MASTER'S THESIS

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Evaluating online customer data helpfulness to set targets: a QFD perspective

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Contents

Retrieving knowledge and useful information from customers is crucial to develop customer-focused products and maintain the market share. With the rapid growth of the Internet, the ability of users to create and publish content has generated a wealth of product information from customers' point of view. Given the abundance of large scale, publicly available data social media can enable novel social ways of providing and receiving feedback from new products and concepts.

In order to avoid information overload, identifying and analyzing helpful reviews has become a critical challenge. Identifying helpful online reviews and learning how to extract valuable data from product design perspective has become a crucial task due to the existing information overload –identifying what is relevant to analyze is a key task for companies.

Existing studies have focused on identifying variables that affect the perceived helpfulness of an online comment. To the best author's knowledge, actual studies about helpfulness do not consider the Quality Function Deployment perspective on evaluating to what extend the customer data from social media is helpful to set objective targets.

The thesis aims to evaluate social media data helpfulness from the designer's perspective taking as basis QFD. Evaluating this, the work hypothesis is that the helpfulness definition has to move beyond, taking into consideration what is needed to build The House of Quality, a key tool in product design. To do so, an exploratory analysis of real public data from Twitter, Facebook and iMore forum is taken as basis. The purpose of undertaking exploratory research is primarily to investigate and to identify if the proposed variables for defining review's helpfulness currently existing in the literature review can help designers in target setting within a QFD perspective

The presented thesis shows that to go further within target setting is needed to have the QFD perspective: not all current exposed variables do not help to explain online reviews helpfulness.

Keywords: Customer Attributes, Customer Needs, Target setting, Engineering characteristics, Helpfulness, Social Media, Product design, Quality Function Deployment, The House of Quality

Preface

Undertaking this Master Thesis in the product design domain has been one of the hugest challenges achieved during our Master Degree in Management Engineering. What we have learned while embarking the thesis will be surely retained in our mind and useful for our professional career. Studying at Luleå University of Technology, and more concretely, at the division of Product and Production Development, and being among talented minds in this department has been certainly a great honor that makes us feel proud and glad. Studying in a cutting edge university has been a priceless opportunity to learn from a green, creative, equal and open country. At the same time, we have felt that the more we have learned, the more we realized that there is so much to do and learn in our thesis scope.

Carrying out the thesis would not have been possible without the privileged help of our supervisor, Anna Martí Bigorra. Our endless thanks to her for the patience, coaching, continuous support and motivation. Also, we would like to thank Professor Magnus Karlberg for the supervision, the good advice and guidance along the way.

Finally, we would like to thank our families and friends, our closest ones, for being our unconditional support even being away from home. Also our Sweden friends, for letting us know that home is just a feeling.

Maria Cambra Obach and Laia Vendrell Fernández
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List of acronyms

CA	Customer Attributes
CN	Customer Needs
CR	Customer Requirements
EC	Engineering Characteristics
H	Helpful
HoQ	House Of Quality
PF	Product Features
QFD	Quality Function Deployment
SD	Sentiment difference
SM	Social Media
NH	Non-helpful

1. Introduction

This section aims to introduce the purpose of the thesis and to provide a general overview of some of the main aspects of the studied topic that has led forth to the development of this master thesis.

The success of a product or a service is largely dependent on to what extent the product or the service satisfies customer needs. One of the principal functions of designers is to enable a concise description of how customer requirement information is integrated into the design of the desired product. During the design process, the designer transforms customer requirements information into explicit product specifications. Today, Quality Function Deployment (QFD) is a widely used methodology to set targets. Employing this procedure, customer needs are systematically matched with the product features and design parameters, improving the product quality (Bergquist et al., 1996). In the QFD analysis, during transferring the wants and needs of the customers into product characteristics, a large number of subjective suppositions are needed from designers. To clearly identify what customers need, users should be involved early and continuously throughout the design and development process (Gulliksen et al., 2003), even though it is difficult for developers to make direct contact with users and observe them (Butler, 1996).

In these current competitive times, product manufacturers need not only to retain their existing customer base, but also to increase their market share. In this way, the success of most firms depends on their ability to identify the needs of customers and to quickly create new products that meet these needs: generating new ideas and developing novel products with new features (Ulrick et al., 2000). Traditionally, customer needs are collected from interviews, questionnaires or surveys, which are often time-consuming and laborious. Nowadays, this opinion data exists under the concept of Big Data, so twitters, blogs and product reviews are revealing consumers' interests and preferences (Wu et al., 2014; Jin et al., 2016). One of the major differences between big data and traditional data may be that the first concept is described by three main characteristics: Volume, Velocity and Variety – 3 Vs (Adrian, 2016).

Given the abundance of large scale, publicly available data social media can enable and significantly increase the collaboration and learning from customers in various ways, for instance by novel social ways of providing and receiving feedback from new products and concepts. Population generates more than 2,5 quintillion bytes of data each day (Wu et al., 2014) and a great part of this data is created through social media sources such as Twitter, Facebook or forums, enabling its users to exchange information in a dynamic way, anywhere and anytime. These data empower designers to obtain customer requirements, facilitating designers to improve their new products while meeting customers' needs.

In order to avoid information overload, identifying and analyzing helpful reviews has become a critical challenge (Otterbacher, 2009; Ghoose et al., 2011; Pan et al., 2011; Zhang (2014); Kim et al., 2006; Liu et al., 2012; Qi et al., 2016). Most of the existing efforts to evaluate review's helpfulness are considered from the consumers' standing (Otterbacher, 2009; Ghoose et al., 2011; Pan et al., 2011; Zhang (2014); Kim et al., 2006). However, not a large number of authors consider and define helpfulness from the product designer's point of view. In fact, it is shown that helpfulness of user reviews from consumer's perspective is not viewed in the same dimensions as designers and engineers do (Liu et al, 2012; Qi et al., 2016).

The above-mentioned studies from the designers' point of view focus on identifying variables that affect the perceived helpfulness of an online comment. In addition, the chosen set of candidate variables are entirely based on the review and website content. In order to classify social media content as helpful or not, the authors train a classifier. Thus, a training dataset is created for this purpose by making a group of designers to label a set of comments as helpful or not. The criteria used by designers to define comments as helpful or not is not provided nor discussed in these studies and thus what helpfulness mean by the designer's perspective remains unknown. This in turn makes difficult to ensure that the classified helpful customer comments will help the actual target setting.

To the best author's knowledge, actual studies do not consider the QFD perspective on evaluating to what extend the customer data from social media is helpful to set objective targets. The authors consider that identifying helpful reviews efficiently and accurately is a critical challenge for market-driven product design. The thesis aims to evaluate social media data helpfulness from the designer's perspective taking as basis QFD. Evaluating this, the work hypothesis is that the helpfulness definition has to move beyond, taking into consideration what is needed to build The House of Quality, a key tool in product design.

1.1 Thesis outline

The body of this thesis is organized as follows. In *Section 1*, introduction to the thesis is provided. In *Section 2* a literature review about QFD and studies aiming to identify helpful social media data for product development are proposed. *Section 3* presents the used methodology through which results are extracted. Results are presented in *Section 4*. Lastly, conclusions and future work are untaken in *Section 5* and *Section 6*, respectively.

2. State of art

This chapter aims to provide an understanding about the work undertaken by different authors about the different theories, concepts and frameworks, which form the theoretical base of the thesis. The chapter gives a comprehensive overview on the topics related to QFD and best practices on extracting helpful user comments from social media data.

The existing literature has been categorized into two broad sections as shown in *Figure 1,* where the reader can see where the focus of the following thesis is.

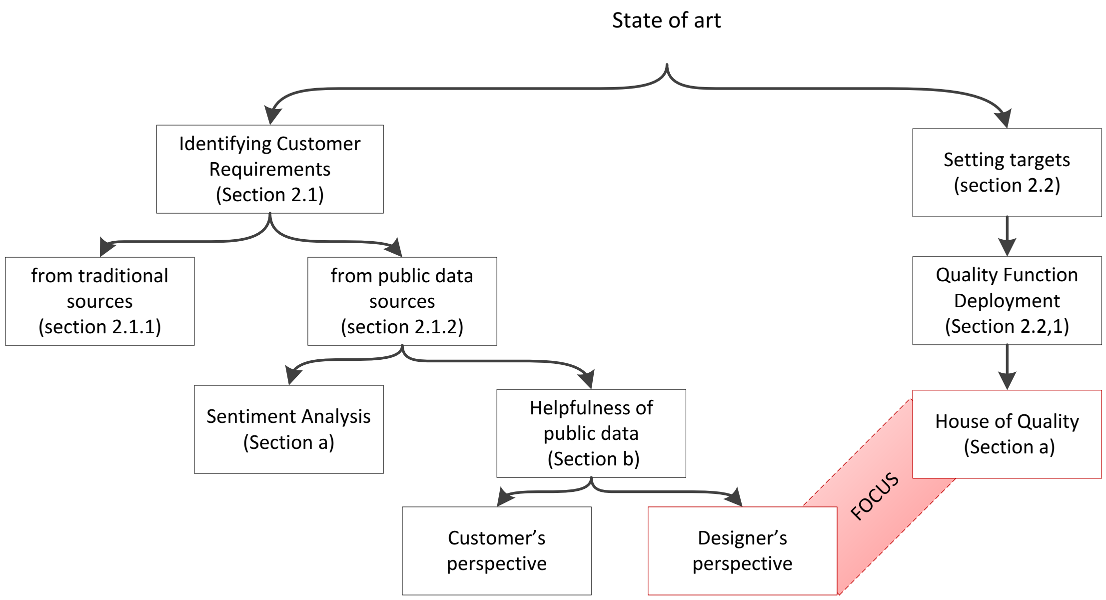


Figure 1. State of art overview

2.1. Analyzing customer needs

One of the product development's most vital functions is product design, where the lead role is defining the physical form of the product to best meet customer needs including engineering design – mechanical, electrical, software, etc. – and industrial design – aesthetics, ergonomics, user interfaces, etc. (Ulrick et al., 2000). The author define that the design of a new product starts with identifying customer needs, establishing target specifications and generating the product concept, testing it and coming up with the final specifications and ending with the new product launch.

2.1.1 Customer data from traditional sources

In the past, new product design process started collecting customer needs from traditional methods. Focus groups, surveys, interviews and questionnaires are some of the more traditional methods of generating customer insight and obtaining information for new product development (Blazevic et al. 2008). These traditional methods have been a key instrument in product design (Buntain et al., 2016): when an organization or a business needed public or consumer opinions, it conducted surveys, opinion polls and focus groups, so acquiring consumer opinions has long been a huge business itself being a long haul and laborious (Matthing et al., 2004; Liu, 2012; Jin et al., 2016).

These methods were needed to elicit customer needs and each one needs plenty of time to interact with customers. One reason is that not only explicit needs, but also hidden needs ought to be identified, those that the customer is not aware of and cannot articulate. This requires that design engineers and industrial designers interact with customers and experience the use environment of the product in different situations. Moreover, customer needs are often expressed in abstract, ambiguous or conceptual terms. Consequently, traditional techniques are often time and cost consuming due to the linguistic analysis of customer needs (Zhou et al., 2015; Timoshenko et al., 2017).
Latterly, the arrival and widespread popularity of social media (SM) has introduced a new source of data and a different perspective from which to examine consumer needs. Social media data is abundant and versatile, can be collected more quickly. One can acquire and analyze SM data much more rapidly than traditional techniques can be designed, implemented and analyzed. In addition, gathering and analyzing data from SM is cheaply than traditional data insight methods and provides a wealth of information about user behavior since social media postings are made outside of the surveyed context (Zhou et al., 2015).

Compared with offline or paper-and-pencil surveys, online reviews provide richer information in less time and at a lower cost, as the respondents are willing to participate independently (Qi et al., 2016).

With the accelerated growth of social media –for example, reviews, forum discussions, blogs, microblogs, comments and postings in social network sites- on the Web, organizations no longer need to conduct surveys, opinion polls and focus groups in order to gather public opinions because there is an abundance of such information publicly available (Dave et al., 2014). However, monitoring opinion sites on the Web and filtering the information in them remains a challenging task (Liu et al., 2013).

2.1.2 Customer data from public data sources

Social media refer to the combination of online tools and systems that enable and seek out participation and contributions by users (Hagen et al., 2009). These tools enable and significantly increase the collaboration and learning from customers in various ways, for instance by novel social ways of providing and receiving feedback from new products and concepts (Jussila et al., 2012). Liu (2012) confirmed that with the explosive growth of social media -for example, reviews, forum discussions, blogs, microblogs, comments and postings in social network sites- organizations are increasingly using the content in these media for decision-making. Indeed, exploiting big consumer data provide new opportunities because of the value of these data in the perspective of product designers, powerful to reveal customers' interest.

The constantly growth of social technologies has meant to have a huge quantity of information posted by consumers on media. This type of consumer-generated information gives an opportunity to the firms to identify customer tastes, preferences and responses on their products and services (Urban et al., 2004). This information, enables designers to obtain CRs, monitor trends of consumer interests and make comparisons with similar products, which facilitate designers to improve their products with novel ideas and response to consumers meeting their needs (Jin et al., 2016).

Online reviews could be the source of innovative ideas, providing input for new product designs and enhancements. Co-creation, the active involvement of customers in the process of new product and service development, has been identified as a reliable source of competitive advantage. From the viewpoint of manufacturers, online reviews are appealing sources of customer needs, especially for those manufacturers who must continually renovate their products in the competitive market. Through online reviews, product designers can listen to the voices of customers in the target market (Qi et al., 2016).

Traditionally, identifying and understanding customer needs starts with gathering raw data from customers and interpreting it in terms of customer needs. The next step is organizing the needs into hierarchy of primary, secondary and tertiary needs and establishing the relative importance of the needs (Ulrich et al., 2012).

Many researchers also employed Kano's model to quantify the importance of CRs. The model serves as a tool for the understanding of CRs and their impacts on customer satisfaction. In this model, different requirements are categorized to must-be attributes, one-dimensional attributes, attractive attributes, indifference attributes, etc. (Jin et al., 2016).

Today companies are not taking fully the advantage of social media possibilities due to, among other reasons, the lack of understanding of the possibilities of social media in innovation, the difficulties in assessing its financial gains and the lack of evidence from similar cases using social media in innovation (Kärkkäinen et al., 2010). In addition, finding and monitoring opinion sites and filtering the information contained in them remains a challenge task because of the proliferation of different characteristics social sites (Liu, 2012). Moreover, due to the huge volume of opinion text, the average human reader will have difficulty identifying relevant sites and extracting and summarizing the opinions in them. For this reason, machine-learning algorithms able to identify what information is relevant to know are required. Automated sentiment analysis systems are for instance an example (Liu, 2012).

A. Sentiment analysis on consumer online opinions

Sentiment analysis, or opinion mining, is the core technique behind social media analysis. It leverages computational linguistics, natural language processing and other methods of text analytics to automatically extract user sentiment or opinions from text sources at any level of granularity –words or phrases up to entire documents. Relatively simple methods for sentiment analysis include word counts –the more a product is mentioned, the more it is assumed to be liked-, polarity lexicons –positive, negative or neutral- or lists of positive and negative terms that can be counted when used and semantic methods that may compute lexical "distances" between a product's name and each of two opposing terms –such as "poor" and "excellent"- to determine sentiment. Approaches that are more complicated distinguish the sentiments about more than one item referenced in the same text item –such a sentence or paragraph (Fan et al., 2014).

Since early 2000, sentiment analysis has grown to be one of the most active research areas in natural language processing (NLP). It is a field also widely studied in data mining, web mining and text mining. In fact, it has spread from computer science to management sciences and social sciences due to its importance to business and society as a whole. Consequently, sentiment analysis systems have found their applications in almost every business and social domain (Liu, 2012).

Manual extraction and analysis of online opinions is infeasible and consequently, automated tools are required. First attempts to extract opinions automatically have focused primarily on polarity of reviews -positive or negative- (Jebbara et al., 2017). Since customer reviews are typically mixed -liking some aspects of a product but criticizing others-, recent research has focused on identifying key product attributes and extracting consumer opinion about each feature (Lau et al., 2014; Ioannis, 2014; Jebbara et al., 2017; Ahmad et al., 2017).

The most basic task in sentiment analysis is to classify opinions as positive or negative. This task can be performed at three levels: document, sentence and aspect level analyses. Document level classifies whether a whole opinion document expresses a positive or negative sentiment. For example, in the context of product development, having a particular product review, the system determines whether the review expresses an overall positive or negative opinion about the product, assuming that each document expresses opinions on a single entity. Sentence level goes to the sentences and determines whether each sentence express a positive, negative or neutral opinion -usually means no opinion. This level of analysis is closely related to subjectivity classification, which distinguishes sentences that express information -called objective sentences- from sentences that express subjective views and opinions -called subjective sentences (Liu, 2012).

The first couple of analysis -document and sentence level- do not strictly recognize what people like and dislike (Hu et al., 2004; Kim et al., 2004; Gamon et al., 2005). Aspect level performs finer-grained analysis, where instead of looking at language constructs as documents, paragraphs, sentences, clauses or phrases, the overall idea of aspect analysis is that an opinion consists of a sentiment -positive or negative- and a target of opinion (Lu et al., 2011; Liu, 2012).

Generally, given a text, aspect-analysis method extracts explicitly expressed aspects in the text and each extracted aspect term is processed individually and a sentiment value is assigned given the context of the aspect term –see Figure 1. Cesarano et al. (2004) discussed sentiment classification stand on adjective phrases only proposing a scale ranging from -1 to +1 for measuring the degree of polarity in sentiments. Later, Benamara et al. (2007) suggested that focusing on both adjectives and adverbs gives more accurate results than exploring adjectives only. Other studies extended this analysis to include verbs along with adjectives and adverbs to extract sentiment analysis (Subrahmanian et al., 2008).

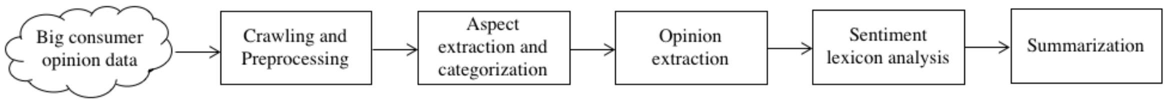


Figure 1. Sentiment analysis pattern.

B. Helpfulness of public data

Helpfulness can be considered from two different perspectives: customers or designers. Different authors have pointed at the helpfulness from customer's perspective. While reading reviews can help the potential customers make informed decisions, in many cases the large quantity of reviews available for a product can be overwhelming and actually impede the customers' ability to evaluate the product. The goal of these authors is to develop models and algorithms for predicting the helpfulness of reviews from consumer point of view, which provides the basis for discovering the most helpful reviews for given products (Korfiatis et al., 2008; Liu et al., 2008; Otterbacher, 2009; Ghoose et al., 2011). On the other hand, other authors (Liu et al., 2012; Qi et al., 2016) have spread their analysis to the designer's perspective, in order to extract information to develop appropriate product improvement strategies. They argue that existing evaluation methods only use the review voting ratios given by customers to measure helpfulness. Meanwhile, as consumers are not obligated to vote such reviews, usually, only a small proportion of the reviews eventually receive sufficient votes. Liu et al. (2012) and Due to the lack of efforts to evaluate helpfulness from consumers' standing, Qi et al. (2016) start to question if consumers view online product reviews helpfulness in the same dimensions as designers and engineers do, ultimately demonstrating that there exists a notable difference on ratings between designers and consumers.

Customer's perspective

So far, the best effort for ranking reviews for consumers comes in the form of votes in forums where customers give "helpful" votes to other reviews in order to rate their usefulness. Ghose et al. (2011) affirmed that the helpful votes are not a useful feature for ranking recent reviews because they are accumulated over a long period of time and also Liu et al. (2013) concludes that there is no strong correlation between the helpfulness voting given by consumers and the one rated by product designers. Hence, there is a visible gap in interpreting helpfulness from product designers' and manufacturing engineers' point of view.

Moreover, Zhang (2014) defined that a helpful review from customer's standing likely provides a large quantity of detailed information about the product. Also, the sentence structure is clear and contains less spelling or grammar errors. And, in comparison, the less helpful reviews provide less information and add no additional value.

Automatically evaluating the quality of online reviews has gradually attracted more attention in recent years and several studies have been carried out (Zhang et al., 2006; Kim et al., 2006; Liu et al., 2007; Ghose et al., 2009; Liu et al., 2013; Kuan et al., 2015; Qi et al., 2016). Most previous works have focused on automatically predicting the quality – helpfulness or usefulness – of reviews by using a set of observed textual or social features. Textual features are the ones based on text statistics while social features are related with the information extracted from the reviewer's social context. Along with classifying reviews as helpful or unhelpful, some authors also considered estimating the helpfulness of reviews by using regression models to generate a quality or helpful rating for each review (Zhang et al., 2014).

Kim et al. (2006) and Liu et al. (2009) also provide a definition of helpfulness. Both articles conclude that helpfulness is the relation between the number of people that finds a review helpful out of the sum of the number of votes. This lead helpfulness to be a number falling in the range [0, 1], and greater value of the fraction imply higher helpfulness.

Liu et al.'s (2008) prediction of helpfulness' model is based on a thorough analysis of some major factors that may affect the helpfulness of a review and identify three most influential ones: reviewer expertise, where they express personal experiences, thoughts and concerns; writing style, due to the large variation of reviewers' background and language skills; and finally, timeliness, in which its been considered that the average declines as time passes by. To this end, an examination of different reviews on several popular websites was conducted to find and evaluate various factors involved in helpfulness. They provided a detailed analysis of the major factors affecting the helpfulness of a review.

Kim et al. (2006) found that the most useful features to determine the helpfulness of online reviews from consumer's point of view were the length of the review, unigrams[1] of the review and the rating of the product. One aim of their paper is to investigate how well different classes of features capture helpfulness of a review. They experimented with various features organized in five types: structural, lexical, syntactic, semantic and metadata.

Structural features are observations of the document structure and formatting. Properties such as review length and average sentence length are hypothesized to relate structural complexity to helpfulness. Lexical features capture the words observed in the reviews. Syntactic features aim to capture the linguistic features of the review. They include the percentage of words that are nouns and the percentage that are verbs. In addition, they determined the percentage of verbs conjugated in the first person and the number of token words that are adjectives or adverbs. Regarding to semantic features, Kim et al. (2006) hypothesize that good reviews will often contain references to the features of a product, including opinion on it, and the sentiment of the words, as positive or negative. Unlike the previous four feature classes, metadata features capture observations which are independent of the text and unrelated with linguistic features, such as number of stars or the rating of the products mentioned in the reviews.

Otterbacher J. (2009) examines the nature of helpfulness too, with the social media source Amazon. The carried-out analysis revealed five underlying quality dimensions related to the helpfulness scores assigned by community participants. However, it also uncovers a strong relationship between the chronological ordering of reviews and helpfulness, which both community participants and designers should keep in mind when using this method of social navigation.

Trying to find the dimensions of helpfulness the authors look to the Management Information Systems literature, where the concept of data quality has been studied extensively. Wang and Strong (1996) analyse what data quality means from data user's perspective. After their investigation, they conduct that there are four major categories of data quality each of which is made up of several dimensions:

- Intrinsic quality: emphasizes that data have quality in their own right. Important dimensions of this attribute include believability, accuracy, objectivity and reputation.

[1] In the fields of computational linguistics and probability, an n-gram is a contiguous sequence of *n* items from a given sample of text or speech. The items can be phonemes, syllables, letters, words or base pairs according to the application. An n-gram of size one is referred to as a "unigram".

- Contextual quality: stresses the need to consider quality with respect to the user's specific task. Its dimensions include relevancy, timeliness, completeness and quantity.
- Representational quality: has to do with the format and meaning of the data. Its key dimensions are interpretability ease of understanding, representational consistence and concise representation.
- Accessibility: concerns whether the user has access to an information system in order to meet her information needs. Its dimensions include accessibility and access security.

