. Thirdly, Flood and Jackson (1991) argue some naïve realism underlies SD. The mental models on which SD models are built, are incomplete and driven by personal subjectivity. However, as Forrester (1961) already noted, the SD modeling process has an iterative nature which allows the modeler to bring the model closer to reality with each iteration. Nevertheless, it should be noted that this is the responsibility of the modeler involved in the study.

3.2.3 Discussion

For the purpose of the current study, SD offers a good tool, as it allows to get an understanding of the existing and new mechanisms of influence. In order to assimilate the model again into only regressive model, approaches such as taken by Bass (1969) and Norton and Bass (1987) might be more appropriate. This might be a proper approach for a follow-up study to the current study. Relating to the criticism of naïve realism, the gap between the mental model and the written and numerical data underlying SD models is an issue (Forrester, 1994). Luna-Reyes and Andersen (2002) argue there is no clear description how and when to use data in this process, which is a potential pitfall to the reliability of the use of SD in academic studies. Regarding to the current study, however, the written database (the literature study) is considered a well-grounded base. Also, the numerical data underlying the proposed mechanism of online influence is gathered using supported methods. Also, as the current study focuses on the behavior of adopters groups, there is no interest in individual decision-making. Therefore there is no issue with regard to the neglect of autonomy in human decision-making.

3.3 Mechanism of online influence

The mechanism of online influence is proposed to include in the Norton-Bass (NB) model to incorporate the influence of online opinion leaders (influencers). The mechanism of online influence has an intermediary function between the existing two mechanisms in the NB model: internal and external influence. Watts and Dodds (2007) suggest influencers have some role in diffusion models, though they are not a separate category of adopters, like influencers and imitators in the NB model. As influencers have an intermediary function to communicate mass communication to their followers, their impact on product diffusion depends on the effectiveness of advertising (mass communication), as modeled by Sterman (2000). As influencers are found to show an interest in the newest technology (van den Bulte and Wuyts, 2007), their influence is largest when a product is launched, and decreases after launch. This is similar to the way the mechanism of external influence is modeled by Sterman (2000), as opinion leaders share this characteristic with innovators. While the effectiveness of advertising depends on the product category, the number of influential mentions can be determined per product. Regarding the mechanism of online influence, this is the parameter that differentiates products diffusion between different products.

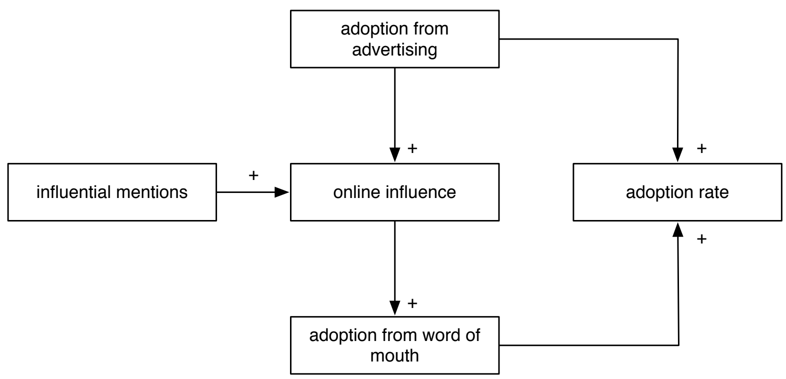
Strictly speaking, online word-of-mouth is not part of the mechanism of online influence. Although it has been argued that online word-of-mouth (OWOM) is different from traditional word-of-mouth (TWOM), no support has been found for different effect sizes on product diffusion. Therefore, OWOM (through participation) is added to the existing mechanism of internal influence, which was previously only fed by TWOM. Participation is modified by sentiment and is similarly modeled as TWOM. By introducing OWOM to the mechanism it now distinguishes between OWOM and TWOM.

3.4 Proposition of parameters

3.4.1 Effect of online influencers

In order to position the effect of influential mentions within the SD model, it is necessary to understand how their influence is exerted. The mechanism of external influence in the Bass model is driven by advertising and other communications that are initiated by the producing firm (Peres, Muller & Mahajan, 2010). Following the model by Watts and Dodds (2007), influential tweets represent the effect influencers have on product diffusion as intermediary between the mass media in the mechanism of external influence and internal influence. The number of influential mentions differs per product, which allows the mechanism of online influence to create a differentiation in diffusion between different products. The number of influential mentions is measured at the moment the launch-spike is at it highest, as this is the moment the product is launched and the mechanism of external influence is triggered. The number of influential mentions is divided by an average number of influential mentions over several products, to allow comparison between different products. The inclusion of this fraction creates results in a very small value if little involvement of influencers is measured, and a larger value if this involvement is larger than average.

The relationship between the mechanisms of external influence, online influence, and internal influence is modeled and calculated as follows:



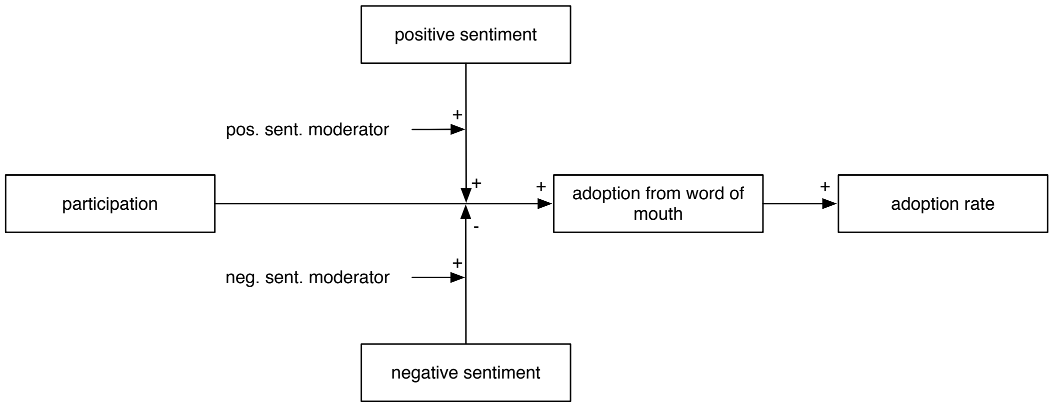
$$Influence = \frac{n_{influencers}}{avg\ n_{influencers}} \times adv.effectiveness \tag{3.1}$$

where $n_{influencers}$ = the number of influential mentions at launch and *adv. effectiveness* = the advertising effectiveness from the Norton-Bass model.

3.4.2 Online word-of-mouth

Participation is directly related to adoption through word-of-mouth. In the traditional Norton-Bass model, this relationship is modeled as 'adoption from word of mouth', which contributes to the mechanism of internal influence. In the current study, it is proposed that online participation adds to this mechanism. Participation is modeled as proposed by Asur and Huberman (2010) as the number of mentions of a certain topic per unit of time (weeks).

Sentiment is considered a moderator of participation, where negative sentiment has a larger effect than positive sentiment. As can be seen in the equation, the moderator enlarges the effects of both positive sentiment (*3.3*) and negative sentiment (*3.6*), as proposed by Park and Lee (2009). In the model, this is corrected by decreasing the overall effect of sentiment. Sentiment is calculated as average value of sentiment per product. Schematically, participation and sentiment are modeled and calculated as follows:



$$participation = \frac{\sum_{i=1}^{n} mentions}{n} \tag{3.2}$$

where n = number of weeks and $mentions$ = the number of mentions in week$_n$.

$$sentiment = \frac{\sum_{i=1}^{m} \left[\frac{(3.3 \times n_{positive})}{(3.3 \times n_{mentions})} - \frac{(3.6 \times n_{negative})}{(3.3 \times n_{mentions})} \right]}{m} \tag{3.3}$$

where m = weeks, $n_{mentions}$ = number of overall mentions, $n_{positive}$ = number of positive mentions, and $n_{negative}$ = number of negative mentions[9].

[9] **Although the number of overall mentions is used in the calculation, it is not modelled because the calculation takes place before sentiment is used as input for the model.**

3.5 System dynamics implementation

As starting point for the system dynamics implementation of the model extension to be proposed serves a system dynamics interpretation of the Norton-Bass model, which is included in appendix D.1.

After implementation of the proposed parameters in system dynamics, the model is visualized in Vensim as represented in figure 3.1. Note that figure 3.1 only contains the first generation of the model. Appendix D.2 contains a visualization of the full model.

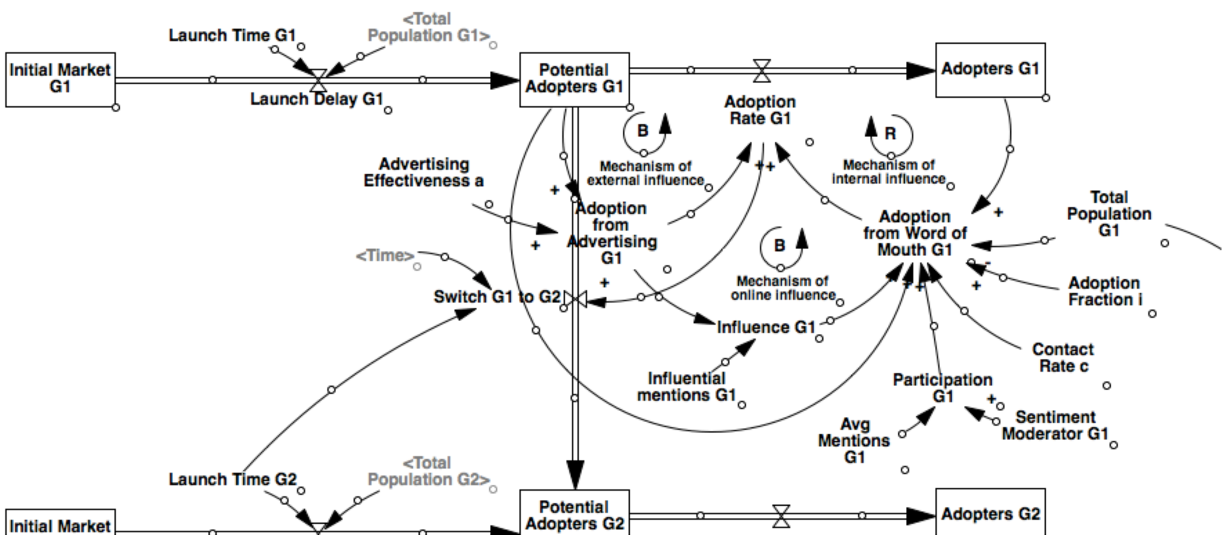


Figure 3.1: System dynamics interpretation of proposed model (generation 1)

3.6 Sensitivity analysis

Sterman (2000) proposes twelve methods to test the model robustness, which are not all applicable to the current study. Three methods apply in this study and are therefore used to test the model: family member, extreme conditions, and sensitivity analysis.

3.6.1 Family member

In order to assess whether the model behaves like its nearest family member (the Norton-Bass model) the full range of each available parameter is tested in Vensim. Using the 'causes strip', the behavior of the model are visualized together with the dependencies between the parameters. Using this method it is concluded here that the proposed extended model shows equal behavior as the Norton-Bass model, and that variance between the two models is explained by the additional parameters of the extension. The contribution of those parameters is as they were expected while modeling.

3.6.2 Extreme conditions

Even when the extension parameters are set to extreme values (1000 times multiplied), the model remains to function as planned. Nevertheless, the extreme values result the model to predict impossible adoption behavior. If the extensions parameters are all set to zero, the model functions as the extension proposed by Norton and Bass (1987). This implies that when products are not represented on Twitter, the model is still able to provide a baseline prediction for these products.

3.6.3 Sensitivity analysis

To study the sensitivity of the model, both influence and participation set to their average values from the dataset (*influence: 408; participation: 833*). The other parameters are systematically changed and their effect on the adoption rate is studied. As modeled, negative sentiment influences the model more significant than positive sentiment. As the effect of sentiment is dependent of the number of mentions, the effect of mentions is larger. This is like it was modeled. If the two differ considerably, the model still behaves as predicted. The timeframe in which the s-curve evolves is considerably lengthened when more negative sentiment is involved or shortened when more positive sentiment is added. When sentiment and influence are compared, it appears the effect of sentiment is smaller than the effect of influence. This follows the design of the model, as sentiment is modeled as a moderator, while influence is a separate mechanism.

In the test, relationships were also reversed. When participation is negatively related to word of mouth, the adoption rate quickly declines to zero. In this case, Twitter is used as negative advice mechanism, which explains the behavior. If influence is negatively related to participation, the adoption rate rises more slowly, since influencers advise their followers not to adopt in that case. Evidently, if positive sentiment is made negative this adds to the negative sentiment already present. The contrary is applicable when negative sentiment is made positive.

One specific sensitivity analysis is done regarding the effectiveness of advertising. Evans (2009) argues that nowadays, this is reduced compared to the original Bass model. In the currently proposed extension, this means that the effects of both the mechanisms of internal and external influence are reduced. However, the effect is partially undone because the influence of advertising now also interacts with the mechanism of internal influence.

4 Reviewing the model parameters

4.1 Introduction

In the literature study, different Twitter parameters and their relation to product diffusion are studied. In this chapter, these parameters are reviewed using longitudinal Twitter data. This is done to get a better understanding of how these parameters contribute to each other and to get a better understanding of their underlying mechanisms. This is done using time series analysis in combination with a qualitative analysis method. Therefore, one specific sub-section is added that addresses the reliability of the used methodology. After the methodology has been elaborated, the different parameters are reported by examining products from three product categories. More specific, section 4.2 describes how the Twitter data was collected, section 4.3 describes an analysis of the data, while section 4.4 provides the results of the review. Finally, in section 4.5 an answer is given on the research question for this chapter:

Sub-question 2:	*What reasons underlie the behavior of the parameters of the mechanism of online influence and online word-of-mouth?*

4.2 Data collection

In order to provide the current study with Twitter data, *Topsy Pro Analytics*[10] is used. This online service allows storing and downloading Twitter-data from July 2010 until today. 'Topsy' literally matches search queries to a Tweet's 'text'-field. Keyword searching is restricted to two keywords per query, which is a shortcoming of the current study. However, this shortcoming is taken into account in the selection of the list of products: only products were selected that can be searched using two keywords.

4.2.1 Product selection

Corpuses of Tweets are created for different products in three product categories: tablets, smartphones, and XBOX360 games. Within the scope of consumer durables more categories are studied. However, results for these categories were inconsistent, which lead to the selection of the three categories mentioned above. Also, other product categories show a wider variety of products, which causes assortments to differ between retail stores. If product assortments would vary too much between stores, Dutch retail stores would not be able to provide the current study with a reliable view on the Dutch market. As a result, this would reduce the reliability of the results of the model testing in the next chapter. Within the three product categories all product launches within the time frame available in Topsy are included. The products per category are selected using online retail store *Bol.com*[11]. The list of products ranges from very popular to less popular

[10] **pro.topsy.com**
[11] **www.bol.com**

products, where it is tried to divide the products approximately equally over the popularity scale. Afterwards, the list is checked in various offline stores to ensure retail managers are familiar with the products involved. Special attention is paid to ensure that only full releases are included in the study. Especially in the case of XBOX360 games (and other software releases) many add-ons are added to the assortment, which are mere upgrades of the latest full release.

4.2.2 Twitter data

The data that was gathered shows the Twitter activity per day for each product, which leads to 834 observations per product per parameter. The curves used to study the parameters showed many fluctuations, which made it difficult to study underlying mechanisms. Therefore, the data was added up per week to get a better overview. This lead to 121 observations per product per parameter from July 6th, 2010 to October 16th, 2012. Data is collected for each application (e.g. iPhone) and the different launched devices within the timeframe available in Topsy. Appendix B provides an overview of the devices that are included in the study. For each application and device, 4 worldwide parameters were stored: mentions, influential mentions, mentions with positive sentiment, and mentions with negative sentiment. Also 2 parameters originating from Dutch posters[12] were stored: mentions and influential mentions. Using the ratio of the worldwide objective and subjective tweets, the Dutch mentions with positive and negative sentiment were calculated as follows:

$$Dutch\ Pos. Mentions = \frac{Worldwide\ Pos. Mentions}{Worldwide\ mentions} \times Dutch\ Mentions \qquad (4.1)$$

$$Dutch\ Neg. Mentions = \frac{Worldwide\ Neg. Mentions}{Worldwide\ mentions} \times Dutch\ Mentions \qquad (4.2)$$

In order to determine a poster's origin, Topsy (2012a) uses a combination of eight methods that together ensure a large confidence: latitude / longitude, user profile, language detection, geo-data of previously posted content, check-ins at physical locations, comparison of tweet time stamps and global time zones, locations mentioned in tweets, and geo-tags for events that are attended. Unfortunately, Topsy is not able to calculate sentiment in Dutch tweets. Nevertheless, using the calculations in equations 4.1 and 4.2 it is assumed the study is provided with plausible sentiment scores. The assumption underlying this argument is that though attention towards a product might not be similar worldwide and in the Netherlands, the division of sentiment-percentages is equal. As Twitter is a worldwide online network, and product launch timing is increasingly global, this assumption is found valid.

Study shows that the algorithm used by Topsy results in 70% agreement with manually reviewed content (Topsy, 2012b). Regarding sentiment analysis where products are involved, Thelwall et al. (2011) show that when product names trigger sentiment, this skews the results. They found this in the case of *HTC's Hero* smartphone. While reviews were rather negative, still its sentiment was found to be positive due to the positive connotation of the device name. Topsy

---

[12] **Twitter users that post a tweet (Thelwall et al., 2011).**

incorporates this function. An illustrative example how misleading product names are taken into account is *'Angry Birds'*. This smartphone app is recognized as product name, and therefore 'angry' does not carry negative sentiment in this context.

