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Thesis

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The effectiveness of electronic word of mouth in the hospital care industry

Author: Nicole Stelea

Student number: 323671

Email address: tnstelea@yahoo.com

Supervisor: Assistant professor dr. Nuno Camacho

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Abstract

Due to changes in the health care market, it is nowadays expected from consumers that they make a decision regarding their hospital based on price – quality considerations. Hospital choice, therefore now has to be treated more as a 'search good', instead of as an 'experience good'. While traditionally, the choice of hospital was largely based on word of mouth, either in the form of referral from the general practitioner or as advice from friends and family, recent efforts have been made to publish more evidence based information, in order to reduce the information asymmetry that is perceived within this field, and to make the quality of medical services more transparent. However, word of mouth (WOM) seems still to be the most relied upon source of information and the emergence of internet has brought along the electronic word of mouth (eWOM). An example of eWOM in the health care sector is reviews on hospitals. Important characteristics of this electronic word of mouth are its valence, volume and dispersion. This study attempts to determine the effectiveness of the electronic word of mouth on a high stakes decision, such as hospital choice.

Keywords: Hospital choice; health marketing; eWOM, word-of-mouth valence; word-of-mouth volume; word-of-mouth dispersion; consumer ratings; choice experiments.

Acknowledgements

Thomas Alva Edison (1847-1931) once said:

"I have not failed. I've just found 10,000 ways that won't work."

Just as Thomas Alva Edison, I have found 10,000 topics that would not work. I had one clear goal in mind: whatever I would write my thesis on, the topic had to be something that made a difference for me and was as well challenging. When I started, I never thought I would end up doing it on the health care industry. However, due to personal circumstances and my own frustrations with this sector in The Netherlands, I ended up being interested in this topic. I would like to thank foremost, my supervisor for his never-ending patience and guidance. Then, I would like to thank Sonya and Philip for being able to make me see things more clear, whenever I felt overwhelmed. Furthermore, I would like to thank my parents and grandparents for supporting me throughout the university and in general, financially and morally. Finally, I would like to thank my friends who have been there with their encouragements and moral support.

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1. Introduction

1.1 Introducing the topic

The healthcare market is acknowledging global changes. The current global cost of healthcare is estimated at $6 trillion to $7 trillion, however it is anticipated that these costs will rise to $12 trillion in the next seven years.[1][2] Particularly, in the western world the health care costs are high.[3][4] In order to make patients more aware of the costs of healthcare services, several measures have been taken in western countries such as United States, The Netherlands and Sweden. Patients are given more freedom when choosing medical facilities or healthcare plans. This change is welcome, as patients have become increasingly empowered and want an active voice in their treatment. However, there is also more expected of patients, namely that they inform themselves about the quality and costs of healthcare providers and that they make a decision based on an educated comparison.

Traditionally, consumers of healthcare based their decision relying upon the referral of their general practitioner and the word of mouth of family and friends (Schwartz et al., 2005). Word of mouth (WOM) has been characterized by Westbrook (1987: p. 261) as “informal communication directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers” and has been around for as long as humanity. However, in order to help patients base their decision on more evidence-based measurements of healthcare providers’ quality, different sources have been made available by the providers themselves or by independent healthcare organizations. Examples of such sources are: hospital reports, satisfaction surveys, hospital websites or rankings. Recent research (Edgman-Levitan and Cleary, 1996; Leister and Stausberg, 2007; Schwartz et al., 2005) has pointed out that these sources are not as much employed in the documentation process of patients, as it is intended by the government. People still base their decision largely on referral or word of mouth (Kenagy, 1999; López et al., 2012).

The emergence of Internet has had an impact on the healthcare system in several ways. First of all, it has facilitated access to an increasing amount of (cluttered) information on

[1] World Health Organization. 2011 WHO Global Health Expenditure Atlas.
[2] Bouwens, J and D.M. Kreuger.(N/A). "Embracing Change: The healthcare industry focuses on new growth drivers and leadership requirements.
[3] C.H. (2013, July 24th). "Searching for a diagnosis".
[4] Hess, A.E.M and M.B. Sauter. (2013, July 2). "Countries that spend the most on health care".

diseases. Furthermore, with the appearance of forums and social media networks, online word of mouth, also named electronic word of mouth (eWOM) can nowadays practically reach everybody who has an electronic device with internet connection. So, the importance of the healthcare 2.0 has also increased. Healthcare 2.0 can be characterized as the active cooperation between patients and healthcare providers, which enhances the effectiveness and the quality of care.[5] In accordance with these changes, review sites have been launched in various countries and patients can value there their experience with a hospital.

With these developments, certain questions arise, such as: how do people interpret the healthcare information, which they find online and is posted by peers and especially, how does that information influence their choice? In short, as the role of the electronic word of mouth increases when orientating ourselves towards products and several services, what is its role within the hospital care industry?

1.2 Problem statement and research objective

This study will look at the impact of certain attributes, namely the valence, volume and the dispersion of the information found on these hospital review sites, on hospital choice. The effectiveness of traditional and electronic word of mouth (eWOM) has been studied before; however most of the studies (Chen et al. 2003; Godes and Mayzlin, 2004; Sen and Lerman, 2007; Hinz et al., 2012) that have looked at the valence or volume of eWOM, have analyzed the individual content of the available posted reviews by determining from each review the tone for example and few of them looked at the impact of the content on the actual decision making process, by employing an experimental study. Also, only three studies (Godes and Mayzlin, 2004; Clemons et al, 2006; Dellarocas et al., 2007) have been identified that have also looked at the dispersion of reviews; however this variable has not yet been analyzed in high-risk goods. Also no study, so far, has looked at the effect of the aggregated review information on decision making, let alone on high stakes decision making, such as when choosing a hospital. High stakes decisions can impose a significant higher amount of stress on consumers than when choosing a brand of a product (Kahn & Luce, 2003). Also, to gain a better understanding of the impact of eWOM on the hospital choice, it will be analyzed how one’s tendency to be a maximizer or a satisficer moderates the effect of the characteristics of eWOM on hospital choice. Again, no other study has looked at the maximizing tendency in high stakes decision making process.

[5] According to the Council of Public Health and Care ("De Raad voor Volksgezondheid en Zorg").

Therefore, the following research question emerges:

What is the effectiveness of online word of mouth on the hospital choice?

In order to provide a consistent answer to this question, the following sub-questions will be analyzed:

- Which sources of information can consumers currently base their decision upon?
- Are consumers aware of the availability of various sources information?
- Do consumers use review information when making their decision?
- How are consumers affected by the valence (positive either negative) of online reviews?
- How are consumers affected by the amount and the dispersion of reviews presented?
- Are consumers' perceptions of review characteristics different when someone is a maximizer or a satisficer and does that influence that persons' choice?

A side note that needs to be made: for the context of this study, it is assumed that patients have free choice of hospital as it is the case in the Dutch health care market. The Dutch health care market acknowledged a significant change in 2006, as the Health Insurance Law[6] was imposed. According to the Health Insurance Law, everybody living[7] in The Netherlands is obliged to have a health insurance. This law was mainly enforced to encourage the free market working of the health care, in order to make citizens more aware about the costs of health and to involve them in making a choice regarding their providers (Reitsema et al., 2012[8]). Also, in order to stimulate the hospitals to deliver good quality against appropriate prices. The way that hospitals get financed in The Netherlands has already been changed since 1 February 2005 and hospitals now are allowed to set their own prices for non-urgent hospital procedures that occur often. Whereas in 2011, it comprised 34% of the performed operations, in 2012 it has already reached 70% of the procedures. The hospitals determine their prices together with the health insurers, and those prices in return influence their profits. As aforementioned, the purpose of these changes is to improve the quality of care and lower the costs. The changes seem to be in line with the wants of the Dutch population, as 90% of the

[6] Zorgverzekeringswet
[7] Everyone that lives and works in the Netherlands and is AWBZ-insured. It does not include those that stay shortly, neither children nor persons that are younger than 18 years.
[8] Reitsma, M., A. Brabers, W. Masmanand J. de Jong. (2012). "De kostenbewuste burger

Dutch wants to be able to choose its own doctor, clinic or hospital and about half of them do not want that their health insurers decide for them.[9]

1.3 Scientific and managerial relevance

This thesis will provide insights on the impact of the electronic word of mouth in high stakes decision making, as it will look at how hospital choice is impacted by online information, but it is also of relevance for the healthcare sector. I decided to focus on the health care sector, as it is an important service industry and as there is “no other service sector that affects quality of life more than health care” (Berry & Bendapudi, 2007, p. 121).

The purpose is to gain a better understanding about how consumers use electronic word of mouth and rating information and how it affects their decisions. Studies have been conducted on the motives of sharing eWOM (Hennig-Thurau et al., 2004), how eWOM affects the sales of particular products (Liu, 2006; Dellarocas et al., 2007) and also one study was conducted on the motives of sharing eWOM in the health care sector (Hinz et al., 2012). However, the field is still in its infancy and there are still no studies on the effect of eWOM on high stakes decision making. In this study, I will attempt to fill the gaps presented by Trigg (2011), regarding gaining a better understanding how patients use information on patient review platforms.

1.4 Structure of the thesis

First, this study will look at how healthcare fits into the consumer decision process and will continue with an analysis of the various sources of information, readily available for consumers to base their decision upon. Then, the existing electronic word of mouth and reviews literature are going to be analyzed and the model will be presented. Furthermore, the method of the study and the experiment will be explained, where after the results are going to be presented. Finally, the conclusion will follow, together with the limitations of the study and the proposed future research.

[9] As found in a study conducted by research agency MWM2. Commissioned by the Zelfstandige Klinieken Nederland (ZKN), meaning the Independent Clinics Netherlands.

2. Hospital choice: patients’ information search strategies

2.1 The consumer decision process during hospital choice

The changes that have taken place in healthcare systems in the western world have led steadily from supply-driven systems towards demand driven systems, in which hospitals are assumed to compete for patients. Accordingly then, the price of health care would fall. One of the main conditions for market mechanism is that consumers have freedom of choice. In order to asses properly their choices and make a decision, consumers need information about their available options. However, it is important to first have a look at the decision process of patients, when they are considering health care services.

There are several assumptions in the literature of choice behavior regarding how people make their decisions. Wolters and Lako (2012) emphasize in their study the difference in choice behavior between ‘search’ goods and ‘experience’ goods.[10] The main difference between these goods is the amount of information that is acquired prior to the purchase. For ‘search’ goods a great deal of information can be acquired, whereas the characteristics for the ‘experience’ goods are hard to be estimated and therefore little information is available (Nelson, 1970; Klein, 1990).

In a market-based healthcare system, patients are expected to treat hospital choice more as a search good and to look rationally at which option serves their best interest. However, Mol (2006) points out that healthcare is not a conventional transaction in which a product is sold against a price, but rather a process in which the interaction between the care giver and the care receiver goes back and forth as long as it is needed. Also, people are not always able to make rational decisions whenever they are healthy,[11] let alone when they are affected by a disease. The impact of a health care decision differs from the impact of choosing a consumer product. Research has indeed pointed out that consequential decisions such as decisions that involve housing, insurance or health care can cause stress and therefore can cause decisions to deviate from normative reasoning (Kahn & Luce, 2003).

Other than the nature of the sought goods, the decision process in healthcare is also affected by the involvement-level of the consumer. Namely, there is the in-control consumer

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[10] Nelson (1970) expanded Stigler's (1961, 1962) theory of search, with a theory of experience goods.
[11] As pointed out by Dan Ariely (2009) in Predictably Irrational, for example.

who searches for information actively, takes decisions himself and considers his general practitioner more as his sparring partner, while the passive consumer rather expects a dominant position from his general practitioner and is largely influenced by earlier experiences of family and friends and trusts upon the expertise of the specialist (Wolters and Lako, 2012). Furthermore, the involvement-level of a patient can also depend on the severity of his or her disease (Edgman-Levitan and Cleary, 1996). However, regardless of how much a patient is involved in the documentation process, research findings conclude that patients do want to be included in decisions regarding a disease or ailment (Wolters and Lako, 2012).

2.2 Types of information: professional sources

Traditionally, patients would base their decision on the advice of the general practitioner and of family and friends (Schwartz et al., 2005[12]; Harris and Buntin, 2008). In the rather demand-driven health care system it is assumed that hospitals compete for patients and that therefore the costs of healthcare will decrease. One of the conditions of competition is transparency; however competition can also enhance transparency (Wolters and Lako, 2012).

Several studies have criticized the lack of transparency in hospital quality (Emmert et al., 2012) and the lack of appropriate sources[13] and therefore, attempts have been made to release more evidence based public information, so that people would rely less on word of mouth of hospital reputation. Examples of such sources that are made public are: (i) report cards, (ii) satisfaction surveys, (iii) hospital websites, and (iv) rankings of hospitals. They can be made available by the government, the hospital itself, independent patient organizations or individual users of health care. These sources have each their own dimensions of usage and credibility.

Report cards: Report cards have been published by hospitals as an attempt to improve the content of medical reputation and to provide performance benchmarks. Its disadvantages are the methodological weakness and the fact that few people actually use them, as they are not easily available. Furthermore, patients do not understand the reported data or are not in the position to make a choice[14] or they do not find it as useful or trustworthy

[12] According to Schwartz et al. (2005) 64% of their respondents thought that their hospital had a good reputation because of their general practitioner, while 31% because of what friends and family had said.
[13] Bates and Gawande pointed out already in 2000, the lack of usage of evidence based information.
[14] As Bates and Gawande (2000) explain, when acutely ill, few of the Americans e.g. will not have the possibility or the will to analyze their options.

as word of mouth (Bates and Gawande, 2000). Schneider and Epstein (1998) found in their study that only 12 percent of the patients that were scheduled to undergo cardiac surgery hospitals in Pennsylvania were aware of a prominent report before the surgery and less than 1 percent of the patients knew the rating score of their surgeon or hospital.

An interesting paradox is that even though public reports are not used as much by consumers, their publication seems to enhance initiatives by hospitals to improve quality (Rothberg et al., 2008).

Satisfaction surveys: Satisfaction surveys are closed-end questionnaires that aim to measure the overall satisfaction of patients. According to research conducted by Edgman-Levitan and Cleary (1996), consumers are not interested in satisfaction surveys as they don't know how to interpret it and if they are biased or not.

Hospital websites: Public information on websites also does not seem to reach patients (Leister and Stausberg, 2007). In Reitsema's (2012) study also only few of the respondents indicated to use the public information that is provided on websites. That is, as well consistent with Harris and Buntin's (2008) finding that even though most of the quality information is available on the internet, its usage rate is relatively low.

Rankings of hospitals: Rankings of hospitals give information on specialty specific or overall hospital reputation scores. The rankings are based on surveys of various actors in the health care industry, such as general practitioners, medical specialists, nurses, residents, hospital managers and board members (Varkevisser et al., 2012). Rothberg et al. (2008) found in their study, a lack of consistent agreement between various rankings as they looked at five leading rating services and that they did not agree on the best performing hospitals, neither on the worst performing ones.[15]

Even though patients indicate to be interested in quality studies about their healthcare providers and their performance (Damman, 2010), few actually look for it (Schwartz et al., 2005). Reitsema et al. (2012)[16] point out that only 40% of the respondents actually look for information in order to choose a hospital and about 51% of those, actively search for information after being referred. The most important reason that they name for not being active is because they already know to which hospital or specialist they will go to. A study by

[15] Lack of consistency across rankings has also been found by Osborne et al. (2010).
[16] Reitsma et al. (2012). "De kiezende burger".

Dijs-Elsinga et al. (2010) has pointed out, as well, that 40% of their respondents were interested in information on the hospital they already went to and not in comparative quality information[17] of various hospitals (Schwartz et al., 2005). Another finding of Reitsema's survey is that people find it hard to make a choice. They do not know based on what they ought to choose, how to value that information and if it is trustworthy. Also, the ones that do not look actively for information themselves are still advised in their choice by their general practitioner.

Literature review, so far, has pointed out that patients do not really inform themselves using the evidence-based information sources. Rothberg et al. (2008) state in their study that it has been argued for already more than a century that public information is not reliable and does not portray the complicated conditions of patients and that therefore it is essential for consumers to have easy to access, interpretable interpret and consistent public information.[18]

2.3 The connected patient: the emergence of patient-generated reviews.

The emergence of Internet has brought a change in the usage of types of information. It has become an important source of information largely because it has low transaction costs and great accessibility (Bates and Gawande, 2000).

The Internet also had a significant impact on looking for information regarding health care. In the beginning, it was mainly used for seeking advice regarding particular medical conditions and not for comparison purposes. Due to the easier availability of information and consumer-oriented pharmaceutical ads[19], more patients started informing themselves on their health conditions online. According to the report *The social life of health information* by Fox and Jones (2009) of the Pew Internet & American Life Project, in 2008, 61%of the American adults looked up health information online, while in 2000, only 25% of the American adults did that. The informed patient seemed to have emerged and was no longer satisfied with the provided possibilities, but wanted to have a voice in his or hers treatment. The shift in control started to move away from the doctor and patients became more empowered, therefore the communication dynamic between doctors and patients also changed. (Smith, 1997; Harrington et al., 2004; Laing et al. 2011).

[17] Harris and Buntin (2008) have also concluded that less than a quarter patients are aware of public available quality comparative information.
[18] Also stated by Harris and Buntin (2008) in their paper "Choosing a Health Care Provider: The Role of Quality Information".
[19] Rooney, K. (2009) "Consumer-Driven Healthcare Marketing: Using the Web to Get Up Close and Personal".

An interesting study is of Hesse et al. (2005), who found that 49,5% of their respondents preferred going to their physician first for health information, however asked for their actual behavior 48,6% reported going online first, while only 10,9 % reported going to the physician first. Also, Murray et al. (2003) found that 97% of the people they inquired about their internet seeking behavior of health information were more confident to talk to their physician about their issues, 96% thought that they had a better understanding of their condition and 85% felt that it had encouraged them to follow upon the advice of the physician.[20]

Of those that looked up health care information, about 60 percent searched for 'user-generated content'. Previous qualitative studies on healthcare choice behavior (Richard et al., 2005; Fanjiang, et al, 2007) point out that, patients prefer to read other patients' experiences online and value the opinion of family, friends and doctors above public quality information.[21] A new type of source of information has, therefore, emerged:

Review/rating sites: As stated by Bates and Gawande (2000), word of mouth has been criticized as being an unreliable benchmark for hospital reputation and quality. On review/rating sites, people rate their hospitals or doctors on various attributes and they present their experience. However, Internet review sites are independent from health care organizations and therefore may be perceived as less biased than for example satisfaction surveys. Furthermore, a review can have more influence than a satisfaction survey response, as those results are combined. Also, in reviews more issues can be presented than in close-ended surveys (López et al., 2012). In the following section, the topic of the (health care) review sites will be treated more in-depth.

2.3.1 Motives for using Review/rating sites in health care

Consumers like shopping online for the reason that they can easily compare services or products. Dellarocas (2003) even states that online review mechanisms are the most powerful ways to generate online word-of-mouth. Consumers turn to rating sites in order to minimize uncertainty and risk (by choosing a credible rating site) and reduce search time (Bakos, 1997; Peterson and Merino, 2003). According to Dabholkar (2006), the respondents of his study self-report that they use rating sites in order 'to make better decisions' and 'to make easier decisions'. Also, Eysenbach (2008) states that consumers use the Internet and

[20] These are just some of their interesting findings on the effect of internet on health seekers.
[21] Wolters and Lako. (2012). "Hoe kiezen patiënten een ziekenhuis?".

make sure that they consider their options in order to ensure that nothing important has been left out. Kenagy et al. (1999), also state that word of mouth is of great importance in health care as consumers want to know how it is evaluated by others.[22] However, consumers need different levels of information depending on their expertise level,[23] but also dependent on the severity of the disease (Edgman-Levitan and Cleary; 1996). According to File et al. (1994), WOM might be particularly significant for the high-risk or intangible-dominant goods or products. Hospital choice can be perceived as a high risk product, if consumers are aware of the information asymmetry, between the doctor and the patient.