Otterbacher J. (2009) concludes that to assess quality in Amazon reviews only the first three categories are needed, because accessibility is not relevant since participants in the community are using the same information system, and incorporates new aspects in each group. In conclusion, the author found that the "helpfulness" of reviews at Amazon is correlated to several dimensions of message quality. Despite its simple nature, the construct of "helpfulness" is able to pick up on some underlying attributes of quality, such as the topical relevancy, objectivity and readability of reviews (Otterbacher, 2009).

Designer's perspective

Liu et al. proposed four principal categories (2012) and Qi et al. extended them to five later on time (2016). They proposed four categories of intrinsic features of reviews based on the results of an exploratory study to understand how designers perceive helpfulness. They start the study with the assistance of design personnel who need to rate the review helpfulness of a number of social media comments –randomly chosen- based on their own design experience or needs. They adopted a five-degree helpfulness evaluation metric which only concerns whether it is helpful or not helpful towards product design. The next step was to follow up two questionnaires. Result analysis of the questionnaires permit to gain several insights regarding why certain reviews are perceived helpful by designers while others not. Understanding designers' opinion and needs enable Liu et al. (2012) to propose four categories of features that model and affect product review helpfulness: linguistic features, product features, features based on information quality and features using information theory.
In addition to define which factors affect review's helpfulness from a product designer's perspective, they conclude that designers' helpfulness rating might not present a strong correlation with the online helpfulness voting ratio and there might be a significant or unacceptable error between both variables.

In the study, some persons expect that they can learn more useful information from longer product online reviews what can be defined for instance by its number of words and its number of sentences. Product designers also appreciate to enquire the reasons behind customers' preferences or complaints on a particular product, such sentiments which are mainly expressed using adjective or adjective plus adverb phrases. The respondents also indicate that they might lose their interest to read and attempt to understand online reviews if there are many grammar errors (number of grammar errors), wrong spellings and if there are many exceptionally long sentences (average number of words per sentence). This leads to came up with linguistic features group.

The research also enlightens that some product designers focus on whether key product features have been mentioned and such product features are considered crucial information carriers when designers are conceiving new product models, so the appearance of some particular product feature might largely influence helpfulness evaluation. In this regard, product features are another important group to consider.

According to the compiled questionnaires some subjects replied “this review mentions many product features” while some argue that “many reviews shared the features he/she likes and dislikes”. These arguments are related with information quality in different aspects: the first argument mentioned the information coverage and the second point the information accuracy. Those aspects inspired the authors to consider information quality as a group of features.

When the sentiment expressed in a review of a product feature deviates from the majority sentiment provided in reviews it will greatly influence designers’ understanding since it is often associated with more details about why a different sentiment is given. Another main conclusion is that a review tends to be regarded as a helpful one if it contains both pros and cons of a product. The appearance of both pros and cons is often referred as divergence of sentiments, another factor that Liu et al. considered in helpfulness modelling. Additionally, a review has more chance to be helpful if expresses a strong viewpoint towards certain product features with convincing arguments. The authors propose to interpret such observations using information theory.

To this discussed groups of features Qi et al. (2016) added a new one: metadata. The author defines metadata as “data about data”. These features are the descriptions of the review text –for example, pros, cons or labels– that are filled by the reviewer so this feature is concerned with the reviewer’s involvement. Within this group, the author also considered the number of helpful votes and the number of replies. The first variable indicates the evaluation level from other consumers, while the second is the general evaluation of the product from the reviewer.

Summarizing author’s contributions in helpfulness conceptualization. *Table A.1* in Appendix A shows all the proposed variables found in literature review.

2.2 Target setting

After identifying customer needs, the next step is to establish target specifications that provide a precise description of what a product has to do, being the translation of the customer needs into technical terms (Ulrich et al., 2000). Quality Function Deployment, or QFD, is commonly used in the product planning stage to define the engineering characteristics and target value settings of new products. A key methodology to translate customer needs into metrics is the House of Quality, a graphical technique used in QFD (Hauser et al., 1988).

2.2.1 Quality Function Deployment

Quality Function Deployment -QFD- (1972) is a commonly and broadly used method for translating the 'voice of the customer' through the various stages of new product deployment with the aim of setting targets. Three of the principal goals of QFD can be described as a better understanding of customer needs, improved product quality and, above all, achieving customer satisfaction (Sullivan, 1986; Hauser and Clausing, 1988).

Customer focus is a key component in a quality product development (Kaulio, 1998). Therefore, the basis of QFD is to translate the desires of the customer into product design or engineering characteristics so design requirements will be based on customer needs and competitive analysis achieving a customer-driven product. The translation is conducted through a chart, called "house of quality" (HOQ) –see Figure 1–, which is the principal tool for QFD. There are a set of standard components of a HOQ, including: customer attributes (CAs) and their relative weights; engineering characteristics (ECs); relationship matrix between CAs and ECs; correlation matrix among ECs; CA and EC benchmarking data; and EC importance (ECI) values and target levels (Kwang-Jae Kim et al., 2006).

A. The House Of Quality (HoQ)

The house of quality begins with the customer, whose requirements are named customer attributes (CAs): sentences customers use to describe products and product characteristics. For example, a car door is "easy to close" or "stays open on a hill"; "doesn't leak in rain" or allows "no (or little) road noise" – a typical application would have 30 to 100 CAs. Back then, CAs are often grouped into bundles of attributes selected by the project team groups and which represent an overall customer concern. Of course, one of the biggest challenges is to interpret customer phrases. Moreover, house of quality measures the relative importance to the customer of all CAs so each attribute has its weight: weightings are displayed in the house next to each CA, usually in terms of percentages, a complete list totaling 100% (Hauser et al., 1988).

Being aware of competitors' focus helps a company to match or exceed their competition and, of course, comparison with the competition can help to identify opportunities for improvement. So, on the right side of the house, opposite the CAs, customer evaluations of competitive products matched with "our own" are listed. Ideally, these evaluations are based on scientific surveys of customers. If various customer segments evaluate products differently -luxury vs. economy car buyers, for example- product planning team members get assessments for each segment (Hauser et al., 1988).

The next step is related with product characteristics in order to meet customer needs, what lays on engineering domain. In this stage, it is needed to describe the product in the language of the engineer. Along the top of house of quality, the design team lists those engineering characteristics (ECs) that are likely to affect one or more of the customer attributes. If a standard characteristic affects no CA, it may be redundant to the EC list on the house, or the team may have missed a customer attribute. A CA unaffected by any EC, on the other hand, presents opportunities to improve product properties. Engineering characteristics should describe the product in measurable terms and should directly affect customer perceptions (Hauser et al., 1988).

The subsequent stage comes up with the cross-functional team, filing in the body of the house, the "relationship matrix", indicating how much each engineering characteristic affects each customer attribute. The team bases their conclusions on expert engineering experience, customer responses and tabulated data from statistical studies or controlled experiments, seeking consensus on these evaluations (Hauser et al., 1988).

Once the team has identified the voice of the customer and linked it to engineering characteristics, it adds objective measures at the bottom of the house beneath the ECs to which they pertain. When objective measures are known, the team can eventually move to establish target values – ideal new measures for each EC in a re-designed product and engineers determine the relevant units of measurement (Hauser et al., 1988).

There are many dimensions to what a consumer means by quality and that is the major challenge to design products that satisfy all of these at once (Garvin, 1987). Strategic quality management means that companies learn from customer experience and reconcile what they want with what engineers can reasonably build (Hauser, 1988).

Before the industrial revolution, producers were close to their customers. Marketing, engineering and manufacturing were integrated in the same individual. Nowadays, marketing people have their domain, engineers theirs. That is how the House of Quality is conceived as the connection between the different functions inside a corporation: is the belief that products should be designed to reflect customers' desires and tastes – so marketing people, design engineers, and manufacturing staff must work closely together from the time a product is first conceived (Hauser, 1988).

The success of a company can only be achieved with a backbone of continual satisfaction on behalf of the customer. In turn, customer satisfaction can only be achieved if we can fulfil the customers' requirements. Hence, the gathering and use of customer attributes is the foundation of QFD.

QFD method links CRs to engineering characteristics (ECs) and, eventually, outputs the values of ECs. It is widely used in conceptual design, product design, process planning, project management, etc. (Chan et al., 2002).

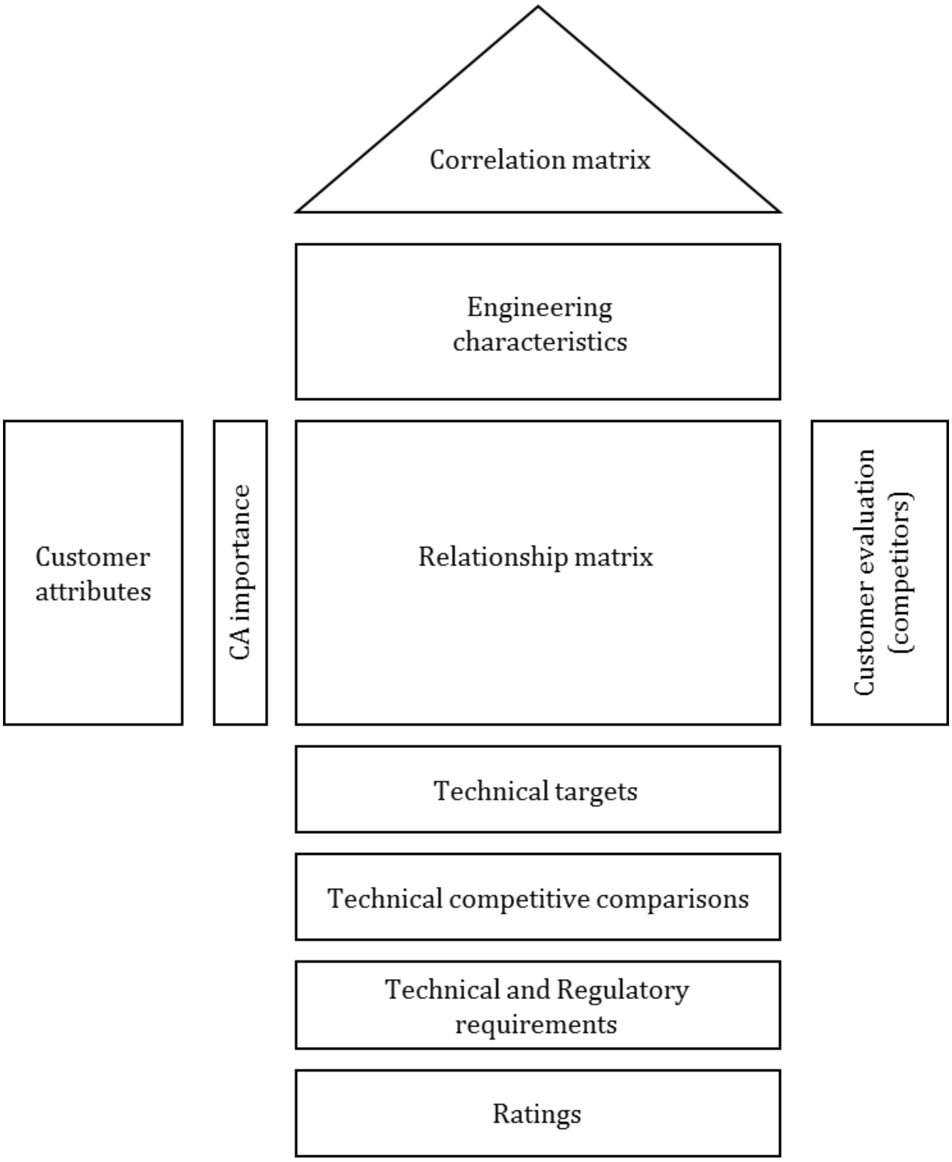


Figure 2. The House of Quality example.

3. Methodology

This chapter aims to provide an understanding of how the thesis has been conducted and why the different tools have been chosen. Furthermore, the section describes the process for how the results have been obtained.

The aim of the methodology expounded right below is to help designers to gather the information from the social media sources that reduce designer assumptions during the target setting. To this end, the methodology has been divided into four steps as shown in *Figure 3*. These are explained in greater detail in the next subsections.

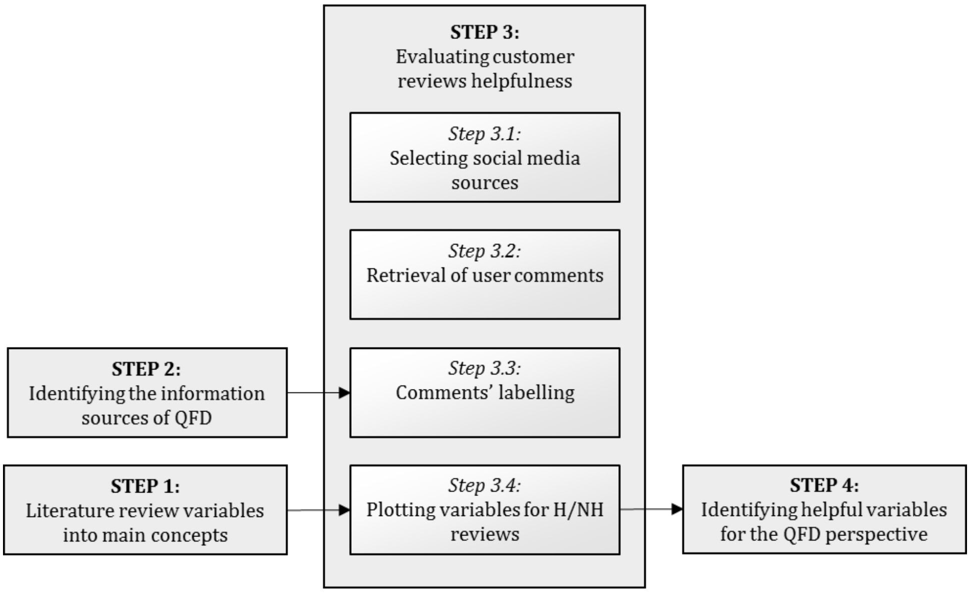


Figure 3. Methodology steps overview

3.1. Step 1: Grouping literature review variables into concepts

Many authors have described helpfulness following different approaches. As described in the literature review, authors have mainly described helpfulness from two perspectives: customers' and designers' –see chapter *2. State of art*. Trying to simplify and to give a complete overview of the work that has been done so far, all the different author's variables have been grouped into concepts as shown in *Table B.1* in Appendix B. This table is a simplified version of the *Table A.1* in Appendix A. While the Table A.1 includes the variables per author, *Table B.1* group the variables into concepts, making easier to know which are the most proposed variables between authors. Going one-step further, *Table B.2* in Appendix B includes those variables that will be measured in the present study. *Figure 4* shows the process followed in the first step of the methodology. The decision of the variables has been undertaken considering that the proposed methodology is hand-operated. Due to this, the variables have been calculated manually since the automatic data processing is not the scope of the thesis[2].

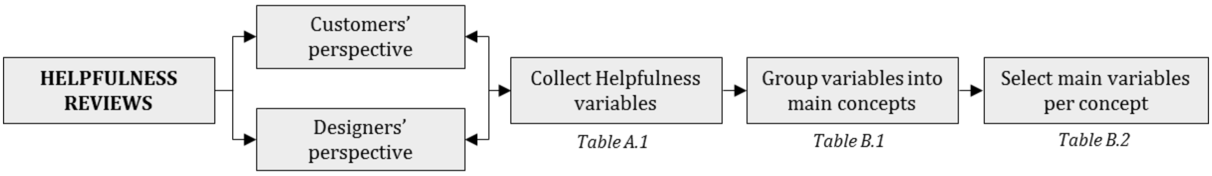


Figure 4. First step overview

Literature review variables have been classified per concepts –see *Table B.1* in Appendix B– and afterward into groups according to if they are comment related or not –i.e. if the variable can be extracted from the review text itself or from the website content, respectively. In the first group, one can observe the variables related with the text –for example, number of words or characters–, and those associated with the impact of the review in the social media –for instance number of elapsed days from the review publication or number of helpful votes received. The text-related variables are further divided into linguistic, sentiment analysis and product features –see *Figure 4*. Moreover, those variables related with the reviewer have been entered in non-comment related cluster reviewer –real name users, age, location or interests.

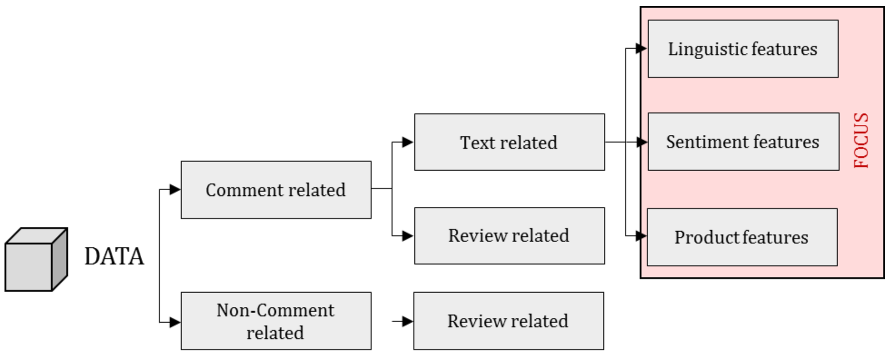


Figure 5. Data grouping overview

After proposing all the variables shown in the *Table B.2* of the Appendix B, the scope of the thesis has focused on comment and text related variables as indicated in *Figure 4*. The reason is that it is assumed that most of the information regarding customer needs and related to product targets comes from the actual comment itself. While excluded from the scope, comment and review-related variables as well as non-comment and reviewer related variables are also relevant, i.e. to define a specific target market –location, age, etc.– as well as to identify potential buyers based on similar networking behavior.

[2] The automatic extraction of public data and its analysis has been widely studied and achieved by various authors. Due to this, automation is not the main objective of the thesis.

The comment and text related variables, which are the focus of this thesis, are shown in *Table 1.*

TEXT RELATED VARIABLES			
	Variable	**Normalized variable**	**Variable type**
V1	# of characters	-	Continuous $\in \mathbb{R}^+$
V2	# of words	# of words/ # of characters	Continuous $\in \mathbb{R}^+$
V3	# of sentences	# of sentences/ # of words	Continuous $\in \mathbb{R}^+$
V4	# of adjectives	# of adjectives/ # of words	Continuous $\in \mathbb{R}^+$
V5	# of adverbs	# of adverbs/ # of words	Continuous $\in \mathbb{R}^+$
V6	# of verbs	# of verbs/ # of words	Continuous $\in \mathbb{R}^+$
V7	# of nouns	# of nouns/ # of words	Continuous $\in \mathbb{R}^+$
V8	# of errors	# of errors/ # of words	Continuous $\in \mathbb{R}^+$
V9	Content format	-	Binary $\in [0,1]$
V10	Sentiment difference	Absolute sentiment difference	Continuous $\in \mathbb{R}^+$
V11	# of product features	-	Continuous $\in \mathbb{R}^+$
V12	# of referred products	-	Continuous $\in \mathbb{R}^+$

Table 1. Text related variables.

As it can be seen in the *Table 2*, most of the variables have been normalized in order to allow the review comparison of the three social media sources considered in the thesis scope, as they have different review characteristics such as different limitation of characters. The variable V2 has been divided by the number of characters in the review in order to know the relation between words and characters. From V3 to V8, the normalizations have been subjected to the number of words contained in the review. The binary variable V9, takes a value of 1 if the review contains hashtags, labels or bold words, and 0 conversely. V10 has been calculated with the expression below (*Eq. 1*), according to the number of positive, negative or neutral adjectives per sentences in a review. Only the existence or not of sentiment in the reviews has been considered, since the first step is involved with knowing if the overall sentence expresses sentiment –a further step would be considering if the polarity of the sentiment in the review is relevant for the QFD method. Consequently, the absolute value of the sentiment difference is considered.

$$Sentiment\ difference = |Nº\ of\ positive\ adjectives - Nº\ of\ negative\ adjectives\,| \quad \text{(Eq. 1)}$$

Finally, the number of product features exhibited in the reviews –i.e. if they talk about the screen display or the engine of the car– and the number of referred products –i.e. if they touch upon more than one product– have also been taken in account.

3.2. Step 2: Identifying information sources of QFD

According to literature review, the HoQ from QFD has been broken down in nine related parts. *Figure 6* shows which HoQ required information have been considered within the thesis scope –the ones marked in green.

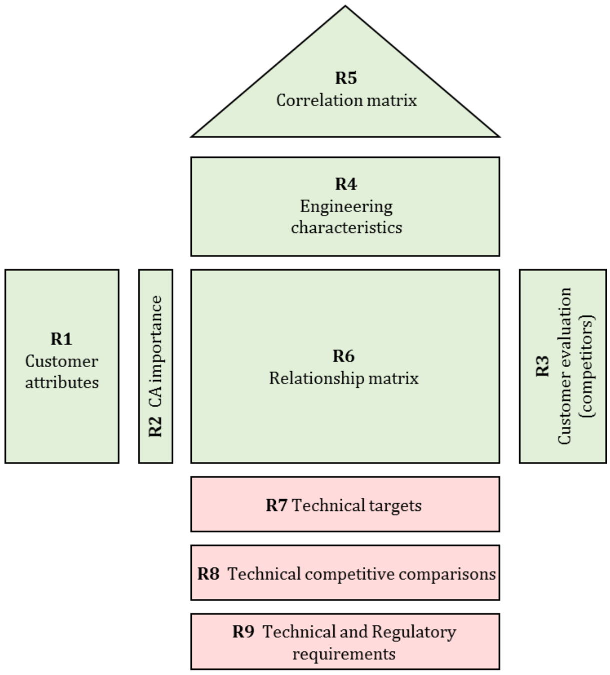


Figure 6. House Of Quality required information within the thesis scope

Only six of the requirements – see *Table 2*– have been considered in the methodology: customer attributes (CA), CA relative importance, customer perception (competitors), engineering characteristics, correlation matrix and finally relationship matrix. The proposed dimensions are aligned with the literature review findings exposed in the second chapter *2. State of art*, following the structure of the HoQ that is used nowadays.

Requirement	Definition
R1	Customer attributes
R2	CA relative importance
R3	Customer evaluation (competitors)
R4	Engineering characteristics and/or product targets related
R5	Correlation matrix
R6	Relationship matrix

Table 2. QFD factors to analyze

The other three HoQ required information have been left out of the scope because of the need of the objective targets to be settled by designers, staying far from customer's decision:

- *Technical targets*: Establishing technical targets for each engineering characteristic and rating the difficulty of achieving that target is a job for designers.
- *Technical competitive comparisons*: This requirement includes information about comparing how the target product performs in comparison to its most serious competitors. Competitive comparisons provide a company with the facts about where its products stand technically in relation to its competitors' products. The values settled in this part of the HoQ are objective and it is not expected that customers write reviews related to technical competitive features.
- *Technical and Regulatory requirements*: There are some requirements that the customers are not likely to identify. These requirement will be either technical or regulatory requirements –such things as government legislation, safety requirements, quality standard requirements, etc. technical

Once the factors have been defined, the aim has been to define which reviews are helpful to achieve the completion of each of the six parts of QFD.

3.3. Step 3: Evaluating the helpfulness of reviews from QFD perspective

3.3.1. Step 3.1: Selecting SM for the analysis

According to the social media classification and the definition carried-out by Scanfeld et al. (2010), different platforms enable people to share their knowledge and experience, creating rich user-generated content. The analysis below studies three main social media sources: social networking websites with **Facebook** data, microblogs gathering data from **Twitter** and Forums – **iMore** forum. These sources have been considered the most popular, useful and proper to work with for this methodology. This is because of their information availability and the proper information one can gather from each of them.

3.3.2. Step 3.2: Gathering review data from social media sources

In order to illustrate the proposed methodology, Volvo V60 will be the product for analyzing Facebook's and Twitter's data meanwhile Iphone 7 from Apple brand is going to be the reference for Forums as a case example. The review data is collected from the social media sources on April 2018 and May 2018.