Regarding influence, Topsy follows the findings by Kwak et al. (2010) that the likelihood that a poster gets attention is a combination of the number of retweets he gets and the number of followers he has (Topsy, 2012c). By doing so, Topsy calculates the centrality of each poster, which is defined as: "*the likelihood of a person receiving attention form any random point on the graph*", which is positively related to opinion leadership (Iyengar, Bulte and Valente, 2011). The influence measure by Topsy (2012c) is transitive, which implies that your influence increases when more attention from other influential posters is received. Additionally, a decay factor ensures that when a poster is inactive for a period, his influence decreases.

4.3 Data analysis

From products in each proposed product category Twitter data is analyzed. The aim is to find patterns in the Twitter parameters that constitute the mechanism of online influence and online word-of-mouth. Using this understanding, the SD model parameters can be refined and more in-depth insights can be generated. For each product, Twitter data was collected for the overall application (e.g. 'iPhone') and recent generations of its devices (e.g. 'iPhone 3GS', 'iPhone 4', 'iPhone 4S', and 'iPhone 5'). In this section, the times series analysis procedure and its reliability is discussed first. Secondly, the sensitivity of the keywords used in the analysis is discussed. Thirdly, the remainer of this section concentrates on the analysis of the parameters that are involved in the model: spikes, mentions (participation), influence, and sentiment.

4.3.1 Time series analysis

By applying exponential smoothing, the data was made more interpretable. For each parameter of each application and device, a prediction model was proposed using Holt's Linear Trend. Holt's Linear Trend is best used when a trend is visible in the data, but no reason to assume seasonality in the data is present (Chatfield, 2000). One might argue that the assumption of no seasonality is invalid; products tend to be launched in a repetitive pattern. However, exploration of the launch dates of the product involved in the study shows such a repetitive pattern can hardly be identified. By using Holt's Linear Trend, the resulting prediction parameters are less viable to random error and allow better comparison, as the general trends are better visible in the resulting curves.

Different approaches exist for the analysis of data such as the Twitter data in the current study. Neuendorf (2002) proposes a quantitative content analysis process, where different time periods are classified and compared to identify trends. This method is well suited to build models. However, the current study is aimed at understanding underlying forces. Therefore, a more qualitative, insightful approach appears more appropriate. In a study similar to the current study, Thelwall (2012) proposes a two-step qualitative approach, which is adopted in the current study.

Firstly, the volumes of the curves of the different parameters are graphically compared between the corpuses. Thelwall (2012) proposes different questions to be asked: is the volume increasing or decreasing over time, is the change constant or are the changes in the broad pattern, are there spikes indicating an event. The second step of the analysis concentrates on the argumentation why certain patterns occur. Using Topsy Pro Analytics, individual tweets contributing to a certain trend are identified to support presumptions from the first step. Other support for presumptions can be found by calculating cross-correlations between different time series. For each observation, support is provided using at least one of these methods.

4.3.2 Reliability

Traditionally, a qualitative approach such as the one adopted in the current study is subject to reliability issues. Therefore, the following procedure is followed to overcome these issues. Firstly, each observation needs to be replicable. In appendix C, each observation is supported by one additional graph that describes the same behavior but comes from a product from another category. Secondly, inter-rater discussions are held to increase reliability. The observations are discussed with a fellow student who was introduced into the followed methodology. If disagreement existed with the other rater, a discussion was held where additional support was provided for the observations. After the observations were processed, they were discussed with a professor of marketing and an assistant professor of marketing. In this discussion the argumentation behind the observed parameters was tested. Their input was used to further refine the argumentation and findings.

4.3.3 Keyword sensitivity

When comparing application curves to device curves, a difference in amplitude becomes apparent. Partly this is because people mention different devices at the same time, which seems logical as not all users have the same generation device. Another explanation is found in the content of the tweets contributing to both curves. It shows that there is a difference in how devices are addressed in tweets. Where one user uses the complete device name (e.g. iPhone 5), another user only refers to the application name (e.g. iPhone).

It appears that if the mentions of the separate devices are added up in the cumulative curve, approximately the same pattern is visible, which is confirmed by a positive cross-correlation between the application curve and the cumulative devices graph *(r=.789)*. This correlation is visible in the curve in figure 4.1. This observation is replicated in data of for the other products as well. There, also considerable large positive correlations between other cumulative devices curves and their application curves are visible *(r=.988 (Apple iPad); R=.577 (FIFA))*. This result is replicated in figure C.1 in appendix C.

The difference in correlation between FIFA and the other products can be explained by the interpretation of this word. Here the application name (FIFA) refers to both the video game and the International Football Association. Two exemplary tweets are: *"@sport1_nl: Blessure Marcelo kost FIFA mogelijk 1,8 miljoen euro"* and *"@erblo: Spelers die uit vorm zijn, schoppen in het nieuwe FIFA ook geen deuk in pakje boter".* Though one might argue that though this is a source of noise in the dataset, still mentions referring to the football federation could still create attention for the game. If other keywords are considered, this might be more troublesome. For instance the videogame Halo refers both to the video game and the lighting effect. This might form part of the reason why a difference exists between the amplitude of both curves.

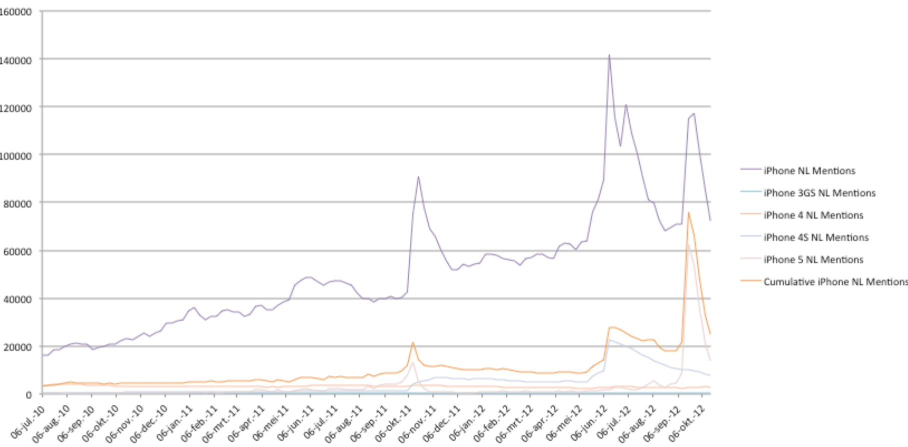


Figure 4.1: iPhone Dutch Mentions

Other ambiguous keyword usage is seen when people use different device names when referring to the same device, which is visualized in figure 4.2. The time frame visualized here is the time around product launch. Before the spike around July 31st there was speculation which name Apple would give their latest iPad. Though they presented 'The New iPad' instead of 'iPad 3' at the launch presentation, the public still uses the name iPad 3 after launch. As can be seen, the blue curve drops quickly, while the orange curve remains at an approximately constant level. Exemplary tweets from the same day around product launch are: *"@veracamilla: Ik wil een iPad3. Maar niet meer als ik me realiseer hoe duur een iPad 3 is."* and *"@boris: I have the new iPad. Cool, but not as cool as when I received the iPad 2. Or the first iPad. Feels more like the iPad 2.1 really."*

Throughout this analysis, no decision will be made yet whether to use the application curve or devices curves. Therefore, both will be addressed in the following sections. In the results-section, it will be argued how to cope with the application and devices curves.

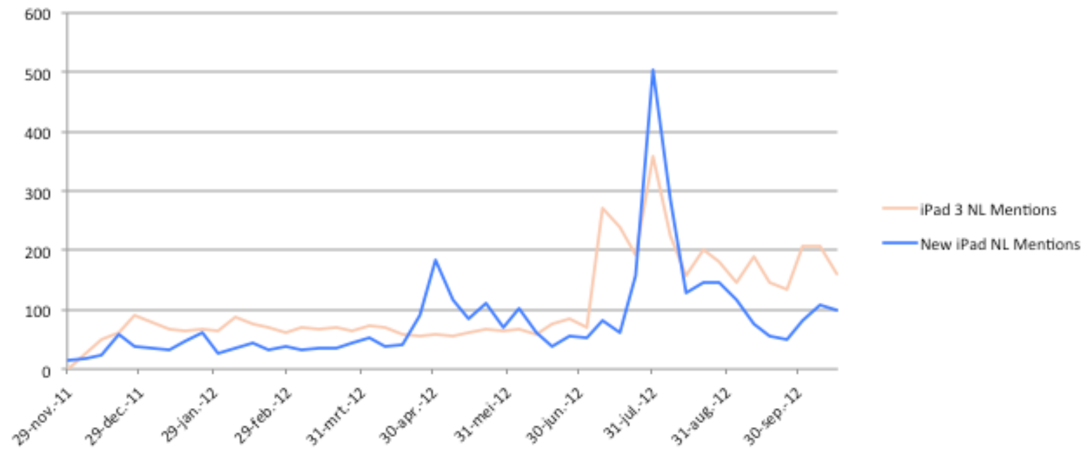


Figure 4.2: iPad 3 and New iPad Dutch Mentions

4.3.4 Spiking events

Throughout the curves, different peaks are visible. Thelwall, Buckley and Paltoglou (2011) identify these as spikes, which are caused by a large increase in certain keyword usage during a short period of time and which can either be caused by internal or external spiking events. This division is traced back in the dataset. Looking at the curves of the current dataset, it appears spikes last for approximately one month. In each product curve, one or more spikes are visible that are caused by their launch, typically an external event. While most products only show one large peak around product launches, XBOX360 games show a different behavior. Figure 4.3 shows three launches of the videogame FIFA, which is illustrative for the launch of other video games. Video games typically show two spikes around their product launch, one resulting from the pre-releases, the other from the official release. Exploration of other game releases shows this behavior is common for game releases, which is visualized in figure C.2 in appendix C. Exemplary tweets for this observation are: *@mryeahdude: FIFA 13 demo downloaden"* and *"@gamerintel: FIFA 13 is the fastest-selling game in 2012"*.

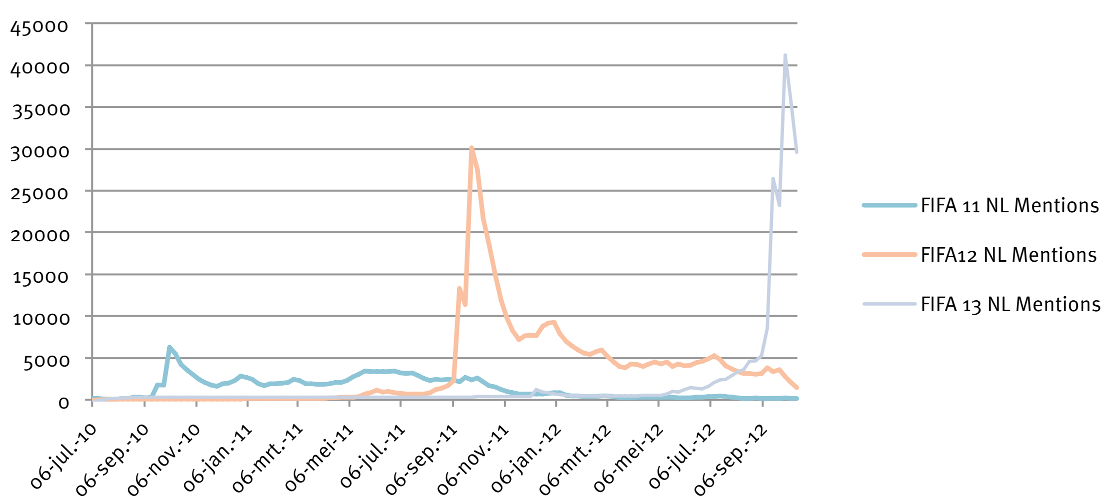


Figure 4.3: FIFA Dutch Mentions

Other external events can also trigger spikes. Two examples were found in the Twitter data. In the data two events were found that are unrelated to product launch but still resulted in spikes. In the iPhone curve a spike is visible on October 5th, 2011, which was the day Apple co-founder and CEO Steve Jobs died, caused by tweets like: *"@iphoneatoz: RIP Steve Jobs (February 23, 1955 – October 5, 2011) Thanks for putting the World at my fingertips"*. Research shows there is still doubt whether this event has had an effect on the value of Apple Inc. Therefore, it remain unclear whether this spike is valuable to be included in diffusion predictions. Another external event which was found back in the Twitter data of 'Call of Duty Modern Warfare' was the Utoya shooting on July 22nd, 2011. The corpus of tweets that compose this spike contains tweets in which the game is connected to the shooting and news messages in which its role is argued: *"@miilkkk: There's been so many shootings at Virginia Tech that they should make their school a map on Modern Warfare 3… yeah I said it"*. However, as the sales of the latest version of this game are breaking records[13], it is questionable if these internal spiking events have an influence of product diffusion.

Besides spikes caused by external events, internal events can also cause temporal increases in keyword usage. Like Thelwall, Buckley and Paltoglou (2011) find in their study, in the current study spikes occur due to viral campaigns. Single tweets are retweeted so often they form a relatively large part of the tweet corpus. Often these are promotional campaigns where posters profit from retweeting the original communication: *"@telefoonwinnen: RT ALS JIJ DE BLACKBERRY BOLD 9900 WIL WINNEN ! FOLLOW @TelefoonWinnen OM KANS TE MAKEN. #TELEFOONWINNEN"*.

4.3.5 Mentions

Regarding the devices curve, it appears that the times a device is mentioned rises quickly before product launch, and declines slowly to a rather constant level. This is visible in figures 4.1 and 4.3, and is replicated in figure C.2 in appendix C. This behavior is further examined in section 4.3.6, where it is compared to behavior of influencers.

If we concentrate on the times an application is mentioned however, we see a different behavior. When the occurrence of spikes is left out of consideration for the moment, it appears a constant rising curve is visible in the application-curve. It also appears that the derivative of the trend line describing this behavior tends to change at the moment a new product is launched, which is indicated by a spike. This observation is best visible in figure 4.4, where the trend line changes direction at the launch of Apple's 'the New iPad'.

The corpuses of tweets that contribute to the mentions-curves after launch merely contain tweets about user experiences and product reviews: *"@ProductReview.com.au: 13 things the Samsung Galaxy S3 can do you don't know about +url."*. In the cases of tablets and mobile phones a big part of the corpus contains tweets about related apps that are launched on the devices. The corpus of tweets for video games mostly contains gameplay fragments and notifications that a poster is playing a certain game: *"@StupidFootball: I'm playing FIFA 13. Does anybody know what*

[13] **http://www.telegraph.co.uk/technology/video-games/video-game-news/8884726/Call-of-Duty-Modern-Warfare-3-breaks-sales-records.html**

button makes Robin van Persie elbow players in the head?". Summarizing, non-influential mentions mostly report of the daily use of products.

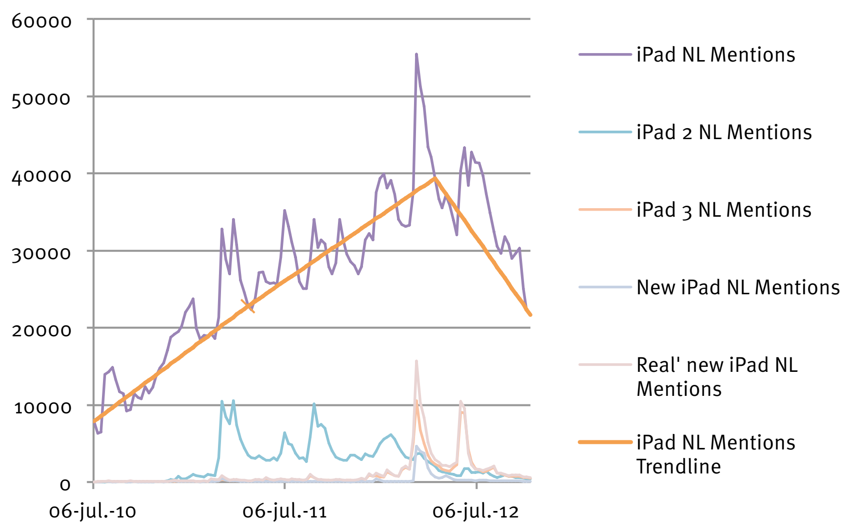


Figure 4.4: iPad Dutch Mentions

4.3.6 Influence

Within the corpus of tweets mentioning a product, there is a part that is found to be influential. These tweets come from users that the current study has identified as online influencers. This influence is derived from their number of followers, the impact (number of retweets) of their tweets, their interactivity with other influencers, and their activity on Twitter (Topsy, 2012).

As the group of online influencers is a small portion of the total population, the number of influential tweets is smaller as well. If the percentage of influential tweets of the total mentions is calculated, it appears this is not stable between different devices and other applications. Another difference between mentions and influence can be seen in the shapes of the curves. Figure 4.5 and 4.6 show the mentions curve and the influential mentions curve for the applications iPad and iPhone. It shows that though the number of overall mentions increases over time, the number of influential mentions decreases over time. This results in a mirrored image of the two curves.

Research using Topsy Pro Analytics reveals that there is a difference between the contents of influential mentions and non-influential mentions. Often influential mentions are retweets of either influential or non-influential mentions. A striking difference is that influential mentions often refer to launch announcements and provide previews of the product to be launched. Exemplary tweets are: *"@dannyhogenboom: "Apple onthult iPhone 5 op 12 september"* and *"@ed_games: Week 13 in trailers: Max Payne 3".* In the FIFA devices, this shows in previews in the form of screenplay images. For the iPad and iPhone this shows in speculation about the name and appearance of the to be launched product.

