Emotions and Topics in Online WOM: Application of Latent Semantic Analysis

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A Thesis

in

John Molson School of Business

Presented in Partial fulfillment of the Requirements

For the Degree of

Doctor of Philosophy at

Concordia University

Montreal, Quebec, Canada

May 2013

CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

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Entitled: Emotions and Topics in Online Word of Mouth: Application of Latent Semantic Analysis

and submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Business Administration

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

Emotions and Topics in Online WOM: Application of Latent Semantic Analysis

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Concordia University, 2013

The Web has changed the way that consumers express their opinions. They can now post reviews of products and express their opinions on almost anything on the websites. Potential customers often search online for product information and they often have access to hundreds of product reviews from other customers. Some of the reviews are found to be more helpful than other reviews as evidenced the potential customer's helpfulness vote. This online word-of-mouth (WOM) behavior represents new and measurable sources of information.

Recent research has shown that helpfulness votes of customer reviews can have a positive influence on sales. While it is clear that helpfulness vote of a review is important, less is known about why certain pieces of online review are more helpful than others. Despite the fact that, customers encounter a variety of emotions in a purchase situation and those emotions are likely to be documented in the review, few researches have investigated how emotions elicited by the review affect the helpfulness of the review beyond the valence. Do discrete emotions have differential informational value in this case? Based on cognitive appraisal theory, in the first essay of this dissertation, I examine how specific emotions (hope, happiness, anxiety, disgust etc.) embedded in the review affect the helpfulness votes of potential customer. I adopt a quantitative content analysis (Latent Semantic Analysis) approach to measure emotions in these reviews.

In the second essay of the dissertation, I explore how the topics of online reviews differ between positive and negative reviews. Examination of real product reviews shows that there are thematic differences between them. Also, service related complains are found to be more helpful by potential customers. This enables us to better understand the conceptual differences in WOM .

Lastly, in the third essay, I compare two text mining techniques: Latent Semantic Analysis and Probabilistic Latent Semantic Analysis (PLSA) in extracting common themes in the positive and negative product reviews. Results shows that the choice of text mining approaches should be based on the goal of the marketing researcher. If the goal is to learn about a specific brand, PLSA might reveal more specific information. However, if the goal is to learn about important aspects of a broader product category, LSA works better in terms of interpretability.

DEDICATION

To the loving memory of my father, Dr. Nuruddin Ahmad

ACKNOWLEDGEMENTS

First, I would like to express my deepest gratitude to my supervisor Professor Michel Laroche, Royal Bank Distinguished Professorship in Marketing . I have been gaining a lot of insight from him, not only because of the academic advice he has provided, but also because of the encouragement he has given. He has given me much needed flexibility without compromising quality of the work. I would like to sincerely thank my examining committee members, Professors Michele Paulin, RBC Professorship in Strategic Relationship Marketing and Professor Sylvain Senecal, RBC Financial Group Chair of E-commerce for their comments and useful suggestions throughout the process of this research. Without their support the realization of this research would not have been possible.

I would also like to thank my colleague Ebrahim Mazaheri who has offered me much support during my coursework and research. AND my parents, I cannot express my heartfelt love for them with words. I am writing these lines and my heart is being filled with endless loving memories of my father, thank you for teaching me to dream and making me who I am today. Thank you Ma for showing me the paths of patience and honesty. These will forever be a part of my life. Finally, I would like to thank my husband, Mahmud, for the never-ending love and incredible support he has given me over the years. Last but not at all the least, thank you my little princess for being so patient all these years. I owe you!

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CHAPTER 1

INTRODUCTION AND RATIONALE

Alice wants to buy a blender for her kitchen. She prefers to buy online to save her time; more importantly, she likes to go through some of the online customer reviews of blenders in a website like Amazon to gain knowledge about different brands and their advantages and disadvantages. She really likes the idea that these reviews are written by people like her and she feels comfortable to trust these reviews. She reads some of the reviews and finds a few of these reviews very helpful to decide about her blender purchase. After buying and using that blender for some time, Alice goes back to the review website to express her opinion about that particular blender. Did she make a good decision or a bad one? Did her expectation match with the product performance? Which reviews did she think helpful? How did she arrive at the purchase decision after reading the reviews in the first place? These questions and many more can be answered by properly analyzing this word-of-mouth (WOM) data. Online WOM behavior thus represents measurable sources of information. Techniques are now being developed to infer the hidden information and intention.

In the dissertation titled "Emotions and topics in online word of Mouth: Application of Latent Semantic Analysis", questions related to online word of mouth (numerical and text) have been examined. The dissertation asks the following three questions and develops three essays in an attempt to answer these questions:

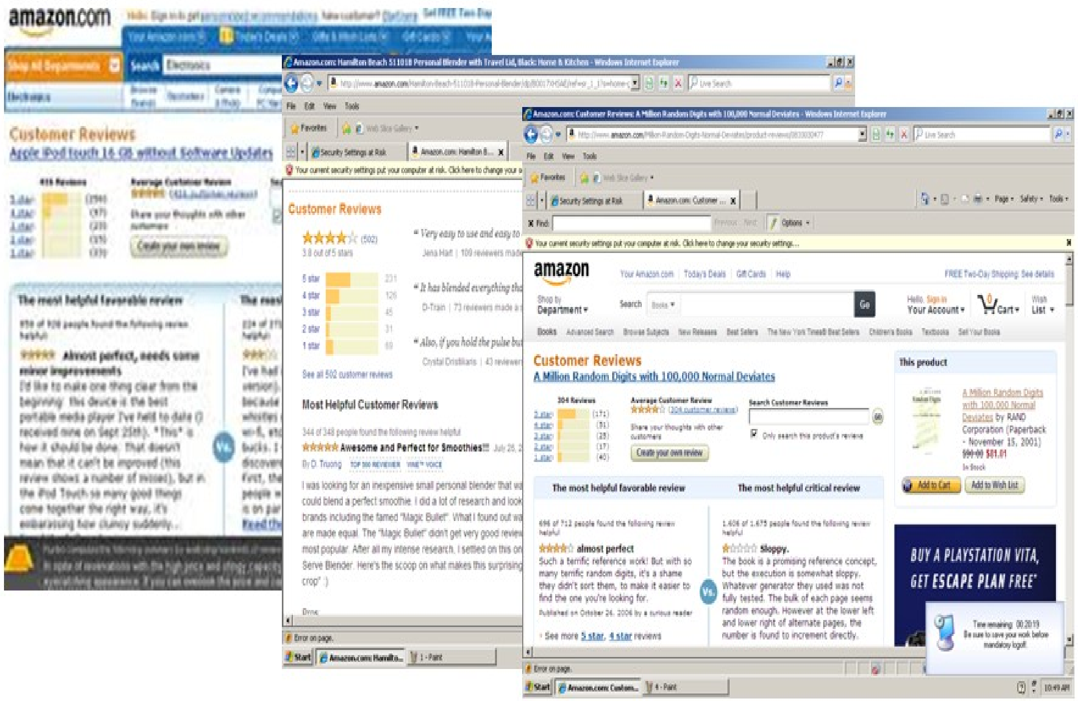

Figure 1: Example of Product Reviews (retrieved from Amazon.com)

Research Question 1: Some of the reviews are found to be more helpful than other reviews as evidenced by the potential customer's helpfulness vote often found in a website like Amazon. Some of the reviews also contain emotions happiness, disgust etc. Do these emotions have differential impact on helpfulness of the review?

Research Question 2: What are the main themes or topics in online product reviews? Do they differ between positive and negative review? Do these topics affect helpfulness of the review?

Research Question 3: Analyzing customer review data often needs data mining and Text mining techniques. What type of text mining techniques should a marketing specialist use to look at the market?

The first part of this research investigates emotions expressed in the product review. Recent research has shown that customer reviews and the helpfulness vote can have a positive influence on sales (Liu, 2006). While it is clear that helpfulness vote of a review is important, less is known about why certain pieces of online review are more helpful than others.

Past research has shown that valence (positive and negative) and volume of the product review affect helpfulness vote of a review (Mudambi & Schuff, 2010). However, valence defined by positive and negative may not be sufficient to examine the effect of a wide variety of emotions described in reviews. Emotions of the same valence can be further divided according to their appraisals (Tiedens & Liton, 2001). For example, love hope, happy, excitements are all positive emotions but they are distinct according to their appraisals. Research demonstrates that these fine grained emotions may have distinct influences on decision making and cognitive processing (Nabi, 2003). In a consumption situation, people often encounter these emotions (Ritchins, 1997) which may range from happiness, hopeful, joy, and love to sadness, anger, disappointment etc. Therefore, this part examines how discrete emotions embedded in the review affect the helpfulness votes of potential customer.

A quantitative content analysis approach is employed to measure emotions in these reviews. Specifically, a text mining technique, Latent Semantic Analysis (LSA)

(Deerwester et al., 1990) which is able to extract emotions in a text is employed to measure emotional content of the product review. This field experiment was augmented with laboratory experiment data to increase the validity of the result.

After examining the effect of emotions on the helpfulness vote, the dissertation goes further and examines other driving factors of the helpfulness vote. For this, the themes or topics of online reviews and difference among positive and negative reviews are examined. This exploratory examination of real product reviews shows that there are thematic differences between them. Positive reviews tend to focus on the product; on the contrary negative reviews tend to report service related failure. Next, the effect of these topics on the helpfulness vote of the review is examined.

The examination of helpfulness vote requires the use of real customer reviews. However, it involves large dataset and traditional way of analysis might not reveal the pattern. Therefore the use of quantitative method is warranted. The examples of these techniques are Latent semantic Analysis and probabilistic Latent Semantic Analysis. These techniques have been used in the previous researches of this dissertation. Therefore in the last essay we compare two text mining techniques: Latent Semantic Analysis and Probabilistic Latent Semantic Analysis (PLSA) (Hoffmann, 1999) in extracting common themes in the positive and negative product reviews. Results shows that the choice of text mining approaches should be based on the goal of the marketing researcher. Both techniques have advantages and disadvantages. This essay runs a comparative study and tries to understand the suitability of these text mining techniques for marketing context.

This research has wide range of practical implications. In today's digital world where Alice's story is a typical purchase scenario, it is crucial for the marketing researchers to try to understand what persuades a potential customer when S/he reads a review. How the subject matter topics and emotions expressed in the reviews affect a potential customer? These can be answered by properly analyzing the customers' reviews available on the internet. However, usually these data are huge and determination of the appropriate tools to analyze these huge data including numerical and unstructured text data is critically important. Computer science literature has been focusing on analyzing these unstructured data for a decade. Marketing Science literature needs to analyze/adapt these techniques according needs and applicability of this discipline to enhance the usability. This research sheds light on these cutting-edge issues. The findings are also applicable to other marketing contexts such as advertising and customer to customer interaction.

1.1 Contribution of the Thesis

- Although a range of emotions are expressed in customers review, very few studies have examined the effect of these emotions on the potential customers. We explained that not all the discrete emotions have the same effect. . This contributes to the better understanding of discrete emotions and their effects in an information seeking situation.

- We also examined the underlying process of the above mentioned effect and thus provided the answer *why* the effect will be observed.

- Motive and consequences of online word of mouth have been examined in the literature. Although motive provides some idea about what is being said in the WOM, a direct content analysis of the reviews have been mostly overlooked mostly because of the fact that in the pre-internet era, WOM were not traceable. This essay fills the gap and shows what is actually being talked about in a review.

- The previous study also focuses on the thematic difference between positive and negative reviews. It also contributes to the growing literature on what kind of information are found helpful in a decision making / information searching situation

- For the sake of generalizability, the essays utilized text mining techniques (in combination with controlled experiments). Recently the techniques of text analysis are being explored in Marketing Discipline. The thesis also contributes to this area of research by adapting a text mining technique to extract emotions in a Marketing setting.

- Lastly, the last essay compares two text mining techniques from a marketing manager's perspective. This contributes to the growing need of analyzing user generated content by marketers.

1.2 Organization of the Thesis

The rest of the thesis is organized as follows:

CHAPTER 2: Literature Review

This chapter provides an overall perspective on the whole research program and reviews the state of the art literature of Online Word of Mouth, Emotions, Topics and use of content analysis in Marketing.

CHAPTER 3: How do fine-grained emotion affect helpfulness vote of a product Review?

This chapter reviews the related work and develops hypotheses regarding discrete emotions expressed in the reviews and their effect on perceived helpfulness of reviews. It then supports the claim with the help of controlled and field experiments

CHAPTER 4: Exploring Conceptual Differences between Positive and Negative Reviews and its Effects on Perceived Helpfulness.

This chapter reviews the related work regarding motives and contents expressed in the reviews. It is an exploratory research. The topics are extracted from the actual reviews and in depth analysis is done. The study then examines the effect of these topics on the perceived helpfulness. The result is analyzed and discussed.

CHAPTER 5: A Comparative study of Latent Semantic Analysis and Probabilistic Latent Semantic Analysis on extracting topics in product reviews.

This chapter compares two text mining techniques (Latent Semantic Analysis and Probabilistic Latent Semantic Analysis) to see their suitability of the use in marketing context.

CHAPTER 6 : Conclusion and Summary

This chapter discusses the overall result of this research program and concludes with limitation and future research directions.

1.3 Presented and Under Review Manuscripts from the Thesis

Ahmad, Shimi N. and Michel Laroche (May, 2012), "How Do Fine-Grained Emotion Affect Helpfulness Vote of a Product Review? Evidence from User Generated Content Using Latent Semantic Analysis," 41st Academy of Marketing Science Conference, New Orleans, LA. (Abstract only)

Ahmad, Shimi N. and Michel Laroche (June, 2012), "A Comparative Study of Latent Semantic Analysis and Probabilistic Latent Semantic Analysis on Extracting Topics in Product Reviews," 23rd AMA's Annual Advanced Research Technique (ART) Forum, Seattle, WA. (Abstract only)

Ahmad, Shimi N. and Michel Laroche, "How Do Fine-Grained Emotion Affect Helpfulness Vote of a Product Review? Evidence from User Generated Content Using Latent Semantic Analysis," *Journal of Retailing* (under review)

CHAPTER 2

LITERATURE REVIEW

2.1 Electronic Word of Mouth (eWOM) and its Content

Customers are informed more than ever before. Despite the fact that the customers mostly purchase offline, information search and collection are performed online majority of time. Therefore, the content which are available in the web play a crucial role on the customer's decision making process. Customers' purchase decisions can be influenced by others' opinions, or word of mouth (WOM), and/or others' actions, or observational learning (OL) (Chen, Wang & Xie, 2011). Literature has suggested that both volume and valence of word of mouth influence future customers. For example, Khare Labrecque, & Asare, 2011) argued that WOM message's persuability depends on WOM-relevant characteristics such as WOM volume. Posted reviews are expected to influence the message recipients or the potential customer in the same direction of their valence (positive versus negative) with negative message with more intensity (Chakravarty, Liu & Majumdar, 2009).

2.2 Emotions in WOM

In customer research, emotions experienced by customers are classified traditionally in two groups: positive and negative (Westbrook, 1997, Oliver,1993, Derbaix,1995). Some researchers classify emotions in pleasure, arousal and dominance dimensions (Holbrook, & Hirschman, 1982).) and argue that the value of the dimensions vary depending on the specific emotions. Upbeat, warm or negative (Mano & Oliver,1993) are another structure of emotions experienced by customers. In discrete emotions theory, emotions can be differentiated on the number of dimensions such as action tendencies, motivation, etc. other than valence (Ruth et al., 2002). Recent research has started to investigate a more comprehensive view of emotions where similar discrete emotions are treated as factors (Laros & Steenkamp, 2004). Each discrete emotion has its own unique feature that can have different impact on outcome variables than its valence only. Therefore, there is ample evidence that customers experience a range of emotions and it is likely that these emotions will be expressed in the word of mouth; little research has investigated how these emotions affect the future customers. Negatively valenced product reviews have been shown to be more helpful than the positive ones (Chakravarty, Liu & Majumdar, 2009). This gap in literature is discussed in more detail in chapter 3.

2.3 Message Framing, Discrete Emotions and Persuasion

In the customer research, most discrete emotions research has investigated the interaction between mood and emotions elicited by advertisements (Mukherjee & Dube, 2012). Fear appeal is the most research discrete emotion (Dillard, 1993). However, eWOM resembles more to message framing because there is no reason to assume that customers who are reading several reviews of a product or service will feel every emotions described in the reviews. For this reason, the knowledge in advertising is not directly transferable to the research on how each of the discrete emotions embedded in the message influence the message recipient. The majority of framing literature to date has focused on the cognitive effects rather than the emotional effects while at the same time many scholars have called for more research on how emotion can affect attitude change (Dillard, 1993; Gross, 2008).

Relevant to this area of research, although political consultants have been using emotion in political campaigns for years, surprisingly few scholars have examined how emotional aspects of campaign messages influence political persuasion (Gross & D'Ambrosio, 2004). Moreover, discrete emotions are likely to have particular implication for the process, direction of persuasive influence and appropriate application context (Nabi, 2003). Thus there is a greater need for investigation of persuasive effects of discrete emotions. More on the direction of persuasion is discussed in chapter 3.

2.4 Content Analysis

To better understand eWOM (what customers are saying and thinking, what other customers think about a particular review, is there pattern? and many more questions), content analysis is a reliable method. “Content analysis is a method of analyzing written, verbal or visual communication messages“ (Cole, 1988). This method is being used in many disciplines such as Sociology, Psychology, Marketing, and Communication for a very long time. It was introduced to analyze newspaper and magazine articles, advertisements and political speeches (Harwood & Garry 2003). It enables the researcher to test theoretical issues to enhance understanding of the data. Moreover, “through content analysis, it is possible to distil words into fewer content related categories. It is assumed that when classified into the same categories, words, phrases and the like share the same meaning” (Cavanagh, 1997).

However, the method is criticized by people in the quantitative field mainly. For some people, it is a simplistic technique that is not subjected to detailed statistical analysis and therefore sometimes very subjective in nature. The content analysis is often considered as qualitative research. This analysis (classification or revealing any aspect of the data) is most often done by human coders.

Nowadays, people generate a lot of content in web in the form of blogs, product reviews, videos etc. For sociology, psychology, communication, marketing and many other experts, this brings a huge opportunity to analyze these data. This data is often very reliable as people are not biased by interviewer and experiment setting. People express their feelings and opinions without any intervention. Moreover, these data are freely available. So, there has been a recent trend of analyzing these data to reveal behavioral pattern, social interaction and human communication. However, these user generated content are generally huge and it is often impossible to analyze these data by human coders alone. Quantitative methods have been developed to analyze these data. There are lots of text mining techniques which can be used to infer pattern in the text data, classify and make groups of data. These can also reveal behavioral pattern. These methods are based on statistical foundation and/or other quantitative techniques. Therefore, these methods overcome the limitation of the traditional content analysis by providing numerical measure attached to it. However, people criticize these methods for being overly depended on data and for lacking human intelligence in the process of revealing the patterns. The techniques are being improved and are trying to achieve the accuracy of human coders without compromising the speed and capability of analyzing huge amount of data.

Among those techniques Latent Semantic Analysis (Deerwester et al., 1990) is one of the oldest one. This method is based on the word co-occurrence and not really founded on statistics. However, this method yields fairly accurate result that match with human coder in terms of accuracy of classification and retrieval. The next version of this method is Generative models. This family of models is based on statistical foundation and topics are found according to the probability of the terms belonging to the topic. Example of these kinds of models is Probabilistic Latent Semantic Analysis (Hoffman, 1999) or Latent Dirchilit Analysis (LDA). These provides some superior results in terms of retrieval, however, LSA also has some unique advantages which will be discussed later in the thesis.

Overall, these models are quantitative content analysis methods with the advantage of analyzing huge data without human intervention. Moreover, decisions are based on probabilities. The rest of the thesis uses quantitative content analysis techniques for the experimental purposes.

CHAPTER 3

ESSAY 1

Discrete emotions and Customers perceived helpfulness of the Review: Application of Latent Semantic Analysis.

Abstract

With the growth of internet usage, customers often search online for product information and have access to dozens or hundreds of product reviews from other customers. While it is clear that not all customer reviews are helpful, less is known about why certain online reviews are more helpful than others. Past research demonstrated that valence of a review affects the informational value of the contents and thus the perceived helpfulness of the review. However, in a purchase or information search situation, people encounter a variety of emotions which are likely to be expressed in the reviews. Potential customers read the reviews to collect or verify information and to see what other people think. Despite the fact that reviews contain emotions, few studies have investigated how emotions expressed in the review affect the helpfulness of the review. Do discrete emotions have differential informational value in this case? In this article, we build on cognitive appraisal theory to examine how discrete emotions (e.g., hope, happiness, anxiety, and disgust) embedded in the reviews affect the helpfulness votes of potential customers. We hypothesize that reviews containing emotions associated with certainty are more helpful and that reviews containing emotions associated with uncertainty are less helpful regardless of their valences. We adopt a quantitative content analysis approach to measure emotions in these reviews. Specifically, we use Latent Semantic Analysis (LSA) to measure the emotional contents of the reviews. Findings demonstrate

that discrete emotions have differential effects on the helpfulness of the reviews. By analyzing actual customer review data from Amazon.com, we contribute to a better understanding of what makes customers' reviews helpful in their decision process.

Keywords: Online word of mouth; Cognitive Appraisal theory; Certainty; Latent semantic analysis.

3.1 Introduction

With the growth in internet use, customers increasingly search for online information prior to purchase. They look for basic information on a product or a third party opinion on the product. Nowadays, whether the real purchase is done online or in store, the information search process is usually executed online. These potential customers often have access to many review websites (manufacturer's or third party site) which contain product descriptions, expert reviews, automated recommendations as well as reviews from other customers. Although each of these options has the potential to influence future customers on their process of choosing or buying (Chen & Xie 2005; Forman, Ghose & Wiesenfeld 2008), research has shown that customers trust other customer's opinions more than experts' (Senecal & Nantel, 2004).

In the literature, valence (positive/negative) and volume of the peer generated product reviews influence the sales of the product (Chevalier & Mayzlin 2006; Ghose & Ipeirotis 2006). Chen, Dhanasobhon, and Smith (2008) indicate that the quality of the review as measured by helpfulness votes also positively influences sales. As defined by Mudambi and Schuff (2010, p-186), "a helpful customer review is a peer-generated product evaluation that facilitates the customer's purchase decision process." Since the helpful product reviews influence other potential customers and in turn sales, examining the content characteristics that make a product review helpful is managerially and theoretically important.