Although several comments of each product have been found in the social media sources, 40 reviews from each SM source have been selected randomly –without method or conscious decision, gathering the first 40 reviews related with the analyzed product– for, afterwards, being classified according their helpfulness for constructing each of The House of Quality factors.

Figure 7 shows a review example about the products chosen for the three selected SM sources: A for Facebook, B for Twitter and C for iMore Forum, respectively. The reviews show the name of the reviewer, the comment or review content itself, the number of likes or retweets, the number of responses and the review date. All the extracted reviews are summarized in Appendix C.

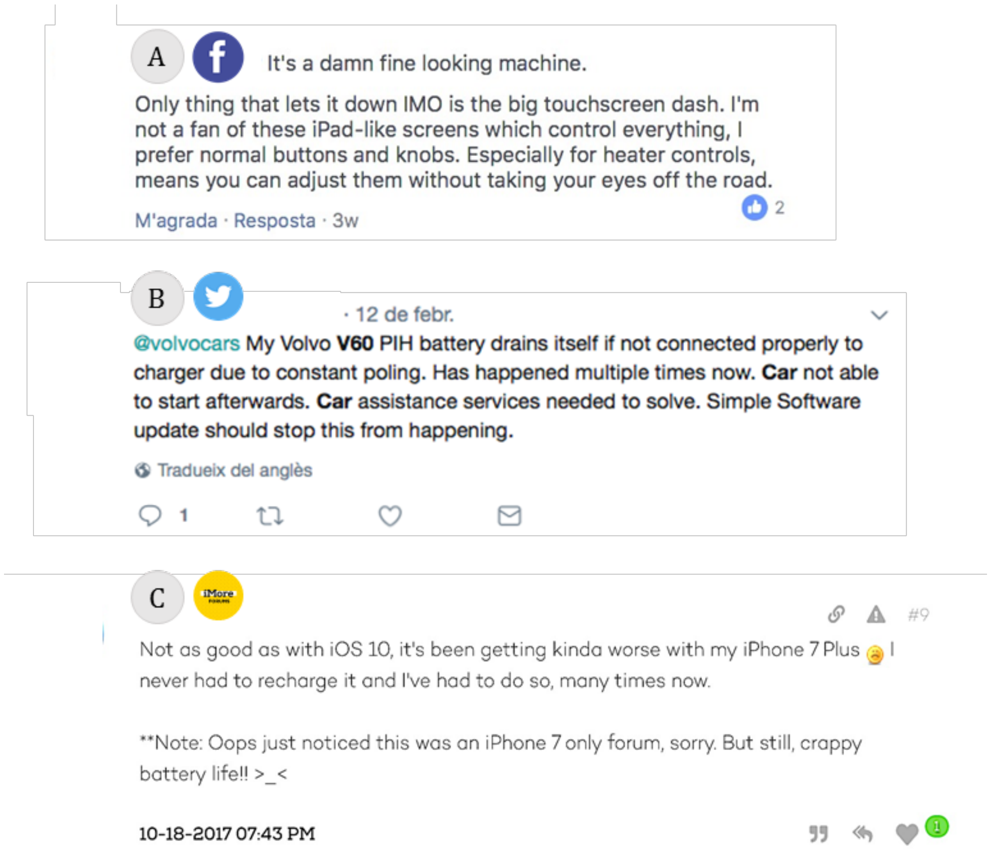


Figure 7. Reviews of Volvo V60 and Iphone 7 in Facebook and Twitter, and iMore forum respectively.

Note that in Step 1 it has been seen that the variables have been normalized. This is because the social media sources show some limitations or differences in their characteristics. For instance, Twitter has a maximum number of characters for the reviews. Normalizing most of all the variables allows the comparison between SM sources.

3.3.3. Step 3.3: Evaluating helpfulness

Every extracted comment from social media sources has been labelled as helpful or unhelpful by two independent engineers from a product designer standing. Due to the common variety and detail information granularity in the customer comments, they are labelled as helpful or unhelpful for each of the six HoQ groups of required information identified previously in Step 2. The results have been later summarized in a matrix by each engineer. In case label differed, the completion of the matrix has been asked to a product design expert with the purpose of untie. The considered helpfulness of the reviews for each SM source has been summarized in Appendix D.

3.3.4. Step 3.4: Plotting variables for H/NH reviews

Results from previous step are used to identify what variables from *Table 1* in the Step 1 are significant –or helpful- to complete the HOQ. Thus, the variables from *Table 1* are first extracted from the 40 comments of each social media data with a handpicked process. The values are summarized in Appendix E for each of the SM sources.

Consecutively, the data associated to each variable is plotted in order to identify if correlation to helpfulness related with each of the HoQ required information exists.

4. Results and analysis

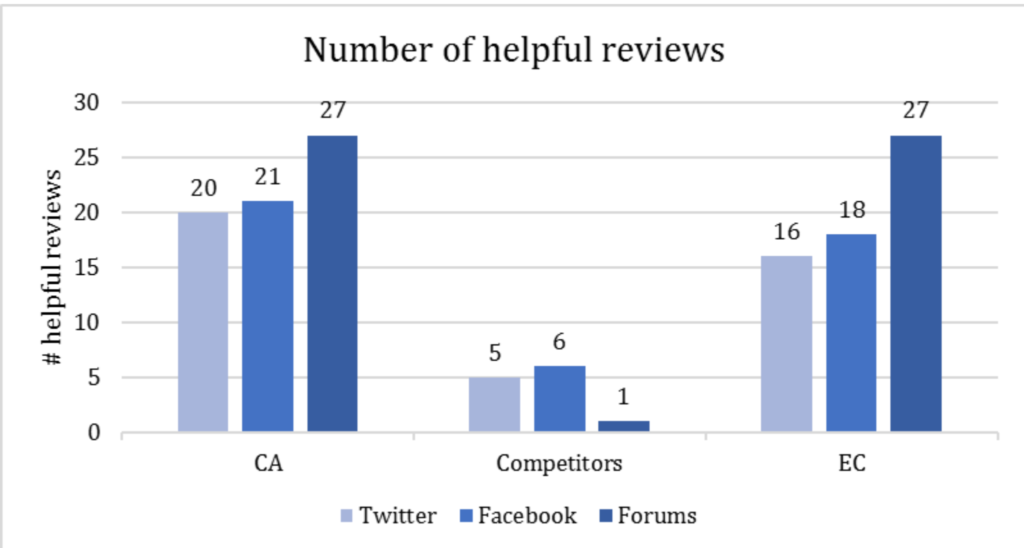
In this section, the gathered data is displayed. The principal aim is to illustrate which variables are significantly helpful during the conduct of The House of Quality and consequently discuss the helpfulness of the variables that previous authors propose from the QFD's perspective.

After analyzing the gathered reviews' data, some graphics have been created to illustrate the findings and outcome in a simplified manner. The main goal is to define which variables among the ones selected in the previous *Methodology* section are significant in order to distinguish if a review is helpful for designers on the task of completing the HOQ.

To this end, the section has been divided into different parts that refer to the different results obtained in each step of the proposed methodology after defining HOQ required information –R1 to R6.

4.1 Helpfulness of reviews

As it can be seen in the following *Graphic 1*, all the reviews chosen as helpful have been plotted in different groups, separated by the three requirements that are going to be analyzed – R1, R3 and R4 –. It can be seen that, in the evaluation of customer attributes, at least half of the reviews have been considered helpful, while in the competitors' analysis almost all the reviews have been considered unhelpful. Regarding to R4, it has been noted a significant difference between helpfulness in Forums respect the other ones. Comparing the social media sources in R1 and R3, forums have the most helpful reviews, while Twitter and Facebook are almost in the same level.



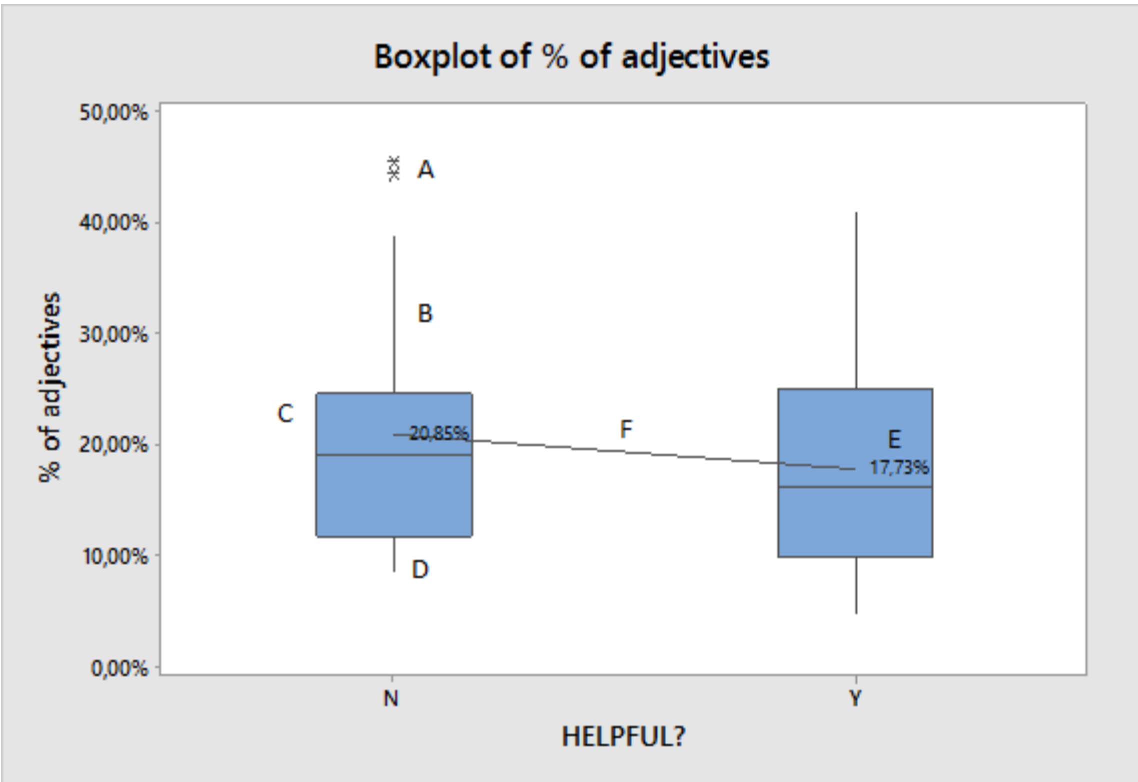
Graphic 1. Number of helpful reviews per HoQ required information for each SM

The results of the analysis could be expected since Forums is a social media source focused on the products, while the others are also employed for a personal use.

4.2 Variable extraction of reviews and plotting

The different variables are obtained for each of the reviews and shown in Appendix D. The values obtained are visualized with boxplots for each variable -see Appendix E. The boxplot illustrates the spread of each sample of data –helpful and unhelpful reviews- and also show the difference between the means for each variable, discriminating between H and NH reviews. Information about the tails of the distribution is given and the 25th, 50th and 75th percentiles –also known as the lower quartile (Q1), median (Q2) and upper quartile (Q3) are characterized.

In resume, the graphics show outliers (A), upper whisker (B), interquartile range box (C), lower whisker (D), the mean value for H/NH reviews (E) and the mean connect line (F). X-axis corresponds to the helpfulness classification –H/NH– and Y-axis corresponds to variable value. See *Graphic 2*.



Graphic 2. Percentage of adjectives boxplot

4.3 Hypothesis test

One can use the 2-sample t-test[3] to compare the averages between two groups –in this case, H/NH groups– and determine if there is a significant difference between them. For that purpose, for each factor of the HoQ, the hypothesis test has been carried out for each variable. The objective is to know if the variable helps to define the factor in the HoQ construction, detecting if there is a significant difference between the two samples for each of the variables.

In this study, the p-value and the t-test are selected to carry out the test. If the p-value is less than or equal to 0.05 –a-level– or the t-value is more or equal to 2, the null hypothesis will be rejected and consequently, there is a difference in average helpful and not helpful reviews for a specific variable.

The test also constructs a confidence interval that gives detail about the difference between the two groups. Analyzing the data with an a-level of 0.05 allows getting the 95% confidence interval. This interval tells that, based on the sample data, one can be 95% confident that the true mean difference between the variable in the two populations is between the confidence interval. All extracted tests are included in Appendix E.

Table 3 show the significant variables to define each factor for Twitter, Facebook and Forum reviews. The significant variables are chosen as inputs for the helpfulness in the HoQ factors construction.

[3] The tests have been conducted with the Minitab statistical software

	QFD variables					
	R1	R2	R3	R4	R5	R6
Variable	CA	CA importance	Competitors evaluation	EC	Correlation matrix	Relationship matrix
# of characters	✓✓✓	✗	✗	✓✓✓	✗	✗
# of words / # of characters	✗	✗	✗	✗	✗	✗
# of sentences / # of words	✓✓	✗	✓	✓✓	✗	✗
% of adjectives	✗	✗	✗	✓	✗	✗
% of adverbs	✓✓	✗	✗	✗	✗	✗
% of verbs	✓✓	✗	✗	✓	✗	✗
% of nouns	✗	✗	✗	✗	✗	✗
# of errors / # of words	✓✓	✗	✗	✓	✗	✗
Content format	✗	✗	✗	✗	✗	✗
Absolute sentiment difference	✗	✗	✗	✗	✗	✗
# of PF	✓✓✓	✗	✗	✓✓	✗	✗
# of referred products	✓✓	✗	✗	✓✓	✗	✗

Table 3. Significant variables for HoQ construction for social media sources

As it can be seen in the *Table 3* above, the significant helpful variables when extracting customer attributes from Twitter reviews in order to build the HoQ, have been: the average number of characters, the proportion of adverbs, verbs and errors, the absolute sentiment difference and, finally, the number of product features referred in the review. All of these variables have showed higher averages in their numbers for helpful reviews than for non-helpful –all the T-Values can be seen in the E Appendix.

After doing the analysis, it has been seen how important is sentiment analysis when extracting customer attributes from the reviews. For this reason, it was foreseeable that the number of adverbs were significant when talking about customer features' extraction. As shown in the Appendix E, the number of adverbs for customer attributes analysis is higher if the review is considered helpful, with a T-Value of -2,17.

The number of adjectives were also expected to be significant since the sentiment analysis was carried-out from the polarity of them. Nevertheless, after checking the plots showed in Appendix D, it has been seen that the P-Value presented a value of 0,931 – while it is being considered significant under 0,05 – and also that the means between H and NH reviews have been considerably similar. This fact could have taken place because of the size of the sample analyzed, or maybe because the NH reviews also present adjectives, but not related with any customer attribute.

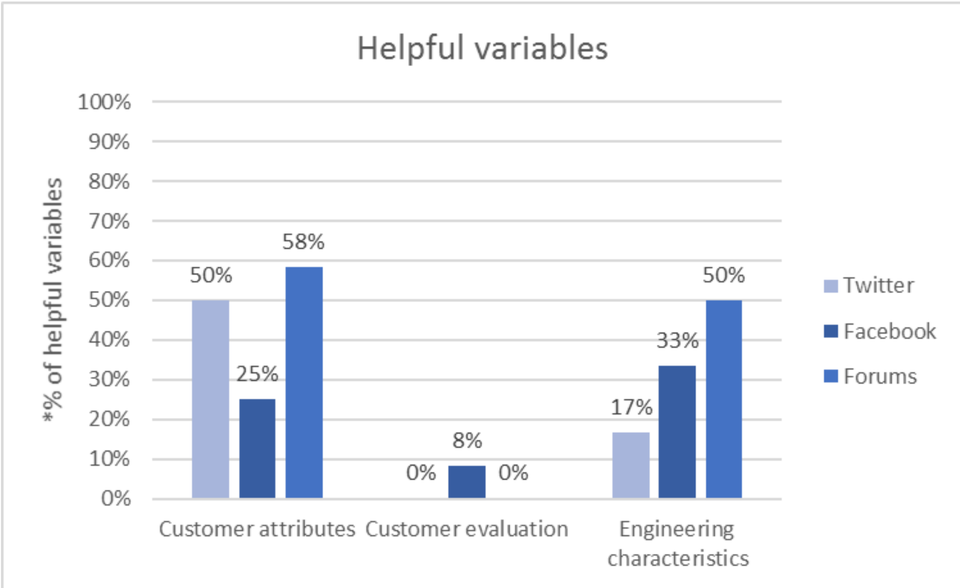
Customer evaluation was considered one of the factors that its information could be extracted from product reviews. After watching the results, it has been seen that none variables present a significance in showing competitors information in the product reviews. In respect of encountering engineering characteristics in Twitter reviews, only the average number of characters and also the number of product features showed have act as significant, with T-Values of -2,68 and -3,18, respectively. In addition, their means are higher if the review is considered helpful.

By far, the most significant variable affecting the HoQ in Twitter reviews has been the number of product features contained in the comment, with a T-value of -3,81. This matter was expected because as many product features mentioned in the reviews, more likely to be helpful for product design.

According to Forum reviews, and differing from last analysis, length of the sentences and number of verbs have been considered significant for customer attributes and for engineering characteristics. Both variables present a high average when the review is considered non-helpful. This fact can be concluded because forums do not present any limitation on the written characters, and it has been seen that the non-helpfulness reviews tend to have longer sentences that the considered helpful ones, and so more verbs can be fitted on the comments. All the other variables showed in Forums analysis have showed a higher average in helpful reviews. Finally, one has to mention that the number of product features per number of words has also been, by far, the most significant variable in this study, with a T-Value of -8,71 and one mean of 2,30, as for customer attributes as for engineering characteristics.

Unlike forums and Twitter, Facebook reviews present less significant variables. Nevertheless, number of product features variable is also significant for R1 as in the other SM sources, presenting a T-value of -4,62. After analyzing the results, one can conclude that this variable is the most significant in order to define R1 in HoQ for all the analyzed SM sources. In addition, other significant variables as number of characters in the review and sentence/word ratio define R1.
For the first time, R3 has a significant variable. The ratio between sentences and words is significant for this part of the HoQ, with a T-value of 3,05.
Finally, R4 presents three significant variables: number of characters, the ratio of sentences and words and the number of adjectives, presenting a T-value of -2,77; 3,38 and 2,52; respectively.

In the *Graphic 3* that can be seen above, the proportion of helpful variables out of the total has been charted in order to see the quantity of significant variables affecting to each of the requirements. This results show that, in the majority of the cases, Forums is the social media source that contains more significant variables to construct HoQ. In a customer attributes point of view Twitter is in the second place while, for extracting engineering characteristics is better Facebook. This last social network is the only one that holds significant variables for extracting customer evaluation data.



Graphic 3. Helpful variables percentage per HoQ required information for each SM

5. Discussion and conclusions

This chapter aims to give an answer to the initial scope by summarizing the conclusions that can be drawn from this research.

Many authors have studied online reviews attributable to their rich content and high reliability. Unlike ample research from the consumer perspective, the aim of this thesis is approached from the product design standing. The goal is to demonstrate if there is an existing GAP between the currently proposed review variables –supposedly helpful- and The House of Quality construction for product design.

5.1 Existing variables in literature review

After witnessing an increasing popularity in the helpfulness of product online opinions analysis from customer and, to a lesser extent, product design standing; one can still find a gap between the information extracted from product reviews and one of the most widely tools used in product design, The House of Quality.

Opinion analysis should give designers a useful tool to analyze the voice of the customer through consumer opinions that provide important insights to designers that can be a clue during the setting targets process.

Along these lines, the research has been focused, firstly, on analyzing which are the currently variables that define helpfulness from both perspectives –consumers' and designers'. According to the aim of evaluating if the presently proposed variables are helpful in terms of The House of Quality, a study about how design engineers actually perceive helpfulness has been carried out through social media reviews analysis.

Based on the insights, the thesis has come up with the significance of each variable in order to define if a review is helpful or not based on the QFD perspective. Conclusions about the current work can be extracted.

First, the proposed variables for defining review helpfulness should be standing from the QFD perspective. We consider that a review is helpful if it helps to fill out The House of Quality so the translation from customer attributes to product targets may be easiest. In general, most of the proposed variables do not currently help to build the HOQ. Since the HoQ is divided into six main factors –see Table 2 in section *3.Methodology*– one can conclude that most of the suggested variables in literature review help to understand only three factors: R1, R3 and R4. Instead, R2, R5 and R6 cannot be defined with the actual proposed variables. In fact, this happens because each review is studied individually, what makes impossible to extract a general overview of the extracted reviews as a group, what could help to achieve an aggregate conclusion.

For example, correlation matrix, R5, refers to the engineer characteristics relationship, i.e. how each of the technical descriptions impact each other. This factor involves analyzing more than one engineer characteristic and it depends on engineering knowledge. Something similar happens with the relationship matrix, R6, which refers to the relationship between customer needs and the company's ability to meet those needs –engineering characteristics. A designer tries to answer: What is the strength of the relationship between the technical descriptions and the customer needs? In this case, no proposed variables are analyzing the sentiment strength between customer needs –R1- and engineering characteristics –R3.

Second and consequently, most of the variables that exist in the literature review are related with the extraction of customer attributes and engineering characteristics, as sentiment analysis has been focused, in most cases, on extracting these features. For example, the product feature extraction can help to set customer attributes and engineer characteristics –by far, it is a significant variable to define both factors. Coherently, there is a connection between a product feature, i.e. "battery life" and one possible CA as "My iPhone is turned off quickly, the lifetime is about 6 hours" and one possible EC as "Battery duration". In this case, CA are more related with the sentiment analysis while EC are more connected with an objective statement.

Finding variables to help the mapping of customer needs to engineering characteristics is required to facilitate and diminish the decision-making subjectivity and product designers' assumptions.

5.2 Proposed variables

Related to the three uncompleted factors in terms of proposed variables, one can conclude a new approach to assed user reviews helpfulness is needed in order to find connections between variables.

Table 6 includes an initial picture of which variables may be extracted to fill up the missing factors of the QFD –R2, R5 and R6. In addition, R3 is contemplated in order to define carefully new variables that may help its detection.

Factor	Proposed variable
F2: CA importance	Frequency of the CA in the overall reviews
	Customer rating of the review with a specific CA
F3: Customer evaluation of competitors	# of brand nouns
	# of product model nouns
	# of positive words associated to a brand noun

	# of negative words associated to a brand noun
R5: Correlation matrix	# sentiment difference between EC in a same review
F6: Relationship matrix	# sentiment difference between CA and EC in a same review
	Distance between a CA and EC in a sentence
	Distance between a CA and EC in a review

Table 4. Proposed variables for R2, R5 and R6

5.4 Limitations

One limitation in the research is that the dataset size may be resulted from a major number of reviews. Since the task of collecting and analyzing data has been manually, the amount of data has been limited.

6. Future work

This section, gives an insight of the future work of analyzing social media reviews from a designer point of view.

As it has been described above, the scope of this methodology has been constrained in a manual analysis of the social media reviews, in order to extract those significant variables from a product designer point of view. This matter has **limited the number of variables** that have been analyzed to evolve the methodology, since there were no ways to analyze them manually – for example, the exploration of unigrams and bigrams. Hence, the first proposal for a further work is to create an automatically method, such as an algorithm, that could enable to easier extract the random reviews from social media sources as well as gathering the proper data variables from each of them. Thus, the sample could be enlarged and could encompass all the reviews found about the chosen product in the social media source.

As already mentioned in chapter 3, general review variables and those related with the reviewers itself have not taken part of this study. The second suggest for a future work, thus, will be considering this data in order to better test the helpfulness of the reviews, with the review related variables, and to segment them to markets, with the reviewer related variables. This latter analysis will be useful in case of seeking to launch the product in a specific market as for instance, in a particular consumer age range, or maybe for only a specific country.

Additionally, the quantification of the helpfulness of a review remains unknown. Finding a way to quantify the helpfulness can be an important achievement in product design's field as it can help to identifying helpful reviews in a simpler way.