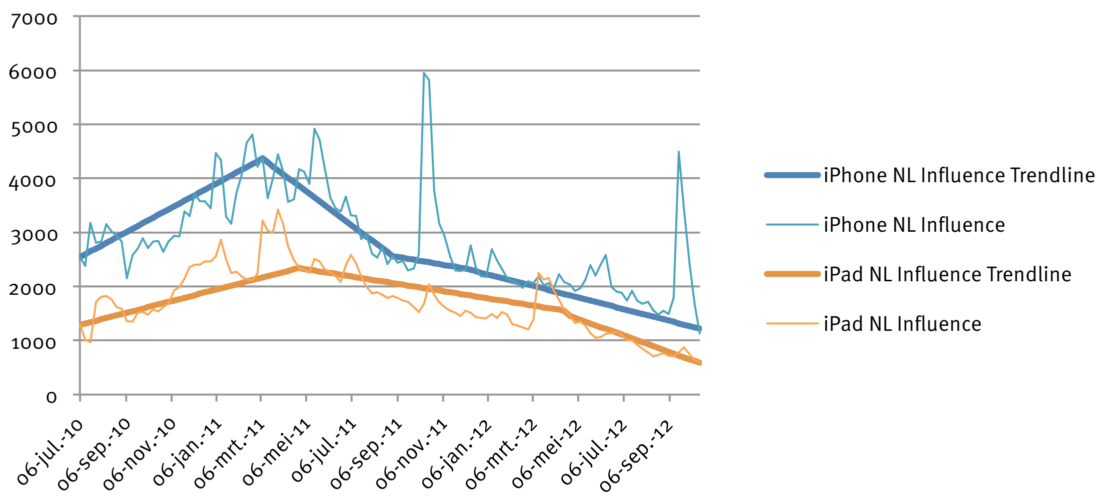


Figure 4.5: iPhone and iPad Dutch influential mentions

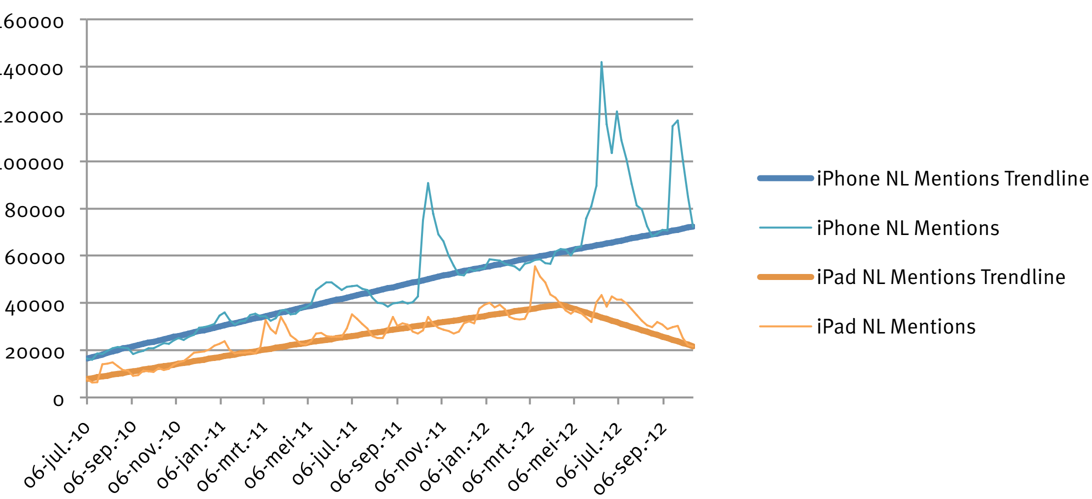


Figure 4.6: iPhone and iPad Dutch Mentions

In the previous section, it appears that there are little influential mentions that have a function after product launch. If the mentions and influential mentions curves in figure 4.7 are compared, this can be explained visually. It appears that while ordinary mentions quickly rise from approximately zero to a spike at launch, influential mentions show a longer ramp-up. After launch, ordinary mentions slowly decrease to a steady level, while influential tweets quickly decrease to a minimal level near to zero. If the trend lines in figure 4.7 are compared visually, though at a different amplitude, they show a reflected image. This behavior was found in many other products as well, and is replicated in figure C.3 in appendix C.

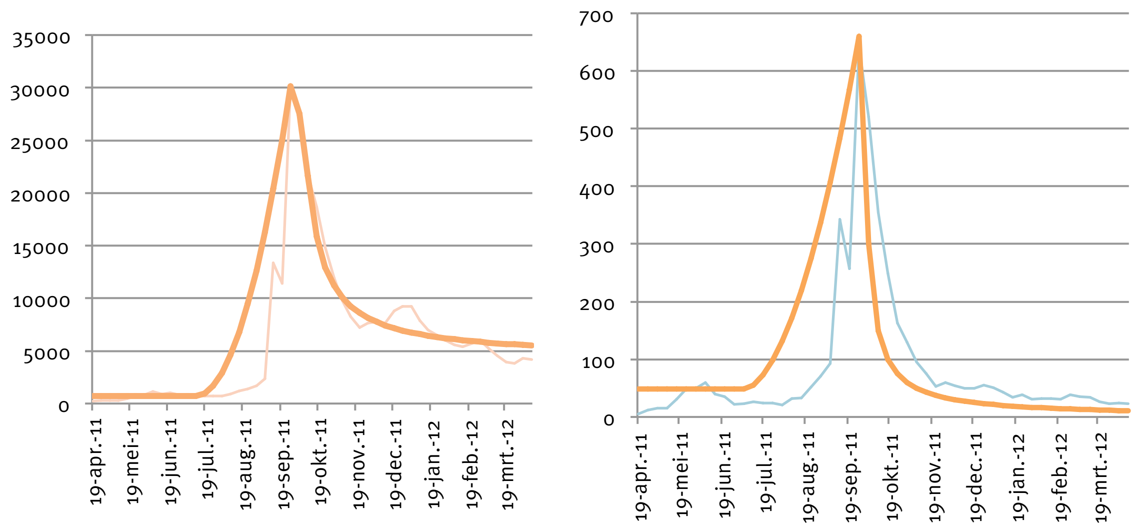


Figure 4.7: FIFA 12 Dutch Mentions (L) and Influential mentions (R)

4.3.7 Sentiment

Thelwall, Buckley and Paltoglou (2011) find that while negative sentiment increases after a spike, while positive sentiment remains constant. In the dataset of the current study, the only product showing the behavior as described by Thelwall et al. (2011) is Apple's iPhone (application), as can be seen in figure 4.8. In the curve, it appears generally there are more mentions with positive sentiment than negative sentiment, which supports the findings by Jansen et al. (2009). However, two spikes are visible. The first negative spike occurs around October, 2011. Analysis of tweets posted in that period show that it is caused both by the death of Steve Jobs and the launch of iPhone 4S. Though the product launch causing the second spike is not per se a negative one, the negative spike follows the findings by Thelwall et al. (2011). The other, larger spike occurs around July, 2012. If we only consider the application curve, no explanation can be found for this behavior. Also, using this curve, it is difficult to see what the overall sentiment is around the product. Unfortunately, other products (applications and devices) do not snow any behavior that can be linked to the findings by Thelwall et al. (2011). Many fluctuations are visible which cannot be explained by any supporting tweets.

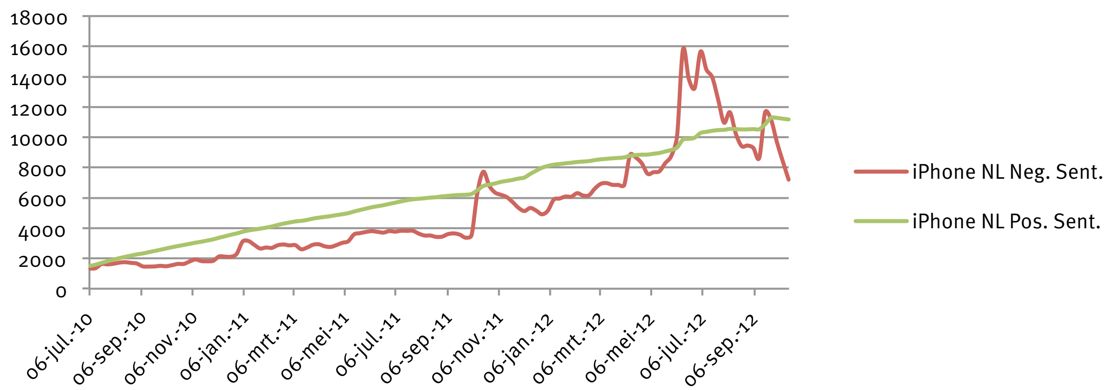


Figure 4.8: Sentiment mentions around iPhone

Figure 4.9 shows the difference in positive and negative sentiment for the both application and the devices. Using this curve, we can propose an explanation for the sudden negative spike in July 2012. At each launch of an iPhone device, the device-sentiment curve rises, while a negative spike is visible in the application curve at that point. Though this finding appears a valuable addition to the findings by Thelwall and his colleagues (2011), unfortunately this result cannot be replicated for other products in the dataset.

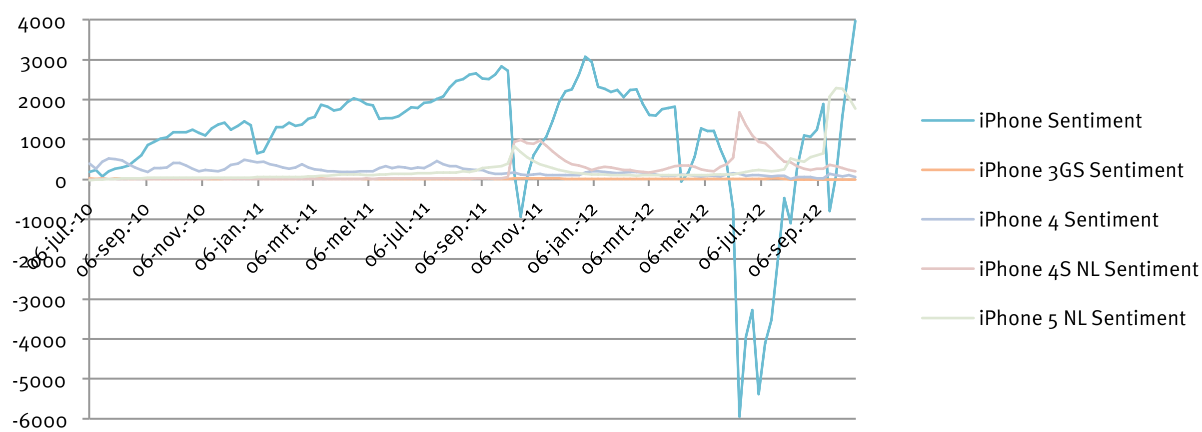


Figure 4.9: iPhone sentiment differences

Although no replicated evidence was found to support the findings of Thelwall et al. (2011) reliably, one general insight is found in the data. The sentiment curves follow the mentions-curve, which gives an indication of the general sentiment about the product. If there are fluctuations on this curve, there is either more positive or more negative sentiment than ordinary. Therefore, figure 4.10 shows the difference between positive and negative sentiment relative to the number of Dutch mentions. In the curve, each product is visualized from the time it was launched until its successor is launched. As the number of mentions decreases to a value near zero at that time, to much fluctuation is brought to the curve. The average percentages within the visible time-frames (FIFA10: μ = 4%, n = 15; FIFA11: μ = 3%, n = 42; FIFA12: μ = 5%, n = 57; FIFA13: μ = 2%; n = 5), allow comparison between devices, and between devices of applications within a certain product category.

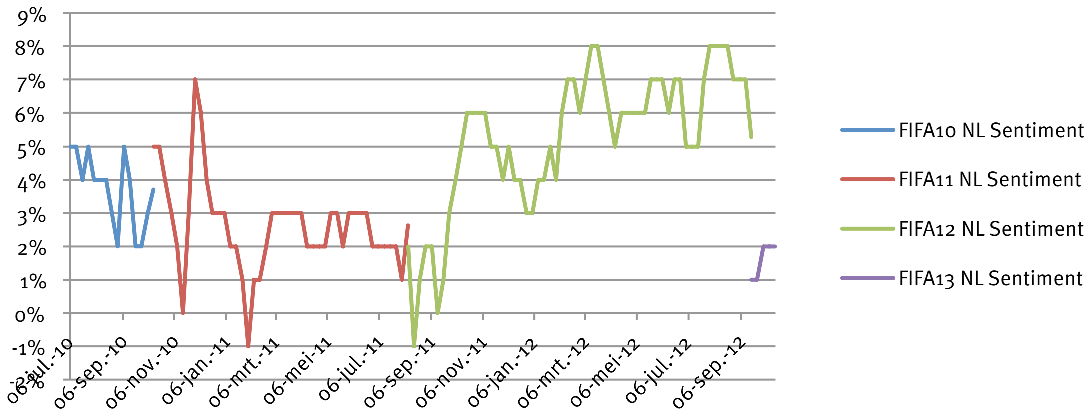


Figure 4.10: FIFA sentiment relative to Dutch mentions

4.4 Results

4.4.1 Keyword usage

Throughout the analysis in the previous sections, both the application-curve and the devices-curves have been analyzed. The cumulative mentions-curve and the application-curve show matching patterns though at a lower amplitude. However, keywords can refer to multiple objects, which clouds the corpus of tweets related to a product. In order to avoid references to keywords that are not related to the product intended, as was the case with FIFA and Halo, it is suggested here to restrict to device names in further analyses. Although it increases the reliability of the analysis, a downside to this advice is that it limits the size of the corpus of tweets, which may be problematic when products are involved that are less well known.

In order to allow valid comparison, it is important that the same keyword selection strategy is used for each product in the comparison. Ultimately, comparing application and device curves delivers skewed results. More specific, when comparing less generic named products (e.g. notebooks), keywords should be chosen at the same level of detail to avoid a comparison of apples and oranges.

4.4.2 Spiking events

The analysis in this study confirms the findings by Thelwall et al. (2011) that spikes in product-related mentions-curves can either be caused by internal or external events. In most of the cases, they are related to product launches, a typical external event. However, other external and internal events can also result in spikes. Regarding the current study it is important to find out what causes a spike and how it could be related to product diffusion. If spikes occur apart from product launches, extra research is needed to identify its origin. In that case management judgment is needed to argue whether the event should be taken into account in a diffusion model such as the extension proposed in the current study.

The analysis shows that spikes subdivide the applications curve into separate curves from which the behavior can be appointed to a single device. Naturally, differences in amplitudes of spikes are caused by different levels of arousal. However, no underlying argument could be provided to support this assumption. Because of that observation, the amplitude of spikes is left out of consideration. Nevertheless, the timing of the spikes is taken into account. It was found that the duration of a spike is approximately one month. Therefore, the timing of the spike and the number of mentions a month after the spike emerged are taken into account in the model.

4.4.3 Participation

When the mentions-curve has regained a moderate level after a spike comes to an end, the mentions-curve remains at a rather constant level until a new spike emerges. If this spike is caused by the introduction of a new product, this causes the mention-curve of the current product to decline in amplitude. Therefore, the range in between spikes that indicate product launches should be taken into account in calculating participation. Also, as participation is found to be positively related to product diffusion (e.g. Gruhl et al., 2005; Pang & Lee, 2008), it is suggested here to use the average mentions per week as measure for online word-of-mouth.

4.4.4 Influence

A small part of the tweet corpus consists of tweets from posters considered as influential. Topsy Pro Analytics labels poster as influential when they are retweeted often, have many followers, receive attention from other influencers, and are active in discussion. If the devices curves are considered, it appears influencers show an interest in product to be launched, and this interest is lost quickly after launch. Also, relating to the application-curve it shows that while the mention-curve still increases, the influential mentions curve decreases over time. On can argue that though product sales are still rising, the interest of influencers is lost. This is confirmed by the identification of the types of users that are found to be influential. These are users that forward news items and product announcement. These come from sources that are identified as mass media, which shows resemblance to the model as proposed by Watts and Dodds (2007). Another argumentation can be followed which resembles the characterization of influence by van de Bulte and Wuyts (2007) that influencers have an increased interest in new product, but lose this interest when more innovative product become available. To-be-launched products might not create enough arousal, perhaps because the innovative character is too low. Perhaps, the characterization by van der Bulte and Wuyts (2007) can be updated by stating that influencers have an increased interest in innovative new products, and that their interest is lost after product are launched.

It shows that influencers use a combination of retweets from other (non-influential) mentions to exert their influence and self-composed messages. This links to the model by Watts and Dodds (2007), where influencers use information either coming from mass communication or from other actors in the network. As they serve as diffuser of information, they are labeled as influential in their network. Another important finding is that the percentage of influential mentions in the total corpus of tweets on a product is not constant between different products. This implies that influencers show different levels of interest for different products. Thereby, influencers can stimulate product diffusion in the model if their arousal is high, which can be measured by a large amount of influential mentions relative to non-influential mentions.

4.4.5 Sentiment

Though literature exists that describes the flow of sentiment over time around product launches, no replicable support was found in the current study to support the findings by Thelwall et al. (2011). Nevertheless, differences are visible between devices and application regarding the percentages of positive or negative mentions and neutral mentions. Here it appears that different products show different levels of sentiment. Although the analyzed applications all show reasonably equal levels of sentiment, it is imaginable that products that are valued highly positive or negative result in larger differences between positive or negative and neutral tweets.