It is also documented that product type, valence (positive/negative), and volume of the review affect the helpfulness votes of a review (Mudambi & Schuff 2010). However, valence as defined by positive and negative may not be sufficient to capture the impact of a wide variety of emotions described in customer reviews. In a consumption situation, people encounter emotions which may range from happiness, joy and love to sadness, and disappointment (Ritchins, 1997). Often customers choose to spread the word by writing a review on a website. Therefore, it is likely that potential customers, who visit a website with the intention of gaining knowledge, encounter these reviews containing varied emotional content related to customer experiences. Research demonstrates that discrete emotions of the same valence may have distinct influences on decision making (Raghunathan, Pham & Corfman 2006) or information processing (Tiedens & Linton 2001) and thus emotions of the same valence may have very differential impacts (Nabi, 2003). However, the influence of the emotional content beyond positive and negative valence of WOM on other potential customers is yet to be examined.

In this article, we examine the discrete emotional contents (e.g. happiness, hopefulness, disgust, and anxiety) of a review and their effect on the potential customer as evidenced by the helpfulness votes. In other words, we try to answer the following research question: *Do potential customers find a content of a review more or less helpful depending on the discrete emotions expressed in the review?* We build on cognitive appraisal theory to answer this question. Based on this theory, discrete emotions can be classified along a certainty appraisal dimension among others. Some emotions are associated with certainty and some are with uncertainty regardless of their valence. Drawing on the literature, we propose that reviews containing certainty emotions are more helpful and that certainty mediates this process.

We content analyze the real reviews from the Amazon website by adopting a word pattern recognition approach to measure emotions in these reviews. Specifically, Latent Semantic Analysis (LSA) is used to measure the emotional attributes and the effects of these emotions on customer's perceived helpfulness of the review are examined. We also test our hypotheses in experimental settings by manipulating the specific emotions expressed in a review. The combination of the field study and the experiments ensure the generalizability and validity of our findings.

This chapter is organized as follows: First, we review the relevant literature in three areas: word of mouth, customer emotional experiences and cognitive appraisal theory of emotions. These lead to the conceptual development of the hypotheses. Next, we present our data and methodology along with the findings. We conclude with a discussion and the implications of this research.

3.2 Literature Review

3.2.1 Word of mouth message content

Prior research on online word of mouth extensively examined message content characteristics. For example, volume (Chevalier & Mayzlin 2006; Liu 2006), valence (Duan, Gu & Whinston 2008; Liu 2006) and dispersion (Godes & Mayzlin 2004) of word of mouth messages were shown to affect product sales. Cheema and Kaikati (2010) experimented and discussed the effects of uniqueness in WOM recommendations. In the context of product reviews, Mudambi and Schuff (2010) found that people thought a review to be more or less helpful depending on the valence, volume and total votes of the review. Negative messages are likely to have stronger effects than positive ones (Chakravarty, Liu & Majumdar 2009). However, Mudambi and Schuff (2010) argued that product type (utilitarian or experience) moderate this relationship.

Although this research stream suggests that emotional aspects of the content as evidenced by valence of a review affect the helpfulness vote of a product review, surprisingly little attention was paid to this area. Past research demonstrated that an array of emotions is experienced in a purchase situation (Richins, 1997). Ruth, Brunel and Otnes (2002) elaborated this point with an example: “a customer may feel surprised and happy to find a product on sale which s/he intends to buy. However, s/he might be disappointed to know that her/his favorite color is not on the shelf and actually be angry if the sales person does not help find the right product.” Thus, customer’s experiences involve not only the experience with the core product but also the service and other aspects in the whole buying process. Nowadays, customers often share these experiences through word of mouth using the internet. In fact, the WOM model has been transformed from the organic intercustomer influence model (one customer influencing another customer) to the network coproduction model (every customer influences every other customer) (Kozinets, Valck, Wojnicki & Wilner, 2010). Therefore, online product reviews or word of mouth are very likely to contain varied emotional content felt in the real buying experiences. Customers experiencing sadness, anger, joy and satisfaction are reported to be more likely to be engaged in word of mouth (Nyer, 1997). In another research stream, there is evidence that each discrete emotion has its own unique characteristics that can have different effects on outcome variables than only valence (Nabi, 2003). Therefore, it is interesting to examine how these discrete emotions in a product review affect potential customers.

3.2.2 Cognitive Appraisal Theory and Consumption Emotions

The Cognitive appraisal theory of emotion is often used to understand many consumption situations (Ruth et al. 2002). Nyer (1997) documented the relationship between the appraisal patterns and consumption/post consumption emotions. Appraisal theories claim that emotions are induced from processing or evaluating personally relevant information (Smith & Ellsworth 1985). The meanings of a situation or surroundings come through the appraisal process that individuals take. Situations are evaluated and judged on different dimensions including, but not limited to, valence.

The primary cognitive appraisal is the valence and this is conceptualized as the extent to which the situation tends to have positive or negative outcomes on the evaluator (Lazarus 1991). Other appraisals are: (2) anticipated need to expend effort; (3) certainty; (4) need to allocate attention to the situation; (5) other agency (responsibility control); (6) self-agency; (7) fairness; (8) a situation that is beyond anyone's control; and (9) presence of a goal or obstacle to the goal (Ellsworth & Smith 1988). Thus emotions can be classified along these dimensions and are associated with certain appraisal patterns. For example, although hope and anxiety are of positive and negative valence respectively, they both are placed close to each other at one end of the certainty cognitive appraisal. On the other hand, happiness and disgust are associated with certainty. And despite the fact that they are of opposite valence, they are placed very close to each other on certainty appraisal. Moreover, hope/anxiety resides at one end and happiness/disgust resides on the other end of the certainty appraisal and thus differentiating themselves in terms of certainty. In the context of product reviews, the reviews very often contain varied emotional content induced in the whole buying or decision making process. However, the emotions induced in these situations are associated with cognitive appraisals. In other words, the emotions expressed in the text reflect how the customer lived the whole situation. When a potential customer reads this, the emotional perspective taken by the poster may influence the reader. Among other dimensions, certainty has been deemed quite important in the determination of emotional reactions (Tiedens & Linton, 2001). In this research, we look at certainty appraisal.

3.2.3 The role of certainty in the helpfulness vote of a review

The literature recognized the "helpfulness vote" of a product review as a measure of word of mouth adoption (Li & Zhan 2011). WOM adoption is defined as the attitude change of a receiver as a result of accepting what the communicator advocates. This is an effective measure of WOM persuasion (Li & Zhan 2011). There is evidence that perceived review helpfulness might predict review adoption (Saussman & Seigal 2003). Therefore, to study the effect of certainty appraisal on the helpfulness vote, we take a look at the attitude certainty and persuasion literature.

As mentioned before, certainty appraisal (Smith & Ellsworth 1985) differentiates emotions on the basis of the certainty and predictability that it conveys about a situation. The certainty appraisal has been conceptualized as the "extent to which the outcome of a situation is perceived to be known with confidence or the degree to which future events seem predictable versus unpredictable" (Roseman 1986; Smith & Ellsworth 1985). Some emotions are associated with feeling certain; individuals know what is happening in the current situation and have a feeling of certainty and confidence in predicting future situations (Tiedens & Linton 2001). For example, when people feel disgust, they report thinking that the situation is unpleasant and that they are certain and confident about what is happening. In contrast, when people feel anxious, the situation is unpleasant but also uncertain and less predictable. Therefore, certainty-related emotions tend to express a higher certainty and confidence while uncertainty related emotions express low confidence about the surroundings (Tiedens & Linton 2001).

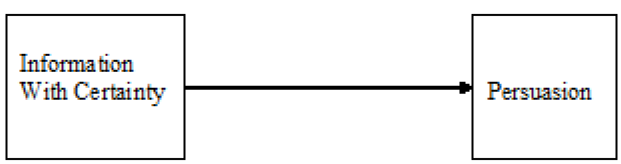

Figure 2a: Relation between certainty and helpfulness

We suggest that this difference in certainty affects WOM adoption. Indeed, the literature suggested that recommendations with certainty and confidence are more influential than uncertain ones (Sniezek & Van Swol 2001). In a judge-advisor setting, the authors found that expressing high confidence by advisors had a positive effect on judges' trust rating and judges were more likely to follow their advice. More directly relevant here, in a word of mouth situation, Karmarkar and Tormala (2009) found evidence that certainty expressed by customers rather than experts or critics induced greater persuasion. Participants were more persuaded when the source of the message were other customers and expressed high compared to low certainty. Moreover, the confidence heuristic which states that individuals expressing high levels of confidence are more influential than those expressing lower levels of confidence has consistently been supported in the literature (Karmarkar & Tormala 2011; Price & Stone 2004). Although the literature suggests that expressed certainty may boost influence on others, it is interesting to know if certainty expressed through the certainty appraisal of emotions would result in the same outcome.

Prior research suggested that emotions act as frames (Nabi, 2003). Framing theory states that the way of presenting information and the perspective taken in the message influence the receiver's response. Entman (1993) argued "to frame is to select some aspects of the perceived reality and make them more salient in a communicating context in such a way as to promote a particular problem definition, causal interpretation, moral evaluation and/or treatment recommendation." Nabi (2003) suggested that emotions can also be used as frames. The author illustrated this with an example: if a report about a crime is focused on a potential threat, it is expected to elicit fear. On the other hand, the same news can be reported with an "anger" frame focusing on the blame on the perpetrators. The author argues that the message receiver response to these reports will be different depending on the emotional frame although the essential message content remains the same. Therefore, different discrete emotions can promote different message processing with cognitive appraisal as the moderator (Nabi 2002; Tiedens & Linton 2001).

Taken these altogether, some emotions are associated with certainty (happy, disgust) and some emotions are associated with uncertainty (hope, anxiety). A potential customer would find a review associated with high certainty appraisal to be more certain. Since expressed certainty is more influential, we propose that s/he would find it to be more helpful (certainty is more influential in an information exchange situation). On the other hand, reviews containing uncertainty will be less helpful.

The graphical representation of the model is shown in Figure 2.

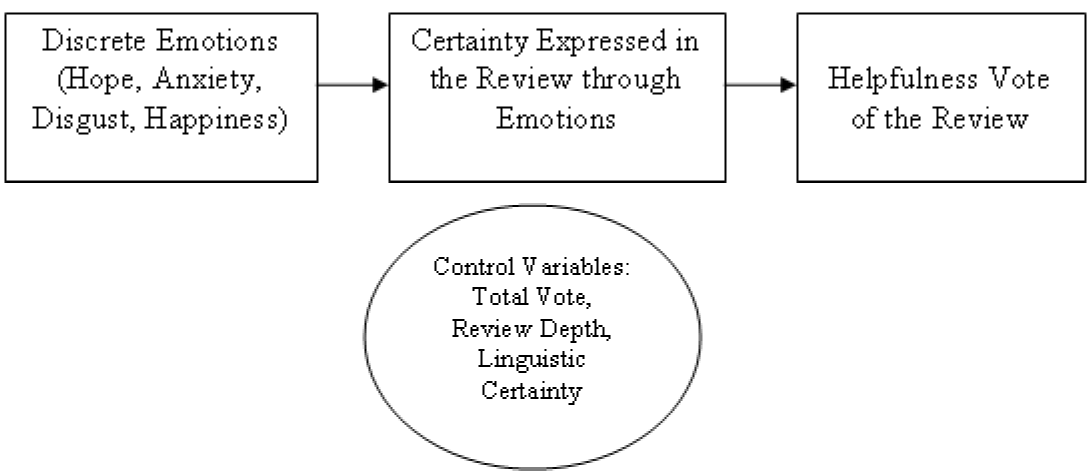

Figure 2b: Conceptual model linking discrete emotions and helpfulness vote

H1: Hope in the review has a negative effect on helpfulness of the review.

H2: Happiness in the review has a positive effect on helpfulness of the review. Happiness in the review will be more helpful than hope in the review.

H3: Anxiety in the review has a negative effect on helpfulness of the review.

H4: Disgust in the review has a positive effect on helpfulness of the review. Disgust in the review will be more helpful than anxiety in the review.

H5: Certainty expressed through these emotions mediates the effect of emotions on the helpfulness vote.

3.3 Research Methodology

We examine how discrete emotions expressed in the reviews affect the helpfulness of a review. We go beyond valence and examine the certainty expressed through these emotions and their effects. We use a field study combined with experiments where we manipulate the independent variables. In study 1 we use real consumer reviews and analyze it by using quantitative text analysis. It enhances generalizability. Next, to pinpoint the source of variation, we turn to lab and experiments. We manipulate our independent variables in Study 2 and 3 and study the effect.

	Methodology used	Purpose
Study 1	Quantitative Text Analysis (Latent Semantic Analysis)	Generalizability
Study 2	Experiments	Analyzing cause and effect in control environment
Study 4	Experiments	Analyzing cause and effect in control environment

Figure 3: Progression of Studies

Variables	
Independent	Discrete Emotion
Dependant	Helpfulness Vote
Control	Linguistic Certainty Argument Quality Rating Total vote Word count

Figure 4: Variables of the Studies

3.4 STUDY 1:

3.4.1 A field study of emotions and helpfulness vote of a product review

The data for this study came from the online reviews available through Amazon.com. This dataset has been used in prior research and is publicly available for research (Blitzer, Dredze & Pereira, 2007). Although the data dates back to 2006, there is no reason to expect that people wrote and reacted differently at that time. We are examining the effect of certainty expressed through emotions on perceived helpfulness. As mentioned before, the effect of certainty on persuasion has been examined for a long time, and therefore, it is believed that the use of this dataset is appropriate for the purpose of this study. Amazon.com provides consumer reviews on the product page along with general information on product and price. For the purpose of this study, we chose to use the reviews on kitchen appliances from the above mentioned dataset since this product domain does not have emotional product attributes. For example, books or movies have emotional product attributes (e.g. a sad movie, or a comic book). Therefore, the emotional content of a review solely comes from consumers' opinions of the product and experiences.

We analyzed 15701 reviews in total. The dependent variable helpfulness was measured by the percentage of people who found a review helpful (Helpfulness %). This was derived by dividing the number of people who found the review helpful by the total votes. The total vote was the number of people who responded to the question "was this reviews helpful to you?"

3.4.2 Coding the reviews

Reviews are automatically coded for happy, hope, anxiety and disgust. Word count, number of causation and certainty words, affect words and social words have been coded by LIWC. The details of these variables coding are described below. Coding of automatic discrete emotions algorithm and its foundation are described in the next sections.

3.4.3 Latent Semantic Analysis

A text analysis algorithm, Latent Semantic Analysis (LSA) (Deerwester, Dumais, Furnas, Landauer & Hashman, 1990), is used for coding every review on four hypothesized discrete emotions (i.e. hope, happy, anxiety, and disgust). We obtained the scores for each of the emotions for each of the product review. LSA extracts concepts hidden in the text data based on word usage and word co-occurance within the documents. It does not have an *a priori* theoretical model. For this algorithm, first a term by document matrix X is constructed from the text data. This matrix holds the frequency of all terms in all documents in a given collection. We used the American National Corpus for this purpose. Then singular value decomposition (SVD) is applied to the term-by-document matrix (X). It represents terms and documents with fewer dimensions and thus creates a new vector space. By retaining a small number of significant factors k, X can be approximated by $X = T_k S_k D_k^T$. Therefore, contextual information is exploited from the document-level word co-occurrences in a large corpus and the information is stored in a relatively low dimensional vector space. Then, emotion categories (i.e. happy, hope, anxiety, and disgust) are constructed by combining the specific word denoting the emotion and its associated synonyms. These words are then converted into a “pseudo-document,” and mapped into the low dimensional vector space. Finally, the emotional score of a given consumer review is determined by converting it in a “pseudo-document” and by computing its distance to all emotion categories pseudo-documents. This algorithm is well established in automatic sentiment analysis and adapted from Bellegarda (2011). The algorithm is depicted in Figure 3 and is implemented in Matlab. Examples of real reviews which have high scores for hope, happiness, disgust or anxiety are presented in Table 1.

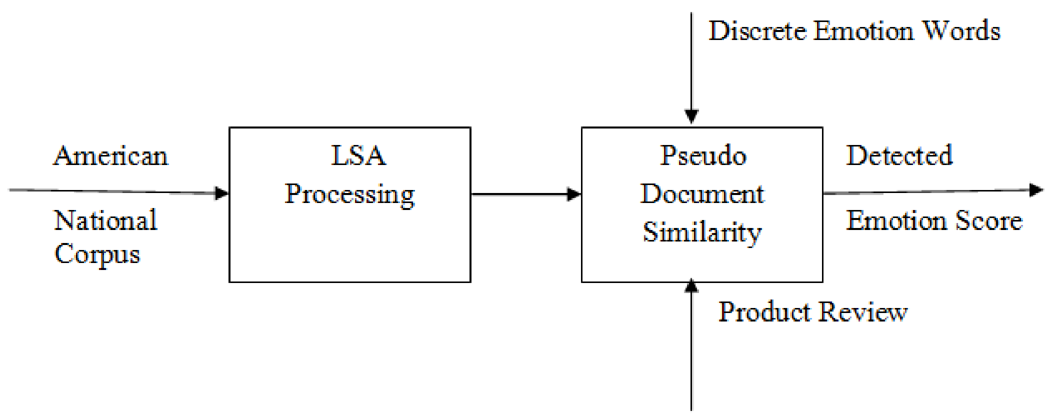

Figure 5: Emotion Analysis using Latent Semantic Analysis

Examples of review containing hope

Example 1: I am replacing the same product that I have used continually for the past nine years or so. It has been an indispensable part of our kitchen all those years and we hope this new one will continue the tradition.

Example 2: This was purchased as a wedding present. I do not yet know what the couple thinks of it but it is what they requested.

Comments: Core relational theme of Hope is "fearing the worst but yearning for the better". In the first example, the reviewer explicitly expresses their hope. In the second one, 'hope' is not explicitly expressed; however, the LSA system has given it a higher score on hope. Implicitly, the reviewer hopes that it will be liked (although he might fear that the couple might not like it).

Examples of review containing Happiness

Example 1: Perfect for New Users

I have never owned a crock pot before, so I was a little apprehensive. I did a lot of research and finally settled on this item because of size, price and shape of the unit. I am extremely happy with the product. It is perfect for a first time user - not too complicated, but has everything you need to make the most basic or more complicated recipes. It did not smell at all on first use (many pots have that reputation). It is very attractive and fits nicely on my countertop. The inner ceramic part is very sturdy and cleans up very easily. I do recommend for first-time users that you purchase one good cookbook (many are carried on Amazon). I purchased several, and my favorite so far is "The Gourmet Slow Cooker" I have tried several recipes and they were all perfect. I am converted to crock-pot cooking!!

Comments: Core relational theme of happiness is "making reasonable progress toward to realization of a goal". The reviewer was apprehensive at first, but became happy when he realized that he achieve his goal after the long effort of researching.

Examples of review containing Disgust

Bits of metal is not what I want with my cheese

At first I was pretty happy with the grater, but after a few days of use I started to notice that I was getting small shavings of metal as well as shredded cheese. I am no longer using it and would not recommend it to anyone.

Comments: Core relational theme of Disgust is 'taking in or being too close to an indigestible object or idea" which is actually expressed in the review. The author was disgusted with the fact that metal pieces got mixed up with the cheese!

Examples of review containing Anxiety

It's less trouble driving to carvels

The machine leaked after we poured in the liquid ingredients. The mix in dispenser did not operate properly, all we put in were sprinkles. The ice cream did not harden enough until about 25 minutes; kids cannot wait that long. We could have driven to the local ice cream store and back by this time. Save your money, buy an old fashion ice cream maker instead at least your kids will get a workout and be occupied at the same time.

Comments: Core relational theme of Anxiety is 'facing an uncertain threat about the outcome". We see in the review that the poster expresses the anxious 25 minutes when he waited and was uncertain about the outcome.

Table 1: Examples of real product reviews

3.4.4 Dependent and control variables

The dependent variable is the measure of helpfulness vote for each of the review. This is expressed in percentage. For example, "5 out of 10 people found the review helpful" is expressed as 0.5. The independent variables are the scores for the each of the emotions (i.e. hope, happy, anxiety, and disgust).

We included the total number of votes on each review's helpfulness (total votes) as a control variable given that the dependent variable is a percentage. Review extremity (measured as the star rating) and its squared value are included as control variables since the literature has shown an inverted U shape relationship of rating with the helpfulness vote (Mudambi & Schuff, 2010). We also control for several content characteristics. Amount of information content of a review or review depth (measured by word count) is included as a control variable. A computer program LIWC (Pennebaker, Booth & Francis, 2007) counted the number of causation (e.g. because, or hence) and certainty words (e.g. always, or definitely) in the review which measure the certainty expressed and quality of the argument respectively (Newman, Pennebaker, Berry & Richards, 2003; Tausczik & Pennebaker, 2010). Some words and expressions signal the presence of certainty information which indicates the degree of the writer's confidence (Rubin, Liddy & Kandoo, 2005). By controlling for the linguistic certainty, we could be more confident of our findings. The use of LIWC is well-established in current consumer research (Berger & Milkman, 2012; Pang & Lee, 2008). Berger and Milkman (2012) studied the effect of discrete emotions on virality of a text. The authors used LIWC to count the affect laden words which indicated overall emotionality of the text and investigated the effect of it. Moreover, the authors manually coded the discrete emotions to see the effect on the virality. Since affective framing regardless of discrete emotions can impact persuasion (Mayer & Tormala, 2010), we also included affect as control variable. We included the variable social as it is well documented in the literature that social influence has impact on persuasion (Cialdini, 2007). LIWC counts the number of social words and it has been demonstrated to detect meaning of social processes and relationship (Tausczik

& Pennebaker, 2010).

3.4.5 Data analysis

We used the Tobit regression to analyze the model because our dependent variable (helpfulness) is censored and has been used in past research in similar contexts (Mudambi & Schuff, 2010). Since Amazon does not indicate the number of persons who read the review, there might be a selection bias in the sample. It is unlikely that all readers of the review voted on helpfulness. This can cause biased estimation of OLS and GLS. Thus estimation through Tobit regression is more appropriate (Mudambi & Schuff, 2010).

