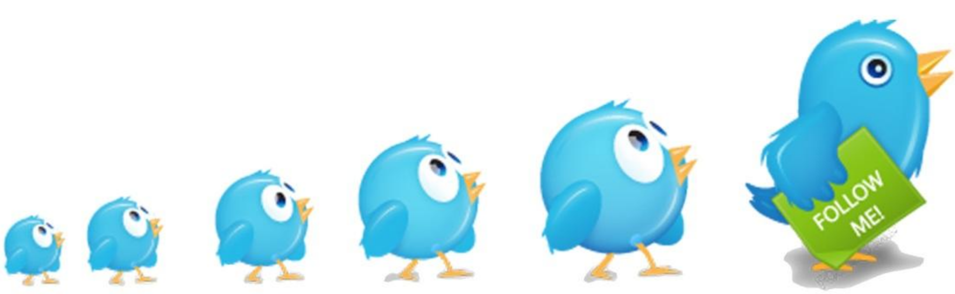
ELECTRONIC WORD-OF-MOUTH

VS.

SOCIAL ELECTRONIC WORD-OF-MOUTH

“Product reviews on traditional **product review websites** *compared* to product reviews on **Twitter**”



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Abstract

The popularity of the social media networking website Twitter has increased enormously. Everyday people use Twitter to talk about their daily lives, but they also talk, complain, or even attack companies about their failing or disappointing products and services. Traditionally, product reviews are expressed on product review websites and belong to *electronic-word-of-mouth* (EWOM) communications. Tweeted complaints can also be seen as product reviews, only these Tweets are expressed on a different source. Considering the social nature of Twitter, we cannot say that Tweeted complaints belong to the traditional EWOM product reviews.

Therefore, we sought support for the definition of product reviews as *social-electronic-word-of-mouth* (S-EWOM) communications. The main objective of this study was to investigate the impact of negative product reviews, written on a EWOM source and written on a S-EWOM source. More specifically, the impact of negative product reviews written on product review websites was compared to the impact of negative product reviews written on Twitter. Impact referred to the credibility perception, to the attitude toward product and to the purchase intention after reading the product reviews. Two studies were conducted to answer this research question. First, a preliminary investigation was conducted to identify the main differences between product reviews on product review websites, and product reviews on Twitter. Second, an online questionnaire, in which participants were exposed to four product reviews, was conducted. One condition consisted of product reviews written on a product review website (Amazon.com), and in the other condition participants were exposed to product reviews on Twitter. After each product review, participants were asked to answer questions regarding credibility, attitude toward product and purchase intention. The four product reviews differed in terms of product type (camera and tablet) and message quality (low and high).

The findings did not show major differences in impact between the two sources. The attitude toward product was more affected after reading product reviews on the product review website, than on Twitter. Nevertheless, the attitude toward product was affected on Twitter, but was more negative after reading a product review on the product review website. When taking the message quality into consideration, only the perceived credibility was higher for high quality product reviews on a product review website, than for high quality product reviews on Twitter. Lastly, high quality product reviews on both sources were perceived as more credibility, and affected the attitude toward product and purchase intention more, than low quality product reviews. In conclusion, the findings of this study contribute to the EWOM field by considering Twitter as a new form of EWOM, which we call S-EWOM. Traditional product reviews have an impact on the perceived credibility, attitude product and the purchase intention after reading negative product reviews. However, negative product reviews on Twitter also have an impact on consumers, and this impact should definitely not be denied.

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1. Introduction

"Marketers keep telling brand owners to use social media to engage their customers. But there are times companies must wish they had just bought a print ad instead".

(PaidContent, 21 January, 2012)

In today's society the use of social media is almost inevitable. The use of social media has not only become a part of people's daily lives, many companies have started to adopt social media channels, such as Twitter, Facebook, and YouTube in their marketing and communication strategies. On the world wide web, conversations take place all the time; about politics, fashion, pop-stars, brands, about just anything to think of. Moreover, people are able to listen, view, and read what is going on in the world, as well as engage in creating own content such as (micro) blogs, videos, mash-ups, and many more (Stokes & the Minds of Quirk, 2011). The users of social media are able to search the internet for information about a certain company, product, or service. While companies in the past only communicated (one-way) toward their consumers, today consumers are also in the position to send messages toward and about a company's product or service: in a positive as well as in a negative way. As social media gave companies the opportunity to develop effective and more personal marketing and communication campaigns, it also gave the public a voice and platform to share content and truly inform others. Since the Internet began in the early 1990s, social media are its most popular applications (Kirshnamurthy, Gill, & Arlitt, 2008). The fast communication nature of the Internet and the accessibility of social media make it easy for the public to share or forward their views and opinions, to respond and to build on them. All of this can contribute to the perception of a company; the public are powerful in this respect (Stokes & the Minds of Quirk, 2011).

1.1. The past: traditional word-of-mouth

In the past, the above described situation looked completely different. Before the advent of the Internet, consumers relied on other people's opinions about a particular product or service (Pollach, 2006). In this context, 'other people' were mainly friends, family members or relatives who lived in the same neighborhood and talked with each other face-to-face. This type of communication became widely known as *word-of-mouth communication* (WOM). WOM is defined as interpersonal and informal person to person communication, about a company, a product, or a service between two or more consumers (Arndt, 1967; Anderson, 1998; Laczniak, DeCarlo, & Ramaswami, 2001; Brown, Barry, Dacin, & Gunst, 2005). Most WOM is concerned with positive or negative evaluations of a company, a product, or a service. Furthermore, it is considered as the most powerful and dominant influence on consumers' evaluations, because of its non-commercial nature. Moreover, it is perceived as more credible and useful than market-generated information, such as advertisements from the company itself (e.g. Herr, Kardes, & Kim, 1991; Bickart & Schindler, 2001; Ha, 2002).

1.2. Today: electronic-word-of-mouth

With the advent of the Internet, a switch in communication began to take place. Consumers started to move from only engaging in face-to-face communications, to engaging in online conversations (Pollach, 2006). The Internet was a perfect new medium for consumers to express and share their feelings toward a company and its products or services. It became a major source of information about many things: books, travelling, movies, etc. (Ratchford, Talukdar, & Lee, 2001). It also gave consumers a voice and a medium. This type of communication became known as *electronic-word-of-mouth communication* (EWOM). EWOM can be defined as any positive or negative statement about a company, product or service made by a former, actual, or even a potential consumer via Internet-based technologies. These statements are available to a wide variety of people on the Internet (consumers to consumers, but also consumers to producers) (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Cheung & Lee, 2008; Litvin, Goldsmith & Pan, 2008).

Different from traditional WOM, EWOM is not limited to face-to-face communication with the few people a consumer might know, but it allows communication with a diverse geographically-dispersed group of people (Ratchford et al., 2001; Cheung, Lee, & Rabjohn, 2008). EWOM has opened up the world of individuals, and extended the immediate contacts toward otherwise unknown people to the entire Internet world. WOM was generally a process where information was shared among a small group of people (Steffes & Burgee, 2008; Chueng, Luo, Sia, & Chen, 2009). Another difference is that with traditional WOM people obtain information from familiar people, while EWOM is often concerned with source unfamiliarity. The information could be perceived as less credible because of the unknown source. Thus, the content of the message and the source from which the information is obtained, is an important element to overcome credibility issues (Lee, Park, & Han, 2007). Furthermore, consumers are not restricted to time and location with EWOM; they can read and participate at their own pace. Moreover, the messages are stored on the Internet for some time, and consumers can easily filter and compare reviews they are interested in (Chueng et al., 2009). Lastly, while WOM is synchronous communication, EWOM can be compared to asynchronous email-communication where sender and receiver are separated by both time and space (Steffes & Burgee, 2008).

Product reviews

EWOM comes in various forms, such as complaint discussion threats, online chat forums, instant messaging, blogs, online communities, newsgroups, and product reviews on a product review website. These different forms of EWOM result in various forms of value to the consumer (Gruen, Osmonbekov, & Czaplewski, 2006). Especially, product reviews are of particular interest to this study. This study focuses on the value of product reviews from two different sources and the first source is a product review website. We chose to focus on product reviews websites for the following reasons. First, Hennig-Thurau et al. (2004) reported that worldwide approximately nine to ten million online opinions are available on online product review websites (e.g. Epinions.com and Consumerreview.com). By the exponential growth of the Internet the past years, it can be assumed that this number has been growing. Second, in general consumers rely more on information provided by other customers than marketing advertisements of the company itself (e.g. Sen & Lerman, 2007; Blackshaw, 2008). Third, people make offline decisions on the basis of online information (Lee, Park, & Han, 2008).

Product reviews are written by consumers to inform potential buyers about the negative features against, and the positive arguments in support of a product or service (Pollach, 2006). Product reviews provide additional consumer-oriented information created by consumers themselves. Whereas sellers of a product provide more product-oriented information such as the technical aspects, performances of the product in relation to the technical standards, and product attributes, consumer-oriented product reviews provide more information in terms of usage, and measure the product's performance from the perspective of the consumers. Moreover, consumers might provide information that sellers are unable or unwilling to answer (Park & Lee, 2008). Consequently, they either recommend or discourage others from buying the product (Sen & Lerman, 2007). An important characteristic of a product review website is that it enables interaction between consumers; consumers are able to read, react, and respond to online product reviews. It has become very easy for consumers to obtain information, but also to share their opinions about products on special product review websites such as Epinions.com, and Consumerreview.com, but also e-commerce websites such as Amazon.com provide consumers the opportunity to post product reviews themselves.

1.3. The future: social-electronic-word-of-mouth?

The Internet landscape is dramatically changing: communication between consumers and how they gather and exchange information about products, and how they consume and use this information is completely different from the past. Due to the rising *new media*, consumers have the opportunity to actively provide and seek information about new products or services. Furthermore, it enables the audience to talk about, and with each other (Hennig-Thurau et al., 2010). Besides the variety of new options for consumers, new media also provided companies new ways to communicate with their customers. A revolutionary trend in the field of new media are the *social media*. Social media are defined by Kaplan and Heanlein (2010) as “a group of Internet-based applications that build on the ideological and technological foundations of web 2.0, and allow the creation and exchange of user-generated-content” (p.61). The most popular and well-known social media are Facebook, LinkedIn, YouTube, and Twitter. Almost all social media networking websites serve the goal of sharing content with friends, or even with the entire world. Sharing content refers to feelings and thoughts, but also to videos, photos, etc.

Due to social media, an individual is able to communicate with hundreds or even thousands of other people about companies, products and services. Thus, the impact of communication between consumers, but also the impact of communication between consumers and companies have greatly increased (Mangold & Faulds, 2009). Therefore, companies have started to hire employees to monitor, and take part in online conversations that concern the company. Companies can see what customers are thinking and need to adapt their marketing and communication strategies according to this information (Miller, 2009). These days, companies are even advised to pay attention to webcare, which includes monitoring the negative as well as the positive reactions of consumers about the company. Companies can then respond in the form of an apology, provide additional information, or forward the consumer to customer-service, etc. (Kerkhof, Schultz, & Utz, 2011). By giving a reaction to these consumer comments, companies are avoiding reputational damage. Reputation management has become even more important than it already was. All of this makes social media different from the traditional EWOM, which we can call *social-electronic-word-of-mouth communication* (S-EWOM).

Twitter

By the advent of social media, product reviews did not only appear on the traditional product review websites, they also appeared on social media channels. Initially, text blogs were the first forms of social media. These blogs were owned and written by individuals who regularly posted commentaries and dairies (including text, videos, and links to other blogs and websites) (Berthon, Leyland, Plangger, & Shapiro, 2012). In 2006, a new type of blogging platform (regularly used to express feelings and experiences about a product) was launched: the micro blogging website Twitter. Twitter is a real-time information network that connects people with each other. Moreover, Twitter users post updates (Tweets) about what is happening in their daily lives. A Tweet can basically contain anything: ranging from someone saying what he/she is eating, to breaking news updates. Together with Facebook, Twitter is one of the most popular social media networking website. Since its launch, Twitter has 462 million registered accounts. From those registered accounts, 140 million of active users send approximately 340 million

Tweets each day (Twittermania.nl, 2012). This makes Twitter the second product review source of interest to this study.

According to the social media classification model of Kaplan and Haenlein (2010), Twitter falls in-between social networking websites and blogs. Twitter has a low to medium degree of media richness, but a high level of self-disclosure. Twitter has some distinctive characteristics that make it a unique medium. First of all, one Tweet can only contain 140 characters, which makes it unique compared to traditional product review websites that allow more characters to write a product review. Second, Twitter is an extremely fast and immediate medium because of its mobile nature. Tweets can be read from a normal Internet browser, but also from special applications for mobile phones and tablets. Third, besides the Tweets of followers that appear in a user's timeline, users can also actively search for Tweets about companies, products, and services posted by complete strangers.

In the past, consumers were forced to complain via telephone, via email, or via a special company complaints forum on the Internet. Nowadays, consumers can also complain via Twitter. Despite of the Tweets' quality and the limited number of characters, people indeed complain and write short reviews via Twitter. An example of a complaining Tweet about a mobile phone is: "*Basically it sucks. The new Samsung Galaxy S III super phone may have one weak spot: the display*". A Tweeted complaint can be seen as negative EWOM, more S-EWOM due to its social nature, and if it constitutes information about a product it can be seen as a negative product review. Traditional negative EWOM communications can influence potential buyers in their buying process, and prevent them from buying the product. It can even harm the reputation, image, or financial position of a company (Hennig-Thurau et al, 2010). However, there is no evidence whether these negative Tweets (S-EWOM) have the same impact. Due to the fact that Twitter is an extremely fast medium to spread around information, Tweets can be shared and forwarded extremely quickly with thousands or even more people all over the world at the same time (Landau, 2011). Jansen, Zhang, Sobel, and Chowdury (2009) showed that people use Twitter to find general information, to ask questions, and to take part in other information-seeking and sharing activities about companies and products. Their investigation also showed that 19% of all Tweets mentioned a brand name. The reach of this new form of EWOM is greater than traditional WOM and eventually may become greater than EWOM on product review websites. The influence of Twitter is increasing each day (Jansen et al., 2009) and with heading to almost 250 million active users by the end of 2012, it can be concluded that Twitter has become an important communication tool.

It is not just individuals who mingle with companies and its products online. Celebrities have also started to set up 'buzz' about a certain company, brand, or product. Recently, a famous Dutch journalist started a boycott against a Dutch meat fabricant via several social media channels, including Twitter (@unoxmutsboycot), and even McDonalds experienced setting up a failing Twitter campaign, called #McFail (Volkskrant, 2012; PaidContent, 2012). That being said, the Internet landscape is changing each day, and the conversations between companies, brands and consumers are becoming part of daily life. Companies have started to set up teams that daily monitor social media activity, including special Twitter teams. For example, the Dutch airline company KLM is 24/7 available for customers on Twitter. The stream of Tweets on Twitter are a useful tool for companies to solve problems of customers relatively fast, and get some valuable insights in the digital mood of their customers, or to get a glimpse of the live conversations that take place. Companies can monitor the public sentiment or even help shape it (Miller, 2009).

The main question that aroused from this changing Internet landscape is: what is the impact of these negative Tweets about products? If someone is looking for a new product to buy, but they are not completely sure about their decision, do they search for the latest comments about that product on Twitter? For example, do they search for Tweets mentioning the product, and more importantly do consumers trust these messages on Twitter and does it affect their behavior? This last question becomes an important issue because companies are monitoring what is said about their products, and consumers spread around their experiences about products. These messages are certainly read, but whether they really affect consumers is a relevant topic today. Furthermore, can we indeed call Twitter a new source of (S)EWOM that influences potential buyers?

1.4. Negativity effect

In this study, we will focus on negative product reviews for four reasons. First, negative WOM information has been proven to be more helpful than positive WOM information to sort out the low quality from the high quality products (Pollach, 2006; Lee et al., 2008). Second, during the evaluation of a product, consumers tend to pay more attention to, and weight negative information heavier than positive information (Herr, Kardes and Kim, 1991). Third, a satisfied customer will tell only some people about his/hers positive experience with a product, while a dissatisfied customer will tell everybody he/she meets (Chatterjee, 2001; Blackshaw, 2008). Lastly, empirical evidence shows that extremely dissatisfied customers, more than satisfied customers, exert greater WOM (Richins, 1983; Anderson 1998).

Although research has already investigated the influence of negative product reviews on product review websites, the impact of negative product reviews on Twitter is relevant nowadays. Especially because many companies try to monitor negative activities of consumers on Twitter without having much academic knowledge about the impact of these Tweets. Negative complaints on Twitter about a company's products or services can be directly forwarded to other people and can be traced by other traditional media channels. The reach of social media is therefore huge and many times larger than traditional WOM. The power of product reviews, and particularly the impact of consumers spreading around this negative information should not be overlooked (Cheung & Lee, 2008). Thus, it is expected that a 'negativity effect' appears: consumers will perceive negative information as more reliable and subsequently will have a stronger impact on consumer behavior (Chevalier & Mayzlin, 2003; Lee et al., 2007; 2008; Willemsen, Neijens, Bronner, & De Ridder, 2011).

1.5. Research plan

Much research has focused on EWOM and its message credibility, and the way it affects consumer behavior. However, the effect of social media as EWOM is a relatively new field of research. Especially, the social media network Twitter is frequently used to spread around a negative experience about a product. The impact of negative product reviews on Twitter has not been investigated in comparison to the 'traditional' product review websites. This study contributes to the existing research on WOM, but adds a completely new dimension to it by exploring the impact of negative product-related Tweets as S-EWOM.

Consequently, the main objective of this study is to investigate the impact of negative product reviews, written on two completely different sources, on a consumer. Impact will be assessed by examining how consumers perceive, and are affected by negative product reviews written on a product review website compared to negative product reviews written on Twitter. The way how consumers 'perceive' a product review refers to the credibility of the information, and the way how consumers are 'affected' refers to the attitude toward product and the purchase intention after reading the message. The source of the product review and the message quality were used as variables to explain the impact.

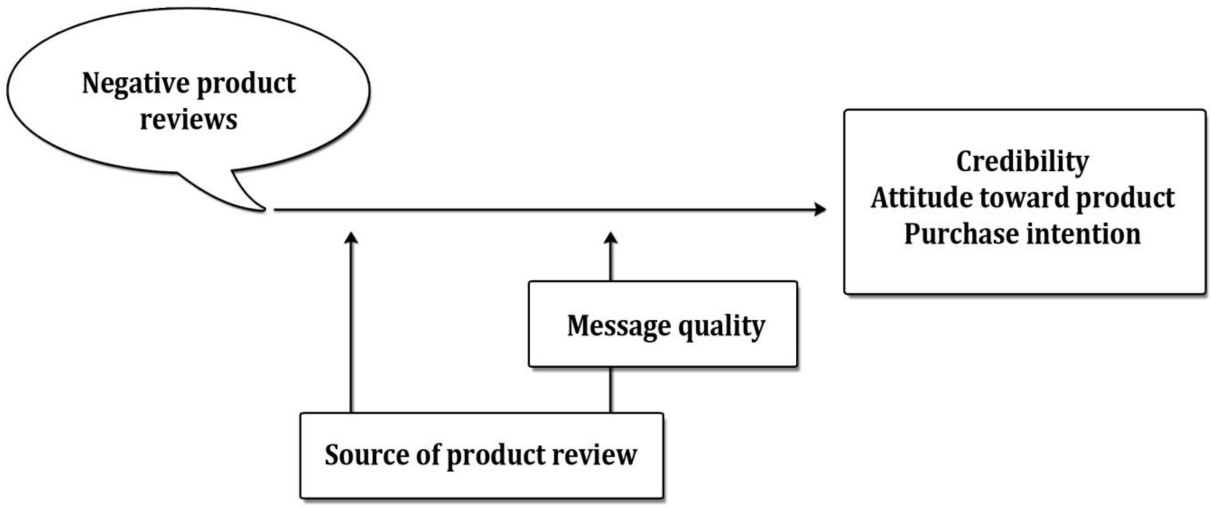

Figure 1. *Relation between the variables and the impact of negative product reviews.*

2. Theoretical framework

In the past, numerous researchers have focused on what leads to posting and reading EWOM (e.g. Hennig-Thurau & Walsh, 2003; Hennig-Thurau et al., 2004). However, researchers also investigated how consumers perceive, and are affected by EWOM in terms of perceived credibility (e.g. Cheung et al., 2009; Doh & Hwang, 2009), attitude toward product (e.g. Lee et al., 2008, Doh & Hwang, 2009), purchase intention (e.g. Lee et al., 2007, Doh & Hwang, 2009) or product sales (e.g. Chevalier & Mayzlin, 2006; Zhu & Zhang, 2010). Hereby, the source credibility, attitude toward product, and purchase intention were proven to be affected. Little, prior work investigated the impact of micro-blogging as a new source of EWOM, which makes it an interesting and relevant new topic in academic research. Therefore, with the advent of social media, this study investigates whether negative product reviews on Twitter have the same impact on consumers as the traditional EWOM messages on a product review website. Moreover, it might be that Twitter is the future of EWOM and indeed becomes a powerful social EWOM source (S-EWOM). The main research question of this study is formulated as follows:

RQ:

"What is the impact of negative product reviews on *product review websites* compared to the impact of negative product reviews on *Twitter* on a consumer?"

This study mainly builds further on existing research on EWOM, and the little existing literature on Twitter as EWOM. The subsequent paragraphs will lay the academic foundations of this study and its proposed hypotheses. First, the already investigated impact of EWOM and its predicting and outcome variables will be described. Second, product review websites as EWOM and Twitter as S-EWOM will be discussed. Subsequently, support for the proposed hypotheses will be given.

2.1. (E)WOM and the influence on consumer perception and behavior

A considerable amount of research, dated back to 1955, showed the significantly impact of WOM on consumer behavior and product choice (Katz & Lazarsfeld, 1955; Arndt, 1967; Engel, Blackwell, & Kegerreis, 1969; Richins, 1983). Even more importantly, the persuasive and highly effective nature of WOM is attributed to the fact that in many situations consumers trust the opinions and experiences of other consumers more than the traditional marketing tools, such as personal selling or advertisements (Katz & Lazarfeld, 1955; Engel et al., 1969; Goldsmith & Horowitz, 2006). The motives of consumers to seek opinions of others on the Internet, was investigated by Goldsmith and Horowitz (2006). They reported eight distinctive factors: risk reduction, lower price certainty, by accident, information is easily obtained, because others do it too, because it is cool, because of stimulation from offline input such as TV, and to get information prior to a purchase. Hennig-Thurau et al. (2004) added to this by examining the motives of consumers to post product reviews. They suggest four primary factors that lead to EWOM behavior: the desire for social interaction, desire for economic incentives, concern for other consumers, and the potential to enhance self-worth.

Numerous studies attempted to investigate whether negative product reviews or positive product reviews exert more power. Although there is theoretical motivation for the effect of both, abundant studies found support for the negativity effect. For example, Cheung and Lee (2008) found that the intention to shop was significant lower after being exposed to negative EWOM. Chevalier and Mayzlin (2003) found that negative product reviews had more impact on product sales than positive product reviews. Others also examined the proportions of negative and positive product reviews, and the quantity of product reviews on consumer behavior (Lee et al., 2007; 2008; Lee & Park, 2008, Park & Kim, 2008; Doh & Hwang, 2009). Lee et al. (2008) found that as the proportion of negative product reviews increased, consumers conformed more to the product reviews, and became more unfavorable toward the product. They argue that the involvement of a consumer with the product interacts with this effect. The involvement of a consumer with the message and the product is widely examined by an abundant number of researchers (Petty & Cacioppo, 1983;1984, Lee & Park, 2007, Lee et al., 2007; 2008).