4.5 Conclusion

In this chapter, the aim was to study that causes the mechanism of online influence and online word-of-mouth to behave as it does. It appeared that influential mentions, which contribute to the mechanism of online influence, show a different behavior than non-influential mentions. This justifies the design decision to model the influence of online influence different than word-of-mouth. Also, the functioning of spikes to indicate events was traced back in the Twitter data. However, it was noted that different events occur in the data that have no relation to product diffusion, but are still visible in the mentions-curves. Special attention should be paid to these when product diffusion is simulated using the SD model. Participation and sentiment were also traced back in the data. Participation appeared to be stable over time, until a new product is launched. Few insights were generated on sentiment. Nevertheless, the study indicates that sentiment can differ between different generations of products.

Different insights were generated that allow the SD model to generate more insightful results. Also, different insights were generated that are useful in the use of the SD model. Also, support was found for different design choices in the modeling process. Therefore, the model as it was modeled in chapter 3 is found adequate to be tested in the following chapter.

5 Testing the model

5.1 Introduction

Now an understanding is generated behind the parameters that are introduced to the Norton-Bass model, the current chapter focuses on the question whether the proposed model can indeed generate more specific product diffusion forecasts. In order to do so, a dependent variable needs to be proposed to test the model. Optimally, data underlying this variable would be sales data with a longitudinal character. Unfortunately, these have appeared to be unavailable due to confidentiality. Therefore, two surveys were held under retail stores managers to create sales rankings at two measurement points for the products involved in the study. Thereby, the test of the model gets a more cross-sectional character, as the sales rankings only allow testing on several occasions. Summarizing, this chapter aims to answer the following research question:

Sub-question 3:	*Is the Norton-Bass model able to provide product-specific diffusion forecasts after incorporation of the mechanism of online influence and online word-of-mouth?*

As this chapter involves three research tasks, each section is divided into two sub-sections, which related to the sales data and Twitter data as input for the SD model. Section 5.2 describes the collection of this data per type of data. Section 5.3 describes the analysis of this data. In section 5.4 the outcomes of the test come together and findings are discussed.

5.2 Data collection

5.2.1 Sales data

An online survey was developed to obtain sales data for 18 consumer electronics products from Dutch retailers. The survey was conducted in two phases: in the first survey the retailers were asked to rank a pre-defined set of products within four categories on the sales in their stores. In the second phase, an additional survey was conducted to verify the results gathered in the first survey and to gain insights on the how the follow-up generations of the involved products diffuse in the market. After the first survey was discussed with an assistant professor of marketing, it was piloted with one respondent. As it appeared no changes were necessary, this pilot survey was added to the results. As the second survey had the same character as the first, it was not piloted. The results of the first phase were gathered and submitted mid-July, 2012, while the results of the second phase of the survey were gathered and submitted in the second week of November, 2012. Both surveys are included in appendix F.1 and F.2.

In total, 22 retail store managers agreed to participate in the first survey after they were contacted in person. Retail stores were selected ranging from specialist stores to larger department stores like 'Mediamarkt' and 'Saturn', and were all located in the South and South-

West of the Netherlands (Tilburg, Eindhoven, Breda, 's Hertogenbosch, Utrecht). After the acquisition was done, an explanation of the study and a link to the online survey was sent by e-mail. In total, 12 retail store managers participated in the study, which results in a response rate of 54.5%. Besides offline retail stores, 5 online webshops were included in the survey. Using the sales-ranking option in the webshop, the involved products were rated. The webshops that were included were all rated top 3 in their category according to *thuiswinkelawards.nl*[14]. Inquiry with webshop practitioners has shown products rankings on these websites in reliable and that rankings involve a moving average algorithm to ensure historical data is also incorporated in the rankings. More specific, table 5.1 shows the participation of the retail managers in the different categories.

For the second survey, the respondents of the first survey were addressed again. Two agreed to participate in the second survey, which resulted in a response rate of 9,1%. The two respondents that did participate were both managers of large consumer electronics warehouses. As the response rate was found too low, their responses were used to verify the results from the first questionnaire. To create a second sales ranking, the same webshops were used again, these are also included in table 5.1.

Table 5.1: Survey response per category

Product category	Survey 1		Survey 2
	Offline retailers	Online retailers	Online retailers
Smartphones	3	4	4
Tablets	7	4	4
XBOX360 games	3	4	4

5.2.2 Model data

Two types of parameters are necessary for the model to function properly: parameters per product category and parameters per product. Using market reports, information about population sizes were gathered for each category. Also, parameters for the mechanisms of internal and external influence were looked up. If no market report was found, values for similar product categories were used, as suggested by Mahajan, Muller and Bass (1990).

Norton and Bass (1987) indicate that the market for an application increases per generation. However, no supporting numerical data was found. Therefore, it is assumed that the number of potential adopters increases by a factor *1.25* per generation. Also, to allow proper comparison, it is assumed the market potential is equally divided over the number of products in the study within each category. Therefore, the number of potential adopters per product is the number of potential adopters per category divided by the number of products in the comparison. Table 5.2 summarizes the parameters that are included in the model per category.

[14] **Thuiswinkelawards.nl is an initiative from the official organization representing the interests of Dutch online retailers.**

Table 5.2: Bass model parameters

Category	M (Millions)*	P	Q
Smartphones	1,400[1]	0,45[4]	0,04
Tablets	1,000[2]	0,60[5]	0,05
XBOX360 games	3,000[3]	0,12[7]	0,01

* Yearly demand of total category measured in 2011
[1] GFK (2011)
[2] GFK (2012)
[3] NVPI (2011)
[4] Based on iPhone: http://www.dolcera.com/wiki/index.php?title=Bass_Diffusion_Analysis_for_OLED_display_phones
[5] Based on sales figures from Lawsuit Apple vs Samsung. iPad shows faster and greater adoption and compared to eBook parameters (0,017 / 0,543).
[6] http://marketingstrategicmanagement.blogspot.nl/2010/03/2014-ebooks-takeoff-and-inflection.html
[7] Based on video-on-demand service http://webdocs.stern.nyu.edu/marketing/SNamPaper.pdf

Per product, model parameters were calculated using data gathered on Topsy Pro Analytics. For each product the following measures were measured or calculated: time of launch related spikes, average mentions in period between two spikes, average positive and negative sentiment in that period, and the height of the influence spike. This is done for as many generations as were available within the time frame available in Topsy Pro Analytics. The influence spike was directly extracted from the web-application, the other values were calculation using excel according to the equations suggested in section 3.4. When it appeared in the data that very little data was available for recent launched products (less than 7 weeks since launch), its diffusion was forecasted using its own ‘influence-spike’ and mention-data from the previous generation.

As output from the system dynamics model, the adoption rate was used for each product. Although this does not directly tell us which product was sold best, it predicts how many devices are sold in the week indicated. This resembles the line of questioning in the retailer surveys, as they were asked how well the product has been sold in the past period. Also, the Norton-Bass assumes that every potential adopter eventually adopts the product. Therefore, if the number of adopters would have been used and enough time would be available, each product would have been sold equally.

5.3 Data analysis

5.3.1 Sales data

Although retailers were selected which were assumed to offer a large assortment of products within their respective category, not all retailers sold all pre-selected products. This resulted in missing values in the rankings. As proposed by Hair (2010), when additional cases were available for the involved products, missing values were replaced using case substitution. If no additional cases were available, they were deleted from the analysis. Hair (2010) argues that in the case of rankings this procedure results in more realistic values, rather than calculation methods (e.g. mean substitution). In the first survey, 12 out of 96 rankings were missing (12,5%), which resulted in the deletion of 3 products from the analysis. In the second survey, 11 out of 87 rankings were missing (12,6%), which resulted in the deletion of 1 additional product from the analysis.

In order to assess the reliability of agreement between the different raters, the free-marginal multi-rater kappa was calculated for each product-category. This measure suits the current analysis, as it is suitable for multiple raters and since it allows raters to leave cases blank if they are not acquainted with them. Also, in contradiction to Fleiss' kappa, it is less influenced by prevalence and bias, which leads to the paradox of high agreement and low kappa. Values of kappa may range from -1.0 to 1.0, where -1.0 indicates perfect disagreement below chance, and 1.0 indicating perfect agreement above chance (Randolph, 2005). Randolph uses .7 as rule of thumb for good agreement. However, as is common in other social studies, lower values around .2 are found acceptable. Moreover, high values would be suspicious, as it seems unnatural to have each store sell the same amounts of products. Reasons for this could be retailers personal preference, price reductions, and sales targets on specific products.

The agreement between raters and kappa was calculated for online and offline retailers separately as well as in aggregate. It appears that overall, differentiating between online and offline retailers lead to lower agreement and levels of kappa. Therefore, it is decided to consider the market as in aggregate. In the first survey, all product categories show inter-rater agreement of at least 31%, which, except for smartphones, leads to fair or higher agreement. In the case of smartphones, the data shows that the low agreement is caused by products that are rated lower in sales. The first two (Apple iPhone 4S and Samsung Galaxy SII) are rated clearly first and second. The reason for the lower agreement percentage is caused by the low agreement on the less sold smartphones, as there is great diversity in the offered smartphones in that segment. In the second survey, overall the inter-rater agreement was higher.

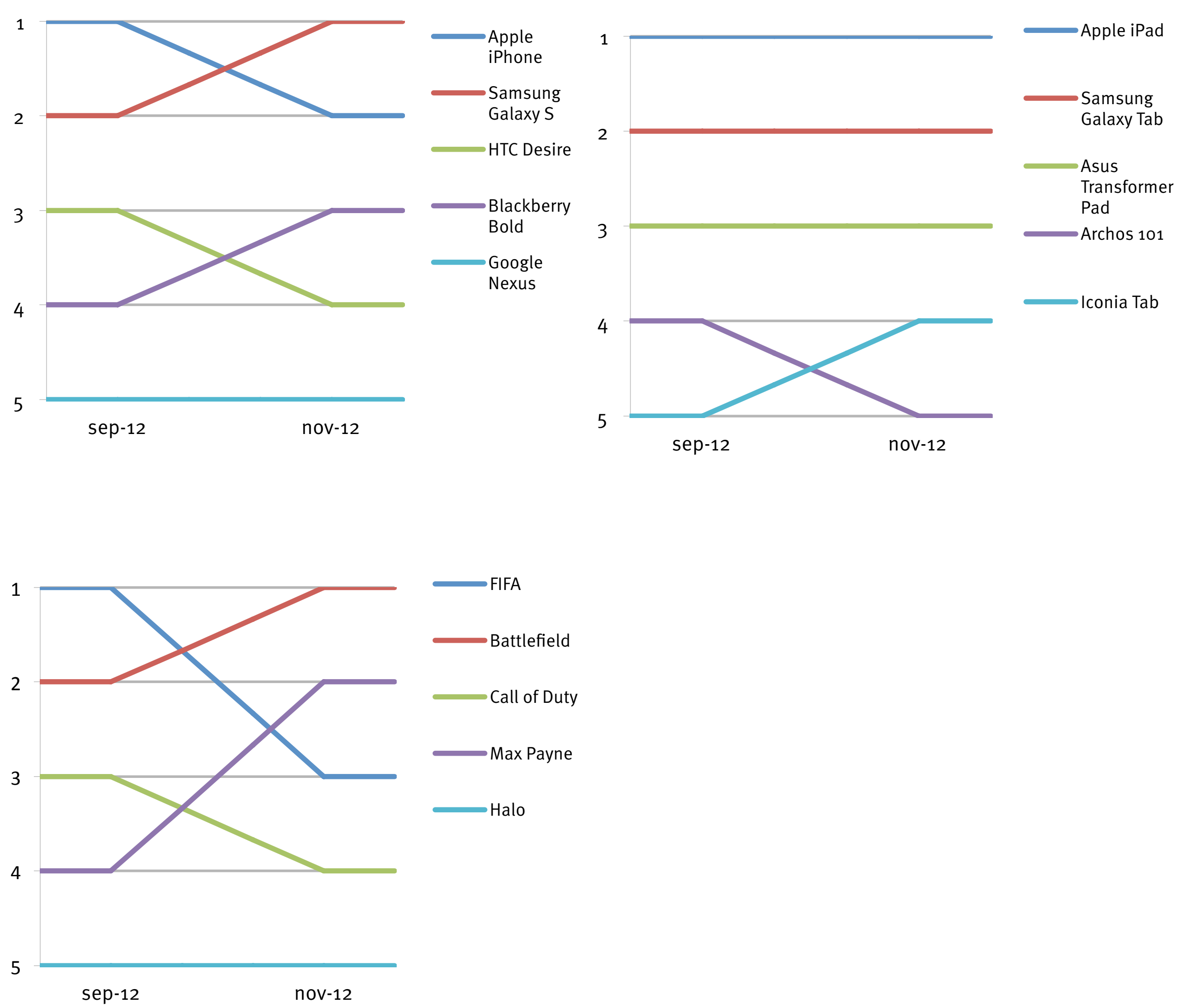
Table 5.3: Rater agreement and free-marginal multi-rater kappa

Category	Survey 1		Survey 2	
	Agreement	Kappa *	Agreement	Kappa *
Smartphones	*31.4%*	*.143*	*80.0%*	*.75*
Tablets	*39.0%*	*.241*	*60.0%*	*.50*
XBOX360 games	*60.3%*	*.524*	*60.0%*	*.50*

** Free-marginal multi-rater kappa indicates level of agreement: <.00: poor; .01 – .20: slight; .21 – .40: fair; .41 – .60: moderate, .61 – .80: substantial; .81 – 1.00: perfect*

To come to the ranking as provided in figure 5.1, the individual cases were summarized. For each product the number of times is was ranked 1st, 2nd, 3rd, 4th, 5th or 6th were counted. If counts were the same for two product, they were differentiated on their nearest difference. In the second survey the rankings that were calculated were verified. If differences existed between the results from the first survey and the verification, the data from the verification in the second survey got preference. The same methodology was followed for the first and the second survey. This method results in the rankings in figure 5.1 and the table in appendix G.

Figure 5.1: Products sales rankings



5.3.2 Model data

The model has provided the current study with data to test its functioning. Table 5.4 compares the data that was output from the retailer survey and data that was output from the system dynamics (SD) model. The data was compared on the measuring periods that were using in the survey. In both occasions, the comparison periods are indicated by the red areas in figure 5.2. Figure 5.2 shows the SD model output from smartphones only. In appendix H, all the SD model output for all categories is provided. In the remainder of this sub-section, the results for each category are briefly mentioned and special observations are enlightened in more detail.

Figure 5.2: SD model output for smartphone-category

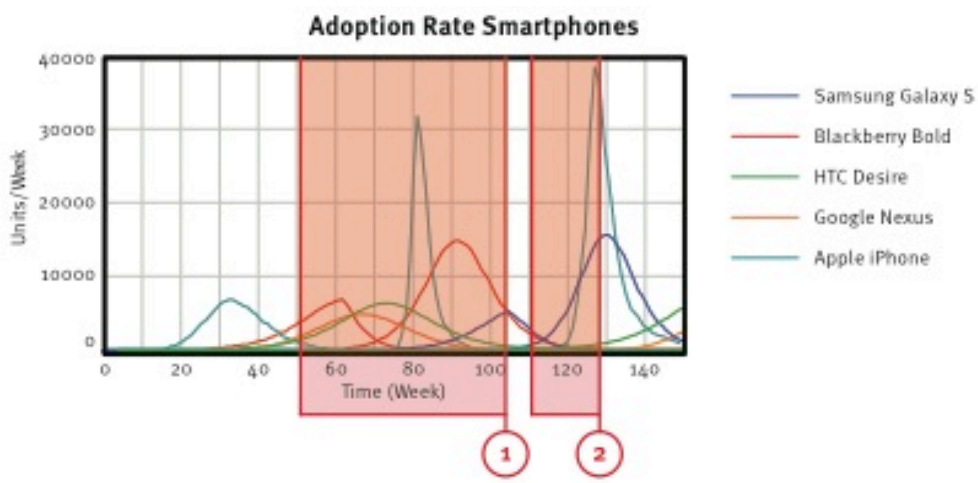


Table 5.4: Model data and sales data compared

Product category	Device	July '12		Nov. '12	
		Model	Sales	Model	Sales
Smartphones	Apple iPhone	1	1	2	2
	Samsung Galaxy S	3	2	1	1
	HTC Desire	4	3	3	4
	Blackberry Bold	2	4	5	3
	Google Nexus	5	5	4	5
	Nokia E	–	–	–	–
Tablets	Apple iPad	1	1	1	1
	Samsung Galaxy Tab	2	2	5	2
	Asus Transformer Pad	4	3	3	3
	Archos 101 G	5	4	4	5
	Acer Iconia Tab	3	5	2	4
	Asus Eee Pad	–	–	–	–
XBOX360 games	FIFA	1	1	4	3
	Battlefield	3	2	1	1
	Call of Duty	2	3	3	4
	Max Payne	4	4	2	2
	Halo	5	5	5	5

The model indicates that Apple's iPhone is sold well, which resembles the sales data. However, in the second survey it appeared that *Samsung's Galaxy S3* sells better at the moment, indicated by a large number of mentions (*855*). Indeed, the model shows it sells well, but the peak for *iPhone 5* is much larger. This is caused by both a large number of mentions and influential mentions. The large difference in values between the products, while this is not reflected in their ranking, indicates some other force must underlie this large peak. In the first measurement period, *Blackberry Bold* shows considerable diffusion, which is explained by many mentions (*623*), while there is a low level of influence (*24*). Further, the other products in the analysis show approximately similar levels of diffusion in the analysis periods, which makes it difficult to rank them based on the model outcomes.