The following model is estimated:

$$\text{Helpfulness\%} = \text{happy} + \text{hope} + \text{anxiety} + \text{disgust} + \text{rating} + \text{rating}^2 + \text{vote} + \text{wc} + \text{affect} + \text{social} + \text{certain} + \text{certain}^2 + \text{cause}$$

3.4.6 Findings

The findings are shown in Table 3a and indicate the effects of the predictor variables. The summary statistics of the variables of the model are presented in Table 2. The result (Model 3, Table 3a) shows that expressed anxiety has a negative effect on the helpfulness vote of a review. Moreover, the effect of happiness and disgust are also supported in the hypothesized direction. Happiness and disgust have a positive effect on the helpfulness vote of a review. These findings still hold when we control for information depth, argumentation and linguistic certainty. Linguistic certainty seems to have an inverted U relationship with the dependent variable. However, we did not find support for the effects of hope. Although hope and happy are positive emotions, they are hypothesized to have opposite effects on the helpfulness vote. Except the effect of hope, these findings are consistent with our hypotheses that certainty expressed through discrete emotions drives helpfulness.

	M	SD
Happy	0.179	0.0258
Hope	0.182	0.0253
Disgust	0.153	0.0297
Anxiety	0.157	0.0283
Rating	3.99	1.504
Word count	101.21	91.093
Affect	6.98	4.17
Social	4.39	3.74
Argument	2.525	2.28
Certainty	1.56	1.79

Table 2: Variables' Descriptive Statistics

	Model 1	Model 2	Model 3
Predictors			
Happy	1.477177 ***	1.507947***	0.768670**
	(0.379089)	(0.368562)	(0.363539)
Hope	-0.617435 *	-0.735982**	-0.225259
	(0.375257)	(0.364731)	(0.359076)
Disgust	2.502318***	0.969989*	1.059761**
	(0.540873)	(0.528450)	(0.525086)
Anxiety	-3.832514***	-2.223298***	-1.962205***
	(0.487941)	(0.477457)	(0.471497)
Controls			
Rating		5.774867***	4.679939***
		(0.984318)	(0.973772)
$Rating^2$		-0.308779**	-0.087566
		(0.157480)	(0.155937)
Total Vote		-0.152341***	-0.272648***
		(0.023942)	(0.024102)
Content Controls			
Argument			-0.263032**
			(0.086265)
Information Depth			0.038046***
			(0.002348)
Linguistic Certainty			1.259732***
			(0.199963)
$Certainty^2$			-0.160381***
			(0.024659)
Affect			-0.483496***
			(0.051879)
Social			-0.282382***
			(0.053131)
Log Liklihood (model)	-73270	-72820	-72514

*** Significant at p<0.001, ** Significant at p< 0.05, * Significant at p<0.1

Table 3a : Model Comparison

We also ran other models with different dependant variables. Instead of helpfulness percentage as a dependant variable, we ran the analysis with only total number of helpfulness vote. The result is shown in Table 3b. It can serve as robustness check of our findings because the independent variables are predicting helpfulness of the review. The result shows that the effect o hope, happy, anxiety and disgust are indeed in the hypothesized direction but they were not significant. We believe this is because of the noise in data. Since percentage of helpfulness is more accurate measurement of the helpfulness of the review than the total number of "yes" vote alone, we see an weaker effects of our predictor variable on the helpfulness vote. For example, " 5 out of 10 people found this review helpful" is not same as "5 out of 30 people found this review helpful." Although in both of the cases total number of yes vote is the same, the former one is more helpful than the later one for obvious reason (and therefore percentage is a better measurement of helpfulness). We believe, for this noise in data (when our dependant variable is total number of people of found the review helpful), we found directional support but could not achieve significance.

We also ran the analysis with total number of votes as the dependant variable. It can be argued that if voting "yes" means " I have found the review helpful" and voting "no" means " I have not found this review helpful", then the total number of votes can be regarded as a measure of attention. When we ran this analysis, not surprisingly, the previous hypotheses do not hold. The results seem to indicate that reviews with low ratings gain more attention, so does long reviews. Moreover, hope has a positive effect on attention and disgust has a negative effect on attention. Since this is not our central focus of our research, we did not analyze this in great detail. However, it is interesting to see how the result changes in this case.

Dependant Variables	Number of helpfulness vote	Total number of votes
Predictor variables		
Happy	0.04 (0.047)	0.025 (0.120)
Hope	-0.021 (0.046)	0.574*** (0.119)
Disgust	0.050 (0.068)	-0.592*** (0.174)
Anxiety	-0.097 (0.061)	0.061 (0.156)
Rating	0.615*** (0.125)	-2.960*** (0.322)
Rating^2	-0.037 (0.020)	0.362 (0.052)
Total Vote	0.766 *** (0.033)	Used as DV
Argument	-0.015 (0.011)	0.028 (0.029)
Information Depth	0.006*** (0.0003)	0.020*** (0.001)
Linguistic Certainty	0.056** (0.026)	-0.019 (0.066)
Certainty^2	-0.008** (0.003)	0.006 (0.008)
Affect	-0.033*** (0.007)	-0.079*** (0.017)
Social	-0.041*** (0.007)	0.011 (0.018)

Table 3b : Analysis with other DVs

3.4.7 Discussion

The analysis of real consumer reviews sheds new light on which reviews are perceived to be more helpful than others. Our findings reveal that reviews containing emotion associated with high certainty are perceived to be more helpful. In general, reviews containing emotion associated with uncertainty are less helpful. This result still holds when we control for amount of information and certainty expressed through linguistics. Particularly, our findings show that reviews containing disgust and happy have a positive effect and reviews containing anxiety have a negative effect on perceived helpfulness. To directly test the process behind these results and the effects of these discrete emotions, we used some experiments.

3.5 STUDY 2:

3.5.1 Negative Emotions and Helpfulness Vote

We study the effects of negative emotions (i.e. anxiety and disgust) on the helpfulness votes. First, we want to directly test the causal effects of these discrete emotions on the helpfulness votes. The field study provided evidence for the negative emotions: anxiety and disgust. Here we manipulate the emotions in a more controlled setting and study the effects. We also test the mechanism behind these effects. We investigate if the certainty (or uncertainty) expressed through these emotions indeed mediates the process.

Data were collected by ways of an online survey of US residents (via Mechanical Turk or MT). Recent consumer studies (Goodman and Malkoc 2012b; Raghubir, Morwitz, and Santana 2012) have used MT and it is regarded as a valuable source for data collection (Goodman, Cryder, and Cheema 2012a). To ensure quality, we only included participants who had more than a 90% approval rate. We asked participants to read a product review and then indicate if they found the review helpful. The scale was adapted from the review usefulness scale used in Sen and Lerman (2007). We manipulated the product review with discrete emotions (i.e. anxiety and disgust).These mock reviews were adapted from real reviews which had high score on these discrete emotions on the Latent Semantic Analysis (LSA) system. We also included a control condition which did not express any emotion. The contents of the messages were kept the same for all the conditions. The emotions expressed were tied to the product (i.e. "I am anxious about the new blender performance" or "disgusting performance"). The central aspect of the hypotheses is that emotions can be associated with cognitive appraisals. A certain emotion is evoked according to the appraisal or core relational theme. For example, hope arises when the situation is uncertain and positive. Therefore mere presence of emotional words may not represent the emotional perspective taken by the poster. Consistent with other emotional framing research (Nabi, 2003), a context is created according to the emotion. In both of the emotions stimuli, consumers had a bad experience with the previous model, and they have not used the newer model and newer model has got some good reviews. In the disgust conditions, the consumer was disgusted with the older model performance and do not want to try the product again. In the anxiety condition, the consumer had the same experience and is apprehensive about the new blender performance. The manipulation check was successful in each study stimuli and confirmed that these expressed anxiety and disgust, but not any other emotion. To rule out the alternative explanation that the manipulation changed the mood state of the participants and that contributed to the effect, we ran a confound check. The result confirmed that the manipulation did not alter participant's mood state[1]. For example, the participants in the anxiety condition did not feel more anxious ($M=2.53$ than the participants in the control condition ($M= 2.83$; $F(1, 58)= 0.456$, $p=0.502$ after reading the stimuli. Also, the participants in the disgust condition did not feel more disgust ($M=2.36$ than the participants in the control condition ($M= 2.47$; $F(1, 58) = 0.052$, $p=0.820$ after reading the stimuli.

3.5.2 Study

Four hundred and fifty participants were compensated $.25 to complete the study. All participants (43% male) were US residents with an average age of 33.6 years. They either read an anxiety, disgust or control version of a product review (see Appendix). The participants then rated how helpful the review was. We also measured the extent of certainty that participants thought the reviewer had in the review about his experiences. This scale was adapted from Tiedens and Linton (2001).

3.5.3 Anxiety Findings

The participants reported that they were less likely to find a review helpful when they were in the anxiety condition than when they were in control condition. This was driven by the decreased in certainty. Participants found a review less helpful if they were in anxiety condition (M = 3.30) as opposed to the control one (M = 3.74; F (1,298) = 4.109, p<0.05). Moreover, the control condition (M = 3.584) evoked more certainty than the anxiety condition (M = 3.04; F (1, 298) = 7.884, p< 0.05). As predicted, this decrease in certainty mediated the effect of the anxiety condition on helpfulness. The Sobel mediation test confirmed that certainty mediated the effect of anxiety condition on helpfulness (Sobel z = 2.76, p<0.05). Since bootstrap method is known to be superior to other methods (Hayes 2009) of mediation testing, we also performed a bootstrap analysis. Bootstrapping involves repeated extraction of samples from the data set (in this case 5000 samples were used). The 95% confidence interval for the effect size of the indirect path through certainty was 0.06 to 0.39 and did not include zero, indicating that it is a significant mediator.

3.5.4 Disgust findings

The participants reported that they were more likely to find a review helpful when they were in the disgust condition than when they were in control condition. This was driven by the increase in certainty. Participants found a review more helpful if they were in disgust condition (M = 3.74) as opposed to the control one (M = 3.30; F (1,298) = 10.07, p<0.05). Moreover, the disgust condition (M = 4.79) evoked more certainty than the control condition (M = 3.58; F (1, 298) = 35.12, p< 0.01). As predicted, this increase in certainty mediated the effect of the anxiety condition on helpfulness. The Sobel mediation test confirmed that certainty mediated the effect of disgust condition on helpfulness (Sobel z = 5.67, p<0.01). Bootstrap analysis shows that the 95% confidence interval for the effect size of the indirect path through certainty was 0.67 to 1.37 and did not include zero, indicating that it is a significant mediator.

Moreover, comparison between disgust and anxiety condition shows that disgust condition (M= 4.45) found the review more helpful than anxiety condition (M=3.30; F(1,298)= 22.67, p< 0.01; . Here also, the certainty plays the mediating role in the relationship. The Sobel mediation test confirmed that certainty mediated the effect of disgust condition on helpfulness (Sobel z = 8.1246, p<0.01). Bootstrap analysis shows that the 95% confidence interval for the effect size of the indirect path through certainty was 1.09 to 1.80 and did not include zero, indicating that it is a significant mediator.

3.5.5 Discussion of Study 2 findings

The experimental results support our hypotheses related to negative emotions. It also reinforces the findings obtained in our field study. These results were found for both certain and uncertain discrete emotions. The reviews with certainty related negative emotions are perceived to be more helpful than uncertainty related negative emotions. The findings also support the hypothesized mediation process. Certainty mediated the impact of discrete emotions on perceived helpfulness.

3.6 STUDY 3:

3.6.1 Positive Emotions and Helpfulness Vote

We study the effects of positive emotions (i.e. hope and happy) on the helpfulness votes. The field study provided evidence for the positive emotions: happy. However, we did not get support for hope. Here, we directly manipulate the emotions in a controlled setting and investigate the effects.

The manipulation check was successful in each study stimuli and confirmed that expressed hope and happy, but not any other emotion. To rule out the alternative explanation that the manipulation changed the mood state of the participants and that contributed to the effect, we ran a confound check. The result confirmed that the manipulation did not alter participant's mood state**1**. For example, the participants in the happy condition did not feel happier (M= 4.89) than the participants in the control condition (M= 4.51; F (1, 58) = 1.207, p=0.277) after reading the stimuli. Also, the participants in the hope condition did not feel more hopeful (M=2.86 than the participants in the control condition (M= 2.70; F (1, 58) = 0.134, p=0.715 after reading the stimuli.

3.6.2 Study

Four hundred and thirty participants were compensated $.25 to complete the study. All participants (46% male) were US residents with an average age of 32.5 years. They either read a hope, happy or control version of a product review (see Appendix).

3.6.3 Hope Findings

The participants reported that they were less likely to find a review helpful when they were in the hope condition than when they were in control condition. This was driven by the decreased in certainty. Participants found a review less helpful if they were in hope condition (M = 4.44) as opposed to the control one (M = 5.01; F (1, 277) = 8.308, p<0.01). Moreover, the control condition (M = 6.02) evoked more certainty than the hope condition (M = 5.17; F (1, 258) = 25.351, p< 0.01). As predicted, this decrease in certainty mediated the effect of the hope condition on helpfulness. The Sobel mediation test confirmed that certainty mediated the effect of anxiety condition on helpfulness (Sobel z = -4.75, p<0.001). Bootstrap analysis shows that the 95% confidence interval for the effect size of the indirect path through certainty was -0.9857 to -.3956 and did not include zero, indicating that it is a significant mediator.

3.6.4 Happy Findings

The participants reported that they were more likely to find a review helpful when they were in the happy condition than when they were in control condition. Participants found a review more helpful if they were in happy condition (M = 5.22) as opposed to the control one (M = 5.01). Although this effect was directionally supported, the difference was not significant. However, comparison between happy and hope condition shows that happy condition (M= 5.22) found the review more helpful than hope condition (M=4.44; F(1,287)= 17.35, p< 0.001); Moreover, the happy condition (M = 6.09) evoked more certainty than the hope condition (M = 5.17; F (1, 272) = 37.33, p< 0.001). Here also, the certainty plays the mediating role in the relationship. The Sobel mediation test confirmed that certainty mediated the effect of disgust condition on helpfulness (Sobel z = 5.59, p<0.01). Bootstrap analysis shows that the 95% confidence interval for the effect size of the indirect path through certainty was 0.52 to 1.05 and did not include zero, indicating that it is a significant mediator.

3.6.5 Discussion of Study 3 findings

The experimental results support our hypotheses related to positive emotions. The reviews with certainty related positive emotions are perceived to be more helpful than uncertainty related negative emotions. The findings also support the hypothesized mediation process. Certainty mediated the impact of discrete emotions on perceived helpfulness. Now, if certainty is mediating this process, if we increase certainty with words in uncertain emotions stimuli, the effect of uncertainty (less helpfulness) should diminish. To test these we ran another set of studies where we alter the uncertainty emotions stimuli (anxiety and hope) by inserting sentences that express certainty about the whole situation (i. e. "I am pretty sure that newer model will not be good either" or "I am confident that it will be a great addition to your kitchen" .

One hundred and fifty participants read an anxiety version with certainty (hereafter anxiety-certain condition) of the product review. The participants in the anxiety-certain condition are more likely to find a review more helpful (M=3.77) than the participants in the anxiety condition (M=3.30; $F(1, 298)$= 4.30, $p<0.05$). The anxiety-certain condition evoked more certainty (M=4.21) than the anxiety condition (M=3.04; $F(1,298)$= 39.94, $p<$ 0.001). Lastly, this increase in certainty mediated the process. The Sobel mediation test confirmed that certainty mediated the effect of disgust condition on helpfulness (Sobel z = 5.54, p<0.01). Bootstrap analysis shows that the 95% confidence interval for the effect size of the indirect path through certainty was 0.67 to 1.34 and did not include zero, indicating that it is a significant mediator.

One hundred and fifty participants read a hope version (with certainty words) (hereafter hope-certain condition) of the product review. The participants in the hope-certain condition are more likely to find a review more helpful (M=5.05) than the participants in the anxiety condition (M=4.44; F(1, 287)= 9.925, p<0.01). The hope-certain condition evoked more certainty (M=5.62) than the hope condition (M=5.17; F (1,272)= 7.54, p< 0.001). Lastly, this increase in certainty mediated the process. The Sobel mediation test confirmed that certainty mediated the process (Sobel z = 2.70, p<0.01). Bootstrap analysis shows that the 95% confidence interval for the effect size of the indirect path through certainty was 0.11 to 0.68 and did not include zero, indicating that it is a significant mediator.

These studies further support our hypotheses and the mediation process. The studies found support for the notion that reviews containing uncertainty emotions are perceived to be less helpful. The studies also provide evidence for the robustness of the valence on this effect. Moreover, the decrease in certainty actually mediates the process. It also provides strong support for our hypotheses in the sense that, increasing emotional content does not necessarily increase helpfulness. For example, increasing hope or anxiety does not increase perceived helpfulness.

3.7 General Discussion

Increasingly, customers are using online information sources for making a decision prior to purchase. Along with other information, customers are particularly interested in other customer's reviews since these reviews are seen to be more credible than even the experts' (Senecal and Nantel 2004). In this situation, some reviews are perceived to be more helpful than others making it very important to examine what makes a review helpful. Some studies examined the content characteristics of a product review (Duan et al. 2009; Mudambi and Schuff 2010). These studies mainly focused on the valence (positive or negative) of the product review along with volume, and product type, among others. However, research documented distinct effects of discrete emotions on the outcome variable (Dillard 1993; Nabi 2003) despite the fact that these emotions can be of the same valence. Clearly, the positive/negative dimension cannot capture all the dynamics present in these complex situations. Moreover, it is very likely that the customer reviews contain varied emotional content since customers express their consumption experiences which may range from sadness, joy to anger and disgust. However, little attention was paid to discrete emotion's effects on the perceived helpfulness of the review.

This article examines the role of discrete emotions on the perceived helpfulness of a review. In so doing, we combine an analysis from a field study with those from a series of controlled experiments. We documented the emotional content characteristics along with its mediation process. Departing from previous studies of examining the valence as one of the content characteristics of helpful customer reviews, we focused on discrete emotions. Building on cognitive appraisal theory, we hypothesized that reviews containing emotions associated with certainty are perceived to be more helpful and that reviews containing emotions associated with uncertainty are perceived to be less helpful. These two types of emotions (certainty and uncertainty) come from cognitive appraisal theory which groups emotions according to several appraisals or dimensions and provide the answer to why a certain emotion was induced in a situation. Therefore, the emotions actually express the perspective taken by the reviewer. Moreover, the literature has consistently supported for the notion that information with certainty is perceived to be more influential (Price & Stone 2004). In a discrete emotion context, indeed in a series of studies we found that certainty emotions are more helpful and uncertainty emotions are less helpful. For generalization, we included certain and uncertain emotions with both positive and negative valences. It suggests that emotions of the same valence may have different impacts. Moreover, certainty mediates this process.

In the field study, real reviews from Amazon were examined. We found support for our hypotheses for two positive emotions even after controlling for information content and linguistic certainty. In a series of controlled experiments, we manipulated the discrete emotions. Across experiments, our result consistently showed that certainty emotions are perceived to be more helpful. We also examined the mediation process and found that certainty was the key variable which is mediating the relationships between discrete emotions and helpfulness. It is interesting to see that more of an emotion does not necessarily lead to more helpfulness rating. For example, more of hope and anxiety do not increase helpfulness. This also rules out an alternative explanation that more of an emotion was causing this result.

3.8 Theoretical implications

Our findings expand the current understandings of the role of discrete emotions. There is an urgency to examine the role discrete emotions beyond the positive/negative valence dimension (Nabi 2003) since emotions of the same valence may have different effects on the outcome variable. This study contributes to this area of research by demonstrating that although hope and happy (or anxiety and disgust) are of same valence, they have different effects on the perceived helpfulness of the reviews. Many of the discrete emotion studies focus on incidental and integral emotional mood (Winterich & Haws, 2011) and their effects. Instead of focusing on mood, this research focuses on discrete emotions as a source of information. Therefore, it contributes to the growing literature on the framing effects of discrete emotions. This research stream suggests that the effect of content depends on how the information is presented in terms of emotions. The same piece of information may have different impacts if it is framed with different discrete emotions.

This research also contributes to the certainty and persuasion literature. The literature has long documented the robust effects of certainty and confidence in influencing information seeking and adoption situations. Information with certainty is viewed to be more persuasive (Sneizek & Van Swol, 2001). However, given that some emotions express higher certainty than others, it is important to study the effects of certainty expressed through discrete emotions. This research fills the void by demonstrating the effects of certainty expressed through emotions in an opinion seeking situation.

Moreover, this topic is very relevant and important specially now, when people are increasingly relying on others' reviews or comments for consumption. However, these online data are huge and often involves text data. These text data open the opportunity for more research since it is a door to customers' minds. There is a major need for quantitative content analysis to better understand online customer behavior. As echoed in various studies, it is often difficult to code data. In this research, we applied a text analysis method to code the emotions in the product review data. This method can be used in other contexts to extract emotions from a text. By adopting the established method from computer science literature to a marketing context, we contribute to the emerging area of text analysis in marketing.

3.9 Marketing implications

These findings have important implications for marketing managers. Since some discrete emotions are more helpful than others, when emphasizing positive buying experiences in an advertisement or online contents, these finding will provide useful guidance to managers. In a manufacturer's website, the positive reviews from customers are often displayed. High certainty related emotions in a review will more likely help the manufacturer. Similarly, when providing any content (either in advertisement or information) related to consumption experiences, positive certainty related emotions should be used.

Moreover, there is great need today for managing online sentiments. The negative comments can eventually lead to a negative opinion about the product in general and thus may affect potential sales. Therefore, it is very important to address the certainty related negative emotions so that potential customers are not influenced. Every effort has to be made to eliminate the cause of these negative emotions. It might not be humanly possible to address all concerns and therefore, managers should be very vigilant about the certainty related negative emotions.