In sum, it is nowadays crucial to understand better how this online WOM regarding health care services, that mostly takes the form of patient-generated hospital reviews, influences hospital choice.

[22] In line with Edgman-Levitan and Cleary's (1996) findings, which indicate that consumers want to know how others evaluate care and value their friends' and family's opinion more than other source data.
[23] Park, D., and S. Kim. (2008) "The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews".

3. Theory & hypotheses: the role of valence, volume and dispersion

3.1 A broad analysis of previous studies of (electronic) word of mouth

Previously, word of mouth (WOM) has been defined as: "*oral person to person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, a product or a service"* (Arndt, 1967: p.3). Prior research (Bickart and Schindler, 2001) shows that consumers discount WOM when they perceive that the communicator has a personal interest in recommending the sale. In the context of diffusion of innovations, research has found that the effect of the word of mouth (WOM) is perceived stronger than the effectiveness of advertising (Katz and Lazarfeld, 1955; Engel et al., 1969; Day, 1971). Bass (1995) and Moore (1995) even state that WOM is the factor that affects most sales in the diffusion process. Consumers trust WOM because they perceive it as independent from advertisers and marketeers effort to persuade them into a purchase. The power of WOM has increased with the advent of Internet, as electronic word of mouth (eWOM) reaches nowadays millions of internet users (Duan et al., 2008). The internet has also facilitated the process for spreading and gathering objective and subjective information regarding products and services (Hennig-Thurau et al., 2004).

Hennig-Thurau et al. (2004) characterize eWOM as "*any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet*." As Andreassen and Streukens (2009) pointed out, we largely base our understanding of the eWOM on the literature research of traditional WOM, however it is of importance to keep in mind that eWOM also has distinctive characteristics. Cheung and Thadani (2010) point out four unique points of eWOM, when compared to WOM:

(1) Greater scale and speed of diffusion. As mentioned beforehand, information reaches not only many more receivers, but also much faster;
(2) More persistent and accessible;
(3) Easier to measure;
(4) Harder to determine credibility of the source.

Several studies have looked into the motives why people look for eWOM (Goldsmith and Horowitz, 2006; Dabholkar, 2006) and why consumers share eWOM (Hennig-Thurau et al., 2004; Yoo and Gretzel, 2008).

More recent studies have started to look how people use that information in purchase decisions (Chevalier and Mayzlin, 2006; Sen and Lerman, 2007; Vermeulen and Seegers, 2008). One study has even looked at the effect of eWOM in healthcare. However, no study has yet looked at the effect of eWOM on the decision making process of a high stakes service, e.g. health care.

	Journal	**Valence**	**Volume**	**Dispersion**
Chatterjee, P. (2001). "Online Reviews: Do Consumers Use Them?"	Advances in Consumer Research	x	x	
Chen, Y. et al. (2003). "Marketing Implications of Online Consumer Product Reviews"	Working paper: University of Florida		x	
Chevalier J.A. & D. Mayzlin. (2006). "The Effect of Word of Mouth on Sales: Online Book Reviews"	Journal of Marketing Research	x	x	
Clemons, E.K. et al. (2006). "When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry"	Journal of Management Information Systems	x		x
Dellarocas, C. et al. (2007). "Exploring the value of online product reviews in forecasting sales: the case of motion pictures"	Journal of Interactive Marketing	x	x	x
Duan, W.et al. (2008). "Do online reviews matter — An empirical investigation of panel data?"	Decision Support Systems		x	
East, R. et al. (2008). "Measuring the impact of positive and negative word of mouth on brand purchase probability"	International Journal of Research in Marketing	x		
Gauri, D.K. et al. (2008). "Role of word of mouth in online store loyalty"	Communications of the Association for Computing Machinery	x	x	
Godes, D. & D. Mayzlin. (2004), "Using Online Conversations to Study Word-of-Mouth Communication"	Marketing Science		x	x
Hinz, V. et al. (2012). "Electronic word of mouth about medical services"	Research paper: Hamburg Center for Health Economics	x		
Huang, J.H & Y. F. Chen. (2006). "Herding in Online Product Choice"	Psychology & Marketing	x		
Lee, M., et al. (2009). "Effects of valence and extremity of eWOM on attitude toward the brand and website"	Journal of Current Issues and Research in Advertising	x		
Lee, J. et al. (2008). "The effect of negative online consumer reviews on product attitude: An information processing view"	Electronic Commerce Research and Applications	x	x	
Litvin, S.W. et al. (2006). "Electronic word-of mouth in hospitality and tourism management"	Tourism Management	x		
Liu, Y. (2006). "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue"	Journal of Marketing	x	x	
Park, C. & T.M. Lee. (2009). "Information direction, website reputation and eWOM effect: A moderating role of product type"	Journal of Business Research	x		
Park, D.-H. et al. (2007). "The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement."	International Journal of Electronic Commerce		x	
Park, D. & S. Kim. (2008). "The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews"	Electronic Commerce Research and Applications		x	

Resnick P. & R. Zeckhauser. (2002). "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System"	The Economics of the Internet and E-Commerce. Advances in Applied Microeconomics, Vol. 11.	x		
Sen, S & D. Lerman. (2007). "Why are you telling me this? An examination into negative consumer reviews on the web"	Journal of Interactive Marketing.	x		
Vermeulen, I.E. & D. Seegers. (2008). "Tried and tested: The impact of online hotel reviews on consumer consideration"	Tourism Management	x		
Zhang, J.Q. et al. (2010). "When does electronic word-of-mouth matter? A study of consumer product reviews"	Journal of Business Research	x		

Table1. Summary of the Literature on eWOM, Reviews and Ratings

3.2 Key characteristics of eWOM employed in this study

Several key characteristics of (electronic) word of mouth have been identified from the past literature, such as valence, volume, source credibility, tie strength and expertise level (Godes and Mayzlin, 2004; Huang and Chen, 2006; Cheung and Thadani, 2010). This study will focus on the valence, volume and the dispersion of eWOM. The same characteristics were employed in Dellarocas et al.'s (2007) paper on movie ratings. Quite some studies that have analyzed eWOM are based upon movie ratings, however this study is determined to research if the same results emerge when evaluating a ‘need’ service instead of a ‘want’ service, whose customers thus face substantial more stress when making decisions than in different service industries (Berry and Bendapudi, 2007).[24]

- *Valence: Positive WOM versus Negative WOM debate*

A review can either recommend or discourage the buy or usage of a product or of a service. It can have a positive, negative or rather neutral tone. According to studies conducted by Resnick and Zeckhauser (2002), Lagu et al. (2010) and Hinz et al. (2012) a large portion of the total reviews is positive.[25] However, according to the traditional word of mouth literature, negative information has more effect on consumers than positive information does (Arndt, 1967; Herr, Kardes and Kim, 1991, Sweeney et al., 2005). This is in line with the negativity bias that has been pointed out in various studies that can be found in the literature review of Baumeister et al. (2001). The same finding goes for electronic word of mouth (Chevalier and Mayzlin, 2006; Lee, Rodgers and Kim, 2009). Park and Lee (2009) have found that

[24] However, it must be mentioned that there is no doubt that the choice process for the chronic ill will differ even more, because this group will choose more aware regarding the effectiveness of the medical treatment.
[25] Resnick and Zeckhauser (2002) found that 99.1% of customer feedback on eBay was positive, while 0,6% was negative and 0,3% was neutral. Lagu et al. (2010) identified 33 physician-rating websites and found that 88% of 190 reviews were positive, 6% were neutral and other 6% were negative.

experience goods in comparison with search goods have a greater damage in eWOM because of negative eWOM, as it emphasizes customer's uncertainty and fear triggered by the information asymmetry that characterizes experience goods. Chatterjee (2001) even argues that it is common knowledge in research that a satisfied customer might tell some people, but a dissatisfied will tell everybody about it.

However, there are also studies that contradict the claim that negative eWOM is more effective than positive eWOM (Gershoff et al, 2003; Sorensen & Rasmussen, 2006; East et al., 2008). A study by Oetting et al. (2010) has found that negative WOM spreads barely better than positive WOM and respondents could remember more positive word of mouth (89%) than neutral (4%) or negative word of mouth (7%). Also, Gauri, Bhatanagar and Rao (2008) have found that positive reviews have a great impact on repurchase intentions.

Finally, other studies such as of Liu (2006) and Duan et al. (2008) have even found in their research on word-of-mouth regarding movies that valence does not have explanatory power, while Dellarocas et al. (2007) have found that it does have a significant impact on eWOM.

This debate regarding the valence of reviews, leads to the first hypothesis:

H1: *Positive WOM has a stronger effect on hospital choice than negative WOM;*

In the literature, valence means largely the tone of a message or review, if it is positively or negatively framed. In this research, as it will not focus on individual reviews, but rather on the aggregate level, the tone will be measured with the help of the average grade of the hospital as compared to the average grade of all hospitals. The average grade has been chosen, as it indicates the satisfaction or dissatisfaction with the service. Positive eWOM is employed to reflect satisfaction, while negative eWOM is used to express dissatisfaction. So, of a below-average rated hospital, it will be assumed that it had a greater amount of negative WOM, while of a higher-than-the-average rated hospital it will be assumed that it had a greater amount of positive WOM. Therefore, it is expected that patients will prefer hospitals with a higher average grade to those with a lower average grade.

- *Volume*

Godes and Mayzlin (2004) have found in their study that volume of online information, also on movies, does not have explanatory power. However according to Liu's (2006) study, volume does have explanatory power. Other studies have looked into this characteristic as well and a higher amount of posts has been proven to have a positive effect on sales of products (Chevalier & Mayzlin, 2006; Duan et al. 2008; Park, Lee and Han, 2007). Also, Hanson and Putler's study (1996) showed that consumers tend to choose to download software with higher download counts. Huang and Chen (2006) also found in their study that sales volume and number of positive as compared to negative reviews had an influence in online product choices, implying that customers engage in herding behavior. Or as Dellarocas et al. (2007) stated it, the more a product or a service is being discussed, the more others also become aware of it. In order to shed more light on this issue, the volume of reviews is included in this research and the following hypothesis emerges:

> **H2:** *A higher volume of reviews has a stronger effect on hospital choice than a lower volume of reviews;*

Volume will be, presented in two levels, namely a low level of volume and a high level.

- *Dispersion*

This study will attempt to provide also an insight in what effect the volume of online reviews has on hospital choice, combined with varying proportions, as suggested by Lee, Park and Han (2008). Godes and Mayzlin (2004) were among the first to look at what is the impact of the dispersion of the online information. According to their study, dispersion had explanatory power and is therefore of greater importance than volume. Doh and Hwang (2009) state in their study that the direction of eWOM reviews (positive or negative) has an impact on its readers' response. According to them, consumers rely more on eWOM if the direction of the reviews is the same. Clemons, Gao and Hitt (2006) looked at the dispersion of online ratings on sales growth rate of craft beer and have found that dispersion is significantly related to sales growth (while the number of ratings or the volume of sales wasn't). Dellarocas et al. (2007) have also looked at dispersion in their paper and state that valence, volume and dispersion all have statistical significant power. Therefore, dispersion is included in order to assess its importance in high stakes decision and the following hypothesis will be tested:

> **H3:** *A higher level of dispersion will have a stronger negative effect on hospital choice than a lower level of dispersion of reviews;*

The first model will therefore comprise the effect of valence, volume and dispersion on hospital choice.

3.2.1 Moderating effect: satisficers versus maximizers

According to rational utility theory, people are rational choosers and choose the best option that is presented to them. However, recent economic theory has pointed out that the principles of rational utility theory are frequently violated (Kahneman & Tversky, 1979, 1984; Tversky & Kahneman, 1981) and in particular the assumption that an individual has full information about the (consequences of the) choices he makes. Simon (1955) introduced an alternative in which he claims that maximization or achieving the best possible option is rarely ever possible due to the complexity of human environment and constraints in the human ability to process information and therefore some will 'satisfice' their goals instead of maximizing them. In short, they will rather settle for the good enough option instead of pursuing the best possible option.

Research (Beattie et al., 1994) has pointed out that adding a choice possibility to the choice set does not necessarily make an individual better off and that people would rather have others choose for them. Half a century later, Schwartz et al. (2002) have developed a maximizing tendency scale. With that scale, they found that maximizers experience less happiness, optimism, life satisfaction and self-esteem, while a significant correlation was found with depression, regret and perfectionism. Furthermore, they have also found that maximizers engage more in social comparisons than satisficers and are also more affected by social comparisons. They also mention that as a maximizer will want the best option, it will encounter an exhaustive search of possibilities and as it is practically impossible to ever have all the knowledge regarding something; possible constraints will be imposed on that search. A maximizer will experience regret of the chosen option, even though it was the best option out of the set of considered possibilities; however, it was not the best option in all its respects. Also, maximizers might be less likely to adapt than satisficers as they have higher standards of acceptability and their decisions have higher search costs, so they have 'more to lose'. Some of the studies that followed have looked at how maximizers/satisficers report their decision making performance (Bruine de Bruin et al, 2007; Parker et al., 2007), while few studies have looked at how maximizers/satisficers actually perform in their choices (Polman, 2010; Jain et al., 2013). These studies have found that overall, maximizers not only seem to think they perform worse, but also do so in some cases (Parker et al., 2007; Jain et al., 2013). Bruine de Bruin et al. (2007) also found that satisficers make more often more objective decisions than maximizers. According to research conducted by Polman (2010), maximizers seem to make worse, but also better decisions as compared to satisficers, as they look for more information and have more options to choose from.

In this thesis, it will also be analyzed how hospital choice, based on review characteristics, is influenced by a person's tendency to be a maximizer or a satisficer. It is expected that the moderator will affect stronger the variable Dispersion, as that variable requires more attention from the subjects, than the other two variables, valence and volume. Overall, I expect that maximizers will consider that they do not have enough information in order to make an appropriate choice and therefore the difference in odds for them will be smaller as compared to the one for satisficers. The following hypotheses emerge:

H4: *Dispersion will have a stronger negative influence on hospital choice when a person is a maximizer than it will have as observed in the first model.*

H5a: *The odds for a hospital with high valence getting chosen as compared to a hospital with low valence will be smaller for maximizers than for satisficers.*

H5b: *The odds for a hospital with high volume getting chosen as compared to a hospital with low volume will be smaller for maximizers than for satisficers.*

H5c: *The odds for a hospital with high dispersion getting chosen as compared to a hospital with low dispersion will be smaller for maximizers than for satisficers.*

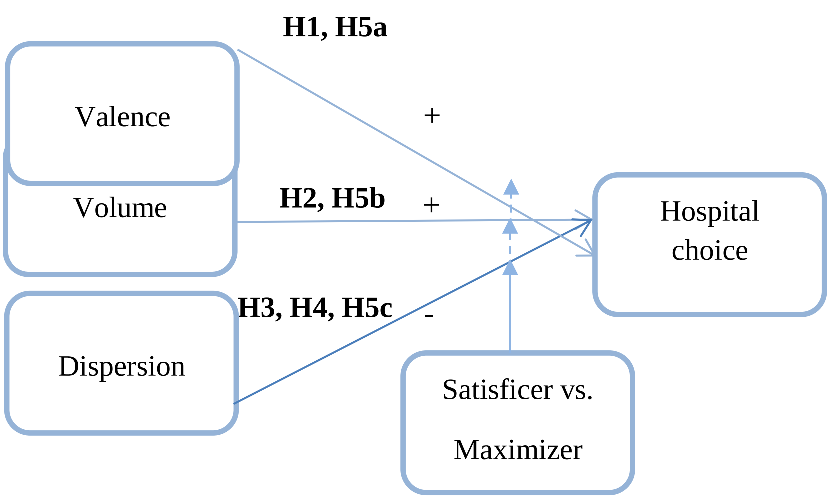


Figure 1. Conceptual framework for model 1 and model 2: the effect of volume, valence, dispersion and the moderator on hospital choice

Also, a third model will be analyzed as an additional empirical goal of this paper that will look into how maximizers/satisficers grade hospitals, based on the review characteristics. It is expected that maximizers will evaluate hospitals lower than satisficers as they consider that they do not have enough information to make an appropriate evaluation. However, as there are still some missing links and there are still too few studies on actual choice behavior, these suppositions will not be hypothesized in this paper.

The third model looks as follows:

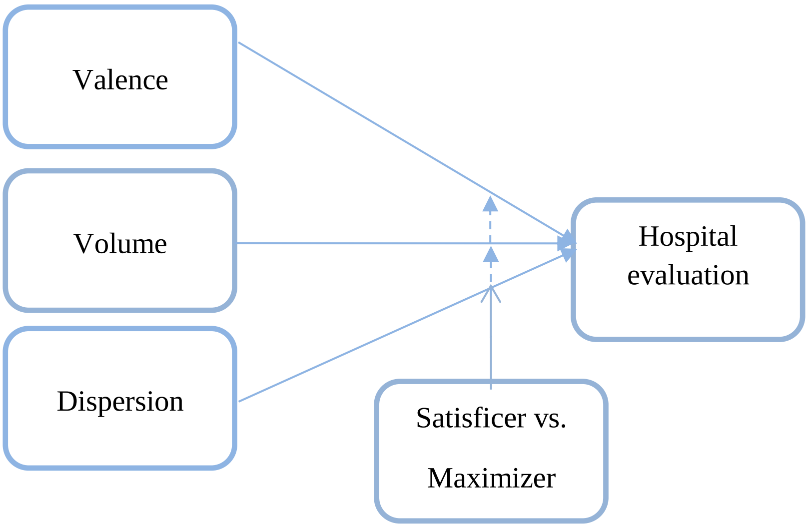


Figure 2. Research model nr.3: the effect of volume, valence, dispersion and the moderator on the evaluation of a hospital.

4. Method

4.1 Designing the experiment

For this study, a 2x2x2 within subjects choice experiment has been chosen in order to gather the data. Even though the theory that formed the basis for choice modeling was already formulated by Thurstone in 1927, choice experiments have become increasingly important in the past 20 years. Two paths have been developed in the choice modeling literature: the reference alternatives (Hensher, 2004; Rose et al., 2007) and the efficient design of choice sets (Huber and Zwerina, 1996; Zwerina, Huber and Kuhfeld, 1996). In this study, the latter one has been assumed. According to Huber and Zwerina (1996) there are four principles that need to be satisfied when designing an efficient choice design, namely: (i) level balance, (ii) orthogonality, (iii) minimal overlap and (iv) utility balance. The level balance is achieved when all the factor levels appear an equal amount of time in the experiment. In order for the design to be orthogonal, all pairs of factor levels have to appear equally for each pair of factors. A full factorial design is per definition orthogonal. Minimal overlap indicates that a factor level should repeat itself as few as possible within the design. Utility balance is used so that alternatives within a choice set will have more equal choice probabilities (Huber and Zwerina, 1996). For the experiment, the Yates standard order was used. The runs are depicted in table 2 and 3. In the experiment, the runs were randomly paired and presented to subjects. A replicate was added in order to increase the sample size and therefore the precision. As it is a within subject design, each subject experienced each condition.

Hospital	Valence	Volume	Dispersion
1	7,2	10	low
2	8,2	10	low
3	7,2	60	low
4	8,2	60	low
5	7,2	10	high
6	8,2	10	high
7	7,2	60	high
8	8,2	60	high
Dispersion low: 80% close to the mean			
Dispersion high: 20% close to the mean			

Table 2. Hospital profiles

The profiles were paired together in order to ensure efficiency of the model. However, because one of the independent variables (dispersion) depended on the value of another variable (volume), constraints on the choices had to be placed. The design attempted to exclude as much as possible those dominated choices. Blocking was applied in order to reduce the cognitive effort of the respondents and to increase response efficiency (Johnson et al., 2013). A flaw was observed, in the sense that the model did not capture properly the between choice difference for dispersion. In other words, the choices that were paired together never contained the exact same dispersion level. Note that even though in the hospital profile table (table 2) two levels of dispersion are presented, in reality those levels depended upon the volume, so when a hospital had a low dispersion, and 10 reviews, the distribution looked as follows: 1 positive review, 8 neutral reviews and 1 negative review, while when the volume was 60 and dispersion low, the distribution was 6 positive reviews, 48 neutral reviews and 6 negative reviews. When dispersion was high, and there were 10 reviews presented, there were 4 positive reviews, 2 neutral and 4 negative reviews, while when the volume was 60, there were 24 positive reviews, 12 neutral and 24 negative reviews. As mentioned, because the variables were dependent on each other, when a hospital had the same volume and dispersion rate, it became a dominated choice.