Another line of research focused on the influence of different product types as predictor variables (Sen & Lerman, 2007; Park & Lee, 2009; Mudambi & Schuff, 2010). For instance, Sen and Lerman (2007) found a difference between hedonic and utilitarian products. Negative product reviews concerning utilitarian products were perceived as more useful than positive product reviews. Lastly, Doh and Hwang (2009) found support that product reviews have an impact on the credibility of the message, the attitude toward product and website, and the purchase intention. They examined how the causal relationship between the ratio of the messages (positive-negative) interacted with prior knowledge and product involvement of consumers. These researchers did not focus on the impact of one single product review, but focused on the impact of multiple product reviews.

In conclusion, an enormous amount of studies focused on the impact of EWOM on consumers. However, little to none academic researchers focused on the impact of product reviews on two completely different sources of which one is a social media website. Deduced from an extensive literature review, we chose to focus on credibility, attitude toward product, and purchase intention as the outcome variables of EWOM. The following paragraphs, based on theoretical evidence, will explain these effects of (E)WOM in more detail.

Credibility

One distinctive characteristic of EWOM is that it is openly accessible and that product reviews are written by a wide variety of reviewers. This has made the Internet an attractive source for consumers to gain advice about products. At the same time it has increased the concern that unfamiliar users with unknown motives could also post messages on the Internet. It is not always possible to critically assess the information that has been written on the Internet, as it was with the advice obtained from familiar people (Chueng et al., 2009). Therefore, credibility issues have always been a major concern for consumers to adopt EWOM. Especially with Twitter as a new source of EWOM, it is important to investigate how consumers judge the credibility of the information

Credibility is a critical issue in order to share information effectively (Chen, Dhanasobhon, & Smith, 2008). Moreover, information credibility has found to be an important predictor of a consumer's further actions. Unless information has found to be credible, consumers are not acting upon the information they have read (Wathen & Burkell, 2002; McKnight & Kacmar, 2006; Cheung et al., 2009). Thus, a consumer will not be affected by a product review, unless they perceive the information as credible. Credible information constitutes reliability and consumer trust (Chen et al., 2008), and can be defined as "trust in information" (Briggs, Burford, De Angeli, & Lynch, 2002). It involves the extent to which one perceives information as believable, trustworthy, knowledgeable, and competent (Flanagin & Metzger, 2000). Expertise and trustworthiness are two factors that determine the credibility of a reviewer (Ohanian, 1990; Fogg et al., 2001; Cheung et al., 2008; 2009; Tanaka et al., 2010). People tend to believe information from a high credit source (high degree of trustworthiness and expertise) more than from a low credit source (Cheung et al., 2008; 2009; Ohanian, 1990).

The source (medium) and message are considered as important antecedents in the assessment of information credibility. In the literature, source and medium are usually treated as the same construct (Wathen & Burkell, 2002), and will be treated as one in the current study. Source credibility can be defined as the extent to which an information source is perceived to be believable, competent and trustworthy by the message receivers. The quality of the message is vital with the credibility assessment (Petty & Cacioppe, 1986). As the source (medium) and the message are two critical factors in assessing the credibility of information, this study will take these two factors as predictor variables. As mentioned, credibility is essential for the adoption of information, and subsequent is of influence on the attitude toward product and the eventual purchase intention.

Attitude toward product and purchase intention.

EWOM is important for consumers because they perceive a certain amount of risk when buying products online (Chueng & Lee, 2008). Many consumers that want to purchase something online tend to wait and observe the advice or experiences of others before considering buying themselves. This can be explained by the theory of reasoned action. According this theory, subjective norms, such as social influence or WOM recommendations, are important factors that can affect a person's attitude and behavior (Fishbein & Ajzen, 1965). Research has suggested that information from external sources, such as an online product review, can increase a consumer's confidence about their attitude toward some object. This attitude, favorable or unfavorable, can then lead to behaviors of consumers in a later stadium (Fazio & Zanna, 1981).

The impact of WOM on purchase intention is undeniable. Research dated back to 1967, already found evidence that exposure to positive WOM increases the likelihood of purchasing a product, while exposure to negative WOM decreases the likelihood of purchasing the product (Arndt, 1967). However, consumers perceive a higher risk buying a product when there is not enough information available beforehand. People base their offline purchase decisions on the basis of the online available information (Lee et al., 2007). Therefore, the influence of product reviews on consumers to purchase a product is high (Pollach, 2006). Product reviews influence a consumer's attitude toward a product and in turn lead to the decision of buying a particular product or not.

2.2. Product review websites as EWOM

As already mentioned before, EWOM can take place in many different ways on the Internet. It enables consumers to obtain information about products and services from other customers. These opinions are available to a large number of people and provide product evaluations, and have a major impact on consumers' product attitude and purchase behavior, and thus on the success of products (Hennig-Thurau & Walsh, 2003; Chevalier & Mayzlin, 2006; Park & Kim, 2008). In this study, we focus on EWOM through product review websites.

In general, online product reviews can be defined as product evaluations by peer-consumers about a particular product or service posted on a company or third party website (Kumar & Benbasat, 2001; Mudambi & Schuff, 2010). As mentioned, we focus on the last one. Product review websites have become a global phenomenon offered to consumers in many countries, and in many different ways (e.g. in combination with e-commerce; Amazon.com, or review websites that show the best deals and then directs one to a seller website; Consumersearch.com). Although these websites differ in format, they have similar functions. They enable consumers to read the opinions of others, but they also enable consumer to contribute themselves by writing about their own experiences (Hennig-Thurau & Walsh, 2003;

Bailey, 2005). Furthermore, Chatterjee (2001) stated that the quantity of EWOM information available online is far more voluminous compared to the information that is available offline. These product reviews, from a wide variety of sources, are mostly presented simultaneously together on the same website. Because product reviews appear in a written form, people can easily observe and compare the quantity and quality of these product reviews (Lee et al., 2008). Product reviews are also archival, because they stay visible on a product review website for a certain period of time.

However, these websites are not only a place for sharing information, they also have the potential to influence consumers as they are used as a supplementary source of information (Cheung et al., 2009). Senecal and Nantel (2004) found that consumers who consulted product reviews selected the recommended products twice as often as those consumers who did not consulted the product reviews.

2.3. Twitter as S-EWOM

EWOM messages on product review websites are not a new field of study. However, with the advent of social media and the rising popularity of Twitter, not many of them have considered Tweets as a unique, new form of EWOM. The main aim of this study is to add a new dimension to the (E)WOM theory, by considering Twitter a new EWOM source: *social-electronic-word-of-mouth* (S-EWOM). The distinctive characteristics of Twitter make it an interesting EWOM research topic.

As mentioned before, Twitter is a real-time micro-blogging service on which users can describe things they are interested in, or on which they express an attitude toward something in short blog posts (Tweets, of maximal 140 characters). These Tweets can be distributed by instant messages, mobile phones, emails, or just via the website of Twitter (Jansen et al., 2009). People use micro-blogging to talk about their daily activities and to seek or share information (Java, Song, Finin, & Tseng, 2007). The extremely fast communication nature of Twitter directly impacts EWOM communication. More specifically, Twitter allows its users to share their thoughts (e.g. negative or positive sentiments) and opinions about a product or service almost anywhere (e.g. while sitting in the train, getting some food, or just when sitting behind a computer), anytime (24/7), to almost anyone (who is connected to the Twitter network). The reach of Twitter is one of a scale that has not been seen in the past (Jansen et al., 2009).

The shortness of a Tweet makes Twitter a unique medium and different from the more traditional EWOM mediums. The maximum allowed number of characters prevents users from writing long and extensive thoughts. Basically, in terms of length, a Tweet can be compared to a typical newspaper headline or subhead. This makes them easy to produce, consume, and reproduce (re-tweet) (Milstein, Chowdhury, Hochmuth, Lorica, & Magoulas, 2008). Tweets are asynchronous in that users can choose from whom to receive updates from (in a user's own timeline). However, they also have a synchronous part in that users can directly communicate with each other. Tweets are also archival in that they stay online, and are searchable via the Twitter website, and via search engines on the Internet. Recently, Twitter has prohibited the function to search for Tweets older than seven days. When posting a Tweet online, they become visible for anyone with an Internet connection. Twitter does not limit the access to Tweets to registered users (Jansen et al., 2009).

Precisely, the fact that Twitter is a fast medium that offers immediate sentiment, provides companies the opportunity to gain insights in the affective reactions of consumers toward their products or services. Adding the immense usage worldwide to this, makes it an interesting tool to consider as S-EWOM source. Little prior literature focused on this topic. The only study that provides useful insights for the purpose of this study, was conducted by Jansen et al. (2009). They analyzed more than 150.000 Tweets containing branding comments, sentiments, and opinions, and found some useful results. First, as Java et al. (2007) already suggested, people use Twitter as a source to seek information. 29% of the Tweets were providing or seeking information concerning some brand. Second, 19% of the analyzed Tweets mentioned an organization, or product brand in some way. According to the researchers, this indicated that Twitter is a fruitful medium for viral marketing campaigns and web care (e.g. customer relationship management: CRM). Third, and most relevant for this study, 20% mentioned a brand and expressed an opinion (negative or positive) toward that brand, product, or service. Twitter is a social communication medium that can affect brand awareness in a positive and certainly also in a negative way. 33% of the Tweets expressed a negative sentiment, while 52% of the Tweets expressed a positive sentiment. This finding was in line with previous research, that states that extremely negative and extremely positive customers are more likely to express their feelings toward a brand, than consumers with moderate experiences (Anderson, 1998).

People can easily access Twitter and send Tweets through a variety of devices; one is not restricted to computer. A person can read, but can also immediately react to the experiences of others with products or services. This is exactly why Twitter differs from other sources on which products are evaluated. The immediacy of Twitter at the point of purchase could be a critical factor for consumers to decide whether to purchase or not. Contrary to the purpose of the current study, Jansen et al. (2009) did not evaluate the impact of Tweets as S-EWOM on consumers. They identified that consumers talk about brands, companies products, and services, but not how these Tweets influence consumers' perceptions and behavior. Therefore, this study attempts to builds further on the existing literature on product reviews websites as EWOM, but also on the study of Jansen et al. (2009) that as one of the first identified Twitter as a (S)EWOM communication source that cannot be disregarded in the future.

2.4. Hypotheses

2.4.1. Source of product review

Mudambi & Schuff (2010) defined product reviews as "peer-generated product evaluations posted on company or third party websites" (p.186). However, not many researchers focused on the impact of product reviews between two 'third party' websites. This study focuses on two 'third party' websites that serve as the source of the product review. A distinction is made between the traditional EWOM in the form of product reviews on a product review website, and S-EWOM in the form of Tweets on Twitter.

According the attribution theory, the platform (source) on which EWOM is posted, is essential for the persuasiveness of the product review. The theory suggests that when consumers are exposed to a message, they make an attempt to assess whether the message is accurate. If the message lacks credibility, it will be disregarded, and thus will not be very persuasive (Kelley, 1967; Buda, 2003). The characteristics of the EWOM platform are important for the persuasiveness of the platform (Cheung & Zhou, 2010). Brown, Broderick, and Lee (2007) also found that the source of the message is related to how consumers perceive the credibility of the EWOM information.

In the past, the credibility of WOM was concerned with the physical and social cues of the reviewer, in EWOM communications these cues are not accessible. Reviewers can express their feelings toward and experiences with a certain product without revealing their real identity (Cheung, Lee, & Rabjohn, 2008). Therefore, more salient cues that show some information about the reviewers' credibility need to be visible. Previous literature (e.g. Chen et al., 2008) suggested that rating systems, such as the helpfulness systems on product review websites (e.g. Amazon.com, Cnet.com), convey some information about the credibility of the reviewer's message. The proportion of helpful votes can serve as a quality and trustworthiness indicator of the product review's content. If a product review has a low helpfulness score, consumers will perceive that review as unreliable. Chen et al. (2008) also found that product reviews with a high proportion of helpful votes have a stronger impact on the product sales, than product reviews with a low proportion of helpful votes. Additional support was found by Cheung et al. (2008) who found that if messages are perceived as more useful, the willingness to adopt the message is also higher. Due to the fact that many review websites contain a helpfulness rating system, it is expected that the availability of these systems will contribute to the perceived credibility of the information, to the attitude toward product and the purchase intention.

Pan & Zhang (2011) found evidence that longer product reviews are perceived as more helpful than shorter product reviews. They found that long positive product reviews are more helpful than short negative product reviews. However, in the present study we expect that the same holds for long negative product reviews. Mudambi & Schuff (2010) found that review depth positively influences the perceived helpfulness of a product review. They did not make a distinction between negative or positive product reviews. Longer product reviews had a significant effect on the helpfulness score and, as argued by Chen et al. (2008), this helpfulness score also impacts product sales. In-depth information reduces the uncertainty about the quality of the product, and helps the consumer in the decision making process by increasing the confidence in the decision. Research dated back to the 1970s already reported that the increasing availability of information, increases the confidence of the decision maker (Tversky & Kahneman, 1974).

The effect of review length is moderated by the type of product. Moreover, the effect of review length is stronger for search and utilitarian products, than for experience and hedonic products (e.g. Mudambi & Schuff, 2010). Search products are goods of which consumers can obtain information about quality prior to a purchase (e.g. cameras). The attributes of search products are objective, easy to compare, and one's senses are not crucial to evaluate the quality (Nelson, 1970). Utilitarian products are those that are usually purchased because of their specific functionalities (e.g. computers). One unique characteristic of a Tweet is that it may only contain 140 characters, while product reviews may contain more characters. A Tweet can only provide a brief synopsis of a product review. Due to the difference in review depth, it will be expected that product reviews on a product review website will be more credible and have a greater impact on consumers, than product reviews on Twitter.

Not many researchers have focused on the credibility of Tweets, and especially not many researchers compared the credibility of these Tweets to the credibility of other online sources. Very recently, Schmierbach and Oeldorf-Hirsch (2012) investigated the credibility of news on a newspaper website (New York Times), to the credibility of the same message on Twitter (only shorter). They found that the credibility of information on Twitter is considered as less credible, than news stories posted on a newspaper website. Although the initial message differs from product reviews, it gives an indication of the credibility of Twitter. Due to the limited number of studies on the impact of Twitter, the above mentioned studies were used to propose the first hypothesis. Subsequently, the following hypothesis is proposed:

H1: Negative product reviews written on a product review website will be perceived as *more credible,* and will have a *greater impact* on the *attitude toward product* and the *purchase intention,* than on Twitter.

Note that, at this moment the impact of product review websites will be, slightly, greater than on Twitter. However, due to exponential growth and popularity of Twitter usage it will be expected that the difference is relative small and might become even greater in the future. Besides the source of a product review, the quality of the message is also considered as an important predictor of the impact of a product review. Subsequent paragraph will go deeper into this subject.

2.4.2 Message quality

Basically there are two types of product reviews: low quality and high quality. The message quality of a product review can be defined according to the information characteristics: relevancy, understandability, reliability, and sufficiency (Petty & Cacioppo, 1983; 1984; McKinney, Yoon, & Zahedi, 2002; Lee et al., 2007;2008). In short, relevancy refers to consistency between the information provided in the product review and the information a consumer needs to evaluate the product. Reliability refers to the degree one can depend on the information. Understandability refers to the ease of understanding the information in the message. Lastly, sufficiency refers the message's level of detail. A high quality product review contains objective statements that are clear and logical, and because they are more logical they are more persuasive. The information in a high quality product review is understandable, reliable and based on specific facts about the product. In contrast, a low quality product review contains subjective and emotional statements that are irrelevant, unreliable, and difficult to understand. Moreover, these reviews contain insufficient reasoning with no factual information (Petty, & Cacioppo, 1983; 1984; Lee et al., 2007; 2008).

Most buyers are anonymous when posting information on the Internet. People will not easily adopt or trust a product review on the Internet, especially when it does not provide enough in-depth information (Ratchford et al., 2001). As Wathen and Burkell (2002) stated in their study, the message itself is essential for information credibility. Internally a message should be consistent, and externally the message should be clearly and concisely presented.

Lee et al. (2008) found that high quality negative product reviews have a greater impact on consumer attitude than low quality negative product reviews. Consumers who were exposed to negative product reviews of high quality, reported a less favorable attitude toward a product, than consumers who were exposed to negative product reviews of low quality. The same researchers found that the quality of a product review also affects the consumers' purchase intentions. High quality product reviews have a greater positive effect on consumers' purchase intentions (Lee et al., 2007). Although in the last study the reviews were positive, we expect that the message quality of negative product reviews has the same impact. Negative high quality product reviews would then negatively influence consumers purchase intentions.

Argument strength is also concerned with the message quality and the way consumers perceive information as having convincing and valid arguments that support the position of the reviewer (Chueng et al., 2009). Cheung et al. (2009) found support that when a product review appears to have many valid and supporting arguments, the reader adopts a positive attitude toward, and perceives the message as more credible. In contrast, when a product review appears to have invalid non-supporting arguments, the reader adopts a negative attitude toward, and perceives the message as less credible. Other studies also demonstrated that argument strength directly influences the attitude of the reader. Strong messages with objective and easy to understand arguments, are more effective than weak messages with subjective and emotional arguments (Petty & Cacioppo, 1983; 1984).

In this study we make a clear distinction between high and low quality product reviews. Product reviews with strong argumentation belong to the category of high quality messages, and product reviews with weak argumentation belong to the category of low quality messages. According to the previous discussed studies, it is predicted that in general, higher quality product reviews will be perceived as more credible, and consequently have a greater impact on a consumers' attitude toward product and purchase intention, than low quality product reviews. Although the effect of high quality product reviews is highly expected, the possible effect of low quality product reviews should not be disregarded. All online product reviews are supposedly based on consumers' evaluations of already purchased products, and are written on the web without any standard format (Lee & Park, 2008). Consumers can basically write anything they want and publish it on the Internet. Consumers use all types of product reviews to obtain information. Hence, the low quality reviews are still expected to have an impact. Subsequently, the following hypothesis is proposed:

H2: High quality product reviews will be perceived as *more credible*, and will have a *greater impact* on the *attitude toward product* and the *purchase intention* on a product review website and on Twitter, than low quality product reviews.

However, due to ability to write more extensive and throughout product reviews on a product review website, compared to the limited number of characters of a Tweet, a third hypothesis is proposed:

H3: High quality product reviews will be perceived as *more credible*, and will have a *greater impact* on the *attitude toward product* and the *purchase intention* on a product review website, than high quality product reviews on Twitter.

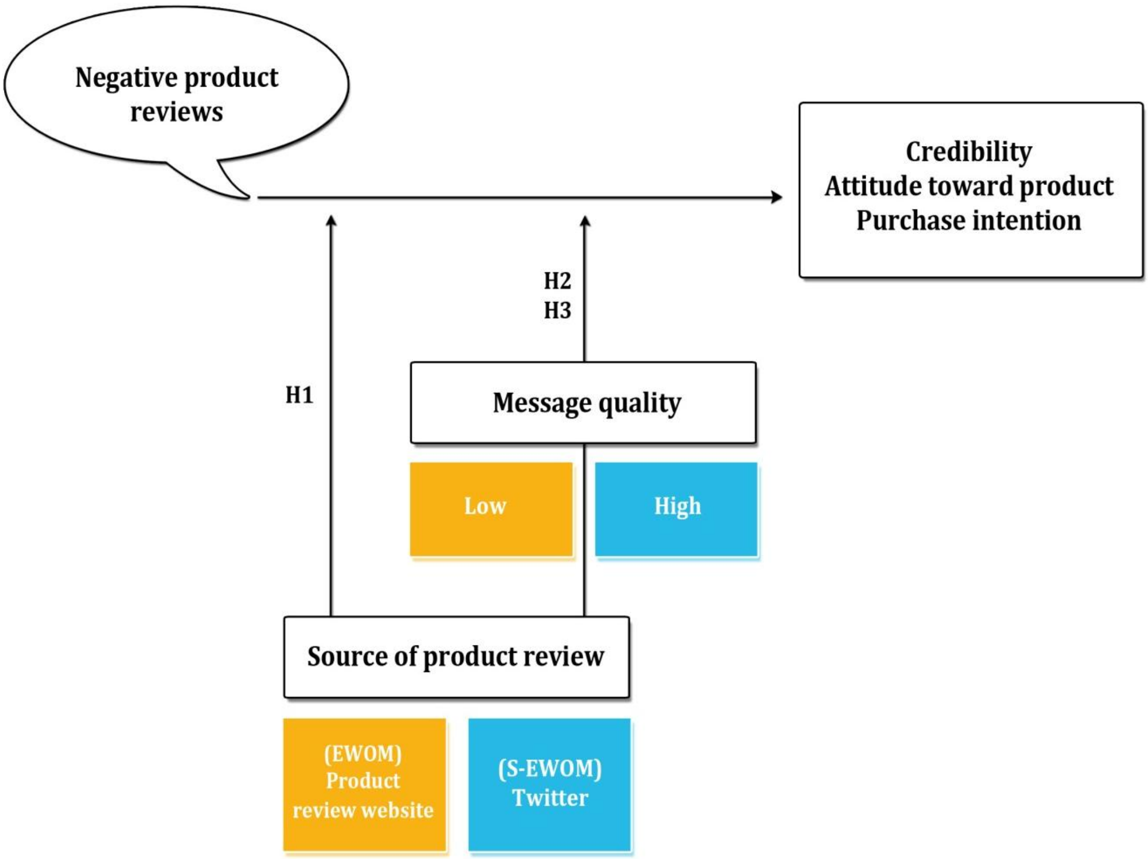

Figure 2. *Research model*

3. Methodology

The main aim of the current study was to investigate how consumers evaluate the credibility of negative online product reviews on a specific product review website compared to product reviews on Twitter. It further analyzed the attitude toward product and the purchase intention after reading a product review. Investigating how consumers evaluate different types of negative product reviews is useful to gain more understanding in the effect of EWOM from different sources. First, the differences between the two sources needed to be identified; the differences between product reviews written on a product review website and product reviews written on Twitter were analyzed. Second, the way consumers perceive the credibility of negative product reviews from two different sources was analyzed. Hereby we also examined whether there was a difference in attitude toward product and purchase intention after reading the product reviews. The subject of credibility assessment referred to the message about the product itself, not to the sender of the message or the product's brand.

Two studies were conducted: (1) a qualitative preliminary investigation was conducted, to identify the main differences and similarities between product reviews written on a product review website and product reviews written on Twitter. This study identified differences in product reviews from the producers' side. (2) In the second study an online questionnaire was conducted to examine the impact of negative product reviews from a product review website, and the impact of negative product reviews from Twitter. Besides the two different sources, the online questionnaire also measured the impact of low and high quality product reviews. The main focus of this study was to investigate the impact and perception of product reviews from the consumers' side.

Both studies were concerned with online product reviews. On the Internet a wide variety of product reviews are available, and about almost any product a product review can be found. For the purpose of this study, we decided to focus on one product domain: electronic products. This product domain was chosen for three reasons. First, the electronic market is a highly competitive market that sells information-intensive and mostly expensive (durable) products. Therefore, consumers probably use online product reviews to obtain other people's opinions before making their actual purchase. Conversely, consumers also want to share their own opinions and experiences about a product when they bought an electronic product themselves (Pollach, 2006). Second, electronic products are commonly and frequently purchased in online shops. Third, consumers most likely rely on the experiences and opinions of others because most electronic products are complicated and consumers lack the expertise themselves (Lee et al., 2007).

4. Study 1: Qualitative preliminary investigation

4.1. Methods

The product reviews in this study are written by consumers on two different types of sources; on a product review website, and on Twitter. Most product evaluations are not written by consumers following a structured format (Park & Kim, 2008; Pollach, 2008). As a result, reviews can take different forms. Some reviews are simple recommendations that contain extremely negative or positive features about a product, while some recommendations contain objective and detailed product evaluations with supporting comments (Willemsen et al. 2011). As suggested in previous research, reviews are not created equally, and they are also not evaluated equally (Lee et al., 2007; 2008; Chen et al., 2008; Willemsen et al., 2011). Presumable, product reviews written on different review sources with different characteristics, will greatly vary in their structure and content. Therefore, this preliminary investigation was conducted to examine the general differences and similarities in product reviews written on the two primary sources of this study: Amazon.com and Twitter. The findings of this investigation were used as guidelines to design the online questionnaire for the second study.