3.10 Limitations and Future Research

Like any research, the current study is not without limitations. First, the field study used a small dataset. This might be the reason for the non-significance of the two negative emotions. Also, the dataset dated back to 2005. Although there is no reason to believe that the findings would be any different in a newer dataset, repeating the study might be useful. Including reviewer related variables in the model can be a promising future extension of this work. There is also some need for research in finding content characteristics that play a moderating role on the effects found in this research. Such moderation approach will broaden the current understanding of the customer reviews and their impacts. Future research might also examine if the product and service related customer reviews would behave in the same way. For example, the effect might not hold for customer reviews on vacation places and tours. Since the choice of this vastly depends on interpersonal tastes, potential customers might not find a review more or less helpful depending on their emotions.

Future studies might also examine the effects of discrete emotions on other outcome variables such as product sales. The literature examined the effects of valence and volume on product sales (Liu, 2006). It is important to test if the emotions expressed in the reviews would also affect sales. Further research is also needed for other discrete emotions associated with cognitive appraisals. Among these, fairness appraisal seems to be very promising. It is intuitive that high fairness appraisal might be more helpful in an opinion seeking situation. Self responsibility appraisal might also be very interesting to look at. Lastly, the text mining approach is still in its infancy. Developing and validating text mining techniques for marketing contexts is an important need.

3.11 Study Stimuli

High Happy: I am replacing my blender with the same brand blender that I have used continually for the past nine years or so. I am extremely happy with this blender! It has been an indispensable part of our kitchen all those years. It is not too complicated, but has everything you need. SO happy I bought it! It would be a great addition to your kitchen.

Low Happy I am replacing my blender with the same brand blender that I have used continually for the past nine years or so. It has been an indispensable part of our kitchen all those years. It was not too complicated, but had everything you need. The new blender will serve my purpose as before. It would be a great addition to your kitchen.

High Disgust: I bought this ice cream maker for my little ones. At first, everything seemed ok. But after a few days of use I started to notice that I was getting small shavings of metal in my ice cream! It is totally disgusting. Crank and cast-iron gears rub against each other during use that leaves sharp metal shavings in the ice cream! I am no longer using it.

Low Disgust: I bought this ice cream maker for my little ones. At first, everything seemed ok. But the ice cream took about 30 minutes to get hardened. There were also problems with the crank and the gears…loud noise. We could have driven to the local ice cream store by the time the ice cream hardened. I am no longer using it.

High Hope: I am replacing my blender with the same brand blender that I have used continually for the past nine years or so. It has been an indispensable part of our kitchen all those years. It was not too complicated, but had everything you need. I am hopeful about the new blender and hope this new one will continue the tradition.

Low Hope: I am replacing my blender with the same brand blender that I have used continually for the past nine years or so. It has been an indispensable part of our kitchen all those years. It was not too complicated, but had everything you need. The new blender will serve my purpose as before. It would be a great addition to your kitchen.

High Anxiety: I bought this ice cream maker for my little ones. At first, everything seemed ok. But the ice cream didn't harden enough until about 30 minutes. Anxious moments! We were even more anxious because crank and cast iron gears were making noise. We could have driven to the local ice cream store by the time the ice cream hardened. I am no longer using it.

Low Anxiety: I bought this ice cream maker for my little ones. At first, everything seemed ok. But the ice cream took about 30 minutes to get hardened. There were also problems with the crank and the gears…loud noise. We could have driven to the local ice cream store by the time the ice cream hardened. I am no longer using it.

CHAPTER 4

Essay 2

Exploring Conceptual Differences between Positive and Negative Reviews and its Effects on Perceived Helpfulness.

Abstract

The Web has fundamentally changed the way that customers express their opinions. They can now post reviews of products at merchant sites and express their views on almost anything in Internet forums, discussion groups, and blogs. There is a vast amount of user generated content reviewing a product or service. From a marketer viewpoint, it is important to know what is in the reviews because this is an open door to the customer minds. Although literature has focused on the antecedents and consequences of word of mouth, the content of online word of mouth has been largely ignored (some exceptions, Kim, Lee & Ragas, 2011; Cambell et al., 2011). In this part of the dissertation, the content of online word of mouth has been explored. To explore the thematic differences between positive and negative review, an automatic text mining technique, latent Semantic Analysis has been used. It should be noted that LSA with different variation was also used in the previous research. It was found out that negative reviews tend to report more service related failure than positive reviews. Next, I explore the types of topics that are found to be more helpful than others. More specifically, the effect of topics on the helpfulness is investigated. This research sheds light on that by first exploring the topics of positive and negative reviews and then examining the effect of these topics on the perceived helpfulness.

4.1 Introduction

The Web has fundamentally changed the way customers express their opinions. They can now post reviews of products at merchant sites and express their views on almost anything in Internet forums, discussion groups, and blogs. This online word-of-mouth behavior represents new and measurable sources of information for marketing intelligence. Techniques are now being developed to exploit these sources to help companies and individuals to gain such information effectively and easily.

There is a vast amount of user generated content reviewing a product or service. From a marketer viewpoint, it is important to know what is in the reviews because this is an open door to the customer minds. In the pre internet era, it was very difficult to track and measure the consequences of word of mouth since most of these opinions were expressed verbally and to limited number of people. However, with the change in the way of expressing opinions, word of mouth tracking has been easier. Marketers are now able to see what is being said in the customer reviews, blogs, posts, virtual brand communities etc. However, a vast majority of literature has mostly focused on the antecedents and consequences of word of mouth. It has been shown that word of mouth can affect product sales and there are number of variables that affect the motives of word of mouth. With some exceptions, the content of online word of mouth has been largely ignored (Kim, Lee & Ragas, 2011; Cambell et al., 2011). In this part of the dissertation, the content of online word of mouth has been explored. Generally speaking, the positive reviews contain the good aspects of an offering and the negative reviews contain the aspects which the customer didn't like. Prior research has shown that negative reviews have stronger effect on sales than the positive reviews (Duan, Gu & Whinston, 2008). However, there is a little research on the content of positive and negative reviews. More specifically, do the themes of positive and negative reviews differ more than the valence? If so, in what respect? In this exploratory research, I try to explore these aspects.

As mentioned before, the availability of word of mouth data has been increased exponentially with the rise of web usage. This advantage comes with another obstacle. This huge unstructured data needs to be analyzed in a systematic fashion which requires rigorous application of sophisticated mathematical techniques. To explore the thematic differences between positive and negative review, an automatic text mining technique, latent Semantic Analysis has been used. It should be noted that LSA with different variation was also used in the first essay. Although the algorithm to extract emotional content is different from exploring the topics in the content, the basic premise on which the technique is established is the same. It leverages on hidden meaning of the text. The result of this research shows that negative reviews tend to report more service related failure than positive reviews. Next, different topics and its relation to helpfulness vote are examined. More specifically, the previous essay examines the effect of emotional content on the helpfulness of the review. Here, the effect of review topics in on the helpfulness is investigated. People write about various aspects of the product and services. However, all the topics might not be of interest in terms of making purchase decision to a potential customer. This research sheds light on that by first exploring the topics of positive and negative reviews and then examining the effect of these topics on the perceived helpfulness. Since helpfulness vote contribute to the product sale (Chen et al., 2008), examining the driving factors of helpfulness vote is very important. Moreover, by knowing the factors discussed in positive and negative reviews, marketing managers will be better able to adapt their products according to the need of the customers. Moreover, the topics also reveal the important factors that are considered by the customers. This information is of great importance to build the brand strength.

4.2 Literature Review

Electronic Word of Mouth (eWOM hereafter) is defined as the "any positive or negative statement made by the potential, actual or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al., 2004, p39). The interest in online word of mouth has increased in recent years because of its ability to affect several key marketing variables. This effect of eWOM has been investigated in many empirical studies. For example, Chevalier and Mayzlin (2006) examined the effect of eWOM on the product sales and this effect is also echoed in other studies such as Goldsmith and Horowitz (2006). De Bruyn and Lillien (2008) examined the customer decision making process and how eWOM affect this process. Lee, Rodgers and Kim (2009) investigated the attitude towards brands and websites expressed in electronic word of mouth.

4.2.1 Motivation to Engage in Word of Mouth

While one stream of research in word of mouth investigates the consequences of word of mouth, the other stream deals with the antecedents and the motives of WOM. There is a rich literature that has examined the motive of customers as to why they share word of mouth (Dichter, 1966; Sundaram, Mitra & Webster, 1998). Traditionally content analysis or surveys have been used to explore the motives of the customer for providing eWOM. Prior research has demonstrated that there are mainly four dimensions for which customers contribute to word of mouth. Dichter (1966) showed in traditional or offline WOM that, product involvement, self involvement, other involvement and message involvement are the motives of word of mouth. Later, Engel et al. (1993) confirmed the findings. Sundaram et al. (1998) study echoed the same dimensions except the message involvement. Dellarocas and Naryan (2006) developed a theoretical model of customer motives based on the theory of public good in economics. The authors posit that 1. Product involvement 2. Message involvement 3. Self involvement 4. concern for others 5. Social benefits are the main reasons why customers engage in word of mouth. Sweeney et al. (2012) characterize word of mouth to contain three factors namely cognitive content (reflects the nature of WOM content, i.e how informative, reliable and clear), Richness of WOM (reflects the extent to which the message is vivid, elaborate and reinforcing) and lastly, Strength of Delivery (reflects the way the message is delivered , i.e how strongly the message is delivered). Later, Soutar, Sweeney and Mazzarole (2009) grouped the positive WOM message senders into four distinct groups (namely involved, uninvolved, realistic, and emotional senders). The groups varied in motivation, situational, and demographic characteristics. The study highlighted that there are different types of WOM communication that vary across given message. There were tow key differentiators that varied across these four groups and these are service interaction and personal contribution to the communication. In another study, three most frequent reasons for sharing word of moth was revealed: firstly, if someone is asked about a definite service, secondly a coincidental conversation and thirdly an intense satisfaction or dissatisfaction about a service provider. The authors also found out that WOM usually contain two types of content, Quality oriented and Price and Value oriented (Gangold, Miller & Brockway, 1999). In a recent meta-analysis, it has been demonstrated that satisfaction, loyalty, quality, commitment, trust and perceived value are the antecedents of word of mouth where valence of the WOM, types of product and WOM incidence act as moderators (Matos & Rossi, 2008).

Therefore, there is an ample research on what motives to people to engage in word of mouth. However, motivation only cannot infer the content of WOM. For example, a customer might be very dissatisfied with a service provided by a company. Although, dissatisfaction is a cause to engage in WOM, nothing can be inferred about what actually made this customer dissatisfied. This piece of information might help marketing managers to remove that unwanted phenomenon from the service. Therefore, analysis of the content of WOM is extremely important.

4.2.2 Online Word of Mouth

The motives in the context of Electronic word of mouth (eWOM) have also been examined (Hennig-Thurau et al., 2004). The authors found that 1. Venting negative feelings 2. Positive Self enhancement 3. Concern for other Customers and Helping the company 4. Social benefits and 5. Economic incentives are the motivation for customers to be involved in online word of mouth. Recently, Berger and Iyengar (2012) demonstrate that conversation channel shape what is discussed. Specifically, in online posts or text (where you have to think what you are going to write), more interesting products (have something unique/special to talk about) are discussed about more than boring ones. In channels where conversations are expected to occur more continuously (face-to-face or on the phone), interesting products might not be the focus of discussion.

The message characteristics of eWOM have also been investigated. Many of the studies measured eWOM on the basis of frequency counts or volume (Chevalier & Mayzlin 2006; Liu, 2006). This has let to mixed results and thus other message characteristics should be carefully examined (Sweeney, Soutar & Mazzrol, 2012). eWOM's valence (Basuroy, Chatterjee & Ravid, 2003; Chevalier & Mayzlin, 2006; Duan, Gu & Whinston, 2008; Liu 2006), dispersion (Godes & Mayzlin, 2004) have also got attention in many studies. The rational and emotional dimensions of the message have been looked at (Allsop et al., 2007) . Words and language style have also been examined in some studies (Gabbott & Hogg, 2000). Moreover, message provider characteristics, such as reputation (Hu, Liu & Zhang 2008), experience (Bone, 1995), and need for uniqueness (Cheema & Kaikati 2010) as well as message recipient characteristics, such as expertise (Bansal & Voyer, 2000); situational and product characteristics (Hogan, Lemon & Libai 2004) have also been the focus of many studies.

Overall, there is an ample research on the antecedents and consequences of WOM and also eWOM . These motives provide us some insight about the content of the word of mouth (please refer to Table 2.1 for key references). However, one aspect of the eWOM is scarce in the eWOM research. The content or topics of the reviews have not been examined in great detail with some exceptions (Campbell et al., 2011; Lee, Kim & Ragas, 2011). For example, Lee et al. (2011) studied "what is In " the reviews rather than what motivated to write the review. The authors found differences in review length and quality in experience and search goods.

Study	Content	Motives
Gangold, Miller & Brockway, 1999	Quality Perceived Value	
Hennig-Thurau et al., 2004	Venting negative feelings Positive Self enhancement Concern for other Customers and Helping the company Social benefits Economic incentives	
Dellarocas and Naryan (2006)		Product involvement Message involvement Self involvement concern for others Social benefits
Sweeney et al. (2012)	Cognitive content Richness of WOM Strength of Delivery	
Campbell et al. (2011a)	Emotive Conceptual Collaborative Oppositely	

Table 4 : Important Studies Relating to WOM Content and Motives

Tucker (2011) content analyzed yelp reviews and discovered some key characteristics of the reviews. According to the author, the reviews can be in general classified to three categories: cool, funny and useful. In these reviews service quality, atmosphere of a restaurant and price seemed to be important topics of the reviews. Campbell et al. (2011a) based their study on a large set of customer conversations about a two customer generated ads uploaded to Youtube. Sometimes customers become the brand ambassador and make their own ad on the product. Due to the free video platforms like youtube, these ads can be uploaded there. Many other customers see this video and start to talk about the product and ad. The authors developed a typology of these reactions to these ads along emotive/conceptual and collaborative/ oppositely dimensions. In a different study Campbell et al. (2011b) uncovered how customer's comments reflect each brand and ads For example: comments on Ipod dance advertisement was reflected by the words 1. ipod cool, song, Gabrealtvs, lol, 2. Mac-PC ad was by Unofficial , Song , Young folks, 3. Starbucks coffee by money, people, kid, starving 4. Think Australia people, funny love. Therefore, by content analyzing the comments, the perception about the ad or the brand can be inferred. This is very important piece of information given that, this information provides access to customers mind and perception.

The present study takes this direction by exploring what is in the positive and negative reviews. In this attempt, first an in depth content analysis (by extracting common themes in the review) is performed to see the similarities and differences between positive and negative eWOM. Later, the relationship between these topics and perception of helpfulness of these contents to other potential customers in their decision making process is examined. As mentioned in the previous research that in a website like

Amazon, a product contains thousand of reviews and each review can be rated as helpful or not by the readers of the reviews. Like before, this number of helpfulness vote has been taken as the measure of perceived helpfulness of that review. Along this line, Cao, Duan and Gan (2011) uncovered the factors in customer's reviews and their effect on the perceived helpfulness. However, the authors didn't focus on topics discussed in the review. In contrast, the present study focuses on the topics or concepts expressed in the reviews by using Latent Semantic Analysis followed by a factor analysis after a manual inspection of the terms associated with a concept. After that, the relation between these concepts and helpfulness vote was explored.

To carry out this study, real reviews from Amazon.com were collected and content analyzed by Latent Semantic Analysis. Text mining techniques are being used in Marketing and have a lot of potential to be used by market researcher to obtain a Market-Structure Surveillance (brand comparison in a market) and other relevant information (Netzer, Feldman, Goldenburg & Fresko, 2012). The mathematical background of the technique used in this study is discussed in the subsequent sections.

4.2.3 Latent Semantic Analysis: the Background

Latent semantic analysis (Lauder & Duamais, 1997) allows for extraction of concepts hidden in text data and holds great promise for free text analysis, as it allows for identification of key common themes in a collection of documents without an a priori theoretical model, based solely on word usage within the documents. Customer reviews are likely to have common topics about a specific product. Latent semantic factors reveal these common themes/topics of the reviews by relying on common word patterns.

Some mathematical details (singular value decomposition, TF-IDF, factor rotation) on which LSA is based are presented in the next.

4.2.4 Singular Value Decomposition. The mathematics of LSA are based on a matrix operation called singular value decomposition (SVD), applied to a term-by-document matrix holding the frequency of use of all terms in all documents in a given collection. Given a $t \times d$ matrix X of terms by documents containing raw or weighted term frequencies, with rank $(X) = r < \min(t,d)$, the SVD of X is given by $X = TSD^T$, where T is the $t \times r$ matrix of eigenvectors of the square symmetric matrix of term covariances XX^T, D is the $d \times r$ matrix of eigenvectors of the square symmetric matrix of document covariances XTX, and S is an $r \times r$ diagonal matrix containing the square roots of eigenvalues (called singular values) of both XX^T and X^TX. Then, TS are the factor loadings for terms and DS are the factor loadings for documents. Retaining a small number of significant factors k, X can be represented by its least squares approximation = $T_kS_kD_k^T$.

4.2.5 Inverse Document Frequency (TF-IDF) Transformation: Inverse document frequency transformation, commonly referred to as TF-IDF, is a traditional approach to term-frequency weighting (Han & Kamber 2006). As a part of the TF-IDF transformation, the raw term frequencies are replaced by the product $w_{ij} = tf_{ij} * idf_i$, where $idf_i = \log2(N/n_i) + 1$, N is the number of documents in the collection, tf_{ij} is the raw term frequency of term i in document j, n_i is the term frequency of term i in the entire collection of documents, and the inverse document frequency (IDF) idf_i serves as a metric of rarity of term i in the entire collection of documents. Such transformation promotes the occurrence of rare terms and discounts the influence of more common non-stopwords such as “information” or “system.” After weighting, the term frequencies are typically also normalized so that the sum of squared transformed frequencies of all term occurrences within each document is equal to one .

A number of alternative term frequency transformations have been proposed in the literature. Some of them, notably the log-entropy transformation (Lauder & Duamais, 1997), have been found to outperform TF-IDF for purposes of information retrieval and document classification. For purposes of document summarization, however, one may want to try more than one transformation to ensure interpretative consistency.

4.2.6 Factor Rotations. Rotations of loadings can be performed in a number of ways. One way would be to first rotate the term loadings $L_T = T_kS_k$ into L_TM, by multiplying them by a rotation matrix M according to some term structure simplification criterion and then reciprocate with the rotation of the document loadings matrix $L_D = D_kS_k$ into L_DM. A second way to perform loading rotations would be to first rotate the document loadings L_D and then reciprocate with the rotation of L_T. A third way would be to implement a matching rotation technique that combines L_T and L_D, for we apply varimax. rotations on the term factor loadings alone. The rationale behind this choice is that a simpler term structure will facilitate factor interpretation in a more straightforward manner than a simpler document structure. The same rotations are subsequently applied to the document structure so that both terms and documents maintain the same factor space representation.

4.3 Methodology

The analysis begins by compiling the list of all terms used in all the reviews. Therefore it is a huge matrix which consist of all the terms (words) used in all the reviews and their respective frequency in each of the reviews. For example if only 5 reviews ae considered, there might be 250 unique words used in all the reviews. Then a matrix is constructed with a dimension of 250 X 5. So each row will contain the frequency of one word in each of the 5 reviews. Then the unique terms (those appearing in only one document) are removed. That reduced the size. Trivial English words (stopwords) such as "and," "the," and so on are also removed as they do not contribute to infer meaning of the context. This step further reduced the size. Then term suffices are removed (known as term stemming). For example, we replaced "easier," "easiest," "ease," and "easy" by "eas–." A tabulation of the retained terms and their appearance in the documents produced a term frequency matrix with 1,046 rows (terms) and 148 columns (reviews) for the positive reviews and 1,190 rows (terms) and 258 columns for negative reviews. The raw term frequencies were transformed using a weighting and normalization scheme known as inverse document frequency (IDF) weighting or TF-IDF. Such transformation promotes the occurrence of rare terms and discounts the influence of more common non-stopwords . The transformed term frequency matrix was then subjected to a SVD. This decomposition produced term eigenvectors, document eigenvectors, and square roots of eigenvalues, known as singular values, appearing in descending order. A 10 factor solution is retained and is used in subsequent factor analysis. As mentioned before, first 7 factors in the positive review and first 6 factors in the negative review seem to have meaning in terms of associated words. Next manual inspection picked the terms associated with each factor picked along with its adjusted frequency for each of the review from the adjusted SVD matrix. These terms are then subjected to factor analysis. Lastly the factor scores of each factor are obtained for each of the review. These factor scores are the independent variables for the Tobit regression. It is presented in figure 4 graphically.