Choice set	Block 1	Block 2
1	H1 & H5	H8 & H1
2	H8 & H4	H7 & H3
3	H3 & H6	H5 & H4
4	H7 & H2	H6 & H2
5	H4 & H6	H4 & H2
6	H2 & H8	H3 & H8
7	H5 & H3	H2 & H5
8	H1 & H7	H6 & H1

Table 3. Questionnaire 1 design

As identification is more important than efficiency, a new design was made that rather paid attention to that. Johnson et al. (2013) also mention in their paper that practical designs may deviate from strict orthogonality and that it is recommended to eliminate implausible combinations. They emphasize that dominated choices do not offer information on trade-off preferences. The new design violated the balance condition as not all levels of a factor appear in the design, but still satisfied the minimal overlap condition, as the choice options in the questions contain different levels of a factor. However, this model that fully ruled out dominated choice captured only choices with the same dispersion or with higher dispersion. However, it needs to be specified that choices were also randomized within the choice pairs, therefore to some, also the reversed choice were presented, eliminating concerns.

In both designs the items in the choice set and the choice sets were counterbalanced in order to avoid order, fatigue and practice effects.

Choice set	Pairs
1	H1&H6
2	H1&H7
3	H1&H8
4	H2&H3
5	H2&H7
6	H2&H8
7	H3&H7
8	H3&H8
9	H6&H7

Table 4. Questionnaire 2 design

4.2 Carrying out the experiment

The experiment was carried out online, with the help of survey platform, Qualtrics. Results were gathered in two samples, the first sample was subjected to the first questionnaire design (**sample 1**; see table 3), while the second sample was subjected to the second questionnaire design (**sample 2**; see table 4) and was used as a robustness check for the results of the first sample. In both samples, subjects were introduced to the topic and the choice process was explained, where after they had to make their eight, respectively nine choices and had to answer some questions for assessing the manipulation check, but also had to give their own grades for the hospitals.[26] The hospitals were presented in each choice pair with the same picture and were merely named H "no. from 1 till 8" in order not to influence the subjects with exogenous factors. Finally, the participants were asked a set of questions about their personality and they had to answer some demographic questions.

Participants

The *first sample* was recruited mostly among students of the Erasmus University Rotterdam. A sample of 62.5 was needed, according to the formula[27], on next page:

[26] Only from the first sample, manipulation check data and evaluation grades were collected.
[27] Orme, B. (2010). "Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research". Second Edition, Madison, Wis.: Research Publishers LLC.

$$(1)\frac{nta}{c} \geq 500$$

Hundred and sixty students filled it in (N=160), however because eight choices were made by each, that resulted in 1280 choices that were made. The average age of the sample is 25.4. Most of the participants had finished a master degree and most are earning below €15.000 a year. For the *second sample* 56 respondents were needed and 121 people participated, what resulted in 1089 overall choices. The average age of this sample was higher, namely 33.8, as the participants were recruited among graduates. Interesting observation is that most of the participants have also finished their master and are earning below €15.000 (it must be admitted though that the average earned is higher than what in the first sample was reported and it must also be considered that there were also persons that would rather not report their earnings and therefore chose the lowest income group).

4.3 Statistical method

Binary (or simple) logistic model is employed in the first two models in order to analyze the results. This form of statistical analysis is like multiple regression, but the dependent variable is categorical and independent variables are continuous or categorical (Field; 2009). The dependent variable is whether or not a hospital has been chosen in each pairwise choice ($Y_{ic} = 1$ vs. $Y_{ic} = 0$); therefore a binary logit model is used. In the *first model*, it will be analyzed to which rating characteristics people pay attention. The model can be characterized, as follows:

$$(2)\ P\left(Y_{icj} = 1\right) = \frac{1}{1+e^{-(b_0+b_1X_{1icj}+b_2X_{2icj}+b_3X_{3icj})}}$$

Where *i* defines the respondent, *c* indicates the choice set and *j* indexes the hospitals.

$$(3)\ Y_{icj} = \begin{cases} 1\ if\ hospital\ is\ chosen\ U_{icj} > 0 \\ 0\ if\ hospital\ is\ not\ chosen\ U_{icj} < 0 \end{cases}$$

$$(4)\ U_{icj} = V_{icj} + \varepsilon_{icj},\ where$$

$$(5)\ V_{icj} = b_0 + b_1 Valence + b_2 Volume + b_3 Dispersion$$

with low Valence= 0	low Volume = 0	low Dispersion = 0
while high Valence =1	high Volume = 1	high Dispersion = 1

The *second model* can be depicted by the following formula and can be plugged in, instead of formula 5:

(6) $V_{icj} =$

$b_0 + b_1 Valence + b_2 Volume + b_3 Dispersion + b_4(Valence \text{ x } D\_Maximizer) +$

$b_5(Volume \text{ x } D\_Maximizer) + b_6(Dispersion \text{ x } D\_Maximizer)$

with low Valence = 0   low Volume = 0   low Dispersion = 0   low D_maximizer = 0
and high Valence = 1   high Volume = 1 high Dispersion = 1 high D_maximizer = 1

The second model looks at the effect of eWOM on choice in pairwise comparisons, which divulges preference through choice, while the third model has rather a self-reported evaluation of the different hospitals. The *third model* is employed in order to assess the importance of testing the effects of the predictor variables on two distinct, dependent variables. This model will be analyzed with the help of a multiple linear regression model. Note that all the independent variables are categorical. The main model is depicted as follows:

(7) $Evaluation_{ij} = [b_0 + b_1\, Valence_j + b_2\, Volume_j + b_3\, Dispersion_j +$

$b_4\, D\_maximizer_{\mathrm{i}} + b_5\, Interaction\, (Valence_j * D\_maximizer_i) + b_6\, (Volume_j *$

$D\_maximizer_i) + b_7\, (Dispersion_j * D\_maximizer_i)] + \varepsilon_{ij}$

with low Valence= 0   low Volume= 0   low Dispersion= 0   low D_maximizer=0
and high Valence= 1 high Volume= 1 high Dispersion = 1 high D_maximizer=1

Where, *i* stands for the respondent and *j* for hospital.

Evaluation is measured by asking subjects to rate two randomly chosen hospitals themselves on a scale from 1 till 10 (grades with decimals were possible). All the hospitals had again the same image, in order not to affect the experiment. An example of how the information was acquired can be found in the Appendix B in figure 1. Note that D_maximizer = 0 means that a person is a satisficer, while D_maximizer=1 means that a person is a maximizer.

Variables

Valence was coded with a 0 for a low value (7.2) and with a 1 for a high value (8.2). The variable Volume was as well coded with a 0 for its low value (10) and with a 1 for the high value (60). Dispersion was coded with a 0 for low Dispersion and 1 for high Dispersion. D_maximizer was coded with a 0 for satisficer and a 1 for maximizer. More information on the variables can be found in the Appendix B tables from 1 to 4.

5. Results

The manipulation check (table 5) indicates that the values for volume and dispersion were relatively successful manipulated. Respondents were asked to answer to the following statements: “All in all, I think patient reviews for this hospital are quite positive.”, “I think this hospital has received a lot of reviews from other patients.”, “I think that there is a lot of agreement among the patients who reviewed this hospital.”, on a (Likert) scale from 1 to 5 (1=strongly disagree to 5=strongly agree). For valence (between groups p = 0.006), it can be observed that the discrepancy between the two averages is lower, than for the other two variables. However, the valence values for the hospitals with the same volume and dispersion are just slightly lower in each case for the low profiles than for the high profiles, as it can be seen in table 5 of the Appendix B. That indicates that the respondents had some troubles with perceiving either of the levels (low or high). The mean of volume (between groups p = 0.000), is lower for the hospitals with low volume than it is the case for hospitals with high volume. This can also be seen in table 5 of the Appendix B. That indicates that people overall disagreed (≈2,099) with the statement that the hospital had received a lot of reviews when it had a ‘low’ value (10) and agreed (≈3,853) when it had a ‘high’ value (60). Also, the means for dispersion (between groups p = 0.000) points out that people agreed (≈3,766) with the statement that there was agreement among the reviews when the hospital had a ‘low’ dispersion and disagreed with the statement when the hospital had a ‘high’ dispersion.

	Hospital no.	µ Valence	σ Valence	p-value
low	1,3,5,7	2.834	0.854	0.000
high	2,4,6,8	3.19	0.828	0.000
		µ Volume	σ Volume	
low	1,2,5,6	2.101	0.943	0.000
high	3,4,7,8,	3.839	0.732	0.000
		µ Dispersion	σ Dispersion	
low	1,2,3,4	3.78	0.824	0.000
high	5,6,7,8	2.137	0.978	0.000

Table 5. Averaged manipulation check values per low/high profiles.

Table 6 of Appendix B also has interesting results, as it comprises where subjects considered they looked most at. According to those findings, they paid more attention to volume and dispersion, than to valence. Also strikingly is, that they reported to pay more attention to low volume than to high volume.

5.1 Model 1

Sample 1

In SPSS, the forced entry method was used. The interaction term between the three variables was not included in the model, as analysis pointed out it was not significant (X^2 = 0.170, p=.680).

The R-values of the predictor were calculated according to the following formula:

$$(8)\ R = \sqrt{\frac{z^2-2df}{-2LL(\text{baseline})}}$$

The predictors Valence and Volume prove to have a positive, but quite small contribution (R=.164), respectively (R=.1919). While the predictor Dispersion also has a positive R-value, it has a larger contribution to the model (R=.337). However, as the R-value is dependent on the Wald statistic it is not a reliable value, therefore the R^2 was calculated. As SPSS only computes Cox and Snell's R^2 and Nagelkerke's R^2, the Hosmer and Lemeshow R^2 was computed with the help of the following formula:

$$(9)\ \mathrm{R}^2 = \frac{\left(-2LL(\text{baseline})\right)-\left(-2LL(\text{new})\right)}{-2LL(\text{baseline})}$$

The R^2 = .186 (Hosmer & Lemeshow), R^2 =.227 (Cox & Snell) and R^2 =.303 (Nagelkerke), indicating how much of the variability of hospital choice is explained by the predictors. So, the model correctly classifies 70% of the choices, as it can be seen in the table 10 of the Appendix B. All three predictor variables are significant at a significance level of 0.05 and have therefore a significant contribution on hospital choice; however the constant proves to be not significant.

From the results, we can see that the odds ratio of the predictor Valence is greater than 1, namely Exp. (B) = 2.478 and it indicates that as the predictor increases, the odds of the outcome occurring increase. Better said, if a hospital has a high Valence, the odds of that hospital getting chosen increases 2 and a half times as compared to a hospital with low valence, everything else held constant. This result is in line with our theoretical expectations and therefore **H1** is not rejected.

The odds ratio value of the predictor Volume (Exp. (B) = 2.914) is as well greater than 1, meaning that if a hospital has a high Volume, its odds of getting chosen increases. So, hospitals with high Volume have almost 3 times higher odds of getting chosen than hospitals with low Volume, all held constant. This result is also in line with what was hypothesized and therefore **H2** is not rejected.

Finally, the predictor Dispersion has an odds ratio lower than 1 (Exp. (B) = 0.151), meaning that as the predictor increases, the odds of the outcome occurring decreases. So, if Dispersion is high, the odds of a hospital getting chosen decreases. Hospitals with high Dispersion have 6.6 lower odd of getting chosen than hospital with low Dispersion, all others held constant. Testing for multicollinearity (VIF value 1 for all predictor variables; none have high variance for the same eigenvalue – Appendix B tables 14 and 15), overdispersion and looking at the residuals have not given any remarkable results (table 12 and 13 in Appendix B). Finally, bootstrapping was applied to the forced entry method, in order to cross-validate confidence intervals. From these results we can conclude that H3 is not rejected.

	b	**SE**	**Wald**	**df**	**Sig.**	**95% CI for Odds Ratio**		
						Lower	Odds ratio (Exp. (B))	Upper
Constant	**-0.042** [-0.209, 0.130]	0.085	0.25	1	0.617		**0.958**	
Valence	**0.908** [0.647, 1.093]	0.092	97.054	1	0.000	2.069	**2.478**	2.969
Volume	**1.07** [0.904, 1.252]	0.093	132.717	1	0.000	2.429	**2.914**	3.496
Dispersion	**-1.892** [-2.087, -1.716]	0.094	405.682	1	0.000	0.125	**0.151**	0.181
Note. R^2 = .186 (Hosmer & Lemeshow) .227 (Cox & Snell) .303 (Nagelkerke). Model χ^2 (1) = 660.334, $p < 0.05$								

Table 6. Results logistic regression model 1 - sample 1, predicting whether a hospital was chosen [95% bootstrap confidence intervals based on 1000 samples]

5.1.1 Differenced results

For the analysis of the data a new dataset was created in which the differences between the variables are calculated. This dataset is believed to offer a better explanation of the relation between the dependent variable and the independent variables. The dependent variable was therefore coded into the question “Did the participants choose the second hospital?” (1 = yes, 0 = no). The difference for the independent variable ‘valence’ was coded as -1 = H2 has a lower valence than H1, 0 = both hospitals have the same value, 1 = H2 has a higher valence than H1; the difference for ‘volume’: -1 = H2 has a lower; the predictor variable ‘dispersion’: -1 = H2 lower dispersion (meaning better).

	b	**SE**	**Wald**	**df**	**Sig.**	**95% CI for Odds Ratio**		
						Lower	Odds	Upper
Constant	**-1.219** [-1.705, -0.829]	0.199	37.635	1	0.000		**0.296**	
Valence			99.866	2	0.000			
Valence (1)	**1.274** [0.908, 1.664]	0.192	44.196	1	0.000	2.456	**3.577**	5.208
Valence (2)	**2.109** [1.730, 2.581]	0.214	96.850	1	0.000	5.414	**8.240**	12.541
Volume			80.963	2	0.000			
Volume (1)	**1.112** [0.767, 1.509]	0.185	36.098	1	0.000	2.115	**3.040**	4.370
Volume (2)	**2.212** [1.752, 2.750]	0.246	80.903	1	0.000	5.642	**9.136**	14.795
Dispersion	**-2.121** [-2.465, -1.854]	0.148	206.192	1	0.000	0.090	**0.120**	0.160
Note. R^2 = .263 (Hosmer & Lemeshow) .227 (Cox & Snell) .303 (Nagelkerke). Model χ^2 (1) = 660.334, $p < 0.05$								

Table 7. Results logistic regression model 1 - sample 1, predicting whether the second hospital was chosen [95% bootstrap confidence intervals based on 1000 samples]

The differenced model of the first sample has slightly improved R^2 values than the normal model. Therefore, the differenced model predicts better the variability of hospital choice, as it captures the choice differences. As it can be observed in the Appendix B table 22, for Valence, the reference group is when the valence of H2 is lower than of H1. Valence (1) indicates the difference between if the hospitals both have the same valence and if H2 has a lower valence. Valence (2) represents the difference between if H2 has a higher valence than H1 and if H2 has a lower valence than H1. The same goes for Volume (1) and (2). Dispersion however has only one coefficient as it lacks the category that both hospitals have the same dispersion. The variable Valence is significant ($p \leq .05$). The odds of Valence (1) and Valence (2) are greater than 1, meaning that as Valence increases the chances of the second hospital getting chosen increase as well. However, Valence (2) category seems to have a far greater effect (Exp. (B) = 8.240), indicating that the second hospital had twice as higher odds of being chosen when it had a higher valence than the first hospital as compared to when it had a lower valence than the first hospital, than when the hospitals had the same valence as compared to when the second hospital had a lower Valence. Volume (1) and Volume (2) give similar results, when the second hospital had a higher volume than the first hospital as compared to than when it had the lower volume than the first hospital, it had almost three times as higher odds of getting chosen than when the hospitals had the same volume, as compared to when the second hospital had the lower volume than the first hospital. Dispersion has an even lower value than in the normal model of the first sample. The coefficient indicates that the odds between if the second hospital has higher dispersion than the first hospital as compared to if it has lower dispersion than the second hospital decreases by more than 8 times. The tables related to this model can be found in the Appendix B – table 22 to 29.

As mentioned, a robustness check of these findings was performed by gathering data of a second sample. The results of this second sample can be found in the Appendix A.

According to these findings, I do not reject **H1**, as a higher Valence and therefore, positive eWOM seems to have a more strong effect. However, this result must be treated with caution as the manipulation check for the concluded that lower value was not necessarily perceived as low enough and therefore also not necessarily as negative WOM. Due to restrictions to the model, the value was not lowered further, even though this risk was anticipated. I also do not reject **H2** and **H3** as the levels were perceived correctly and the analysis indicated that indeed hospitals with a higher number of reviews have higher odds of being chosen and hospitals with higher dispersion have lower odds of getting chosen. It must be noted however, that the results of the second sample indicate that dispersion might not influence hospital choice as strongly, as indicated in model 1. However, the direction (positive/negative) of the sign of the relation remains the same.

5.2 Model 2

Nine questions were included in the questionnaire in order to test a person's tendency of maximization. The questions were taken from the paper of Diab et al. (2008)[28], who in part base their scale on Schwartz et al. (2002) maximization's scale and the construct is measured by statements, for which the respondent has to indicate his tendency to agree/disagree.[29] For all the data the median was calculated and a person was considered as a maximizer when the mean of its answers exceeded the overall median. A reliability analysis was run in order to test if the scale is reflecting consistently the construct. Cronbach's α ≈ 0.821>0.7 for the moderator satisficer/maximizer, indicating a high reliability of the scale (see the Appendix B - table 37). The validity was also tested, with the help of factor analysis and Kaiser-Meyer-Olkin and Bartlett's test has given a value of ≈0816>0.6 significant at a significance level of 0.05. The results for this sample are given below:

	b	SE	Wald	df	Sig.	95% CI for Odds Ratio		
						Lower	Odds	Upper
Constant	**-0.057** [-0.225, 0.131]	0.085	0.454	1	0.501		**0.944**	
Valence	**1.118** [0.862, 1.403]	0.136	68.028	1	0.000	2.346	**3.060**	3.991
Volume	**1.408** [1.125, 1.705]	0.141	100.012	1	0.000	3.101	**4.086**	5.384
Dispersion	**-2.525** [-2.847, -2.231]	0.151	278.819	1	0.000	0.060	**0.080**	0.108
D_maximizer by Valence	**-0.344** [-0.680, -0.026]	0.164	4.363	1	0.037	0.514	**0.709**	0.979
D_maximizer by Volume	**-0.552** [0.890, -0.203]	0.170	10.567	1	0.001	0.413	**0.576**	0.803
D_maximizer by Dispersion	**1.091** [0.727, 1.473]	0.186	34.273	1	0.000	2.066	**2.978**	4.291
Note. R^2 = .196 (Hosmer & Lemeshow) .238(Cox & Snell) .318 (Nagelkerke). Model χ^2 (1) = 696.658 $p< 0.05$								

Table 8. Results logistic regression model 2, predicting whether a hospital was chosen [95% bootstrap confidence intervals based on 1000 samples]

The R-value is positive for each of the predictors. The predictors Valence and Volume have a quite small (R=.136), respectively (R=.166) contribution. While the predictor Dispersion also has a positive R-value, it has a larger contribution to the model (R=.279). The interaction effect for D_maximizer and Valence has an R-value of only .026. For

[28] Diab et al. 2008. Are maximizers really unhappy? The measurement of maximizing tendency.
[29] Likert-scale: 1=strongly disagree to 5=strongly agree.