Amazon.com has been chosen because of four reasons. First, it is one of the largest international e-commerce website, that combines e-commerce with the possibility to post product reviews. Second, it has one of the largest active reviewing community. Third, the collaborative nature of Amazon.com has been imitated by other internet retailers. Fourth, all product reviews written on the website will actually appear visible, they are not censored to prevent companies from getting harmed by the product reviews. Furthermore, Amazon.com has proven to be a useful website for analyzing EWOM. Many researchers have used Amazon.com for analyzing the content characteristics, and for analyzing the influence of product reviews on the purchase intention, attitude toward product, and credibility of EWOM messages (e.g. Dave, Lawrence, & Pennock, 2003; Chevalier & Mayzlin, 2006; Mudambi & Schuff, 2010; Pan & Zhang, 2011; Willemsen et al., 2011.)

In this small qualitative preliminary analysis seven characteristics of product reviews were analyzed from the side of the producer: (1) ratings and comments, (2) perceived usefulness, (3) review valence, (4) review length, (5) message quality, (6) argumentation, (7) reviewers' credibility. All these seven factors were found to be important in the evaluation of product reviews, and could be of influence on the credibility of a product review, the attitude toward product, and the purchase intention.

4.1.1. Variables

In this section, the motivations for choosing the seven characteristics will be clarified and justified according to available literature. The criteria by which these seven characteristics were analyzed and coded will also be explained in more detail.

Ratings & Comments

According to Park & Kim (2008), online product reviews are open-ended in that they contain consumer-written comments and ratings. First, comments refer to a consumer's assessment of the reviewed product. These written comments, in the textual content part of the product review, are the positive and/or negative product evaluated features of the product. Furthermore, comments also give consumers the opportunity to react to other consumers product reviews. For the purpose of this study, it was analyzed whether Amazon.com and Twitter allow its users to add comments to a written product review.

Second, ratings display a summary of the overall assessment of the product, and mostly appear in the form of five-star recommendations. Often these ratings are prominently shown at the surface level of the product review (Willemsen et al., 2011). An extremely negative reviewed product is rated low (one star), an extremely positive reviewed product is rated high (five stars), and a moderate reviewed product with both positive and negative comments, is rated with three stars (Mudambi & Schuff, 2010). The possibility of posting an overall rating about the product on Amazon.com and Twitter was analyzed. Although the rating system will be most likely available on Amazon.com, the way Twitter users express their overall feeling toward a product is of special interest. The number of characters to express a feeling or an opinion toward a product is limited, and without a rating system, the rating needs to be expressed textually. Therefore, it was analyzed how Twitter users express (in words most likely) their overall rating.

Perceived usefulness

The perceived usefulness is also an important characteristic of a product review. As the ratings, the perceived usefulness often appears on the surface level of the product review. Moreover, the perceived usefulness of a product review is a significant predictor of a consumer's willingness to comply with the product review (Cheung, Lee, & Rabjohn, 2008). These peer-rating systems enable consumers to vote whether they found a product review helpful in their decision making process. It also enables consumers to search and filter more effectively through the overload of information on a product review website (Willemsen et al., 2011). The perceived usefulness of a product review gives an indication of the content's message quality (Chen et al., 2008). Zhu and Zhang (2010) suggested that most of the useful or useless votes are given by consumer who are in the middle of their decision making process. Therefore, these scores serve as an aid in the purchase decision of a particular product, reduces the uncertainty about a product, and increases the confidence of the consumer.

This study analyzed whether and how both sources enable its users to indicate the product review usefulness. Hereby the possibility of adding a usefulness score was important. As the rating possibilities, Amazon.com most likely allows its users to add a usefulness score. However, for the purpose of the current study it was also interesting to detect how Twitter users express the usefulness of a product review (Tweet).

Review valence

The valence of a product review refers to whether the message is framed positively (e.g. a praise message) or negatively (e.g. a complaint message). A negative product review emphasizes the weaknesses or problems of the product, while a positive product review emphasizes the strengths of the product (Cheung et al., 2009). As already mentioned before, many product review websites contain star-ratings. These star-ratings, mostly displayed at the surface level, show the reviewers' assessment of the product. At the same time, this also indicates the valence of the product review. Presumably, reviews with a high star number have a more positive valence than reviews with a low star number (Pan & Zhang, 2011). Previous literature has proven that a positive relation between the valence of a product review and the behavior of consumers exist. Hence, when a product review has a more positive valence, more people are likely to purchase the reviewed product, while a negative product review has the adverse effect (Willemsen et al., 2011).

The current study focuses on negative product-related reviews. It was analyzed how consumers can detect the valence of a product review. For example, is the valence immediately visible at the surface level of the product review, are the product reviews arranged by valence, or is the consumer obliged to read the content of the product review in order to detect the valence?

Review length

A product review can have different structures, forms and lengths. Moreover, written on sources with different characteristics, the possibilities to write an extensive lengthy review can differ. Pan and Zhang (2011) reported that review length matters in the evaluation of product reviews; longer product reviews are likely to contain more information compared to short product reviews. Furthermore, a longer product review can contain more concrete, detailed product-attributed information, and information about where and how the product was used (Mudambi & Schuff, 2010; Pan & Zhang, 2011). This increase of information in the decision making process serves as a confidence boost for the decision maker (Tversky & Kahneman, 1974; Mudambi &

Schuff, 2010). Longer product reviews will be perceived as more convincing than shorter product reviews. Although a longer product review can be more expressive and extensive, this will not immediately mean that it is of high quality.

Additionally, length can also reflect the involvement of the reviewer. The higher a consumer is involved, the more willing the reviewer is to provide helpful information to support other consumers in their purchase decisions (Pan & Zhang, 2011). Especially in this study the length of the product reviews can greatly vary across the two sources. Review length was analyzed by the number of typed characters and the number of typed words.

Message quality

Although message quality is concerned with argumentation quality, in this analysis the two variables were examined independently of each other. The quality of product reviews on the Internet greatly varies, many product reviews simply contain emotional sentences such as *"I just do not like this mobile phone at all".* Such sentences do not contain constructive evaluations of the reviewed products (Chen & Tseng, 2011). As already mentioned before, the perceived helpfulness score of a product review could serve as an indicator of the message quality (Chen et al., 2008). However, Liu, Cao, Lin, Huang, & Zhou (2007) found that these ratings are not sufficient enough to evaluate the real message quality and are influenced by three types of biases: imbalanced vote bias, winner circle bias, and early bird biases. First, the imbalanced vote bias means that consumers on the Internet tend to evaluate the opinions of others positively rather than negatively. Second, the winner circle bias means that reviews that already received many useful votes, will continue to receive many of those votes. Lastly, the early bird bias proposes that the earlier a review is posted, the more votes it will receive (Chen & Tseng, 2011).

In this preliminary investigation a readability test and a content test have been conducted to examine the overall quality differences in product reviews on Amazon.com and on Twitter. Specifically, the readability test provides information about the quality of the review in terms of readability and understandability (Korfiatis, García-Bariocanal, & Sánchez-Alonso, 2011). First, the product reviews were tested with the Flesh-Kincaid formula (Kincaid, Fishburn, Rogers, & Chissom, 1975), which combines the number of syllables or words in the text (syntactic complexity) with the number of sentences (semantic complexity). This formula is widely used to evaluate the complexity of a message in order to determine the minimal age group (number of years of education needed) that is able to comprehend the message.

Second, the message quality was analyzed. We defined two basic types of message qualities (high and low), but for the purpose of this study the message quality was analyzed according to the framework of Liu et al. (2007). They propose a SPEC (specification) framework with four categories to detect and filter low-quality product reviews from high-quality product reviews. The four categories are: best review, good review, fair review, and bad review. First, a best review is a rather complex and detailed evaluation about a product. Usually, a best review serves as main reference for consumers and is sufficient to read before making the actual purchase. In addition, best reviews are often written in a structured format that is easy to understand. Second, a good review is a less complete review, but still contains some supporting evidence about a product. It can still be considered as a strong and influential reference for consumers, but it will not be the only product review consumers look at before making a purchase decision. Third, a fair review does not take all aspects of a product into consideration and is not a detailed product evaluation. It takes only one or two factors into account, and talks less about other aspects of a product. As fourth, a bad review is often an incomplete and misleading product review. It does not evaluate specific product features, but talks more about general topics. Thus, a bad review can be considered as a useless product review.

The product reviews in appendix I are examples of the four categories. Note that these product reviews are examples and that some words are omitted to save space. These four categories served as baseline to evaluate the product reviews and filter out the high quality from the low quality ones on Amazon.com and on Twitter. A clear distinction between high quality and low quality product reviews could be made, and were used to design the message manipulations for the online questionnaire. Although Tweets are shorter, they still contained information that could be analyzed according to the SPEC framework.

Argumentation

Besides the valence statements in a product review, reviewers use argumentative statements to support their opinion, and argumentation (strength) is also related to the quality of information (Cheung et al., 2009). The proportion of arguments is related to the intention of a consumer to comply with the message and can also affect the attitude toward the message. An increasing number of arguments can positively affect persuasion (Petty & Cacioppo, 1984). The same authors also state that when a consumer is unmotivated and unable to think about a message, and no other salient cues are at hand, they apply a sort of heuristic rule that says: “the more arguments, the better”. Therefore, the number of arguments (argument quantity) was analyzed. With the presence of arguments a message is judged more persuasive, and makes a consumer more confident with the messenger (Willemsen et al., 2011).

The quality of arguments has also been proven to be an important element that consumers use to rate a reviewers' credibility. Consumers do not blindly follow comments of others, and do not believe the opinion of others when these are not supported with strong and valid arguments (Chueng et al., 2009). According to Lee et al. (2007), two types of product reviews exist; weak product reviews and strong product reviews. The first type, weak product reviews, consists of subjective and emotional statements, and lack strong argumentation (e.g. "*It is so bad that I am not going to buy another one*"). In the second type, strong product reviews, the claims are backed-up with reasonable arguments (e.g. "*This product is twice as slow as other comparable goods and more expensive*"). In appendix I examples of a product review with strong and a product review with weak argumentation can be found.

It is assumed that argumentation can have an influence on the consumers' attitude toward product, and the purchase intention. Furthermore, the credibility of a product review could be judged differently when it contains strong argumentation. Amazon.com and Twitter greatly differ in the maximum allowed number of characters to write a product review or a Tweet. Therefore, it is expected that reviews on Amazon.com will contain more arguments than reviews written on Twitter. The argumentation quality (weak or strong) and the argumentation quantity (number of arguments) was analyzed. It was of interest to investigate the differences in the potential of writing a product review with high or low argumentation quality and quantity.

Reviewers' credibility

Cheung et al. (2009) found that the credibility of the reviewer is an important determinant for the credibility of a product review and the effectiveness of communication. In short, many studies defined credibility as the extent to which one perceives a message as believable, trustworthy, knowledgeable, and competent. Credibility is often concerned with two factors: expertise and trust. Expertise in online environments can be based on text-based resources and claims provided by the reviewers themselves (Brown et al., 2007). The product reviews of reviewers that claim to have expert knowledge regarding a reviewed product, are mostly perceived as useful and credible. Expertise is used to evaluate the credibility of unfamiliar information (Willemsen et al., 2011).

Characteristics of a reviewer, such as attractiveness, and physical appearance, are difficult to access in the online environment. Reviewers can write product reviews without revealing their real identity (Cheung et al., 2008). Therefore, other more salient cues about a reviewer's reputation and trustworthiness should become accessible for the consumer. Most product reviews contain rating systems that convey information about a reviewer's trustworthiness. Additionally, consumers can indicate their trust in the reviewer based on his or her past contributions and postings. The ranking of the reviewer would then serve as an indicator of the reviewer's reputation and credibility. Besides the reviewers' ranking, personal information can also indicate the trustworthiness of the reviewer (Cheung et al., 2009). Chen et al. (2008) used the "top" reviewers and the "spotlight" reviews of Amazon.com in their study to investigate the quality of the reviewer (i.e. the reputation and trustworthiness). The spotlight reviews are shown apart from and before the other reviews. In this preliminary investigation, it was investigated whether it was possible to detect the credibility of the reviewer in terms of trust and expertise. More specifically, do Amazon.com and Twitter show consumers information about the reviewers' trustworthiness in terms of posting history, reputation, and personal information? Do they also show content features (e.g. expertise claims, professions or hobbies indicated in the profile of a user) that indicate the expertise of the reviewer?

4.1.2. Review sources

As already mentioned before, the review sources for this analysis were the product review website Amazon.com and Twitter. Beforehand assessing the seven criteria, the general structure of Amazon.com and Twitter were examined. In fact, the two sources are not really comparable with each other. Each source serves a different goal: Amazon.com is an e-commerce website that combines selling products with consumer interaction by allowing consumers to post extensive product reviews about the products Amazon.com sells. Twitter is a real-time information network that allows its users to post short messages (Tweets) about ideas, opinions, experiences, news, etc. that keeps them busy. Both structures will most likely differ greatly from each other: Amazon.com is directly concerned with product reviews, while Twitter is indirect a medium that could be used for posting product reviews.

Three major differences emerged from this examination. First, the messages on both sources are differently displayed. On Amazon.com product reviews are structured and displayed according to product. For each product, all product reviews are chronologically displayed from the most favorable and helpful to the least favorable and less helpful product review. In addition, consumers can also choose to see the newest product reviews. Consumers can click on the type of product review they want to read: positive (5 or 4 star), neutral (3 star), or negative (1 or 2 star). Furthermore, the most helpful favorable product review and the most helpful critical product review are prominently displayed before the chronologically displayed list of product reviews. The average rating of the product, and the amount of product reviews posted, for that particular product, are also displayed. Tweets are displayed in a user's timeline. This timeline shows the most recent Tweets from a user's followers. When a user is looking for Tweets about a particular product, a search query should be entered in the search bar. The most recent Tweets mentioning the product are then shown. However, the timeline displays everything that has been said about that particular product (search query); the Tweets are not chronologically ordered regarding content, but regarding time of posting (most recent first). Thus, when typing in a product name, not only Tweets that evaluate the product are displayed, but all Tweets that mention the search query are displayed to the user.

Second, Twitter has a restriction concerning the search of Tweets, it does not allow its users to search for Tweets older than seven days. Consequently, when an user searches for information about a certain product, only the most recent messages will be displayed (not older than seven days). Amazon.com, on the other hand, shows all product reviews despite of how old the product reviews are.

Third, and as already mentioned before, Twitter is a fast and easy medium for posting product reviews: a Tweet becomes immediately visible after posting. This is different from posting a product review on Amazon.com. There is a short delay between posting a product review and the time it appears online. Before a product review becomes visible online, Amazon.com screens a product review on inappropriate content (e.g. scandalous or insulting language use is prohibited). Although this difference is not immediately visible at the surface level, it is a major difference between the two sources. Screenshots of the surface level structures of Amazon.com and Twitter are attached in appendix II.

Although both sources differ from each other, they are similar in that the total quantity of product reviews is large on both source. Unfortunately, the exact number of product reviews on Amazon.com and on Twitter was not traceable online. Nevertheless, an illustration of the enormous number of product reviews on Amazon.com and Twitter can be given. Xie and Chen (2004) stated that Amazon.com has approximately ten million product reviews per product category. At this moment, Amazon.com has 16 product categories. The total amount of product reviews could be calculated by multiplying the ten million product reviews per category with the 16 product categories. This led to a total of 160 million product reviews. Because the research of Xie and Chen was conducted in 2004, the 160 million product reviews is an estimation. It is plausible that this number has grown in the past eight years. Jansen et al. (2009) stated that in approximately 19% of the Tweets a brand or product name is mentioned. Nearly 20% of these Tweets contain expressions or sentiments about these brands or products. Active Twitter users post approximately 340 million Tweets each day (Twittermania.nl, 2012). Considering the above mentioned facts, we could calculate and estimate the quantity of product reviews on Twitter. We took 19% of the 340 million Tweets, and calculated that 64.6 million Tweets mention a brand or product name. Of these 64.6 million Tweets, 20% contains an expression or sentiment about a brand or product. Thus, we can say that, each day, approximately 12.9 million product review are posted on Twitter.

4.1.3. Procedure

As explained in detail in the previous sections, seven characteristics were analyzed according to a set of predetermined criteria. A summary of the analyzed criteria, and the way the criteria were coded is attached in appendix III. In addition to these criteria, additional comments and remarkable differences were also observed. Moreover, this preliminary investigation served as an additional aid to design the main online questionnaire.

In total, 80 product reviews were selected for this analysis: 40 product reviews from Amazon.com, and 40 product reviews from Twitter. These 40 product reviews consisted of four electronic products per source. The product reviews were about cameras, tablets, TV's, and mobile phones. Thus, 10 product reviews about cameras, 10 product reviews about tablets, 10 product reviews about TV's, and 10 product reviews about mobile phones were collected. This led to a total of 40 product reviews from Amazon.com, and the exact same number of product reviews were collected from Twitter. Although 80 product reviews seems limited, the main purpose of this analysis was to gain some more understanding about the general differences in product review sources. The product reviews were selected without scanning the content beforehand. For Amazon.com the product reviews were selected by just taking the first one available for a particular product. For example, when selecting a product from Amazon.com, first the features, the price, and other information about the product were displayed. The overall product rating, visualized with stars, was also displayed. A small link, displaying the total amount of product reviews for that particular product, was displayed next to the overall product rating. This link directed to the product review page. On this page, the product reviews were ordered according to their perceived helpfulness score. It was also possible to view the newest product reviews, by selecting the option 'newest first'. We decided not to change anything, and selected the product reviews from the original product review page. From this page on, the first product review was selected. The main focus of the current study are negative product reviews. Therefore, we only selected one and two star product reviews.

This process was more difficult for Twitter, because the product reviews did not directly appear in the timeline. Therefore, the search function of Twitter was used to find product reviews. Search terms (e.g. camera fail, iPad, etc.) were used to find Tweets that expressed opinions or experiences with a product. After typing in a search term, many Tweets appeared, and the first Tweets that evaluated the product negatively were selected for this analysis. The product reviews were randomly selected, no selection was made concerning brand name. The reason for this was that there was no interest to identify the product review differences per brand, but product review differences per source.

After examining the general structures of Amazon.com and Twitter, the surface levels of the product reviews were compared with each other. Subsequently, the availability of the variables perceived usefulness, review valence, and comments and ratings could be analyzed. Then, the variables concerned with the content of the product reviews were also analyzed. The variables concerned with content were: message quality (readability tests and message quality), argumentation (quantity and quality), and reviewers' credibility (trust and expertise).

4.2. Results

In this section the results per variable are reported. Each section contains a summary of the main findings. For the variables review length, message quality, argumentation, and reviewers' credibility an overall summary of the descriptive statistics is provided.

Ratings and comments

Both Amazon.com and Twitter offer their users the option to comment to a message. However, the extent to add a comment differs. On Twitter, an individual can add a comment by placing an 'at sign' and the 'username' toward the messenger. It is the same as posting a Tweet, only the 'at sign' and 'username' have to be inserted. It is also possible to reply directly by clicking on the 'reply' button. On Amazon.com, users can use the 'add a comment' function to add a comment. The main difference is the maximum allowed number of characters, on Twitter users can only write a Tweet of 140 characters, while on Amazon.com the limit is 5.000 words.

On Twitter, users cannot place an overall product rating and it cannot be detected at the surface level. However, Twitter users used valence statements in their Tweets that indicated their attitude toward the product. Thus, indirect product ratings could be given in the text. The most commonly used valence statements will be discussed in the review valence part. Amazon.com does allow its users to detect the overall rating of the product at the surface level. Users who have written a product review give the product an overall score by assigning stars. As mentioned before, the most favorable product will receive five stars, while the least favorable product will receive one star. It is also possible to assign four, three and two stars.

Perceived usefulness

Amazon.com enables consumers to indicate the perceived usefulness of the product review. Consumers can indicate whether they found a product review helpful or not. Thus, the helpfulness score on Amazon.com is the same as the perceived usefulness score. For example, the helpfulness score is displayed above the actual product review as "*10 out of 40 people found the following review helpful*". Beneath the written product review, Amazon.com asks consumers to indicate whether they found a product review helpfulness or not: "*Help other customers find the most helpful reviews. Was this review helpful to you"* (answer possibilities: yes/ no).

Twitter, on the other hand, does not have such a function. The only possibility to indicate the usefulness of a Tweet (or product review) is to re-tweet, comment, mention the reviewer, or favorite the Tweet. Favoring a Tweet indicates that a user likes the Tweet and wants to follow more Tweets of the same person. Moreover, all these functions could be used to indicate some kind of agreement or disagreement with the Tweet.

Review valence

The main focus of this study are negative product reviews, therefore, all the reviews that have been collected for this analysis were negative. In order to detect the valence of a product review on Twitter, consumers have to read the content of the Tweet. There is no valence indication at the surface level of a Tweet, or in the timeline of Twitter. As already mentioned, the valence of a product review on Amazon.com is indeed visible at the surface level. Besides this, the product reviews can be categorized according to valence (or by the most recent reviews). Consumers can search through positive or negative product reviews and filter out the ones they want to read.

Although Twitter does not show the valence of the Tweet at the surface level, reviewers used valence statements that made clear whether they were satisfied or dissatisfied with a particular product. Additionally, some reviewers even used hash tag (#) signs to highlight their opinion. It was interesting to see that reviewers from both sources used many of the same valence statements. Some of the valence statements that frequently appeared were: *"disappointing", "fail", "not worth", "annoying", "frustrating", "bad", "poor", and "useless"*. A considerable amount of negative product reviews on Amazon.com also pointed out some positive features of a product. However, the negative features of a product dominated the content of the product review.

Review length

As expected, product reviews written on Amazon.com were significantly longer than product reviews written on Twitter. An independent t-test showed that there was a significant difference between the amount of words ($t(78)$=5.87, p=.000, ω=.295) and characters ($t(78)$=5.90, p=.000, ω=.297) of a product review on Amazon.com compared to Twitter. However, this result was not surprising given the restriction of 140 characters per Tweet. Product reviews on Amazon.com are limited to 5.000 words. A product review on Amazon.com had a mean of 399.10 (*SD*:407.32) words, and 2142.25 (*SD*:2167.59) characters, while a product review on Twitter had a mean of 21.05 (*SD*:4.28) words, and 120.88 (*SD:*23.51) characters. As the standard deviations show, the number of words and characters extremely varied per product review (table 1). The longest review on Amazon.com contained 2.404 words, and 12.563 characters, while the longest review on Twitter contained 28 words, and 140 characters. The shortest review on Amazon.com contained 54 words, and 272 characters, while the shortest product review on Twitter contained 10 words, and 28 characters.

Amazon.com enables consumers to write an extensive product review with a high number of supporting arguments. Kendall's tau correlation test showed a positive relationship between the number of words (τ=.47, p=.000) and characters (τ=.46, p=.000), and the message quality on Amazon.com.

Table 1.

Descriptive statistics of the variable review length.