Regarding the tablet category, again Samsung's and Apple's products are ranked high, which is shows most clearly in the first timeframe. This is reflected in the parameters, as their influence and participation is considerably larger. Therefore, the other products clearly diffuse slower. In the second timeframe, again the iPad and Galaxy Tab are ranked the highest, while the Asus Transformer Pad is ranked third by the Vensim model, which is resembled in the sales data.

For the XBOX360 games, the model outcomes show FIFA diffuses the fastest in all generations. This matches the sales ranking in the first timeframe, while there is a difference in the second timeframe. Interesting in the second timeframe is that there is a combination of recently and sooner released products. While their diffusion rates are different, their diffusion periods cause the model outcomes to resemble the second sales ranking.

In the parameter data, no exceptional values were found for sentiment. Earlier in this thesis it was argued that sentiment would only fulfill a role when levels would be considerably positive or negative were found. Within the current analysis, these are not found. Therefore, no findings are discussed here regarding sentiment. In future studies, products which are already found to be criticized could be included to develop this parameter further.

5.4 Discussion

After the data was collected per product, it appears that in each category there are two or three products that are mentioned often on Twitter, while there is also a group that appears to get little attention on Twitter. For instance, tablets by *Apple* and *Samsung* seem to get a lot of attention, while similar products by *Asus* or *Acer* seem rather absent on Twitter. Evidently, this has an impact on the model outcomes. The little availability of data for the more unknown product creates some uncertainty in the model outcomes. As the numbers of Dutch mentions are often as small as one or two, it is unclear whether they are structural or based on chance. Therefore, the rankings for these products are uncertain as well. If we concentrate on the product where substantial data is available, it appears the model is a good predictor of the sales data. Also, a clear difference can be seen in products that are ranked high and low in the sales data. The ranking provided by the model shows clear differences for products high in the sales rankings, while the sales rankings and model outcomes show higher discrepancies for the products ranked lower in the sales data.

In the current model both participation and influence relate to diffusion speed. Nevertheless, the effect of participation is larger than influence. An exemplary result of this finding is that Google's Nexus phone shows a longer diffusion period than Blackberry's Bold phone. Related to that observation is that the Blackberry diffused at a higher pace. This is caused by intensive word of mouth in the case of the Blackberry, while the Google Nexus has more influencers referring to it in their mentions. This finding appears logical, as the influence of word of mouth has longer carryover effects, while influence can exert their influence most optimally in the beginning of the diffusion process. If their influence is large enough, they can stimulate the take-off of the diffusion process, while word-of-mouth can extend the diffusion process.

If the data-points are compared, it shows that the first data-point shows more similarities between the model and sales data. There is a larger timeframe to compare the data and newly released products have not shown their full potential yet: their forecasts are based on the number of influential mentions and the behavior of the previous generation. This shows that previous generations of product are not a good predictor for the sales of new products. Perhaps should newly launched products only be modeled on the effect of online influencers, as their influence is known at the time of launch. This makes their role in the model even more important.

Some product manufacturers in the analysis are brands that are often referred to as 'hot brands' [15]. Examples of these brands are Samsung and Apple. It appears that the diffusion rates for products from these brands (e.g. Apple iPhone) are very high, and as a result their diffusion periods very short. In a real-life situation, the stocks for the involved product would be updated, so the diffusion does not have to stop. This is a shortcoming of the Bass model: when the attention is too high, there is no option for re-supply: the stock of potential adopters cannot be updated. Another line of arguing could be that because these brands are 'hot brands', their presence in online social networks is overdone. Many of their mentions do not directly relate to product diffusion, which results in too high diffusion rate forecasts.

A serious shortcoming of the comparison is that it compares ranked data measured on a specific point in time and longitudinal data from the model. Therefore, there is no reference for the length of diffusion periods for the products to be modeled. Adjustments in participation and influence result in adjustments in the diffusion period, however it is difficult to judge whether these periods are correct. If the diffusion of the iPhone in figure 5.2 is considered, it shows that the diffusion period is very short. In reality, it is evident that when a product diffuses such a high pace, forecasts are adjusted and stock increases are arranged.

Though the first intention of the model was to create forecasts that could be measured at a certain point in time, as discussed, issues with timing do not allow this. Nevertheless, if the results are interpreted using a larger timeframe, the predictive power of the model seems adequate. If it would be further refined using longitudinal sales data for several products, it power could be extended to creating forecasts and provide product-specific diffusion measurements at specific points in time.

---

[15] **Other typologies might be in place here also.**

5.5 Conclusion

In this chapter, the model that was developed in this study is tested using cross-sectional product sales data. Although, some products appeared troublesome in the analysis, the model seems to approach sales data rather well. Especially when a considerable large corpus of tweets is available as input, the model appears to be functioning properly. Thereby, the research question to this chapter can be answered positively: the model is able to provide product-specific diffusion forecasts for the three product categories that were tested. Also, the inclusion of online influencers and online word-of-mouth allows the model to differentiate between products within a category. This gives the model additional quality over the Norton-Bass model, which was chosen as starting point for the study. Another quality the model has over the traditional Norton-Bass model is that is differentiates between generations of products, while the traditional Norton-Bass model considers diffusion of innovation to be equal between generations.

Nevertheless, some shortcomings need to be overcome in order for the model to be a properly functioning extension of the Norton-Bass model. Firstly, longitudinal sales data allows more modeling iterations, which could provide higher forecast accuracy. Secondly, a solution should be provided for products that are not well represented on Twitter. A solution for this could be to create a threshold for data to be included. Numbers of mentions that are too low should be excluded, as they have appeared to be unreliable. That way, products can be differentiated from the category baseline if Twitter data provides an indication to do so.

6 Conclusions and reflection

6.1 Conclusions

The current study was conducted to find out how the Norton-Bass model could be extended in order to incorporate the influence of online social networks. In a sequential modeling process, a model is proposed that incorporates the influence of online social networks.

The literature study revealed that the Norton-Bass model (Norton & Bass, 1987) is a more appropriate starting point for the current study than the traditional Bass model (Bass, 1969). The Norton-Bass model is more suitable to predict diffusion of contemporary consumer electronics products, which have a multi-generational character. The behavior of the Norton-Bass model relies on the mechanisms of external influence, which is driven by advertising, and on the mechanism of internal influence, which is driven by word-of-mouth. In this study, online word-of-mouth is added to the mechanism of internal influence. Also, an additional mechanism is proposed: the mechanism of online influence, in which online opinion leaders (influencers) have an intermediary role between mass media and word-of-mouth.

At the beginning of this study, several suggestions were made how the Bass (or Norton-Bass) model could be adjusted to remain state-of-the-art (Peres et al., 2010). The model that is developed in this study satisfies several of these suggestions. Firstly, by adding more social influences the model is now able to provide brand (or product) level analysis, rather than industry level analysis. Also by including Twitter as online social network, the model includes small-world networks, rather than an aggregate of the market. Finally, different types of social interactions are included, which are not restricted to the traditional sense of word-of-mouth. The influence of mass communication is re-defined by introducing the mechanism of online influence. Also, online word-of-mouth is added to represent more types of interpersonal communication.

6.1.1 Online influencers

The literature study revealed that opinion leaders do not have a formal role in product diffusion. Rather they have a role as diffuser of information from mass media to word-of-mouth. Therefore, in order to incorporate the role of influencers in the Norton-Bass model, an extension is proposed in which they are an intermediary between mass communications and word-of-mouth. Their influence is modeled as proposed in the network influence model by Watts and Dodds (2007). Through the inclusion of the mechanism on online influence, the Norton-Bass model now is able to distinguish products, rather than predicting the diffusion of product categories. The study shows that online influence has the largest effect on product diffusion at the beginning of the process. The findings show that large online influence causes the diffusion rate to rise faster at the beginning of the process. If influence is lower, the process takes longer to take-off.

Within the corpus of tweets per product, there is a part coming from influential users. It appears the number of these influential mentions builds up slowly before launch, and declines quickly after launch. This indicates an interest in to be launched products, while interest drops after the product is launched. Although this behavior has similarities with the behavior of innovators in the Norton-Bass model, there is one important difference. Innovators need to be actual adopters of the innovation, while the content of the influential tweets indicates they do not necessarily come from adopters. Influential tweets do not necessarily come from adopters, they are diffusers of product-related information coming from (online) mass media. Thereby, it appears that the mechanism of online influence in the SD model as was proposed by Watts and Dodds (2007): posters that are influential in their context serve as diffusers of information to their followers. They do this by retweeting information that they find valuable.

Also, it appears that their influence is independent of the total interest in a product. This is found since the number of influential mentions is not a fixed percentage of the total number of mentions in the corpus of tweets. In essence, this means that when a corpus of tweets contains relatively many influential mentions, the effect of influencers on product diffusion is larger. Thereby, they can stimulate the diffusion of a product that normally would not have diffused as well. This potentially makes Twitter not only a monitoring platform, but also a platform of influence.

6.1.2 Online word-of-mouth

Besides influence, another parameter that contributes to the ability of the model to distinguish products is online word-of-mouth. In the literature study it is argued that online word-of-mouth is considerably different from traditional word-of-mouth. Therefore it is included in the existing mechanism of internal influence, alongside traditional word-of-mouth.

Online word-of-mouth is measured in participation, which is the times a product is mentions per week. This measure builds up fast at product launch, and slowly decreases to a constant value until a new generation is launched. At the launch of a new product in line, the cannibalistic effects of the new generation product cause the curve to decrease to zero. Per generation, differences in sentiment can be seen. Furthermore, there is little change over time in both positive and negative sentiment. Nevertheless, since there is a moderating effect of sentiment, differences between generations of products can contribute to the diffusion of that product. Online word-of-mouth appeared to be the main determinant of differences in the diffusion curve over time. While influence has its largest effect at the beginning of the process, the stimulating effects of online word-of-mouth last longer.

6.1.3 Spiking events

One special finding of this study is an addition to the study by Thelwall et al. (2011), who provide insights on spikes in mention-graphs. Indeed, two types of events are visible in the graph showing the number of mentions of a product: internal and external events. Regarding product diffusion, one specific type of external event is important: product launches. These provide an indication how the different generations of a product are diffused over time. As was found to be the case for XBOX360 games, launch spikes can have many shapes. In that case, they show a double spike, which results from a segmented product launch: beta and full releases. Although no evidence was found that the shape of this spike has a relation to product diffusion, this is still an interesting finding. Other product category might have different shaped launch-spikes. In the study, it was also seen that when there is speculation about product names, this results in spikes which are spread out over different product names. Thought this has not been studied in the current study, future studies might reveal relations between launch spike-shapes and product diffusion.

6.2 Managerial implications

The current study has several important implications which are relevant to practice. Firstly, regarding its use in practice, a more relevant research question could be how the Norton-Bass model could be adapted to let managers profit from the opportunities online social networks offer. Criticism on diffusion models is that they are difficult to interpret by management and that they are costly (Kahn, 2002). Using Twitter data has one big advantage over other data sources: information is free and publicly accessible. This allows management not only to involve their own products in forecasts, but also to include products by competitors.

Moreover, Lyneis (2000) finds System Dynamics is flexible enough to update the model even while the product is being diffused. By doing so during the first two weeks after launch, deviations between forecasts and sales can be reduced to 8% (instead of 47% on average) (Fisher, Raman & Sheen McClelland, 2000). Services like Topsy Pro Analytics allow practitioners to update their forecasts based on real-time Twitter information. Future versions of the proposed model might even incorporate this update function, providing practitioners with updated market information at a glance.

Perhaps the most important advantage the currently proposed extension has over the Norton-Bass model is that it allows brand-specific forecasts, rather than industry-specific forecasts. The Norton-Bass model, like the traditional Bass model, only allows prediction per product category, since their used parameters of internal and external influence are generic per category. Thereby, the model from this study becomes more relevant to practitioners.

Like Kahn (2002) finds, the current model does not provide reliable forecasts if used isolated from other information sources: management insights are necessary to interpret the outcomes and additional product knowledge is needed to explain pattern that emerge in the parameter estimates. Exemplary are the different types of events that can trigger a spike in the data. Here, management judgment is needed to determine whether they have implications on product diffusion.

6.3 Academic implications

The current study provides a new extension of the popular Norton-Bass model (and thereby to the Bass model), which addresses the challenge proposed by Peres, Muller and Mahajan (2010) to model the influence of online social networks on product diffusion. While Bass assumes the mechanism of internal and external influence to be independent, the current study includes an interaction between them in the form of the mechanism of online influence.

Using time series analysis, a group of mentions within the corpus of Tweets was found that is considered more influential than other mentions. These are influential because they (1) come from posters with large share of followers, or (2) show great relevance in the context, which is indicated by many retweets. The number of influential mentions rises slowly to a peak at product launch, after which the number drops quickly to a low level. Although this behavior resembles behavior of innovators as proposed by Bass (1969), more in-depth analysis shows the posters of these influential mentions are not necessary adopters of the innovation themselves. More, they act like opinion leaders and diffuse information about the innovations involved. Therefore, the Norton-Bass model is connected to the network influence model by Watts and Dodds (2007). This also implies the population is not homogeneous as Bass suggests: besides innovators and imitators, a third, non-formal category can be added: influencers or online opinion leaders. By proposing the inclusion of the mechanism of online influence, the current study provides a role for opinion leaders in product diffusion models and thereby connects diffusion theory to network theory. Further studies might reveal more similarities between both fields of research and allow more connections.

6.4 Limitations and recommendations for further research

An evident limitation of the current study is the absence of longitudinal sales data as dependent variable. If this would have been available, more in-depth time series analysis would have been possible. Also, timing issues in the proposed extension could have been resolved, as sales curves could be used to guide the model outcomes. Moreover, more detailed sales data would allow to study how the total market potential is divided over the different product, while it was now assumed the market is divided equally over the involved products for each category. All together, overcoming this limitation would have enable to model to create more reliable forecasts and would have made the model more directly applicable to practice.

The unavailability of longitudinal sales data also has had an implication on the modeling process. Modeling in system dynamics is an iterative process, which allows the modeler to get closer to reality with each iteration. In order to do so, the accuracy of the model needs to be increased with each iteration. As this study did not have this information present, no direction could be given to the refinement of the model. If this data is present in future studies, this refinement can be done and the model can be improved. Also, this refined model could eventually be put back into a likelihood function as the Bass model and Norton-Bass model were originally proposed. This would allow academics to place this model in proper perspective, without having to overcome objections regarding the use of system dynamics.

The current study adopts Twitter as measurement instrument. Though this has proven itself as good measurement instrument, questions arise whether other online social networks would have delivered the same results. Other networks imply different groups of users. If for instance, the recently launched online network Pinterest[16] would have been used, it is assumable that merely women were included in the study, as this is the target group of this network. Therefore, exploration of other online social networks could reveal different online social networks that could be valuable. Also, while reviewing the parameters, it appeared that not all products are mentioned on Twitter. Also, not all product categories could be integrated, as the setup of product portfolios did not allow this. Two solutions to this issue are proposed here. Firstly, additional study on Twitter search strategies could overcome these issues. Secondly, the inclusion of more online social networks could provide a more representative view of products that are mentioned over these networks.

In the literature review, it was argued that no distinction could be made between adopters and non-adopters of previous generations of product. If this would be the case, the generalized Norton-Bass model by Jiang and Jain (2012) could have been used. Especially since it has appeared that the mechanism of online influence not only involves adopters but also non-adopters. Future studies could focus more in-depth insights in the population involved in the model to develop this notion further.

Now it has been established that there is a role for opinion leaders in diffusion theory, more in-depth sociometrics can allow future studies to get a better understanding of their relation to participations and sentiment. In order to evaluate this, more raw data should be taken into account, rather than the composed metrics provided by online applications like Topsy Pro Analytics.

[16] **www.pinterest.com**

References

Anderson, E.W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research* ***1*** *(1).* Pp. 5-17.

Asur, S. & Huberman, B.A. (2010). Predicting the Future with Social Media. Retrieved online from: http://arxiv.org/abs/1003.5699

Bass, F.M. (1969). A New Product Growth for Model Consumer Durables. *Management Science* ***15*** *(5).* Pp. 215-227.

Bass, F.M. (2004). Comments on "A New Product Growth for Model Consumer Durables": The Bass Model. *Management Science* ***50*** *(12).* Pp. 1833-1840.

Berger, J. & Iyengar (2012). Different Drivers of Online and Offline Word of Mouth. Proc. Of the 39th Annual Association for Consumer Research Conference.

Bollen, J., Mao, H. & Zeng, X. (2011). Twitter Mood Predicts the Stock Market. *Journal of Computational Science* ***2*** *(1).* Pp. 1-8.

Brown, J., Broderick, A.J. & Lee, N. (2007). Word of mouth communication within online communities: Conceptualizing the online social network. Journal of Interactive Marketing **21**. Pp. 2–20.

Chatfield, C. (2000). Time Series Forecasting. Chapman and Hall / CRC Press, London (UK).

Curtis, S. (2012, February 28). Twitter Allows Marketeers to Mine Historical Tweets. Retrieved from: http://news.techworld.com/applications/3340744/Twitter-allows-marketeers-to-mine-historical-tweets/

Danaher, P. J., B. G. S. Hardie & W. P. Putsis. (2001). Marketing-mix variables and the diffusion of successive generations of a technological innovation. *Journal of Marketing Research* ***38*** *(4)*. Pp. 501-514.