D_maximizer and Volume R-value is .049. For D_maximizer and Dispersion R=.095, indicating that out of the three interactions, this one predicts best the variability. The R^2 values are .196 (Hosmer & Lemeshow) .238 (Cox & Snell) .318 (Nagelkerke), a slight improvement in how well the predictor variables predict the variability of hospital choice, as compared to the previous model. The classification table shows us that at first the model correctly classified 50% of the hospitals, but this has risen now 70% of the hospitals, as it can be noted in tables 38 and 39 of Appendix B

All the predictors are significant ($p<0.05$). The intercept means that a hospital has the same odds of 0.944 times getting chosen, when a hospital has low valence, low volume and a low dispersion. Furthermore, looking at the odds ratios we observe that the odds of the predictors Valence and Volume are also in this sample greater than 1, meaning that as valence or volume have a high value the odds of a hospital getting chosen increases. However, their odds ratios have increased, while the odds of Dispersion are almost half of what they were in the first model, due to the effect of the interactions with the moderator. Better explained, a hospital with high valence has 3.060 times higher odds of getting chosen as compared to a hospital with low valence, all other variables held constant. In the case of Volume, a hospital with high volume has 4.086 times higher odds of getting chosen as compared to a hospital with low volume. The odds ratio for Dispersion is still smaller than 1, indicating that as Dispersion is increasing, the odds of a hospital getting chosen decrease. A hospital with high dispersion has 0.080 times the same odds of getting chosen as compared to a hospital with low dispersion, all else held constant, indicating that hospitals with high dispersion are highly unattractive. As these odds are lower than in the first model, I do not reject **H4**. However, these results should at all times be interpreted with caution as the level of the variable Dispersion might have been overemphasized.

The regression also tells us about the interaction effects between the main effects and the moderator. Namely, that the odds of a hospital with high valence getting chosen by a satisficer are 3.060 times the same as for a hospital with low valence, everything else held constant. For a maximizer, that odds ratio is (3.060*0.709) =2.17 times the same. Therefore, I also do not reject **H5a**, as indeed the odds ratio between hospitals with high valence as compared to hospitals with low valence is lower for maximizers, than for satisficers and the difference between the two is significant ($p<.05$). For a hospital with high volume, the odds of being chosen by a satisficer are 4.086 times the same as for a hospital with low volume, everything else held constant. While, for a maximizer the odds ratio is (4.086*0.576)=2.354

times the same for a hospital with high volume getting chosen as compared to low volume, all ceteris paribus. So, **H5b** is also not rejected. The odds for a hospital with high dispersion getting chosen by a satisficer are 0.080 times the same as for a hospital with low dispersion, all held constant. For a maximizer, the ratio is (0.080*2.978) = 0.238 times the same, for a hospital with high dispersion as compared for a hospital with low dispersion, when everything is held constant. This is a particularly striking result, causing **H5c** to be rejected.

This result can be perhaps explained by the fact that indeed this variable requires more of their attention (also as this variable varies with volume and further has a fixed range; so when a hospital has a valence of 7.2 and another one 8.2, and both have the same volume let's say 10 and the distribution is the same so if high: 4 negative, 2 neutral and 4 positive reviews, it means that the negative reviews are more negative for the lower valence hospital). Maximizers will analyze this variable more than satisficers, who will just be satisfied with the given information. This would reinforce Polman's (2010) and Jain et al.'s (2013) belief that maximizers tend to have higher response variability, as they are set to find the 'best' option and worry more and therefore that translates into the variability of their answers and results.

In this sample, no overdispersion has been identified. I found a slight sign of possible multicollinearity (VIF value over 3), but the residuals did not indicate anything wrong with the data, as it is observed in table 41 and 42 in Appendix B. Finally, bootstrapping was applied to the forced entry method, in order to cross-validate confidence intervals. In the Appendix A, an analysis of the model with only the interaction between Dispersion and D_maximizer has been included.

5.3 Model 3

In the questionnaire, each subject had to evaluate two randomly chosen hospitals (out of the eight total hospitals) by answering questions about the perceived levels of the variables, but also by indicating which grade they thought each of the two hospitals deserved. The average evaluation grade per hospital profile is summarized in the tables below:

Hospital	Valence	volume	Dispersion	N	own grade
1	7.2	10	0	37	7.10
2	8,2	10	0	38	7.55
3	7,2	60	0	39	6.93
4	8,2	60	0	39	7.78
5	7,2	10	1	38	6.60
6	8,2	10	1	39	7.20
7	7,2	60	1	37	6.91
8	8,2	60	1	39	6.65

Table 9. Average grade per hospital given by the subjects

The average grade of their own evaluation of the hospitals indicates a more favorable impression of hospitals with a lower dispersion, as opposed to the ones with a higher dispersion. It can also be noted, that for hospitals with a low dispersion, the first hospital is lower evaluated than the second as its Valence is lower and the same goes for hospitals 3 and 4. The hospitals with the higher dispersion are lower graded, as probably they are perceived as more risky. Here, as well hospital 5 is graded higher than 6 as their Volume is equal, but the Valence differs. An interesting result is however the evaluation of hospital 8, which has a lower grade than hospital 7, despite the fact that it has a higher Valence and an equal Volume variable. Also, when looking at the variable Volume, the grades do not show a clear pattern.

<u>Cleaning the data</u>

For the third model, a new dataset was employed that contained the hospital profiles and the grades they had received. Two cases were removed out of the 320 observations as they were graded with a 0, while in the description it was indicated that the grading boundaries were 1 and 10. Also, the dichotomous variables Valence and Volume have been recoded into 0 and 1 (instead of their low and high values), in order to facilitate interpretation of the results.

Results

Descriptive Statistics			
	Mean	Std. Deviation	N
Evaluation	7.134	0.987	298
Valence	0.517	0.501	298
Volume	0.497	0.501	298
Dispersion	0.510	0.501	298
D_maximizer	0.540	0.499	298
Valence_D_maximizer	0.262	0.440	298
Volume_D_maximizer	0.279	0.449	298
Dispersion_D_maximizer	0.268	0.444	298

Table 10. Descriptive statistics linear model

First, a simple regression was run in order to look at the effect of the main variables on the dependent variable. The model that corresponds to the regression looks as follows:

	b	SE	β	t	Sig.	Collinearity Statistics
						VIF
Constant	7.173	0.126		56.870	0.000	
Valence	0.401	0.109	0.203	3.685	0.000	1.005
Volume	0.041	0.109	0.021	.378	0.705	1.002
Dispersion	-0.517	0.109	-0.262	-4.758	0.000	1.001
D_maximizer	-0.007	0.109	-0.003	-.061	0.952	1.008
Note R^2= .111						

Table 11. Linear regression results of Valence, Volume, Dispersion and D_maximizer on Evaluation grade.

The intercept of the model indicates that a hospital will be evaluated with a 7.173, when a hospital will have low valence, volume and dispersion and a person is a satisficer. All variables held constant, a high valence (b=0.401, t=3.685, p<.05) increases the evaluation grade of a hospital by 0.401 points as compared to low valence. Volume (b=0.041) is not significant (t=0.378, p>.05). Furthermore, the evaluation grade decreases by 0.517 when Dispersion (b=-0.517, t=-4.758, p<.05) is high as opposed to when it is low, while all other variables are held constant. The variable D_maximizer (b=-0.007) is also not significant (t=-0.061, p>.05). In the next model, the interaction terms were included between the moderator D_maximizer and the predictor variables in order to look at whether one of them had significant impact on the grading of the hospital. The results of the regression are summarized in a table on the next page.

	b	SE	β	t	Sig.	Collinearity Statistics
						VIF
Constant	**7.405** [7.130; 7.682]	0.167		44.376	0.000	
Valence	**0.343** [0.072; 0.610]	0.159	0.174	2.153	0.032	2.207
Volume	**0.036** [-0.281; 0.331]	0.159	0.018	.226	0.821	2.191
Dispersion	**-0.891** [1.171; -0.612]	0.158	-0.452	-5.629	0.000	2.183
D_maximizer	**-0.411** [-0.870; 0.002]	0.219	-0.208	-1.873	0.062	4.166
D_maximizer by Valence	**0.116** [-0.298; 0.540]	0.216	0.052	.535	0.593	3.148
D_maximizer by Volume	**-0.022** [-0.456; 0.397]	0.216	-0.010	-.102	0.919	3.261
D_maximizer by Dispersion	**0.694** [0.255; 1.085]	0.215	0.312	3.225	0.001	3.173
Note R^2= .143						

Table 12. Linear regression Valence, Volume, Dispersion and D_maximizer and interaction effect on Evaluation grade [95% bootstrap confidence intervals based on 1000 samples]

The R^2 of the model indicates that the model accounts for 14.3% variation in evaluation grades. So 85,7% of the variation is still unexplained. Bootstrapping was applied to the forced entry method, in order to cross-validate confidence intervals. The constant of the model indicates that hospital will be evaluated with a 7.405, when a hospital will have low valence, volume and dispersion and a person is a satisficer. For Valence (b=0.343, t=2.153, p<.05), when all variables are held constant, a high valence increases the evaluation grade of a hospital by 0.343 points as compared to low valence. Volume (b=0.036, t=.226, p>05), is not significant. For Dispersion (b=-.891, t=-5.629, p<.05), when dispersion is high, the evaluation grade decreases by 0.891, as compared to when dispersion is low, while all other variables are held constant. D_maximizer is not significant at the 5% level, even though it is at the 10% level so marginally significant (b=-.411, t=-1.873, p=.06).

The interaction between the moderator and valence (b=.116 t=.535, p>.05) and the moderator and volume (b=-0.022, t=-.102, p>.05) prove also not to be significant. The interaction between D_maximizer and Valence would have suggested that satisficers grade a hospital with high valence with 0.343 points higher than they grade a hospital with low valence, everything else held constant. Also, a hospital with low valence would have a grade lower with 0.411 when graded by maximizers as opposed to satisficers, all held constant.

Hospitals with high valence would be graded with 0.459[30] points more than a hospital with low valence by a maximizer. Hospitals with high valence would get evaluated with 0.295[31] lower by maximizers than by satisficers. The interaction between Volume and the moderator, would have suggested that a hospital with high volume would be graded with 0.036 points more than a hospital with low volume, when graded by a satisficer, all held constant. Also, hospitals with low volume would have a 0.411 lower grade, when graded by maximizers, as compared to satisficers, all ceteris paribus. Hospitals with high volume would have 0.036+-0.022=0.014 higher grade than hospitals with low volume, when graded by maximizers. Further, hospitals with high volume would get -0.411-0.022=0.433 points lower when graded by maximizers, as compared to when graded by satisficers.

The interaction between D_maximizer and Dispersion (b=0.694, t=3.225, $p<.05$) suggests that satisficers will grade a hospital with high dispersion with 0.891 less than a hospital with a low dispersion. Also, for hospitals with low dispersion, it is predicted that they will have a grade lower with 0.411when graded by maximizers than by satisficers. Hospitals with high dispersion will get evaluated with 0.197[32] less than hospitals with low dispersion will by maximizers, all held constant. That means that hospitals with high dispersion as compared to hospitals with low dispersion are getting lower grades from satisficers and maximizers. Furthermore, hospitals with high dispersion will get evaluated by maximizers with 0.283[33] higher than by satisficers. This reinforces the finding observed in model 2, namely that maximizers as they worry more and perhaps also give more attention to this variable, they will be more determined to find an 'appropriate' grade and therefore the variability in their answers increase, as compared to the previous two variables where they possibly underperformed, as they simply considered as not enough information to base their decision upon.

[30] 0.343+0.116= 0.459.
[31] -0.411+0.116=-0.295.
[32] -0.891+0.694= -0.197.
[33] -0.411+0.694= 0.283.

6. Conclusion and recommendations

6.1 Conclusion

With the ongoing changes in the health care systems in the Western countries, hospital choice is encouraged by governments to be treated as if it is a ‘search good’, instead of an ‘experience good’. The assumption is that in the ‘demand driven’ health care system, hospitals will compete for patients and eventually, the costs of health care will fall. In order to ensure that patients can base their choice upon more evidence-based sources, several sources of information have been made available. However, research (Edgman-Levitan and Cleary, 1996; Leister and Stausberg, 2007; Schwartz et al., 2005) has proven that these sources are not as widely used as intended, and patients still base their decision on referral and word of mouth. A relatively developing source of information in health care are review sites. In this thesis the effects of valence, volume and dispersion of reviews were analyzed on hospital choice. One previous research has been found that has conducted research on the word of mouth on medical services (Hinz et al. 2012). The effect of dispersion however was not researched yet on a high stakes decision. Also, it was analyzed how these characteristics affect hospital choice, by determining if a person was a satisficer or a maximizer. This was assessed by asking subjects to reveal their preferred choice, when choosing between pairwise comparisons. Moreover, the study also had an additional empirical goal of determining the effect of eWOM in self-reported evaluation of different hospitals.

According to the findings, valence, volume and dispersion of reviews have a significant impact on hospital choice. Furthermore, positive eWOM has a stronger influence than negative eWOM on hospital choice, as does a higher level of volume of reviews as opposed to a lower level. Also, for both the effect is positive, meaning that as valence and volume have a higher level, the odds of a hospital getting chosen increase. Dispersion, on the contrary, has a negative effect on hospital choice, and therefore the odds of hospital choice decrease when a hospital has a higher level of Dispersion. That can be explained by the fact that people do not want a high level of dispersion in an 'experience good' (and also one with a higher risk of 'purchase'), for which information asymmetry exists. It must be noted though, that hospitals with high dispersion seem to have slightly higher odds of getting chosen by maximizers than by satisficers (even though the odds are still small). This is perhaps, because maximizers spend more attention on dispersion as they want to give the most appropriate grade. This result is also observed in the evaluation of hospitals, as maximizers give a slightly higher grade to hospitals with high variance than maximizers do. For hospitals with high valence their odds to get chosen increase as expected, with a higher rate for satisficers than for maximizers and the same goes for hospitals with high volume. However, the effects of these two variables are not significant when the maximizing tendency of the respondent is analyzed on hospital evaluation.

Hypothesis	Hypothesis Testing
1	Not Rejected
2	Not Rejected
3	Not Rejected
4	Not Rejected
5a	Not Rejected
5b	Not Rejected
5c	Rejected

Table 13. Hypotheses table

In short, the results of this thesis reinforce findings of previous eWOM literature. However, as the manipulation check indicated, subjects had some trouble with the variable valence and due to flaws in the design, which might have caused an overemphasized effect of dispersion, the findings of this research are restricted to this sample and the generalizability of this model is affected.

6.2 Limitations and further research:

The largest limitation of the model is the fact that one of the independent variables (dispersion) was dependent upon the level of the other predictor variable (volume). As mentioned in the paper, due to this limitation, dominated choice had to be ruled out and that in turn affected the efficiency of the model. The second sample, which was used as a robustness check, however deviated from orthogonality and violated the balance condition. Most of the designs nowadays are tested for D-efficiency with software packages. Unfortunately, this was not employed, as there is no information on priors available and no software available. A good lesson from Johnson et al. (2013) is that indeed *optimal* is a very valuable word when conducting experimental design.

A limitation of the layout of the questionnaire could be that people paid more attention to distribution, also because it was the only variable depicted in a graph. A similar experiment could be run, in which it is not illustrated or all the variables are in some visual way represented. However, in real life people are also distracted by certain things and do not distribute their attention evenly.

Another limitation is the way valence was measured. Perhaps, in future research more categories can be employed, instead of just positive and negative, for example also a neutral value. Also, more extreme values could be used to measure the positive and negative eWOM. Hinz et al. (2012) have found that a high majority of the posted reviews are extreme, either highly positive or highly negative. Another proposal would be to show the subjects several reviews in order to determine a classification scale (e.g. very negative, negative, neutral, positive, and very positive) and then incorporate those reviews into the research. Furthermore, it could be looked at if the order[34] in which such reviews are shown has an impact on the hospital choice.

Also, another limitation could also be the previous experience of subjects and the differences between various health care systems. In some countries, people are not at all used with reviews for medical facilities. A cross-cultural study can be conducted in order to determine if results would differ across different cultures or health care systems.

Because of the time and length constraint of the master thesis, choices had to be made regarding which variables would be analyzed. Firstly, it must be noted that in 'real life', people do genuinely care more about the message of the review itself and also take into account the 'brand' (or in this case the reputation) or what they know about a hospital.[35] Also, in 'real life' the grades and distribution of the reviews will not be fixed, but would rather fluctuate with time. These things are unfortunately, not captured by the model. Perhaps future research could take some of these things into consideration.

I decided not to focus on expertise level and weak tie as characteristics of eWOM, because after considering the previous literature, I did not consider them relevant enough to be included. The importance of weak tie has been researched in the traditional WOM literature, where it has been identified that a strong tie has a more impact on the receiver's opinions and actions than a weaker tie (Godes & Mayzlin; 2004). However, in the online environment the provider of the WOM may not rely on the strength of the social tie and therefore it can be assumed that the tie strength of the eWOM is very weak (Chatterjee, 2001;

[34] For example, if a negative review is shown before a positive review and changing that order, while having the same (amount of) reviews each time.
[35] Think for example of the incident in The Netherlands, in the Maasstad hospital.

Ward & Ostrom, 2006). Previous studies have also shown that consumers rather consider cues of others when making decisions and those opinions have more impact than reviews of experts. (Huang and Chen, 2006; Chen et al., 2003). That was the reasoning why expertise-level has not been included in this study.

Another factor that has been left out is credibility. One of the concerns was regarding the anonymity of the reviews. Chen et al. (2003)[36] already mention in their paper that because of the anonymity of the reviews, one cannot know if they are not posed by a company or in this case by an employee of the hospital and might be biased. Lagu et al. (2010) found in their study that some physicians admittedly write reviews about themselves. Chen et al. (2003) attempted to look at the validity of online reviews. In their study they found that reviews from consumer magazine sites and independent websites are not less valid than traditional surveys and find that the accuracy increases as the number of postings increase. Other research has even pointed out that web-based word of mouth is perceived as credible and relevant way of communication (Bickart and Schindler, 2001; Hung & Li, 2007; Nielsen, 2007). That can be attributed to informational social influence and the herding behavior of consumers (Huang & Chen; 2006). Trigg (2011) and López et al. (2012) rightfully point out that anonymity might make patients more at ease when providing feedback and in order to improve health care feedback is necessary, even though it is anonymous. Therefore, perhaps it would be interesting to research in the future, at an individual level of the reviews, how credible reviews are believed by others to be? Do consumers manage to identify if reviews are posted by staff or biased actors?

Furthermore, an interesting suggestion for future research is to look at the impact of electronic word of mouth about physicians on the hospital choice. How do the grades of doctors in a hospital affect hospital choice? Also, when going through the reviews on the review sites I noticed that people seemed to be more satisfied with smaller sized hospitals. It would be interesting to look at what effect the size of the hospital has on how hospitals are graded. Another possible future research that is also tied to hospital grades would be to look if the grading of hospitals on review sites is consistent with hospital rankings

It would also be interesting to try to determine if electronic word-of-mouth has an impact on hospital reputation. Perhaps, a 'real world' research could be done, retrospective of the choice behavior and the influence electronic word of mouth had on it.

[36] Sen & Lerman (2007) and Lagu et al. (2010) also treat this issue.

Finally, future research could also focus on including how contented maximizers or satisficers feel with their evaluation of the hospitals. It would be also interesting to vary the amount of choices perhaps in one sample or even in one of the randomized choice set block to have 2 choices per choice pair and in the other one to have for example 4 choices and see how increasing the choice possibilities affects the subjects.

Reference List

Andreassen, T. W. and S. Streukens. (2009). "Service innovation and electronic word-of mouth: is it worth listening to?". *Managing Service Quality*, *19*(3), 249-265.doi: 10.1108/09604520910955294.

Ariely, Dan. (2009). Predictably irrational. New York: Harper.