Review length		*Words*		*Characters*	
Source	Product	M	SD	M	SD
Amazon.com	Camera	291.00	168.28	1576.00	927.73
	Tablet	417.60	336.17	2284.90	1889.65
	TV	575.50	677.05	3050.20	3548.75
	Mobile Phone	312.30	250.81	1657.90	1335.99
	Total:	399.10	407.32	2142.25	2167.89
Twitter	Camera	21.20	3.80	122.40	22.04
	Tablet	21.00	5.16	116.80	28.96
	TV	21.00	5.56	121.30	27.84
	Mobile Phone	21.00	2.75	123.00	18.06
	Total:	21.05	4.28	120.88	23.51

There were no significant correlations between the amount of words (τ=-.02, p=.871) and characters (τ=.06, p=.666), and the message quality for Twitter product reviews. Specifying this more, an one-way ANOVA showed that there was only a significant difference between the number of characters and the message quality of product reviews on Amazon.com (F(3,36)=2.89, p=.049, r=.19). A post-hoc test (bonferroni) revealed that a best review (from the SPEC framework) (M:4059.00, SD:1559.02) had significantly more characters than a bad review (M:1097.67, SD:827.04) (p=.036).

The same results were found for the relationship between argumentation quality, and the number of words (τ=.52, p=.000), and characters (τ=.51, p=.000) of a product review on Amazon.com. Again, no relationship was found between the argumentation quality, and the number of words (τ=-.03, p=.849), and characters (τ=.05, p=.683) of product reviews on Twitter. An one-way ANOVA only showed significant differences between the number of words (F(2,37)=5.88, p=.006, r=.24) and the number of characters (F(2,37)=6.32, p=.049, r=.25) on the argumentation quality for Amazon.com. Furthermore, a post-hoc test (bonferroni) showed significantly that strong product reviews had more characters (p=.005) (M:3571.71, SD:3053.84) and words (p=.007) (M:660.21, SD:579.502), than weak product reviews (words; M:199.23, SD:151.01, characters; M:1051.77, SD:804.73).

Message quality

First, the readability of the product reviews were analyzed according the Flesch-Kincaid formula (table 2). The most complex product review on Amazon.com had a Flesch-Kincaid score of 11.60.

This score did not differ much from the most complex product review on Twitter, which had a score of 10.60. Furthermore, at least a 4th grade student (score: 4.10) is able to read the simplest review on Amazon.com, and a 2nd grade student (score: 2.40) is able to read the simplest review on Twitter. The average readability score for Amazon.com was 7.72 (SD:1.96), against the average score of 5.51 (SD:1.90) for Twitter. An independent t-test showed that this difference was significant ($t(78)=5.13$, $p=.000$, $\omega=.239$), suggesting the that product reviews on Twitter are less complex than product reviews on Amazon.com. Product reviews on Amazon.com are longer, and thus could consists of more complex sentences and words. Pearson product-moment correlation coefficients did not show a significant relationship between the number of words ($r=.07$, $p=.663$), characters ($r=.09$, $p=.592$), and the readability score of product reviews on Amazon.com. This relationship between the number of words ($r=-.11$, $p=.518$), characters ($r=.06$, $p=.708$), and the readability score was also not significant for product reviews on Twitter.

Second, the message quality of the product reviews was analyzed according the SPEC framework (Liu et al., 2007). The analyzed product reviews were assigned a score from 1 to 4 according to their message quality (1= best review, 2= good review, 3= fair review, 4= bad review) (table 2). Most product reviews on Amzon.com were fair product reviews (35%), and more than half of the product reviews on Twitter were bad reviews (58%). Cross tables showed that the message quality of the product reviews significantly differed between Amazon.com and Twitter ($\chi^2(3)=13.09$, $p=.003$).

Table 2.

Descriptive statistics of the Flesch-Kincaid readability test, and the frequencies (Freq.) and percentages (%) of the message quality.

	Flesch-Kincaid readability score			*Message quality*		
Source	Product	M	SD	Type	Freq.	%
Amazon.com	Camera	7.80	2.03	Best review	6	15
	Tablet	8.73	2.17	Good review	8	20
	TV	7.92	1.74	Fair review	14	35
	Mobile Phone	6.41	1.30	Bad review	12	30
	Total:	7.72	1.96	Total:	40	100
Twitter	Camera	6.46	1.41	Best review	0	0
	Tablet	5.56	1.57	Good review	2	5
	TV	4.82	2.24	Fair review	15	37.5
	Mobile Phone	5.19	2.24	Bad review	23	57.5
	Total:	5.51	1.90	Total:	40	100

This suggests that there were significantly more best (15%) and good (20%) product reviews on Amazon.com, than best (0%) and good (5%) product reviews on Twitter. However, both Amazon.com (65%) and Twitter (85%) had more bad and fair product reviews than best and good product reviews.

As the scores indicate, product reviews on Amazon.com were more complex, but they contained a detailed product evaluation. On Amazon.com consumers have the space to write extensive product reviews with supporting evidence, which is not possible on Twitter. The product reviews written on Twitter were mostly useless reviews which did not evaluate specific product features. These product reviews were more general opinions about, or experiences with a product. An example of a bad review on Twitter*: "Do not buy Panasonic plasma TV. Unless you want severe headaches & stress".* Nevertheless, there were product reviews that took features about the product into account: *"After 12hrs trialing the #GalaxyS3 am back on #iPhone. Nice screen, light. Lack of apps: "Tweetbot, Nike Fuelband, Movescout, WSJ, Bloomberg".*

Argumentation

Argumentation was analyzed according to quantity and quality (table 3). The argumentation quantity and argumentation quality of product reviews on Amazon.com have a significant positive relation (τ=.57, p=.000), this relationship was not significant for product reviews on Twitter (τ=-.12, p=.43).

Table 3.

Descriptive statistics of argument quantity, and the frequencies (Freq.) and percentages (%) of the argument quality.

Argumentation	Quantity			Quality		
Source		M	SD		Freq.	%
Amazon.com	Camera	6.70	4.47	Strong	14	35
	Tablet	9.30	7.48	Mediocre	13	32,5
	TV	9.40	7.41	Weak	13	32,5
	Mobile Phone	5.60	4.55	Total	40	100
	Total:	7.75	6.15			
Twitter	Camera	1.20	0.42	Strong	1	2.5
	Tablet	1.30	0.48	Mediocre	16	40
	TV	1.40	0.52	Weak	23	57.5
	Mobile Phone	1.60	0.67	Total	40	100
	Total:	1.38	0.54			

First, argumentation quantity was analyzed by counting the number of arguments. As expected, an independent t-test showed that product reviews on Amazon.com significantly contained more arguments (*M*:7.77, *SD*:6.15), than product reviews on Twitter (*M*:1.38, *SD*:0.54), ($t(78)=6.53$, $p=.000$, $\omega=.343$). This was not surprising due to the restriction of 140 characters for a Tweet; there is not much space to write a review with many arguments. Although the differences are high, product reviews on Twitter can contain some arguments, and one product review on Amazon.com also contained just one argument. Nevertheless, the difference between the product review with the most arguments (27) on Amazon.com, and the product review with the most arguments on Twitter (3) was quite large.

Second, the argumentation quality was analyzed. Not surprising, the argumentation quality was related to the message quality on both Amazon.com ($\tau=.76$, $p=.000$) and on Twitter ($\tau=.78$, $p=.000$). On Amazon.com most product reviews had strong argumentation (35%), while only 2.5% of the product reviews on Twitter had strong argumentation. The majority of the product reviews on Twitter consisted of weak argumentation (57.5%), and on Amazon.com 32.5% of the product reviews consisted of weak argumentation. Cross tables confirmed the differences in argumentation quality between Amazon.com and Twitter ($\chi^2(2)=14.36$, $p=.001$). Indeed, looking at the product reviews on Twitter, most contained weak, irrelevant and subjective argumentation. This review, for example, was considered as weak: "*Kindle: The most useless fucking device I have ever encountered. Worst user interface. Who doesn't automatically sort by Author? Fucks*".

Reviewers' credibility

This variable was analyzed according to two criteria; trust and expertise (table 4). First, the trustworthiness of the reviewer. Amazon.com has a reviewers ranking, which indicates the rank of the reviewer. This rank is determined by the overall helpfulness score of all product reviews written by that person and the total number of product reviews written. Additionally, reviewers can earn a special reviewers rank. If a reviewer has a rank better than 1000, the reviewer will receive a 'top reviewers badge'. There are six badges that can be earned: Top 1000 Reviewer, Top 500 Reviewer, Top 100 Reviewer, Top 50 Reviewer, Top 10 Reviewer, and #1 Reviewer. Twitter does not has such a reviewer's ranking.

Furthermore, trust can be gained by the amount of personal information a reviewer has added to his or hers profile. On Amazon.com this was information such as; profile picture, location, birthday, personal interests, and a link to the personal website. Examples of personal information on Twitter: real profile picture (some used an image), personal website (also LinkedIn, and Facebook were used), location, personal interests, and a link to the personal website. Conversely, using an alias or a fake profile picture can lead to less trust. In order to get an impression of the amount of personal information on Amazon.com and on Twitter, the personal information was counted and assigned to one of the three personal information categories (1= no, 2= few, 3= much). The indication of name and profile picture was analyzed separately. The majority of reviewers on Amazon.com indicated no personal information (57.5%), while the majority of the reviewers on Twitter indicated much personal information (65%). Cross tables showed that the amount of personal information significantly differed between Amazon.com and Twitter ($\chi^2(2)=21.92$, $p=.000$).

Amazon.com assigns special name badges to its users. An example of a name badge that can gain trust, is the 'real name' badge. The real name badge indicates that the reviewer uses its real name (credit card name). Some users posted anonymous product reviews with an alias, Amazon.com calls these users 'pen name reviewers'. Twitter does not have such a system. However, with registration users have to fill in a username; this could then be a real name or a pen name. From the product reviews collected from Amazon.com, 50% used a real name (surname and last name needed to be displayed), while on Twitter 87.5% used their real name. Cross tables showed that this difference was significant ($\chi^2(1)=13.09$, $p=.001$).

Furthermore, 92.5% of the reviewers on Amazon.com displayed no profile picture, while 30% of the reviewers on Twitter displayed no profile picture. Thus, the majority of reviewers on Twitter displayed a profile picture (70%), while this was the minority on Amazon.com (7.5%). Again, cross tables showed that these differences were significant ($\chi^2(1)=32.92$, $p=.000$). The profile picture was analyzed in terms that the picture needed to be of a real person, assumable the reviewer (not of child, pet, celebrity, or an image).

Secondly, expertise was analyzed by the possibility to add expertise claims that indicate expertise with the product. Results showed that both sources can contain expertise claims in the content of the product reviews, but also in the personal information (e.g. interests, profession) part. More specifically, 22.5% of the reviews on Amazon.com claimed expertise. An example of this was: "*Being a professional DP […], use other Panasonic products professionally […]*". Additionally, 27.5% of the product reviews on Twitter claimed expertise in some way. For example expertise on Twitter could be detected by reading other Tweets from that user's timeline (more Tweets from the same field of expertise), or by the profession of a user. Cross tables showed that these differences between Amazon.com and Twitter were not significant ($\chi^2(1)=0.27$, $p=.797$).

Table 4.

Frequencies (Freq.) and percentages (%) of the reviewers' credibility.

Reviewers' credibility		*Trust*			*Expertise claims*		
Source			Freq.	%		Freq.	%
Amazon.com	*Name*	Real-name	20	50	Yes	9	22.5
		Pen-name	20	50	No	31	77.5
		Total:	40	100	Total	40	100
	Personal information	Many	6	15			
		Few	11	27.5			
		No	23	57.5			
		Total	40	100			
	Profile picture	Yes	3	7.5			
		No	37	92.5			
		Total:	40	100			
Twitter	*Name*	Real-name	35	87.5	Yes	11	27.5
		Pen-name	5	12.5	No	29	72.5
		Total:	40	100	Total	40	100
	Personal information	Much	26	65			
		Few	7	17.5			
		No	7	17.5			
		Total	40	100			
	Profile picture	Yes	28	70			
		No	12	30			
		Total:	40	100			

5. Study 2: Online questionnaire

5.1. Methods

5.1.1. Design

In this study a 2 x 2 factorial experimental design was employed to test the proposed hypotheses. The two independent variables are the source of the product review (Amazon.com/ Twitter), and the message quality of the product review (high/low). Furthermore, the dependent variables in this design are the credibility of the product review, the attitude toward product, and the purchase intention. The expectation was that the source of the product review, and the quality of the product review would influence the perceived credibility of the product review, the attitude toward the product, and the likelihood to purchase the product. The main purpose of this online questionnaire was to analyze negative product-related reviews from the perspective of the consumer (reader of the review).

The study employed a between-subject experimental design, wherein participants were either exposed to product reviews on Amazon.com, or to product reviews on Twitter. There were two reasons for choosing a between-subject experimental design. First, a between-subject experimental design avoided the confounding effect of participants noticing the true meaning behind the experiment. Second, the influence of product reviews between the two sources could be analyzed independently of each other. Thus, the experimental design consisted of two conditions. In the first condition, participants were exposed to negative product reviews on Amazon.com, while the participants in the second condition were exposed to negative product reviews (Tweets) on Twitter. In each condition, participants were exposed to four different product reviews. These product reviews were manipulated in terms of message quality and product type. As the message quality was the second independent variable, we incorporated this variable within the two conditions. Meaning that both conditions contained low and high quality product reviews.

5.1.2. Stimuli

The impact of negative product reviews was examined by exposing the participants to product reviews on either Amazon.com, or on Twitter. In order to keep consistency between the two studies, Amazon.com was again used for this study. The message manipulations were designed regarding the selected product reviews from the first study. Furthermore, the same electronic products as in the preliminary investigation were used to develop the manipulations for the online questionnaire. The product reviews used in the preliminary investigation contained brand names, but these were excluded in the manipulations for the current questionnaire. The main reason for this was that it could lead to a confounding effect. It can lead to biased results when participants have a preference for a particular brand beforehand. The effect of the message was essential in this study and not the brand name associated with the reviewed product. Thus, the product reviews did not include brand names to avoid any brand effect. The brand names were replaced by just mentioning the product name (e.g. tablet instead of iPad). This was in line with previous research concerned with the effectiveness of product reviews (Lee et al., 2007).

At first, participants would be exposed to eight different product reviews. However, after pre-testing the length and the time it took to complete the questionnaire, two products were excluded from the questionnaire. Filling out the questionnaire completely took too long, and this could have led to biased results (e.g. uncompleted and less accurate completed surveys). Therefore, the product reviews about a mobile phone and a TV were excluded from the questionnaire. Only product reviews about a camera and a tablet were included in the final questionnaire. The reason for excluding the mobile phone and the TV were that a mobile phone is mostly not purchased (people subscribe for a subscription), and a TV is compared to a tablet a relatively old, less new product. A tablet is a very popular device at the moment. Moreover, a tablet and a camera are products that consumers most likely want to research prior to a purchase. The messages differed on two points: message quality (high/low) and type of product (camera/tablet). To create a realistic situation, the scenarios were identical in terms of look and feel of how a real product review on Amazon.com and Twitter would look like. The message manipulations are attached in appendix IV.

Source/medium

As already mentioned before, the study consisted of two experimental conditions. The first experimental condition contained negative product-related reviews on Amazon.com. As in the preliminary analysis, Amazon.com was used as product review website. The second product review source was Twitter. Participants in the second condition were exposed to negative product-related reviews on a Twitter. Both manipulations were developed by copying the exact template and lay-out of the Amazon.com website and of a Tweet. Important characteristics identified in the first study were used to design the manipulations. This was important to create realistic replications of the two sources.

Amazon.com displays an overall assessment of the product via a rating system. All product reviews in the current study were negative evaluations of a product, therefore, all products were rated with one star. This indicated that the reviewer was extremely negative toward the product (Mudambi & Schuff, 2010). Moreover, it served as an additional aid to amplify the negative nature of the product review. Although two star ratings are also negative, those were not included in the design to avoid confusion amongst the participants, and to avoid participants perceiving the review as less negative than intended.

Similar to the ratings, the perceived usefulness often appears at the surface level of product reviews. On Amazon.com this is called the perceived helpfulness score and is displayed at the surface level as: "105 out of 230 people found this review helpful". It has proven to be an important characteristic of a product review and predictor of a consumer's willingness to comply with the message. At the bottom of a product review consumers are asked to indicate the helpfulness of the product review with a 'yes' or 'no'. Therefore, the perceived helpfulness score of Amazon.com was also included in the design.

The main manipulations in the Twitter condition were the personal information (e.g. profile picture, real name and username), and the ability to re-tweet, reply, and favorite the Tweet. Both Amazon.com and Twitter display the real name or username of the reviewer. Personal information can be an indicator of trust (Chueng et al., 2009), and the preliminary analysis showed that most reviewers wrote reviews with their real name (surname and last name). Therefore, (fictitious) real names were displayed at the surface levels of the manipulations. Fictitious names were invented for privacy reasons, and to prevent participants from being familiar with the reviewer. The 'comment' functions (for Twitter 'reply@') were also included in the designs.

Message quality

Within each condition participants were exposed to one high and one low quality product review per product. Two products were used for this study: a camera and a tablet. Thus, in each condition participants were asked to read four product reviews. The product reviews in the preliminary investigation were separately analyzed according their message quality and their argumentation. In this study, the message quality and the argumentation were taken together to develop the low quality and high quality product reviews. Furthermore, the product reviews from the preliminary investigation were used as a reference to develop the message manipulations for the online questionnaire. The low quality messages contained elements from the SPEC framework's 'bad' reviews, which did not evaluate specific product features (Liu et al., 2007). The arguments were weak (quantitative and qualitative), and consisted of subjective and emotional statements, without useful information (Lee et al., 2007; 2008). The high quality messages contained elements from the SPEC framework's 'best' and 'good' reviews. These messages were rather complex and contained detailed product evaluations (Liu et al., 2007). The arguments of these high quality messages were strong with clear, specific, and understandable arguments which were backed-up with sufficient reasoning (Lee et al., 2007; 2008).

Although the perceived usefulness is not a sufficient indicator of the message quality (Liu et al., 2007), it was used as an additional aid in the Amazon.com condition, to distinguish the high quality messages from the low quality messages. For example, a low quality product review contained *'30 of 110 people found the following review helpful'*, while a high quality product review contained *'140 of 160 people found the following review helpful'.* Lastly, the readability of the message manipulations were tested with the Flesh-Kincaid formula (Kincaid et al., 1975). Accordingly, the readability scores of the high and low quality messages varied from a 4.9 to 7.4 minimal age group to comprehend the message (table 5 shows a complete overview of the Flesh-Kincaid scores).

5.1.3. Procedure

The questionnaires were distributed between the 19th of June and the 6th of July 2012. There were no restrictions that prohibited anyone to participate. Participants were primarily gathered by Email, Facebook, Twitter, and LinkedIn. An email message with a request for filling out the questionnaire was sent to a large number of family members, friends, and relatives. The same sort of request was posted on the Tilburg University's Communication and Information Sciences Facebook page. Private Facebook friends were also asked to fill out the questionnaire. An additional Tweet was posted on Twitter to request followers to fill out the questionnaire. Furthermore, a direct Tweet (with an at sign mentioning a name) was also sent to social media and marketing professionals, and to websites/forums that have a Twitter account (e.g. @Frankwatching, @OMNlinkedin, @Marketingfacts) with the same request.

Table 5.

Message quality of the review manipulations in term of the Flesh-Kincaid grade level (readability of the messages).

	Source	Message quality	Product	Words	Characters	Flesh-Kincaid grade level
1	Amazonz.com	Low quality	Camera	180	956	5.7
2	Amazon.com	Low quality	Tablet	152	817	6.8
3	Amazonz.com	High quality	Camera	206	1102	6.7
4	Amazon.com	High quality	Tablet	226	1215	5.9
1	Twitter	Low quality	Camera	17	91	4.9
2	Twitter	Low quality	Tablet	21	117	5.6
3	Twitter	High quality	Camera	23	139	7.4
4	Twitter	High quality	Tablet	22	135	5.4

An example of a request on Twitter: "*Innovative research on the impact of online reviews by a master student Communication Sciences. Pls help me graduate. http://bit.ly/Lx8UQX RT*". Lastly, people were requested to fill out the questionnaire via special social media and online marketing groups on LinkedIn.

Approximately a week later, a reminder was sent via the same channels to the same people and groups. All requests contained a link to the questionnaire, which automatically assigned the participants at random to one of the eight questionnaire versions. More specifically, per condition four different questionnaire versions were developed. Per version, the sequence of the product reviews was randomly ordered. Thus, not all participants were exposed to the same order of product reviews: see table 6 for the eight versions of the questionnaire. Via an account obtained from the University's Dcilab, the online questionnaires were developed via the tool Lime Survey. Via Lime Survey a questionnaire in the style and layout of Tilburg University could be developed. The Dcilab provided the possibility to distribute the different questionnaire versions at random. The complete questionnaire is attached in appendix IV.

The first part of the questionnaire presented an introduction about the investigation to the participants. The actual questionnaire consisted of four parts; general information, product reviews, general attitude toward product reviews and electronics, demographics, and an ending wherein participants were thanked for their participation.

Table 6.

Different versions of the questionnaire; divided in terms of message quality (MQ) and product (P).

Amazon.com							
Version 1		*Version 2*		*Version 3*		*Version 4*	
MQ	P	MQ	P	MQ	P	MQ	P
Low	Camera	High	Tablet	High	Camera	Low	Tablet
High	Tablet	Low	Camera	Low	Tablet	High	Camera
High	Camera	Low	Tablet	High	Tablet	Low	Camera
Low	Tablet	High	Camera	Low	Camera	High	Tablet
Twitter							
Version 1		*Version 2*		*Version 3*		*Version 4*	
MQ	P	MQ	P	MQ	P	MQ	P
Low	Camera	High	Tablet	High	Camera	Low	Tablet
High	Tablet	Low	Camera	Low	Tablet	High	Camera
High	Camera	Low	Tablet	High	Tablet	Low	Camera
Low	Tablet	High	Camera	Low	Camera	High	Tablet

Each condition contained the same set of questions, only in one condition the questions were pointed at Amazon.com and in the other condition the questions were pointed at Twitter. In the general information part, participants were asked whether they ever visited a product review website, and if they were familiar with either Amazon.com or Twitter. If the answer was no, a short introduction was shown; if the answer was yes, two questions about usage characteristics followed. In part two, participants were explained that they were about to see a couple of product reviews, and were asked to answer the accompanied questions after each review. The accompanied six items measured the credibility of the product review, the attitude toward product, and the likelihood to purchase the product after reading the product review. Part three consisted of eight items that served as control measurements. These items measured the participants' general attitude toward product reviews, the general attitude toward information on Amazon.com or Twitter (depending on the condition), and the product involvement. Lastly, questions about gender, age, and education were asked. After that, participants were thanked for their participation.

5.1.4. Participants

The questionnaire was available online from the 19th of June to the 6th of July. This resulted at first in 146 participants. However, 40 participants did not complete the entire questionnaire and thus were excluded from the analysis. It resulted in 106 participants that filled out the complete questionnaire. In total, 45 (42.5%) female and 61 (57.5%) men, with an average age of 31.57 (*SD:* 11.85) participated. The youngest participant was 20 years old and the oldest participant was 68 years old. More than half of the participants were highly educated (76.4%), from these participants 36.8% were currently studying or completed higher education (e.g. HBO), and 39.5% were currently studying or completed university education (bachelor or master).

At random, participants were assigned to either the Amazon.com condition or the Twitter condition. This random distribution resulted in 51 participants in the Amazon.com condition, and 55 participants in the Twitter condition. The ages of the participants ranged from 22 to 59 years old (M:32.92, SD:11.81) in the Amazon.com condition, and from 20 to 68 years old (M:30.31, SD:11.85) in the Twitter condition. There were no significant age differences between the two experimental conditions ($t(104)=1.14$, $p=.259$). The Amazon.com group consisted of 20 (39%) female, and 31 (61%) male participants and the Twitter group consisted of 25 (45%) female, and 30 (55%) male participants. There were no significant gender differences between the two conditions ($X^2(1)=0.42$, $p=.516$). Although the majority of participants in both conditions were highly educated, the participants in the Twitter condition were slightly higher educated than those in the Amazon.com condition (Amazon.com: 75%, Twitter: 79%). There were no significant differences (two-sided Fisher's Exact Test, p=.369) detected in the level of education between the two conditions.