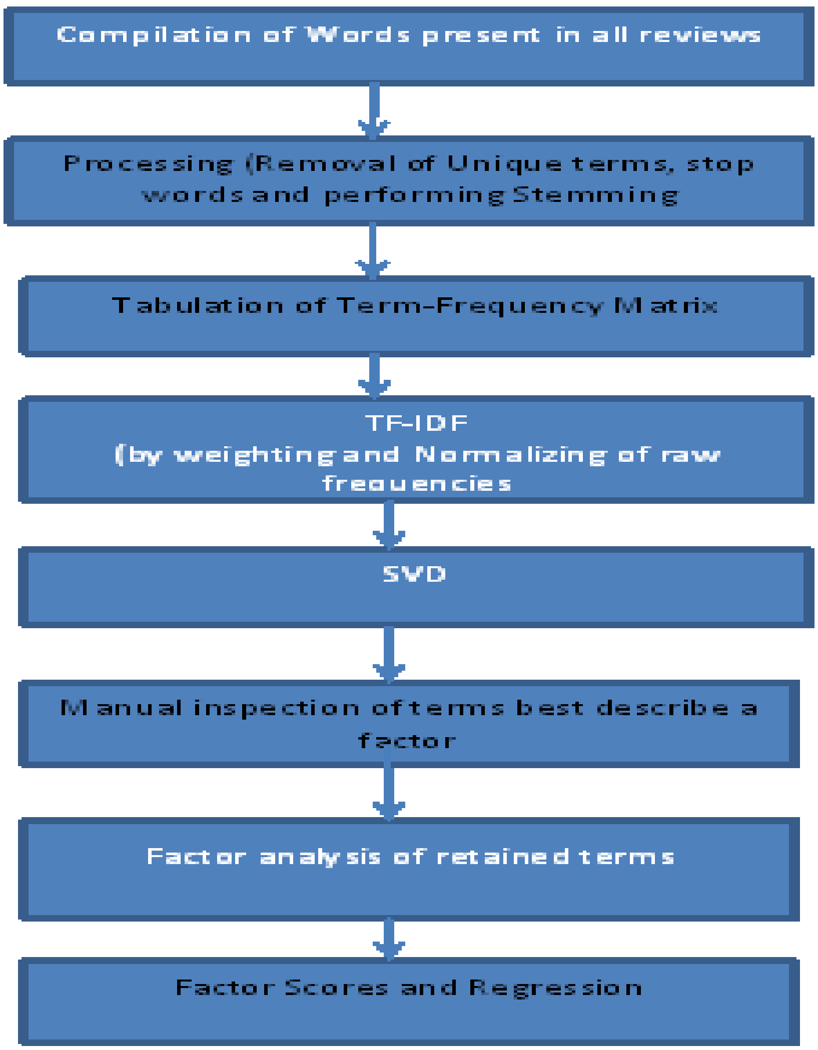

Figure 6: Algorithm Flow Chart

4.4 Analysis

Data

For the purpose of initial experimentation, the data for this study came from the online reviews available through Amazon.com. These data are publicly available for research and have been used in the prior research (Blitzer, Dredze & Pereira, 2007). The reviews are from November, 2007. Review data on Amazon.com is provided through the product page, along with general information on product and price. For the purpose of this study, we chose to use the reviews on kitchen appliances. There were 406 reviews including 148 positive reviews and 258 negative reviews. The reviews having star rating 4 and above are categorized as positive and reviews having star rating 1 and 2 are categorized as negative reviews. We extract the hidden concepts of positive and negative reviews using the method mentioned above.

4.5 Results

4.5.1 Negative Reviews

The rule for keeping eigenvectors is not clear in the literature. Following factor analysis, usually eigenvectors which have value greater than 1 are kept. Sometimes a graph of the eigenvectors is helpful. Here, while performing SVD, 10 eigenvectors were kept to represent the whole data because of the fact that the other factors were not representing a topic that is interpretable. Since interpretation is the key to this research, we retained the eigenvectors in a way that the corresponding factors represent a meaning. Therefore, there were ten groupings of words that can be evaluated. However, six prominent factors emerge from the negative reviews and the rest of the four factors does not express any meaning in particular and therefore was not presented in the subsequent analysis.

Factor 1—(**Online Order Anomaly**). The first factor is mainly about annoying aspect of online ordering, slow service, mismatch with the review posted earlier.

Factor 2-(Core Functionalities) In this factor the frustration with the product's core functionalities is expressed. Unlike positive review's core functionalities dimension, it is associated with "terrible" "stuck"(opposite of non stick) etc. So, this factor taps on quality concept.

Factor 3-(Mishandling) This factor corresponds to mishandling and how the service fails to take care of the product delivery. Customers are also concerned about return and refund policies. This is unique to the online retailing phenomenon. There is a lot of disutility cost associated with online buying from the customer's perspective. Mishandling of the product expresses that aspect.

Factor 4- (Warning). This factor relates to the opposite of recommendation factor of positive review. Customers want to warn other potential customers about malfunction of the product's core functionalities. This taps to the concern for others concepts found in the literature (Dellarocas & Naryan (2006)

Factor-5 (Value) Customers are comparing the price and quality and thus portraying the product as lesser value. This concept has also been reported in the literature (Gangold, Miller & Brockway, 1999)

Factor-6 (Shipping Charge). Shipping charge has always been a huge drawback in the context of online marketing. This issue has been brought up in this factor.

The top terms (here words) which are loading on each factor are shown in Table 5. The bold terms in table are the key words associated with the factor.

	Top terms of negative reviews
F1 **Online Order Anomaly**	amazon annoyed battery bowl coffe customer delivery disappoint email forward give go item online order price product purchase read receive return review say sell service slow sold super supplier teflon
F2 **Core Functionalities**	bacon bake cake clean coat complete cook cool egg fry heat inch madelin metal non nonstick oil pan pot release don fit set side silicon spray springform stick stuck terrible traditional store
F3 **Mishandling**	amazon arrive box break broken disappoint fragil give glass item large live month need order pack piec plate properly quality receive refund replace return review send side thin up wine
F4 **Warning**	bare bread control cook cuisinart doesn work fact feature grill heat lightli look luckily mean month oven part problem rack replace set side start thought timer toast toaster turn warn
F5 **Value**	blade bread buy chef chip cut discard discoveri doesn dont dull feel handl henckel inch knife knive metal need plan price quality set sharp soft thick thin wusthof sharpen dissapointment
F6 **Shipping Charge**	amazon big buy ship charg cream deal design don fal garment heat hold hose hot ice iron item market miss pay product profession sew steam steamer tank waste water

Table 5: Negative Reviews Factor

4.5.2 Positive reviews

Like negative reviews, 10 SVD factors were retained to represent the whole data. Predominantly, seven factors emerge from the positive reviews. The rest of the four factors were not included in the subsequent analysis due to loss in meaning: As it can be seen from the cluster of words, each factor conveys a concept.

Factor 1- (**Core Functionalities**) Customers are paying attention to the core functionalities of the product and expressing that these product do a good job in performing the core functionalities. This taps to the quality and satisfaction concept found in previous studies (Motaos and Rossi, 2008).

Factor 2- (Aesthetic, More Functionalities) In this factor the aesthetic of the product (look, design), more functionalities (how it fits the kitchen) are discussed. Customers also express their concerns about the product (even who liked it found some problem with it)

Factor 3-(Branding) This factor corresponds to branding in general. Customers are comparing the product with other brands in the market as evidenced by the words "differ","hundreds" , "cutting edge" "analogy", "brand" etc. Products lifetime use and price comparison are also pointed out

Factor 4- (Technical Aspect). This factor relates to more advanced customer who know about the technical aspect of the product. "Motor", "power", "processor", "speed" ,"need" ,"does", "don" indicate that these are more critical and knowledgeable talk. Wojnicki and Godes (2010) show that customer propensities to talk about satisfying and dissatisfying experiences depend in part on their desire to communicate domain expertise. This factor certainly expresses that.

Factor-5 (Online Specific): Customers also let the other customers know about the information search process. "review", "search" and "post' are indicative of that. The online information search discussion is an integral part of eWOM content.

Factor-6 (Helping the Company). As found in the prior research that one of the motives of WOM is to help the companies (Henning-thrau et al., 2004). This factor taps on that aspect. High loading terms are "company" Duty" "nice" "buy" "customer" **"service"** etc

Factor-7 (Affective) This factor expresses the affective side of positive WOM which leads to "recommend" ,"top" "wedding" "gift" "family" "love" "enjoy" words. As found in Campbell et al. (2011) that customers express emotion in eWOM .

	Top 30 Terms (Positive Review)
F1 **Core Functionalities**	bake blue cake calphalon clean coat cook creuset dishwash easy flat fry grease handle heat muffin non nonstick oil pan set side spray stainless stick stir surface ware wash wonder
F2 **Aesthetic, More Functionalities**	bad bagel bake braun bread button consume counter design heat kitchen look muffin oven perfectly pick piece problem pull retro room slice slot super toast toaster whatsoever wide small
F3 **Branding**	analogy chef chore cuttting edge cutleri differ global henckel hundred knife knive lifetime beauty blade block box brand carv nice price pro roast set sharpen sharper shear slice steak
F4 **Technical Aspect**	fit hand kitchenaid look love mix mixer motor need potato power processor quart short speed store whip wonder attach beater big bowl cake case cloth cover cream doesn don dough
F5 **Online Specific**	braun brew coffe cream cup dark drip fantast grind ground hot ingredients kettle love machine maker mug pour post press processor review run search space stop tea want water whistl
F6 **Helping the Company**	blade buy company customer dish disk duty everyday food hot ingredient kettle knives machine month need nice processor product quiet save service skillet steamer storage stuck tea water work
F7 **Affective**	awesome bar beauty calphalon clad clean color embroidery enjoy family gift haven love mattress month nonstick pillow purchase quality recommend seen set shaker sheet size skillet stainless top wedding

Table 6: Positive Reviews Factors

4.5.3 Comparison Of Positive and Negative eWOM

As we can see from the factors of positive and negative reviews, the positive reviews are more about the product itself (core functionalities, aesthetic, technical aspect, branding etc). On the other hand, the negative reviews tend to report more service related failure (online order, delivery mishandling, shipping charge etc). However, in the both kind of review, reviewers show the concern for other customers either by recommending the product or warning about the product. Another similarity is that in both types reviews the success or failures of the core functionalities are discussed. It should be noted that customers discuss about their online shopping experience (information search to mishandling of the product to online order anomaly etc.). Customers do not necessarily discuss this aspect in the positive reviews (if everything goes right) but discuss a lot in the negative reviews.

4.5.4 Factor Analysis

The SVD result gives an overall perspective of the content of the online reviews. The result of the factors depends on the interpretation of the associated words. To make the result more objective, the words which best describe a factor are picked manually. Consequently, for each of the factors, there are associated words (manually picked from the top 30 loadings words and best describe the factor). A factor analysis is run with these words. However, this factor analysis is performed on the matrix obtained by SVD (not on the original matrix). The reason behind this is the fact that the approximate matrix after SVD better represent the data (often correcting for the true relationship) (Deerwester et.

al., 1990). Next, a regression analysis is run with the factor scores as independent variables and helpfulness vote as the dependant variables. Tobit regression is chosen again for the fact that the dependant variable (helpfulness vote) is bounded between 0 and 1. The result of factor analysis and regression is presented next.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.438	36.301	36.301	9.119	35.073	35.073
2	5.277	20.296	56.597	4.927	18.949	54.022
3	4.031	15.504	72.102	4.265	16.405	70.427
4	3.370	12.962	85.064	3.806	14.637	85.064
5	1.273	4.896	89.960			
6	1.023	3.934	93.894			
7	.779	2.995	96.889			
8	.531	2.042	98.931			
9	.192	.739	99.670			
10	.086	.330	100.000			
11	2.124E-15	8.170E-15	100.000			
12	1.344E-15	5.168E-15	100.000			
13	1.262E-15	4.855E-15	100.000			
14	1.092E-15	4.200E-15	100.000			
15	8.386E-16	3.225E-15	100.000			
16	5.702E-16	2.193E-15	100.000			
17	3.937E-16	1.514E-15	100.000			
18	1.913E-16	7.359E-16	100.000			
19	-3.345E-17	-1.287E-16	100.000			
20	-7.216E-17	-2.775E-16	100.000			
21	-2.217E-16	-8.529E-16	100.000			
22	-6.163E-16	-2.370E-15	100.000			
23	-7.812E-16	-3.005E-15	100.000			
24	-1.064E-15	-4.094E-15	100.000			
25	-1.247E-15	-4.795E-15	100.000			
26	-1.402E-15	-5.393E-15	100.000			

Table 7: Factor Analysis of Negative Reviews

It can be seen from the table 7 that 4 factors cumulatively represent around 86% of the variability of the data set which is high. Although, terms from six factors are included for the initial analysis, 4 factors are retained because of the low and/or cross loadings of the terms associated these two factors. Finally the following four factors emerged.

	Component			
	Online Anomaly	Shipping Mishandling	Shipping Charge	Core functionalities
V33	**.900**	.097	.306	-.042
V39	**.946**	-.185	-.064	-.070
V251	**.404**	-.177	.132	-.198
V291	**.876**	-.223	-.087	-.040
V342	**.942**	-.133	-.075	-.135
V428	**.948**	-.181	-.010	-.006
V705	**.969**	-.084	.060	-.043
V710	**.852**	.344	.220	-.137
V865	**.790**	.252	.205	.037
V866	**.721**	.382	.079	-.099
V955	**.689**	.087	-.384	-.341
V1035	**.955**	-.173	.015	-.028
V702	-.088	-.226	.113	**.875**
V1020	.049	-.151	-.175	**.927**
V1060	.016	-.072	.093	**.857**
V1096	-.177	.010	-.057	**.964**
V49	-.109	**.952**	.183	.029
V118	-.116	**.962**	.060	-.033
V430	-.094	**.822**	-.271	-.095
V719	.008	**.846**	-.226	-.119
V798	.076	**.881**	-.137	-.154
V852	.601	**.426**	.095	.090
V150	.116	-.064	**.957**	-.031
V635	-.076	-.090	**.915**	-.081
V667	-.020	-.149	**.910**	-.105
V924	.200	-.002	**.922**	.139

Table 8: Rotated Component Matrix of Negative Reviews

The rotated matrix shows that, term loadings are high. In table 8, the first column represents the variable (here words/terms) and the rest of the column represents the loading for each factor. The associated words in each factor properly represent each factor which justifies the use of factor analysis. It is more quantitatively confirmatory when a topic is represented by high loading associated words rather than grouping based on SVD.

Factor	Associated Words
Online Order Anomaly	Amazon,Annoyed,Customer, Disappointment, Email, Forward, Online, Order, Review, Return, Slow, Supplier
Core Functionalities	Traditional, Oil, Stuck, Terrible
Shipping Mishandling	Arrive, Broken, Fragile, Pack, Properly, Replace
Shipping Charge	Ship, Charge, Market, Miss

Table 9: Factors and their Associated Words (Negative Reviews)

Table 9 shows that associated words represent the factors fairly well. "Return", "slow", "Disappointment", "annoyed customer" represent the topic of online order anomaly. The other factors and their associated words are representative of the topic.

Next, positive reviews are examined. LSA (SVD technique) extracted seven meaningful topics. The words associated with the seven topics are taken from the adjusted SVD matrix along with their loading measure for all 148 reviews. This matrix is then subjected to factor analysis. Unlike negative reviews, all the factors could be retained although some words were discarded due to low and/or cross loadings. The seven factors expressed almost 93% of data variability.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.562	20.506	20.506	5.997	18.740	18.740
2	6.175	19.298	39.804	5.467	17.083	35.823
3	5.181	16.191	55.995	4.789	14.967	50.790
4	4.178	13.057	69.052	4.695	14.671	65.460
5	3.614	11.295	80.347	4.309	13.467	78.927
6	2.410	7.531	87.878	2.530	7.906	86.833
7	1.600	5.001	92.879	1.935	6.046	92.879
8	1.184	3.700	96.579			
9	.854	2.669	99.248			
10	.241	.752	100.000			
11	1.457E-15	4.553E-15	100.000			
12	1.058E-15	3.307E-15	100.000			
13	8.610E-16	2.691E-15	100.000			
14	7.282E-16	2.276E-15	100.000			
15	6.375E-16	1.992E-15	100.000			
16	5.731E-16	1.791E-15	100.000			
17	4.605E-16	1.439E-15	100.000			
18	3.852E-16	1.204E-15	100.000			
19	3.155E-16	9.858E-16	100.000			
20	1.482E-16	4.633E-16	100.000			
21	4.546E-17	1.420E-16	100.000			
22	-9.775E-17	-3.055E-16	100.000			
23	-1.779E-16	-5.561E-16	100.000			
24	-3.745E-16	-1.170E-15	100.000			
25	-4.326E-16	-1.352E-15	100.000			
26	-4.629E-16	-1.446E-15	100.000			
27	-6.453E-16	-2.017E-15	100.000			
28	-6.810E-16	-2.128E-15	100.000			
29	-1.114E-15	-3.481E-15	100.000			
30	-1.137E-15	-3.553E-15	100.000			
31	-1.663E-15	-5.197E-15	100.000			
32	-2.166E-15	-6.767E-15	100.000			

Table 10: Factor Analysis of Positive Reviews

In table 11, the first column represents the variable (here words/terms) and the rest of the column represents the loading for each factor. Like before, the factor loadings were high and ensured the validity of the factors.

	Component						
	Branding	Affective	Service	Technical Aspect	Core Functionali	Aesthetics	Online Specific
V418	.001	-.054	-.063	-.095	**.975**	-.051	.023
V431	.051	-.014	.158	-.104	**.768**	-.057	.175
V606	.036	-.037	-.153	-.127	**.969**	.088	-.029
V893	.018	.009	-.143	-.040	**.975**	.047	-.021
V1008	.311	.480	-.110	.402	**.655**	-.004	-.032
V260	-.126	.067	-.258	-.025	-.051	**.777**	.000
V538	-.012	-.097	.120	.095	.032	**.976**	-.096
V657	-.022	.345	.023	-.140	.059	**.749**	.339
V845	-.339	.052	-.156	-.093	-.123	**.451**	.770
V49	-.127	-.313	.293	**.781**	-.023	-.033	.314
V227	-.120	-.017	.058	**.922**	.242	-.066	-.008
V593	.122	-.148	-.080	**.872**	-.218	-.084	-.022
V691	-.030	-.002	-.063	**.973**	-.147	.064	-.107
V865	-.101	-.021	.277	**.906**	-.201	-.003	.167
V684	-.028	.053	-.170	.213	.218	-.139	**.892**
V35	**.971**	.110	.143	-.118	-.009	-.084	-.024
V103	**.788**	.288	-.118	.299	.061	-.123	.010
V270	**.930**	-.238	-.133	-.104	.155	.039	-.132
V310	**.978**	-.063	.107	-.120	.064	-.014	.023
V414	**.976**	-.128	.096	-.094	-.095	-.029	-.014
V522	**.854**	-.135	-.307	.095	.094	-.029	-.173
V187	-.229	-.022	**.878**	-.046	-.153	-.112	-.152
V239	-.190	.066	**.959**	.100	-.011	-.034	.024
V603	.467	.066	**.832**	.229	.031	.142	-.010
V802	.144	-.083	**.964**	.068	-.062	-.048	-.123
V53	-.054	**.976**	-.005	-.094	-.065	-.091	.124
V76	.401	**.822**	.026	-.191	.072	-.027	-.091
V325	-.157	**.709**	.395	-.082	-.093	-.152	.032
V409	-.090	**.925**	-.089	-.155	.037	.034	-.127
V437	-.087	**.754**	.214	.071	-.274	.197	-.114
V738	-.124	**.837**	-.072	.044	.154	.148	.176
V1015	-.034	**.665**	-.536	-.170	.130	.019	.280

Table 11 : Rotated Matrix of Positive Factors

The following the factor and the associated words. The associated words provide the content of the topic.

Factors	**Associated Words**
Core Functionalities	Grease, Handle, Non-Stick, Dish wash, Easy
Aesthetics	Design, Look, Perfectly, Small
Technical Aspect	Motor, Speed, Power, Attach, Cover
Online	Post
Branding	Analogy, Differ, Brand, Edge, Global, Lifetime
Service	Customer, Duty , Nice, Service
Affective	Awesome, Beauty, Enjoy, Gift, Haven, Recommend, Wedding

Table12: Factors and their Associated Words (Positive Reviews)

Table 12 shows that associated words represent the factors fairly well. “Grease”, “Handle”, “Non-Stick”, “Dish wash”, “Easy” represent the topic of core functionalities. The other factors and their associated words are representative of the topic.

After the factor analysis, the factor scores for each review were saved and were subjected to tobit regression next.

4.5.5 The Regression Analysis

A Tobit regression analysis is conducted with the factor scores of each review to see which factors are perceived helpful. In other words, when a review contains a specific factor, does it contribute to the perceived helpfulness. The results are the following:

	Value	Standard Error	Z	P
Intercept	7.102	0.1855	38.278	0.00e+00
Online Order Anomaly	0.956	0.1865	5.126	2.96e-07***
Shipping Mishandling	0.578	0.1865	3.101	1.93e-03***
Shipping Charge	0.170	0.1859	0.912	3.62e-01
Core Functionalities	-0.325	0.1859	-1.748	8.05e-02

**$p<0.05$, $R2=0.07$

Table 13: Regression Analysis Negative Reviews

The result from the negative reviews regression analysis reveals that “online order anomaly” and “ shipping mishandling” contribute to the perceived helpfulness of the review. From the positive review, it can be seen that the "technical aspect", "core functionalities" and "aesthetics" contribute to the perceived helpfulness.

	Value	Std. Error	Z	P
Intercept	0.87644	0.0178	49.176	0.00e+00
Branding	-0.00304	0.0179	-0.170	8.65e-01
Affective	0.00466	0.0179	0.261	7.94e-01
Service	0.00859	0.0179	0.480	6.31e-01
Technical Aspect	0.03832	0.0179	2.141	3.23e-02**
Core Functionalities	0.03601	0.0179	2.012	4.42e-02**
Aesthetics	0.04278	0.0179	2.392	1.67e-02**
online	0.01209	0.0179	0.676	4.99e-01

**$p<0.05$, R2=0.15

Table 14: Regression Analysis Positive Reviews

4.5.6 Review clustering

We also cluster the positive and negative reviews. Five cluster solution for each review is obtained. The result is shown at the end of this chapter. The manual inspection show that the clusters actually correspond to the factors mentioned above (factors of reviews). This is possibly because usually each review contains one of the topics of the review. This clustering solution provides validity to the factor analysis result as the factors and cluster match with each other (please refer to appendix for results)

4.6 Discussion

The topics in online reviews of kitchen appliances reveal that there are differences between positive and negative reviews. Basically, the negative reviews tend to report service related failure in a product review. For example, online order anomaly, shipping mishandling, shipping charge etc. In a product purchase situation, the service associated with it (shipping and handling, credit card processing, refund, replace) are thought to be a means of buying the product online and therefore, expected to be without hassle. The customers expect the uncertainty to come from the product itself and not from the services. Consequently, when this expectation is violated (delivered late, broken, high shipping charge etc), the customers complain about it and that comes up in the negative reviews. When a potential customer reads about these service failures, it facilitates their decision process by providing information on moral violation. Therefore, the potential customers find these reviews helpful. There are also negative core functionalities aspect expressed in the reviews. When they get the information about the related service which is part and parcel of this purchase process, they feel to be better informed and find these reviews helpful.

On the other hand, when a positive review discuss about good aspect of service, customers do not find this piece of information helpful possibly because of the fact that customers expect the associated service to work well. So when it works well, the potential customers find this piece of information trivial and therefore do not find it helpful. However, as mentioned before, when the services do not work well and customers complain, potential customers find that information helpful (demonstrated by negative reviews "shipping mishandling") because of expectation violation (Campo, Cameron, Brossard & Frazer, 2004). An expectancy is what people predict will happen, rather than what they desire. The Violations Theory attempts to explain one's reactions to unexpected behavior of the other party. People attribute various meanings to the violation and this strong perspective has the potential to influence people.