Arndt, J. (1967). "Role of product- related conversations in the diffusion of a new product". *Journal of Marketing* Research. *4*(3).291–5.

Bakos, Y. (1997, December). "Reducing Buyer Search Costs: Implications for Electronic Marketplaces". *Management Science*. 43:12.

Bass, F.M. (1995). "Empirical generalizations in marketing science: A personal view". *Marketing Science*.14(3). G6−G19 (2 of 2).

Bates, D.W. and A.A. Gawande. (2000). "The impact of the Internet on quality measurement". *Health Affairs* 19(6), 104–114.

Baumeister, R.F., E. Bratslavsky, C. Finkenauer and K.D.Vohs. (2001). "Bad is stronger than good". *Review of General Psychology*. *5*. 323–370.

Beattie, J., J. Baron, J.C. Hershey and M.D. Spranca. (1994). "Psychological determinants of decision attitude". *Journal of Behavioral Decision Making.* 7. 129–144.

Berry, L.L., and N. Bendapudi. (2007). "Health care: a fertile field for service research". Journal of Service Research. 10(2). 111–122.

Bickart, B., and R. Schindler. (2001)."Internet forums as influential sources of consumer information". *Journal of Interactive Marketing*. *15*(3), 31–40.

Bouwens, J and D.M. Kreuger.(N/A). "Embracing Change: The healthcare industry focuses on new growth drivers and leadership requirements". Russell Reynolds Associates. Accessible online at: http://www.russellreynolds.com/content/embracing-change-healthcare-industry-focuses-new-growth-drivers-and-leadership-requirements.

Bruine de Bruin, W., A.M. Parker and B. Fischhoff. (2007). "Individual differences in Adult Decision-Making Competence". *Journal of Personality and Social Psychology*. 92. 938–956.

Buttle, F.A. (1998). "Word of mouth: Understanding and managing referral marketing”. *Journal of Strategic Marketing*. *6*(3). 241-254. doi: 10.1080/096525498346658

Chatterjee, P. (2001). " Online review: do consumers use them?". *Advances in Consumer Research. 28*. 129–133.

C.H.(2013, July 24th). "Searching for a diagnosis". The Economist. Retrieved from: http://www.economist.com/blogs/democracyinamerica/2013/07/high-cost-health-care-0

Chen, Y., S. Fay and Q. Wang. (2003). "Marketing implications of online consumer product reviews". Working paper. University of Florida. Gainesville, FL.

Cheung, C.M.K. and D.R Thadani. (2010, June)."The Effectiveness of Electronic Word-of Mouth Communication: A Literature Analysis". Paper presented at *23rd Bled eConference eTrust: Implications for the Individual, Enterprises and Society*(pp.329-345). Slovenia.

Chevalier, J. and D. Mayzlin.(2006, August)."The Effect of Word of Mouth on Sales: Online Book Reviews". *Journal of Marketing Research*. XLIII. 345–54.

Clemons, E.K., G. Gao and L.M. Hitt. (2006). "When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry". *Journal of Management Information Systems*. 23(2).149-171.

Dabholkar, P. (2006). "Factors Influencing Consumer Choice of a ‘Rating Web Site’: An Experimental Investigation of an Online Interactive Decision Aid". *Journal of*

Marketing Theory and Practice. *14*(4). 259-273.
Damman O.C. (2010). "Public reporting about healthcare users' experiences: the Consumer Quality Index. Keuze-informatie over de ervaringen van zorggebruikers: de Consumer Quality Index".(Doctoral dissertation). University of Tilburg. Retrieved from: http://www.nivel.nl/sites/default/files/bestanden/Proefschrift-the-Consumer-Quality Index.pdf?
Day, G.S. (1971)."Attitude change, media and word of mouth". *Journal of Advertising Research*. 11(6). 31–40.
Dellarocas, C. (2003)."The digitalization of Word-Of-Mouth: Promise and Challenges of Online Reputation Mechanisms". *Management Science*. *49*(10).1407-1424. doi:10.1287/mnsc.49.10.1407.17308.
Dellarocas, C., X. Zhang and N. Awad. (2007). "Exploring the value of online product reviews in forecasting sales: The case of motion pictures". *Journal of Interactive Marketing*. 21(4). 23-45.
Diab, D. L., M.A. Gillispie and S. Highhouse. (2008). "Are maximizers really unhappy? The measurement of maximizing tendency". *Judgment and Decision Making*. 3. 364–370.
Dijs-Elsinga, J., W. Otten, M. Versluijs, H.J. Smeets, R.Vree, W.J van der Made and J. Kievit. (2010). 'Choosing a hospital for surgery: the importance of information on quality of care". *Medical decision making*. 30(5). 544-555. doi:10.1177/0272989X09357474.
Doh, S. J. and J.S. Hwang. (2009). "How Consumers Evaluate eWOM (Electronic Word of-Mouth) Messages". *Cyberpsychology & Behavior*. 12(2). 193-197.
Duan, W., B. Gub and A.B, Whinston. (2008). "Do online reviews matter?— An empirical investigation of panel data". *Decision Support Systems*. *45*(3). 1007–1016.Doi: 10.1016/j.dss.2008.04.001.
East, R., K. Hammond and W. Lomax. (2008). "Measuring the impact of positive and negative word of mouth on brand purchase probability". *International Journal of Research in Marketing. 25*. 315-224.
Edgman-Levitan S. and P.D Cleary. (1996). "What information do consumers want and need?". Health Affairs. 15. 42-56.
Eysenbach, G. (2008). "Credibility of Health Information and Digital Media: New Perspectives and Implications for Youth". *Digital Media, Youth, and Credibility* (pp. 123–154). Edited by Miriam J. Metzger and Andrew J. Flanagin. The John D. and Catherine T. MacArthur Foundation Series on Digital Media and Learning. Cambridge, MA: The MIT Press. doi: 10.1162/dmal.9780262562324.123.
Emmert M, R. Gemza, O. Schöffski and S. Sohn. (2012). "Public reporting in Germany: the content of physician rating websites". Methods of Information in Medicine. 51 (2).112-120.doi:10.3414/ME11-01-0045.
Engel, J.F., R.J. Kegerris and R.D. Blackwell. (1969). "Word of mouth communication by the Innovator". *Journal of Marketing* . 33(3). 15–19.
Fanjiang, G. et al. (2007). "Providing Patients Web-Based Data to Inform Physician Choice: If You Build It, Will They Come?". *Journal of General Internal Medicine*. 22(10). 1463–1466.
Field, A. (2009). *Discovering statistics using SPSS*. (3rd ed.). London: Sage Publications Ltd.
Field, A. (2013*). Discovering statistics using SPSS*. (4th ed.). London: Sage Publications Ltd.
File, K.M., D.S.P. Cermak and R.A. Prince. (1994). "Word-of-mouth effects in professional services buyer behavior". *The Service Industries Journal .14*(3). 301–314. doi:

10.1080/02642069400000035
Fox S and S. Jones. (2009) "The Social Life of Health Information". Pew Internet & American Life Project.
Gauri, D., A. Bhatnagar and R. Rao. (2008)."Role of Word of Mouth in Online Store Loyalty". *Association for Computing Machinery.* Communications of the ACM, 51(3). 89-91.
Gershoff A.D., A. Mukherjee and A. Mukhopadhyay. (2003)."Consumer acceptance of online agent advice: extremity and positivity effects". *Journal of Consumer Psychology*. *13*(1&2). 161–70.
Godes, D. and D. Mayzlin. (2004). "Using Online Conversations to Study Word-of-Mouth Communication". *Marketing Science*. *23*(4). 545–60.
Goldsmith, R. E. and D. Horowitz. (2006). "Measuring motivations for online opinion seeking". *Journal of Interactive Advertising. 6*(2). 3–16.
Hanson, W.A. and D. S. Putler. (1996, October). "Hits and Misses: Herd Behavior and Online Product Popularity". *Marketing Letters*. 7. 297-305.
Harrington J., L.M. Noble, S.P. Newman. (2004). "Improving patients' communication with doctors: a systematic review of intervention studies". *Patient Education and Counseling.52*(1). 7-16.
Harris K, and M. Buntin. (2008). The RAND Corporation. "Choosing a Health Care Provider: The Role of Quality Information". Princeton, NJ: Robert Wood Johnson Foundation; Research Synthesis Report No. 14.
Hennig-Thurau, T., K.P. Gwinner, G. Walsh, and D.D. Gremler. (2004), "Electronic word -of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the Internet?". Journal of Interactive Marketing. 18(1). 38-52.
Hensher, D.A.(2004). "Identifying the influence of stated choice design dimensionality on willingness to pay for travel time savings". *Journal of Transport Economics and Policy*. *38*(3). 425–446.
Herr, P. M., F. R. Kardes and J. Kim. (1991). "Effects of Word-of-Mouth and Product Attribute Information on Persuasion: An Accessibility - Diagnosticity Perspective". *Journal of Consumer Research*.*17*(5). 454–465.
Hess, A.E.M and M.B. Sauter. (2013, July 2). "Countries that spend the most on health care". 24/7 WallSt. Retrieved from: http://247wallst.com/special-report/2013/07/02/countries-spending-the-most-on-healthcare
Hesse B.W, D.E. Nelson, G.L Kreps, R.T. Croyle, N.K. Arora, B.K. Rimer and K. Viswanath. "Trust and sources of health information: the impact of the Internet and its implications for health care providers: findings from the first Health Information National Trends Survey". *Archives of Internal Medicine. 165*(22). 2618–2624. doi: 10.1001/archinte.165.22.2618.165/22/261
Hinz, V., F. Drevs, and J. Wehner. (2012). "Electronic word of mouth about medical services". Hamburg Center for Health Economics. Universität Hamburg. Retrieved from: http://hdl.handle.net/10419/65671.
Huber, J. and K. Zwerina.(1996, August). "The Importance of Utility Balance in Efficient Choice Designs". *Journal of Marketing Research*. *33*(3). 307-317
Huang, J.-H., Y.-F. Chen. (2006). "Herding in online product choice". *Psychology& Marketing. 23*(5). 413–428. doi:10.1002/mar.20119.
Hung, K.H. & Li, S.Y. (2007). "The influence of eWOM on virtual consumer communities: social capital, consumer learning, and behavioral outcomes". *Journal of Advertising Research. 47*(4). 485–495.

Jain, K., Bearden, N. J., & Filipowicz, A. (2013)."Do maximizers predict better than satisficers?". *Journal of Behavioral Decision Making. 26*. 41-50.
Johnson, F.R., E. Lancsar, D. Marshall, V. Kilambi, A. Muehlbacher, D.A. Regier, B.W. Bresnahan, B. Kanninen, J.F.P. Bridges. (2013). "Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force". *Value in Health. 16.* 3-13.
Jung K., R. Feldman and D. Scanlon.(2011). "Where would you go for your next hospitalization?" *Journal of Health Economics*. *30* (4): 832–841. doi.10.1016/j.jhealeco.2011.1005.1006.
Kahn, B.E. and M. F. Luce. (2003). "Understanding High-Stakes Consumer Decisions: Mammography Adherence Following False-Alarm Test Results". Marketing Science, 22(3). 393–410
Kahneman, D., and A. Tversky. (1979). "Prospect theory: An analysis of decisions under risk". *Econometrika*. 47. 263–291.
Kahneman, D., and A. Tversky. (1984). "Choices, values, and frames. American Psychologist". 39. 341–350.
Katz, E. and P. Lazarsfeld. (1955) *Personal Influence*. New York: Free Press.
Kenagy J.W., D.M. Berwick and M.F. Shore. (1999) "Service quality in health care". *Journal of American Medical Association. 281*(7). 661– 665.
Klein L.R. (1998). "Evaluating the potential of interactive media trough a new lens: Search versus experience goods". *Journal of Business Research*. 41(3). 196-203.
Lagu T., N.S. Hannon, M.B. Rothberg and P.K. Lindenauer. (2010). "Patients' Evaluations of Health Care Providers in the Era of Social Networking: An Analysis of Physician Rating Websites". *Journal of General Internal Medicine*. *25*(9)**.** 942-946.
Laing, A, D. Keeling and T. Newholm. (2011). "Virtual communities come of age: Parallel service, value, and propositions offered in communal online space". *Journal of Marketing Management*. *27*(3-4). 291-315.
Lee, J., D.-H .Park, and I. Han. (2008). "The effect of negative online consumer reviews on product attitude: An information processing view". *Electronic Commerce Research and Applications*.. 7(3). 341 -352.
Lee, M., S. Rodgers and M. Kim. (2009). "Effects of valence and extremity of eWOM on attitude toward the brand and website". *Journal of Current Issues and Research in Advertising. 31*(2). 1–11.
Leister, J., and J. Stausberg.(2007). "Why do patients select a hospital? A conjoint analysis in two German hospitals". Journal of hospital marketing & public relations.17(2), 13–31.
Litvin, S. W., R. E. Goldsmith and B. Pan (2008). "Electronic Word-of-Mouth in Hospitality and Tourism Management". *Tourism Management.* 29. 458-68.
Liu, Y. (2006). "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue". *Journal of Marketing*. 70(3), 74 - 89.
López A, A. Detz, N. Ratanawongsa and U. Sarkar. (2012)."What patients say about their doctors online: a qualitative content analysis". *Journal of General Internal Medicine. 27(*6). 685–692. doi: 10.1007/s11606-011-1958-4.
Mol A. (2006). "De logica van het zorgen, actieve patiënten en de grenzen van het kiezen". Amsterdam: van Gennep.
Moore, G. (1995). *Crossing the chasm.* New York. HarperCollins Publishers.
Murray E, B. Lo, L. Pollack, K. Donelan, J. Catania, K. Lee, K. Zapert and R. Turner. (2003). "The impact of health information on the internet on the physician patient relationship: patient perceptions". *Archives of Internal Medicine*. *163*(14). 1727–1734.doi: 10.1001/archinte.163.14.1727.163/14/1727

MWM2. (2012, June 7). "Onderzoek vrije artsenkeuze". Zelfstandige Klinieken Nederland. Retrieved from: http://www.zkn.nl

Nelson P. (1970). "Information and consumer behavior" . *The Journal of Political Economy*. 78*(2)*. 311-319.

Nielsen Report.(2007, October). "'Word-of-mouth' the most powerful selling tool: Nielsen Global Survey - Traditional Media Advertising Still More Credible Worldwide Than Ads on Search Engines, Web Site Banners and Mobile Phones". Nielsen. www.nielsen.com

Oetting, M., M. Niesytto, J. Sievert and F. Dost. (2010, October). Positive word-of-mouth is more effective than negative – because it sticks!. Trnd research – word—of-mouth monitor. 1-15.

Orme, B. (2010). "Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research". Second Edition, Madison, Wis.: Research Publishers LLC.

Osborne N.H., L.H. Nicholas, A.A. Ghaferi, G.R. Upchurch Jr. and J.B. Dimick. (2010). "Do popular media and internet-based hospital quality ratings identify hospitals with better cardiovascular surgery outcomes?" Journal of the American College of Surgeons. *10*(1). 87–92.

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

Park, D.-H., J. Lee and I. Han. (2007). "The effect of online-consumers reviews on consumer purchasing intention: the moderating role of involvement". *International Journal of Electronic Commerce*. *11*(4). 125–148.

Park, D.-H., and S. Kim. (2008)."The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews". *Electronic Commerce Research and Applications*. 7. 399–410.

Parker, A. M., W. Bruine de Bruin and B. Fischhoff. (2007). "Maximizers versus satisficers: Decision making styles, competence, and outcomes." *Judgment and Decision Making*. 2. 342–350.

Peterson, Robert A., and Maria C. Merino (2003)."Consumer Information Search Behavior and the Internet". *Psychology and Marketing*. *20*(2).99-121.

Polman, E. (2010). "Why are maximizers less happy than satisficers? Because they maximize positive and negative outcomes". *Journal of Behavioral Decision Making*. 23. 179–190.

Raad voor de Volksgezondheid & Zorg. (2010). "Gezondheid 2.0". The Hague. Retrieved from: http://rvz.net/uploads/docs/Advies_-_Gezondheid_20.pdf

Reitsma, M., A. Brabers, W. Masmanand J. de Jong. (2012). "De kostenbewuste burger". NIVEL (Netherlands Institute for Health Services Research). Retrieved from: http://nvl002.nivel.nl/adlibweb/detail.aspx.

Reitsema M., A. Brabers, W. Masman and J. de Jong. (2012). "De kiezende burger". NIVEL (Netherlands Institute for Health Services Research). Retrieved from: http://nvl002.nivel.nl/adlibweb/detail.aspx.

Resnick P. and R. Zeckhauser. (2002). "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System". In M.R. Baye, editor, The Economics of the Internet and E-Commerce, volume 11 of Advances in Applied Microeconomics. Elsevier Science.

Richard, S.A., S. Rawal, and D.K. Martin. (2005). "Patients' Views about Cardiac Report Cards: A Qualitative Study". *Canadian Journal of Cardiology*. *21*(11). 943–947.

Rooney K. (2009). "Consumer-driven healthcare marketing: Using the Web to get up close and personal". *Journal of Healthcare Management*. *54*(4). 241-251.

Rose, J.M., M.C.J. Bliemer, D.A. Hensher and A.T. Collins. (2008). "Designing efficient stated choice experiments in the presence of reference alternatives". *Transportation Research. 42B*(4)., 395-406.
Rothberg M.B., E. Morsi, E.M. Benjamin, P.S. Pekow and P.K. Lindenauer. (2008). "Choosing the best hospital: the limitations of public quality reporting". *Health Affairs*. 27(6). 1680–1687.doi: 10.1377/hlthaff.27.6.1680.
Schneider, E.C. and A.M. Epstein. (1998). "Use of Public Performance Reports: A Survey of Cardiac Surgery Patients". *Journal of the American Medical Association*. 279 (20).1638-1642.
Schwartz, B., A. Ward, J. Monterosso, S. Lyubomirsky, K. White and D.R. Lehman. (2002). "Maximizing versus satisficing: happiness is a matter of choice". *Journal of Personality and Social Psychology*. 83(5). 1178–1197.
Schwartz L.M., S. Woloshin and J.D. Birkmeyer. (2005) "How do elderly patients decide where to go for major surgery? Telephone interview survey". BMJ. 331:821 doi:10.1136/bmj.38614.449016.DE.
Sen, S. and D. Lerman. (2007). "Why are you telling me this? An examination into negative consumer reviews on the Web". *Journal of Interactive Marketing*. *21*(4). 76–94.
Simon, H. A. (1955). "A behavioral model of rational choice". *Quarterly Journal of Economics*. 59. 99–118.
Smith R. (1997). "The future of healthcare systems". *British Medical Journal*. *314*. 1495 1496.
Sorensen, A.T. and S.J. Rasmussen. (2004). "Is Any Publicity Good Publicity? A Note on the Impact of Book Reviews". Working Paper, Stanford University.
Stigler, G. (1961, June). "The Economics of Information.". *The Journal of Political Economy*. 69(3). 213-25.
Stigler, G. (1962, October). "Information in the Labor Market." *The Journal of Political Economy*. 70(5). 94-105.
Sweeney, J.C., G.N. Soutar and T. Mazzarol. (2005)."The difference between positive and negative word-of-mouth—emotion as a differentiator". In *Proceedings of the ANZMAC 2005 Conference: Broadening the Boundaries* (pp. 331–337). Perth, Australia: University of Western Australia.
Thurstone, L. (1927). A law of comparative judgment. *Psychological Review*. 34. 273–286.
Trigg, L. (2011). "Patients' opinions of health care providers for supporting choice and quality improvement". *Journal of Health Services Research & Policy*. 16 (2). 102–107.
Tversky, A., and D. Kahneman.(1981). "The framing of decisions and the psychology of choice". *Science.* 211. 453–458.
Vermeulen, I. E., &Seegers, D. (2009). "Tried and tested: The impact of online hotel reviews on consumer consideration". *Tourism Management. 30*, 123-127
Varkevisser, M., S.A. van der Geest and F.T. Schut. (2012). "Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands". *Journal of Health Economics*. *31*(2). 371–378.
Ward, J.C., and A.L. Ostrom. (2006). "Complaining to the masses: The role of protest framing in customer-created complaint web sites". *Journal of Consumer Research. 33*(2). 220—230.
Westbrook, R.A.. (1987). "Product/Consumption-Based Affective Responses and Post purchase Processes". *Journal of Marketing Research*. *24* (3), 258-270.
World Health Organization. 2011 WHO Global Health Expenditure Atlas. Retrieved from: http://www.who.int/nha/atlas.pdf
Wolters, P. J. & C.J. Lako. (2012). "Hoe kiezen patiënten een ziekenhuis? ". *Tijdschrift voor*

gezondheidswetenschappen. 90(1). 45-50

Yoo K.H. and U. Gretzel. (2008). "What motivates consumers to write online travel reviews?" Journal of Information Technology & Tourism. 10(4). 283–295.