Lead users also can be an important part in helpfulness definition. As they are facing needs months or years before the bulk of that marketplace, the information contained in their reviews could be useful for defining the HoQ. The current emphasis in discovering lead users among all the potential customers has come to our attention. For these reason, the next research proposal is to determine which variables can be extracted from the reviews in order to find social media lead users that will ensure their helpful reviews with probably helpful information for HoQ completion.

Finally, it can also be considered to examine more social media sources than those that have been raised in the actual work, such as Amazon, the world's largest online retailer, where several product reviews can be spotted. Making this enhancement of social media sources will definitely make a big step forward for companies in order to find out what are their actual customers' – or future ones' – requirements.

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Appendix A: Literature review helpfulness variables

First appendix collects the variables regarding helpfulness in literature review

Author and Year	Nº	Feature / Variable	Description	Data source
Helpfulness from customer's point of view				
Otterbacher, 2009	1	Cosine	Quantifies the extent to which a review is similar to the textual description of the product provided on its main page. Cosine between review and textual product description represents the similarity between the texts.	Amazon
	2	Bigram overlap	Proportion of bigrams (i.e. sequences of two words) in the review, which also appear in the product description.	Amazon
	3	Normalized longest common subsequence between the two texts were calculated	It first finds the longest phrase that the two texts have in common. The length of this phrase is then normalized by the length of the review.	Amazon
	4	Product rating	Rating on a 5-point scale assigned by reviewer	Amazon
	5	Reviewer uses real name	Categorical variable; yes if the review is displayed with a "real name" badge	Amazon
	6	Reviewer has top reviewer badge	Categorical variable; yes if the reviewer has a high rate	Amazon
	7	Reviewer's rank in the community	Reviewer rate in the social media source	Amazon
	8	Total reviews contributed by reviewer	Total number of reviews written by the reviewer	Amazon
	9	# Helpful votes received	Total number of helpful votes the review has received	Amazon
	10	Perplexity of textual review	Quantifies the deviation of a review from what is expected. First, the creation of a review is viewed as a sequence of randomly selected words. The random variable, X, can take on values (words) in a discrete set of symbols, which is the vocabulary used across all reviews of a particular product. In other words, the distribution of the variable X is estimated based on the entire set of reviews of the product. The perplexity quantifies the extent of "surprise" in the review, given the distribution of X the extent of "surprise" in the review, given the distribution of X	Amazon
	11	Entropy of textual review	The entropy of a review is literally the average uncertainty of the variable X	Amazon
	12	Centroid or textual centrality score of the product review	Quantifies the extent to which a review contains a large number of words that are statistically important across all reviews about that product	Amazon
	13	# Sentences	Total number of sentences in a review	Amazon
	14	# Words	Total number of words in a review	Amazon
	15	# Days lapsed	Total number of days lapsed since the earliest review was posted about the respective product	Amazon
	16	Characters-to-sentence ratio	Characters per sentence average ratio	Amazon
	17	Words-to-sentence ratio	Words per sentence average ratio	Amazon

Ghoose et al., 2011	1	Retail price	The retail price at Amazon.com	Amazon
	2	Sales rank	The sales rank within the product category	Amazon
	3	Average rating	Average rating of the posted reviews	Amazon
	4	Number of reviews	Number of reviews posted for the product	Amazon
	5	Elapsed date	Number of days since the release of the product	Amazon
	6	Moderate review	Does the review have a moderate rating (3 star rating) or not	Amazon
	7	Helpful votes	The number of helpful votes for the review	Amazon
	8	Total votes	The total number of votes for the review	Amazon
	9	Helpfulness	Helpful votes / Total votes	Amazon
	10	Reviewer rank	The reviewer rank according to Amazon	Amazon
	11	Top-10 reviewer	Is the reviewer a Top-10 reviewer?	Amazon
	12	Top-50 reviewer	Is the reviewer a Top-50 reviewer?	Amazon
	13	Top-100 reviewer	Is the reviewer a Top-100 reviewer?	Amazon
	14	Top-500 reviewer	Is the reviewer a Top-500 reviewer?	Amazon
	15	Real Name	Has the reviewer disclosed his/her real name?	Amazon
	16	Nick name	Does the reviewer have a nickname listed in the profile?	Amazon
	17	Hobbies	Does the reviewer have an "about me" section in the profile?	Amazon
	18	Birthday	Does the reviewer list his/her birthday?	Amazon
	19	Location	Does the reviewer disclose its location?	Amazon
	20	Web Page	Does the reviewer have a home page listed?	Amazon
	21	Interests	Does the reviewer list his/her interest?	Amazon
	22	Snippet	Does the reviewer has a description in the reviewer profile?	Amazon
	23	Any disclosure	Does the reviewer list *any of the above* in the reviewer profile?	Amazon
	24	Number of past reviews	Number of reviews posted by the reviewer	Amazon
	25	Reviewer history macro	Average past review helpfulness (macro-averaged)	Amazon
	26	Reviewer history micro	Average past review helpfulness (micro-averaged)	Amazon
	27	Past helpful votes	Number of helpful votes accumulated in the past from the reviewer	Amazon
	28	Past total votes	Number of total votes on the reviews posted in the past for the reviewer	Amazon
	29	Length (chars)	The length of the review in characters	Amazon
	30	Length (words)	The length of the review in words	Amazon
	31	Length (sentences)	The length of the review in sentences	Amazon
	32	Spelling errors	The number of spelling errors in the review	Amazon
	33	ARI	The Automated Readability Index for the review	Amazon
	34	Gunning Index	The Gunning-Fog index for the review	Amazon
	35	Coleman-Liau Index	The Coleman-Liau index for the review	Amazon
	36	Flesch Reading Ease	The Flesch Reading Ease score for the review	Amazon
	37	Flesch-Kincaid Grade Level	The Flesch-Kincaid Grade Level for the review	Amazon
	38	SMOG	The Simple Measure of Gobbledygook score for the review	Amazon
	39	AvgProb	The average probability of a sentence in the review being subjective	Amazon
	40	DevProb	The standard deviation of the subjectivity probability	Amazon

Pan et al., 2011	1	# of reviews of a product	The number of posted reviews for a product at the time of data collection	Amazon
	2	Age of review (in days)	Time elapsed (in days) since the date on which a review was posted	Amazon
	3	Customer rating in stars	The number of stars a reviewer gives as the overall assessment of the product. This variable captures the valence of the review content	Amazon
	4	# of characters	The number of typed characters in a product review	Amazon
	5	Product type	A dummy variable with 1 and 0 indicating experiential and utilitarian products, respectively	Amazon
	6	Helpful votes	The number of consumers who found a product review helpful	Amazon
	7	Number of rates	The total number of consumers who have rated the review	Amazon
Zhang, 2014	1	Sentence count	The number of sentences	Amazon
	2	Token count	The total number of tokens of a review describing the length of a review	Amazon
	3	Token per sentence	The average number of tokens in a sentence. It described average sentence length of a review	Amazon
	4	Noun percentage	The percentage of tokens which are nouns	Amazon
	5	Verb percentage	The percentage of tokens which are verbs	Amazon
	6	Adjective percentage	The percentage of tokens which are adjectives	Amazon
	7	Adverb percentage	The percentage of tokens which are adverbs	Amazon
	8	Polarity	The difference between positive and negative words in a review out of the total number of positive and negative words in a review	Amazon
	9	Subjectivity	The total number of positive and negative words out of the total number of words in a review	Amazon
	10	Positive references	The total number of positive words out of the total number of words in a review	Amazon
	11	Negative references	The total number of negative words out of the total number of words in a review	Amazon
	12	Sentiment difference	The difference between positive and negative words in a review out of the total number of words in a review	Amazon
	13	Error per sentence	Average number of grammatical error and misspelled words per sentence in a review	Amazon
	14	Rank of the reviewer	The rank of the reviewer	Amazon
	15	Helpful percentage	The helpful percentage of the votes received on reviewers' previous reviews	Amazon
	16	Past reviews	The number of prior reviews a review's author has written	Amazon
	17	Rating	Consumer rating	Amazon
	18	Age	The number of days since the review was posted	Amazon

Kim et al., 2006	1	Length	The total number of tokens in a syntactic analysis of the review	Amazon
	2	Sentential	Observations of the sentences, including the number of sentences, the average sentence length, the percentage of question sentences, and the number of exclamation sentences	Amazon
	3	HTML	Two features for the number of bold tags <b> and line breaks 	Amazon
	4	Unigram	The tf-idf statistic of each word occurring in a review	Amazon
	5	Bigram	The tf-idf statistic of each bi- gram occurring in a review	Amazon
	6	% of nouns	Percentage of tokens that are nouns	Amazon
	7	% of verbs	Percentage of tokens that are verbs conjugated in the first person	Amazon
	8	% of adjectives	Percentage of tokens that are adjectives	Amazon
	9	% of adverbs	Percentage of tokens that are adverbs	Amazon
	10	Product-Feature	The number of product features mentioned in a review	Amazon
	11	General-Inquirer	The number of sentiment words in a review referring to a product feature	Amazon
	12	Stars	The rating score of the review	
Helpfulness from designer's point of view				
Liu et al., 2012	1	# of words	Total number of words in a review	Amazon
	2	# of sentences	Total number of sentences in a review	Amazon
	3	Average words	Average number of words per sentence	Amazon
	4	# of adjectives	Total number of adjectives in a review	Amazon
	5	# of adverbs	Total number of adverbs in a review	Amazon
	6	# of grammar errors	Total number of grammar errors and wrong spellings in a review	Amazon
	7	# of subjective sentences	Total number of subjective sentences in a review	Amazon
	8	# of objective sentences	Total number of objective sentences in a review	Amazon
	9	# of total elapsed days	Time elapsed in days since the date on which a review was posted	Amazon
	10	# of referred products	Total number of referred products in the review	Amazon
	11	# of product features	Total number of referred products in the review	Amazon
	12	# of sentences referring to product features	Total number of sentences referring to mentioned product features in the review or comment	Amazon
	13	# of product features / # of sentences referring to product features	Relation between the total number of product features mentioned and the total number of sentences referring to mentioned product features in the review or comment.	Amazon
	14	# of sentences referring to product features / # of sentences	Relation between number of sentences referring to product features and the total number of sentences in the review or comment	Amazon
	15	The self-information sum of product features	Estimation of the information gained for different sentiments for a product feature occuring in a review	Amazon
	16	The divergence of sentiment sentences	Sum of self-information for three different sentiment (positive, negative and neutral) for every product feature occuring in a review	Amazon
	17	The strength of sentiment sentences	Sum of the maximum of self-information for three different sentiments for the sum of the different product features mentioned in a review	Amazon

Qi et al., 2016	1	# of words	Total number of words in a review	Amazon
	2	# of sentences	Total number of sentences in a review	Amazon
	3	Average length of sentence	Average number of words per sentence	Amazon
	4	# of adjectives	Total number of adjectives in a review	Amazon
	5	# of adverbs	Total number of adverbs in a review	Amazon
	6	# of subjective sentences	Total number of grammar errors and wrong spellings in a review	Amazon
	7	# of objective sentences	Total number of subjective sentences in a review	Amazon
	8	# of total elapsed days	Total number of objective sentences in a review	Amazon
	9	# of referred products	Time elapsed in days since the date on which a review was posted	Amazon
	10	# of product features	Total number of referred products in the review	Amazon
	11	# of sentences referring to product features	Total number of referred products in the review	Amazon
	12	# of product features / # of sentences referring to product features	Total number of sentences referring to mentioned product features in the review or comment	Amazon
	13	# of product features / # of sentences	Relation between the total number of product features mentioned and the total number of sentences referring to mentioned product features in the review or comment.	Amazon
	14	# of sentences referring to product features / # of sentences	Relation between number of sentences referring to product features and the total number of sentences in the review or comment	Amazon
	15	The self-information sum of product features	Estimation of the information gained for different sentiments for a product feature occuring in a review	Amazon
	16	The divergence of sentiment sentences	Sum of self-information for three different sentiment (positive, negative and neutral) for every product feature occuring in a review	Amazon
	17	The strength of sentiment sentences	Sum of the maximum of self-information for three different sentiments for the sum of the different product features mentioned in a review	Amazon
	18	# of reviews	Total number of posts posted by the reviewer in the past in that social media source. The volume of reviews posted indicates the expertise of the reviewer.	Amazon
	19	The grade of reviewer	The grade of a reviewer indicates the reviewer's activeness on the website: if the reviewer is highly active, is more likely to provide thorough explanations of their viewpoints.	Amazon
	20	Whether pros is filled or not	Does the review have pros?	Amazon
	21	Whether cons is filled or not	Does the review have cons?	Amazon
	22	# of labels	Total number of labels in the review	Amazon
	23	# of helpful votes	Total number of helpful votes obtained indicates the evaluation level from other consumers	Amazon
	24	# of replies	The total number of replies indicates the evaluation level from other consumers	Amazon
	25	# of stars	The total number of stars indicates the evaluation level from other consumers	Amazon

Table A.5. Variables for describing helpfulness from two points of view.

Appendix B: Helpfulness variables grouped into concepts

Second appendix gathers all the authors proposed variables related with helpfulness definition taking into account if they have been related with customer's or designers' perspective.

Group	Concept	Nº times per concept	Variables	Nº times per variable	References	Customer's perspective	Designer's perspective
LINGUISTIC FEATURES	% of adjectives	4	# of adjectives	2	Zhang (2014); Kim et al. (2006)	X	X
			% of adjectives	2	Liu et al. (2012); Qi et al. (2016)		
	# of words	10	# of words	6	Otterbacher (2009); Ghoose et al. (2011); Zhang (2014); Kim et al. (2006); Liu et al. (2012); Qi et al. (2016)	X	X
			Average words	1	Liu et al. (2012)		
			Words per sentence ratio	2	Otterbacher (2009); Zhang (2014)		
			Average length of sentence	1	Qi et al. (2016)		
	# of sentences	6	# of sentences	6	Otterbacher (2009); Ghoose et al. (2011); Zhang (2014); Liu et al. (2012); Qi et al. (2016); Kim et al. (2006)	X	X
	# of characters	3	Length (chars)	2	Pan et al. (2011); Ghoose et al. (2011)	X	
			Characters-to-sentence ratio	1	Otterbacher (2009)		
	# of adverbs	4	# of adverbs	2	Liu et al. (2012); Qi et al. (2016)	X	X
			% of adverbs	2	Zhang (2014); Kim et al. (2006)		
	# of errors	3	# of spelling errors	1	Ghoose et al. (2011)	X	X
			Error per sentence	1	Zhang (2014)		
			Grammar errors	1	Liu et al. (2012)		
	Perplexity of textual review	1	Perplexity of textual review	1	Otterbacher (2009)	X	
	Entropy of textual review	1	Entropy of textual review	1	Otterbacher (2009)	X	
	Centroid of textual review	1	Centroid of textual review	1	Otterbacher (2009)	X	
	# of verbs	2	% of verbs	2	Zhang (2014); Kim et al. (2006)	X	
	# of nouns	2	% of nouns	2	Zhang (2014); Kim et al. (2006)	X	
	# of unigrams	1	# of unigrams	1	Kim et al. (2006)	X	
	# of bigrams	2	# of bigrams	2	Otterbacher (2009); Kim et al. (2006)	X	
	Content format	2	# of labels	1	Qi et al. (2016)	X	X
			HTML	1	Kim et al. (2006)		

SENTIMENT ANALYSIS	Sentiment	17	Positive references	1	Zhang (2014)	X	X
			Negative references	1	Zhang (2014)		
			Polarity	1	Zhang (2014)		
			Subjectivity	1	Zhang (2014)		
			Sentiment difference	1	Zhang (2014)		
			# of subjective sentences	2	Liu et al. (2012); Qi et al. (2016)		
			# of objective sentences	2	Liu et al. (2012); Qi et al. (2016)		
			# of question sentences	1	Kim et al. (2006)		
			# of exclamation sentences	1	Kim et al. (2006)		
			The divergence of sentiment sentences	2	Liu et al. (2012); Qi et al. (2016)		
			The strength of sentiment sentences	2	Liu et al. (2012); Qi et al. (2016)		
			Average probability of a sentence being subjective	1	Ghoose et al. (2011)		
			St Dev of the subjectivity probability	1	Ghoose et al. (2011)		
	Textual similarities with external texts	2	Cosine	1	Otterbacher (2009)	X	
			Normalized longest common subsequence between two texts	1	Otterbacher (2009)		
PRODUCT FEATURES	# of product features	12	# of product features	3	Kim et al. (2006); Liu et al. (2012); Qi et al. (2016)	X	X
			General-Inquirer	1	Kim et al. (2006)		
			# of sentences referring to PF	2	Liu et al. (2012); Qi et al. (2016)		
			# of PF / # of sentences referring to PF	2	Liu et al. (2012); Qi et al. (2016)		
			# of sentences referring to PF / # of total sentences	2	Liu et al. (2012); Qi et al. (2016)		
			Self-information sum of PF	2	Liu et al. (2012); Qi et al. (2016)		
	Product information	4	# of referred products	2	Liu et al. (2012); Qi et al. (2016)	X	X
			Product type	1	Pan et al. (2011)		
			Product rating	1	Otterbacher (2009)		
	Reviews posted of a product	2	# of reviews posted of a product	2	Ghoose et al. (2011); Pan et al. (2011)	X	
	Other	2	Retail price	1	Ghoose et al. (2011)	X	
			Sales rank	1	Ghoose et al. (2011)		

REVIEW RELATED	# of elapsed days	6	# of elapsed days	6	Otterbacher (2009); Ghoose et al. (2011); Pan et al. (2011); Zhang (2014); Liu et al. (2012); Qi et al. (2016)	X	X
	# of helpful votes	11	# of helpful votes	4	Otterbacher (2009); Ghoose et al. (2011); Pan et al. (2011); Qi et al. (2016)	X	X
			Total votes	1	Ghoose et al. (2011)		
			Helpful votes / Total votes	2	Ghoose et al. (2011); Zhang (2014)		
			Reviewer history macro	1	Ghoose et al. (2011)		
			Reviewer history micro	1	Ghoose et al. (2011)		
			Past helpful votes	1	Ghoose et al. (2011)		
			Past total votes	1	Ghoose et al. (2011)		
	Review rating	11	# of replies	1	Qi et al. (2016)	X	X
			Stars	2	Kim et al. (2006); Qi et al. (2016)		
			Average rating of posted reviews	1	Ghoose et al. (2011)		
			ARI	1	Ghoose et al. (2011)		
			Gunning Index	1	Ghoose et al. (2011)		
			Coleman-Liau Index	1	Ghoose et al. (2011)		
			Flesch Reading Ease	1	Ghoose et al. (2011)		
			Flesch-Kincaid Grade Level	1	Ghoose et al. (2011)		
			SMOG	1	Ghoose et al. (2011)		
			Moderate review	1	Ghoose et al. (2011)		
REVIEWER RELATED	Reviewer uses real name	3	Real name	2	Otterbacher (2009); Ghoose et al. (2011)	X	
			Nick name	1	Ghoose et al. (2011)		
	Reviewer information	7	Hobbies	1	Ghoose et al. (2011)	X	
			Birthday	1	Ghoose et al. (2011)		
			Location	1	Ghoose et al. (2011)		
			Web Page	1	Ghoose et al. (2011)		
			Interests	1	Ghoose et al. (2011)		
			Snippet	1	Ghoose et al. (2011)		
			Any disclosure	1	Ghoose et al. (2011)		
	Reviewer rating	8	Reviewer has top reviewer badge	1	Otterbacher (2009)	X	X
			Reviewer's rank in the community	3	Otterbacher (2009); Ghoose et al. (2011); Qi et al. (2016)		
			Top-10 reviewer	1	Ghoose et al. (2011)		
			Top-50 reviewer	1	Ghoose et al. (2011)		
			Top-100 reviewer	1	Ghoose et al. (2011)		
			Top-500 reviewer	1	Ghoose et al. (2011)		
	Reviews posted of a reviewer	4	Total reviews posted by the reviewer	4	Otterbacher (2009); Ghoose et al. (2011); Zhang (2014); Qi et al. (2016)	X	X
	Customer rating	2	Customer rating	2	Pan et al. (2011); Zhang (2014)	X	

Group	Concept	References	Customer's perspective	Designer's perspective
TEXT RELATED	% of adjectives	Kim et al. (2006); Liu et al. (2012); Zhang (2014); Qi et al. (2016)	X	X
	# of words	Kim et al. (2006); Otterbacher (2009); Ghoose et al. (2011); Liu et al. (2012); Zhang (2014); Qi et al. (2016)	X	X
	# of sentences	Otterbacher (2009); Ghoose et al. (2011); Zhang (2014); Liu et al. (2012); Qi et al. (2016); Kim et al. (2006)	X	X
	# of characters	Otterbacher (2009); Pan et al. (2011); Ghoose et al. (2011)	X	
	# of adverbs	Kim et al. (2006); Liu et al. (2012); Zhang (2014); Qi et al. (2016)	X	X
	# of errors	Ghoose et al. (2011); Liu et al. (2012); Zhang (2014)	X	X
	# of verbs	Zhang (2014); Kim et al. (2006)	X	
	# of nouns	Zhang (2014); Kim et al. (2006)	X	
	Content format	Kim et al. (2006); Qi et al. (2016)	X	X
	Sentiment difference	Kim et al. (2006); Ghoose et al. (2011); Liu et al. (2012); Zhang (2014); Qi et al. (2016)	X	X
	# of product features	Kim et al. (2006); Liu et al. (2012); Qi et al. (2016)	X	X
REVIEW RELATED	# of elapsed days	Otterbacher (2009); Ghoose et al. (2011); Pan et al. (2011); Zhang (2014); Liu et al. (2012); Qi et al. (2016)	X	X
	# of helpful votes	Otterbacher (2009); Ghoose et al. (2011); Pan et al. (2011); Zhang (2014); Qi et al. (2016)	X	X
	Review rating	Kim et al. (2006); Ghoose et al. (2011); Qi et al. (2016)	X	X
REVIEWER RELATED	Reviewer uses real name	Otterbacher (2009); Ghoose et al. (2011)	X	
	Reviewer information	Ghoose et al. (2011)	X	
	Reviewer rating	Otterbacher (2009); Ghoose et al. (2011); Qi et al. (2016)	X	X
	Reviews posted of a reviewer	Otterbacher (2009); Ghoose et al. (2011); Zhang (2014); Qi et al. (2016)	X	X
	Customer rating	Pan et al. (2011); Zhang (2014)	X	

Appendix C: Extracted reviews

First appendix collects the reviews extracted from different social media sources considered in the thesis: Facebook, Twitter and iMore forum. The publication date and hour, and hyperlink of each review is specified.

C.1 Twitter reviews

Table A.1 contains the fourteen Twitter reviews gathered for the study. For this social media source, data pertaining to Volvo V60 model has been gathered on April and May 2018. Only tweets containing the model of the car have been extracted –V60. The publication hour is referenced in Central European Time zone –CET.