The other factors extracted in the positive reviews are Branding, Affective, Technical aspect, core functionalities, Aesthetics, online. Among these, technical aspect, core functionalities and aesthetics are found to be helpful. Again, when a potential customers reads a positive review, she/he expects that the writer thinks it is better than the other brands- making the topic "branding" somewhat trivial and not helpful. However, it may be a good source of information for the marketing managers who might have a keen interest in knowing the brands to which a particular brand is compared to. Potential customers read the positive reviews to gain knowledge and remove uncertainty about the product. More information about the product therefore becomes very helpful to potential customers. As indicated by Andreasen & Ratchford (1976) information such varies according to the extent to which the needed information are objective or subjective. Some information, such as the location of a store, is essentially objective in character and can be obtained easily and reliably. Other information may require more information since they pertain either to personal preferences (who gives the "best" permanents) or to uncertain future outcomes (which brand of appliance requires least repairs). As preference of a kitchen appliance is a subjective information and everyone's perspective is welcome from a potential customer's perspective. Therefore, core functionalities, aesthetics and information on technical aspect are helpful in the decision making process. Moreover, literature has shown that when people convey domain knowledge to others, they are seen as expert and expert advice is usually influential (Sniejek & Swol, 2001). Technical aspect of the review expresses knowledge of the actual machine of the appliances. It can be also seen from the words expressed in topic. "Motor", "Speed", "Processor" are the associated words. So, the reviews which are expressing knowledge about this domain specific information are likely to be more helpful. It is also evident from the result.

Therefore, customers write many things about a product and product experience. Positive reviews contain positive aspects of the product. On the other hand, negative reviews contain negative aspect of the product and a variety of information on the service failure. Since the service associated with a online product purchase is expected to be efficient, any deviation from that invoke a larger need of expressing that in a review. Therefore, a trend of reporting service failure emerges in the negative reviews. Positive reviews usually report good aspect of the product with some information on good quality service.

Later, when a potential customers read these reviews with an intention to gain knowledge or remove uncertainty about the product, positive reviews which contain product related information (core functionalities, technical aspect and Aesthetic) are found to be helpful as this provide information. On the other hand, negative reviews which report service related failure express expectation violation and this is powerful to influence future customers. The trend shows that these reviews are more helpful.

4.7 Limitations and Future Research

Although the study uses quantitative content analysis which may provide some accuracy measure of the result, there are some limitations of the study. The number of terms (words) retained for each factor is much lower than what was found after performing SVD. This has potential on posing limitation on the interpretation of the factors. However, I tried to eliminate this problem by manually picking some words (which are not only based on high loadings). The terms which seemed to fit a factor from human knowledge among the first 30 terms (according to the loading) were chosen. This way we retained high loading as well as meaningful words associated with a factor. However, as mentioned before, there is a possibility that the low number of words associated with the factors may bias the result. Research in this area which deals with reliability and validity of the method in the marketing context is needed.

It would be very interesting to see the comparison between product and service reviews. As seen in this product review, positive reviews talk more about the functionalities of the product and the negative reviews express service opinion. In case of services, how this dynamics will change is worth investigating. It might be possible that, the differences seen the product review might not be present in the service review. Will the service failure be more pronounced in both cases? How the intangible aspects of the service affect the content of the positive review will be very interesting to watch.

As has been discussed in the discussion session, literature implies that what kind of information is sought affects the type of information that will be found to be helpful. Since utilitarian and hedonic products are likely to have different criteria for information search , investigation on these will also yield interesting results. It would be desirable to build a comprehensive typology of the information search behavior as found in eWOM.

CHAPTER 5

Essay 3

A Comparative study of Latent Semantic Analysis and Probabilistic Latent Semantic Analysis on extracting topics in product reviews.

5.1 Introduction

The web has grown like never before and consequently opinions about product/ services are found very easily. Customers can now post reviews at various sites and express their views on almost anything in forums, discussion groups, and blogs (Dellarocas & Narayan, 2005). Blogs, social networks like Facebook and Twitter, e-commerce sites, etc contain huge amount of opinions. Usually these opinions are to help other customers or friends. However, the vast availability of such reviews/opinions is sometimes overwhelming and many times overload them. If someone searches for a blender at Amazon.com, she/he will encounter hundreds if not thousands of reviews of blenders. For marketing researchers, these opinions are the goldmine since this provides them with the customer perspective of their product. Therefore, online word-of-mouth is an important source of information for marketing researchers. However, such overwhelming amounts of information make it difficult to get an idea about the product's perception. Consequently, summarization or any other kind of meaningful representation of this data is very critical. Techniques such as text mining are being used to understand what these customers are talking about the products/services (Guo et al., 2009).

In the computer science literature, over the last few years, the task of summarizing opinions or reviews has become a central research area among the text mining community. As mentioned before, these opinions may come from text data such as blogs or reviews as well as numerical data such as star ratings. Earlier studies in this area were limited to sentiment prediction (positive or negative). However, the techniques have become more sophisticated and studies generally report aspects/topics, textual summaries etc. The different formats and techniques provide different level of understanding or precision on the topic. Some of these approaches rely on simple heuristics, while others use robust statistical models. Therefore, when using, the users has to adopt these methods to their own needs. As mentioned before, computer science literature has been researching in this area over a decade now. However, if marketers want to leverage the strength of this huge textual data, they have to be able to tailor these methods according to their own needs. The strength of statistical power and intuition of marketers have to come together to fully utilize this opportunity. With this in mind, this research project focuses on comparing two text mining techniques from a marketer's perspective. In the current study, two techniques: Latent Semantic Analysis (Deerwester et al., 1990) and Probabilistic Latent Semantic Analysis (Hoffman, 1999) are compared on reviews posted by customers on Amazon website. Common themes of reviews are extracted by using LSA and PLSA among positive and negative reviews in two contexts. First, the reviews are taken from the category of kitchen appliances (used before in Essay1 and Essay 2) where there were different brands and kitchen products within this category reviews. Second, only one brand of a product's review is examined. Their performances are compared in these two scenarios. These two scenarios are fundamentally different as seen from market researcher's perspective. The first scenario provides information about the whole market in that product category. It can be considered as market surveillance. On the other hand, the second scenario examines a single brand. This is useful for brand managers when an in depth analysis is needed of a particular brand. The current study compares two techniques in these two scenarios so as to see if the performance of these two techniques would be different depending on the context.

The rest of the research is organized as follows: We review literature where Latent Semantic Analysis or Probabilistic Latent Semantic Analysis has been used in topic extraction from the customers' review or related text. Experimentation is presented next along with results. Discussion is followed next.

5.2 Literature Review

With the emergence of Internet, the user generated content (UGC) has exploded. Marketers are analyzing these data to learn more about market and customers. UGC are very often the text data (blogs, reviews, social interactions). With this in mind, marketing scholars have started to use text analysis to gain knowledge. A special issue in *Marketing Science* was published in 2012 to encourage and flourish the research in this area. The scholars examined a range of issues such as how and why people make UGC contributions (Moe & Schweidel, 2012; Ransbotham, Kane & Lurie, 2012). Also the impact of UGC has been investigated (Zhang, Evgeniou, Padmanabhan & Richard, 2012) New methods for analyzing UGC data have been looked at (Netzer, Feldman, Goldenberg & Fresko, 2012; Ghose, Ipeirotis & Li, 2012). Netzer et al. (2012) used user generated text data to learn about market structures and competitive landscape insights.

The authors developed perceptual map of market without interviewing a single customer by utilizing text mining techniques on UGC. Ghose et al. (2012) generate a ranking system by using data from different sources including social media. Text miming techniques were used here to build such a system. Recently, AMA's advanced research technique forum has dedicated the whole conference (2012) dealing with text analysis research.

To begin with the related work in this research area, first, the background in opinion summarization is discussed since our experimentation of this research closely relates to this area. Opinion summarization provides idea about the whole document collection in brief. Sentiment prediction can be used as opinion summary because the aggregating sentiment score will provide an overall idea about the documents in the collection. Usually Sentiment classification is one of the important steps in analyzing this data. In this process, orientation of sentences or the whole documents are identified. This will result in overall summarization of the documents as users get an idea about what is being said (positive and negative). There are several approaches in identifying sentiments which finds out the adjective in the text and thus tries to understand the positivity or negativity of the text. Some studies (Kamps & Marx 2001) used WordNet-based approach, using semantic distance from a word to "positive" and "negative" as a classification criterion. This idea was used in the first essay to identify discrete emotions in the reviews. While the results of sentiment classification can be used as a simple summary, methods have been improved a lot. Researchers are trying to make automatic human understandable summaries.

Extracting common themes from user generated content can be considered as summarizing the content since it tends to reflect the whole content. Many techniques have been used to summarize opinions in user generated contents such as Latent Semantic Analysis. Turney and Littman (2003) found that cosine distance can be used in latent semantic analysis (LSA) space to measure topic in the text. This method (LSA) mainly relies on the co-occurrence of the word and is not based on statistical modeling. Recently, topic model has become the center of interest in this area. Topic model can be defined as generative probabilistic model. It is based on solid foundation of statistics. Vocabulary distribution is used to find topics of texts. Basically, it first identifies the word frequencies and relation between other words (co-occurrences) effectively. There are several topic modeling approaches. Probabilistic Latent Semantic Analysis (PLSA) (Hofmann,1999) and LDA (Latent Dirichlet Allocation) are the important ones.

A little example of topic modeling might be intuitive. Let's say, word X and Y usually always occur together, and word X and Z rarely occurs together, it might be safe to assume that X and Y constitute a topic whereas Z is involved in another topic. So, the goal of these approaches is to identify a set of topics or themes from a large collection of documents. It is also possible to find documents that most relate to one of the topics.

If a document collection contains blender reviews, some of the themes may be processor, cost, design etc. The themes that are extracted from the topic modeling may be the product feature or sentiments. For example, if the positive and negative reviews talk about different feature or topics about the product, then the model may identify the positive and negative topics along with product features. In this case, it works as identifying feature and also sentiments. From this family of models, Probabilistic Latent

Semantic is chosen. There are other methods where aspect or features are identified, sentiments of these texts are predicted and then overall summary is presented (Hu and Liu, 2004). In fact, there is a vast research investigating this algorithm for summarization using different technical methods. For example, Ku, Liang & Chen (2006) used frequency of the terms for feature identification and used sentiment words to assign opinion scores. Lu et al. (2009) used natural language processing techniques to K (K= any number) interesting aspects and utilized bays classifier for sentiment prediction. Mei, Ling, Wondra, Su, & Zhai (2007) and Titov and McDonald (2008) deviated from this algorithm. Both the papers used topic sentiment mixture models or joint topic and sentiment modeling. These types of models extract topics and sentiments together. Titov and McDonald (2008) utilized multi-grain LDA for this problem. It should be noted that in the current study does not focus on summary presentation instead it focuses on features and their sentiment orientation. Summary can be presented in mainly two ways: one is called Extractive summaries and the other is called Abstractive summaries. In the former one sentences from the documents collection is identified to represent the summaries. On the other hand, later does not use own sentences for summarization. For the obvious reason of simplicity, the former is more often used. Summary presentation is often used to make the summary of the reviews more understandable to customers. From a managerial perspective, they need to know in detail, what is being said about a particular feature. Therefore, this study concentrates and experiments on topic extraction and the suitability of two techniques from a managerial perspective.

5.2.1 Latent Semantic Analysis

LSA is only briefly discussed here for the sake of completeness since it has been discussed in the previous chapter. LSA extracts concepts hidden in text data without an a priori theoretical model and is based solely on word usage within the documents. It represents terms and documents with fewer dimensions and thus creates a new vector space (Han & Kamber, 2006). The LSA is actually singular value decomposition (SVD), applied to a term-by-document matrix (X) holding the frequency of use of all terms in all documents in a given collection. By retaining a small number of significant factors k, X can be approximated by $X = T_k S_k D_k^T$ .Term loadings ($L_T = T_k S_k$) are rotated (varimax rotation is used) to obtain meaningful concepts of the document collection. However, unlike previous study, factor analysis is not performed for mainly two reasons. Firstly, this study compares two text mining techniques namely LSA and PLSA and therefore there is no need for the factor scores in this study. The algorithm is shown in figure 5. Secondly, the previous research has demonstrated the validity of uncovered concept through factor analysis. In this study, LSA (Landauer, Foltz, & Laham, 1998). is implemented using Matlab TMG graphical user interface.

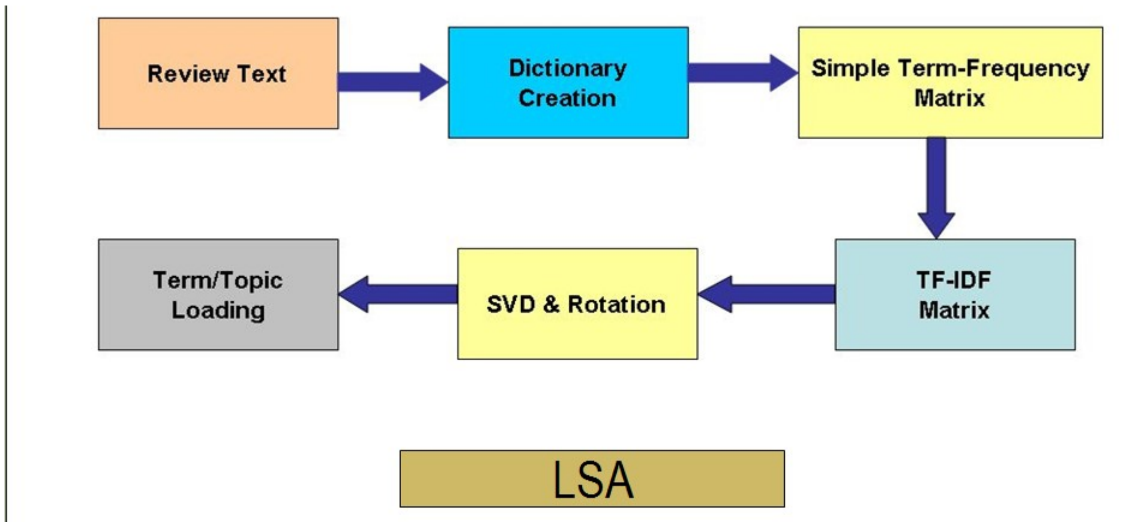

Figure 7: Algorithm Flow Chart (LSA)

5.2.2 Probabilistic Latent Semantic Analysis

The PLSA model has been firstly presented and successfully applied in text mining by (Hofmann, 1999). PLSA is based on maximum likelihood principle, which is derived from statistical principle, while LSA utilizes the $L2$ or Frobenius norm as an optimization criterion.

Basically, the PLSA model is based on a statistic model called aspect model, which can be utilized to identify the hidden semantic relationships among general co-occurrence activities. In a general sense, PLSA can be viewed as follows:

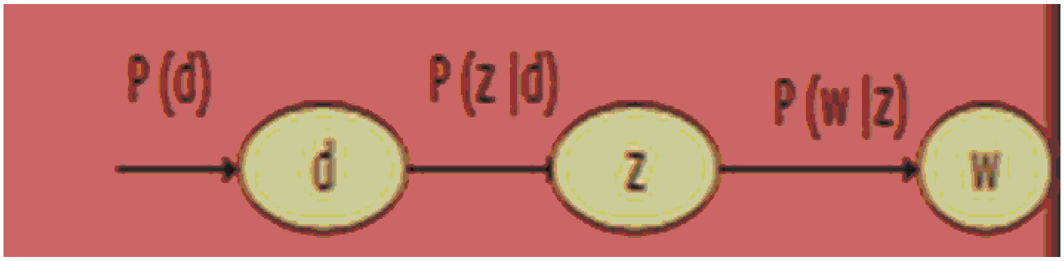

Figure 8: PLSA model

Given the aspect model in the context of "review", it is first assumed that there is a latent factor space $Z=\{z1,z2, ...,zl\}$ and each co-occurrence observation data is associated with the factor z_k.

The goal of PLSA is to determine the conditional probabilities, in turn, to reveal intrinsic relationships among reviews based on the computed semantic probabilities.

Firstly, let's introduce the following probability definitions:

$p(d)$ denotes the probability that a particular review d will be observed in the occurrence data,

$P(z_k|d)$ denotes a review-specific probability distribution on the unobserved class factor z_k.

$P(w|z_k)$ denotes the class-conditional probability distribution of words over a specific latent variable z_k.

Based on these definitions, the probabilistic latent semantic model can be expressed in following way:

1. Select a review *d* with probability *P(d)*,

2. Pick a hidden topic z_k with probability $P(z_k|d)$,

3. Generate a word *w* with probability $P(w|z)$.

Therefore, A joint probability model over D x W is defined by

$$P(d,w) = P(d)P(w \mid d), \quad P(w \mid d) = \sum_{z \in Z} P(w \mid z)P(z \mid d)$$

Based on the previous equation *P(d, w)* can be represented by the following equation

$$P(d,w) = \sum_{z \in Z} P(z)P(d \mid z)P(w \mid z)$$

The parameters of the models $P(z)$, $P(w|z)$ *and* $P(d|z)$ are estimated while maximizing the likelihood of the observations. Thus the joint probability of the DxW model can be obtained. In this model, P(z), $P(w|z)$ *and* $P(d|z)$ are the parameters. For the corpus, the joint probability of sample S is

$$P(S) = \prod_{w \in W} \prod_{d \in D} P(w,d)^{n(w,d)}$$

Where n(w,d) is the frequency of the co-occurrence.

In order to determine P(S), equation (2) is converted to log scale

$$\log P(S) = \sum_{d \in D} \sum_{w \in W} n(w,d) \log P(d,w) =>$$

$$L(\theta) = \sum_{d \in D} \sum_{w \in W} n(w,d) \log[P(z)P(d \mid z)P(w \mid z)]$$

To get the maximum likelihood estimation (MLE) of the parameters, the EM algorithm (DEmpster et al. 1977) is used.

E step

Initialize the values of the parameters and then compute the expectation of L(θ)

$$Q(\theta) = \sum L(\theta) \times P(z \mid d, w)$$

Maximize the function in E step

$$P(z \mid d, w) = \frac{P(z, d, w)}{P(d, w)} = \frac{P(z)P(d \mid z)P(w \mid z)}{\sum_{z' \in Z} P(z')P(d \mid z')P(w \mid z')}$$

Where

$$d \in D, w \in W, z \in Z$$

M step

The goal is to maximize the function Q(θ). So the Lagrange multipliers λ1, λ2 λ3 are introduced. The following constraints are imposed:

$$\sum_{z \in Z} P(z) = 1 \quad \sum_{d \in D} P(d \mid z) = 1 \quad \sum_{w \in W} P(w \mid z) = 1$$

The target function is

$$QQ = \sum_{z \in Z} (\sum_{d \in D} \sum_{w \in W} n(w, d) \log[P(z)P(d \mid z)P(w \mid z)] * P(z \mid d, w)$$
$$- \lambda_1 (\sum_{z \in Z} P(\mathrm{z}) - 1) - \lambda_2 (\sum_{d \in D} P(\mathrm{d}) - 1) - \lambda_3 (\sum_{w \in W} P(w) - 1)$$

To maximize, the derivatives of the target function with respect to P(z) and λ1 are taken and set to zero (the process for λ2, λ3 are the same)

$$\frac{\partial QQ}{\partial P(z)} = \frac{\sum_{d \in D} \sum_{w \in W} n(w,d) * P(z \mid d, w)}{P(z)} - \lambda_1$$

If this is equal to zero, the following results:

$$P(z) = \frac{\sum_{d \in D} \sum_{w \in W} n(w,d) \times P(z \mid d, w)}{\sum_{d \in D} \sum_{w \in W} n(w,d)}$$

The computing process is the same and other parameters are obtained by the following equations through iterations.

$$P(w \mid z) = \frac{\sum_{d \in D} n(w,d) \times P(z \mid d, w)}{\sum_{d \in D} \sum_{w' \in W} n(w',d) \times P(z \mid d, w')}$$

$$P(d \mid z) = \frac{\sum_{d \in D} n(w,d) \times P(z \mid d, w)}{\sum_{d' \in D} \sum_{w \in W} n(w,d') \times P(z \mid d', w)}$$

$$P(z \mid d, w) = \frac{P(z,d,w)}{P(d,w)} = \frac{P(z) \times P(d \mid z) \times P(w \mid z)}{\sum_{z' \in Z} P(z') \times P(d \mid z') \times P(w \mid z')}$$

When the result converges, the iteration process can be terminated.

The flow chart of this process is shown graphically:

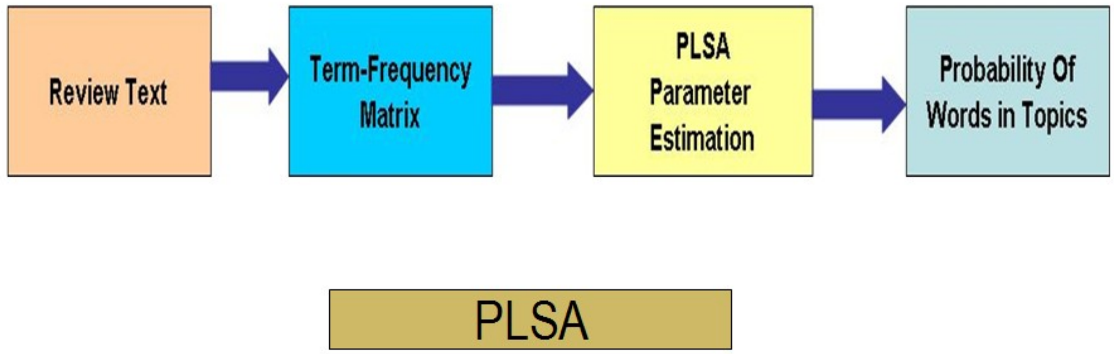

Figure 9: Algorithm Flow Chart (PLSA)

5.2.3 Difference between LSA and PLSA

Both LSA and PLSA can find the latent semantic space in a given corpus. But there is an important difference between the two methods. Firstly, SVD is based on Matrix decomposition. The reduced matrix is the F-norm approximation of the term frequency matrix, while PLSA relies on the likelihood function and wants to get the maximization conditional probability of the model. It introduces a prior probability of the latent class. The prior probability for a class is the probability of seeing this class in the data for a randomly chosen record, ignoring all attribute values. Mathematically, this is the number of records with a class label divided by the total number of records. Using EM algorithm, a local maximum of likelihood function can then be obtained. Secondly, LSA does not define a properly normalized probability distribution and X may even contain negative entries while in PLSA, the matrix of the co-occurrence table is a well-defined probability distribution and the factors have a clear probabilistic meaning. Below are some similarities and differences between LSA and PLSA in brief form.