Zhang, J.Q., G. Craciun and D. Shin. (2010). "When does electronic word-of-mouth matter? A study of consumer product reviews". *Journal of Business Research*. *63*(12). 1336-1341.

Zwerina, K., J. Huber, and W. Kuhfeld. (1996). "A general method for constructing efficient choice designs". Working paper, Fuqua School of Business, Duke University.

Appendix A

Model 1

Sample 2

	b	SE	Wald	df	Sig.	Ratio	95% CI for Odds	
						Lower	Odds (Exp. (B))	Upper
Constant	**-0.133** [-0.280, 0.15]	0.075	3.195	1	0.074		**0.875**	
Valence	**0.253** [0.069, 0.434]	0.092	7.619	1	0.006	1.076	**1.288**	1.541
Volume	**0,397** [0.210, 0.598]	0.092	18.743	1	0.000	1.242	**1.487**	1.779
Dispersion	**-0,247** [-0.432, -0.065]	0.092	7.288	1	0.007	0.652	**0.781**	0.934
Note. R^2 = .01 (Hosmer & Lemeshow) .014 (Cox & Snell) .018 (Nagelkerke). Model χ^2 (1) = 30.055, $p< 0.05$								

Table 1. Results logistic regression model 1 - sample 2, predicting whether a hospital was chosen [95% bootstrap confidence intervals based on 1000 samples]

Due to ruling out dominated choice, while still trying to maintain an orthogonal design, the category for Dispersion = both for the same hospitals was omitted. In order to tests if this had serious implications for the model, as discussed above, I gathered a second sample using an alternative questionnaire design.This second sample ruled out dominated choices and presented all the remaining choices, but did not maintain the orthogonal design. The matched pairs, for both samples, were presented in the previous section. The results for this sample are given below:

The R-value is positive for each of the predictors. Therefore, now as the predictor Dispersion increases (has a high value), so does the likelihood of the hospital getting chosen. The R^2 values are .01 (Hosmer & Lemeshow) .014 (Cox & Snell) .018 (Nagelkerke), indicating that the predictor variables predict less well the variability of hospital choice than in the first model and poorly, overall.

Nevertheless, all the predictors are significant. Furthermore, looking at the odds ratios we observe that the odds of the predictors Valence and Volume are also in this sample greater than 1, meaning that as valence or volume have a high value the odds of a hospital getting chosen increases. The odds ratio of Valence indicates that the odds of a hospital with high valence being chosen are 1.288 higher than a hospital with low valence, all other variables held equal. Compared to the previous model, the effect is almost half. The odds ratio (for Volume is also almost twice as small as compared to the first sample and it indicates that a hospital with high Volume has 1.487 times higher odds as compared to hospitals with low Volume, when all other thing are held equal. The odds ratio for Dispersion has increased in value as opposed to the results of the first sample, however it is still smaller than 1, indicating that even though the its importance might be overemphasized in the results of the first sample, it is still the case that as Dispersion is increasing, the odds of a hospital getting chosen decrease. A hospital with high Dispersion has 0.781 times the same odds of being chosen as compared to a hospital with low dispersion. It should also be noted that this model fits the data less well than the one for the first sample. No overdispersion or multicollinearity (VIF value close to one for all predictor variables; none have a high variance for the same eigenvalue) was found for this sample and residuals did not indicate anything wrong with the data (table 18 to 21 in Appendix B).

The classification plot of the second sample (figure 3 in Appendix B) also indicates that the points are quite clustered in the center of the plot, meaning that the model might not predict the choices well. In the first sample (figure 2 in Appendix B), the points are further away from the center. These findings are reinforced by the percentages in the classification tables (table 16 and 17 in Appendix B).

Differenced results

		Frequency	**Parameter coding**	
			(1)	(2)
Valence	H2 lower valence	363	0.000	0.000
	both same valence	242	1.000	0.000
	H2 higher valence	484	0.000	1.000
Volume	H2 lower volume	121	0.000	0.000
	both same volume	605	1.000	0.000
	H2 higher volume	363	0.000	1.000
Dispersion	both same dispersion	242	0.000	
	H2 higher dispersion	847	1.000	

Table 2. Categorical Variables Codings – Sample 2 differenced

Also, the differenced model of the second sample shows improved R^2-values. However, its values are still lower than the ones of the first sample. In this model, valence and volume are coded just like in the differenced model of the first sample. For dispersion, however, the category both hospital have the same dispersion is now the reference group. The variable Valence is significant (*p≤.05).* The odds for Valence (1) and Valence (2) are higher than 1. Therefore, as Valence increases the odds of the second hospital getting chosen increases. However, Valence (2) category seems to have a slightly greater effect (Exp. (B) = 2.33) than Valence (1), indicating that the second hospital had higher odds of being chosen when it had a higher valence than the first hospital as compared to when it had a lower valence than the first hospital, than when the hospitals had the same valence as compared to when the second hospital had a lower Valence. The same result can be observed for the predictor Volume. Dispersion is just like in the differenced model of the first sample, lower than it was predicted by the second sample, indicating that as dispersion increases, the odds of the second hospital getting chosen decrease. The coefficient indicates that the odds between if both hospitals have the same dispersion as compared to if the second hospital has a higher dispersion than the first hospital decreases by more than 1.7 times. The corresponding tables to this model can be found in Appendix B – table 30 to 36).

	b	**SE**	**Wald**	**df**	**Sig.**	**95% CI for Odds Ratio**		
						Lower	Odds	Upper
Constant	**-0.928** [-1.443, -0.441]	0.255	13.205	1	0.000		**0.395**	
Valence			14.482	2	0.001			
Valence (1)	**0.55** [0.72, 1.042]	0.245	5.028	1	0.025	1.072	**1.734**	2.804
Valence (2)	**0.846** [0.410, 1.301]	0.227	13.843	1	0.000	1.492	**2.33**	3.639
Volume			25.399	2	0.000			
Volume (1)	**0.697** [0.258, 1.151]	0.223	9.741	1	0.002	1.296	**2.007**	3.108
Volume (2)	**1.159** [0.710, 1.610]	0.239	23.471	1	0.000	1.994	**3.186**	5.091
Dispersion	**-0.55** [-1.047, -0.087]	0.245	5.028	1	0.025	0.357	**0.577**	0.933
Note. R^2 = .028(Hosmer & Lemeshow) .038 (Cox & Snell) .05 (Nagelkerke). Model χ^2 (1) = 41.733, $p< 0.05$								

Table 3. Results logistic regression model 1 - sample 2, predicting whether the second hospital was chosen [95% bootstrap confidence intervals based on 1000 samples]

Model 2

	b	SE	Wald	df	Sig.	95% CI for Odds Ratio		
						Lower	Odds	Upper
Constant	**-0.048** [-0.215, 0.118]	0.085	0.324	1	0.569		**0.953**	
Valence	**0.914** [0.745, 1.109]	0.093	97.604	1	0.000	2.081	**2.494**	2.990
Volume	**1.078** [0.896,1.268]	0.093	133.641	1	0.000	2.448	**2.939**	3.528
Dispersion	**-2.195** [-2.432, -1.955]	0.121	329.606	1	0.000	0.088	**0.111**	0.141
D_maximizer by Dispersion	**0.548** [0.297, 0.823]	0.130	17.675	1	0.000	1.340	**1.730**	2.234
Note. R^2 = .191 (Hosmer & Lemeshow) .233(Cox & Snell) .310 (Nagelkerke). Model χ^2 (1) = 678.288 $p< 0.05$								

Table 4. Results logistic regression model 2, predicting whether a hospital was chosen [95% bootstrap confidence intervals based on 1000 samples]

Looking at the main effects and the interaction between D_maximizer and Dispersion gives the following results: the R-value of the predictors Valence and Volume is quite small (R=.164), respectively (R=.193). While the predictor Dispersion also has a positive R-value, it has a larger contribution to the model (R=.304). The interaction effect has an R-value of only .062. The R^2 values are .191 (Hosmer & Lemeshow) .233 (Cox & Snell) .310 (Nagelkerke), indicating how well the predictor variables predict the variability of hospital choice when just an interaction between the variable Dispersion and the moderator is included. It is slightly less than in the full model, however it indicates that the interactions between D_maximizer and Valence and Volume add few explanation in the variability of the model. The model still classifies instead of 50% of the hospitals, when only the constant is included, 70% of the hospitals correctly.

All the predictors in this regression are as well significant. The intercept means that a hospital has the odds of 0.953 times same getting chosen, when a hospital has low valence, low volume and a low dispersion. However, neither in this case is it significant. Furthermore, looking at the odds ratios we observe that the odds of the predictors Valence and Volume are also in this sample greater than 1, meaning that as valence or volume have a high value the odds of a hospital getting chosen increases. In the case of Valence, a hospital with high valence has 2.494 times higher odds of getting chosen as compared to a hospital with low valence, when all other variables are held constant. For Volume, a hospital with high volume has 2.939 times higher odds than a hospital with low volume, all variables ceteris paribus. The odds ratio for Dispersion is still smaller than 1, indicating as Dispersion is increasing, the odds of a hospital getting chosen decrease. Furthermore, the odds ratio for the interaction is greater than 1, so as Dispersion has a high value and a person is a maximizer, the odds of a hospital getting chosen increases. For Dispersion, a hospital with high Dispersion has 0.111 times the same odds of getting chosen as a hospital with low dispersion, all held constant. For a maximizer, the odds ratio is (0.111*1.730)= 0.192 times the same, for a hospital with high dispersion as compared for a hospital with low dispersion, when everything is held constant. Also in this sample, no overdispersion was found. The multicollinearity (VIF value close to one for all predictor variables; none have a high variance for the same eigenvalue) look better than in the previous model and the residuals did not indicate anything wrong with the data (table 49 to 53 in Appendix B).

Note: When looking at a moderator relationship, it is common practice to include the main effect as well in the model. However, there are exceptions, such as when predicting new values. The model with the main effect is included in the Appendix B (table 54 and 55).

Appendix B

Average grade:	8,2
Total reviews:	10

How would you grade this hospital based on the information that was given to you? (1/10; grades with decimals are also possible)

Figure 1. Example of how hospitals were asked to be graded for the third model.

Valence					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	155	48.7	48.7	48.7
	1	163	51.3	51.3	100
	Total	318	100	100	

Table 1. Frequency table Valence

Volume					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	157	49.4	49.4	49.4
	1	161	50.6	50.6	100
	Total	318	100	100	

Table 2. Frequency table Volume

Dispersion					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	158	49.7	49.7	49.7
	1	160	50.3	50.3	100
	Total	318	100	100	

Table 3. Frequency table Dispersion

D_maximizer					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	150	47.2	47.2	47.2
	1	168	52.8	52.8	100
	Total	318	100	100	

Table 4. Frequency table D_maximizer

Hospital	Valence	Volume	Dispersion	N	µ Valence	σ Valence	µ Volume	σ Volume	µ Dispersion	σ Dispersion
1	7.2	10	0	38	3.158	0.855	2.421	0.948	3.632	0.883
2	8.2	10	0	40	3.475	0.751	2.175	0.874	3.700	0.758
3	7.2	60	0	40	3.250	0.840	3.821	0.698	3.725	0.933
4	8.2	60	0	41	3.512	0.711	4.024	0.612	4.049	0.669
5	7.2	10	1	41	2.415	0.706	2.024	0.987	1.951	0.893
6	8.2	10	1	40	2.900	0.871	1.800	0.883	2.050	0.986
7	7.2	60	1	38	2.526	0.687	3.947	0.769	2.105	0.863
8	8.2	60	1	42	2.881	0.772	3.619	0.795	2.429	1.107

Table 5. Manipulation check results

	Hospital no.	µ Valence	σ Valence	p-value
low	1,3,5,7	3.465	1.016	0.000
high	2,4,6,8	3.607	1.003	0.000
		µ Volume	σ Volume	
low	1,2,5,6	4.000	0.857	0.000
high	3,4,7,8,	3.888	0.866	0.000
		µ Dispersion	σ Dispersion	
low	1,2,3,4	4.044	0.669	0.000
high	5,6,7,8	4.124	0.781	0.000

Table 6. Average reported values of attention for each predictor and its levels.

H	Median - Valence	Median - Volume	Median - Dispersion
1	3	2	4
2	4	2	4
3	3	4	4
4	4	4	4
5	2	2	2
6	3	2	2
7	2	4	2
8	3	4	2

Table 7. Median manipulation check

H	Mode - Valence	Mode - Volume	Mode - Dispersion
1	4	2	4
2	4	2	4
3	4	4	4
4	4	4	4
5	2	2	2
6	3	1	2
7	2	4	2
8	3	4	2

Table 8. Mode manipulation check

Model 1

Sample 1

Observed			Predicted		
			Hospital chosen		Percentage Correct
			not chosen	chosen	
Step 0	Hospital chosen	not chosen	0	1280	0
		chosen	0	1280	100
Overall Percentage					**50**

Constant is included in the model.

Table 9. Classification table Model 1 – Sample 1- Step 0

Observed			Predicted		
			Hospital chosen		Percentage Correct
			not chosen= 0	chosen=1	
Step 1	Hospital chosen	not chosen = 0	896	384	70
		chosen = 1	384	896	70
Overall Percentage					**70**

The cut value is .500

Table 10. Classification table, sample 1

Model 1 - Sample 1		
Step 0		p-value
-2LL	3548.914	
Step 1		
Chi-square	660.334	
-2LL	2888.58	
Cox & Snell R^2	0.227	
Nagelkerke R^2	0.303	
Hosmer –Lemeshow Chi-square	3.373	0.761

Table 11. Regression detailed data, sample 1

```
             Step number: 1

             Observed Groups and Predicted Probabilities

     400 +                                                                                                    +
I                                                                                                    I
         I                                                                                                    I
F        I            c             c  c                  c  c                  c  c             c            I
R    300 +            c             c  c                  c  c                  c  c             c            +
E        I            n             c  c                  c  c                  c  c             c            I
Q        I            n             c  c                  c  c                  c  c             c            I
U        I            n             n  n                  c  c                  c  c             c            I
E    200 +            n             n  n                  c  c                  c  c             c            +
N        I            n             n  n                  c  c                  c  c             c            I
C        I            n             n  n                  n  n                  c  c             c            I
Y        I            n             n  n                  n  n                  c  c             c            I
     100 +            n             n  n                  n  n                  n  c             c            +
         I            n             n  n                  n  n                  n  n             c            I
         I            n             n  n                  n  n                  n  n             c            I
         I            n             n  n                  n  n                  n  n             n            I
Predicted ---------+---------+---------+---------+---------+---------+---------+---------+---------+----------
Prob:   0       .1        .2        .3        .4        .5        .6        .7        .8        .9         1
  Group:  nnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnncccccccccccccccccccccccccccccccccccccccccccccccccc

          Predicted Probability is of Membership for chosen
          The Cut Value is .50
          Symbols: n - not chosen
                   c - chosen
          Each Symbol Represents 25 Cases.
```

Figure 2. Classification plot - sample 1

		Hospital chosen	Valence	Volume	Dispersion	Predicted probability	Predicted group
1		not chosen	high	high	high	0.510612	chosen
2		chosen	low	low	low	0.489388	not chosen
3		not chosen	low	high	high	0.296274	not chosen
4		chosen	low	high	low	0.736351	chosen
5		not chosen	low	low	high	0.126237	not chosen
6		chosen	high	high	low	0.873763	Chosen
7		not chosen	high	low	high	0.263649	not chosen
8		chosen	high	low	low	0.703726	Chosen
9		chosen	high	high	low	0.873763	Chosen
10		not chosen	low	high	high	0.296274	not chosen
11		chosen	low	high	low	0.736351	Chosen
12		not chosen	high	high	high	0.510612	Chosen
13		chosen	high	low	low	0.703726	Chosen
14		not chosen	low	low	high	0.126237	not chosen
15		not chosen	high	low	high	0.263649	not chosen
Total	N	15	15	15	15	15	15

Limited to first 15 cases.

Table 12. Case summaries for the first sample.

		Analog of Cook's influence statistics	Leverage value	Standard residual	Normalized residual	Deviance value	DFBETA for constant	DFBETA for Valence	DFBETA for Volume	DFBETA for Dispersion
1		0.00188	0.00180	-1.19657	-1.02145	-1.19549	0.00159	-0.00198	-0.00192	-0.00138
2		0.00188	0.00180	1.19657	1.02145	1.19549	0.00369	-0.00198	-0.00192	-0.00138
3		0.00070	0.00166	-0.83899	-0.64885	-0.83829	-0.00022	0.00137	-0.00088	-0.00126
4		0.00058	0.00161	0.78300	0.59837	0.78237	0.00091	-0.00081	0.00128	-0.00121
5		0.00017	0.00117	-0.51982	-0.38010	-0.51951	-0.00057	0.00068	0.00071	-0.00077
6		0.00017	0.00117	0.51982	0.38010	0.51951	-0.00005	0.00068	0.00071	-0.00077
7		0.00058	0.00161	-0.78300	-0.59837	-0.78237	-0.00017	-0.00081	0.00128	-0.00121
8		0.00070	0.00166	0.83899	0.64885	0.83829	0.00099	0.00137	-0.00088	-0.00126
9		0.00017	0.00117	0.51982	0.38010	0.51951	-0.00005	0.00068	0.00071	-0.00077
10		0.00070	0.00166	-0.83899	-0.64885	-0.83829	-0.00022	0.00137	-0.00088	-0.00126
11		0.00058	0.00161	0.78300	0.59837	0.78237	0.00091	-0.00081	0.00128	-0.00121
12		0.00188	0.00180	-1.19657	-1.02145	-1.19549	0.00159	-0.00198	-0.00192	-0.00138
13		0.00070	0.00166	0.83899	0.64885	0.83829	0.00099	0.00137	-0.00088	-0.00126
14		0.00017	0.00117	-0.51982	-0.38010	-0.51951	-0.00057	0.00068	0.00071	-0.00077
15		0.00058	0.00161	-0.78300	-0.59837	-0.78237	-0.00017	-0.00081	0.00128	-0.00121
Total	N	15	15	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 13. Case summaries for the first sample.

Model		**Collinearity Statistics**	
		Tolerance	VIF
1	Valence	1.000	1.000
	Volume	1.000	1.000
	Dispersion	1.000	1.000

Table 14. Multicollinearity check, sample 1

Model		Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Valence	Volume	Dispersion
1	1	3.323	1.000	0.00	0.00	0.02	0.03
	2	0.447	2.727	0.00	0.00	0.17	0.82
	3	0.228	3.818	0.00	0.00	0.81	0.15
	4	0.002	39.828	1.00	1.00	0.00	0.00

a. Dependent Variable: Choiceset

Table 15. Multicollinearity check, sample 1

Sample 2

Observed			Predicted		
			Hospital chosen		Percentage Correct
			not chosen	chosen	
Step 0	Hospital chosen	not chosen	0	1088	0
		chosen	0	1090	100
Overall Percentage					**50**

Constant is included in the model.