De Matos, C.A. & Rossi, A.D.V. (2008). Word-of-mouth communications in marketing: a meta-analytic review of the antecedents and moderators. *Journal of the Academy of Marketing Science* ***36.*** Pp. 578-596.

Esch, F.R., Langner, T., Schmitt, B.H. & Geus, P. (2006). Are Brands Forever? How Brand Knowledge and Relationships Affect Current and Future Purchases. *Journal of Product & Brand Management* ***15*** *(2).* Pp. 98-105.

Evans, D.S. (2009). The Online Advertising Industry: Economics, Evolution, and Privacy. *Journal of Economic Perspectives* ***23*** *(3).* Pp. 37-60.

Fisher, M.L., Raman, A., Sheen McClelland, A. (2000). Rocket Science Retailing is Almost Here: Are You Ready? *Harvard Business Review*

Flood, R.L. & Jackson, M.C. (1991). Creative Problem Solving: total System Intervention. *Wiley, Chichester.*

Forrester, J.W. (1961). Industrial Dynamics. MIT Press: Cambridge (MA).

Forrester, J.W. (1994). System dynamics, systems thinking, and soft OR. *System Dynamics Review* ***10****.* Pp. 245-256.

GFK (2011). De Smartphone Revolutie. *Retail Vision.* Pp. 18 – 19.

GFK (2012). Jaargids 2012: Inzichten en marktontwikkelingen in de Benelux. G Available online: http://www.gfk.nl/jaargids/2012

Gillin, P. (2007). The New Influencers: An Marketer's Guide to the New Social Media. Fresno (US): *Quill Driver Books.*

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

Gruhl, D., Guha, R., Kumar, R., Novak, J. & Tomkins, A. (2005). The Predictive Power of Online Chatter. *Proc. Of the 11th ACM SIGKDD Int. Conf. on Knowledge Discovery in Data Mining.* Pp. 78-87.

Hair, J.F., Black, W.C., Babin, B.J. & Anderson, R.E. (2010). Multivariate data analysis: A global perspective (7th ed.). New Jersey (CA): *Pearson.*

Harzing, A. (2012). Journal Quality List (42nd ed.). Retrieved from www.harzing.com.

Hennig-Thurau, T., Gwinner, K.P., Walsh, G. & Gremler, D.D. (2004). Electronic Word-of-Mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet. *Journal of Interactive Marketing* ***18*** *(1)*. Pp. 38-52.

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

Jackson, M.C. (1994). Critical systems thinking: beyond the fragments. *System Dynamics Review* ***10.*** Pp. 213-229.

Jackson, M.C. & Keys, P. (1984). Towards a System of Systems Methodologies. *Journal of the Operational Research Society* ***35*** *(6).* Pp. 473-486.

Jansen, B.J., Zhang, M., Sobel, K. & Chowdury, A. (2009). Twitter Power: Tweets as Electronic Word of Mouth. *Journal of the American Society for Information Science and Technology* ***60*** *(11).* Pp. 2169-2188

Jiang, Z. (2010). How to give away software with successive versions. *Decision Support Systems* ***49*** *(4). Pp.* 430-441.

Jiang, Z. & Jain, D.C. (2012). A generalized Norton-Bass model for mulitgeneration diffusion. *Management Science* ***58*** *(5).*

Jun, D. B. & Y. S. Park. (1999). A Choice-Based Diffusion Model for Multiple Generations of Products. *Technological Forecasting and Social Change* ***61.*** Pp. 45-58.

Kahn, K.B. (2002). An Exploratory Investigation of New Product Forecasting Practces. *Journal of Product Innovation Management* ***19.*** Pp. 133-143.

Katz, E. & Lazarsfeld, P.F. (1955). Personal Influence: The part played by people in the flow of mass communications. Glencoe (IL): *Free press.*

Katz, E. (1957). The Two-Step Flow of Communication: an up-to date Report on an Hypothesis. *Public Opinion Quarterly* ***21*** *(1).* Pp. 61-78.

Kim, N., D. R. Chang & A. D. Shocker. (2000). Modeling intercategory and generational dynamics for a growing information technology industry. *Management Science* ***46.*** Pp. 496-512.

Kittur, A. & Kraut, R.E. (2008). Harnessing the Wisdom of Crowds in Wikipedia: Quality Through Coordination. *Proc. Of the 2008 Conf. on Computer Supported Cooperative Work.*

Kozinets, R.V., de Valck, K., Wojnicki, A.C. & Wilner, S.J.S. (2010). Networked Narratives: Understanding Word-of-Mouth Marketing in online communities. *Journal of Marketing* ***74.*** Pp. 71-89.

Kwak, H., Lee, C. Park, H. & Moon, S. (2010). What is Twitter, a Social Network or a News Media? *Proc. Of the International conference on World wide Web 2010.*

Lane, D.C. (2000). Should System Dynamics be Describes as a 'Hard' or 'Deterministic' Systems Approach. *Systems Research and Behaviural Science* ***17.*** Pp. 3-22.

Lucking-Reiling, D., Bryan, D., Prasad, N. & Reeves, D. (2007). Pennies from eBay: The determinants of price in online auctions. *Journal of Industrial Economics* ***55***. Pp. 223-233.

Luna-Reyes, L.F. & Andersen, D.L. (2003). Collecting and Analyzing Qualitative Data for System Dynamics: Methods and Models. *System Dynamics Review* ***19*** *(4).* Pp. 271-296.

Lyneis, S.M. (2000). Corporate Planning and Policy Design: A System Dynamics Approach. Cambridge (Mass.): *MIT Press.*

Mahajan V. & E. Muller. (1996). Timing, Diffusion, and Substitution of Successive Generations of Technological Innovations: The IBM Mainframe Case. *Technological Forecasting and Social Change* ***51***. Pp. 109-132.

Mahajan, V., Muller, E. & Bass, F.M. (1990). New Product Diffusion Model in Marketing: A Review and Directions for Research. *Journal of Marketing* ***54*** *(1).* Pp. 1-26.

Mishne, G. & Glance, N. (2006). Predicting Movie Sales from Blogger Sentiment. *AAAI 2006 Spring Symposium on Computational Approaches to Analysing Weblogs.*

Moore, G.A. (2006). Crossing the Chasm: Marketing and Selling Disrutive Products to Mainstream Consumers (Red. Ed.). New York (US): *HarperCollins Publishers.*

Neuendorf, K.A. (2002). The content analysis guidebook. London (UK): *SAGE.*
Norton, J.A. & Bass, F.M. (1987). A diffusion theory model of adoption and substitution for successive generations of high-technology products. *Management Science* ***33*** *(9)*. Pp. 1069-1086.

NVPI (2011). Interactiefmarkt 2011. Available online via: www.nvpi.nl/sites/default/files/nvpi-marktinformatie-interactief-2011.pdf.

Pang, B. & Lee, L. (2008). Opinion Mining and Sentiment Analysis. *Foundations and Trends in Information Retreival* ***2*** *(1-2).* Pp. 1-135.

PeopleBrowsr. (2011). Kred: Measurable Influence [PowerPoint slides]. Retrieved from http://www.slideshare.net/peoplebrowsr/kred-measurable-influence-we-all-have-influence-somewhere?ref=http://www.kred.com/

Peres, R., Muller, E. & Mahajan, V. (2010). Innovation Diffusion and New Product Growth Models: A Critical Review and Research Directions. *Int. Journal of Research in Marketing* ***27*** *(2).* Pp. 91-106.

Randolph, J. J. (2005). Free-marginal multirater kappa: An alternative to Fleiss' fixed-marginal multirater kappa. *Joensuu University Learning and Instruction Symposium 2005.*

Rangaswamy, A. & Gupta, S. (2000). Innovation Adoption and Diffusion in the Digital Environment: Some Research Opportunities. In: Mahajan, V., Eitan, M. & Wind, Y. (Eds.) (2000). New-product Diffusion Models. Norwell (US): *Kluwer Academic Publishers*.

Richardson, G.P. (2011). Reflections on the Foundations of System Dynamics. *System Dynamics Review **27** (3).* Pp. 219-243.

Robinson, J. P. (1976). Interpersonal Influence in Election Campaigns Two Step-flow Hypotheses. *Public Opinion Quarterly **40** (3)*. 304–319.

Rogers, E. M., & Cartano, D. G. (1962). Methods of Measuring Opinion Leadership. *Public Opinion Quarterly **26**. Pp.* 435-41.

Rogers, E.M. (2003). Diffusion of Innovations (5th Ed.). New York (US): *The Free Press.*

Rosen, E. (2009). Buzz: Real Life Lessons in Word-Of-Mouth Marketing. Profile Books, London (UK).

Speece, M. W. & D. L. MacLachlan. (1995). Application of a multi-generation diffusion model to milk container technology. *Tech. Forecasting and Social Change **49***. Pp. 281-295.

Sterman, J.D. (2000). S-Shaped Growth: Epidemics, Innovation, Diffusion, and the Growth of New Products. In: Sterman, J.D. (2000). Business Dynamics: Systems Thinking and Modeling for a Complex World. Boston (US): *McGraw-Hill.*

Sussan, F., Gould, S. & Weisfeld-Spolter, S. (2006). Location, Location, Location: The Relative roles of Virtual Locations, Online Word-of-Mouth (eWom) and Advertising in the New-Product Adoption Process (extended abstract). *Advances in Consumer Research (33).* Pp. 649-650.

Thelwall, M., Buckley, K., & Paltoglou, G. (2011). Sentiment in Twitter events. Journal of the American Society for Information Science and Technology **62** (2). Pp. 406-418

Tong, R.M. (2001). An Operational System for Detecting and Tracking Opinions in On-line Discussions. *Working Notes of the ACM SIGIR 2001 Workshop on Operational Text Classification.*

Topsy (2012a). Geotagging methodology. Available online: *https://help.topsy.com/customer/portal/articles/669106-geotagging-methodology*

Topsy (2012b) Sentiment analysis methodology. Available online: *https://help.topsy.com/customer/portal/articles/669162-sentiment-analysis-methodology*

Topsy (2012c) Influence methodology. Available online: *https://help.topsy.com/customer/portal/articles/669115-influence-methodology*

Trusov, M., Bucklin, R.E. & Pauwels, K. (2009). Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social networking Site. *Journal of Marketing* ***73*** *(5).* Pp. 90-102.

Van den Bulte, C. & Wuyts, S. (2007). Social networks and marketing. Cambridge (Massachusetts): *Marketing Science Institute.*

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

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

Appendix

Appendix A: Literature rating

A.1 Literature Search strategy

As this literature review typically has two distinct faces: a historic regarding diffusion theory, and a more recent regarding social media, two distinct literature search strategies were used. As main search engine, Google Scholar was used. This was done because it does not only include classical academic resources, but also includes recognized material available on websites and blogs. For both topics a combination of keyword-search and snowballing was used. If an article was found using snowballing (and articles referred to in them), it was only included if it met the set requirements.

Using the Journal Quality List (Harzing, 2012), the publications found were rated using the Institute of Management Journals Listing (EJL '12) and the Australian Business Deans Council Journal Ranking List (ABDC '10). These were used as they were used in previous courses and have appeared to be proper indicators of the quality of publications.

A.2 Diffusion Theory publications

As mentioned in the introduction, different criteria were used for publications regarding diffusion theory and social media. As diffusion theory is more dated, each publication needed to have at least 100 citations. Moreover, if ranked using ABCD it should be at least a 'highly regarded journal in the field or subfield' (A or A*) or ranked on the EJL ranking (STAR: top journal, P: best journal, PA: aspirant journal, S: recognized, or M*: top managerial).

Table A.1: Articles relating to diffusion theory

Authors	Year	Topic	Type	Citations	ABDC '10	EJL '12
Anderson	1998	Word of mouth	Journal	777	A*	P
Bass	1969	Bass Model	Journal	3886	A*	STAR
Bass	1980	Bass Model	Journal	301	A*	
Bass	2004	Bass Model	Journal	3886	A*	STAR
Bass, Jain & Krishnan	2000	Bass Model	Book	286	n.a.	
Bass, Krishnan & Jain	1994	Bass Model	Journal	394	A*	STAR
Cachon & Swinney	2011	Product Diffusion	Journal	21	A*	STAR
Chanarsekaran & Tellis	2007	Product Diffusion	Book	52	n.a.	
Danaher et al.	2011	Norton-Bass model	Journal	137	A*	S
Grewal et al.	2000	Opinion Leaders	Journal	73	A	S
Jiang	2010	Norton-Bass model	Journal	5	A*	P
Jiang & Jain	2012	Norton-Bass model	Journal	1	A*	STAR
Jun & Park	1999	Norton-Bass model	Journal	67	A	S
Kim et al.	2000	Norton-Bass model	Journal	83	A*	STAR
Krishnan, Bass & Kumar	2000	Product Diffusion	Journal	110	A*	S
Lyneis	2000	System Dynamics	Book	239	n.a.	n.a.
Mahajan & Muller	1996	Norton-Bass model	Journal	190	A	S
Mahajan, Muller & Bass	1990	Bass Model	Journal	1438	A*	STAR
Norton & Bass	1987	Bass Model	Journal	526	A*	STAR

Norton & Bass	1992	Bass Model	Journal	123	A	M*
Pae & Lehmann	2003	Product diffusion	Article	35	A*	P
Peres, Muller & Mahajan	2010	Product Diffusion	Journal	61	A	STAR
Rangaswamy & Gupta	2000	Product Diffusion	Book	286	n.a.	
Rogers	2003	Product Diffusion	Book	40608	n.a.	
Speece & MacLachlan	1995	Norton-Bass model	Journal	50	A	S
Sterman	2000	Bass Model	Book	4862	n.a.	
Van den Bulte & Wuyts	2007	Product Diffusion	Book	99	n.a.	
Westbrook	1987	Word of mouth	Journal	1302	A*	S

A.3 Social Media publications

For social media, less journals were ranked on ABCD '10 or EJL '12. If ranked, they should be at least a recognized journal (A) on ABCD '10, or at least 50 citations. If they are not ranked, they should also be referred to at least 50 times (excluding sources used as example).

Table A.2: Articles regarding social media

Authors	Year	Topic	Type	Citations	ABDC '10	EJL '12
Allsop, Basett & Hoskins	2007	Word of mouth	Journal	84	A	S
Baccianella, Esuli & Sebastiani	2010	Sentiment Analysis	Proceedings	83	n.a.	
Bal et al.[17]	2011	Sentiment Analysis	Proceedings	1	n.a.	
Berger & Iyengar	2011	Word of mouth	Proceedings	31	n.a.	
Berger, Sorensen & Rasmussen	2010	Word of mouth	Journal	28	A*	STAR
BlendTec	2011	Social Media (example)	Website	n.a.	n.a.	
Bollen, Mao & Zeng	2011	Social Media	Journal	116	n.a.	n.a.
Burt	1999	Social Networks	Journal	229	A*	
Chevalier & Mayzlin	2004	Word of Mouth	Proceedings	902	n.a.	
Corliss	2009	Social Media	Website	n.a.	n.a.	
Curtis	2012	Twitter	Blog	n.a.	n.a.	
Esch, Langner, Schmitt & Geus	2006	Firm value	Journal	134	B	
Esuli & Sebastiani	2006	Sentiment Analysis	Proceedings	543	n.a.	
Evans	2009	Advertising	Journal	36	A*	
Fellbaum	2005	Sentiment Analysis	Book	7575	n.a.	
Fisher, Ramam & Sheen McClelland	2000	Social Media	Journal	194	A	M*
Gill, Hultink[18], Saaksajarvi & Wang	2012	Social Media	Proceedings	n.a.	n.a.	
Gillin[19]	2007	Social Media	Book	76	n.a.	
Gruhl, Guha, Kumar, Novak & Tomkins	2005	Social Media	Proceedings	161	n.a.	
Hennig-Thurau, Gwinner, Walsh & Gremier	2004	Social Media	Journal	567	B	S

[17] This article describes a method used by a variety of customers of Teezir.nl, which was a company connected to this study in an early stage.
[18] Erik-Jan Hultink is also considered a recognized author within his field of research.
[19] Hennig-Thurau is considered a highly recognized author within this field.

Authors	Year	Topic	Type	Citations	ABDC '10	EJL '12
Hennig-Thurau, Wiertz & Feldhaus	2010	Word of Mouth	Proceedings	n.a.	n.a.	
Huberman, Romero & Wu	2009	Twitter	Journal	320	n.a.	
Jansen, Zhang, Sobel & Chowdury	2009	Twitter	Proceedings	756	n.a.	
Kahn	2002	Forecasting	Journal	71	A*	P
Kaplan & Haenlein	2010	Social Media	Journal	475	C	
Katz	1957	Social Networks	Journal	895	A	
Katz & Lazarsfeld	1955	Social Networks	Book	3122	n.a.	
Kittur & Kraut	2008	Social Media	Proceedings	167	n.a.	
Kozinets et al.	2010	Social Media	Journal	187	A*	STAR
O'Reilly	2005	Social Media	Website	5469	n.a.	
Pang & Lee	2008	Sentiment Analysis	Journal	921	n.a.	
PeopleBrowsr	2011	Social Media	Website	n.a.	n.a.	
Phelps, Lewis, Mobilio, Perry & Raman	2004	Social Media	Journal	231	A	S
Rosen	2009	Social Media	Book	27	n.a.	
Safko	2010	Social Media (example)	Book	123	n.a.	
Strickland	2008	Social Media	Website	n.a.	n.a.	
Surowiecki	2005	Social Media	Book	3448	n.a.	
Sussan, Gould & Weisfeld-Spolter	2006	Word of mouth	Journal	12	B	
Telegraaf	2012	Twitter	Blog	n.a.	n.a.	
Tong	2001	Social Media	Proceedings	101	n.a.	
Trusov, Bucklin & Pauwels	2009	Social Media	Journal	198	A*	STAR
Twitter Developers	2012	Twitter	Website	n.a.	n.a.	
Van Riet	2009	Social Media	Blog	n.a.	n.a.	
Watts & Dodds	2007	Social Media	Journal	409	A*	STAR
Watts & Strogats	1998	Social Networks	Journal	15767	n.a.	