- LSA and PLSA perform dimensionality reduction
    - In LSA, by keeping only K singular values
    - In PLSA, by having K aspects
- Comparison to SVD
    - T Matrix related to P(d|z) (doc to aspect)
    - D Matrix related to P(z|w) (aspect to term)
    - S Matrix related to P(z) (aspect strength)
- The main difference is the way the approximation is done
    - PLSA generates a model (aspect model) and maximizes its predictive power
    - Selecting the proper value of K is heuristic in LSA
    - Model selection in statistics can determine optimal K in PLSA

5.2.4 Performance Measure

To compare two techniques, one needs to evaluate the performance of the techniques. The best evaluation would be human observation to all cases. However, because of limited resources, few scenarios are analyzed in detail. In addition to rigorous quantitative evaluation, qualitative observations are widely used to analyze example results (Mei et al. 2007; Titov & McDonald, 2008). Among the quantitative measure precision, recall curve is the most widely used measure (Titov & McDonald, 2008).

Precision is defined as the number of relevant words retrieved divided by number of all words retrieved. This provides a measure of accuracy. We also counted the number of irrelevant words to get a better picture.

$$\text{Precision} = \frac{\#(\text{relevant items retrieved})}{\#(\text{retrieved items})} = P(\text{relevant}|\text{retrieved})$$

Moreover, the following classification helps in the measure of accuracy:

	Relevant	Nonrelevant
Retrieved	true positives (tp)	false positives (fp)
Not retrieved	false negatives (fn)	true negatives (tn)

Here, we also measured false positives and compare between these two techniques. We want false positives to be low. Since we do not have a list of total relevant words (for conversational text, it is difficult to develop and measure), we did not use recall or false positive/negative as a measure of performance.

5.3 Data and Results

As mentioned before, for the purpose of this study, the performance of PLSA and LSA are compared in two different contexts: one is extracting topics from reviews of a particular brand and the other is extracting topics from reviews of a product category. To empirically compare the hidden topics/factors and the associated words, LSA and PLSA are applied to reviews of “Rose Handbag by FASH” which are obtained from Amazon. There were a total of 389 reviews of this brand. This constitutes the first context.

The review data on the kitchen appliances analyzed in the previous chapters were used. This constitutes the broader product category reviews. These dataset contains reviews of several brands and products under kitchen appliances umbrella.

Firstly, LSA and PLSA are used to extract topics from the reviews of “Rose Handbag by FASH” and compared with each other. The reviews are slatted in two categories. The reviews which got star rating 3 or more were classified in the positive reviews. On the other hand reviews with star rating 1 and 2 are classified in negative reviews. In the LSA model, three dimensions are retained after SVD and also three topics are extracted from the PLSA model because of the fact that the dimensions in LSA are comparable to topics in PLSA. For the positive reviews, the three topics/factors are named as “Leading positive attributes of the product”, “Core functionalities” and “Affective” based on the associated words retrieved by the both methods. On the other hand, for the negative reviews, the three topics are ‘Not Leather’, “Problems”, “Service failure”.

Factors/Topics	PLSA	LSA
Leading positive attributes of the product	Large, Roomy, Stylish, Price, Quality, Amazing, Beautiful, favorite, Bag, outfit	Beautiful, Nice, Color, Design, Happy, Thank, shoulder, picture, review, purse
Core Functionalities	Shoulder, Strap, Texture, Material, Pattern, Double, Zipper, Pocket, inside, fashion	Shoulder, Strap, Pattern, pocket, Zipper, inside, price, pretty, color, order
Affective	Birthday, Gift, Friend, Love, Pretty, Sister, Happy, Pink, Picture, Look	Birthday, Gift, Fun, Sister, Love, Favorite, Happy, Price, Absolute, please

Table 15: Comparison of PLSA and LSA Factors (and Associated Words) of the Positive Reviews of Handbag

Factors/Topics	PLSA	LSA
Not Leather	Plastic, Leather, Real, Expect, Zip, Spacious, Pink, Bad, Bag, color,	Plastic, Leather, Pleather, Real, Expect, Bad, Boo, Spacious, Bag, zip
Problems	Color, material, Look, Photo, Picture, Rough, Thread, Handbag, Leather, Pleather,	Deceive, Pink, Picture, Peach, Issue, color , Seller, Ugly, Massive, Photo
Service Failure	Broken, pieces, contact, Customer, Help, Product, Quality, Attach, phone, Amazon	Break, Pieces, Cheap, Faulty, phone, Receive, Decent, Zip, Close, Money

Table 16: Comparison of PLSA and LSA Factors (and Associated Words) of the Negative Reviews of Handbag

The comparison of the word associated with each topic shows that topics extracted by PLSA have more interpretability and contain more information. For example, for the positive reviews, the words which have high probability to be in the topic ("Leading Positive Attribute of the Product") are "large", "roomy", "price", "quality" (colored in pink). However, these important terms (since these words imply the competitive advantage of the brand and the topic) were not picked up by LSA. Moreover among the the words picked up by LSA, "review" , "purse", "thank", "shoulder" (colored in orange) are not relevant to this topic. The remaining words both in LSA and PLSA (colored black) contribute to the meaning of the factors (in both LSA and PLSA they are either relevant or neutral words). By neutral, we mean the words which are relevant and contributes to the better interpretation of the factor but does not have unique power like the orange words in PLSA. For example, "amazing", "beautiful", "nice" etc contribute to the meaning of the "lading positive attributes" and help in the interpretation that customers are happy with these attributes of the product. The results show top 10 terms (according to the probability for PLSA and loadings for LSA). A comparison of relevant and Irrelevant words picked up by both methods are presented below in subsequent

Tables. A human coder (the researcher herself) compares the relative relevance of the words of the two methods.

	PLSA (Retrieved Relevant Words)	LSA (Retrieved Relevant Words)
Leading positive Attributes	Large, Roomy, Stylish, Price, Quality	Color, Design
Core Functionalities	Shoulder, Strap, Texture, Material, Double, Zipper, Pocket, Inside, Pattern	Shoulder, Strap, Pocket, Inside, Zipper, Pattern
Affective	Birthday, Gift, Friend, Love, Sister, Happy	Birthday, Gift, Fun, Sister, Love happy

Table 17: Positive Reviews Relevant Words

	PLSA (Retrieved Irrelevant Words)	LSA (Retrieved Irrelevant Words)
Leading positive Attributes	Outfit	Thank, Picture, Review, Purse
Core Functionalities	Fashion	Order, Price, Pretty, Color
Affective		Price, Absolute, Please

Table 18: Positive Reviews Irrelevant Words

To quantify the performance superiority of the, precision of the two methods are calculated and shown graphically below. The number of irrelevant words picked up by both the methods implies the inferiority of the method. This has been shown in the table below. It is noteworthy that, to be superior technique, a method ha to yield high precision as well as retrieve low irrelevant words. There are some words which are neutral and do not yield additional information about a topic. So, these terms are neither relevant nor irrelevant in these cases. However, these words may help in understanding the meaning of the topic. For example: bag, nice, beautiful etc. In case of positive reviews of a handbag, nice and beautiful or bag do not provide any additional information, but provides more comprehension of the topic. These are not counted towards relevant or irrelevant towards the analysis.

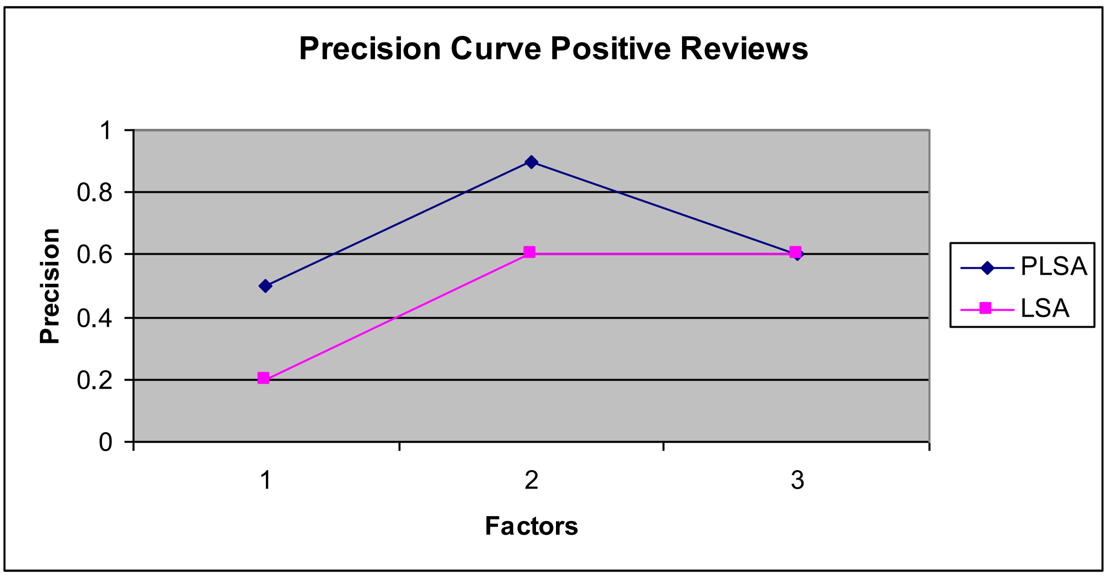

Figure 10: Precision Curve of Positive Reviews

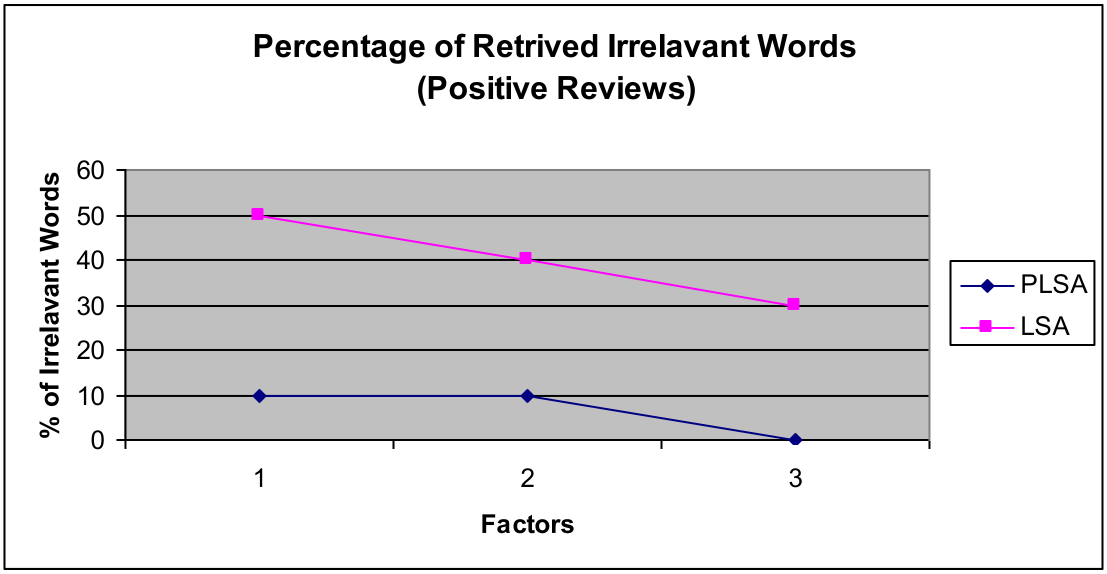

Figure 9: Irrelevant Words of Positive Reviews

For the negative reviews, the same pattern emerges. In the "Problem" topic, PLSA extracts more words with problems like "Rough", "Thread" "Material" etc. than LSA. Both models convey the information that the product does not "look" like the "picture/photo". Moreover, the service failure topic of PLSA also contains more specifics than LSA.

	PLSA (Retrieved Relevant Words)	LSA (Retrieved Relevant Words)
Not Leather	Plastic, Leather, Real, Expect	Plastic, Leather, Pleather, Real, Expect
Problems	Material, Look, Photo, Picture, Rough, Thread, Leather, Pleather	Photo, ugly, Picture, Deceive, Issues
Service Failure	Broken, Pieces, contact, customer, Help, Product, Quality, Attach, Phone, amazon	Break, Pieces, Cheap, faulty, Phone, Receive

Table 19: Negative Reviews Relevant Words

	PLSA (Retrieved Irrelevant Words)	LSA (Retrieved Irrelevant Words)
Not Leather	Spacious, Pink, Color	Spacious, Zip, Boo
Problems	Color	Seller, Massive, Pink, Peach
Service Failure		Zip, Money, Close

Table 20: Negative Reviews Irrelevant Words

Again, the precision of the two techniques for negative reviews are calculated. The Graphical representation of the precision curve is provided in Figure 10:

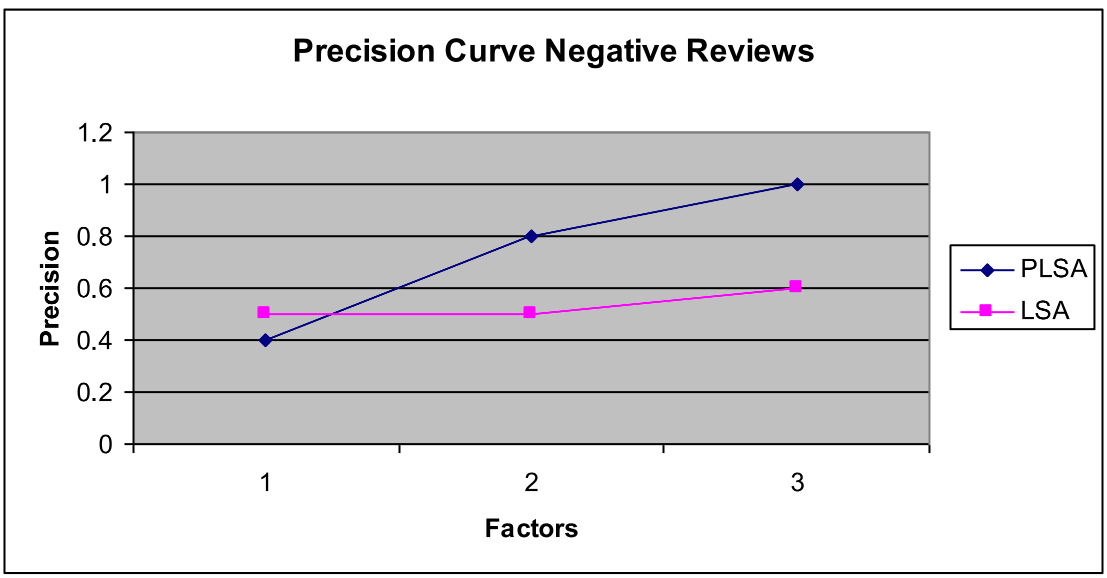

Figure 12: Precision Curve of Negative Reviews

Percentage of irrelevant words retrieved by the techniques is shown below. For each factor, the irrelevant words are counted and percentage is calculated. The graph shows that LSA has much higher percentage of irrelevant words than PLSA.

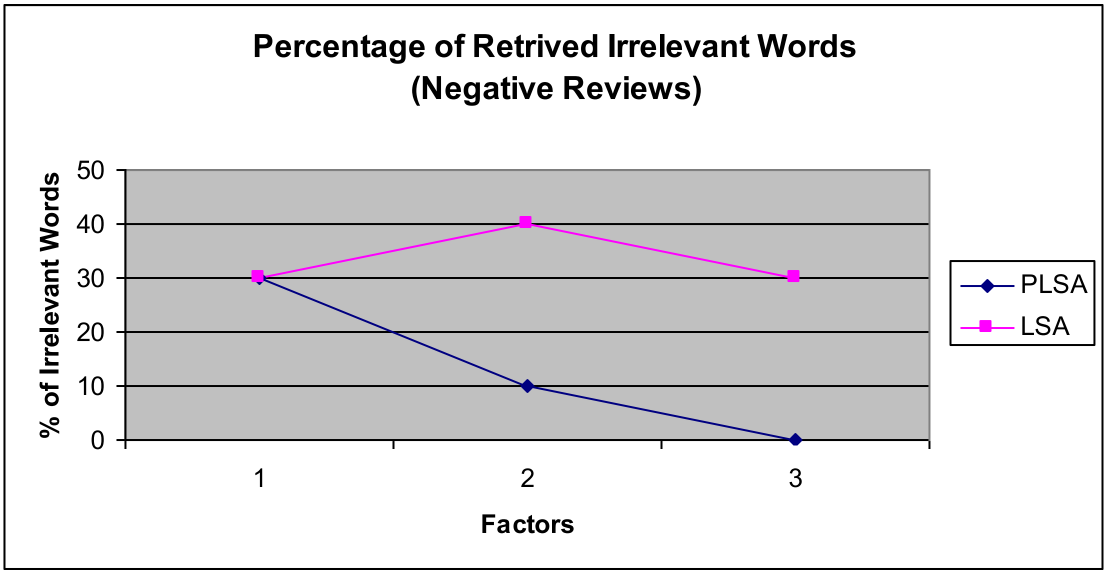

Figure 11: Percentage of Retrieved Irrelevant Words in Negative Reviews

However, the superior performance of PLSA does not exist in every scenario. When LSA and PLSA were applied to a broader category like "kitchen appliances" which contain reviews of various brands and appliances, PLSA has less interpretability since the topics are formed based on a specific appliance (blender, kettle etc.).Conversely, LSA provides general summarization of the important aspects and attributes of this product category. This problem can be attributed to the fact that PLSA tries find the highest probability terms that are likely to occur in the document. On the other hand, LSA tries to infer the topic based on the word co-occurrences.

Factors/Topics	LSA	PLSA
Core Functionalities	bake cake calphalon clean coat cook creuset dishwash easy flat fry grease handle heat muffin non nonstick oil pan set spray stainless stick stir surface ware wash wonder	absorb casserole cast cook cost creuset dish distribute dutch easily efficiency enamel flavor heat heavy iron lodge material oven pan roast season size skillet surface tend vessel whisk (oven, Pan, Skillet)
Aesthetic, more functionalities and small problem	bad bagel bake braun bread button consume counter design heat kitchen look muffin oven perfectly pick piece problem pull retro room slice slot super toast toaster whatsoever wide small	bagel bake bread buy calphalon coat cook don easy fan fry grill heat look meat muffin need non oil oven pan put scale side stick toast toaster (Baking)
Branding	analogy chef chore cutting edge cutlery differ global henckel hundred knife knives lifetime beauty blade block box brand carve nice price pro roast set sharpen sharper shear slice steak	amazon beater blade brand carve cut dough hand henckel kitchen kitchenaid knife knives mix mixer nice plastic price processor set sharpen slice spin steamer steel weight wet whatsoever whine whip (knives)
Technical aspect	fit hand kitchenaid look love mix mixer motor need potato power processor quart short speed store whip wonder attach beater big bowl cake case cloth cover cream dough	bowl box chopstick company cream customer excel fire food handle hot ice install kettle lunch machine microwave minute pour product protect remove service shear tea warranty water whistle (kettle, Tea)
Affective	awesome bar beauty calphalon clad clean color embroidery enjoy family gift haven love mattress month nonstick pillow purchase quality recommend seen set shaker sheet size skillet stainless top wedding	cocktail coffee cone cup drink enjoy fine food glass grind hours juice lose machine maker model mug press quiet read remain screw sheet spin tea thermoset top

Table 21: Comparison of PLSA and LSA factors (associated words) of the positive reviews of kitchen appliances.

It can be seen that LSA extracts topics that provide information about an attribute of the product category. For example, it can be inferred by looking at the factors extracted by LSA that, customers talk about core functionalities, aesthetics, branding, Technical aspect and affective content in the reviews. However, if the topics of PLSA are examined, it is evident that the topics are extracted according to the appliances. For example, first topic relates to "oven, pan, skillet", the second one relates to "baking", the third one "Knives" and then "kettle and tea". Unlike LSA topics, these do not express core topics of the reviews. Therefore, from a managerial perspective, information in the topics extracted by PLSA has little to no use. On the other hand, the topics in LSA provide the perspective of what customers generally look for in this product category. For example, customers are happy if the appliances serve an aesthetic purpose in addition to the core functionalities and technical superiority. Moreover, this category seems to be a popular choice for gift giving. Customer also compares different brands to purchase in this product category. All these information helps a manager to decide about the attributes new product in the category or improvisation of the product. Therefore, in this scenario, LSA works better in terms of interpretability. We do not produce a performance measure curve for this section because the result supporting the superiority in LSA is very obvious. As discussed the grouping of words are completely different and performance measure curve (or the table of relevance measurement) will not provide any valid comparison since there is no overlap of relevant and irrelevant words.

5.4 Conclusion

With the growth of internet usage, there is a vast availability of user generated contents. For the market researcher, these contents are utterly useful and important. These contents are mainly in the form text. In marketing, the use of content analysis goes back several decades. Qualitative content analysis reveals patterns and trends especially in a social setting. However, contents found in the web are huge in size and usually are not suitable for manual analysis. Therefore, an intelligent and automated method is needed where the analysis of large amounts of data is required.