The participants were first asked if they ever visited a product review website, 85.8% reported that they did. This percentage was also high per condition, 90% in the Amazon.com condition and 82% in the Twitter condition. More than half of the participants (65%) in the Amazon.com condition reported to be familiar with the product review website. The same counts for the participants in the Twitter condition, the majority of these participants (84%) reported to be familiar with Twitter. Nevertheless, from the participants that reported to be familiar with Amazon.com (N=33), 64% reported to visit the website 'less than once a month'. Subsequently, 56% reported that they have 'ever visited Amazon.com for product reviews' (N=15) (Note that the participants that reported to 'never' visit Amazon.com were excluded from this question, and were not calculated). In the Twitter condition only 26% of the participants, that reported to be familiar with Twitter (N=46), reported to use Twitter 'once or more than once a day'. Furthermore, a very small percentage of 6% reported to have 'ever visit Twitter for product reviews' (N=2) (note that the participants that reported to 'never' visit Twitter were excluded from this question, and were not calculated). The detailed characteristics of the participants is attached in appendix V.

3.1.5. Measurements

The three dependent variables assessed in this study were: the credibility of the product review, the attitude toward the product, and the likelihood to purchase the product after reading the product review. Participants were exposed to these measurement items after each review.

Credibility

The perceived credibility of the information in the product review was measured with three items. These items were obtained from the study of Cheung et al. (2009). Participants were asked to indicate their agreement, on a 7-point Likert scale, with the following statements: *"I think this review is factual"*, *"I think this review is accurate"*, and *"I think this review is credible"*.

Attitude toward product

After being exposed to a product review, participants were asked to indicate their overall feeling toward the product. The items were obtained from the marketing scales handbook (Bruner, 2009), and were compiled from previous studies (e.g. Baker, Honea, & Russell, 2004; Tybout, Sternthal, Malaviya, Bakamitsos & Park, 2005) to a set of two statements: *"I am negative/ positive toward the [product name]"*, and *"I think the [product name] is of low/high quality"*.

Answers were given on a 7-point Likert scale with bipolar anchors ("negative" to "positive, and "low" to "high" quality).

Purchase intention

The likelihood to purchase the product after reading the product review was measured with one item: *"Assuming you are interested in [product name], would you be less or more likely to purchase the product?"*. Answers were given on a 7-point Likert scale that was scaled from "less likely" to "more likely". The item was obtained from the study of Kozup, Creyer, and Burton (2003).

5.1.6. Control measurements

In order to control for individual differences that could affect the impact of negative product reviews on the consumer, three control measures were added at the end of the questionnaire. The control variables used in this study were: general attitude toward product reviews, general attitude toward information on Amazon.com or Twitter, and product involvement.

General attitude toward online product reviews

The individual attitude toward EWOM and online product reviews could be of influence on the impact of these negative product reviews. Four items were used to measure these individual differences. Participants were asked to indicate their agreement, on a 7-point Likert scale, with the following statements: *"When I buy a product online, I always read reviews that are presented on the web"*, *"When I buy a product online, the reviews presented on the web are helpful for my decision making"*, *"When I buy a product online, the reviews presented on the web make me confident in purchasing the product"*, and *"If I don't read the reviews presented on the web when I buy a product online, I worry about my decision"*. The items were obtained from the studies of Lee et al. (2007), Park and Kim (2008), and from Park and Lee (2009).

General attitude toward product review source

People that are unwilling toward information on Amazon.com or on Twitter may not be easy to manipulate by exposing them to a negative (or positive) product review. This was checked by two items, obtained from the study of Lee et al. (2007). Participants were asked to rate, on a 7-point Likert scale, whether they disagreed or agreed with the following two statements: *"In general I believe the information I read on Amazon.com/ Twitter"*, and *"In general I think product reviews on Amazon.com/ Twitter are helpful"*.

Product involvement

The product categories in this study were electronic products. The extent to which people are involved with these products could be of influence on how people perceived the message manipulations in this study. Therefore, the participants' involvement with electronic products was measured with two items, on a 7-point Likert scale, taken from the study of Zaichkowsky (1985). Participants were asked to indicate their agreement with the following statements: *"I usually take many factors into account before purchasing electronic products"*, and *"I usually spend a lot of time choosing what kind of electronic products to buy".*

5.2. Results

5.2.1. Data preparation and analysis

Before hypotheses testing, the data needed to be prepared. First, new variables of the means of individual items were computed to one variable. Second, analyses were conducted to detect possible outliers that could influence the results (e.g. including analyses of the z-scores, Q-Q plots, histograms, and box plots). Although there were some outliers, and not all data was normally distributed, there was no valid reason to the delete these cases. Moreover, the answers of these cases were double checked on extreme deviations from other answers. The deviations were not caused by serious answer mistakes of participants, by provable differences in the answer pattern, or by cases that did not belong to the intended population of investigation. Therefore, it was decided to leave the outlier cases in the data set. Third, the normal distribution of the data was tested. The Kolmogorov-Smirnov test showed that the dependent variables (credibility and attitude toward product) were normally distributed (table 7), and the 5% trimmed means were not extremely different from the mean scores. Fourth, homogeneity of variance tests were conducted and proved to be significant for the dependent variables (table 8). Important to note is that the data was split to analyze the data per condition, which resulted in a relatively low N per condition (Amazon.com N=51, Twitter N=55). Fifth, the scales were checked on their internal reliability by using Cronbach's Alpha. Although all scales proved to be reliable, one item from the 'general attitude toward product reviews' scale was removed for a better Cronbach's Alpha (table 9). Sixth, independent t-tests and cross tables already indicated that there were no significant age, gender, and educational differences between groups (see section 3.2.4. participants). A seventh analysis of covariance was conducted to measure whether the control variables were of influence on the dependent variables. Lastly, independent t-tests and a mixed ANOVA were used to test the proposed hypotheses.

Table 7.

Scores of the Kolmogorov-Smirnov normal distribution for the dependent variables: credibility, attitude toward product, and purchase intention.

	Statistic	df	*p*
Amazon.com			
Credibility	0.83	51	.200
Attitude toward product	0.11	51	.095
Purchase intention	0.13	51	.038*
Twitter			
Credibility	0.9	55	.200
Attitude toward product	0.9	55	.200
Purchase intention	0.12	55	.037*

Note: * p <.05

Table 8.

Scores of Levene's test of homogeneity of variance for the dependent variables: credibility, attitude toward product, and purchase intention.

	Statistic	df 1, df 2	*p*
Credibility	2.84	1, 104	.095
Attitude toward product	2.53	1, 104	.115
Purchase intention	0.28	1, 104	.599

Table 9.

Scale reliability

Scale name	Cronbach's Alpha (α)	Number of items	Deleted items
Credibility	.860	3	0
Attitude toward product	.889	2	0
Purchase intention	-	1	-
General attitude toward product reviews	.837	4	1
Attitude toward product review source	.856	2	0
Product involvement	.919	2	0

Note: Cronbach's Alpha (α) was not calculated for the measurement of purchase intention, because it consisted of only one item.

5.2.2. Participants and product review usage characteristics

More than half of the participants reported that they had visited a product review website before (85.8%). Participants reported a positive attitude toward product reviews (*M*:5.19, *SD*:1.08). An independent t-test proved that participants who had visited a product review website before (*M*:5.37, *SD*:1.03) were more positive toward online product reviews than participants that did not (*M*:4.67, *SD*:1.21, $t(104)=2.06$, $p=.042$, $\omega=.030$).

Furthermore, independent t-tests showed there were no significant differences between familiarity with the source and the general attitude toward the source. Participants that reported to be familiar with Amazon.com (*M*:4.50, *SD*:1.01) did not have a significantly different attitude toward product reviews on Amazon.com than non-familiar participants (*M*:4.06, *SD*:1.07, $t(49)=1.47$, $p=.147$). The same was detected in the Twitter condition ($t(53)=-1.09$, $p=.280$). Non-familiar (*M*:3.78, *SD*:1.50) participants did not have a significantly different attitude toward product reviews than familiar participants (*M*:3.25, *SD*:1.29).

Pearson product-moment correlation coefficient was used to investigate whether high frequencies of visiting Amazon.com or Twitter, was associated with a higher attitude toward the source. The results showed that there is a very small positive relationship between frequencies of visiting and the attitude toward Amazon.com. However, this relationship was not signification ($r=.08$, $p=.657$). Contrary, high frequencies of visiting Twitter was significant related to a higher attitude toward Twitter: there was a medium to large positive effect ($r=.44$, $p=.002$).

Participants that reported to visit Amazon.com for product reviews (N=15) were slightly more positive toward product reviews on Amazon.com (*M*:4.86, *SD*:0.87), than the ones that did not (N=11) visit Amazon.com for product reviews (*M*:4.29, *SD*:1.01). An independent t-test showed, as expected, that these differences were not significant ($t(23)=1.51$, $p=.146$). Additionally, the few participants that reported to visit Twitter for product reviews (N=2) were positive toward Twitter (*M*:5.00, *SD*:0.00) while the participants that did not visit Twitter for product reviews (N=33) were less positive toward the information on Twitter (*M*:3.54, *SD*:1.23). However, these differences were also not significant ($t(33)=1.65$, $p=1.08$).

5.2.3. Control variables

All control variables were tested on differences between the two conditions and on a correlational relationship between the dependent variables. These correlations were further investigated by an analysis of covariance, to investigate the possible influence of the control variables on the dependent variables.

General attitude toward online product reviews

The general attitude toward product reviews was initially assessed by four items, but after the reliability analysis, one item was deleted. A one-sample t-test showed that the participants were generally positive toward product reviews (test value=3.5; M:5.19, SD:1.08, $t(105)=16.16$, $p=.000$). There was a high effect-consistency of 93.4%. An independent t-test showed that there were no significant differences in attitude toward product reviews between the two conditions (Amazon.com: M:5.20, SD:0.90, Twitter; M:5.18, SD:1.22, $t(104)=5.01$, $p=.946$).

General attitude toward product review source

Participants were asked to indicate their agreement with two items that measured their general attitude toward information on either Amazon.com or on Twitter. An one-sample t-test (test value=3.5) showed that participants were generally positive toward, and think product reviews on Amazon.com are helpful (M:4.34, SD:1.04, $t(50)=5.78$, $p=.000$). The effect-consistency of 80.4% indicated that a high number of participants were positive toward product reviews on Amazon.com. With a mean score of 3.34 (SD:1.33) participants in the Twitter condition seemed slightly negative. However, this mean score was not significant ($t(54)=-0.91$, $p=.366$). Furthermore, there was a significant difference between the attitude toward product reviews on Amazon.com and the attitude toward product reviews on Twitter ($t(104)=4.32$, $p=.000$, $\omega=.143$).

Product involvement

As electronic products were used in the message manipulations, two items measured whether participants were involved with electronics. An one-sample t-test (test value=3.5) showed that participants were highly involved with electronics (M:5.11, SD:1.39, $t(105)=11.95$, $p=.000$). 86.4% (effect-consistency) of the participants indicated to be highly involved with electronic products. Additionally, an independent t-test indicated that there were no differences in product involvement between the participants that were in the Amazon.com (M:5.21, SD:1.26) condition and the ones that were in the Twitter condition (M:5.02, SD:1.50, $t(104)=0.70$, $p=.488$).

Correlations and covariance analysis

Before the hypotheses testing, an one-way analysis of covariance (ANCOVA) was conducted to control for other variables that could influence the dependent variables. The control variables (and frequency of visiting) were, independently of each other, analyzed on covariance with the dependent variables. Thus, the analysis consisted of four covariates. First, the correlations amongst the control variables and frequency of visiting were determined. Results showed that the highest correlation was $r=.65$, and existed between general attitude toward product reviews and product involvement in the Twitter condition (see appendix VI for a complete overview of the correlation coefficients).

The assumptions of a one-way ANCOVA were tested beforehand, and after this the ANCOVE analysis could be conducted. The ANCOVA results indicated that three covariates significantly predicted the dependent variable credibility. These covariates were general attitude toward product reviews ($F(1,103)=5.01$, $p=.017$, $r=.22$), general attitude toward product review source ($F(1,103)=27.51$, $p=.000$, $r=.46$), and product involvement ($F(1,103)=5.93$,$p=.017$, $r=.71$). Consequently, these covariates needed to be taken into account when interpreting the results of the tested hypotheses.

5.2.4. Dependent variables

Participants were exposed to negative product-related reviews from either Amazon.com or from Twitter (Tweet). Immediately after being exposed, participants had to answer questions regarding the credibility of the message, the attitude toward the product, and their purchase intention after reading the product review.

Credibility

An one-sample t-test showed that the participants judged the credibility of the message slightly above the average test value of 3.5 (Amazon.com; M:3.74, SD: 0.76, Twitter; M:3.58, SD:0.95). However, only the scores of Amazon.com were significantly above the test value ($t(50)=2.24$, $p=.030$) and had an effect-consistency score of 60.8%. The scores of Twitter were not significant ($t(54)=0.59$, $p=.593$).

Attitude toward product

An one sample t-test showed that the attitude toward the product was below the average test value of 3.5 for product reviews on Amazon.com (M:3.35, SD:0.71), and on Twitter (M:3.06, SD:0.74). These scores were not significant below 3.5 in the Amazon.com condition ($t(50)=-1.51$, $p=.139$), but proved to be significant in the Twitter condition ($t(54)=-4.40$, $p=.000$). The 70.9% effect-consistency score indicated a high percentage of participants that reported a negative attitude toward the product after reading the negative Tweet.

Purchase intention

The purchase intentions of the participants were low, and the likelihood to purchase the product was slightly lower in the Twitter (M:3.06, SD:0.88) condition than in the Amazon.com (M:3.21, SD:0.83) condition. A one-sample t-test showed that the purchase intention of the participants was significantly lower than the test value (3.5) in both conditions (Amazon.com; $t(50)=-2.54$,

p=.014, Twitter; $t(54)$=-3.73, p=.000). The effect consistency score was stronger for the Twitter condition (70.9%) than for the Amazon.com condition (64.7%).

As an addition, it was investigated whether there were significant differences between the variables: visiting product review websites, familiarity, frequency, and visiting Amazon.com or Twitter for product reviews on the dependent variables. Results are attached in appendix VII, but the main interesting findings are reported here. First, an independent t-test showed that participants in the Twitter condition, who indicated to have ever visited product review websites, had a significantly lower attitude toward product ($t(53)$=-2.41, p=.019, ω=.080) and lower purchase intention ($t(53)$=-2.23, p=.030, ω=.068), than participants who did not.

Second, another independent t-test showed that participants who indicated to be familiar with Amazon.com had a significantly lower attitude toward product ($t(49)$=-2.72, p=.009, ω=.111) and were less likely to purchase the product ($t(49)$=-3.67, p=.001, ω=.196), than non-familiar user. Only the purchase intention of participants familiar with Twitter was significantly lower ($t(53)$=-2.25, p=.029, ω=.068), compared to the non-familiar participants.

5.2.5. Hypotheses testing

This part is concerned with testing the proposed hypotheses. The study attempted to investigate how the source of a negative product review, and the message quality influences the credibility of the message, the attitude toward the product, and the likelihood to purchase the product. The consumers that are affected the most would rate the product reviews more credible, but will have a more negative attitude toward the product, and the likelihood to purchase the product would be lower, than other consumers. The main interest of this study was to investigate whether these consumers are differently affected due to the source (Amazon.com compared to Twitter) on which the negative product review is presented. A detailed description of the descriptive statistics is reported in table 10, and visualized in figure 3 to 7.

Table 10.

Descriptive statistics: mean scores (M) and standard deviation (SD) of the credibility, attitude toward product, and purchase intention.

Manipulations			Credibility		Attitude toward product		Purchase intention	
Source	*Product*	*Message quality*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Amazon.com	Camera	Low	2.64	1.07	3.96	1.09	3.80	1.23
		High	4.79	1.23	2.86	1.05	2.82	1.34
	Tablet	Low	2.77	1.20	3.67	1.00	3.61	1.08
		High	4.75	1.22	2.91	1.09	2.59	1.06
		Total:	3.74	0.76	3.35	0.71	3.21	0.83
Twitter	Camera	Low	2.83	1.25	3.22	1.03	3.38	1.11
		High	4.06	1.26	2.69	0.84	2.63	1.13
	Tablet	Low	3.11	1.27	3.30	1.17	3.36	1.22
		High	4.30	1.25	3.03	1.19	2.85	1.37
		Total:	3.58	0.95	3.06	0.74	3.06	0.88

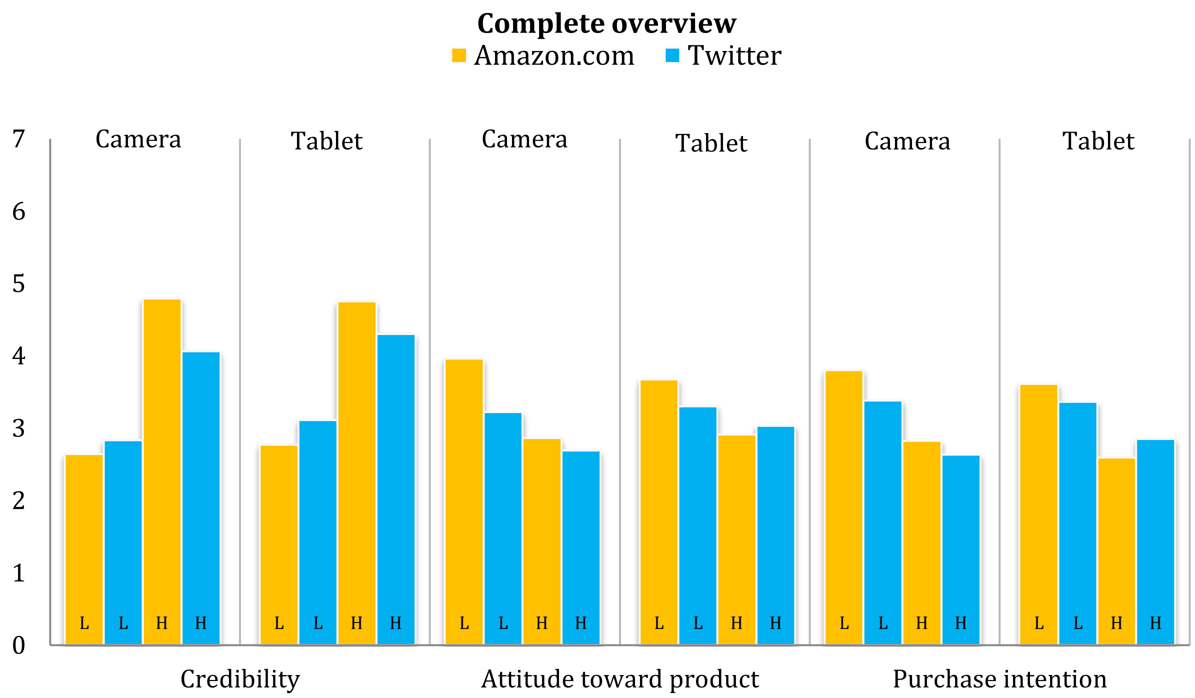

Figure 3. *Bar chart of the mean scores of the variables credibility, attitude toward product, and purchase intention per experimental condition (Amazon.com and Twitter) and the manipulations within the conditions (message quality: L= low, H= high; product type: camera and tablet).*

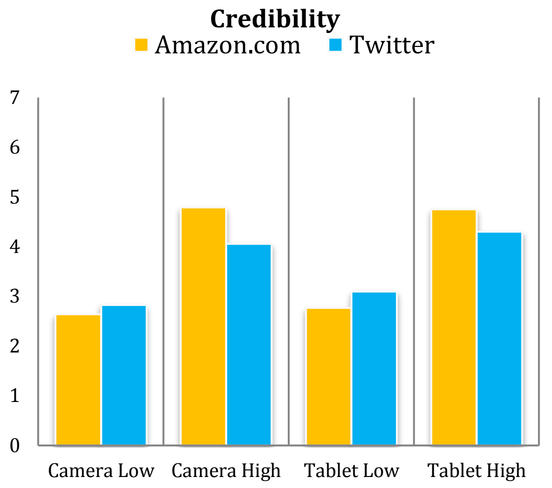

Figure 4.

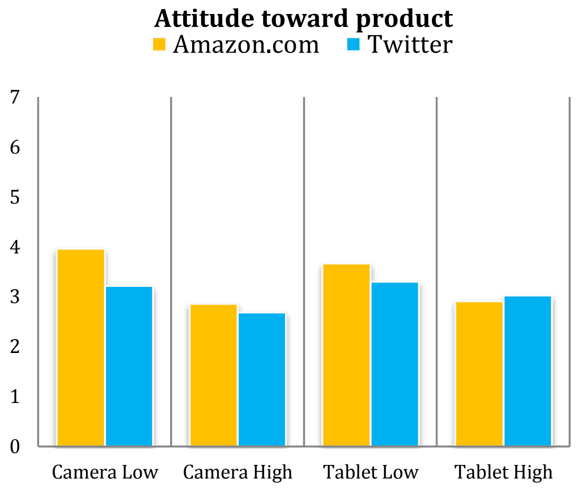

Figure 5.

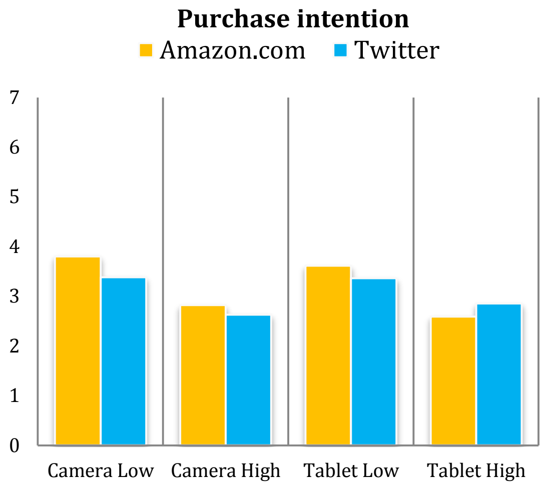

Figure 6.

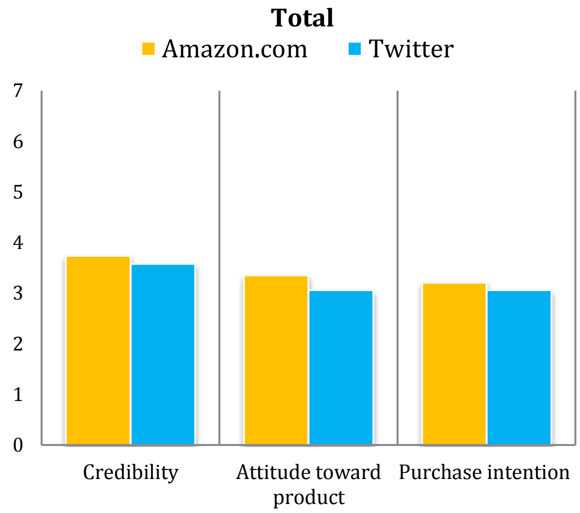

Figure 7.

Figure 4-7. *Independent bar charts of the mean scores of the dependent variables credibility, attitude toward product, and purchase intention per experimental condition (Amazon.com and Twitter) and the manipulations within the conditions (message quality: high and low; and product type: camera and tablet).*

Hypothesis 1

An independent t-test was conducted to analyze whether consumers significantly evaluate product reviews on Amazon.com differently from product reviews on Twitter. It was expected that the credibility of a product review on Amazon.com would be higher, than on Twitter. Furthermore, part b of the hypothesis proposes that the attitude toward product would be lower after reading a negative product review on Amazon.com, than after reading a negative product review on Twitter. The likelihood of purchasing the product would also be lower after reading a negative product review on Amazon.com, than on Twitter.