Appendix B: Included products

Table B.1: Included products

XBOX360 GAMES	G1		G2		G3	
	Product	Launch	Product	Launch	Product	Launch
Fifa	Fifa 11	01-10-'10*	Fifa 12	30-09-'11	FIFA 13	15-06'-12
Battlefield					Battlefield 3	28-10-'11
Call of Duty	Call of Duty Black Ops	09-11-'10	Call of Duty MWIII	08-11-'11	Call of Duty Black Ops II	01-11-'12
Halo					Halo 4	06-11-'12
Max Payne					Max Payne 3	18-06-'12

MOBILE PHONES	G1		G2		G3	
	Product	Launch	Product	Launch	Product	Launch
Apple iPhone	Apple iPhone 4	30-07-'10	Apple iPhone 4S	28-10-'11	Apple iPhone 5	12-09-'12
Samsung Galaxy S			Samsung Galaxy S2	15-02-'11	Samsung Galaxy S3	29-05-'12
Google Nexus			Google Nexus S	01-12-'10	Google Galaxy Nexus	01-11-'11
HTC Desire			HTC Desire HD	01-01-'11*	HTC Desire X	01-09-'12*
BlackBerry Bold			BlackBerry Bold 9780	27-11-'10	BlackBerry Bold 9900	01-08-'11*

TABLETS	G1		G2		G3	
	Product	Launch	Product	Launch	Product	Launch
Acer Iconia Tab	Acer Iconia Tab A100	21-06-'11	Acer Iconia Tab A200	01-02-'12*	Acer Iconia Tab A210	01-06-'12*
Asus Transformer Tab	Asus Transformer Pad TF101	06-04-'11	Asus Transformer Pad TF201	29-11-'11	Asus Transformer Pad TF300T	01-05-'12*
Apple iPad			Apple iPad 2	25-03-'11	Apple iPad 3	23-03-'12
Samsung Galaxy Tab			Samsung Galaxy Tab	08-06-'11	Samsung Galaxy Tab2	22-08-'12
Archos 101	Archos 10.1	31-08-'10	Archos 101 G9	01-02-'12*	Archos 10.1 XS	15-09-'12

Appendix C: Replication results and illustrative tweets

C.1 Keyword sensitivity (Assassin's Creed)

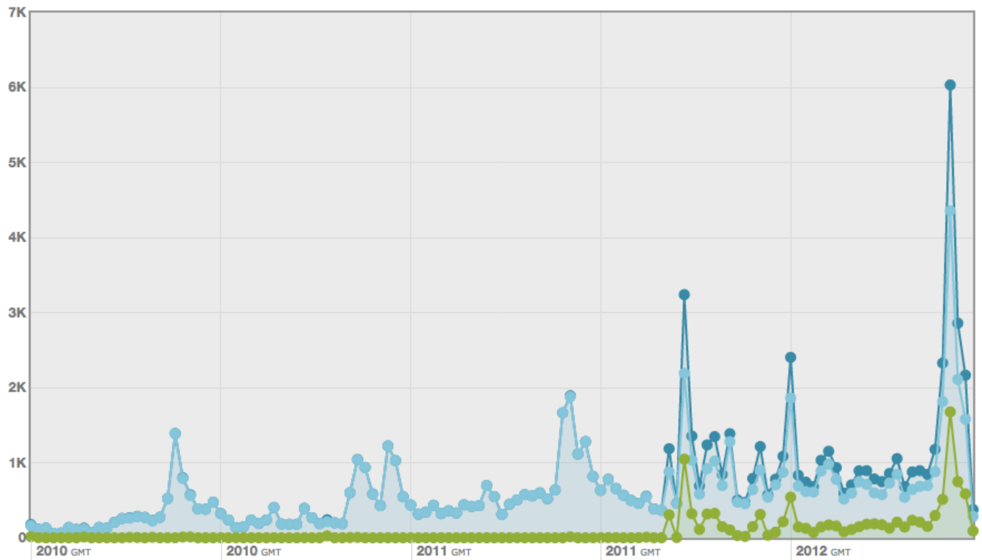


Figure C.1: The application and mentions graph show similar behavior

C.2 Double spiking events and constant mentions (Battlefield 3)

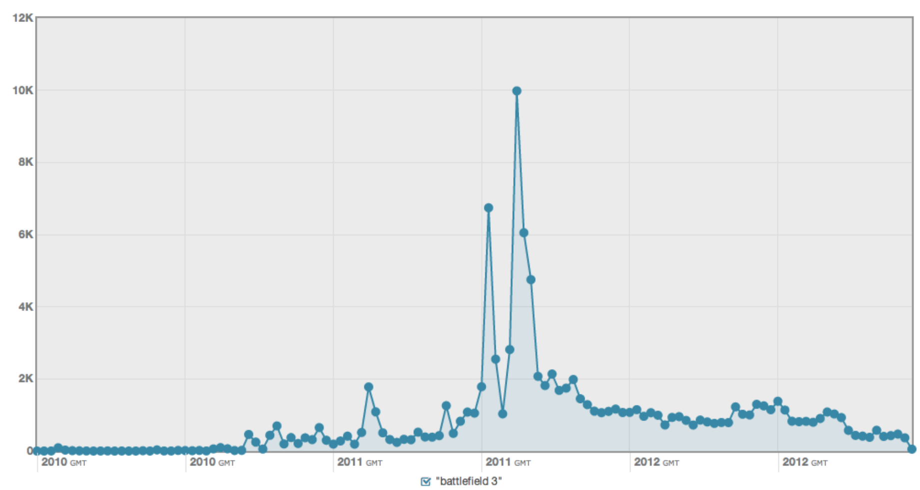


Figure C.2: Battlefield also shows a double spike around launch and shows a constant level of mentions after launch

C.3 Influence (FIFA 13)

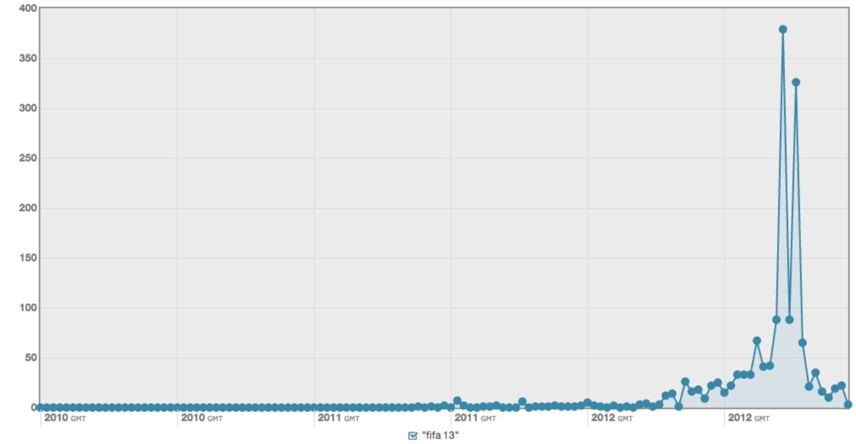


Figure C.3: Influence around FIFA 13 builds up slowly, while it declines quickly after launch

C.4 Sentiment (Call of Duty)

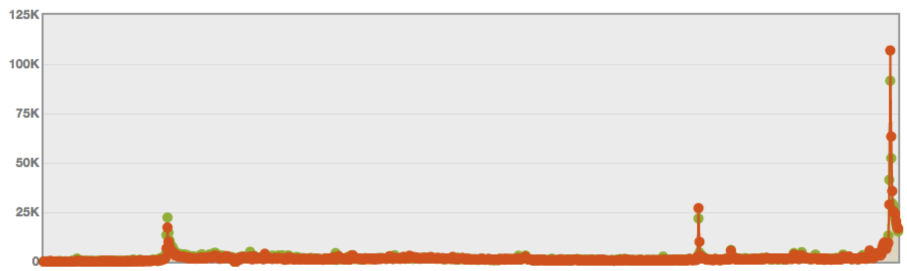
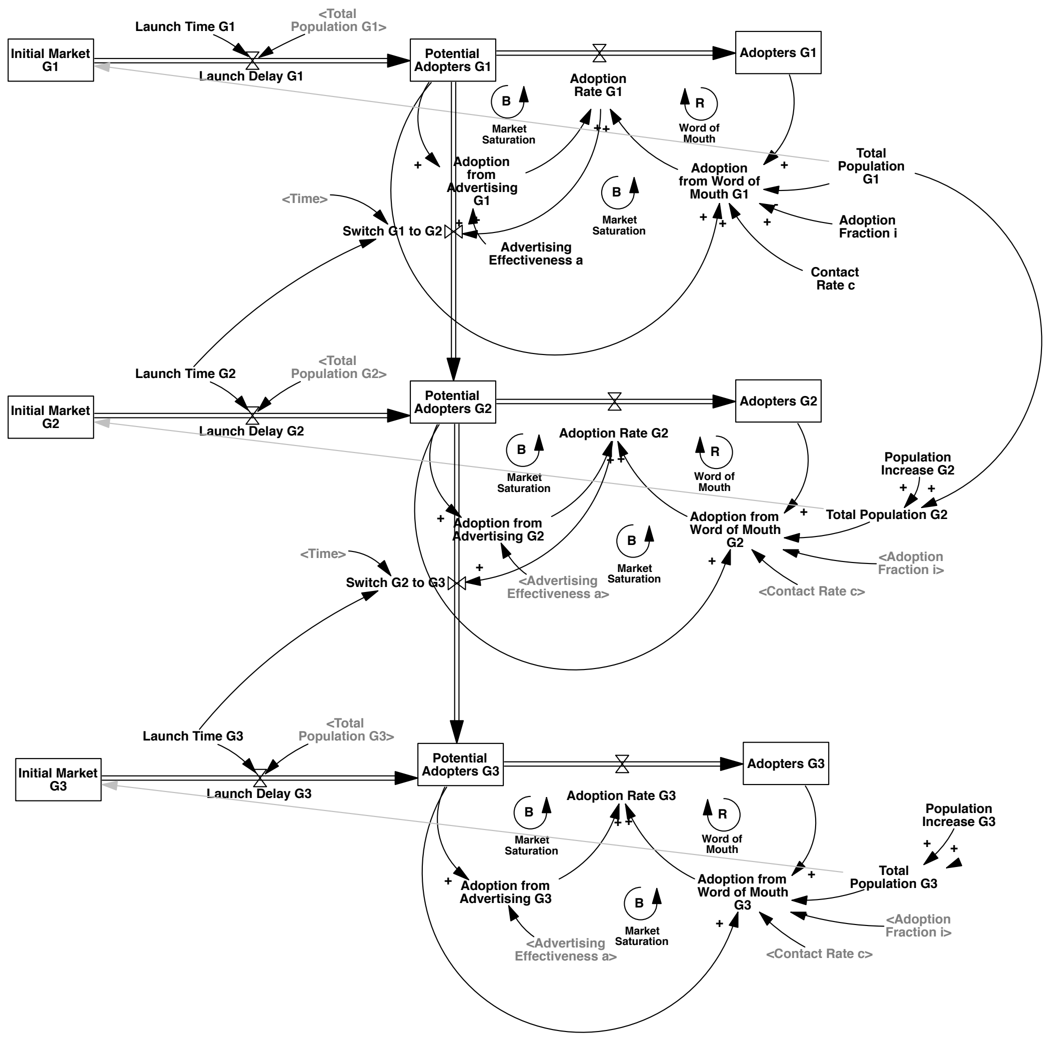


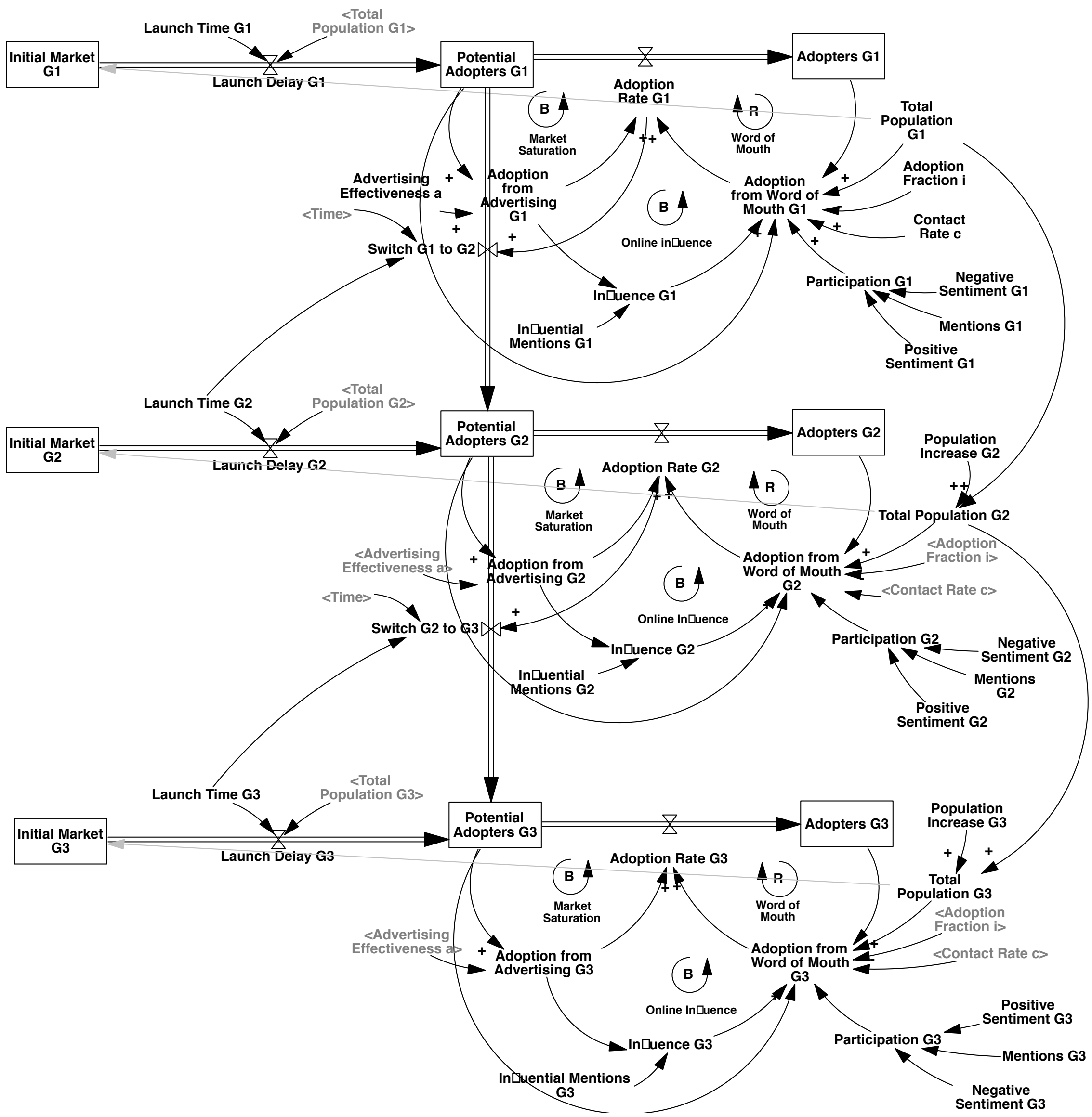
Figure C.4: Sentiment around Call of Duty shows a constant level (note that the mentions scale is enormous)

Appendix D: System dynamics models

D.1 System dynamics implementation of Norton-Bass model



D.2 System dynamics implementation of proposed extension



Appendix E: Model parameters

XBOX360 GAMES	G1						
	Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Assassin's Creed II	Assassin's Creed Brotherhoc	19-11-'10	25	133	14	8	66
Fifa 12	Fifa 11	01-10-'10*	18	2317	184	120	775
Battlefield 3							
Call of Duty	Call of Duty Black Ops	09-11-'10	24	907	128	120	1932
Halo 3							
Max Payne 3							

MOBILE PHONES	G1						
	Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Apple iPhone	Apple iPhone 4	30-07-'10	9	1144	59	34	911
Samsung Galaxy S							
Google Nexus							
HTC Desire							
BlackBerry Bold							

TABLETS	G1						
	Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Acer Iconia Tab	Acer Iconia Tab A100	21-06-'11	56	60	2	0	9
Asus Transformer Tab	Asus Transformer Pad TF101	06-04-'11	45	5	0	0	2
Apple iPad							
Samsung Galaxy Tab							
Archos 101	Archos 10.1	31-08-'10	14	12	1	0	4

G2						
Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Assassin's Creed Revelations	15-11-'11	77	125	13	6	22
Fifa 12	30-09-'11	70	4883	778	387	1028
Call of Duty MWIII	08-11-'11	76	4125	161	1953	313

G2						
Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Apple iPhone 4S	28-10-'11	74	3783	381	202	1813
Samsung Galaxy S2	15-02-'11	38	937	108	29	20
Google Nexus S	01-12-'10	27	172	18	6	193
HTC Desire HD	01-01-'11*	32	215	42	5	123
BlackBerry Bold 9780	27-11-'10	26	623	231	6	24

G2						
Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Acer Iconia Tab A200	01-02-'12*	88	24	1	0	7
Asus Transformer Pad TF201	29-11-'11	79	0	0	0	0
Apple iPad 2	25-03-'11	43	4132	366	41	1284
Samsung Galaxy Tab	08-06-'11	54	1409	110	47	3152
Archos 101 G9	01-02-'12*	88	6	3	1	1

G3						
Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Assassin's Creed III	31-10-'12	127	*125*	*13*	*6*	30
FIFA 13	27-09-'12	124	*4883*	*778*	*387*	379
Battlefield 3	28-10-'11	73	978	92	79	283
Call of Duty Black Ops II	01-11-'12	127	1980	161	1953	205
Halo 4	06-11-'12	128	*52*	*8*	*4*	31
Max Payne 3	18-06-'12	108	327	28	20	30

G3						
Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Apple iPhone 5	12-09-'12	120	1864	236	96	2727
Samsung Galaxy S3	29-05-'12	105	1545	150	63	144
Google Galaxy Nexus	01-11-'11	127	340	28	14	147
HTC Desire X	01-09-'12*	118	49	26	0	31
BlackBerry Bold 9900	01-08-'11*	62	855	276	13	88

G3						
Product	Launch	Launch (week)	Mentions	Positive	Negative	Influence
Acer Iconia Tab A210	01-06-'12*	105	18	0	0	5
Asus Transformer Pad TF300T	01-05-'12*	101	4	0	0	2
Apple iPad 3	23-03-'12	95	1720	288	36	862
Samsung Galaxy Tab2	22-08-'12	97	350	27	16	1163
Archos 10.1 XS	15-09-'12	120	8	3	1	4

Appendix F: Retailer survey

F.1 First survey

Onderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

Geachte deelnemer,

Ten eerste willen wij u hartelijk bedanken voor uw deelname aan ons onderzoek. Deze benchmark-studie is onderdeel van een afstudeeronderzoek waarin de invloed van sociale media op product lanceringen wordt onderzocht. Om het ontwikkelde model te kunnen testen is marktinformatie nodig van recentelijk gelanceerde producten. Aangezien wij ons realiseren dat verkoopinformatie vertrouwelijk is voor zowel producenten als verkopers vragen wij u enkel naar een relatieve inschatting hoe producten presteren ten opzichte van andere producten.