The cut value is .500

Table 16. Classification table, Step 0, sample 2

Observed			Predicted		
			Hospital chosen		Percentage Correct
			not chosen	chosen	
Step 1	Hospital chosen	not chosen	603	485	55.4
		chosen	486	604	55.4
	Overall Percentage				55.4

The cut value is .500

Table 17. Classification table - Step 1- sample 2

Model 1 - Sample 2						
Step 0		p-value		**Step 1**		p-value
-2LL	3019.347			Chi-square	30.055	0.000
				-2LL	2989.292	
				Cox & Snell R^2	0.014	
				Nagelkerke R^2	0.018	
				Chi-square	0.022	1.000

Table 18. Regression detailed data, sample 2

Model		Collinearity Statistics	
		Tolerance	VIF
1	Valence	0.889	1.125
	Volume	1.000	1
	Dispersion	0.889	1.125

a. Dependent Variable: Hospital chosen

Table 19. Multicollinearity check sample 2

Model		Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Valence	Volume	Dispersion
1	1	3.245	1.000	0.00	0.00	0.03	0.03
	2	0.473	2.620	0.00	0.00	0.37	0.56
	3	0.280	3.403	0.00	0.00	0.60	0.32
	4	0.002	41.281	1.00	1.00	0.00	0.09

a. Dependent Variable: Hospital chosen

Table 20. Multicollinearity check sample 2

		Analog of Cook's influence statistics	Leverage value	Standard residual	Normalized residual	Deviance value	DFBETA for constant	DFBETA for Valence	DFBETA for Volume	DFBETA for Dispersion
1		0.00159	0.00139	1.23544	1.06900	1.23458	0.00298	-0.00151	-0.00149	-0.00146
2		0.00122	0.00139	-1.12439	-0.93806	-1.12361	0.00000	-0.00128	0.00131	-0.00133
3		0.00122	0.00139	-1.12207	-0.93545	-1.12129	-0.00260	0.00132	0.00130	0.00128
4		0.00301	0.00205	1.34425	1.20982	1.34287	0.00169	-0.00337	-0.00169	0.00337
5		0.00122	0.00139	-1.12207	-0.93545	-1.12129	-0.00260	0.00132	0.00130	0.00128
6		0.00158	0.00206	1.06670	0.87424	1.06560	-0.00121	0.00121	0.00243	0.00121
7		0.00234	0.00207	-1.22988	-1.06163	-1.22861	-0.00146	-0.00296	0.00146	0.00296
8		0.00159	0.00206	1.06897	0.87668	1.06786	0.00121	-0.00121	0.00244	-0.00121
9		0.00234	0.00207	-1.22988	-1.06163	-1.22861	-0.00146	-0.00296	0.00146	0.00296
10		0.00301	0.00205	1.34425	1.20982	1.34287	0.00169	-0.00337	-0.00169	0.00337
11		0.00234	0.00207	-1.22988	-1.06163	-1.22861	-0.00146	-0.00296	0.00146	0.00296
12		0.00158	0.00206	1.06670	0.87424	1.06560	-0.00121	0.00121	0.00243	0.00121
13		0.00159	0.00206	1.06897	0.87668	1.06786	0.00121	-0.00121	0.00244	-0.00121
14		0.00122	0.00139	-1.12439	-0.93806	-1.12361	0.00000	-0.00128	0.00131	-0.00133
15		0.00159	0.00206	1.06897	0.87668	1.06786	0.00121	-0.00121	0.00244	-0.00121
Total	N	15	15	15	15	15	15	15	15	15

Table 21. Case summaries Sample 2

```
             Step number: 1

             Observed Groups and Predicted Probabilities

     800 +                                                                                                    +
         I                                              c         c                                           I
         I                                              c         c                                           I
F        I                                              c         c                                           I
R    600 +                                              c         c                                           +
E        I                                              c         c                                           I
Q        I                                              c         c                                           I
U        I                                              c         c                                           I
E    400 +                                              n         c                                           +
N        I                                        c     n     c   c                                           I
C        I                                        c     n     c   n                                           I
Y        I                                        c     n     c   n                                           I
     200 +                                        n     n     c   n                                           +
         I                                        n     n     n   n                                           I
         I                                        n     n     n   n                                           I
         I                                        n     n     n   n                                           I
Predicted ---------+---------+---------+---------+---------+---------+---------+---------+---------+----------
  Prob:   0       .1        .2        .3        .4        .5        .6        .7        .8        .9         1
  Group:  nnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnnncccccccccccccccccccccccccccccccccccccccccccccccccc

          Predicted Probability is of Membership for chosen
          The Cut Value is .50
          Symbols: n - not chosen
                   c - chosen
          Each Symbol Represents 50 Cases.
```
Figure 3. Classification plot - sample 2

Sample 1 - Differenced

		Frequency	Parameter coding	
			(1)	(2)
Valence	H2 lower valence	308	0.000	0.000
	both same valence	652	1.000	0.000
	H2 higher valence	320	0.000	1.000
Volume	H2 lower volume	326	0.000	0.000
	both same volume	628	1.000	0.000
	H2 higher volume	326	0.000	1.000
Dispersion	H2 lower dispersion	636	0.000	
	H2 higher dispersion	644	1.000	

Table 22. Categorical Variables Codings – Sample 1 differenced

Observed			Predicted		
			Chose2nd		Percentage Correct
			0	1	
Step 0	Chose2nd	0	645	0	100
		1	635	0	0
Overall Percentage					50.4

Constant is included in the model.

The cut value is .500

Table 23. Classification table, step 0, sample 1 differenced results

Observed			Predicted		
			Chose2nd		Percentage Correct
			0	1	
Step 1	Chose2nd	0	473	172	73.3
		1	159	476	75.0
Overall Percentage					74.1

The cut value is .500

Table 24. Classification table, step 1, sample 1 differenced results

Model 1 - Sample 1 differenced		
Step 0		p-value
-2LL	1774.379	
Step 1		
Chi-square	467.0178	0.000
-2LL	1307.361	
Cox & Snell R^2	0.306	
Nagelkerke R^2	0.408	
Chi-square	5.117	0.529

Table 25. Regression detailed data, sample 1 differenced

Model		Collinearity Statistics	
		Tolerance	VIF
1	Valence	1.000	1.000
	Volume	1.000	1.000
	Dispersion	1.000	1.000
Dependent Variable: Chose2nd			

Table 26. Multicollinearity check - Sample 1 differenced results

Model		Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Valence	Volume	Dispersion
1	1	1.023	1.000	0.16	0.49	0.33	0.00
	2	1.006	1.008	0.36	0.00	0.13	0.51
	3	0.994	1.015	0.28	0.01	0.24	0.48
	4	0.977	1.024	0.19	0.50	0.31	0.02

a. Dependent Variable: Chose2nd

Table 27. Multicollinearity check - Sample 1 differenced results

		Chose2nd	Valence	Volume	Dispersion	Predicted probability	Predicted group	Analog of Cook's influence statistics	Leverage value
1		1	-1	H2 lower volume	H2 lower dispersion	0.22816	0	0.02368	0.00695
2		1	both same valence	both same volume	H2 lower dispersion	0.76273	1	0.00106	0.00341
3		1	1	H2 higher volume	H2 lower dispersion	0.95700	1	0.00014	0.00314
4		1	both same valence	both same volume	H2 lower dispersion	0.76273	1	0.00106	0.00341
5		0	-1	both same volume	H2 higher dispersion	0.09730	0	0.00033	0.00302
6		0	1	both same volume	H2 higher dispersion	0.47039	0	0.00736	0.00822
7		0	-1	both same volume	H2 higher dispersion	0.09730	0	0.00033	0.00302
8		1	-1	both same volume	H2 lower dispersion	0.47334	0	0.00751	0.00670
9		0	both same valence	both same volume	H2 higher dispersion	0.27826	0	0.00171	0.00441
10		1	both same valence	both same volume	H2 lower dispersion	0.76273	1	0.00106	0.00341
11		0	1	H2 lower volume	H2 higher dispersion	0.22609	0	0.00147	0.00500
12		1	1	H2 lower volume	H2 lower dispersion	0.70895	1	0.00262	0.00633
13		0	both same valence	H2 lower volume	H2 higher dispersion	0.11254	0	0.00063	0.00496
14		0	both same valence	H2 higher volume	H2 higher dispersion	0.53673	1	0.00595	0.00511
15		1	both same valence	H2 higher volume	H2 lower dispersion	0.90619	1	0.00029	0.00281
Total	N	15	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 28. Case summaries -sample 1 differenced results

		Standard residual	Normalized residual	Deviance value	DFBETA for constant	DFBETA for Valence (1)	DFBETA for Valence (2)	DFBETA for Volume(1)	DFBETA for Volume(2)	DFBETA for Dispersion
1		1.72513	1.83926	1.71913	0.03067	-0.01364	-0.02126	-0.01820	-0.01380	-0.00346
2		0.73726	0.55774	0.73600	-0.00036	0.00342	0.00130	0.00143	-0.00115	-0.00223
3		0.29696	0.21198	0.29650	-0.00024	-0.00054	0.00124	0.00074	0.00229	-0.00097
4		0.73726	0.55774	0.73600	-0.00036	0.00342	0.00130	0.00143	-0.00115	-0.00223
5		-0.45316	-0.32832	-0.45248	-0.00113	0.00240	0.00231	-0.00079	-0.00011	-0.00143
6		-1.13216	-0.94244	-1.12750	0.00747	0.00141	-0.01058	-0.00917	-0.00543	-0.00338
7		-0.45316	-0.32832	-0.45248	-0.00113	0.00240	0.00231	-0.00079	-0.00011	-0.00143
8		1.22719	1.05483	1.22307	0.00851	-0.01187	-0.00855	0.00574	0.00621	-0.00380
9		-0.80937	-0.62093	-0.80758	0.00166	-0.00341	0.00057	-0.00091	0.00429	-0.00348
10		0.73726	0.55774	0.73600	-0.00036	0.00342	0.00130	0.00143	-0.00115	-0.00223
11		-0.71776	-0.54050	-0.71596	-0.00174	-0.00042	-0.00252	0.00339	0.00409	-0.00224
12		0.83207	0.64074	0.82943	0.00355	0.00118	0.00544	-0.00357	-0.00219	-0.00350
13		-0.48987	-0.35610	-0.48865	-0.00198	-0.00193	0.00150	0.00351	0.00507	-0.00172
14		-1.24370	-1.07637	-1.24052	0.00015	-0.00027	0.00161	0.00083	-0.00846	-0.00251
15		0.44448	0.32174	0.44386	0.00039	0.00025	0.00042	0.00011	0.00247	-0.00161
Total	N	15	15	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 29. Case summaries -sample 1 differenced results

Sample 2 - Differenced

Observed			Predicted		
			Chose2nd		Percentage Correct
			0	1	
Step 0		0	566	0	100
	Chose2nd	1	523	0	0
Overall Percentage					**52.0**

Constant is included in the model.

The cut value is .500

Table 30. Classification table - Step 0 - Sample 2, differenced results

Observed			Predicted		
			Chose2nd		Percentage Correct
			0	1	
Step 1		0	294	272	51.9
	Chose2nd	1	190	333	63.7
Overall Percentage					**57.6**

a. The cut value is .500

Table 31. Classification table - Step 1 - Sample 2, differenced

Model 1 - Sample 2 differenced		
Step 0		p-value
-2LL	1507.976	
Step 1		
Chi-square	41.733	0.000
-2LL	1466.244	
Cox & Snell R^2	0.038	
Nagelkerke R^2	0.05	
Chi-square	0.728	0.994

Table 32. Regression detailed data, sample 2 differenced

		Chose2nd	Valence	Volume	Dispersion	Predicted probability	Predicted group	Analog of Cook's influence statistics	Leverage value
1		0	1	both same volume	H2 higher dispersion	0.51619	1	0.00357	0.00333
2		1	both same valence	both same volume	H2 higher dispersion	0.44249	0	0.00683	0.00539
3		1	1	H2 higher volume	H2 higher dispersion	0.62877	1	0.00287	0.00484
4		1	-1	H2 higher volume	both same dispersion	0.55751	1	0.00430	0.00539
5		1	-1	both same volume	H2 higher dispersion	0.31405	0	0.01820	0.00826
6		1	both same valence	H2 higher volume	H2 higher dispersion	0.55751	1	0.00430	0.00539
7		0	1	H2 lower volume	H2 higher dispersion	0.34711	0	0.00443	0.00826
8		0	1	both same volume	H2 higher dispersion	0.51619	1	0.00357	0.00333
9		1	-1	both same volume	both same dispersion	0.44249	0	0.00683	0.00539
10		0	1	both same volume	H2 higher dispersion	0.51619	1	0.00357	0.00333
11		0	both same valence	both same volume	H2 higher dispersion	0.44249	0	0.00430	0.00539
12		0	1	H2 higher volume	H2 higher dispersion	0.62877	1	0.00824	0.00484
13		0	-1	H2 higher volume	both same dispersion	0.55751	1	0.00683	0.00539
14		0	-1	both same volume	H2 higher dispersion	0.31405	0	0.00382	0.00826
15		0	both same valence	H2 higher volume	H2 higher dispersion	0.55751	1	0.00683	0.00539
Total	N	15	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 33. Case summaries - Sample 2, differenced results

		Standard residual	Normalized residual	Deviance value	DFBETA for constant	DFBETA for Valence(1)	DFBETA for Valence(2)	DFBETA for Volume(1)	DFBETA for Volume2(2)	DFBETA for Dispersion(1)
1		-1.20706	-1.03293	-1.20505	0.00523	-0.00168	-0.00691	-0.00691	-0.00355	0.00168
2		1.28044	1.12248	1.27699	0.00104	0.01224	0.00182	0.00182	-0.00389	-0.00285
3		0.96565	0.76838	0.96331	-0.00515	-0.00259	0.00256	0.00256	0.00774	0.00259
4		1.08391	0.89088	1.08099	0.00663	-0.00227	-0.00144	-0.00144	0.00309	-0.00519
5		1.52830	1.47791	1.52198	0.00000	-0.02654	-0.02654	0.00000	0.00000	0.02654
6		1.08391	0.89088	1.08099	-0.00082	0.00519	-0.00144	-0.00144	0.00309	0.00227
7		-0.92725	-0.72914	-0.92341	-0.01276	0.00000	0.00000	0.01276	0.01276	0.00000
8		-1.20706	-1.03293	-1.20505	0.00523	-0.00168	-0.00691	-0.00691	-0.00355	0.00168
9		1.28044	1.12248	1.27699	0.01043	0.00285	0.00182	0.00182	-0.00389	-0.01224
10		-1.20706	-1.03293	-1.20505	0.00523	-0.00168	-0.00691	-0.00691	-0.00355	0.00168
11		-1.08391	-0.89088	-1.08099	-0.00082	-0.00972	-0.00144	-0.00144	0.00309	0.00227
12		-1.41121	-1.30145	-1.40779	0.00872	0.00439	-0.00433	-0.00433	-0.01310	-0.00439
13		-1.28044	-1.12248	-1.27699	-0.00835	0.00285	0.00182	0.00182	-0.00389	0.00654
14		-0.87188	-0.67663	-0.86827	0.00000	0.01215	0.01215	0.00000	0.00000	-0.01215
15		-1.28044	-1.12248	-1.27699	0.00104	-0.00654	0.00182	0.00182	-0.00389	-0.00285
Total	N	15	15	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 34. Case summaries - Sample 2, differenced results

Model		Collinearity Statistics	
		Tolerance	VIF
1	Valence	0.531	1.882
	Volume	0.930	1.075
	Dispersion	0.534	1.872

Dependent Variable: Chose2nd

Table 35. Multicollinearity check - Sample 2, differenced results

Model		Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Valence	Volume	Dispersion
1	1	2.107	1.000	0.03	0.02	0.03	0.02
	2	1.233	1.307	0.00	0.20	0.32	0.00
	3	0.597	1.878	0.03	0.33	0.63	0.01
	4	0.063	5.790	0.94	0.44	0.02	0.97

Dependent Variable: Chose2nd

Table 36. Multicollinearity check - Sample 2, differenced results

Model 2

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.821	0.823	9

Table 37. Reliability analysis moderator

Observed			Predicted		
			Hospital chosen		Percentage Correct
			0	1	
Step 0	Hospital chosen	0	0	1280	0
		1	0	1280	100
Overall Percentage					50

Constant is included in the model.
The cut value is .500

Table 38. Classification table - Step 0-logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

Observed			Predicted		
			Hospital chosen		Percentage Correct
			0	1	
Step 1	Hospital chosen	0	977	303	76.328125
		1	455	825	64.453125
Overall Percentage					70.390625

The cut value is .500

Table 39. Classification table - Step 1-logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

Model 2		
Step 0		p-value
-2LL	3548.914	
Step 1		
Chi-square	696.658	0.000
-2LL	2852.256	
Cox & Snell R^2	0.238	
Nagelkerke R^2	0.318	
Chi-square	4.911	0.555

Table 40. Regression detailed data, logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

Model		Collinearity Statistics	
		Tolerance	VIF
1	Valence	0.982	1.018
	Volume	0.477	2.095
	Dispersion	0.476	2.099
	D_max_Valence	0.255	3.924
	D_max_Volume	0.248	4.033
	D_max_Dispersion	0.323	3.092
a. Dependent Variable: Hospital chosen			

Table 41. Multicollinearity check logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

Model		Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	Valence	Volume	Dispersion	D_max_ Valence	D_max_ Volume	D_max_ Dispersion
1	1	4.949	1	0.00	0.00	0.00	0.01	0.00	0.00	0.01
	2	0.805	2.480	0.00	0.00	0.03	0.01	0.01	0.00	0.14
	3	0.737	2.591	0.00	0.00	0.00	0.13	0.02	0.08	0.01
	4	0.334	3.852	0.00	0.00	0.15	0.07	0.10	0.06	0.00
	5	0.121	6.394	0.00	0.00	0.21	0.65	0.03	0.19	0.67
	6	0.053	9.695	0.01	0.01	0.60	0.14	0.84	0.66	0.17
	7	0.002	48.719	0.99	0.99	0.00	0.00	0.00	0.00	0.00

a. Dependent Variable: Hospital chosen

Table 42. Multicollinearity check logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

		Hospital chosen	Valence	Volume	Dispersion	D_max_ Valence	D_max_ Volume	D_max_D ispersion
1		0	8.2	60	1	0	0	0
2		1	7.2	10	0	0	0	0
3		0	7.2	60	1	0	0	0
4		1	7.2	60	0	0	0	0
5		0	7.2	10	1	0	0	0
6		1	8.2	60	0	0	0	0
7		0	8.2	10	1	0	0	0
8		1	8.2	10	0	0	0	0
9		1	8.2	60	0	0	0	0
10		0	7.2	60	1	0	0	0
11		1	7.2	60	0	0	0	0
12		0	8.2	60	1	0	0	0
13		1	8.2	10	0	0	0	0
14		0	7.2	10	1	0	0	0
15		0	8.2	10	1	0	0	0
16		1	7.2	10	0	0	0	0
17		1	7.2	10	0	7.2	10	0
18		0	7.2	10	1	7.2	10	1
19		0	8.2	60	1	8.2	60	1
20		1	8.2	60	0	8.2	60	0
Total	N	20	20	20	20	20	20	20

Limited to first 20 cases.