First, the assumptions of the independent t-test needed to be checked. According to the normality test of Kolmogorov-Smirnov, only the dependent variable purchase intention was not normally distributed ($p<.05$) in both conditions. Levene's test of homogeneity of variance showed that all variables were significant. Thus, the homogeneity of variance assumption was not violated. It was advised to interpret these results in conjunction with histograms, P-P plots (or Q-Q plots), and the values of skew and kurtosis. These histograms and plots showed that the data was reasonably normal. Most skew and kurtosis scores showed no extreme deviations from zero. The results should be interpreted with caution. Nevertheless, proposed hypothesis could be analyzed:

H1: Negative product reviews written on a product review website will be perceived as (a) *more credible,* and will have a greater impact on the (b) *attitude toward product*, and the (c) *purchase intention*, than on Twitter.

Results showed that the mean credibility score of product review in the Amazon.com condition was 3.74 (*SD*:0.76), and was indeed higher than the mean credibility score of 3.58 (*SD*:0.95) in the Twitter condition. However, this difference was not significant ($t(104)=0.97$, $p=.334$). The attitude toward product was significantly lower in the Amazon.com (*M*:3.55, *SD*:0.71) condition than in the Twitter (*M*:3.06, *SD*:0.74) condition ($t(104)=2.06$, $p=.042$, $\omega=.030$). The effect size of .030 shows that the effect was strong. There was no significant difference in purchase intention after reading a product review on Amazon.com (*M*:3.21, *SD*:0.83) and after reading a product review on Twitter (*M*:3.06, *SD*:0.88)($t(104)=0.98$, $p=.379$). Only part b of the first hypothesis is accepted, suggesting that a negative product review on Amazon.com has more impact on a consumer's attitude toward product, than on Twitter.

Hypothesis 2

The second hypothesis proposes that product reviews of high message quality would be perceived as more credible, and that negative product reviews of high message quality would result in a lower attitude toward product, and a lower likelihood of purchasing the product. This effect was expected for both conditions. As with testing the first hypothesis, a t-test was conducted. Different from the first hypothesis, message quality was measured within each condition. All participants were asked to rate negative product reviews of low quality, but also product reviews of high quality. Therefore, a paired samples t-test was conducted to analyze the second hypothesis. First, the assumption of a normally distributed sample needed to be analyzed. This assumption was analyzed by computing the differences between the low and high quality scores of each dependent variable. These new variables were then analyzed on a normal distribution. According the normality test of Kolmogorov-Smirnov only the variable purchase intention, in the Twitter condition, was not normally distributed (p<.05). Again, the plots and histograms appeared reasonably normal. Although the results needed to be analyzed with caution, the following hypothesis could be tested:

H2: High quality product reviews will be perceived as (a) *more credible*, and will have a *greater impact* on the (b) *attitude toward product* and the (c) *purchase intention* on a product review website and on Twitter, than low quality product reviews.

As expected, the message quality of a negative product review had a significant effect. High quality product reviews were significantly perceived as more credible (M:4.77, SD:1.06), than low quality product reviews (M:2.71, SD:0.93) in the Amazon.com condition (t(50)=-11.54, p=.000, r=.95). The attitude toward product was significantly lower for high quality product reviews (M:2.89, SD:0.93), than for low quality product reviews (M: 3.81, SD: 0.89) (t(50)=5.77, p=.000, r=.63). The same effect was found for the variable purchase intention, the likelihood to purchase the product was significantly lower after being exposed to a high quality product review (M:2.71, SD:1.05), than after being exposed to a low quality product review (M:3.71, SD:1.03) (t(50)=5.65, p=.000, r=.62). The effect size of .09 for the variable credibility indicated that this effect was the largest.

The same results were found for the Twitter condition. First, the high quality product reviews were judged as more credible (M:4.18, SD:1.15), than the low quality product reviews (M:2.97, SD:1.15) (t(54)=-6.92, p=.000, r=.69). Second, the attitude toward product (M:2.86, SD:0.78) was also significantly lower for high quality product reviews, than for low quality product reviews (M:3.26, SD:1.00) (t(54)=2.92, p=.005, r=.0.37). The purchase intention was also lower for the high quality product reviews (M: 2.75, SD: 1.05), than for the low quality product reviews (M:3.37, SD:1.05) (t(54)=3.98, p=.000, r=.48). The effect size of .63 for the variable credibility indicated the largest effect. As the results already suggest, the second hypothesis is completely accepted.

Hypothesis 3

The third hypothesis consists of a between-subjects measurement (source) and a within-subjects measurement (message quality). Therefore, this hypothesis was analyzed using a two-way mixed ANOVA, and an independent t-test (appendix VIII). The above mentioned results already indicated that negative product reviews of high quality have more impact, than negative product reviews of low quality. However, the main interest is to examine whether this impact of message quality is different between Amazon.com and Twitter. First, the assumptions needed to be tested again. Except for the assumption of sphericity, which could not be checked (due to the two levels of the within variable), the data was reasonably normal distributed, and the homogeneity assumptions were not violated. The following hypothesis was tested:

H3: High quality product reviews will be perceived as (a) *more credible*, and will have a *greater impact* on the (b) *attitude toward product* and the (c) *purchase intention* on a product review website, than high quality product reviews on Twitter.

All dependent variables were analyzed separately. First, there was a significant main effect of message quality on the perceived credibility of the message (F(1, 104)=171.02, p=.000, r=.79). As previous analysis already confirmed, high quality product reviews were perceived as more credible than low quality product reviews. There was no significant effect of source (also confirmed with testing hypothesis one), indicating that there were no differences between the perceived credibility of product reviews on Amazon.com and the perceived credibility of product reviews on Twitter (F(1,104)=0.94, p=.094). However, an interaction effect between the source and the message quality (F(1,104)=11.59, p=.001, r=.32) was found. This suggest, that there was a difference between the perceived credibility of low and high quality product reviews on Amazon.com, and the perceived credibility of low and high quality product reviews on Twitter. Moreover, when looking at the interaction graph, the high quality product reviews on Amazon.com (M:4.77, SD:1.06) seemed to be perceived as more credible than high the quality product reviews on Twitter (M: 4.18, SD: 1.15).

An additional independent t-test was conducted to analyze whether these differences were indeed significant. The results showed a significant difference between the perceived credibility of high quality product reviews on Amazon.com and the high quality product reviews on Twitter (t(1,104)=2.75, p=.007, ω=.060), but not for the low quality messages (t(1,104)=-1.92, p=.199). The effect size showed a moderate to large effect (ω=.060). Hypothesis 3a is accepted.

Second, as already confirmed by the previous analysis, there was a main effect of message quality on the attitude toward product (F(1,104)=39.94, p=.001, r=.53). There was also a significant effect of source (also confirmed by hypothesis 1b), indicating that the attitude toward product after reading the product reviews differed between the two conditions ($F(1,104)=4.25$, $p=.042$, $r=.20$). Furthermore, there was also a significant interaction effect between the source and the message quality on the attitude toward product ($F(1,104)=6.29$, $p=.014$, $r=.24$). This suggest that the attitude toward product, after reading low and high quality product reviews, differed between Amazon.com and Twitter. The interaction graph indicated that the attitude toward product after reading high quality product reviews on Amazon.com (*M*:2.89. *SD*:0.93) and on Twitter (*M*:2.86, *SD*:0.78) are very similar. However, there seemed to be a difference between the two conditions for the low quality product reviews. The interaction graph suggested a lower attitude toward product after reading low quality product reviews on Twitter (*M*:3.26, *SD*:1.00), than after reading low quality product reviews on Amazon.com (*M*:3.81, *SD*:0.89).

An independent t-test was conducted to examine the significance of this observation. Indeed, a significant difference between Amazon.com and Twitter on the attitude toward product was detected for low quality messages ($t(104)=3.00$, $p=.003$, $\omega= .070$), but not for high quality messages ($t(104)=0.17$, $p=.866$). The effect of low quality messages is moderate to large ($\omega=.070$). Hypothesis 3b is not accepted.

Third, there was a main effect of message quality on the purchase intention ($F(1,104)=47.44$, $p=.000$, $r=.56$). This suggests that the purchase intention was significantly lower for negative product reviews of high quality, than for negative product reviews of low quality. As previous analysis already confirmed, there was no significant effect of source, indicating that the purchase intention of consumers between Amazon.com and Twitter was in general the same ($F(1,104)=0.78$, $p=.379$). Furthermore, there was also no significant interaction effect between the source and the message quality on the purchase intention ($F(1,104)=2.49$, $p=.118$). This suggests that the purchase intention after reading product reviews of low and high quality did not differ between Amazon.com and Twitter. Thus, an independent t-test to test these differences was redundant, and hypothesis 3c is not accepted.

6. Discussion and conclusion

The main aim of this study was to investigate the impact of negative product reviews on a product review website compared to negative product reviews on Twitter. Impact referred to the perceived credibility of the information, the attitude toward product, and the purchase intention after reading the product review. Thus, found support for Twitter as S-EWOM. Two studies were conducted to answer this question. In the subsequent paragraphs the main findings, limitations, future research, and implications will be discussed.

6.1. Main findings

As already mentioned, two studies were conducted. The first study, was explorative and aimed at identifying the main differences between the characteristics of a general product review website (Amazon.com) and Twitter. According to a set of predetermined criteria, seven characteristics were analyzed: (1) ratings and comments, (2) perceived usefulness, (3) review valence, (4) review length, (5) message quality, (6) argumentation, and (7) reviewers' credibility. In addition, to answer the research question and the proposed hypotheses, a 2 x 2 factorial experimental design was employed. There were two independent variables: source of the product review (Amazon.com and Twitter), and the message quality (low and high). The dependent variables were credibility, the attitude toward product review, and the purchase intention. Furthermore, the research instrument employed was an online questionnaire.

6.1.1. Findings study 1: qualitative preliminary analysis

The main findings showed that there were indeed some distinctive differences between product reviews on Amazon.com and on Twitter. First, and not surprising as the two sources serve completely different goals, the surface levels completely differed. For example, on Amazon.com the product reviews are structured and chronologically displayed, while the Tweets on Twitter are displayed in a timeline. When a person is looking for information about a particular product on Twitter, they have to enter a search query. Furthermore, both Amazon.com and Twitter enable their users to comment to other users' statements. The overall rating of the product and the perceived usefulness of the product review are displayed at the surface level of Amazon.com, on Twitter this is not visible. Indirect consumers can indicate their overall rating concerning a product in the content of a Tweet. Thus, on Twitter valence statements in the text of a Tweet, can indicate the overall rating of a product. On Amazon.com valence statements are also used, but as an additional aid to amplify the overall feeling with a product. However, due to the availability of a rating system, users can more easily filter out the negative and positive rated product reviews they would like to read.

Due to the maximum number of characters allowed on Twitter, these product reviews were shorter than those on Amazon.com. Product reviews on Twitter were found to be less complex and better readable. Although the product reviews on Amazon.com were more complex, the quality of the product reviews was considerably better. In accordance with the literature, these reviews were written in a structured format, and contained supporting evidence about the product (Liu, et al. 2007). Strongly related to the message quality, was the quantity and quality of the argumentation. As expected, the product reviews on Amazon.com consisted of more and stronger argumentation. The product reviews on Twitter, as defined by Lee and Park (2007), were mostly weak and consisted of emotional statements.

Lastly, the credibility of the reviewer could be fairly easily assessed on both sources. Expertise and trustworthiness are two key factors that determine the credibility of a reviewer (e.g. Fogg et al., 2001; Cheung et al., 2009). In online environments, expertise can be based on text-based resources, thus on the reviewers' self-claims (Brown et al., 2007). On both sources and via several ways, reviewers clamed expertise themselves. For example, in the textual content of the review but also in the personal profile of the reviewer. An indication of a reviewer's trustworthiness is the amount of personal information displayed in the personal profile. Although Amazon.com uses a 'top reviewer' ranking, which is also an indicator of trustworthiness, the trustworthiness of Twitter reviewers could be better assessed. Twitter users displayed more personal information in their personal profile, than the Amazon.com users (e.g. real name, amount of personal information, and profile picture). Concerning the fact that Twitter is a real-time information service that allows users to post Tweets about what they are doing, how they feel, or how they experience a product or service, this was not a real surprise. Above all, Twitter is also a medium through which people communicate (with friends, relatives, and unfamiliar people).

6.1.2. Findings study 2: online questionnaire

Hypothesis 1

The first hypothesis, that negative product reviews written on a product review website would be perceived as more credible, than product reviews written on Twitter, was not supported. Although the credibility was somewhat higher for product reviews on Amazon.com, this difference was not significant. This finding was in contradiction with scholars that pointed to a difference in the perceived credibility between the two sources. For example, Schmierbach and Oeldorf-Hirsch (2012), argued that news messages on Twitter are perceived as less credible than news messages on a newspaper website. Although news and product reviews are two different types of messages, the effect was accounted to the type of source on which the message was displayed. However, in the current study this seemed to be untrue for the type of source on which a product review is displayed. Another study (Chen et al. 2008), reported that the usefulness rating systems of a product review website can serve as an indicator of trustworthiness. Thus, it seemed to indicate that the availability of such a system on Amazon.com, and the absence on Twitter, should have led to a different perceived credibility. Interesting to note, the credibility findings of the preliminary analysis more or less pointed in this direction. It showed that Twitter users expressed expertise, and revealed a considerable amount of personal information. These factors contribute to perception of trustworthiness.

Chen et al. (2008) argued that helpfulness scores also affect product sales. Hereby, the length of a product review has proven to play a role. Moreover, some scholars (Mudambi & Schuff 2010; Pan & Zhang, 2011) stated that the length and depth of a product review affect the helpfulness score, and that the longer the review, the higher the helpfulness score. Furthermore, an increase in information serves as a confidence boost in the decision making process (Tversky & Kahneman, 1974). Thus, as the product sales are affected, then the attitude toward product, and the purchase intentions should be affected first. Therefore, in the second part of the hypothesis we assumed that negative product reviews on Amazon.com would have a greater impact on the attitude toward product and the purchase intention, than on Twitter. This assumption seemed to be supported by the preliminary analysis, which showed that Amazon.com contained a helpfulness system, that the product reviews were significantly longer, that these product reviews contained more arguments, and that they were of better quality than product reviews on Twitter. Interestingly, the assumption was only partially accepted. Although on both sources the attitudes toward product and the purchase intentions were lower after reading the product reviews, the differences between Amazon.com and Twitter were only significant for the attitude toward product.

Hypothesis 2

Many scholars argued that high quality messages are more persuasive than low quality messages (e.g. Petty & Cacioppo 1983;1983, Lee et al., 2007; 2008). Wathen and Burkell (2002) added to this that the message is essential for the credibility of the information. Cheung et al. (2009) supported this view by stating that product reviews with strong argumentation are more effective, and are perceived as more credible. Therefore, the second hypothesis proposed that high quality product reviews would be perceived as more credible, and would have a greater impact on the attitude toward product and the purchase intention, on both a product review website and on Twitter. Indeed, the high quality product reviews in this study were perceived as more credible, and had a greater impact on the attitude toward product, and the purchase intention, than low quality product reviews. This result was significant for both Amazon.com and Twitter. Thus, these findings were also in line with previous research findings.

Hypothesis 3

The third hypothesis combined the first and second hypothesis, and proposed that high quality product reviews on Amazon.com would be perceived as more credible, and would have a greater impact on the attitude toward product and the purchase intention, than high quality product reviews on Twitter. In contrast to the first hypothesis, consumers perceived high quality product reviews on Amazon.com as more credible than high quality product reviews on Twitter. Even though the credibility part was rejected in the first hypothesis, we can now conclude that the higher quality of the product reviews on Amazon.com (as identified in the first study) led to a higher credibility. This finding is supported by Cheung et al. (2009) who found that messages with many valid and strong arguments are perceived as more credible. Additional support for this finding is attributed to the preliminary investigation, wherein we found that product reviews written on Amazon.com consisted of more (quantity) objective, logical, and detailed product evaluations. The difference in the perceived credibility of the high quality product reviews between Amazon.com and Twitter, could also be attributed to the fact that most product reviews on Twitter are of low quality (as identified in the first study).

Many scholars argued that high quality messages are more persuasive. More specifically, Lee et al. (2007) found that high quality messages affected the attitude toward the product more than low quality messages. Lui et al. (2007) added to this that high quality product reviews are strong and influential sources for consumers prior to purchase. Despite these finding, the high quality product reviews from Amazon.com did not have a greater impact on the attitude toward product and the purchase intention, than the high quality product reviews on Twitter. Remarkably, there was a difference in impact between the low quality product reviews on Amazon.com and Twitter.

6.2. Limitations and future research

Although this study found some interesting results, there are some limitations. First, the limited number of analyzed product reviews in the preliminary investigation, and the number of participants that participated in the online questionnaire, make it more difficult to generalize the findings to the entire population. Second, we only used one product domain for both studies, namely electronic products. Previous researchers also used electronic products (e.g. cameras) as experimental products in their study. However it could be that product reviews about other types of products have a different impact on consumers.

Third, this study examined the impact of an individual product review. In real life, consumers are exposed to more negative product reviews. Especially, on Twitter a large amount of Tweets are exposed in one timeline. As an addition to this real life scenario, consumers will most likely look at positive and negative product reviews when deciding to purchase a product or not. For example, previous research that investigated the proportions of negative and positive product reviews found that a few negative messages can be helpful in promoting message credibility, and attitude toward website (Doh & Hwang, 2010).

Fourth, this study did not take into consideration the impact of user characteristics (e.g. familiarity with the medium, involvement, personal characteristics). Moreover, this study found that the attitude toward product reviews, the attitude toward product review source, and the involvement with the product covariate with the dependent variable credibility for Twitter. These findings indicate that these factors were of influence, and thus require further research. Furthermore, the usage of product review websites and the familiarity with the medium (Twitter) were also of influence on the attitude toward product and the purchase intention. These factors could also be of interest for future research. Another interesting finding of the preliminary investigation was that Twitter users indicated much personal information. For example, the majority of users had a profile picture. One possible reason for users to indicate this amount of personal information is that Twitter is a also a personal medium on which friends and relatives communicate with each other, and that it has a high level of self-disclosure (Kaplan & Haenlein, 2010). The follow and follower relationship is also bound to people that are familiar with each other. Brown and Reingen (1987) stated that information obtained from strong ties is considered to be more influential in decision making, than information obtained from weak ties. Therefore, it would be interesting to investigate the impact of product reviews from familiar people to the same product reviews from unfamiliar people, on different sources.

Lastly, and definitely important, the mobile nature of Twitter. As mentioned before, one of the factors that makes Twitter a unique medium is its mobile nature. Basically, people can post Tweets everywhere, anytime, over a multiple of channels. Twitter messages can be received by users as a text message on their mobile phone, on their computer, on their tablet, via email, through RSS feeds, through instant messages, and even through their Facebook account (Krishnamurthy et al., 2008). This study did not address this aspect in the experimental design. The present study mainly aimed at computer use of Twitter, and did not incorporate the different possibilities of receiving a Tweet. Therefore, it would be extremely interesting to investigate the impact of this mobile nature of Twitter on itself, or compared to other forms of EWOM that do not have this mobile nature. For example, it could be investigated how the mobile nature of Twitter is related to offline purchase intentions. Imagine, a consumer is considering to purchase a product, but he or she decides to first look at the opinions of other consumers on

Twitter, because this information is easy and fast received. This raises the question of how these Tweets can then affect the offline purchase intentions of that consumer. It is interesting because previous research already suggested that people base their offline purchase decisions on the basis of the online available information (Lee et al., 2007).

6.3. Implications

6.3.1. Theoretical implications

This study has some theoretical implications. There is an enormous amount of literature available that investigated the effect of EWOM, but almost none have focused on Twitter as EWOM. The one that focused on Twitter as EWOM (Jansen et al., 2009), only concluded that Twitter could be considered as EWOM as many users expressed feelings and opinions about companies, products, and services. Therefore, this study contributes to the research field of EWOM by considering Twitter as a new source of EWOM, naming it S-EWOM, and then comparing it the a more traditional form of EWOM: product review websites. Furthermore, the shortness of a Tweet and the fastness of sending a Tweet are unique features and different from traditional product reviews. By distinguishing two different types of product reviews and adding a new dimension of short product reviews (Tweets as product reviews) to the existing types of product reviews, this study adds a new dimension to the existing EWOM literature.

The characteristics of the EWOM platform (the source) are important for its persuasiveness (Cheung & Zhou, 2010). Furthermore, the source of the message is also related to how consumers perceive and are affected by EWOM information. As the use of social media keeps on growing in the future, more people will also express their opinions and feelings about companies, products, and services on different social media platforms. The preliminary investigation showed that product review websites and Twitter greatly differ from each other. Amazon.com serves the goal of selling products and providing consumers with product reviews. Moreover, consumers go to Amazon.com to search for information about a particular product that they consider buying. When this product is then rated very negatively on Amazon.com, consumer might get unsecure about buying the product. In this way, Amazon.com dissuades the consumer from buying the product. The main goal of Twitter is not to provide consumers with product reviews, but with all kinds of information that a Twitter user is willing to share with others. When a consumer comes across Tweets that are very positive about a certain product (or negative), it could lead to considering or even persuading a consumer to buy the product. Conversely, a negative Tweet could lead to consumers not even start considering buying that particular product.The advent of S-EWOM platforms, together with the existing traditional EWOM platforms, has resulted in a wide variety of platforms with different characteristics on which people post product reviews. Therefore, when scholars consider researching (S)EWOM in the future, the different platforms or sources and their goals, on which (S)EWOM messages are posted, should be taken into account. Many consumers visit product review websites to search for information about products, while on Twitter consumers 'come across' negative or positive Tweets about a product. Thus, visitors of product review websites are already in the buying process, while visitors of Twitter are not, yet, in the buying process.

6.3.2. Practical implications

The findings have some theoretical implications, but there are also some practical implications.. In today's society, more and more companies have started to adapt their marketing and communication strategies according to latest social media developments. Many companies are trying to profile themselves on social media channels, such as Twitter and Facebook, to communicate with their customers. Especially Twitter is an easy and fast medium for companies to get in contact with their customers. On the other hand, Twitter is also an easy and fast medium for consumers to express their dissatisfaction with a company or its products or services. This study proves that these complaining messages have some impact on consumers. The results suggests that the impact of negative product reviews on product review websites are not very different from negative product reviews on Twitter. Therefore, companies should not underestimate the impact of consumers complaining about their products or services on Twitter. Special attention should be paid to Tweets of high quality. These Tweets should certainly not be denied by companies, because they have an impact on the attitude toward product and purchase intention of consumers. It is therefore a good thing that companies have started to monitor conversations on Twitter.

As for now the negative product reviews on product review websites have been perceived as more credible (high quality product reviews), and affected the attitude toward product more negatively (independently of message quality), than product reviews on Twitter. However, the effect of negative Tweets should not be underestimated because the attitude toward product and purchase intention were low after reading the negative product reviews. Considering the exponential growth of Twitter users (and usage) each day, and the results of this study, we assume that the impact of Tweets will keep on growing in the future. Thus, the most important practical implication for marketers is to keep on or start monitoring negative Tweets, and start a conversation with these dissatisfied customers. Moreover, different from the tradition product review websites and the search for Tweets via a search query, Tweets also come across and appear in a user's timeline without searching for them. This could lead to consumers being affected by negative or positive Tweets unsolicited. The fast and mobile nature of Twitter makes it easy for people to share a complaint to millions of other people, who in just one click, spread around the complaint even faster to even more people in the world (and thus start S-EWOM). By this Twitter gave consumers a voice, but at the same time it also gave marketers the opportunity to communicate with these dissatisfied customers, and prevent them from starting a S-EWOM buzz.