Alle informatie die wordt verkregen door middel van deze vragenlijst zal vertrouwelijk worden behandeld. Wij zullen u gedurende het onderzoek op de hoogte houden van resultaten rondom deze vragenlijst. Over ongeveer een maand zult u een herinnering ontvangen wanneer het tweede deel van het onderzoek ingaat, waar gevraagd zal worden naar de prestaties van de betrokken producten ten opzichte van de antwoorden die u in deze vragenlijst geeft. De omvang van dit tweede deel is kleiner dan dit gedeelte en zal worden gebruikt ter validatie van de verkregen resultaten. Mocht u vragen of opmerkingen hebben over dit onderzoek kunt u ons bereiken via e-mail: g.bullens@student.tue.nl of telefonisch via 06 – 44 63 22 86.

In dit onderzoek zullen vragen over vier product-categorien worden gesteld, voorafgegaan door een vraag waarin wordt gevraagd of u in uw dagelijkse werkzaamheden betrokken bent bij de verkoop van producten in die categorie. Indien dit niet het geval is, hoeft u geen vragen te beantwoorden over de categorie en zult u naar de volgende categorie worden gebracht.

Met vriendelijke groet,

Geert Bullens, Msc.
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

Een opmerking over je privacy
Deze vragenlijst is anoniem.
De bewaarde gegevens bevatten geen identiteitsgegevens tenzij je deze bij een vraag hebt ingevuld. Indien je met een toegangscode deelneemt kunnen wij je verzekeren dat deze niet wordt bewaard in combinatie met je antwoorden maar wel is opgeslagen in een aparte tabel. De tabel met toegangscodes wordt gebruikt om na te kijken of een vragenlijst reeds voor de betreffende toegangscode is ingevuld. Er is geen enkele manier om de codes te koppelen aan de antwoorden.

Volgende >>

Afbreken en antwoorden verwijderen

Laad onvoltooide vragenlijst

Deze vragenlijst is nu niet actief. Je antwoorden kunnen niet worden bewaard.

sustainable hosting

Ook een vragenlijst maken? Kijk op Survey123.

Onderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

0% 100%

Mobiele Telefoons

Bent u in uw dagelijkse werkzaamheden betrokken bij de verkoop van mobiele telefoons?

(•) Ja ( ) Nee

Kunt u hier aangeven hoe goed onderstaande producten hebben verkocht / verkopen ten opzichte van elkaar. In de rangschikking staat 1 voor best verkocht, terwijl 6 staat voor minst goed verkocht. Iedere score mag slechts eenmalig worden gebruikt.

	1 (best verkocht)	2	3	4	5	6 (minst goed verkocht)	Niet in assortiment
Apple iPhone 4s	(•)	( )	( )	( )	( )	( )	( )
Samsung Galaxy S2	( )	( )	( )	( )	( )	( )	(•)
Nokia E7	( )	( )	( )	( )	( )	( )	(•)
HTC Desire HD	( )	( )	( )	( )	( )	( )	(•)
BlackBerry Bold 9780	( )	( )	( )	( )	( )	( )	(•)
Google Nexus S	( )	( )	( )	( )	( )	( )	(•)

Kunt u aangeven hoe goed de Apple iPhone 4s verkoopt ten opzichte van zijn voorganger?

Veel minder	Minder	Gelijk	Meer	Veel meer
( )	( )	( )	( )	( )

Kunt u aangeven welke promotionele activiteiten zijn uitgevoerd rondom de verkoop van de Apple iPhone 4s.
Selecteer de toepasselijke opties

- [ ] In-store advertising
- [ ] Prijsreducties
- [ ] Verkooptargets
- [ ] Traditionele advertising (TV, huis-aan-huis, folder)
- [ ] Verkoop vertegenwoordigers producent
- [ ] Anders:

?

In-store advertising: Product specifieke reclameuitingen in de winkel (bijvoorbeeld: displays)
Prijsreducties: Afprijzingen voor dit product specifiek
Verkooptargets: Tegemoetkomingen vanuit de producent om verkoop te stimuleren
Traditionele advertising: Commercials, folders of andere reclame
Verkoop vertegenwoordigers producent: Vertegenwoordigers vanuit de producent die product aanprijzen tegen klanten in de winkel

<< Vorige | Volgende >>

Afbreken en antwoorden verwijderen

Hervat later

Deze vragenlijst is nu niet actief. Je antwoorden kunnen niet worden bewaard.

Onderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

0% 100%

Tablets

Bent u in uw dagelijkse werkzaamheden betrokken bij de verkoop van: TABLETS?

(•) Ja ( ) Nee

Kunt u hier aangeven hoe goed onderstaande producten hebben verkocht / verkopen ten opzichte van elkaar. In de rangschikking staat 1 voor best verkocht, terwijl 6 staat voor minst goed verkocht. Iedere score mag slechts eenmalig worden gebruikt.

	1 (best verkocht)	2	3	4	5	6 (minst goed verkocht)	Niet in assortiment
Acer Iconia Tab A200	(•)	( )	( )	( )	( )	( )	( )
Asus Transformer Pad TF300T	( )	( )	( )	( )	( )	( )	(•)
Apple iPad 2	( )	( )	( )	( )	( )	( )	(•)
Samsung Galaxy Tab 8.9	( )	( )	( )	( )	( )	( )	(•)
Asus Eee Pad Slider	( )	( )	( )	( )	( )	( )	(•)
Archos 101 G9	( )	( )	( )	( )	( )	( )	(•)

Kunt u aangeven hoe goed de Acer Iconia Tab A200 verkoopt ten opzichte van zijn voorganger?

Veel minder	Minder	Gelijk	Meer	Veel meer
( )	( )	( )	( )	( )

Kunt u aangeven welke promotionele activiteiten zijn uitgevoerd rondom de verkoop van de Acer Iconia Tab A200.
Selecteer de toepasselijke opties

- [ ] In-store advertising
- [ ] Prijsreducties
- [ ] Verkooptargets
- [ ] Traditionele advertising (TV, huis-aan-huis, folder)
- [ ] Verkoop vertegenwoordigers producent
- [ ] Anders:

?

In-store advertising: Product specifieke reclameuitingen in de winkel (bijvoorbeeld: displays)
Prijsreducties: Afprijzingen voor dit product specifiek
Verkooptargets: Tegemoetkomingen vanuit de producent om verkoop te stimuleren
Traditionele advertising: Commercials, folders of andere reclame
Verkoop vertegenwoordigers producent: Vertegenwoordigers vanuit de producent die product aanprijzen tegen klanten in de winkel

<< Vorige | Volgende >>

Afbreken en antwoorden verwijderen

Hervat later

Deze vragenlijst is nu niet actief. Je antwoorden kunnen niet worden bewaard.

Onderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

0% 100%

Video Games

Bent u in uw dagelijkse werkzaamheden betrokken bij de verkoop van XBOX 360 games?

(●) Ja ( ) Nee

Kunt u hier aangeven hoe goed onderstaande XBOX 360 games hebben verkocht / verkopen ten opzichte van elkaar. In de rangschikking staat 1 voor best verkocht, terwijl 6 staat voor minst goed verkocht. Iedere score mag slechts eenmalig worden gebruikt.

	1 (best verkocht)	2	3	4	5	6 (minst goed verkocht)	Niet in assortiment
Assassin's Creed II	●	○	○	○	○	○	○
FIFA 12	○	○	○	○	○	○	●
Battlefield 3	○	○	○	○	○	○	●
Call of Duty Modern Warfare III	○	○	○	○	○	○	●
Halo III	○	○	○	○	○	○	●
Max Payne 3	○	○	○	○	○	○	●

Kunt u aangeven hoe goed Assassin's Creed II verkoopt ten opzichte van zijn voorganger?

Veel minder	Minder	Gelijk	Meer	Veel meer
○	○	○	○	○

Kunt u aangeven welke promotionele activiteiten zijn uitgevoerd rondom de verkoop van Assassin's Creed II.
Selecteer de toepasselijke opties

- [ ] In-store advertising
- [ ] Prijsreducties
- [ ] Verkooptargets
- [ ] Traditionele advertising (TV, huis-aan-huis, folder)
- [ ] Verkoop vertegenwoordigers producent
- [ ] Anders:

?

In-store advertising: Product specifieke reclameuitingen in de winkel (bijvoorbeeld: displays)
Prijsreducties: Afprijzingen voor dit product specifiek
Verkooptargets: Tegemoetkomingen vanuit de producent om verkoop te stimuleren
Traditionele advertising: Commercials, folders of andere reclame
Verkoop vertegenwoordigers producent: Vertegenwoordigers vanuit de producent die product aanprijzen tegen klanten in de winkel

<< Vorige | Volgende >>

Afbreken en antwoorden verwijderen

Hervat later

Deze vragenlijst is nu niet actief. Je antwoorden kunnen niet worden bewaard.

Onderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

0% 100%

Digitale Camera's

Bent u in uw dagelijkse werkzaamheden betrokken bij de verkoop van digitale camera's?

Ja Nee

Kunt u hier aangeven hoe goed onderstaande producten hebben verkocht / verkopen ten opzichte van elkaar. In de rangschikking staat 1 voor best verkocht, terwijl 6 staat voor minst goed verkocht. Iedere score mag slechts eenmalig worden gebruikt.

	1 (best verkocht)	2	3	4	5	6 (minst goed verkocht)	Niet in assortiment
Canon EOS 650D							
Nikon D3100							
Canon PowerShot D20							
Nikon Coolpix S9300							
Olympus Tough TG-1							
Sony CyberShot DSC-H90							

Kunt u aangeven hoe goed de Canon EOS 650D verkoopt ten opzichte van zijn voorganger?

Veel minder Minder Gelijk Meer Veel meer

Kunt u aangeven welke promotionele activiteiten zijn uitgevoerd rondom de verkoop van de Canon EOS 650D.
Selecteer de toepasselijke opties

- In-store advertising
- Prijsreducties
- Verkooptargets
- Traditionele advertising (TV, huis-aan-huis, folder)
- Verkoop vertegenwoordigers producent
- Anders:

?

In-store advertising: Product specifieke reclameuitingen in de winkel (bijvoorbeeld: displays)
Prijsreducties: Afprijzingen voor dit product specifiek
Verkooptargets: Tegemoetkomingen vanuit de producent om verkoop te stimuleren
Traditionele advertising: Commercials, folders of andere reclame
Verkoop vertegenwoordigers producent: Vertegenwoordigers vanuit de producent die product aanprijzen tegen klanten in de winkel

<< Vorige Volgende >>

Afbreken en antwoorden verwijderen

Hervat later

Deze vragenlijst is nu niet actief. Je antwoorden kunnen niet worden bewaard.

Onderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

0% 100%

Persoonlijke informatie

Ter afsluiting van deze vragenlijst hebben wij nog enkele persoonlijke gegevens van u nodig. Deze zullen enkel gebruikt worden voor administratieve doeleinden en nooit met derden gedeeld worden.

Hoe lang bent u al werkzaam in uw functie als verkoper / verkoopmanager?
Kies een van de volgende antwoorden

- Minder dan 1 jaar
- Tussen 1 en 3 jaar
- Tussen 3 en 5 jaar
- Langer dan 5 jaar

Op welk e-mail adres kunnen wij u bereiken om u op de hoogte te houden over dit onderzoek en om u te bereiken over de start van het tweede deel van dit onderzoek.

<< Vorige | Versturen

Afbreken en antwoorden verwijderen

Hervat later

Deze vragenlijst is nu niet actief. Je antwoorden kunnen niet worden bewaard.

sustainable hosting

Ook een vragenlijst maken? Kijk op Survey123.

F.2 Second survey

Vervolgonderzoek Consumer Electronics
Innovation, Technology Entrepreneurship and Marketing Group
Faculteit Industrial Engineering
Technische Universiteit Eindhoven

0% 100%

Verkoop sinds eerste onderzoek

In de onderstaande vragen ziet u de resultaten van het eerste onderzoek. De volgorde die daar is aangegeven is de volgorde zoals u gezamenlijk de verkoop van de producten per categorie heeft gerangschikt. Wij zijn nu geïnteresseerd in de verkoop van deze producten sindsdien. Kunt u aangeven hoe onderstaande producten nu verkopen? Opnieuw kunt u het best verkopend product bovenaan plaatsen en het slecht verkopende product onderaan. Indien u een of meerdere categorien niet verkoopt, dan hoeft u deze uiteraard niet te beantwoorden. De getallen tussen de haakjes duiden de rangschikking van het eerste onderzoek aan.

TABLETS

Klik een optie uit de lijst links. Begin met de optie die het meest toepasselijk is en ga door tot de minst toepasselijke optie.

Je keuzes:

Apple iPad 2 (1)
Samsung Galaxy Tab 8.9 (2)
Asus Transformer Pad TF300T (3)
Archos 101 G9 (4)
Acer Iconia Tab A200 (5)

Je rangschikking:

1:
2:
3:
4:
5:

Klik op de schaar naast elk item om de laatst ingevoerde gegevens te verwijderen

SMARTPHONES

Klik een optie uit de lijst links. Begin met de optie die het meest toepasselijk is en ga door tot de minst toepasselijke optie.

Je keuzes:

Apple iPhone 4S (1)
Samsung Galaxy SII (2)
HTC Desire HD (3)
Blackberry Bold 9780 (4)
Google Nexus S (5)

Je rangschikking:

1:
2:
3:
4:
5:

Klik op de schaar naast elk item om de laatst ingevoerde gegevens te verwijderen

DIGITALE CAMERA'S

Klik een optie uit de lijst links. Begin met de optie die het meest toepasselijk is en ga door tot de minst toepasselijke optie.

Je keuzes:

Nikon D3100 (1)
Nikon Coolpix S9300 (2)
Canon EOS650D (3)
Canon PowerShot D20 (4)
Sony Cybershot DSC-H60 (5)

Je rangschikking:

1:
2:
3:
4:
5:

Klik op de schaar naast elk item om de laatst ingevoerde gegevens te verwijderen

XBOX360 GAMES

Klik een optie uit de lijst links. Begin met de optie die het meest toepasselijk is en ga door tot de minst toepasselijke optie.

Je keuzes:

FIFA 12 (1)
Battlefield 3 (2)
Call of Duty Modern Warfare III (3)
Max Payne 3 (4)
Halo III (5)

Je rangschikking:

1:
2:
3:
4:
5:

Klik op de schaar naast elk item om de laatst ingevoerde gegevens te verwijderen

<< Vorige Volgende >>

Appendix G: Product sales ranking

Table G.1: Sales rankings

Product category	Device	July '12	Nov. '12
Smartphones	Apple iPhone	1	2
	Samsung Galaxy S	2	1
	HTC Desire	3	4
	Blackberry Bold	4	3
	Google Nexus	5	5
	Nokia E	–	–
Tablets	Apple iPad	1	1
	Samsung Galaxy Tab	2	2
	Asus Transformer Pad	3	3
	Archos 101 G	4	–
	Acer Iconia Tab	5	4
	Asus Eee Pad	–	–
Digital cameras	Nikon D	1	2
	Nikon Coolpix S9___	2	3
	Canon EOS	3	1
	Canon PowerShot D	4	5
	Sony Cybershot DSC-H	5	4
	Olympus Tough	–	–
XBOX360 games	FIFA	1	2
	Battlefield	2	5
	Call of Duty	3	1
	Max Payne	4	6
	Halo	6	4

Appendix H: Vensim output