There are lot of text mining techniques that are used to reveal trend and patterns in a text data. Every technique has its own advantages and disadvantages. The suitability of the techniques also depends on the context at which this is being used. Although computer science literature has been researching in this area for a long time, marketing discipline has just started to investigate in this area. The knowledge and performance measures of the techniques cannot be directly transferred to the Marketing domain, since the performances are context specific. For example, from a retrieval perspective (in computer science literature), retrieval means if a query word is given to a system, the system's ability to retrieve similar words or documents containing the same topic. So higher the performance, the higher the rate of bring out relevant (similar) words. In the contrary, in this marketing context, the higher the performance, the higher retrieval of Marketing manager's important information terms/documents. Therefore, along this line, the present study investigates the performance of two popular text mining techniques. The study supports the idea that the choice of text mining approaches should be based on the goal of the marketing researchers. As mentioned before, the two contexts were different in terms of specificity meaning that one context contained customer reviews of only one brand of Handbag and the other context contained reviews of different brands and appliances of "Kitchen Products". The results show that, in the former case, PLSA extracted topics that are more meaningful and vivid. It was more interpretable and contained more information. LSA extracted topics did fairly well; but were not as complete as PLSA topics. There were cross word meaning that one word belonged to more than one factors. There was also high number of irrelevant words in a topic compared to PLSA. Based on the precision and number of irrelevant word extracted by these two techniques, it I concluded that in this context PLSA work better in achieving goal.

In the second context where the goal was to learn important topics in that product category, PLSA and LSA were performed. Here also PLSA extracted meaningful topics; but more importantly, these topics were around each appliance. Each topic represented each appliance in the product category "kitchen appliance". More importantly, it did not group the topics according to the discussion topics of the product category (hence product attribute) which are of the main interest from a marketing mangers perspective. For example, PLSA revealed the grouped as Oven, Baking, Knives etc. Usually this information will not provide a marketing manager useful insight. It should be noted that from an information retrieval perspective PLSA might have done a fair or even superior job; however depending on what kind of information is looked for, PLSA is not a superior technique in this context. On the other hand, LSA grouped the topics according to the discussion topics of the review. For example, core functionalities, technical aspect, branding etc. These information are of interest to the marketing manager. Therefore, the study concludes that if the goal is to learn about a specific brand and its positive and negative attributes, PLSA reveals more specific information. However, if the goal is to learn about important aspects of a broader product category, LSA works better. It provides more useful information foe decision making.

5.5 Limitation and Future Research

Like any other studies, this study is not without limitation. First, for the performance measurement, the study uses precision measure which is a measure of number of relevant words retrieved in all retrieved words. However, there are words which are relevant to the topic but not really useful. For example, in the handbag positive reviews, the word "nice", "favorite" do not provide any additional information. But these words are not irrelevant words at all. To be conservative, the present study left these words out from the "relevant" and "irrelevant" word counts so that the results do not get biased. A count of irrelevant words provides another measure of performance which has been used in the current study. However, the main criticism of this kind of performance measure is the subjectivity of the meaning. The precision measure is a YES/NO approach which fail to capture the fuzziness in meaning of the words. Although the present study uses manual inspection along to measure precision, the subjectivity often becomes a problem and may bias the result. However, to combat this problem to some extent, the fuzzy meaning words are left out and a measure of irrelevant words is performed.

Application of text mining in marketing domain is a rising phenomenon. The fact that if a text mining technique is superior in terms of information retrieval (for representing the data, retrieving similar documents, search purposes), it might not be a superior text mining technique for a Marketer's point of view. This idea warrants marketing researcher to experiment with techniques and find their suitability in different marketing contexts and needs.

CHAPTER 6

6.1 OVERALL DISCUSSION

Due to wide availability of user generated content, researchers are interested to analyze these data to better understand about people's behavior, their intention and social actions. Marketers are also being interested since customer's opinion in the web can provide a great deal of information which was unavailable otherwise. The content which are available are mostly text in nature. Therefore to analyze these data, text analyzing techniques are needed. In this dissertation, I analyzed electronic word of mouth (product review) with the help of quantitative content analysis techniques.

As mentioned before, market researchers are very interested in analyzing the opinions of customers. In a series of three essays, I try to analyze electronic word of mouth and techniques needed for analysis. In the first essay I examine if discrete emotions expressed in the product reviews have differential effect on the future customers. It was done by analyzing the effect of these discrete emotion scores on helpfulness vote of a product review. Reviews with helpfulness vote of the product reviews are available in a retail site like Amazon. The analysis shows that indeed, reviews expressing emotions associated with high certainty are more helpful than reviews expressing emotions with less certainty. The claim was also supported by laboratory experiments.

Along these lines, in the second essay, I explore the topics expressed in the positive and negative product reviews. The results shows that positive reviews mostly talk about the product itself, whereas the negative reviews tend to report service related failure. Customers expect smooth delivery and hassle free services when ordering something online. The customers might be uncertain about the product quality and therefore might be more lenient about the product. However, they expect the related service to be smooth. Therefore, when this expectation violation occurs, people get upset and complain more about this. Moreover, the future customers find this services failure related topics to be more helpful than others.

In the last essay, I compared two text mining techniques and measured their performance. The results show that, if a marketing researcher is particularly interested about one brand, PLSA works better. If She/ he is more interested in the broader product category, LSA should be used.

This research has many managerial applications. First of all, knowing that some emotions are more helpful to future customers than others, marketing campaign and advertising should be accordingly based. There is a greater need for monitoring customers' opinion online from a brand manager's perspective. Marketers should avoid inducing negative certainty emotions since this type of emotions will affect future customers profoundly.

Marketers would be able to track their brand performances by analyzing the reviews. This will give them the idea about the negative aspects of his brand and will provide an opportunity to improve that aspect. Another important observation from the study is to improve service related to retailing. Since this failure spreads to future customers and potential customers find this information useful, it is very important to improve the service related to that product. This piece of information may be used for improving a product. For example, if the customer is talking about design in the reviews and a specific brand does not have good design, knowing that it is an important factor to the customers, the product can be improved in look. Also, this information is also useful for new product development in a product category.

Moreover, the research program also indicates the use of text mining technique in two contexts. This is directly applicable in the practice. With the improvement in techniques, Marketers might feel overwhelmed about the suitability of the technique to use. The third research is very closely practice oriented and indicates the direction.

To interpret the results, the following limitations should be taken into consideration. First, to test the model and the Hypotheses in the first essay, real product review has been used. This improves external validity and generalization. However, this comes with the disadvantage of noisy data. In a real product reviews, there is so much noise involved that it was not possible to measure and control for every variables. For example, the reviewers' characteristics were not included in the model as covariates. It is possible that these variables might affect the helpfulness vote. Another potential limitation of the study is the measurement of emotion scores. Text mining is still in its infancy. The reliability and validity of the measurement of emotion is increasing with the development of the techniques but not yet have reached its peak. It might be one source of imperfection of the study. Studies may conduct discriminant validity to more precisely capture the effects. Future research may investigate the proposed relation with more control variables to investigate it more carefully. Studies should investigate the effect of other certain and uncertain emotions to generalize the findings. For example, anger is another high certain emotion which can be investigated to see if the propose relationship holds. Future research may also examine the effect of other cognitive appraisal dimension on the helpfulness vote of a product review. For example, fairness is another cognitive appraisal dimension. There are high fairness and low fairness emotions. It is intuitive that high fairness emotion might be more helpful than low fairness emotions. Future studies may also look into that.

For the second essay, a factor analysis is run to quantify the result. It also provided us with the factor scores which were used in the subsequent analysis. However, a confirmatory factor analysis would have been more conservative. Since, the factor scores were used, we did not proceed to do the CFA. Future studies may also perform the analysis to see the factors in details. Studies should investigate the topics of other product reviews. This will give a more comprehensive view on the topics discussed in different products. This can also extended for service. It will be vey interesting to see how the difference between positive and negative reviews differs in service context. All these results can be used to build a comprehensive typology.

Thirdly, there are many areas open for research in this context. Marketers have to come forward to analyze these valuable text data to better understand today's market and customer behavior. More importantly, these data provide an opportunity of learning about customers. However, it is important that these techniques are developed and adapted by marketers. The reason is, when an information technologist tries to improve a method, his goal might be increase retrieval accuracy. Marketers have different goals from the data. Therefore, it is suggestive that marketers take a step toward this direction. Future research may conduct research on comparing other techniques such as LDA and PLSA. Also marketers need to make the transition by adapting these techniques to marketing context.

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Appendix

Five Cluster solution for positive reviews (only the title showing)

Cluster 1 (33 documents):

Document 3: must have
Document 5: buy it but keep your iron
Document 8: skip cheap imitators with fancy gadgets
Document 15: excellent kettle excellent company
Document 17: all clad 16 quart stainless stockpot
Document 24: oh come on
Document 25: shred away
Document 28: absolutely marvelous
Document 30: for friday cocktails
Document 33: fantastic coffeemaker if you have the space
Document 37: my own tea butler
Document 41: great item
Document 47: cleave your meat in under 10 minutes
Document 50: couldn t live without it
Document 51: seepex dust bin
Document 60: stainless steel is the best
Document 68: does everything
Document 69: squeezes out the competition
Document 70: kitchenaid food processor
Document 71: very good machine enjoy the quietness
Document 76: nice and roomy
Document 77: customers beware
Document 94: cusinart good quality
Document 95: great foodprocessor
Document 98: lovely really lovely
Document 104: wow
Document 105: best lunch box ever hot food stays hot for hours
Document 114: my gorgeous cake
Document 122: great item for a great price
Document 130: stainless is better than nonstick calphalon is best value
Document 132: love this
Document 140: very good but expect some hiccups getting started
Document 146: great little steamer this hs900 model is only 19 99 at target

Cluster 2 (24 documents):

Document 1: best knife ever
Document 4: great pans for the price
Document 16: treadable and edible

Document 18: 1 year of slicing roasts and still carving
Document 19: attachment only has one e not two
Document 20: luxurious beautiful sheets
Document 31: casserole dish
Document 35: a great set at an even greater price
Document 36: black and decker tiered food steamer
Document 39: great knives
Document 40: cutting edge
Document 54: great set of knives
Document 59: useful knife
Document 64: rowenta dz 9080
Document 74: favorite accessory
Document 75: non stick and great for everyday
Document 82: this makes my banana bread look even better
Document 83: surprisingly good kitchen shears
Document 84: classic style
Document 93: well made at a good price
Document 100: the best value i have seen
Document 112: saw it for much more this weekend
Document 119: great little grinder
Document 141: super sharpener

Cluster 3 (48 documents):

Document 2: excellent kid s game
Document 9: perfect and evenly toasted
Document 10: an elegantly designed long wide toaster
Document 11: a step above the rest
Document 12: great ice cream maker
Document 13: great pan for a couple of people
Document 14: some le creuset products need seasoning
Document 22: best way to hang curtains on metal surfaces
Document 26: perfect for slow roasting roasts until the meat falls off the bone
Document 34: hoover vacuum
Document 42: totally worth it
Document 43: olga gill
Document 45: great toaster for a good price
Document 52: whips like a pro
Document 53: excellent pan and great for bench pressing too
Document 55: fantastic deal plenty of light
Document 56: my favorite salad spinner
Document 57: so why did i absolutely love this pan
Document 62: excellent toaster
Document 66: nice set but
Document 67: engineer not a baker
Document 78: i feel like a star now
Document 79: stylish sexy simply the best
Document 87: let me whisk you away

Document 89: a bar favourite
Document 90: great all around pan
Document 92: multi purpose equipment
Document 99: because a one that isn t cold is scarcely a one at all
Document 103: very nicely built aebleskiver pan
Document 106: cooking can be easy
Document 107: 1 2 toaster 1 2 oven
Document 108: the best pan i ve ever had
Document 111: perfect all in one pan
Document 115: i m the baker
Document 117: kitchenaid silicone loaf pan
Document 118: amazing iron for a great price
Document 120: customer reports is right on
Document 125: a great starter piece or addition to your le creuset collection
Document 126: a nice little addition to your home bar
Document 128: great indoor grill
Document 134: outstanding value
Document 135: love it
Document 136: pillow top king fiberbed
Document 137: perfect for new users
Document 138: my favorite grill pan
Document 139: lightweight excellent heat distribution easy clean up
Document 142: works well and looks nice
Document 145: best cake pan you ll ever own

Cluster 4 (11 documents):

Document 6: the more you use it the more you will love it
Document 27: no hassles easy to read
Document 29: strong reliable mixer the best
Document 49: easy amp durable
Document 65: it really does fit
Document 72: size doesn t matter
Document 85: bring the wine out
Document 88: an excellent product
Document 101: great scale
Document 110: a must have for any kitchen
Document 147: outstanding quality and great price

Cluster 5 (31 documents):

Document 7: pre seasoned is a plus but not necessary fabulous oven
Document 21: works well
Document 23: the quot must havequot kitchen gadget
Document 32: versatile oval dish
Document 38: worth the money just for the fun
Document 44: great for a large family
Document 46: just the right size for my family
Document 48: le creuset quality
Document 58: not so much for the big mixers

Document 61: i love this pan
Document 63: wonderful
Document 73: it works like a charm
Document 80: userful wonderful worth the money
Document 81: hot stuff
Document 86: cuisinart is short sighted
Document 91: kitchenaid always has what you need
Document 96: great for a big family
Document 97: good value fire protection
Document 102: microwave egg boiler
Document 109: strong and long lasting
Document 113: best of the small digital thermometers
Document 116: feels like home
Document 121: awsome skillet
Document 123: great design great function
Document 124: your lodge will outlive you
Document 127: lodge pro logic pre seasoned 8 pan is top notch
Document 129: crock pot cheesecakes
Document 131: much cheaper at target
Document 133: good coffee maker
Document 143: canister
Document 144: makes cooking fun

5 Cluster solution for negative reviews (only the title showing)

Cluster 1 (60 documents):

Document 1: don t waste your time or money
Document 3: very poor quality
Document 4: very thin for a name brand towel
Document 10: warning
Document 13: almost useless
Document 21: bits of metal is not what i want with my cheese
Document 24: a very good external design but it does not last very long
Document 25: fiestaware 1 qt pasta bowls i got what i paid for
Document 29: dangerous to your health
Document 41: not the best at all
Document 43: so you want to throw away 30
Document 45: water reservoir poorly designed
Document 49: an investment that s funny
Document 51: nice design but it s broken too
Document 58: broken item
Document 61: another dissapointed cuisinart customer
Document 65: looks don t always count
Document 66: it s less trouble driving to carvels
Document 67: verry disappointed with cuisinart
Document 70: stupid stupid stupid
Document 80: reliability is the issue
Document 81: worse than the ronco machine

Document 82: iced by machine
Document 90: easy to spin but disappointing results
Document 104: buyer beware
Document 106: broken item
Document 107: chips the knife edge
Document 108: very disappointing
Document 109: ok quality not much of an edge
Document 110: just plain terrible
Document 114: not what i expected
Document 115: dirty water drips back onto carpet
Document 126: very disappointed
Document 128: this item does not work
Document 136: very disappointing
Document 139: not for smoothies
Document 155: is this some sort of sick joke
Document 157: non absorbent towels
Document 162: it was great until i washed it
Document 164: get a real grinder
Document 168: i got out while the gettin was good
Document 173: piece of junk
Document 175: glass is fragile
Document 176: works so so company has exaggerated performance claims
Document 178: does not work well to chill wine quickly
Document 185: doesn t do the job
Document 190: vinchilla wine chiller
Document 191: great pasta takes practice
Document 194: battery replacement
Document 196: keep looking
Document 197: wire slicers not durable
Document 200: broken hearted pasta maker
Document 207: perfect for the reckless customer
Document 211: i don t get this positive feed back animal abuse
Document 220: sunbeam 4200 smoothie maker
Document 221: not happy
Document 223: negative on nordic cake keeper
Document 233: mislabeled size
Document 235: they just increased the price
Document 236: defective right out of the box

Cluster 2 (65 documents):

Document 7: the bad reviews are right don t buy it
Document 9: disappointed
Document 12: calphalon
Document 18: not as described
Document 26: not that great
Document 33: would never buy anymore of this
Document 35: overpriced hate this pan

Document 37: impossible to remove the lids
Document 53: not good for smooth surface cooktops
Document 60: disappointment
Document 64: good product terrible vendor buy elsewhere
Document 74: what a disappointment
Document 78: not nonstick
Document 85: arrived broken
Document 86: do not recommend
Document 91: a joke of an appliance
Document 93: ruined my cake
Document 94: stick with metal pans
Document 96: very bad quality
Document 98: light intermittent household use at best
Document 99: bad idea if you are thinking cheesecakes
Document 100: save your money
Document 102: buyer beware
Document 103: caution they don t warn you about a major problem
Document 111: terrible quality
Document 116: stainless not
Document 117: bad quality a review after long term use
Document 125: warning don t buy t fal
Document 130: its ok
Document 131: not up to par
Document 132: not happy with this pan
Document 138: give this one a pass
Document 143: this product is horrible
Document 147: i hate these pillows they smell like a henhouse
Document 154: why anyone thinks this is a good iron is beyond me
Document 158: title says nonstick must be a typo
Document 159: siz is too small
Document 169: one kitchenaid attachment to skip
Document 170: bad vacuum
Document 179: great concept poor design
Document 181: peeling after a couple years
Document 201: auto shutoff is incompatible with sewing and quilting
Document 203: nice but not very durrable
Document 206: wonderful until the handle cracked
Document 212: amazon com delivers used coffee mugs
Document 213: so so
Document 215: godzilla
Document 216: very difficult to clean a truly horrible purchase
Document 217: impossible to clean
Document 218: dishonest marketing
Document 219: ugh
Document 224: not the same as the cast aluminum rose bundt
Document 225: thanks for the reviews

Document 226: not a good foam pump
Document 227: keep away from it
Document 229: it s true this non stick pan is not what it pretends to be
Document 234: way too thin
Document 241: do not recommend
Document 247: very disappointed
Document 251: i don t understand this product
Document 253: cooks only meats well cleaning is a real bear
Document 254: not so good
Document 256: worse frying pan i ever bought
Document 257: if you fry it it will stick
Document 258: pure junk
Cluster 3 (58 documents):
Document 2: don t bother with this model
Document 6: old technology fat separator
Document 8: barely gets one star
Document 11: bad advertising by amazon
Document 14: the cannister is too small
Document 16: life span
Document 17: a bummer for a dyson lover
Document 19: do not buy this brand
Document 22: save your money
Document 23: completely ineffective candy thermometer
Document 36: poor packaging
Document 42: do not buy any self pro pelled hoover vacuums
Document 46: received wrong one three times
Document 47: barely functional but not reliable
Document 54: still waiting
Document 56: broken after 5 months
Document 73: a big mistake
Document 75: returning broken glasses for credit
Document 77: taylor professional thermometer shuts itself off
Document 84: doa
Document 87: horrible product
Document 88: a piece of junk
Document 89: super annoying   sold but did not deliver
Document 92: there are better toaster ovens out there
Document 95: bulb is weak link
Document 105: don t buy this model   honeywell screwed up
Document 121: great for a week then junk
Document 122: would like it if it ever arrived in one piece
Document 124: cookware is fine but bonus item still not here
Document 127: suitable for hard cheeses only
Document 129: beautiful but not reliable
Document 133: never received this item
Document 144: a big fat joke a waste of money

Document 149: very annoyed
Document 150: great as long as it worked
Document 151: no need for cups slurp it off the counter
Document 171: don t buy this piece of junk
Document 172: yuck
Document 177: does nothing in 7 minutes
Document 180: i wish there were zero stars
Document 183: don t buy it
Document 184: good company bad product
Document 186: wrong description on site
Document 188: review of metrokane mighty oj manual juice squeezer
Document 193: ramekins review
Document 195: failed after one use
Document 199: super annoying sold but did not deliver
Document 204: not worth the mess
Document 205: lasted less than year
Document 208: cracked in the oven after 2 months
Document 210: broke three in quick succession
Document 222: looks great but as a toaster much to be desired
Document 228: great device until the probe fails
Document 232: a total piece of crap
Document 244: don t waste your time
Document 245: not a quality product
Document 246: beautiful but not reliable
Document 248: don t order from target

Cluster 4 (59 documents):

Document 5: don t waste your money
Document 15: not worth the shipping even if its free
Document 20: arrived prefilled with dirt and hair
Document 27: 20 hose does not fit hepa hoovers
Document 28: insufficient information in product information
Document 30: deception
Document 31: this oven stinks
Document 32: this dutch oven really stinks
Document 38: i do not like being lied to
Document 39: fondue failure
Document 44: engineering missed again
Document 50: must agree with negative reviews
Document 52: useful but a hazard to the user
Document 55: crap
Document 57: not too acurate
Document 59: if you love your kitchenaid stand mixer this is a no no
Document 62: beware outer shell may melt
Document 63: a good idea disappointing in use
Document 68: good for 4 years
Document 71: you re kidding

Document 72: what a piece of junk
Document 76: exterior exposed lip reaches 250 degrees on auto setting
Document 79: bad design cheap materials
Document 83: buy a good steam iron instead
Document 101: not what i thought it was
Document 112: there are only 4 programming options
Document 113: do not buy
Document 119: awful
Document 120: worst product i ever bought
Document 134: good idea bad in reality
Document 140: piece of junk
Document 141: it s ok but a bit fragile
Document 142: a short but fruitful life
Document 145: i burned my eye pretty bad
Document 146: black goo and funny smell
Document 148: high priced low quality
Document 152: cooker from he
Document 153: get the upgraded grill with the removable plates instead
Document 160: started out good
Document 161: get the upgraded grill with the removable plates instead
Document 163: not from england
Document 165: awful awful tea kettle
Document 166: looks great while it burns you
Document 167: huge disappointment
Document 174: pay more to get something better
Document 187: new french white is terrible please do not waste your money
Document 189: the glass was great but amazon s shipping is the worst
Document 192: horrible set
Document 198: good oven but controls gave out
Document 209: incorrectly described
Document 214: hardly commercial quality
Document 231: i received this as a christmas gift
Document 238: paring knife is so dull i couldn t stand it
Document 239: bad quality control
Document 240: nowhere near as good as genuine wusthof or henckels
Document 242: too slow
Document 243: what is the world coming to
Document 249: discovery
Document 252: horrible bakeware

Cluster 5 (16 documents):

Document 34: this is not kitchenaid quality
Document 40: cute but cute doesn t cut it in a busy kitchen
Document 48: too much work didn t last long
Document 69: def not a good tank
Document 97: the ugliest thing i ever saw

Document 118: dont buy this item
Document 123: bagels yes bread no
Document 135: bad fit
Document 137: jack of all trades master of none
Document 156: how can i
Document 182: designed wrong
Document 202: be carefull i broke two allready
Document 230: i hate it
Document 237: poor color transfer on cups
Document 250: tomato killer
Document 255: not as sturdy as it looks