6.4. Conclusion

Twitter becomes more and more apparent in this social networking society. Therefore, this study sought evidence for Twitter as a new source of EWOM, namely S-WOM. The interest for conducting this investigation emerged from the wide use of Twitter by people to talk about their daily lives, but also to talk, complain, or even attack a company about its lacking products and services. Such utterances are defined as EWOM, and are commonly expressed on product review websites. Considering the social nature of Twitter, that connects millions of people all of the world with each other with only 140 characters a Tweet, we cannot look at Twitter as a traditional form of EWOM. Therefore, we defined product reviews on Twitter as S-EWOM communications.

We first aimed at identifying the main differences between product reviews posted on product review websites (Amazon.com) and product reviews posted on Twitter. Secondly, we attempted to investigate the impact of negative product reviews posted on product review websites compared to the impact of negative product reviews posted on Twitter on consumers. The findings do not show major differences between the impact of product reviews on product reviews websites and product reviews on Twitter. Specifically, the attitude toward product was more affected after reading product reviews on Amazon.com, than after reading product reviews on Twitter. Nevertheless, the attitude toward product was negative after reading product reviews on Twitter, but more negative after reading product reviews on Amazon.com. When categorizing the product reviews into low and high quality messages, the perceived credibility of the product reviews on Amazon.com was higher, than the product reviews on Twitter. Lastly, both the high quality product reviews on Amazon.com and on Twitter were perceived as more credible, and had a greater impact on the attitude toward product and the purchase intention, than low quality product reviews. The findings of this study contribute to the EWOM research and show that Twitter is definitely a source of EWOM, which we can call S-EWOM, and should definitely not be denied in the future.

7. References

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Appendix I: Message quality and argumentation quality

Table 1.

Examples of the four SPEC review categories to identify the quality of a product review: best review, good review, fair review, and bad review (Liu et al., 2007).

Best review	**Good review**
I purchased this camera about six months ago after my Kodak Easyshare camera completely died on me. I did a little research and read only good things about this Canon camera so I decided to go with it because it was very reasonably priced (about $200). Not only did the camera live up to my expectations, it surpassed them by leaps and bounds! Here are the things I have loved about this camera: BATTERY - this camera has the best battery of any digital camera I have ever owned or used. … EASY TO USE - I was able to … PICTURE QUALITY - all of the pictures I've taken and printed out have been great. … FEATURES - I love the ability to quickly and easily … LCD SCREEN - I was hoping … SD MEMORY CARD - I was also looking for a camera that used SD memory cards. Mostly because… I cannot stress how highly I recommend this camera. I will never buy another digital camera besides Canon again. And the A610 (as well as the A620 - the 7.0MP version) is the best digital camera I've ever used.	The Sony DSC "P10" Digital Camera is the top pick for CSC. Running against cameras like Olympus stylus, Canon Powereshot, Sony V1, Nikon, Fuji, and More. The new release of 5.0 mega pixels has shot prices for digital cameras up to $1000+. This camera I purchased through a Private Dealer cost me $400.86. The Retail Price is Running $499.00 to $599.00. Purchase this camera from a wholesale dealer for the best price $377.00. Great Photo Even in dim light w/o a flash. The p10 is very compact. Can easily fit into any pocket. The camera can record 90 minutes of mpeg like a home movie. There are a lot of great digital cameras on the market that shoot good pictures and video. What makes the p10 the top pick is it comes with a rechargeable lithium battery. Many use AA batteries, the digital camera consumes theses AA batteries in about two hours time while the unit is on. That can add continuous expense to the camera. It's also the best resolution on the market. 6.0 megapix is out, though only a few. And the smallest that we found. Also the best price for a major brand.
Fair review	**Bad review**
There is nothing wrong with the 2100 except for the very noticeable delay between pics. The camera's digital processor takes about 5 seconds after a photo is snapped to ready itself for the next one. Otherwise, the optics, the 3X optical zoom and the 2 megapixel resolution are fine for anything from Internet apps to 8" x 10" print enlarging. It is competent, not spectacular, but it gets the job done at an agreeable price point.	I want to point out that you should never buy a generic battery, like the person from San Diego who reviewed the S410 on May 15, 2004, was recommending. Yes you'd save money, but there have been many reports of generic batteries exploding when charged for too long. And don't think if your generic battery explodes you can sue somebody and win millions. These batteries are made in sweatshops in China, India and Korea, and I doubt you can find anybody to sue. So play it safe.

Table 2.

Examples of product reviews with strong and weak argumentation (Lee et al., 2007; 2008).

Weak argumentation	**Strong argumentation**
Should have known better Oh my goodness! – It was not a good choice. I bought this item new at this online store when it first came out. My overall satisfaction is very low. I should have known better than to buy this product. I don't know why I chose it! Save your money and buy something else	*Not so great* This product has very limited battery life. It didn't come with an AC power source. It also has no hold button, which means I have to take out the batteries when I'm not listening. Sometimes, it makes a really high pitched buzz in the earphones
Not worth your money I got this product four weeks ago. I purchased it for my son for our trip to Disney. He loved it but after one week, he didn't play with it anymore. Hmmm. . . This product is not what he wants. Mistake! I shouldn't have chosen it	*Watch out!* I am not satisfied with this product. It is simple but heavy to put around my neck. The sound of the built-in speakers spreads out and the sound is not that good. Because of the multi-functions, the buttons are complicated to use.
Wooooooooow! I searched for days and compared every PMP and finally bought one. I'm really enjoying it and it is tough to put it down. All my friends envy my PMP. Right now I'm writing a review, but I can't wait to play my PMP	The picture on the 3.5' LCD monitor is absolutely amazing, I am really impressed with the colors and the contrast between darks on such a small screen. Plays songs at top-quality sound with 5.1 channels. Almost every format is supported.

Appendix II: Screenshots of product reviews

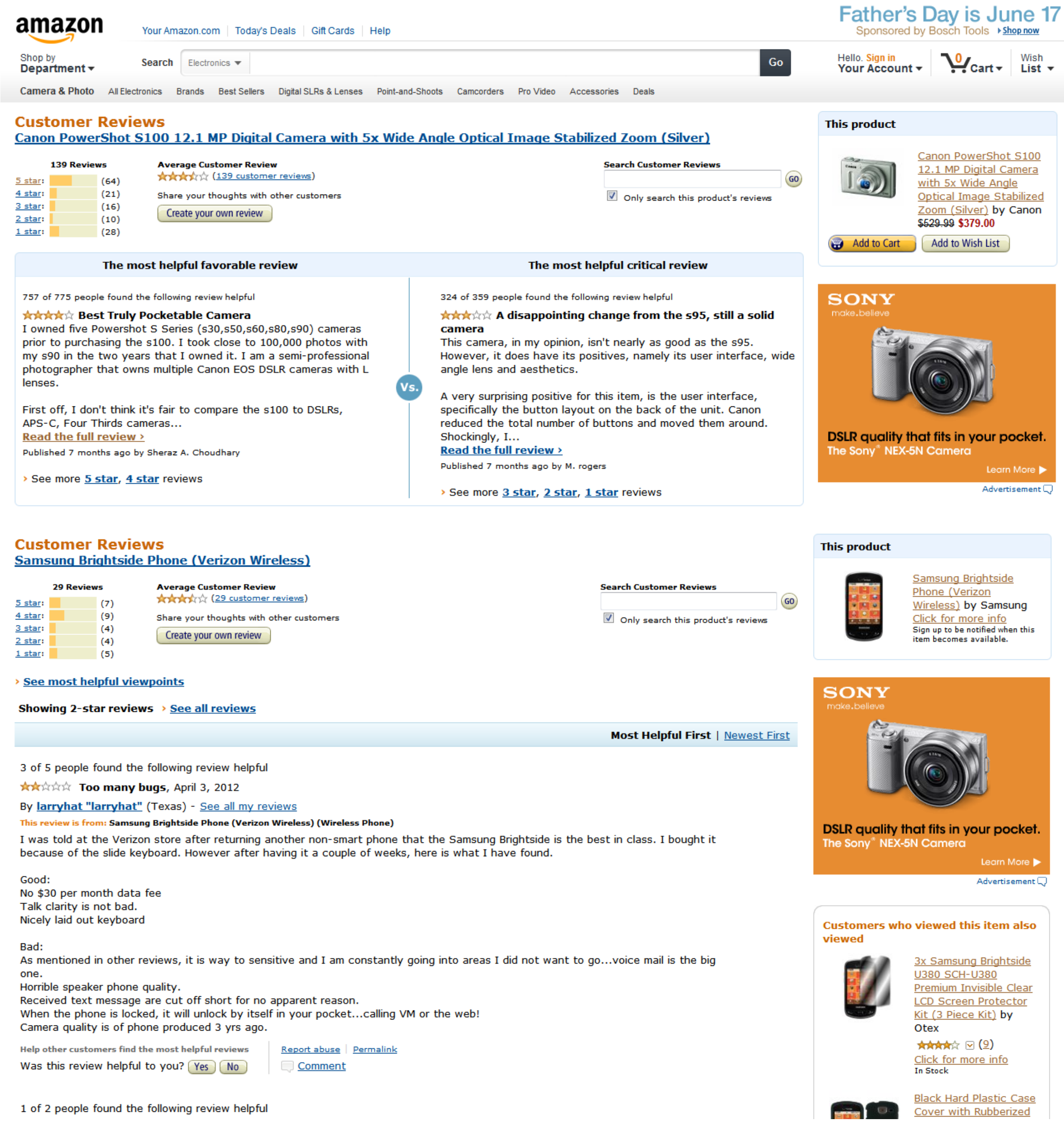


Figure 1. *Screenshots of product reviews on Amazon.com*

Figure 2. *Screenshots of product reviews on Twitter.*

Appendix III: Coding scheme

Table 1.

Coding sheet for analyzing the differences between product reviews on Amazon.com and on Twitter according to the seven characteristics and accompanying criteria.

	1	2	3	4	Comments
Source	Amazon	Twitter			
Product	Camera	Tablet	TV	Mobile phone	
Ratings	*Yes* = It is possible to give the product an overall rating	*No* = It is not possible to give the product an overall rating			*Other features that can be used to express the overall rating of a product*
Comments	*Yes* = It is possible to add comments	*No* = It is not possible to add comments			
Perceived usefulness	*Yes* = It is possible to indicate the helpfulness of the product review	*No* = It is not possible to indicate the helpfulness of the product review			*Usefulness score (if there is any), and other features that can be used to express the perceived usefulness of a product review.*
Review valence – Valence statements	Negative (one-sided)				*Valence statements in the content of the product review*
Review valence - Indication	*Yes* = The valence of the product review is visible at the surface level	*No* = The content of the product review is necessary to read to detect the valence of the product review			
Length – Words	Number of words				
Length – Characters	Number of characters				
Message quality	Best review	Good review	Fair review	Bad review	
Message quality - Readability	*(FK)* = Flesch-Kincaid score				
Argumentation - Quantity	*(Q)* = Number of arguments				
Argumentation - Quality	Strong	Mediocre	Weak		*Sentences or words expressed (weak or strong argumentation)*
Reviewers' credibility - Trust	*Yes* = There is a reviewers' ranking	*No* = There is not a reviewers' ranking			*Different options to express trust features, such as personal information.*
Reviewers' credibility - Expertise	*Yes* = It is possible to indicate expertise claims	*No* = It is not possible to express expertise claims			*Options to claim expertise in the content of a product review.*

Appendix IV: Online questionnaire

[Introduction – Condition 1 & 2]

Hi,

Thank you very much for taking the time to fill out this questionnaire. It will take no more than 15 minutes of your time.

I am a master student of Communication and Information Sciences at Tilburg University. Currently, I am working on my thesis regarding the impact of online product reviews. Your answers will help me gain more insight in this matter. Besides, by filling in this questionnaire you are not only doing me a great favor, you also help me graduate!

There are no wrong or right answers, and all information will be threated strictly anonymous.

Good luck!
Click on 'continue' to start.

[Part 1 – General information – Condition 1: Amazon.com]

[Familiarity]

1. Have you ever visited a product review website?
   1.1. Yes
   1.2. No

2. Are you familiar with Amazon.com?
   2.1. Yes
   2.2. No [show introduction – go to Q5]

Introduction Amazon.com [shown when Q2 = No]
Amazon.com is a multinational e-commerce website that sells products to customers all over the world. Moreover, it is the largest online retailer that sells a wide variety of products such as, electronics, shoes, clothes, toys, books, and many more. Special about Amazon.com is that it hosts one of the largest and most popular online consumer forum where consumers can post product reviews. Besides the product review, consumers give the product an overall rating in the form of stars. An extremely negative reviewed product is rated with one star, and a very positively reviewed product is rated with five stars.

[Usage]

3. How often do you visit Amazon.com, on average?
   3.1. Never [go to Q5]
   3.2. Less than once a month
   3.3. 2 – 3 times a month
   3.4. Once a week
   3.5. 2 – 3 times a week
   3.6. Daily

4. Have you ever visited Amazon.com for product reviews?
   4.1. Yes
   4.2. No

[Part 1 – General information – Condition 2: Twitter]

[Familiarity]

1. Have you ever visited a product review website?
   1.1. Yes
   1.2. No

2. Are you familiar with Twitter?
   2.1. Yes
   2.2. No [show introduction – go to Q5]

Introduction Twitter [shown when Q2 = No]
Twitter is a real-time information network that connects you to the latest stories, ideas, opinions and news about what you find interesting. It enables you to send and read text-based posts. These posts, at the heart of Twitter are small bursts of information called Tweets. Each Tweet is 140 characters long.

[Usage]

3. How often do you visit Twitter, on average?
   3.1. Never [go to Q5]
   3.2. Less than once a week
   3.3. 1-7 times a week
   3.4. 1-5 times a day
   3.5. 6-10 times a day
   3.6. More than 10 times a day

4. Have you ever visited Twitter for product reviews?
   4.1. Yes
   4.2. No

[Part 2 – Manipulations of product reviews – Condition 1: Amazon.com]

On the next pages a couple of product reviews are displayed. Please read the product reviews and try to answer the accompanied questions.

[Product review 1 – Message quality low – Camera]

[Product review 2 – Message quality high – Camera]

amazon

Your Amazon.com | Today's Deals | Gift Cards | Help

Shop by Department

Search Electronics Go

Camera & Photo All Electronics Brands Best Sellers Digital SLRs & Lenses Point-and-Shoots Camcorders

Customer Review

140 of 160 people found the following review helpful

★☆☆☆☆ February 24, 2012

By Lizzy David

Amazon Verified Purchase (What's this?)

I have been a fan of this camera, and the first types of this camera are the best in the history of photography. I got this camera for Christmas but only a week, and 400 shots later I returned it.

Here's why

The good:
- Handy body and light weighted
- Extremely easy to master all controls. Perfect, well laid out menus and controls.
- Great video capability
- Great price for the specs

The bad:
- Picture quality is disappointing and unacceptable; they are soft and miss sharpness.
- 60% of the shots were out of focus. The focusing system in auto picks the "wrong" focus spots most of the time.
- Missing some key image control features that would actually help to overcome the image issues.

I am no novice to photography and have been an enthusiast for over 30 years. This camera was a disappointing experience from manufacturer I hold in the highest esteem.

I am sad to say, but after a week of research I switched and bought another camera. All I can say; make sure to take sample pictures before you buy a camera and ensure you like the results before you buy one. Don't waste your money, like I did!

Help other customers find the most helpful reviews

Was this review helpful to you? Yes No

Report abuse | Permalink

Add a comment

[Product review 3 – Message quality low –Tablet]

[Product review 4 – Message quality high – Tablet]


amazon

Your Amazon.com | Today's Deals | Gift Cards | Help

Shop by Department

Search Electronics Go

Camera & Photo All Electronics Brands Best Sellers Digital SLRs & Lenses Point-and-Shoots Camcorders

Customer Review

200 of 250 people found the following review helpful

March 1, 2012

By Suzan Smith

Amazon Verified Purchase (What's this?)

Part of my job is to evaluate media streaming hardware for an entertainment company. Let me start off by saying I really wanted to love this tablet. Unfortunately, I was not impressed. There are some nice features, but most departments are lacking. After a week of using, this is what I found.

The good:
- It looks and feels nice in your hands, even with the plastic back.
- The stereo speakers at the front are a nice addition.
- Battery life seems decent, about 9 hours.
- Setup was easy.

The bad:
- Unfortunately, it is barely an upgrade from the previous version. Many of the specifics are the same or even worse.
- Compared to similarly priced tablets it does not fare well in any of the benchmark tests, even compared to the original.
- The cameras are horrible and there is no LED flash from the back.
- The display is not as responsive. It sometimes took a second or two for the tablet to react.
- Certain apps don't work on the device, others have reduced functionality.
- Oddly, it takes twice as long to charge when plugged into a computer.

This tablet is a strange product and I would not recommend buying this product. For the same price you can get any number of tablets that give you a better experience.

Help other customers find the most helpful reviews

Was this review helpful to you? Yes No

Report abuse | Permalink

Add a comment

[Part 2 – Manipulations of product reviews – Condition 1]

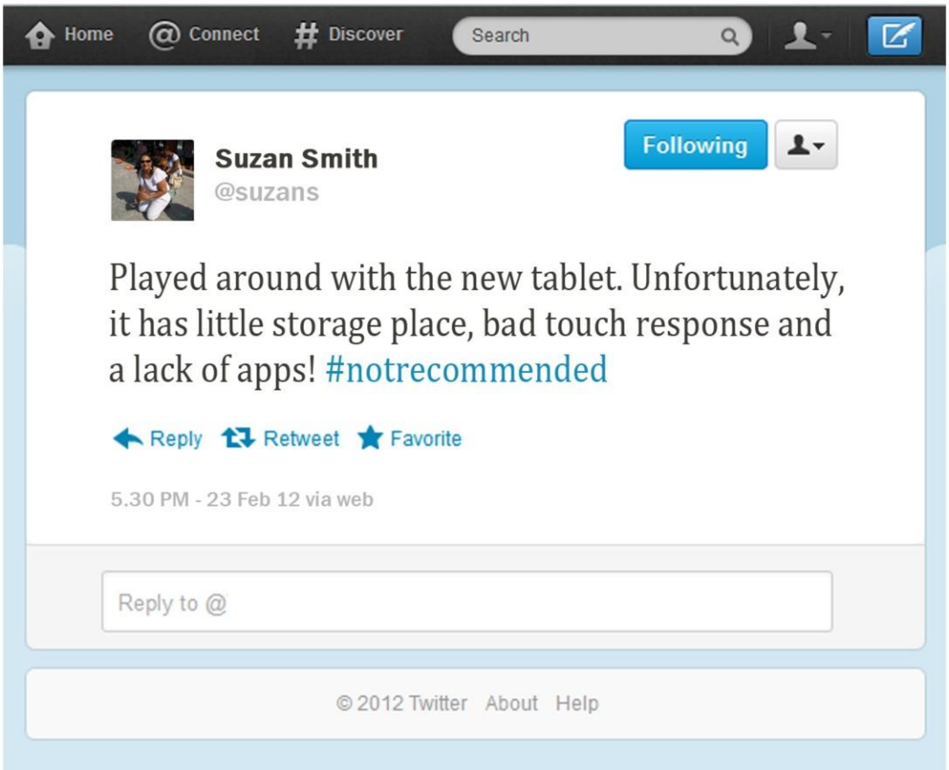
On the next pages a couple of product reviews are displayed, please read the product reviews and try to answer the accompanied questions.

[Product review 1 – Message quality low – Camera]

[Product review 2 – Message quality high – Camera]

[Product review 3 – Message quality low –Tablet]

[Product review 4 – Message quality high – Tablet]



Please answer the following questions according to the product review you just read. *

5. [Credibility]
   5.1. I think this review is *factual.*
   5.2. I think this review is *accurate.*
   5.3. I think this review is *credible.*
   [7-point Likert scale; strongly disagree – strongly agree]

6. [Purchase intention]
   6.1. Assuming you are interested in [product name], would you be *more* or *less likely* to purchase the product, given the information shown?
   [7-point Likert scale; less likely – more likely]

7. [Attitude toward product]
   7.1. I am *positive/negative* toward [product name].
   7.2. I think the [product name] is of *low/high quality.*
   [7-point Likert scale; paired anchors]

You are doing great, so please hang on. You are almost finished!

Note: * these questions were asked after each product review: four times in total.

[Part 3 – General attitude toward product reviews and electronic products]

8. [General attitude toward product reviews – Condition 1 & 2]
   The following questions are about your general attitude toward online product reviews.
   8.1. When I buy a product online, I always read reviews that are presented on the web.
   8.2. When I buy a product online, the reviews presented on the web are helpful for my decision making.
   8.3. When I buy a product online, the reviews presented on the web make me confident in purchasing the product.
   8.4. If I don't read the reviews presented on the webs when I buy a product online, I worry about my decision.
   [7-point Likert scale; strongly disagree – strongly agree]

9. [General attitude toward product reviews – Condition 1: Amazon.com]
   9.1. In general I believe the information I read on Amazon.com.
   9.2. In general I think product reviews on Amazon.com are helpful.
   [7-point Likert scale; strongly disagree – strongly agree]

9. [General attitude toward product reviews – Condition 2: Twitter]
   9.1. In general I believe the information I read on Twitter.
   9.2. In general I think product-reviews on Twitter are helpful.
   [7-point Likert scale; strongly disagree – strongly agree]

10. [Product involvement – Condition 1 & 2]
   10.1. I usually take many factors into account before purchasing electronic products.
   10.2. I usually spend a lot of time choosing what kind of electronic products to buy.
   [7-point Likert scale; strongly disagree – strongly agree]

[Part 4 – Demographics and ending – Condition 1 & 2]

11. What is your gender?
    11.1. Male
    11.2. Female

12. What is your age?
    …

13. What is your current or highest completed education?
    13.1. Primary education
    [NL: basisonderwijs]
    13.2. Lower vocational education (LBO, LTS)
    [NL: lager beroepsonderwijs]
    13.3. Secondary education (VMBO, HAVO, VWO)
    [NL: middelbaar onderwijs]
    13.4. Secondary vocational education (MBO, MTS, MEAO)
    [NL: middelbaar beroepsonderwijs]
    13.5. Higher education (HBO, HEAO, HTS)
    [NL: hoger beroepsonderwijs]
    13.6. University education (Bachelor's degree)
    [NL: wetenschappelijk onderwijs]
    13.7. University education (Master's degree)
    [NL: wetenschappelijk onderwijs]
    13.8. No education
    13.9. Other, namely:
    …

Congratulations, you made it to the end.

Again, I really appreciate your participation.

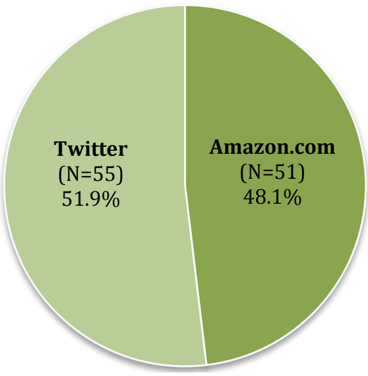
Thank you for your help!