	Review and hyperlink	Publication date and hour	
1	JFX FORTIER @IDEES_JFX · 27 de febr. @volvocars Why did you split that window? It's the only thing **I don't like** on it. It's practically a perfect car! **I** presently own an XC70 and **I** really **don't like** the back of the new V90 cross-country. **I** think **I** will wait before changing for a new Volvo. Bravo for the **V60** 👌👍❤️ *https://twitter.com/IDEES_JFX/status/968521562402910209*	27-02-2018	13:21
2	**TeddYang** @TeddYang · 4 d'abr. I like the all digital display #volvov60 #rdesign instagram.com/p/Bhl0etgnQBK/ Tradueix del anglès *https://twitter.com/TeddYang/status/981412650864259072*	04-04-2018	04:06
3	**Nick Decrock** @ndecrock · 19 de gen. de 2011 Snappy, fast and yet firm. Comfortable Not an Audi, but close. #volvoV60 #testdrive Tradueix del anglès *https://twitter.com/ndecrock/status/27658940951044097*	19-01-2011	06:29
4	**Cape Town Guy** @TheCapeTownGuy · 9 de gen. de 2017 The #VolvoV60 T5 AWD Cross Country is a rugged and versatile vehicle that is **comfortable** on & off road. Full Review: goo.gl/QkrDtx 1 *https://twitter.com/TheCapeTownGuy/status/818408248546131969*	09-01-2017	07:45
5	**Mark Patsavas** @markpatsavas · 21 de febr. En resposta a @volvocars *designed for older generations. newer generations buy electric cars #volvo #future #tesla #ElectricVehicles #tryagain Tradueix del anglès 1 *https://twitter.com/markpatsavas/status/966363654370267136*	21-02-2018	14:27
6	**Johan Schwartz** @johanschwartz · 22 de febr. de 2016 Almost 1100km on 56L, **good** job VOLVO #volvoV60 @VolvoCarSverige *https://twitter.com/johanschwartz/status/701727589233258496*	22-02-2016	08:17

7	! @longmayyourun75 · 23 de febr. En resposta a @volvocars Congratulations! Great design, great car! But 49500€ for a Volvo V60 T6 (company car agenda allows no Diesel anymore) is way too much.Its a pitty! I'll have to exchange my V70 into a Audi, Mercedes or VW in October. I'm disappionted that you let down middle-class segment, again! Tradueix del anglès https://twitter.com/longmayyourun75/status/967038836479025153	23-02-2018	11:09
8	**Concept Creator** @CConceptCreator · 22 de febr. En resposta a @volvocars don't mind my terrible photoshop skills. But I SO would have preferred it this way... Makes it look SO much nicer in my eyes... 1 2 https://twitter.com/CConceptCreator/status/966670585202962434	22-02-2018	10:46
9	**Zebra** @zebra9780 · 22 de febr. En resposta a @volvocars Looks other nice car. Hopefully the trunk is more useful as V70. Tradueix del anglès https://twitter.com/zebra9780/status/966710802261643264	22-02-2018	13:26
10	徐克凡 @Jokerphone · 22 de febr. En resposta a @volvocars Cutting line is wonderful Tradueix del anglès https://twitter.com/Jokerphone/status/966606908810444800	22-02-2018	06:33
11	**Concept Creator** @CConceptCreator · 15 de febr. En resposta a @volvocars Just a shame about those rear lights.... WHY would you make it go inside so much? Just remove that weird extra part it really is ugly on an overall beautiful car. And when I say ugly I mean REALLY ugly... Tradueix del anglès 3 https://twitter.com/CConceptCreator/status/964132775774310400	15-02-2018	10:42
12	**Robert Cech** @outside05 · 9 m Hey @elonmusk @teslarati - the Höhenstraße in #Vienna is not crappy. It's from 1935. But maybe the suspension in a #Tesla #ModelS is not the best. Nice and comfortable in my 2012 **Volvo V60** @VolvoCarSverige https://twitter.com/outside05/status/981821847833628672	05-04-2018	07:12
13	**Alex Grant** @alexgrantuk · 23 de març En resposta a @packlam73 @VolvoCarUK I think it's close. The V90 is incredibly long and low, like a roof-chopped caricature of a V70. I'd argue that the the **V60** is more photogenic, but it's not quite as dramatic in terms of presence. Both are stunning **cars**. Tradueix del anglès 1 https://twitter.com/alexgrantuk/status/977244466363994113	23-03-2018	15:03
14	**jesse** @j3s5ef1n3m4n · 12 de març @JohnGoodenUK I'm a fan of the pod! Regarding your **car** dilemma, check out the swanky patterned cloth interior for the new Volvo **V60**. Slick Scandinavian design, and I gather they make an effort in the sustainability dept. Might be an option! https://twitter.com/j3s5ef1n3m4n/status/973347692297400321	12-03-2018	20:59

15	**ROBIN LLEWELYN-LEACH** @ROBANDTHEMOB · 8 de març En resposta a @ShameADriver @VolvoCarUK Shame they chose to abandon the class-leading D2 104g/KmCo2 emission engine, I'm having in my new **V60** SE Nav with Winter Pack & Active Bi-Xenon lights arriving next month. Someone needs to remind @volvocars that emissions rates determine BIK rates for company **car** drivers ! #fact Traduеix del anglès 1 *https://twitter.com/ROBANDTHEMOB/status/971725181923274752*	08-03-2018	09:31
16	**ROBIN LLEWELYN-LEACH** @ROBANDTHEMOB · 6 de març En resposta a @autocar Shame @volvocars chose to launch such a groundbreaking vehicle, with gas-guzzling 2.0litre petrol and diesel engines a fortnight ago, rather than being patient and choosing the more efficient option now announced. Existing **V60** ordered as my next company lease **car** instead ! 🙁 Traduеix del anglès *https://twitter.com/ROBANDTHEMOB/status/970906954527920128*	06-03-2018	03:20
17	**Martin Ward** @MartinW_cap_hpi · 6 de març The new Volvo **V60**, looks long and sleek, but still has the traditional Volvo looks, a nice looking estate **car**... 1 2 *https://twitter.com/MartinW_cap_hpi/status/970984547516108800*	06-03-2018	08:28
18	**Greg Story** @GregStory1976 · 22 de febr. En resposta a @harrismonkey New **V60** is the best looking estate **car** at the moment, so fresh Traduеix del anglès *https://twitter.com/GregStory1976/status/966709438856990728*	22-02-2018	13:21
19	**Jon Birch** @Jon_Birch · 22 de febr. I've got a massive #want for the new @volvocars **V60** plug in hybrid. Serious fingers crossed it's on the company **car** list when I get to choose in May. #volvo #v60 #newcar #companycar #hybrid Traduеix del anglès *https://twitter.com/Jon_Birch/status/966565479065284610*	22-02-2018	03:49
20	**Jiwan Beth** @JiwanB · 12 de febr. @volvocars My Volvo **V60** PIH battery drains itself if not connected properly to charger due to constant poling. Has happened multiple times now. **Car** not able to start afterwards. **Car** assistance services needed to solve. Simple Software update should stop this from happening. Traduеix del anglès 1 *https://twitter.com/JiwanB/status/963018364720467969*	12-02-2018	08:54
21	**Maheenstar1** @maheenstar1 · 41 min I had an amazing opportunity to make a Volvo V60 for @itzt_ ! #volvo #robloxdev #v60 2 1 5 *https://twitter.com/maheenstar1/status/998318372579434496*	20-05-2018	14:43
22	**tyler** @itzt_ · 18 h quick and dirty visual of the v60 instrument cluster 6 43 *https://twitter.com/itzt_/status/998283776017948672*	20-05-2018	17:26
23	**Dave Humphreys** @LordHumphreys · 6 h "The new Volvo **V60** is probably the most sensible car you can buy, but it comes with a gorgeous veneer of desirability." Read @neilmbriscoe's full first drive review on @completecar buff.ly/2IOncQr 2 3 *https://twitter.com/LordHumphreys/status/998244505622122499*	20-05-2018	09:50

24	**ListersVolvo** @ListersVolvo · 18 de maig Here's a stunning #caroftheweek, our Selekt approved used @PolestarCars **V60**. For just £28,487 and having covered only 6,599 miles, this Q-Car will crack 60 in just five seconds, thanks to #Polestar optimisation - and 345 BHP. socsi.in/PSV60_vOAXd 3 17 *https://twitter.com/ListersVolvo/status/997379240596303872*	18-05-2018	05:31
25	**Neil Briscoe** @neilmbriscoe · 17 de maig **This is a seriously good looking car**, estate or otherwise. #V60 #Volvo 4 11 39 *https://twitter.com/neilmbriscoe/status/997156506645786624*	17-05-2018	14:46
26	**Top Gear** @BBC_TopGear · 16 de maig The all-new V60 arrives with #Volvo in its pomp. Another hit for the Swedes? TG's Volvo V60 review >> topgear.com/car-reviews/vo... 3 26 196 *https://twitter.com/BBC_TopGear/status/996835307461992448*	16-05-2018	17:30
27	**Auto Express** @AutoExpress · 16 de maig **Take a look around the new #Volvo V60**! We've been for a test drive... aex.ae/2rlpB4z 5 7 14 *https://twitter.com/AutoExpress/status/996631336361381888*	16-05-2018	04:00
28	**Autocar** @autocar · 15 de maig **The new Volvo V60 is spacious and comfortable**, with a Scandi-cool design that meets traditional Volvo estate characteristics. Full first drive review: autocar.co.uk/car-review/vol... 1 17 40 *https://twitter.com/autocar/status/996413295950225408*	15-05-2018	13:33
29	**Autocar** @autocar · 20 h **The Volvo V60 estate will be priced from** £31,810. How does that sound? autocar.co.uk/car-news/motor... @VolvoCarUK 2 2 8 *https://twitter.com/autocar/status/998262197129269248*	20-05-2018	16:00
30	**TMS Motor Group** @TMSMotorGroup · 16 de maig **What Car? magazine's verdict** on the New Volvo V60: "Tidy handling, beautifully built, with a comfortable ride. And did we mention it's blooming roomy, too? All round, the V60 is a great estate car." Read the full review: bit.ly/2Il5TGY #Volvo #V60 #NewV60 #WhatCar 2 1 *https://twitter.com/TMSMotorGroup/status/996769390463942657*	16-05-2018	13:08
31	**Shane O' Donoghue** @Shane_O_D · 16 de maig **Volvo has just announced** that its forthcoming new S60 saloon (A4/3 Series/C-Class rival) will never have a diesel engine. Big statement. (pics is of the V60, with which the S60 shares its underpinnings) 1 4 3	16-05-2018	06:11
32	**What Car?** @whatcar · 15 de maig **We know the boot in a @VolvoCarUK** estate car is **a** hugely important feature, so have **a** good look around the new V60 and continue for the full review ow.ly/sZCh30k0Beo 5 10 *https://twitter.com/whatcar/status/996480587358601216*	15-05-2018	18:01
33	**ListersVolvo** @ListersVolvo · 18 de maig **The new Volvo V60 is elegant**, **sporty and** versatile: welcome to a **new** generation of estate car. *https://twitter.com/ListersVolvo/status/997462150607179782*	18-05-20108	11:01

34	**Bahnstorm** @bahnstorm · 20 de maig **If you were thinking of buying a C-Class Estate, you might want to wait until the new Volvo V60 arrives**... bahnstorm.co.uk/news/volvo-v60... *https://twitter.com/bahnstorm/status/998132723603488772*	20-05-2018	07:26
35	**James Stamper** @autonewssiite · 19 de maig **Volvo showcases new V60 model** - The latest **Volvo V60** mid-size estate is already available for order and features tons of goodies that are worth mentioning. This latest generation of 60 series is based on company's Scalable Product Architecture platform and uses a special Driv... *https://twitter.com/autonewssiite/status/997913879563915264*	19-05-2018	16:56
36	**North East Connected** @neconnected · 20 de maig VOLVO CAR UK ANNOUNCES FULL PRICING AND SPECIFICATION DETAILS OF EXCITING NEW V60 - neconnected.co.uk/volvo-car-uk-a... 1 *https://twitter.com/neconnected/status/998156748807704576*	20-05-2018	09:01
37	**Bahnstorm** @bahnstorm · 20 de maig **If you were thinking of buying a C-Class Estate, you might want to wait until the new Volvo V60 arrives**... bahnstorm.co.uk/news/volvo-v60... *https://twitter.com/MotorsMotion/status/998127556086960129*	20-05-2018	07:05
38	**Cars UK** @CarsUK · 18 de maig **Volvo V60 Momentum and Inscription UK price and** Spec OFFICIALLY announced #Volvo **#VolvoV60** #V60Price carsuk.net/volvo-v60-mome... 3 1 *https://twitter.com/CarsUK/status/997507971461632005*	18-05-2018	14:03
39	**Carbuyer** @CarbuyerUK · 15 de maig **Our full verdict on the all-new #Volvo #V60 #estate is now live**: carbyr.uk/2KqjdXd 1 2 7 *https://twitter.com/CarbuyerUK/status/996435144943730690*	15-05-2018	15:00
40	**Cole Marzen** @cole_marzen · 18 de maig **2019 Volvo V60 priced from £31,810 ($42,858)** in the United Kingdom. Deliveries and sales will begin late Q3 2018. #Volvo #V60 **#VolvoV60** 1 1 *https://twitter.com/cole_marzen/status/997584681846689795*	18-05-2018	19:08

C.2 Facebook reviews

	Review and hyperlink	Extraction date and hour	
1	**Tim Choi** It looks like the new V60 has got some extra space. Not like its predecessor. M'agrada · Resposta · 5w *https://www.facebook.com/pg/volvocars/posts/*	01-03-2018	10am
2	**Stefan Maroti** Awesome Volvo. The best ever. Sharp, dynamic and harmonic, in and out. Well done 👍 M'agrada · Resposta · 1w *https://www.facebook.com/pg/volvocars/posts/*	28-03-2018	11am
3	**Richard Loureiro** Sorry V90 you're amazing but your smallest brother V60 is perfect size and design! Volvo what else 👌 2 M'agrada · Resposta · 5w · Editat *https://www.facebook.com/pg/volvocars/posts/*	01-03-2018	10am
4	**Sim Hf** I wanted to order the Momentum V60 but in Belgium it is poorly equiped. There is no navigation, no electrical tailgate and no 18" wheels. For sake, the same Momentum in Netherlnads has these features as standard. This is discrimination against the belgiums. I have been always a volvo driver ffor years but now it becomes difficult to own such expensive car without basic features like a navogation system that you can find standard in many less premium cars. So, I would like to say to Volvocars that the drivers of your cars had enough of your new price and options list policy at least in Belgium. Volvo cars is just getting as the German manufacturers. Producing a car and charging you for options that cost almost the car price. If this is the goal of Volvocars, then I will buy a BMW or an Audi or may be better a KIA. At least they keep their values in the aftermarket. Volvo cars promote many positive values but act the opposite. Farewell. It is done. 2 M'agrada · Resposta · 3w · Editat *https://www.facebook.com/pg/volvocars/posts/*	09-03-2018	11.41am
5	**Stefan Karlsson** The old Volvo's where always abit odd, or last generation atleast, before that I always liked them, I'm bias I guess, as I'm Swedish and think Volvo's are the best thing since oxygen... but anyway, the new design on the new cars is beautiful, best looking cars on the road today in its segments. Not saying all other cars are shit or anything but Volvo is killing it atm! I dont like to over hype or go crazy about a specific model because there is just too many cool and impressive cars out there to do that! Its like saying, uh I only like girls with blonde hair... way to limit your options, seem dumb to me! 😛 M'agrada · Resposta · 5w		
6	**Chris Turner** It's a damn fine looking machine. Only thing that lets it down IMO is the big touchscreen dash. I'm not a fan of these iPad-like screens which control everything, I prefer normal buttons and knobs. Especially for heater controls, means you can adjust them without taking your eyes off the road. 2 M'agrada · Resposta · 3w *https://www.facebook.com/AutoExpress/?hc_ref=ARQepoPOXQVfyQZIZKUBnOBZdzYBRuI2Lik6DD97QXrptreaDS6417wZr920LYqwrRk&fref=nf*	10-03-2018	03.30pm

7	Chris Turner I was hoping to see a front end shot. I quite like the Thor's Hammer headlights on newer Volvos, I think they're the only thing missing from the current V60 M'agrada · Resposta · 6w		
8	Jim Levitt The current V60 is great and different. Yes the dash sucks and it does not have a ton of room behind the seats but it was cool the minute it came out and if you have ever driven a V60 POLESTAR, especially in Polestar Blue, you would know what I mean! This new one is probably light years better in every way and I was told that in person it looks great and drives even better but it doesn't knock my socks off like the current V60 does. Another year or so I may pick up a 2015.5 V60T6 R design, by that time it will cost pennies. Since I'm a dealer I buy wholesale so that will make it even better. I'm old. I don't need nor want a touchscreen car with sub menu after sub menu, too distracting for us and unnecessary. I also heard that the pricing will be similar to the outgoing model so a decently equipped one should not cost more than the mid $40s, tops and if you wait a year you can get one with very low miles for 30K! M'agrada · Resposta · 5w · Editat		
9	Bram Keppens Why do the new models no longer have integrated child seats in option? M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	06-03-2018	08.02pm
10	Eric Frisbie Will the all-inclusive touch screen stick around for a while or will there be plans to incorporate dedicated climate control buttons? I think either this needs to happen or the infotainment system needs a way faster processor! M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	10.03am
11	ShiFan Dong 1) Will there be a Polestar optimization for the #NewV60? 2) Will there be a Polestar engineered car of the #newV60? 3) What's the major differences between the #newV60 and the new V90? Thank you very much, love❤️ you Volvo. M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	10.03am
12	Christian Ubiali Why didn't you made the rear passengers' seats a 40/20/40 configuration? And can we fold forward the front passenger seat? M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	10.03am
13	Scott Marziani Does the 2019 V60 non CC come with a Tempa Spare standard ? I'd imagine that the CC version would, just like the outgoing V60CC. Thank you, very excited for the new V60's arrival! 👍 2 M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	10.03am
14	Oleksandr Shevchenko #1 Would it have USB ports for rear passengers? #2 Can it have kid buster seat integrated? #3 Would be there any neat practical features new to the series? M'agrada · Resposta · 4w · Editat *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	10.03am

15	Aries Woźniak I built one in configurator already. Quite cheap to be honest. 471 000 SEK (About 52 000 dollars) for a almost full equipped with D4 Engine and Inscription. Compared to C-Class for 73 000 dollars, the V60 is a bargain which looks better and feels better than German rival. 1 M'agrada · Resposta · 4w · Editat *https://www.facebook.com/pg/volvocars/posts/*	07-03-2018	10.19am
16	Mike Neirynck V60 beautifull Car ! With the new line the German brands Will face Some hard competition 👌 1 M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	07-03-2018	10.19am
17	Kurt Dreslin Screens get full of fingerprints too and unless it's polestar tuned still can't match bmw performance M'agrada · Resposta · 4w [*https://www.facebook.com/AutoExpress/posts*](https://www.facebook.com/AutoExpress/posts)	10-03-2018	03.30pm
18	Carlos Costa You need a bolder collor pallet. M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	09-03-2018	11.41am
19	Gualberto Baldivieso Very very nice car. And strong segurity M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	06-03-2018	08.02pm
20	Paul Griffin Does the new design have more legroom in the back than the current V60? 2 M'agrada · Resposta · 4w *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	10.03am
21	Erik Ehrhardt Awesome! Make them cheaper so I can buy one. Thanks. 1 Me gusta · Responder · Ver traducción · 2 s *https://www.facebook.com/pg/volvocars/posts/*	02-05-2018	21:55
22	Jasper Visser Looks very nice. My dream car ❤️ Me gusta · Responder · Ver traducción · 2 s *https://www.facebook.com/pg/volvocars/posts/*	02-05-2018	16:20
23	Guy Goerres Please stop the giant touch panel and put some real buttons there!!! Me gusta · Responder · Ver traducción · 2 s *https://www.facebook.com/pg/volvocars/posts/*	03-05-2018	15:38
24	Andrew Jarrow Oh my, very nice , still want the s90 more thou 😁 1 Me gusta · Responder · Ver traducción · 7 s *https://www.facebook.com/pg/volvocars/posts/*	28-03-2018	16:12
25	Michael Ethan Chen Beautiful when is coming to Taiwan? Me gusta · Responder · Ver traducción · 7 s *https://www.facebook.com/pg/volvocars/posts/*	28-03-2018	12:21
26	Shibu Sarkar Save Drive Safe Life Long Life Long Drive Thanks Me gusta · Responder · Ver traducción · 7 s *https://www.facebook.com/pg/volvocars/posts/*	29-03-2018	04:35

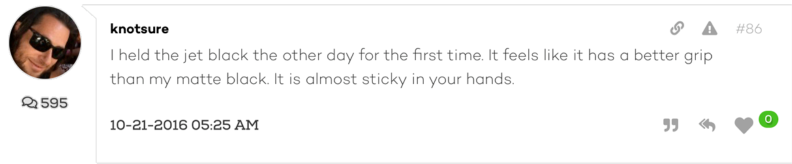
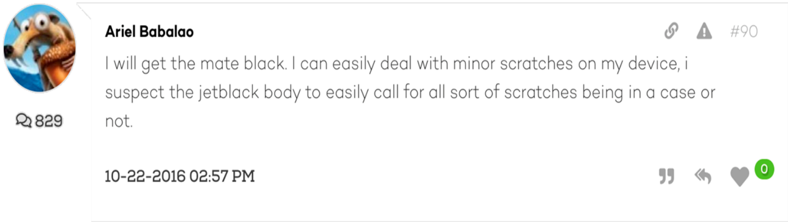
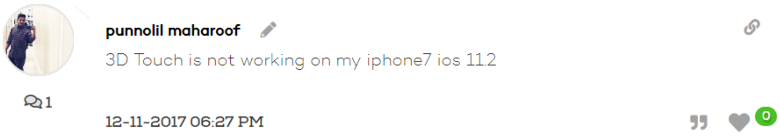
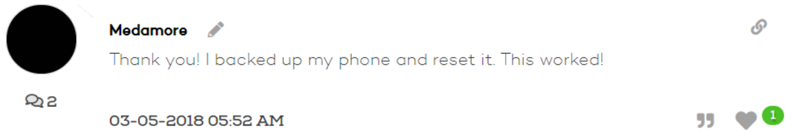
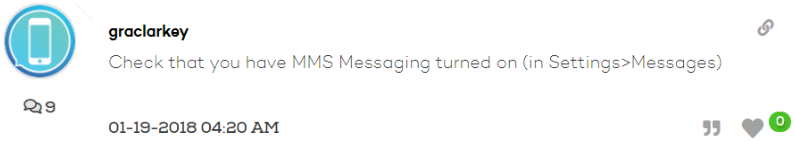
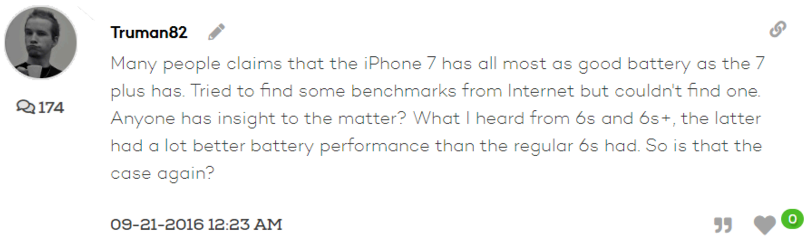
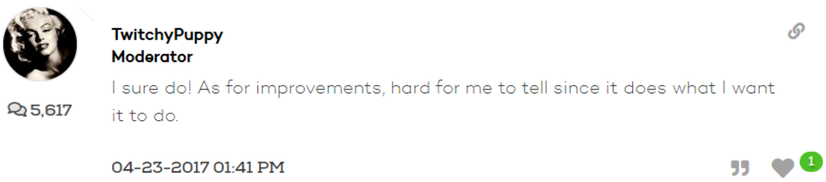
27	**Blerim Cako** volvo the best or nothing Me gusta · Responder · Ver traducción · 7 s *https://www.facebook.com/pg/volvocars/posts/*	01-04-2018	21:31
28	**Darek Gliński** Only Volvo 😍 2 Me gusta · Responder · Ver traducción · 8 s *https://www.facebook.com/pg/volvocars/posts/*	26-03-2018	14:22
29	**Moritz Wieder** It's absolutely beautiful. Me gusta · Responder · Ver traducción · 8 s *https://www.facebook.com/pg/volvocars/posts/*	26-03-2018	12:32
30	**Bryan Ainscough** Any sign of a polestar version of the V60, Volvo ??? Me gusta · Responder · Ver traducción · 10 s *https://www.facebook.com/pg/volvocars/posts/*	10-03-2018	10:17
31	**Alex Merklin** That was one loooooow-riding V60! 😎 Me gusta · Responder · Ver traducción · 10 s 12 *https://www.facebook.com/pg/volvocars/posts/*	09-03-2018	12:28
32	**Paul Visneau** Wayyyyy overpriced not a good way to get out of bankruptcy Me gusta · Responder · Ver traducción · 10 s *https://www.facebook.com/pg/volvocars/posts/*	09-03-2018	20:10
33	**Sergio Delacruz** Excellent Me gusta · Responder · Ver traducción · 10 s *https://www.facebook.com/pg/volvocars/posts/*	09-03-2018	13:48
34	**Per Øyvind Moeng** When will the V60 Cross Country be launched? 3 Me gusta · Responder · Ver traducción · 10 s *https://www.facebook.com/pg/volvocars/posts/*	07-03-2018	10:44
35	**Dennis Bakker** What a beautiful result!! Me gusta · Responder · Ver traducción · 10 s *https://www.facebook.com/pg/volvocars/posts/*	07-03-2018	11:44
36	**Emily Berry** A very lovely car indeed!! 😍 Me gusta · Responder · Ver traducción · 10 s *https://www.facebook.com/pg/volvocars/posts/*	06-03-2018	22:11
37	**Paul Symington** Will it be more economical than the v90cc hed? 3 Me gusta · Responder · Ver traducción · 11 s *https://www.facebook.com/pg/volvocars/posts/*	05-03-2018	16:55
38	**Paul Griffin** Any additional room in the rear seats as the previous S60 was terrible? I know, I've got one. 1 Me gusta · Responder · Ver traducción · 11 s *https://www.facebook.com/pg/volvocars/posts/*	01-03-2018	10:16
39	**Huseyin Omer** it is not just a car. it is science, it is art! Me gusta · Responder · Ver traducción · 11 s *https://www.facebook.com/pg/volvocars/posts/*	27-02-2018	14:11
40	**Joseph T C Liu** Manual transmission for the U.S. market? Me gusta · Responder · Ver traducción · 12 s *https://www.facebook.com/pg/volvocars/posts/*	24-02-2018	05:42