Table 43. Case summaries logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

		Predicted probability	Predicted group	Analog of Cook's influence statistics	Leverage value	Standard residual	Normalized residual	Deviance value
1		0.486	0	0.004	0.004	-1.156	-0.972	-1.153
2		0.486	0	0.002	0.002	1.203	1.029	1.202
3		0.236	0	0.001	0.004	-0.735	-0.556	-0.734
4		0.794	1	0.001	0.003	0.680	0.509	0.679
5		0.070	0	0.000	0.002	-0.382	-0.275	-0.382
6		0.922	1	0.000	0.002	0.404	0.291	0.403
7		0.188	0	0.001	0.003	-0.646	-0.481	-0.645
8		0.743	1	0.001	0.003	0.772	0.588	0.771
9		0.922	1	0.000	0.002	0.404	0.291	0.403
10		0.236	0	0.001	0.004	-0.735	-0.556	-0.734
11		0.794	1	0.001	0.003	0.680	0.509	0.679
12		0.486	0	0.004	0.004	-1.156	-0.972	-1.153
13		0.743	1	0.001	0.003	0.772	0.588	0.771
14		0.070	0	0.000	0.002	-0.382	-0.275	-0.382
15		0.188	0	0.001	0.003	-0.646	-0.481	-0.645
Total	N	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 44. Case summaries logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

		DFBETA for constant	DFBETA for Valence	DFBETA for Volume	DFBETA for Dispersion	DFBETA for D_maximizer by Valence	DFBETA for D_maximizer by Volume	DFBETA for D_maximizer by Dispersion
1		0.001	-0.003	-0.003	-0.002	0.003	0.002	0.002
2		0.004	-0.002	-0.002	-0.001	0.000	0.000	0.000
3		0.000	0.003	-0.002	-0.003	-0.003	0.002	0.003
4		0.001	-0.001	0.003	-0.002	0.001	-0.004	0.002
5		0.000	0.001	0.001	-0.001	-0.001	-0.001	0.002
6		0.000	0.001	0.001	-0.001	-0.001	-0.001	0.001
7		0.000	-0.001	0.002	-0.003	0.001	-0.002	0.003
8		0.001	0.004	-0.001	-0.002	-0.004	0.001	0.002
9		0.000	0.001	0.001	-0.001	-0.001	-0.001	0.001
10		0.000	0.003	-0.002	-0.003	-0.003	0.002	0.003
11		0.001	-0.001	0.003	-0.002	0.001	-0.004	0.002
12		0.001	-0.003	-0.003	-0.002	0.003	0.002	0.002
13		0.001	0.004	-0.001	-0.002	-0.004	0.001	0.002
14		0.000	0.001	0.001	-0.001	-0.001	-0.001	0.002
15		0.000	-0.001	0.002	-0.003	0.001	-0.002	0.003
Total	N	15	15	15	15	15	15	15

Limited to first 15 cases.

Table 45. Case summaries logistic regression Valence, Volume, Dispersion and their interaction effects with D_maximizer on hospital choice

Observed			Predicted		
			Hospital chosen		Percentage Correct
			0	1	
Step 0	Hospital chosen	0	0	1280	0
		1	0	1280	100
Overall Percentage					50

Constant is included in the model.

The cut value is .500

Table 46. Classification table - Step 0 - logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

Observed			Predicted		
			Hospital chosen		Percentage Correct
			0	1	
Step 0	Hospital chosen	0	977	303	76.3
		1	455	825	64.5
Overall Percentage					70.4

The cut value is .500

Table 47. Classification table - Step 1- logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

Model 2		
Step 0		p-value
-2LL	3548.914	
Step 1		
Chi-square	678.288	0.000
-2LL	2870.626	
Cox & Snell R^2	0.233	
Nagelkerke R^2	0.31	
Chi-square	4.893	0.673

Table 48. Regression detailed data, logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

Model		Collinearity Statistics	
		Tolerance	VIF
1	Valence	1.000	1.000
	Volume	1.000	1.000
	Dispersion	0.644	1.553
	D_max_Dispersion	0.644	1.553

a. Dependent Variable: Hospital chosen

Table 49. Multicollinearity check - logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

Model		Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	Valence	Volume	Dispersion	D_max_ Dispersion
1	1	3.743	1	0.00	0.00	0.02	0.02	0.02
	2	0.783	2.186	0.00	0.00	0.07	0.06	0.32
	3	0.262	3.782	0.00	0.00	0.56	0.31	0.37
	4	0.210	4.226	0.00	0.00	0.36	0.60	0.29
	5	0.002	42.273	1.00	1.00	0.00	0.00	0.00

a. Dependent Variable: Hospital chosen

Table 50. Multicollinearity check - logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

		Hospital chosen	Valence	Volume	Dispersion	D_max_ Dispersion	Predicted probability	Predicted group
1		0	8.2	60	1	0	0.43737	0
2		1	7.2	10	0	0	0.48789	0
3		0	7.2	60	1	0	0.23762	0
4		1	7.2	60	0	0	0.73682	1
5		0	7.2	10	1	0	0.09589	0
6		1	8.2	60	0	0	0.87473	1
7		0	8.2	10	1	0	0.20919	0
8		1	8.2	10	0	0	0.70380	1
9		1	8.2	60	0	0	0.87473	1
10		0	7.2	60	1	0	0.23762	0
11		1	7.2	60	0	0	0.73682	1
12		0	8.2	60	1	0	0.43737	0
13		1	8.2	10	0	0	0.70380	1
14		0	7.2	10	1	0	0.09589	0
15		0	8.2	10	1	0	0.20919	0
16		1	7.2	10	0	0	0.48789	0
17		1	7.2	10	0	0	0.48789	0
18		0	7.2	10	1	1	0.15504	0
19		0	8.2	60	1	1	0.57353	1
20		1	8.2	60	0	0	0.87473	1
Total	N	20	20	20	20	20	20	20

Limited to first 20 cases.

Table 51. Case summaries - residuals- logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

		Predicted probability	Predicted group	Analog of Cook's influence statistics	Leverage value	Standard residual	Normalized residual
1		0.437	0	0.002	0.003	-1.074	-0.882
2		0.488	0	0.002	0.002	1.199	1.025
3		0.238	0	0.001	0.002	-0.738	-0.558
4		0.737	1	0.001	0.002	0.782	0.598
5		0.096	0	0.000	0.001	-0.449	-0.326
6		0.875	1	0.000	0.001	0.518	0.378
7		0.209	0	0.001	0.002	-0.686	-0.514
8		0.704	1	0.001	0.002	0.839	0.649
9		0.875	1	0.000	0.001	0.518	0.378
10		0.238	0	0.001	0.002	-0.738	-0.558
11		0.737	1	0.001	0.002	0.782	0.598
12		0.437	0	0.002	0.003	-1.074	-0.882
13		0.704	1	0.001	0.002	0.839	0.649
14		0.096	0	0.000	0.001	-0.449	-0.326
15		0.209	0	0.001	0.002	-0.686	-0.514
Total	N	15	15	15	15	15	15

a. Limited to first 15 cases.

Table 52. Case summaries - residuals- logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

		Deviance value	DFBETA for constant	DFBETA for Valence	DFBETA for Volume	DFBETA for Dispersion	DFBETA for D_maximizer by Dispersion
1		-1.073	0.001	-0.002	-0.002	-0.004	0.004
2		1.198	0.004	-0.002	-0.002	-0.001	0.000
3		-0.737	0.000	0.001	-0.001	-0.002	0.002
4		0.782	0.001	-0.001	0.001	-0.001	0.000
5		-0.449	0.000	0.001	0.001	-0.001	0.001
6		0.517	0.000	0.001	0.001	-0.001	0.000
7		-0.685	0.000	-0.001	0.001	-0.002	0.002
8		0.838	0.001	0.001	-0.001	-0.001	0.000
9		0.517	0.000	0.001	0.001	-0.001	0.000
10		-0.737	0.000	0.001	-0.001	-0.002	0.002
11		0.782	0.001	-0.001	0.001	-0.001	0.000
12		-1.073	0.001	-0.002	-0.002	-0.004	0.004
13		0.838	0.001	0.001	-0.001	-0.001	0.000
14		-0.449	0.000	0.001	0.001	-0.001	0.001
15		-0.685	0.000	-0.001	0.001	-0.002	0.002
Total	N	15	15	15	15	15	15

a. Limited to first 15 cases.

Table 53. Case summaries - residuals- logistic regression Valence, Volume, Dispersion and interaction effects Dispersion with D_maximizer on hospital choice

	B	SE	Wald	df	Sig.	95% CI for Odds Ratio		
						Lower	Odds	Upper
Constant	-0.045	0.097	0.210	1	0.647		0.956	
Valence	0.908	0.092	97.053	1	0.000	2.069	2.478	2.969
Volume	1.070	0.093	132.716	1	0.000	2.429	2.914	3.496
Dispersion	-1.892	0.094	405.683	1	0.000	0.125	0.151	0.181
D_maximizer	0.004	0.091	0.002	1	0.965	0.841	1.004	1.199
Note. R^2 = .186 (Hosmer & Lemeshow) .227 (Cox & Snell) .303 (Nagelkerke). Model χ^2 (1) = 660.336 $p< 0.05$								

Table 54. Logistic regression with moderator effect included as main effect.

The R^2 value of this model is .186 (Hosmer & Lemeshow) .227 (Cox & Snell) .303 (Nagelkerke), explaining 1% less of the variability of the model, than the proposed model. The intercept means that a hospital has the odds of 0.956 times same getting chosen than when a hospital has low valence, low volume, low dispersion and the persons who chooses is a satisficer. The odds ratios of the predictors Valence and Volume are still greater than 1, meaning that as valence or volume have a high value the odds of a hospital getting chosen increases. In the case of Valence, a hospital with high valence has2.478 times higher odds of getting chosen as compared to a hospital with low valence, all other things held equal When a hospital has high volume it has 2.914 times higher odds of being chosen compared to when a hospital has low volume. The odds ratios of the predictor Dispersion is still lower than 1, meaning that as dispersion has a high value, the odds of a hospital getting chosen decreases. D_maximizer is not significant, indicating that indeed it is a moderator.

	B	SE	Wald	df	Sig.	95% CI for Odds Ratio		
						Lower	Odds	Upper
Constant	0.122	0.128	0.909	1	0.340		1.130	
Valence	1.019	0.145	49.066	1	0.000	2.083	2.769	3.682
Volume	1.313	0.149	77.271	1	0.000	2.773	3.716	4.980
Dispersion	-2.580	0.153	284.019	1	0.000	0.056	0.076	0.102
D_maximizer	-0.324	0.172	3.553	1	0.059	0.516	0.723	1.013
D_maximizer by Valence	-0.168	0.189	0.790	1	0.374	0.584	0.845	1.224
D_maximizer by Volume	-0.382	0.192	3.950	1	0.047	0.468	0.683	0.995
D_maximizer by Dispersion	1.207	0.196	38.089	1	0.000	2.278	3.342	4.903
Note. R^2 = .197 (Hosmer & Lemeshow) .239 (Cox & Snell) .319 (Nagelkerke). Model χ^2 (1) = 700.218 p< 0.05								

Table 55. Logistic regression with predictor variables and interactions and moderator effect included as main effect.

The R^2 value of this model is .197 (Hosmer & Lemeshow) .239 (Cox & Snell) .319 (Nagelkerke), explaining 1% less of the variability of the model, than the proposed model. The intercept means that a hospital has the odds of 1.130 times same getting chosen than when a hospital has low valence, low volume, low dispersion and the persons who chooses is a satisficer. This is striking, as it is the only model with the intercept value greater than 1. The odds ratios of the predictors Valence and Volume are also greater than 1, meaning that as valence or volume have a high value the odds of a hospital getting chosen increases. A hospital with high valence has2.769 times higher odds of getting chosen as compared to a hospital with low valence, all held equal. When a hospital has high volume, it has 3.716 times higher odds of being chosen as when a hospital has low volume, all variables ceteris paribus. The odds ratios of the predictor Dispersion is still lower than 1, meaning that as dispersion has a high value, the odds of a hospital getting chosen decreases. D_maximizer is also here not significant, and its interaction with Valence also proves not to be significant. The interaction between D_maximizer and Dispersion is significant, just under the p-value<0.05.

The odds of a hospital getting chosen by a satisficer are 3.716 times the same for a hospital with high volume than for a hospital with low volume. The odds of a hospital with low volume will be 0.723 times the same when chosen by a maximizer, as compared to a satisficer. The odds for a hospital with high volume being chosen by a maximizer are (3.716*0.683)= 2.54 times the same as hospitals with low volume. Hospitals with high volume have the odds of (0.723*0.683)=0.494 times to get chosen by maximizers, as compared to satisficers. The odds for a hospital with high dispersion getting chosen by a satisficer are 0.076 times than for a hospital with low dispersion. The odds for hospitals with low dispersion getting chosen are 0.723 times the same when chosen by maximizers, as compared to satisficers. The odds for hospitals with high dispersion getting chosen are (0.076*3.342)=0.254 times the same than hospitals with low dispersion. The odds for hospitals with high dispersion are (0.723*3.342)=2.416 times the same to get chosen by maximizers as compared to satisficers.

Model 3

Assumptions

When running the model, the casewise diagnostics of the regression model were analyzed and three cases seemed to have standardized residuals values larger than ±3.29 and are more than two standard deviations away from the mean, however they were not deleted, as the Durbin Watson value (1.459) looked fine, Standardized beta's, Cook's Distance, Mahalanobis Distances and the centered leverage values as well. Furthermore, it was also observed that some of the residuals have a lower than allowed covariance ratio, but seen the fact that Cook's distance <1, there is little cause for alarm. Also, deleting the three outliers would not significantly influence the model, the p-p plots of the models can be seen in figure 4.

- Normality

As all the four main variables are categorical it can be expected that the distribution is non-normal (Field; 2013).It can also be noted that the distribution of each variable is negatively skewed. In the P-P plot it can also be observed that the residuals are not normally distributed, but that there is a positive relationship.

- Linearity

In the scatterplot in figure 5 and 6, it can be observed that there is no curvature in the plot with the standardized predicted values and the studentized residuals, but that there is rather a linear relationship.

- Independence of errors

Independent errors: Durbin Watson = .1459, therefore it indicates positive correlation between adjacent residuals.

- <u>Constant variance: homoscedasticity</u>

Variability looks about approximately equally throughout the scatterplot. The points are somewhat vertically clustered together; the variables were controlled for (in the experiment).

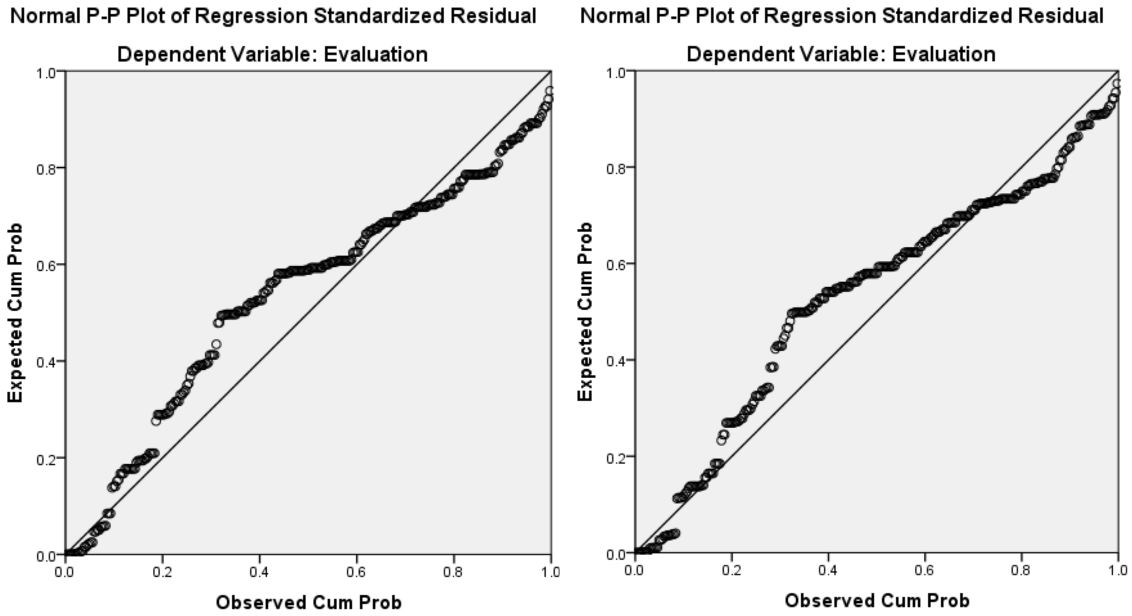
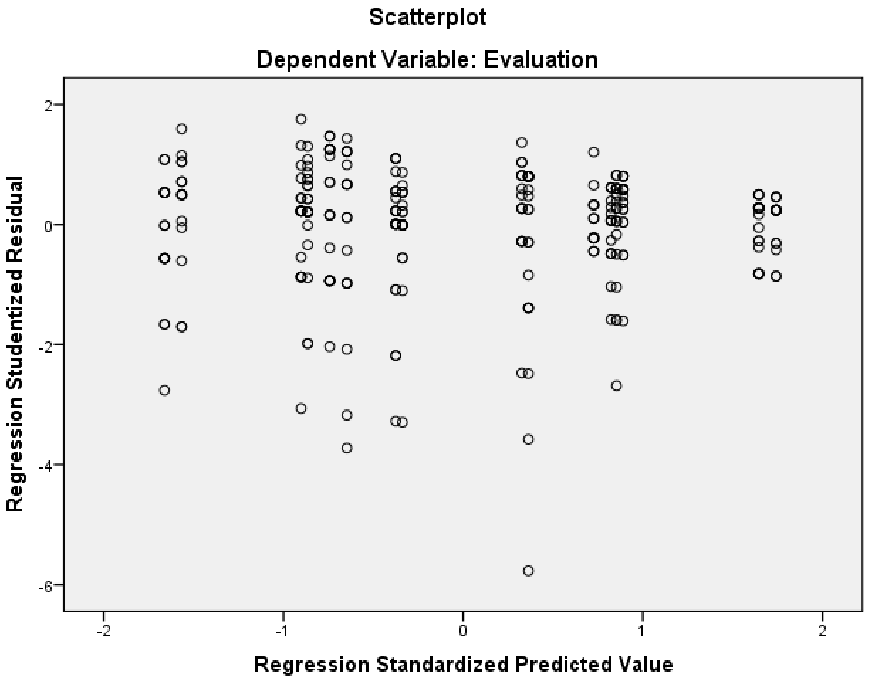


Figure 4. P-P plot linear regression with and without outlier



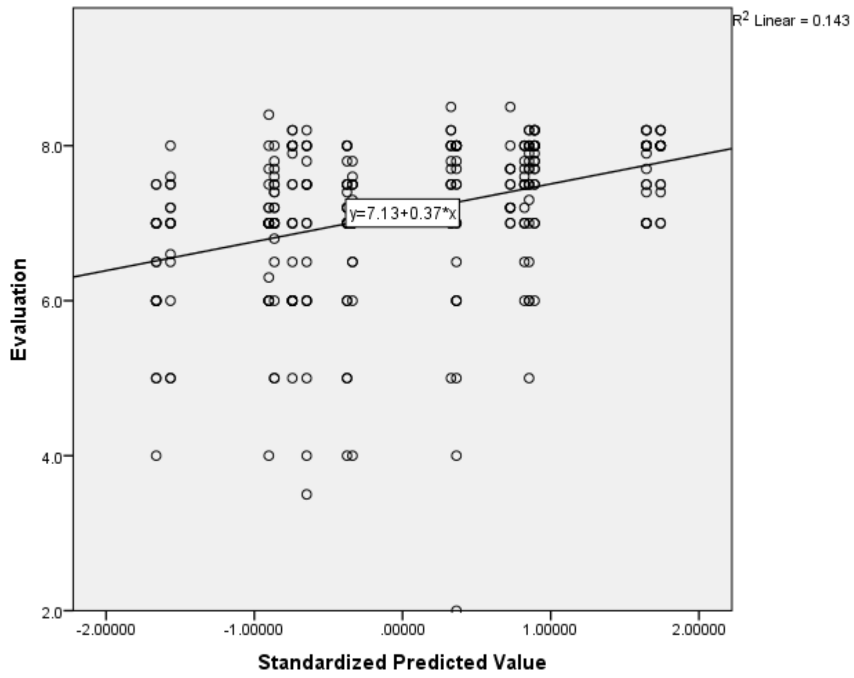


Figure 5. Scatterplot residuals linear regression Valence, Volume, Dispersion and D_maximizer and moderating effects on hospital evaluation

Figure 6. Scatterplot residuals linear regression Valence, Volume, Dispersion and D_maximizer and moderating effects on hospital evaluation