Marlou Propst

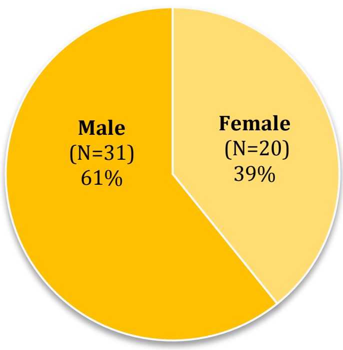
For any questions or comments, send me an email: marloupropst@gmail.com

Appendix V: Participant characteristics

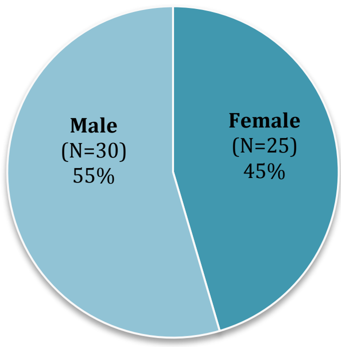
Number of participants
(N=106)



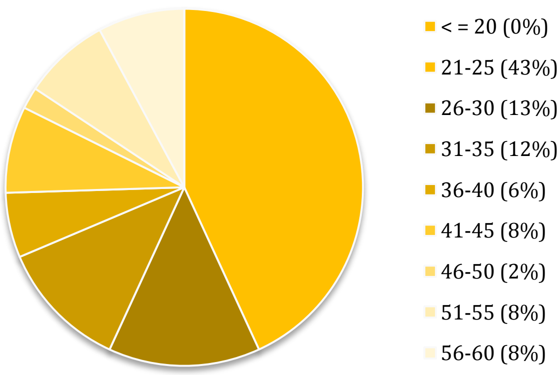
Amazon.com
What is your gender
(N=51)



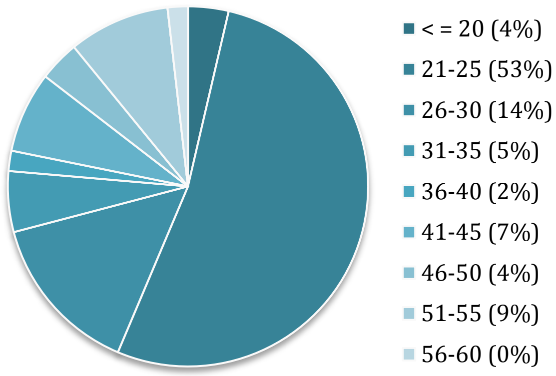
Twitter
What is your gender
(N=55)



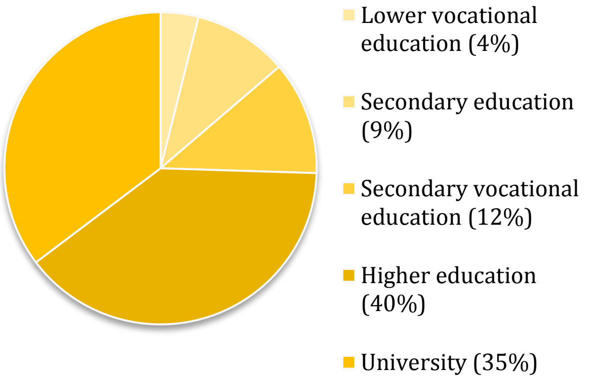
Amazon.com
What is your age?
(N=51)



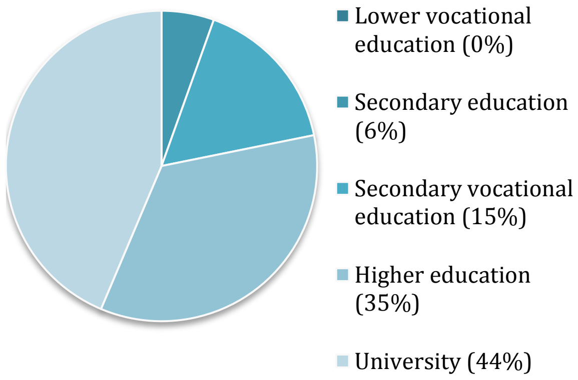
Twitter
What is your age?
(N=55)



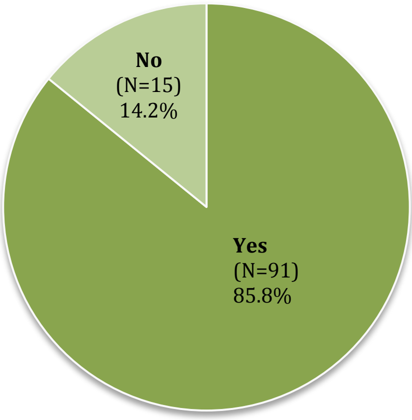
Amazon.com
What is your current or highest completed education?
(N=51)



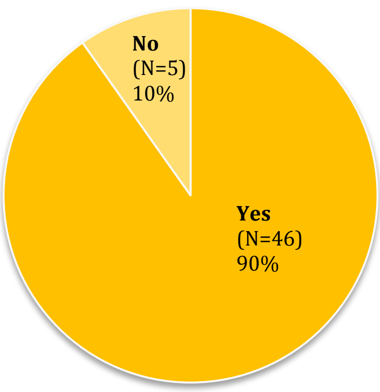
Twitter
What is your current or highest completed education?
(N=55)



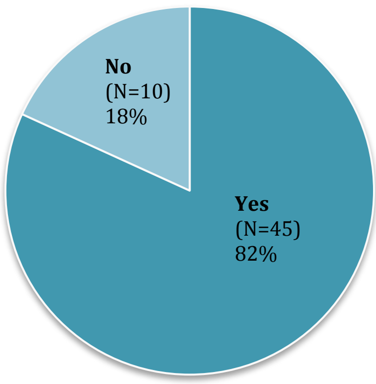
Have you ever visited a product review website?
(N=106)

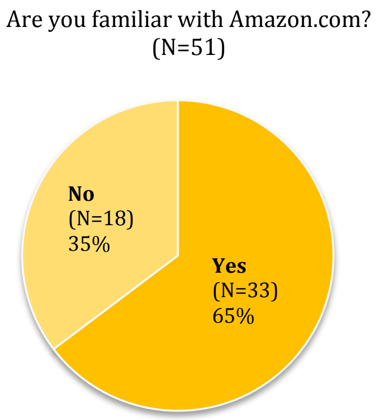


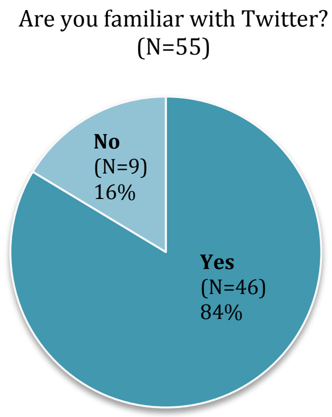
Amazon.com
(N=51)

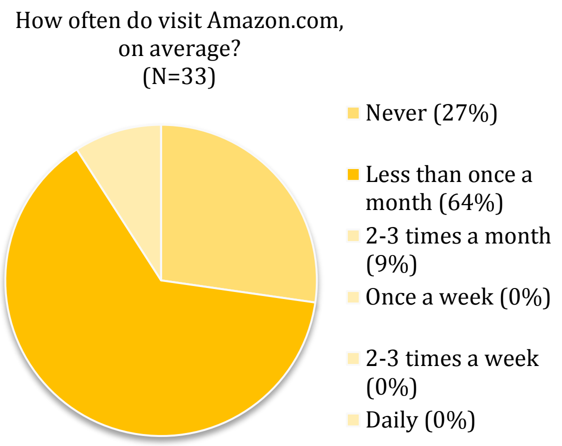


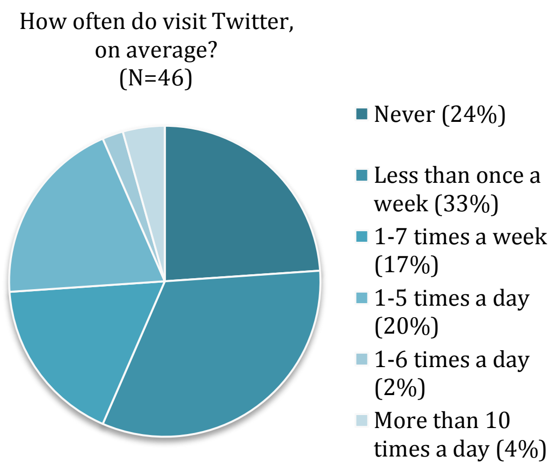
Twitter
(N=55)

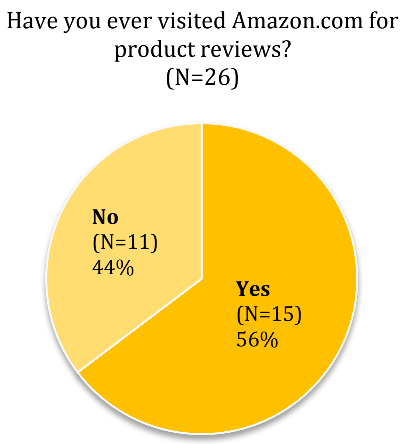


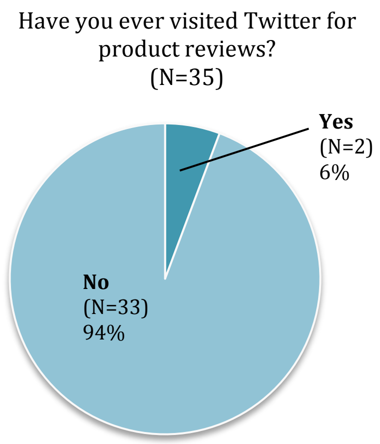

Are you familiar with Amazon.com?
(N=51)
No
(N=18)
35%
Yes
(N=33)
65%


Are you familiar with Twitter?
(N=55)
No
(N=9)
16%
Yes
(N=46)
84%


How often do visit Amazon.com,
on average?
(N=33)
Never (27%)
Less than once a month (64%)
2-3 times a month (9%)
Once a week (0%)
2-3 times a week (0%)
Daily (0%)


How often do visit Twitter,
on average?
(N=46)
Never (24%)
Less than once a week (33%)
1-7 times a week (17%)
1-5 times a day (20%)
1-6 times a day (2%)
More than 10 times a day (4%)


Have you ever visited Amazon.com for
product reviews?
(N=26)
No
(N=11)
44%
Yes
(N=15)
56%


Have you ever visited Twitter for
product reviews?
(N=35)
Yes
(N=2)
6%
No
(N=33)
94%

Appendix VI: Covariance analysis

Table 1.

Pearson product-moment correlation coefficients between the covariate variables.

	Visit frequency	General attitude toward product reviews	Attitude toward product review source	Product involvement
Amazon.com				
Visit frequency	-	-.10	.05	-.11
General attitude toward product reviews		-	.40**	.39**
Attitude toward product review source			-	.45**
Product involvement				-
Twitter				
Frequency	-	.10	.37*	.15
General attitude toward product reviews		-	.20	-.65**
Attitude toward product review source			-	.10
Product involvement				-

Note: ** p <.01

Table 2.

ANCOVA: Analysis of covariance for the dependent variable 'Credibility'.

	b-value	*df*	*F*-value	*p*	*Partial η²*	*r*
General attitude toward product reviews	0.17	(1, 103)	5.01	**.027**	.045	.22
Attitude toward product review source	0.33	(1, 103)	27.51	**.000**	.211	.46
Product involvement	0.15	(1, 103)	5.93	**.017**	.054	.71
Frequency	-0.01	(1,76)	0.01	.936	.00	.00
Contrasts	*Level 2 (Twitter) vs. Level 1 (Amazon.com)*					
General attitude toward product reviews			p = .332			
Attitude toward product review source			p = .229			
Product involvement			p = .462			
Frequency			p = .278			

Table 3.

ANCOVA: Analysis of covariance for the dependent variable 'Attitude toward product'.

	b-value	*df*	*F*-value	*p*	*Partial η²*	*r*
General attitude toward product reviews	-0.08	(1, 103)	1.53	.219	.015	.12
Attitude toward product review source	0.06	(1, 103)	0.93	.337	.009	.09
Product involvement	-0.40	(1, 103)	0.60	.440	.006	.08
Frequency	-0.05	(1,76)	0.42	.522	.005	.07
Contrasts	Level 2 (Twitter) vs. Level 1 (Amazon.com)					
General attitude toward product reviews	p = **.040**					
Attitude toward product review source	p = .131					
Product involvement	p = **.038**					
Frequency	p = .616					

Table 4.

ANCOVA: Analysis of covariance for the dependent variable 'Purchase intention'.

	b-value	*df*	*F*-value	*p*	*Partial η²*	*r*
General attitude toward product reviews	-0.13	(1, 103)	2.69	.104	.025	.16
Attitude toward product review source	0.02	(1, 103)	0.07	.790	.001	.03
Product involvement	-0.04	(1, 103)	0.45	.506	.004	.06
Frequency	0.01	(1,76)	0.02	.892	.000	.00
Contrasts	*Level 2 (Twitter) vs. Level 1 (Amazon.com)*					
General attitude toward product reviews	p = .369					
Attitude toward product review source	p = .482					
Product involvement	p = .357					
Frequency	p = .939					

Note: the results of attitude toward source and frequency should be analyzed with care, because this variable violated the 'independence of independent variable' assumption of ANCOVA. This means that these variables explain some variance of the dependent variable; they share variance but this is not explicitly separated. A possible solution was the randomization of conditions, however this was already the case. Furthermore, the product involvement variable violated the homogeneity assumption with the dependent variables; attitude toward product and purchase intention. The results of Levene's tests were not significant, indicating that the homogeneity assumption was not violated.

Appendix VII: Usage characteristics and dependent variables

Table 1.

Independent t-test for question 1: "Have you ever visited a product review website".

	Yes			No			
	N	M	SD	N	M	SD	
Amazon.com							
Credibility	46	3.75	0.80	5	3.63	0.35	t (49) = 0.32, p = .749
Attitude toward product	46	3.32	0.72	5	3.63	0.58	t (49) = -0.91, p = .367
Purchase intention	46	3.15	0.83	5	3.75	0.71	t (49) = -1.57, p = .123
Twitter							
Credibility	45	3.58	0.98	10	3.54	0.83	t (53) = 0.13, p = .901
Attitude toward product	45	2.95	0.72	10	3.55	0.65	t (53) = -2.41, p = **.019**, ω = .080
Purchase intention	45	2.94	0.85	10	3.60	0.81	t (53) = -2.23, p = **.030**, ω = .068

Table 2.

Independent t-test for question 2: "Are you familiar with Amazon.com/Twitter".

	Yes			No			
	N	M	SD	N	M	SD	
Amazon.com							
Credibility	33	3.76	0.78	18	3.71	0.75	t (49) = 0.21, p = .837
Attitude toward product	33	3.16	0.61	18	3.69	0.77	t (49) = -2.72, p = **.009**, ω = .111
Purchase intention	33	2.92	0.69	18	3.72	0.82	t (49) = -3.67, p = **.001**, ω = .197
Twitter							
Credibility	46	3.52	0.90	9	3.84	1.18	t (53) = -0.92, p = .360
Attitude toward product	46	3.11	0.79	9	2.79	0.39	t (53) = 1.19, p = .241
Purchase intention	46	2.95	0.76	9	3.64	1.24	t (53) = -2.25, p = **.029**, ω = .068

Table 3.

Pearson product-moment correlation coefficient for question 3: "How frequently do you visit Amazon.com/Twitter?".

Amazon.com	Frequency (*r*)
Credibility	.02
Attitude toward product	-.12
Purchase intention	-.02
Twitter	Frequency (*r*)
Credibility	-.02
Attitude toward product	.12
Purchase intention	.03

Table 4.

Independent t-test for question 4: "Have you ever visited Amazon.com/Twitter for product reviews?".

	Yes			No			
	N	M	SD	N	M	SD	
Amazon.com							
Credibility	11	3.99	0.72	14	3.71	0.59	t (23) = 1.08, p = .2.90
Attitude toward product	11	3.14	0.75	14	3.11	0.63	t (23) = 0.11, p = .916
Purchase intention	11	2.89	0.92	14	2.91	0.52	t (23) = -0.08, p = .934
Twitter							
Credibility	2	3.42	0.12	33	3.52	0.94	t (33) = -0.17, p = .870
Attitude toward product	2	3.19	0.88	33	3.12	0.81	t (33) = 0.12, p = .904
Purchase intention	2	3.00	0.00	33	2.92	0.79	t (33) = 0.15, p = .884

Appendix VIII: Hypothesis 3 testing

Table 1.

Results of testing hypothesis 3a (credibility), using a Mixed ANOVA and an independent t-test.

Mixed ANOVA

Test of Within-Subjects Effects

	Type III Sum of squares	*df*	*Mean Square*	*F*-value	*p*	*Partial η²*	*r*
MQ	142.13	1	142.13	171.02	**.000**	.622	.79
MQ x S	9.63	1	9.63	11.59	**.001**	.100	.32
Error (MQ)	86.43	104	0.83	-	-	-	-

Test of Between-Subjects Effects

	Type III Sum of squares	*df*	*Mean Square*	*F*-value	*p*	*Partial η²*	*r*
Intercept	1415.71	1	1415.71	1899.69	.000	.948	-
S	0.70	1	0.70	0.94	.334	.009	-
Error	77.50	104	0.75	-	-	-	-

Independent t-test	*df*	*t*-value	*p*	ω
MQL	104	-.1.29	.199	-
MQH	104	2.75	**.007**	.060

Note: MQ = Message quality (within-subjects measurement), MQL = Message quality Low, MQH = Message quality High, S = Source (between-subjects measurement).

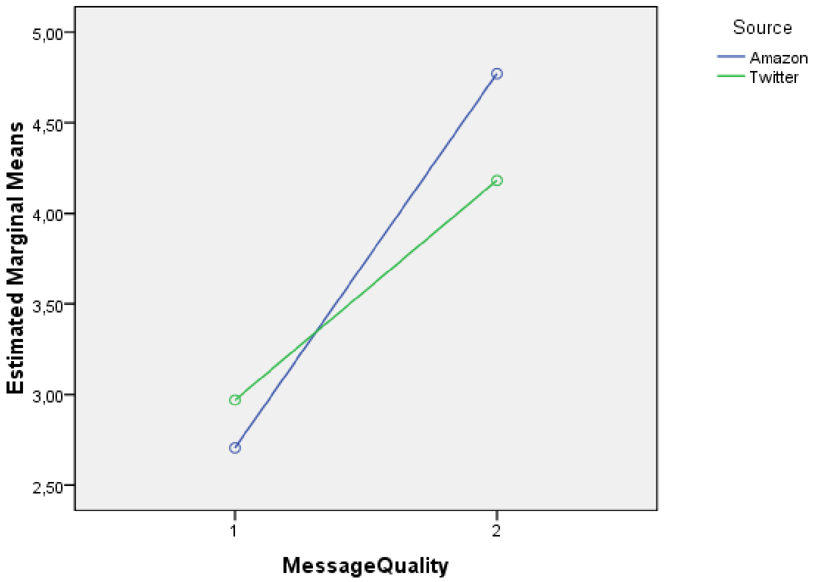


Figure 1. *Interaction between source and message quality for the variable credibility.*

Table 2.

Results of testing hypothesis 3b (attitude toward product), using a Mixed ANOVA and an independent t-test.

Mixed ANOVA

Test of Within-Subjects Effects

	Type III Sum of squares	*df*	*Mean Square*	*F*-value	*p*	*Partial* η^2	*r*
MQ	23.28	1	23.28	39.94	**.000**	.277	.53
MQ x S	3.67	1	3.67	6.29	**.014**	.057	.24
Error (MQ)	60.62	104	0.58	-	-	-	-

Test of Between-Subjects Effects

	Type III Sum of squares	*df*	*Mean Square*	*F*-value	*p*	*Partial* η^2	*r*
Intercept	1087.14	1	1087.14	2058.17	.000	.952	-
S	2.25	1	2.25	4.25	**.042**	.039	.20
Error	54.93	104	0.53	-	-	-	-

Independent t-test	*df*	*t*-value	*p*	ω
MQL	104	2.99	**.003**	.070
MQH	104	0.17	.867	-

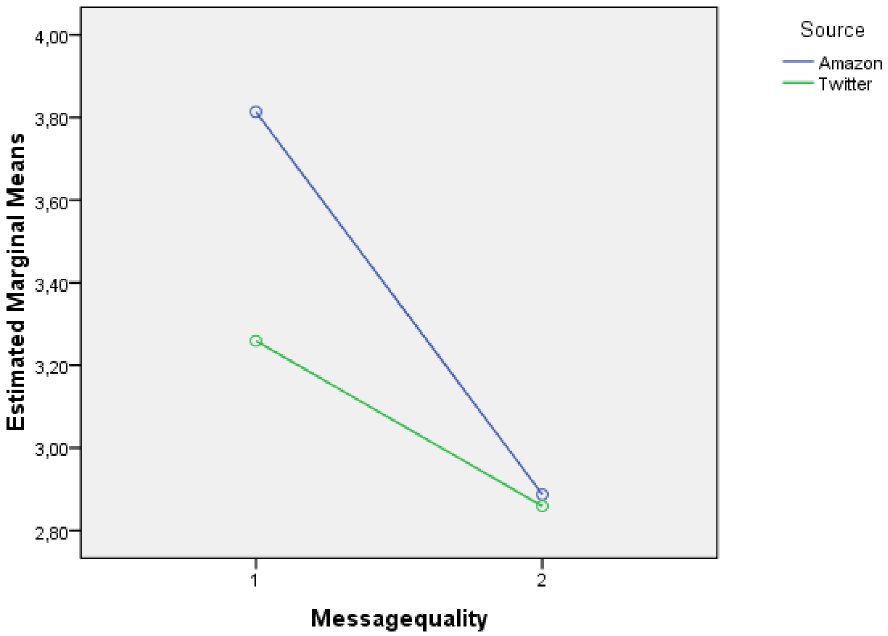


Figure 2. *Interaction between source and message quality for the variable attitude toward product.*

Table 3.

Results of testing hypothesis 3c (purchase intention), using a Mixed ANOVA and an independent t-test.

Mixed ANOVA							
Test of Within-Subjects Effects							
	Type III Sum of squares	*df*	*Mean Square*	*F*-value	*p*	*Partial η²*	*r*
MQ	35.04	1	35.04	47.44	**.000**	.313	0.56
MQ x S	1.84	1	1.84	2.49	.118	.023	-
Error (MQ)	76.81	104	0.74	-	-	-	-
Test of Between-Subjects Effects							
	Type III Sum of squares	*df*	*Mean Square*	*F*-value	*p*	*Partial η²*	*r*
Intercept	1038.64	1	1038.64	1422.07	.000	.932	-
S	0.57	1	0.57	0.78	.379	.007	-
Error	75.96	104	0.73	-	-	-	-

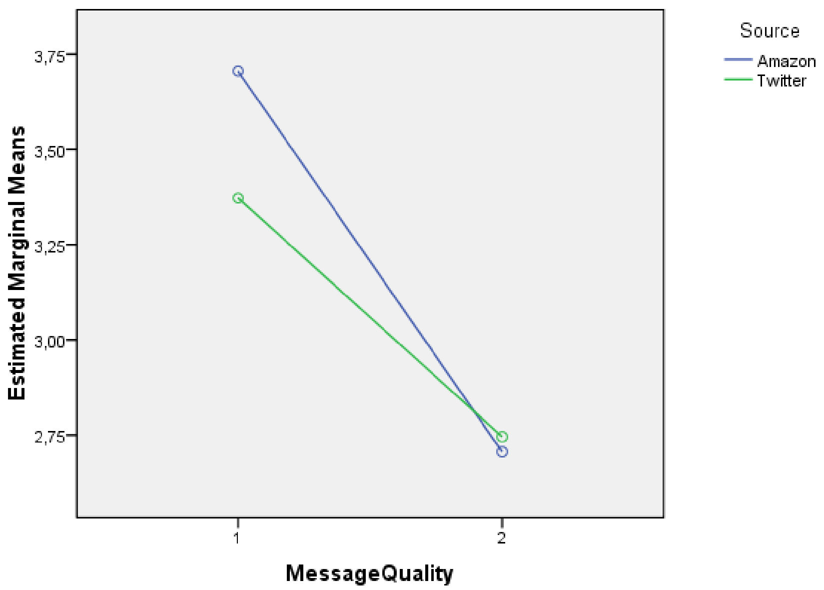


Figure 3. *Interaction between source and message quality for the variable purchase intention.*