C.3 iMore Forum reviews

	Review and hyperlink	Extraction date and hour	
1	8 **jonarteaga6** Definitely Black. I was debating the Jet Black and Black but once I saw it in videos and photos I realized that Jet Black will scratch easily and it is a fingerprint magnet. So I will be going with Black, it looks so stealthy. I have gold iPhone 6s now. 09-08-2016 10:16 AM 0 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get.html*	09-08-2016	10.16 am
2	17 **HBogard** #183 The black or the dark grey iphone is dope and the safest color, not a a fingerprint magnet like jet black and it has most stealthy look to it.. 06-02-2017 05:06 AM 0 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-8.html*	02-06-2017	05.06 am
3	27,193 **Spencerdl** **Moderator** **Apple Watch Champion** #185 Originally Posted by nikkisharif JB isn't as fragile as it seems I totally agree with Nikki. I have the Jet Black as well and it is not a fingerprint magnet nor does it scratch as easily as some may think. I don't have moist hands nor dry hands (somewhere in-between), and I can honestly say that the fingerprint magnet or scratches easily is just not true ...in my experience anyways. Mind you, I don't go caseless to often, but those times when I do, it's just like with any color device, my iPhone has a dedicated pocket and I don't just lay it down anywhere. To be honest, it actually has more grip than the aluminum colors do. nikkisharif likes this. 06-03-2017 08:19 AM 1 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-8.html*	03-06-2017	08.19 am
4	702 **Cladster** #186 I've had one they do mark and scratch easily, not slippery though and the best iPhone to hold since the 5S/SE. 06-03-2017 11:27 PM 0 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-8.html*	03-06-2017	11.27 pm
5	128 **DLieSaS** #135 I prefer the look of Black, but I'd choose Jet Black for its grippyness. 11-28-2016 05:06 AM 0 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-6.html*	28-11-2016	05.06 am

6	693 **linsiris** #9 Not as good as with iOS 10, it's been getting kinda worse with my iPhone 7 Plus I never had to recharge it and I've had to do so, many times now. **Note: Oops just noticed this was an iPhone 7 only forum, sorry. But still, crappy battery life!! >_< 10-18-2017 07:43 PM 1 *https://forums.imore.com/iphone-7/395310-how-your-battery-life-ios-11-0-3-iphone-7-a.html#post3001553*	18-10-2017	07.43 pm
7	46,603 **Just_Me_D** #10 **Ambassador Team Leader** **Senior Moderator** I don't have any complaints with regard to battery life using iOS 11.0.3. For 'me', as long as I can go from 7 am to bedtime on a single charge, I'm satisfied. 10-18-2017 07:51 PM 0 *https://forums.imore.com/iphone-7/395310-how-your-battery-life-ios-11-0-3-iphone-7-a.html#post3001553*	18-10-2017	07.51 pm
8	36 **steve_w_7** #12 The iOS 11 updates have ruined my battery life. I keep hoping that each of the "dot" updates will fix the issue but, so far, that hasn't been the case. I hope to fix the issue with my next update: the Samsung Galaxy Note 8. 10-19-2017 11:18 AM 0 *https://forums.imore.com/iphone-7/395310-how-your-battery-life-ios-11-0-3-iphone-7-a.html#post3001553*	19-10-2017	11.18 am
9	311 **toneofark** #2 It bothers me. I use all different types of headphones and aux cables. Also, I have an Apogee MiC 96k that has a lightning plug, I use it for field and voice recordings. If I'm using the MiC already, I'll have nowhere to plug in the headphones for monitoring. 09-08-2016 08:22 AM 3 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack.html*	08-09-2016	08.22 am
10	34 **Hoggles** #5 I'm OK with no headphone jack. The lightning solution seems fine and this may give me a push to pick up some Bluetooth headphones. 09-08-2016 08:42 AM 3 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack.html*	08-09-2016	08.42 am
11	712 **Jrome.brooks** #30 I was using wireless headphones well before apple started pushing it but it's good to have a headphone jack because batteries die and you and the 7/7plus can't charge your phone and listen to music with some cheap wire headphones while your wireless headphones are charging so they kind of limit themselves on making the push *Last edited by Jrome.brooks; 09-08-2016 at 12:10 PM.* 09-08-2016 11:56 AM 0 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack-2.html*	08-09-2016	11.56 am
12	178 **Ariza16** #31 haha it's good to see some positive comments after reading so many negative ones in several forum questions. I def don't mind it and look forward to trying the AirPods. Rarely used the headphones anyway. Excited for bluetooth headphones, and the new speaker system. 09-08-2016 12:03 PM 0 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack-2.html*	08-09-2016	12.03 pm

13	**mtcowdog** #35 66 Problematic but tolerable. Lightning pulls out too easy to use for wired headphones, and I am apparently an oddball in that I regularly charge my phone and listen to wired headphones, usually in bed. Also, the wireless agenda Apple is pushing is at an early stage where the sound and usability benefits don't quite match the loss of an old and reliable headphone jack. I run with cheap bluetooth headphones and will keep an eye out for better wireless options at reasonable prices. Airpods, for the record, look awful to me. There is no way I would wear those anywhere, and hard plastic, if anything like the pods that come with iPhones, is an unpleasant experience in my ears. Overall, however, it isn't a deal breaker for me. I will adapt. Water resistance is long overdue, so I appreciate that apparently linked feature. 09-08-2016 01:35 PM 1 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack-2.html*	08-09-2016	01.35 pm
14	**nikkimd11** #37 82 I'm having a hard time accepting there is no headphone jack, I particularly use headphones very often especially to listen to music and having to carry an adapter isn't what I had in mind, on the other hand I really like the idea of having 2 more hours of battery life 09-08-2016 02:24 PM 0 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack-2.html*	08-09-2016	02.24 pm
15	**apcman** #39 44 I can live with it but I do think this is the one time apple flipped the switch way too early. The main gripes I have are charging the device and listening to music and now the need for adapter among devices. It's just going to create the need for adapters and taking them on or off. My MacBook doesn't have a lightning port so I'll need an adapter but my phone and iPad do have the port. It just creates more mess and less simplicity. Also as I pointed why should I pick charging my phone and music when before I could do both. The device won't flop but this does scream money grab or they again did not think about this all the way through. 09-08-2016 03:31 PM 0 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack-2.html*	08-09-2016	03.31 pm
16	**Craig** #47 1,730 If an adapter was not an option and/or available I can see the issue. My first complaint when I heard about the missing jack (when a rumor) was that I spent a lot of $$$ on wired headphones. But the adapter solves the issue. I can't see why the whining? It's not a big deal. It's old tech, time to move onward. 09-08-2016 06:46 PM 0 *https://forums.imore.com/iphone-7/371868-you-ok-no-audio-jack-2.html*	08-09-2016	06.46 pm
17	**manni1to** #77 95 Got the black. Dropped it a couple times. Lots of scuffs. They make me crazy. Going to a 7 plus now. Lol. 10-06-2016 08:21 PM 0 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-4.html*	06-10-2016	08.21 pm
18	**ICraig** #84 6 Black is your best bet especially because it wasn't an available color for the 5 and 6 versions. Making it stand out from the rest. Jet black is nice as well but of course as we all know, is prone to fingerprints. If you're not worried about that then both of those options are really good picks. 10-20-2016 04:53 PM 0 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-4.html*	20-10-2016	04.53 pm

19	 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-4.html*	21-10-2016	05.25 am
20	 *https://forums.imore.com/iphone-7/371883-what-color-iphone-7-should-you-get-4.html*	22-10-2016	02.57 pm
21	 *https://forums.imore.com/showthread.php?t=397789&p=3024610&viewfull=1#post3024610*	11-12-2017	06:27 pm
22	 *https://forums.imore.com/showthread.php?t=400492&p=3047869&viewfull=1#post3047869*	05-03-2018	05:52 am
23	 *https://forums.imore.com/showthread.php?t=396262&p=3036885&viewfull=1#post3036885*	19-01-2018	04:20 am
24	 *https://forums.imore.com/showthread.php?t=373538&p=2818170&viewfull=1#post2818170*	21-09-2016	12:23 am
25	 *https://forums.imore.com/showthread.php?t=387719&p=2931932&viewfull=1#post2931932*	23-04-2017	01:41 pm

26	5 **Roman Peterson** So I should wait till 11.1 official release and see a change? 10-18-2017 01:49 PM 0	18-10-2017	01:49 pm
	https://forums.imore.com/showthread.php?t=395310&p=3001294&viewfull=1#post3001294		
27	1,447 **Lee_Bo** **Trusted Member** **Champion** **Ambassador** I'm about the same on 11 as I was on 10. It really depends on the day. Sometimes I can be at 90% at noon and sometimes (like today) I'm at 74% at noon. It really just depends on what I'm going during the day. However, I haven't noticed any major changes in battery life between 10 and 11. 10-19-2017 11:51 AM 0	19-10-2017	11:51 am
	https://forums.imore.com/showthread.php?t=395310&p=3001553&viewfull=1#post3001553		
28	32 **susan2010** Since the update to IOS 11 I cannot turn off my iPhone alarm using the watch. Any ideas how to fix that? 09-29-2017 01:24 PM 0	29-09-2017	01:24 pm
	https://forums.imore.com/showthread.php?t=394617&p=2994991&viewfull=1#post2994991		
29	2 **svensonZH** update to iOS 11.0.02 fixed it for me. 10-04-2017 02:58 AM 0	04-10-2017	02:58 am
	https://forums.imore.com/showthread.php?t=394617&p=2996739&viewfull=1#post2996739		
30	186 **timja** The jet/matt black not available for the 32GB? 09-08-2016 05:11 PM 0	08-09-2016	05:11 pm
	https://forums.imore.com/showthread.php?t=371883&p=2802030&viewfull=1#post2802030		
31	5 **Jenna Ley** If I got one I'd go with rose gold because I just love the color. 09-08-2016 06:24 PM 0	05-09-2016	06:24 pm
	https://forums.imore.com/showthread.php?t=371883&p=2802141&viewfull=1#post2802141		

32	**Tartarus** **Ambassador** 13,906 Those small details never bug me in iOS updates. The pros have always been more than the cons for me. Besides, iOS 11 is more secure than iOS 10 09-20-2017 03:50 AM 0	20-09-2017	03:50 am
	https://forums.imore.com/showthread.php?t=394013&p=2989194&viewfull=1#post2989194		
33	**MikeF808** 36 Not really a question, more of an observation. Why in this day and age does the iPhone still have a physical silent switch? Isn't it time to integrate that in iOS as they've done with the iPad? 06-02-2017 01:24 PM 0	02-06-2017	01:24 pm
	https://forums.imore.com/showthread.php?t=389322&p=2948160&viewfull=1#post2948160		
34	**camaroz1985** **Trusted Member** 631 Wouldn't bother me if all phones followed this. I use bluetooth all the time anyway. 06-20-2017 10:16 AM 1	20-06-2017	10:16 am
	https://forums.imore.com/showthread.php?t=390203&p=2955304&viewfull=1#post2955304		
35	**cactuspete23** 24 When bluetooth audio quality improves in a couple of years, it may be OK, but for now, not happy with reduced sound quality. 06-21-2017 06:33 AM 1	21-06-2017	06:33 am
	https://forums.imore.com/showthread.php?t=390203&p=2955622&viewfull=1#post2955622		
36	**metalchick719** **Trusted Member** 459 I think you should go for the 7, although I prefer the 6s. It's the more recent phone, plus it will still be newer than the 6s once the 8 arrives. 06-05-2017 11:33 AM 2	05-06-2017	11:33 am
	https://forums.imore.com/showthread.php?t=389381&p=2948986&viewfull=1#post2948986		
37	**robertk328** **Champion** **Ambassador** **Moderator** 8,330 Interesting! Did you get it from an authorized seller? 05-12-2017 05:50 AM 0	12-05-2017	05:50 am
	https://forums.imore.com/showthread.php?t=388553&p=2939806&viewfull=1#post2939806		

38	Just_Me_D Ambassador Team Leader Senior Moderator 46,841 Reboot what I assume is your iPhone and/or reset all settings. 04-14-2018 10:41 AM 0 *https://forums.imore.com/showthread.php?t=401989&p=3056996&viewfull=1#post3056996*	14-04-2018	10:41 am
39	1 thats me Mrs McCaffity 1 How do I a add a new iCloud account for find my friends 03-15-2018 04:48 AM 0 *https://forums.imore.com/showthread.php?t=400931&p=3049950&viewfull=1#post3049950*	15-03-2018	04:48 am
40	eyecrispy iPhone 7, iPad Pro & Apple Watch Champion 3,995 Wow. That's a lot of issues! Do you get any error message you could share with us? 03-01-2018 09:31 AM 1 *https://forums.imore.com/showthread.php?t=400492&p=3047037&viewfull=1#post3047037*	01-03-2018	09:31 am

Appendix C: Review's helpfulness evaluation

Third appendix includes classification between H/NH for filling up each factor in the HOQ of each extracted review in each SM source.

The reviews have been classified in helpful –H– or unhelpful –NH– by two engineers – with 1 representing helpful and 0 representing not helpful.

C.1 Twitter reviews

	F1	F2	F3	F4	F5	F6
1	1	0	0	1	0	0
2	0	0	0	0	0	0
3	0	0	1	1	0	0
4	1	0	0	0	0	0
5	1	0	1	1	0	0
6	1	0	0	1	0	0
7	1	0	1	0	0	0
8	0	0	0	0	0	0
9	1	0	0	1	0	0
10	1	0	0	0	0	0
11	1	0	0	1	0	0
12	0	0	0	1	0	0
13	1	0	0	0	0	0
14	1	0	0	1	0	0
15	1	0	0	1	0	0
16	1	0	0	0	0	0
17	1	0	0	0	0	0
18	0	0	0	0	0	0
19	0	0	0	0	0	0
20	1	0	0	1	0	0
21	0	0	0	0	0	0
22	0	0	0	0	0	0
23	1	0	0	1	0	0
24	0	0	0	1	0	0
25	1	0	0	0	0	0
26	0	0	0	0	0	0
27	0	0	0	0	0	0
28	1	0	0	1	0	0
29	0	0	0	0	0	0
30	1	0	0	1	0	0
31	0	0	1	1	0	0
32	1	0	0	1	0	0
33	1	0	0	0	0	0
34	0	0	1	0	0	0
35	0	0	0	0	0	0
36	0	0	0	0	0	0
37	0	0	0	0	0	0
38	0	0	0	0	0	0
39	0	0	0	0	0	0
40	0	0	0	0	0	0

Table C.6. Perceived helpfulness of the fourteen gathered Twitter reviews

C.2 Forums reviews

	F1	F2	F3	F4	F5	F6
1	1	0	0	1	0	0
2	1	0	0	1	0	0
3	1	0	0	1	0	0
4	1	0	0	0	0	0
5	1	0	0	1	0	0
6	1	0	0	1	0	0
7	1	0	0	1	0	0
8	1	0	1	1	0	0
9	1	0	0	1	0	0
10	1	0	0	1	0	0
11	1	0	0	1	0	0
12	1	0	0	1	0	0
13	1	0	0	1	0	0
14	1	0	0	1	0	0
15	1	0	0	1	0	0
16	1	0	0	1	0	0
17	1	0	0	1	0	0
18	1	0	0	1	0	0
19	1	0	0	1	0	0
20	1	0	0	1	0	0
21	0	0	0	1	0	0
22	0	0	0	0	0	0
23	0	0	0	0	0	0
24	0	0	0	0	0	0
25	0	0	0	0	0	0
26	0	0	0	0	0	0
27	1	0	0	1	0	0
28	1	0	0	1	0	0
29	0	0	0	0	0	0
30	1	0	0	1	0	0
31	1	0	0	1	0	0
32	1	0	0	1	0	0
33	1	0	0	1	0	0
34	0	0	0	0	0	0
35	1	0	0	1	0	0
36	0	0	0	0	0	0
37	0	0	0	0	0	0
38	0	0	0	0	0	0
39	0	0	0	0	0	0
40	0	0	0	0	0	0

Table C.7. Perceived helpfulness of the fourteen gathered Forum reviews

Appendix D: Review's variable values

Third appendix includes the values for each value and each review.

D.1 Twitter reviews

Table D.1 contains the value for each variable for all Twitter extracted reviews.

	# of chars	# of words / # of chars	# of sentences / # of words	% of adjectives	% of adverbs	% of verbs	% of nouns	# of errors / # of words	Content format	Absolute SD	# of PF	# of referred products
1	272	19,49%	11,32%	9,43%	7,55%	15,09%	15,09%	0,00%	0	3	2	3
2	49	16,33%	12,50%	12,50%	0,00%	12,50%	12,50%	0,00%	1	0	1	1
3	61	18,03%	18,18%	45,45%	9,09%	0,00%	18,18%	0,00%	1	4	0	2
4	116	18,10%	4,76%	14,29%	0,00%	9,52%	9,52%	0,00%	1	3	0	1
5	118	11,86%	14,29%	21,43%	0,00%	14,29%	21,43%	0,00%	1	0	1	2
6	63	14,29%	11,11%	11,11%	11,11%	0,00%	22,22%	0,00%	1	0	0	1
7	279	17,20%	10,42%	8,33%	4,17%	14,58%	25,00%	4,17%	0	0	2	5
8	126	19,05%	12,50%	8,33%	8,33%	16,67%	8,33%	0,00%	0	2	0	1
9	64	18,75%	16,67%	25,00%	25,00%	16,67%	25,00%	0,00%	0	2	1	2
10	25	16,00%	25,00%	25,00%	0,00%	25,00%	25,00%	0,00%	0	1	1	1
11	202	19,80%	10,00%	17,50%	17,50%	17,50%	7,50%	2,50%	0	4	1	1
12	205	17,07%	11,43%	11,43%	2,86%	8,57%	5,71%	0,00%	1	2	1	2
13	220	18,64%	9,76%	14,63%	12,20%	17,07%	14,63%	2,44%	0	1	2	3

14	240	17,08%	9,76%	9,76%	0,00%	14,63%	21,95%	0,00%	0	2	4	1
15	279	16,49%	4,35%	6,52%	0,00%	10,87%	15,22%	0,00%	1	0	3	1
16	274	15,33%	4,76%	4,76%	4,76%	14,29%	16,67%	0,00%	0	3	1	1
17	112	17,86%	5,00%	25,00%	5,00%	10,00%	25,00%	0,00%	0	1	1	1
18	62	20,97%	7,69%	23,08%	7,69%	7,69%	15,38%	0,00%	0	2	1	1
19	189	17,99%	8,82%	14,71%	0,00%	14,71%	20,59%	0,00%	1	1	1	1
20	274	15,69%	11,63%	11,63%	9,30%	18,60%	20,93%	0,00%	0	1	3	1
21	62	17,74%	9,09%	18,18%	0,00%	18,18%	18,18%	0,00%	1	1	0	1
22	53	16,98%	11,11%	44,44%	0,00%	0,00%	22,22%	0,00%	0	1	0	1
23	181	16,57%	6,67%	20,00%	6,67%	16,67%	13,33%	0,00%	0	3	1	1
24	226	15,93%	5,56%	8,33%	8,33%	16,67%	16,67%	2,78%	1	1	1	1
25	59	16,95%	10,00%	10,00%	20,00%	10,00%	10,00%	0,00%	1	1	0	1
26	102	17,65%	16,67%	38,89%	5,56%	5,56%	11,11%	0,00%	1	0	0	1
27	68	20,59%	14,29%	14,29%	0,00%	14,29%	7,14%	0,00%	1	0	0	1
28	151	14,57%	9,09%	40,91%	0,00%	9,09%	22,73%	0,00%	0	2	1	1
29	71	18,31%	15,38%	23,08%	7,69%	15,38%	7,69%	0,00%	0	0	0	1
30	221	17,19%	7,89%	26,32%	5,26%	7,89%	15,79%	0,00%	1	3	1	1
31	203	16,26%	6,06%	21,21%	6,06%	9,09%	18,18%	0,00%	0	0	1	1
32	148	19,59%	3,45%	20,69%	3,45%	6,90%	17,24%	0,00%	0	2	1	1
33	177	17,51%	6,45%	32,26%	3,23%	12,90%	19,35%	0,00%	0	4	0	1

34	107	18,69%	5,00%	20,00%	0,00%	15,00%	5,00%	0,00%	0	0	0	1
35	208	21,63%	6,67%	20,00%	2,22%	11,11%	22,22%	2,22%	0	1	0	2
36	82	15,85%	7,69%	30,77%	0,00%	7,69%	23,08%	0,00%	0	1	0	1
37	109	15,60%	11,76%	17,65%	0,00%	0,00%	5,88%	0,00%	1	0	0	1
38	100	11,00%	9,09%	9,09%	0,00%	9,09%	27,27%	0,00%	1	0	0	1
39	65	18,46%	8,33%	25,00%	8,33%	8,33%	8,33%	0,00%	1	0	0	1
40	135	14,07%	10,53%	10,53%	0,00%	10,53%	21,05%	0,00%	1	1	0	1

Table D.8. Variables' value for Twitter reviews

D.2 Forums reviews

	# of chars	# of words / # of chars	# of sentences / # of words	% of adjectives	% of adverbs	% of verbs	% of nouns	# of errors / # of words	Content format	Absolute SD	# of PF	# of referred products
1	256	19,92%	7,84%	17,65%	9,80%	13,73%	7,84%	0,00%	0	1	2	2
2	146	20,55%	3,33%	23,33%	6,67%	10,00%	10,00%	3,33%	0	2	3	1
3	566	19,08%	4,63%	12,96%	25,93%	16,67%	10,19%	1,85%	0	3	1	1
4	113	19,47%	4,55%	13,64%	22,73%	18,18%	4,55%	0,00%	0	2	0	3
5	75	20,00%	6,67%	20,00%	6,67%	13,33%	6,67%	6,67%	0	1	2	1
6	149	22,15%	6,06%	18,18%	18,18%	12,12%	3,03%	3,03%	0	2	1	2
7	162	20,37%	6,06%	15,15%	12,12%	15,15%	12,12%	0,00%	0	2	2	1
8	227	20,26%	6,52%	19,57%	4,35%	13,04%	15,22%	0,00%	0	0	2	2
9	262	19,08%	6,00%	10,00%	6,00%	18,00%	16,00%	0,00%	0	0	3	1

10	134	18,66%	8,00%	20,00%	8,00%	16,00%	20,00%	0,00%	0	2	3	1
11	329	17,33%	1,75%	19,30%	8,77%	17,54%	12,28%	0,00%	0	2	3	2
12	269	16,73%	8,89%	20,00%	13,33%	13,33%	13,33%	2,22%	0	2	3	1
13	827	17,41%	4,86%	18,75%	11,11%	11,11%	19,44%	0,00%	0	4	7	1
14	272	19,12%	1,92%	5,77%	17,31%	21,15%	21,15%	0,00%	0	1	3	1
15	646	19,81%	4,69%	8,59%	10,94%	17,97%	18,75%	0,00%	0	2	2	1
16	314	20,06%	7,94%	9,52%	11,11%	19,05%	19,05%	0,00%	0	2	3	1
17	109	21,10%	26,09%	17,39%	8,70%	17,39%	8,70%	0,00%	0	1	1	2
18	300	19,33%	6,90%	20,69%	13,79%	17,24%	10,34%	0,00%	0	2	3	3
19	149	21,48%	9,38%	28,13%	6,25%	12,50%	12,50%	0,00%	0	2	2	1
20	176	20,45%	5,56%	13,89%	8,33%	16,67%	16,67%	2,78%	0	1	2	1
21	50	22,00%	9,09%	27,27%	9,09%	18,18%	18,18%	0,00%	0	0	0	1
22	62	20,97%	23,08%	7,69%	0,00%	30,77%	7,69%	0,00%	0	0	0	1
23	70	15,71%	18,18%	9,09%	0,00%	18,18%	27,27%	0,00%	0	0	0	1
24	320	19,38%	8,06%	16,13%	12,90%	17,74%	17,74%	1,61%	0	2	0	4
25	91	23,08%	9,52%	9,52%	9,52%	23,81%	4,76%	0,00%	0	0	0	1
26	65	20,00%	7,69%	15,38%	15,38%	30,77%	7,69%	0,00%	0	0	0	1
27	292	20,55%	6,67%	8,33%	15,00%	15,00%	15,00%	0,00%	0	1	3	1
28	108	21,30%	8,70%	4,35%	21,74%	17,39%	17,39%	0,00%	0	0	3	1
29	42	21,43%	11,11%	11,11%	0,00%	11,11%	11,11%	0,00%	0	0	0	1

30	50	18,00%	11,11%	22,22%	11,11%	11,11%	11,11%	0,00%	0	0	2	1
31	69	23,19%	6,25%	12,50%	6,25%	18,75%	12,50%	6,25%	0	0	2	1
32	148	20,27%	10,00%	20,00%	13,33%	10,00%	13,33%	0,00%	0	2	2	1
33	197	19,29%	7,89%	7,89%	18,42%	10,53%	21,05%	0,00%	0	0	1	1
34	88	18,18%	12,50%	12,50%	12,50%	25,00%	18,75%	0,00%	0	0	0	1
35	128	18,75%	4,17%	16,67%	12,50%	12,50%	20,83%	0,00%	0	1	1	1
36	150	21,33%	6,25%	25,00%	9,38%	21,88%	3,13%	0,00%	0	1	0	3
37	58	17,24%	20,00%	20,00%	0,00%	10,00%	10,00%	0,00%	0	1	0	1
38	66	18,18%	8,33%	16,67%	0,00%	16,67%	25,00%	0,00%	0	0	0	1
39	59	23,73%	7,14%	21,43%	7,14%	14,29%	14,29%	0,00%	0	0	0	1
40	86	20,93%	16,67%	5,56%	11,11%	22,22%	11,11%	0,00%	0	0	0	1

Table D.9. Variables' value for Forum reviews

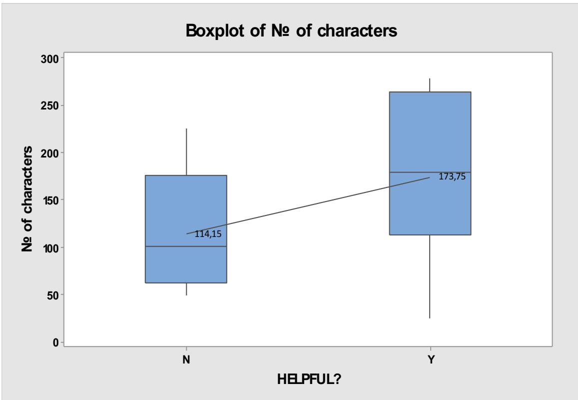
Appendix E: Plots

Fourth appendix includes the plots for each considered variable in the methodology related with each of the six groups of QFD factors, distinguishing between helpful and unhelpful reviews.

E.1 Twitter reviews

F1: Customer Attributes

of characters



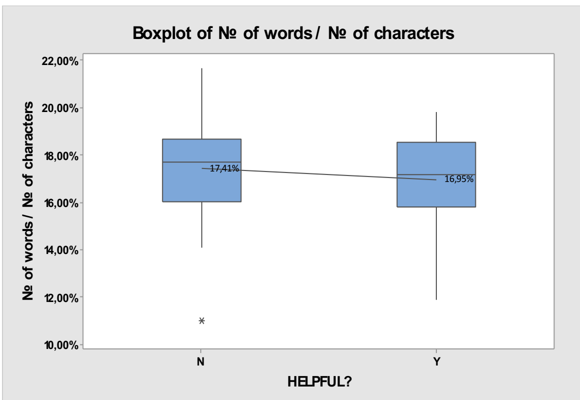
Descriptive Statistics: № of characters

```
Variable         HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
№ of characters  N         20  114,2   59,7     49,0   62,8   101,0  175,5    226,0
                 Y         20  173,8   83,5     25,0  113,0   179,0  264,0    279,0
```

Two-Sample T-Test and CI: № of characters; HELPFUL?

```
Two-sample T for № of characters

                                SE
HELPFUL?   N   Mean  StDev    Mean
N         20  114,2   59,7      13
Y         20  173,8   83,5      19


Difference = μ (N) - μ (Y)
Estimate for difference:  -59,6
95% CI for difference:  (-106,3; -12,9)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,60  P-Value = 0,014  DF = 34
```

of words / # of characters



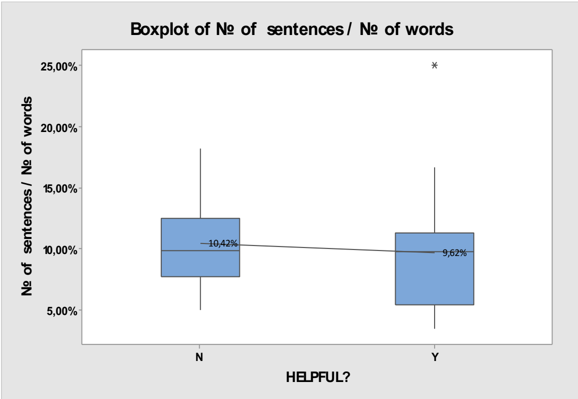
Descriptive Statistics: № of words / № of characters

```
Variable                 HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of words / № of charac N         20  0,17410  0,02413  0,11000  0,16011  0,17694  0,18634
                         Y         20  0,16949  0,01978  0,11864  0,15770  0,17139  0,18503

Variable                 HELPFUL?  Maximum
№ of words / № of charac N         0,21635
                         Y         0,19802
```

Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

```
Two-sample T for № of words / № of characters

HELPFUL?   N    Mean   StDev  SE Mean
N         20  0,1741  0,0241   0,0054
Y         20  0,1695  0,0198   0,0044


Difference = μ (N) - μ (Y)
Estimate for difference:  0,00461
95% CI for difference:  (-0,00954; 0,01876)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,06  P-Value = 0,956  DF = 36
```

of sentences / # of words



Descriptive Statistics: № of sentences / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of sentences / № of w	N	20	0,10418	0,03715	0,05000	0,07692	0,09809	0,12500
	Y	20	0,0962	0,0500	0,0345	0,0536	0,0976	0,1127

Variable	HELPFUL?	Maximum
№ of sentences / № of w	N	0,18182
	Y	0,2500

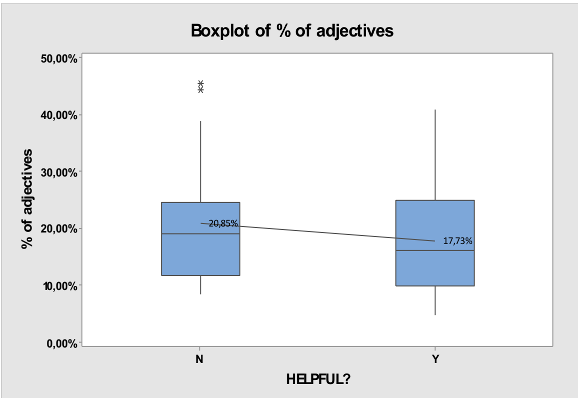
Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

Two-sample T for № of sentences / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,1042	0,0372	0,0083
Y	20	0,0962	0,0500	0,011

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0080
95% CI for difference: (-0,0203; 0,0363)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,22 P-Value = 0,831 DF = 35

% of adjectives



Descriptive Statistics: % of adjectives

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adjectives	N	20	0,2085	0,1131	0,0833	0,1170	0,1909	0,2452	0,4545
	Y	20	0,1773	0,0942	0,0476	0,0982	0,1607	0,2500	0,4091

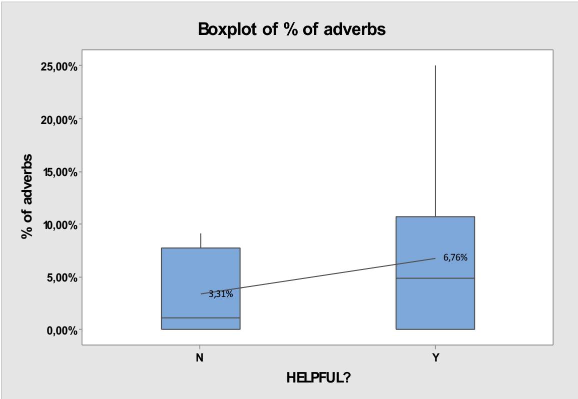
Two-Sample T-Test and CI: % of adjectives; HELPFUL?

Two-sample T for % of adjectives

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,208	0,113	0,025
Y	20	0,1773	0,0942	0,021

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0312
95% CI for difference: (-0,0355; 0,0979)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,80 P-Value = 0,431 DF = 36

% of adverbs



Descriptive Statistics: % of adverbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adverbs	N	20	0,03309	0,03777	0,00000	0,00000	0,01111	0,07692	0,09091
	Y	20	0,0676	0,0723	0,0000	0,0000	0,0488	0,1066	0,2500

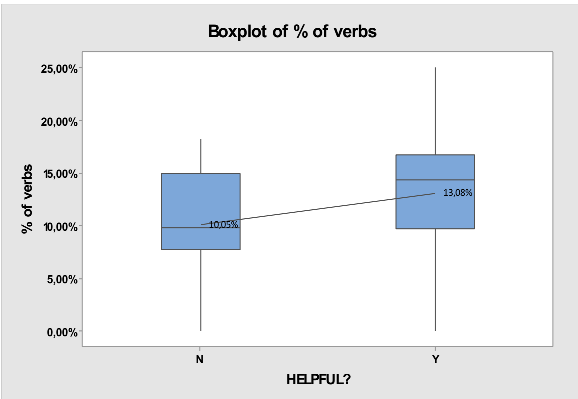
Two-Sample T-Test and CI: % of adverbs; HELPFUL?

Two-sample T for % of adverbs

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,0331	0,0378	0,0084
Y	20	0,0676	0,0723	0,016

Difference = μ (N) - μ (Y)
Estimate for difference: -0,0345
95% CI for difference: (-0,0719; 0,0028)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,17 P-Value = 0,039 DF = 28

% of verbs



Descriptive Statistics: % of verbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of verbs	N	20	0,1005	0,0560	0,0000	0,0769	0,0981	0,1493	0,1818
	Y	20	0,1308	0,0530	0,0000	0,0964	0,1429	0,1667	0,2500

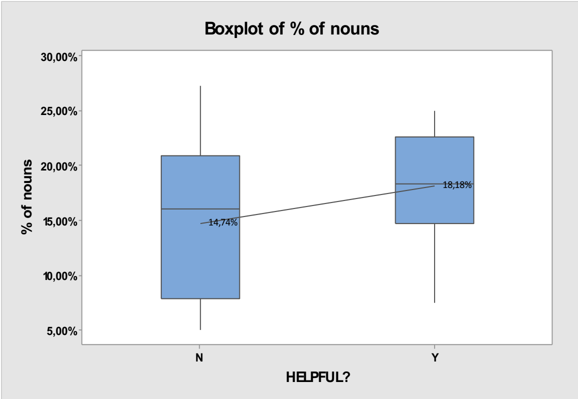
Two-Sample T-Test and CI: % of verbs; HELPFUL?

Two-sample T for % of verbs

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,1005	0,0560	0,013
Y	20	0,1308	0,0530	0,012

Difference = μ (N) - μ (Y)
Estimate for difference: -0,0303
95% CI for difference: (-0,0652; 0,0047)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,05 P-Value = 0,048 DF = 37

% of nouns



Descriptive Statistics: % of nouns

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of nouns	N	20	0,1474	0,0694	0,0500	0,0785	0,1603	0,2094	0,2727
	Y	20	0,1818	0,0551	0,0750	0,1475	0,1830	0,2260	0,2500

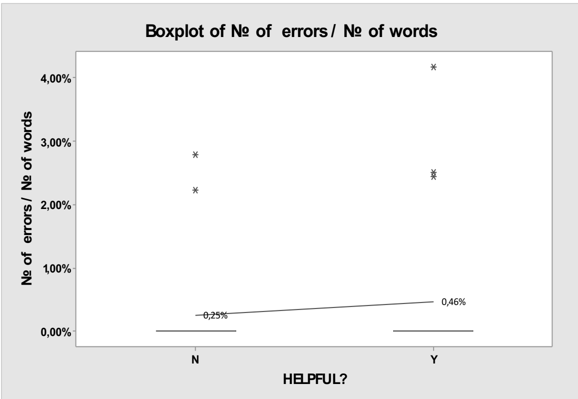
Two-Sample T-Test and CI: % of nouns; HELPFUL?

Two-sample T for % of nouns

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,1474	0,0694	0,016
Y	20	0,1818	0,0551	0,012

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0344
95% CI for difference:  (-0,0746; 0,0057)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,99  P-Value = 0,054  DF = 36
```

of errors / # of words



Descriptive Statistics: № of errors / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of errors / № of word	N	20	0,00250	0,00775	0,00000	0,00000	0,00000	0,00000
	Y	20	0,00455	0,01157	0,00000	0,00000	0,00000	0,00000

Variable	HELPFUL?	Maximum
№ of errors / № of word	N	0,02778
	Y	0,04167

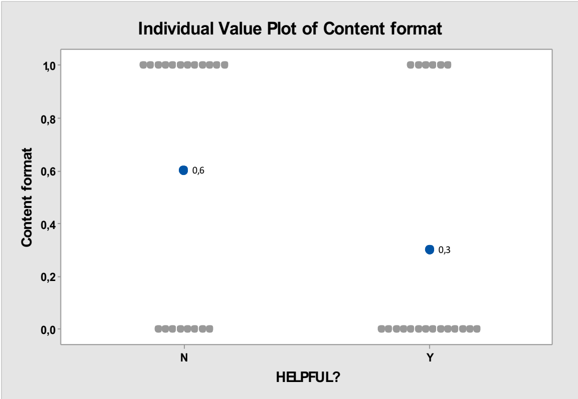
Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

Two-sample T for № of errors / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,00250	0,00775	0,0017
Y	20	0,0046	0,0116	0,0026

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,00205
95% CI for difference:  (-0,00839; 0,00428)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,27  P-Value = 0,030  DF = 33
```

Content format



Descriptive Statistics: Content format

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Content format	N	20	0,600	0,503	0,000	0,000	1,000	1,000	1,000
	Y	20	0,300	0,470	0,000	0,000	0,000	1,000	1,000

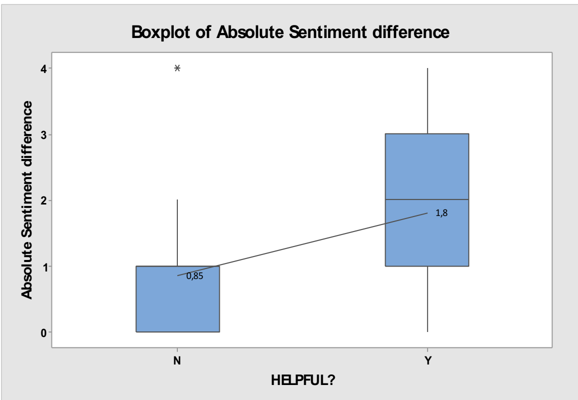
Two-Sample T-Test and CI: Content format; HELPFUL?

Two-sample T for Content format

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,600	0,503	0,11
Y	20	0,300	0,470	0,11

```
Difference = μ (N) - μ (Y)
Estimate for difference:  0,300
95% CI for difference:  (-0,012; 0,612)
T-Test of difference = 0,005 (vs ≠): T-Value = 1,92  P-Value = 0,063  DF = 37
```

Absolute sentiment difference



Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	20	0,850	1,040	0,000	0,000	1,000	1,000	4,000
	Y	20	1,800	1,322	0,000	1,000	2,000	3,000	4,000

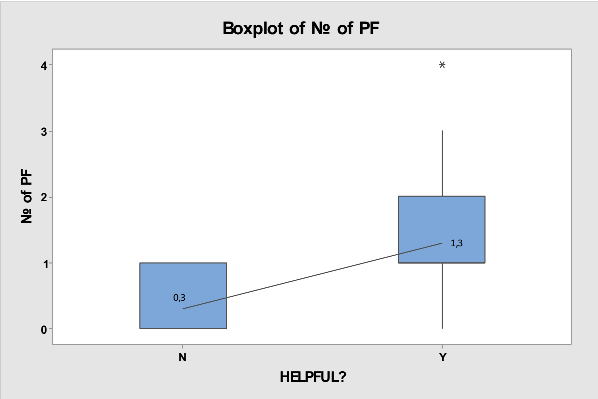
Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

Two-sample T for Absolute Sentiment difference

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,85	1,04	0,23
Y	20	1,80	1,32	0,30

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,950
95% CI for difference:  (-1,713; -0,187)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,54  P-Value = 0,016  DF = 36
```

of PF



Descriptive Statistics: № of PF

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of PF	N	20	0,300	0,470	0,000	0,000	0,000	1,000	1,000
	Y	20	1,300	1,081	0,000	1,000	1,000	2,000	4,000

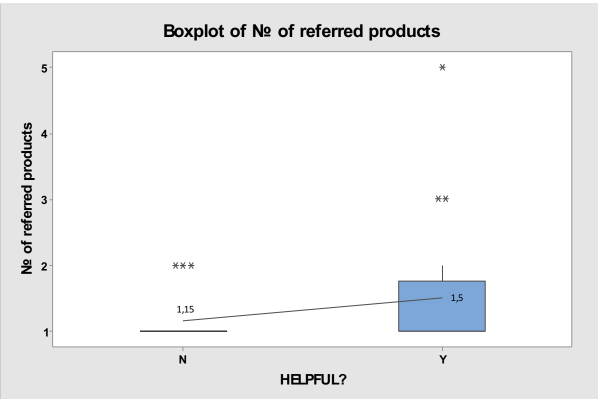
Two-Sample T-Test and CI: № of PF; HELPFUL?

Two-sample T for № of PF

HELPFUL?	N	Mean	StDev	SE Mean
N	20	0,300	0,470	0,11
Y	20	1,30	1,08	0,24

Difference = μ (N) - μ (Y)
Estimate for difference: -1,000
95% CI for difference: (-1,543; -0,457)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,81 P-Value = 0,001 DF = 25

of referred products



Descriptive Statistics: № of referred products

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of referred products	N	20	1,1500	0,3663	1,0000	1,0000	1,0000	1,0000
	Y	20	1,500	1,051	1,000	1,000	1,000	1,750

Variable	HELPFUL?	Maximum
№ of referred products	N	2,0000
	Y	5,000

Two-Sample T-Test and CI: № of referred products; HELPFUL?

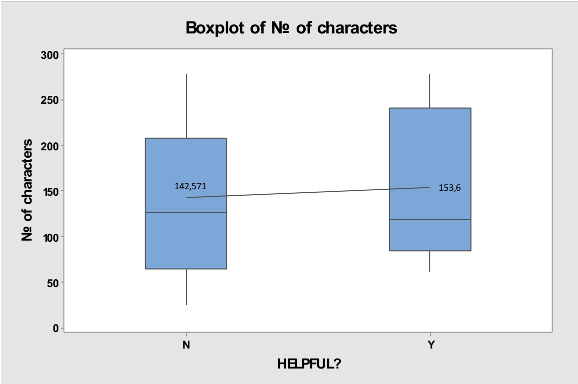
Two-sample T for № of referred products

HELPFUL?	N	Mean	StDev	SE Mean
N	20	1,150	0,366	0,082
Y	20	1,50	1,05	0,24

Difference = μ (N) - μ (Y)
Estimate for difference: -0,350
95% CI for difference: (-0,865; 0,165)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,43 P-Value = 0,167 DF = 23

F3: Customer evaluation (competitors)

of characters



Descriptive Statistics: № of characters

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of characters	N	35	142,6	77,7	25,0	65,0	126,0	208,0	279,0
	Y	5	153,6	86,9	61,0	84,0	118,0	241,0	279,0

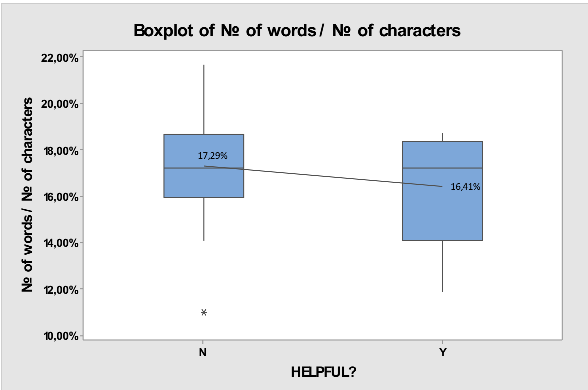
Two-Sample T-Test and CI: № of characters; HELPFUL?

Two-sample T for № of characters

HELPFUL?	N	Mean	StDev	SE Mean
N	35	142,6	77,7	13
Y	5	153,6	86,9	39

Difference = μ (N) - μ (Y)
Estimate for difference: -11,0
95% CI for difference: (-124,9; 102,8)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,27 P-Value = 0,801 DF = 4

of words / # of characters



Descriptive Statistics: № of words / № of characters

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of words / № of charac	N	35	0,17289	0,02132	0,11000	0,15929	0,17195	0,18636
	Y	5	0,1641	0,0270	0,1186	0,1406	0,1720	0,1836

Variable	HELPFUL?	Maximum
№ of words / № of charac	N	0,21635
	Y	0,1869

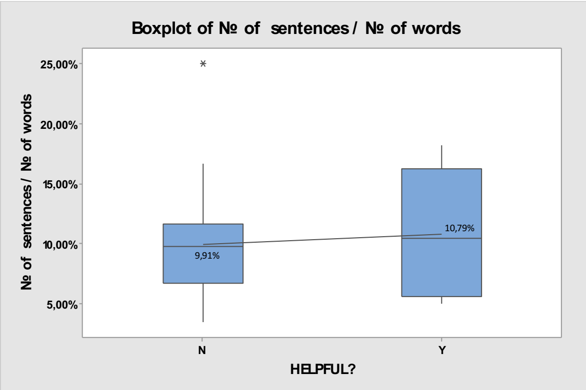
Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

Two-sample T for № of words / № of characters

HELPFUL?	N	Mean	StDev	SE Mean
N	35	0,1729	0,0213	0,0036
Y	5	0,1641	0,0270	0,012

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0088
95% CI for difference: (-0,0262; 0,0438)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,30 P-Value = 0,778 DF = 4

of sentences / # of words



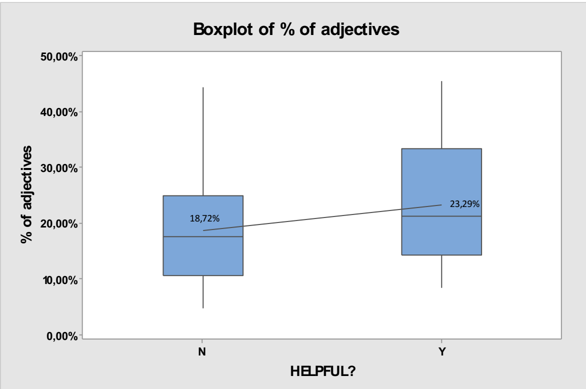
Descriptive Statistics: № of sentences / № of words

```
Variable                  HELPFUL?  N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  sentences / № of w  N        35  0,09908  0,04260  0,03448  0,06667  0,09756  0,11628
                          Y         5   0,1079   0,0554   0,0500   0,0553   0,1042   0,1623

Variable                  HELPFUL?  Maximum
№ of  sentences / № of w  N         0,25000
                          Y          0,1818
```

Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

```
Two-sample T for № of  sentences / № of words

HELPFUL?   N    Mean   StDev  SE Mean
N         35  0,0991  0,0426   0,0072
Y          5  0,1079  0,0554    0,025


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0088
95% CI for difference:  (-0,0805; 0,0629)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,54  P-Value = 0,621  DF = 4
```

% of adjectives



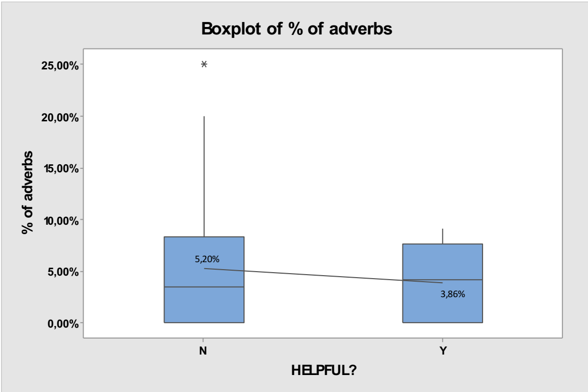
Descriptive Statistics: % of adjectives

```
Variable         HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of adjectives  N         35  0,1872  0,0998   0,0476  0,1053  0,1750  0,2500   0,4444
                 Y          5  0,2329  0,1354   0,0833  0,1417  0,2121  0,3344   0,4545
```

Two-Sample T-Test and CI: % of adjectives; HELPFUL?

```
Two-sample T for % of adjectives

HELPFUL?   N    Mean   StDev  SE Mean
N         35  0,1872  0,0998    0,017
Y          5   0,233   0,135    0,061


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0457
95% CI for difference:  (-0,2202; 0,1289)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,81  P-Value = 0,465  DF = 4
```

% of adverbs



Descriptive Statistics: % of adverbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adverbs	N	35	0,0520	0,0621	0,0000	0,0000	0,0345	0,0833	0,2500
	Y	5	0,0386	0,0394	0,0000	0,0000	0,0417	0,0758	0,0909

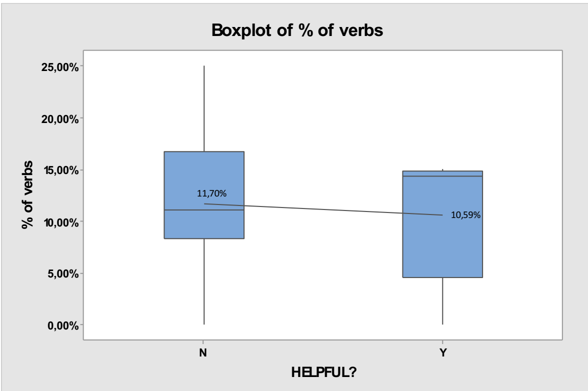
Two-Sample T-Test and CI: % of adverbs; HELPFUL?

Two-sample T for % of adverbs

HELPFUL?	N	Mean	StDev	SE Mean
N	35	0,0520	0,0621	0,011
Y	5	0,0386	0,0394	0,018

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0134
95% CI for difference: (-0,0351; 0,0619)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,41 P-Value = 0,695 DF = 7

% of verbs



Descriptive Statistics: % of verbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of verbs	N	35	0,11705	0,05562	0,00000	0,08333	0,11111	0,16667	0,25000
	Y	5	0,1059	0,0639	0,0000	0,0455	0,1429	0,1479	0,1500

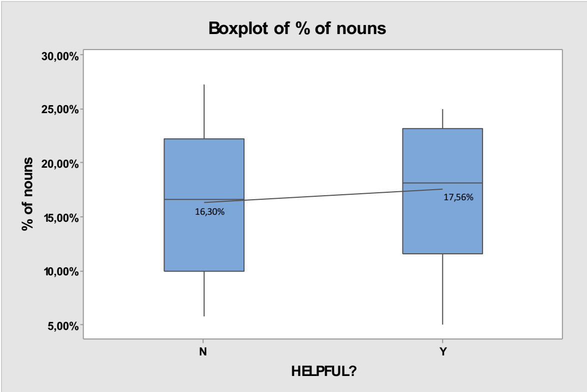
Two-Sample T-Test and CI: % of verbs; HELPFUL?

Two-sample T for % of verbs

HELPFUL?	N	Mean	StDev	SE Mean
N	35	0,1170	0,0556	0,0094
Y	5	0,1059	0,0639	0,029

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0111
95% CI for difference: (-0,0724; 0,0947)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,20 P-Value = 0,849 DF = 4

% of nouns



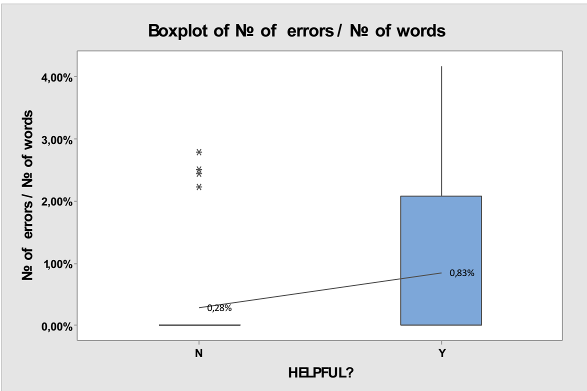
Descriptive Statistics: % of nouns

```
Variable    HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of nouns  N         35  0,1630  0,0636   0,0571  0,1000  0,1667  0,2222   0,2727
            Y          5  0,1756  0,0756   0,0500  0,1159  0,1818  0,2321   0,2500
```

Two-Sample T-Test and CI: % of nouns; HELPFUL?

```
Two-sample T for % of nouns

HELPFUL?   N    Mean   StDev  SE Mean
N         35  0,1630  0,0636    0,011
Y          5  0,1756  0,0756    0,034


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0126
95% CI for difference:  (-0,1111; 0,0860)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,49  P-Value = 0,647  DF = 4
```

of errors / # of words



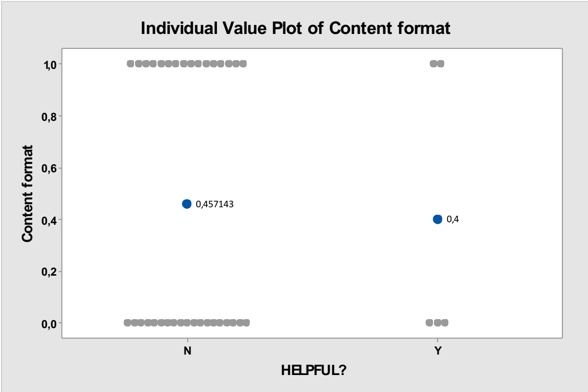
Descriptive Statistics: № of errors / № of words

```
Variable                  HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  errors / № of word  N         35  0,00284  0,00805  0,00000  0,00000  0,00000  0,00000
                          Y          5  0,00833  0,01863  0,00000  0,00000  0,00000  0,02083

Variable                  HELPFUL?  Maximum
№ of  errors / № of word  N         0,02778
                          Y         0,04167
```

Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

```
Two-sample T for № of  errors / № of words

HELPFUL?   N     Mean    StDev  SE Mean
N         35  0,00284  0,00805   0,0014
Y          5   0,0083   0,0186   0,0083


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,00549
95% CI for difference:  (-0,02894; 0,01795)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,24  P-Value = 0,282  DF = 4
```

Content format



Descriptive Statistics: Content format

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Content format	N	35	0,4571	0,5054	0,0000	0,0000	0,0000	1,0000	1,0000
	Y	5	0,400	0,548	0,000	0,000	0,000	1,000	1,000

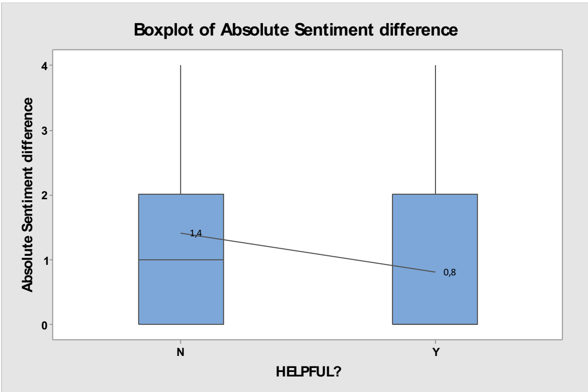
Two-Sample T-Test and CI: Content format; HELPFUL?

Two-sample T for Content format

HELPFUL?	N	Mean	StDev	SE Mean
N	35	0,457	0,505	0,085
Y	5	0,400	0,548	0,24

Difference = μ (N) - μ (Y)
Estimate for difference: 0,057
95% CI for difference: (-0,610; 0,724)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,20 P-Value = 0,849 DF = 5

Absolute sentiment difference



Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	35	1,400	1,193	0,000	0,000	1,000	2,000	4,000
	Y	5	0,800	1,789	0,000	0,000	0,000	2,000	4,000

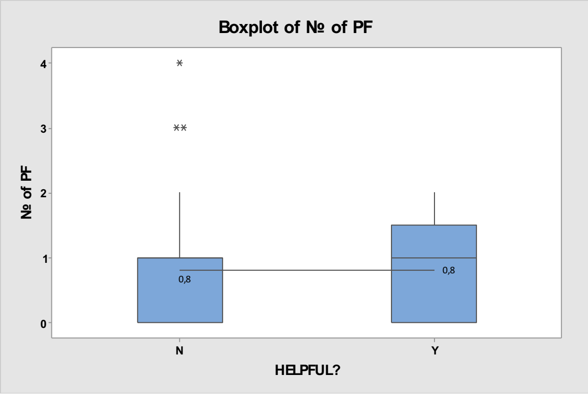
Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

Two-sample T for Absolute Sentiment difference

HELPFUL?	N	Mean	StDev	SE Mean
N	35	1,40	1,19	0,20
Y	5	0,80	1,79	0,80

Difference = μ (N) - μ (Y)
Estimate for difference: 0,600
95% CI for difference: (-1,691; 2,891)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,72 P-Value = 0,511 DF = 4

of PF



Descriptive Statistics: № of PF

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of PF	N	35	0,800	0,994	0,000	0,000	1,000	1,000	4,000
	Y	5	0,800	0,837	0,000	0,000	1,000	1,500	2,000

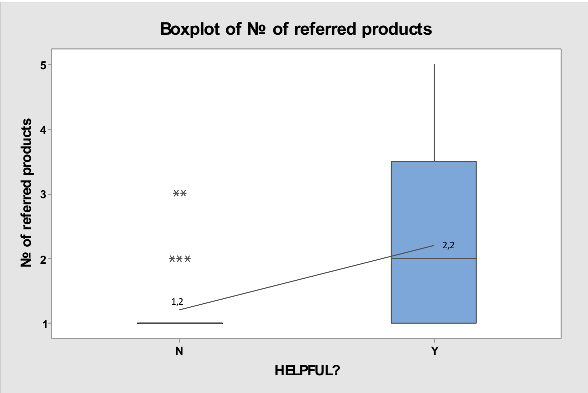
Two-Sample T-Test and CI: № of PF; HELPFUL?

Two-sample T for № of PF

HELPFUL?	N	Mean	StDev	SE Mean
N	35	0,800	0,994	0,17
Y	5	0,800	0,837	0,37

```
Difference = μ (N) - μ (Y)
Estimate for difference:  0,000
95% CI for difference:  (-1,054; 1,054)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,01  P-Value = 0,991  DF = 5
```

of referred products



Descriptive Statistics: № of referred products

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of referred products	N	35	1,2000	0,5314	1,0000	1,0000	1,0000	1,0000
	Y	5	2,200	1,643	1,000	1,000	2,000	3,500

Variable	HELPFUL?	Maximum
№ of referred products	N	3,0000
	Y	5,000

Two-Sample T-Test and CI: № of referred products; HELPFUL?

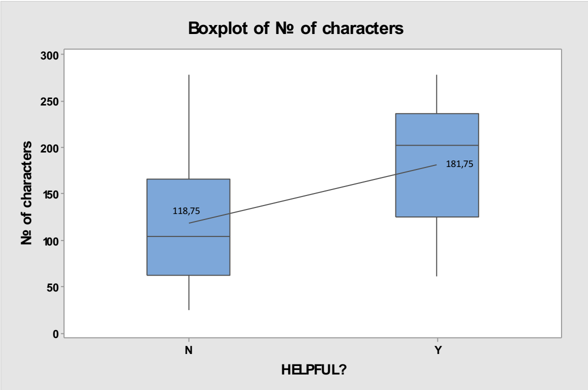
Two-sample T for № of referred products

HELPFUL?	N	Mean	StDev	SE Mean
N	35	1,200	0,531	0,090
Y	5	2,20	1,64	0,73

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -1,000
95% CI for difference:  (-3,055; 1,055)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,36  P-Value = 0,246  DF = 4
```

F4: Engineering characteristics and/or product targets related

of characters



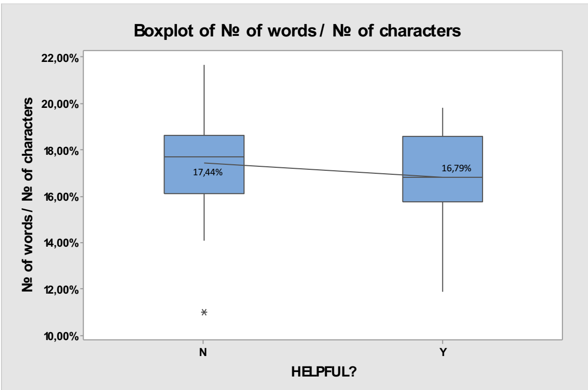
Descriptive Statistics: № of characters

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of characters	N	24	118,8	70,6	25,0	62,8	104,5	166,5	279,0
	Y	16	181,8	74,4	61,0	125,5	202,5	236,5	279,0

Two-Sample T-Test and CI: № of characters; HELPFUL?

```
Two-sample T for № of characters

                                SE
HELPFUL?   N   Mean  StDev    Mean
N         24  118,8   70,6      14
Y         16  181,8   74,4      19


Difference = μ (N) - μ (Y)
Estimate for difference:  -63,0
95% CI for difference:  (-111,0; -15,0)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,68  P-Value = 0,012  DF = 31
```

of words / # of characters



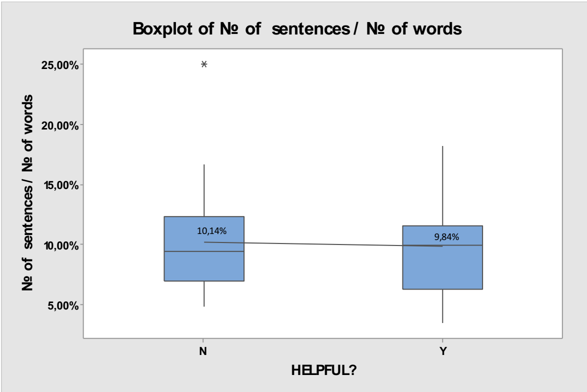
Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of words / № of charac	N	24	0,17438	0,02240	0,11000	0,16082	0,17694	0,18593
	Y	16	0,16792	0,02125	0,11864	0,15752	0,16824	0,18571

Variable	HELPFUL?	Maximum
№ of words / № of charac	N	0,21635
	Y	0,19802

Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

```
Two-sample T for № of words / № of characters

HELPFUL?   N    Mean   StDev  SE Mean
N         24  0,1744  0,0224   0,0046
Y         16  0,1679  0,0213   0,0053


Difference = μ (N) - μ (Y)
Estimate for difference:  0,00645
95% CI for difference:  (-0,00781; 0,02071)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,21  P-Value = 0,837  DF = 33
```

of sentences / # of words



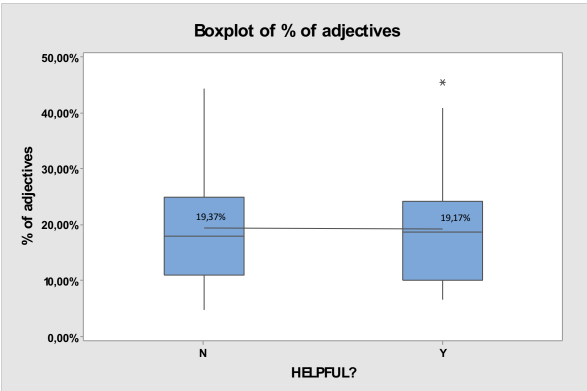
Descriptive Statistics: № of sentences / № of words

```
Variable                  HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  sentences / № of w  N         24  0,10137  0,04562  0,04762  0,06923  0,09424  0,12316
                          Y         16   0,0984   0,0419   0,0345   0,0621   0,0988   0,1158

Variable                  HELPFUL?  Maximum
№ of  sentences / № of w  N         0,25000
                          Y          0,1818
```

Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

```
Two-sample T for № of  sentences / № of words

HELPFUL?   N    Mean   StDev  SE Mean
N         24  0,1014  0,0456   0,0093
Y         16  0,0984  0,0419    0,010


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0030
95% CI for difference:  (-0,0255; 0,0315)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,15  P-Value = 0,885  DF = 34
```

% of adjectives



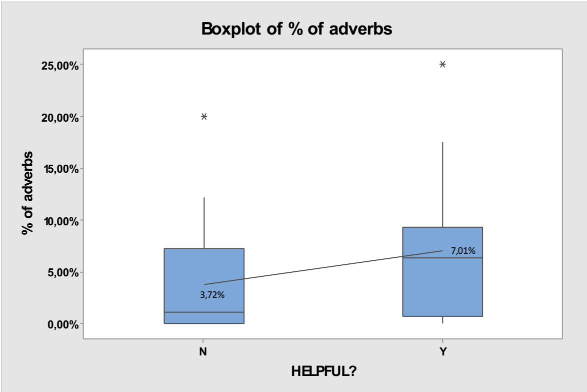
Descriptive Statistics: % of adjectives

```
Variable         HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of adjectives  N         24  0,1937  0,1001   0,0476  0,1102  0,1791  0,2500   0,4444
                 Y         16  0,1917  0,1127   0,0652  0,1009  0,1875  0,2411   0,4545
```

Two-Sample T-Test and CI: % of adjectives; HELPFUL?

```
Two-sample T for % of adjectives

HELPFUL?   N   Mean  StDev  SE Mean
N         24  0,194  0,100    0,020
Y         16  0,192  0,113    0,028


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0020
95% CI for difference:  (-0,0692; 0,0732)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,09  P-Value = 0,931  DF = 29
```

% of adverbs



Descriptive Statistics: % of adverbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adverbs	N	24	0,0372	0,0505	0,0000	0,0000	0,0111	0,0716	0,2000
	Y	16	0,0701	0,0680	0,0000	0,0071	0,0636	0,0925	0,2500

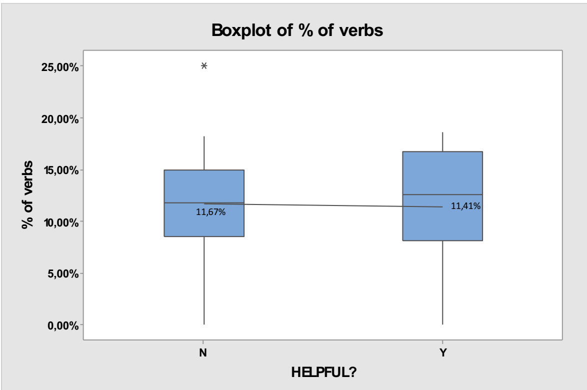
Two-Sample T-Test and CI: % of adverbs; HELPFUL?

Two-sample T for % of adverbs

HELPFUL?	N	Mean	StDev	SE Mean
N	24	0,0372	0,0505	0,010
Y	16	0,0701	0,0680	0,017

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0330
95% CI for difference:  (-0,0739; 0,0080)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,91  P-Value = 0,068  DF = 25
```

% of verbs



Descriptive Statistics: % of verbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of verbs	N	24	0,1167	0,0553	0,0000	0,0852	0,1181	0,1493	0,2500
	Y	16	0,1141	0,0587	0,0000	0,0806	0,1258	0,1667	0,1860

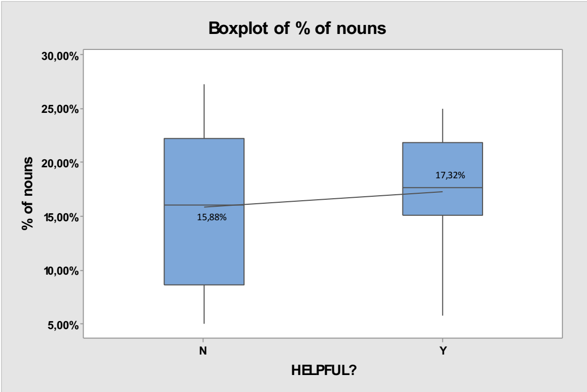
Two-Sample T-Test and CI: % of verbs; HELPFUL?

Two-sample T for % of verbs

HELPFUL?	N	Mean	StDev	SE Mean
N	24	0,1167	0,0553	0,011
Y	16	0,1141	0,0587	0,015

```
Difference = μ (N) - μ (Y)
Estimate for difference:  0,0026
95% CI for difference:  (-0,0352; 0,0404)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,13  P-Value = 0,899  DF = 30
```

% of nouns



Descriptive Statistics: % of nouns

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of nouns	N	24	0,1588	0,0712	0,0500	0,0863	0,1603	0,2222	0,2727
	Y	16	0,1732	0,0532	0,0571	0,1513	0,1771	0,2182	0,2500

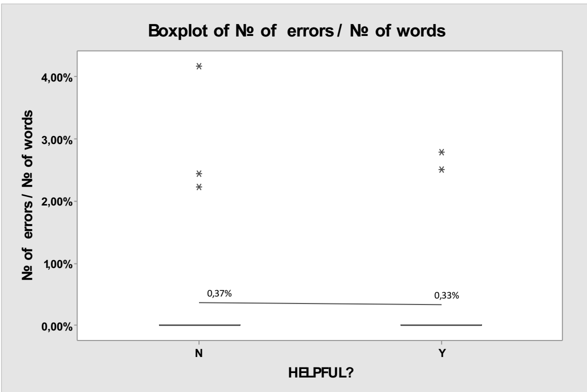
Two-Sample T-Test and CI: % of nouns; HELPFUL?

Two-sample T for % of nouns

HELPFUL?	N	Mean	StDev	SE Mean
N	24	0,1588	0,0712	0,015
Y	16	0,1732	0,0532	0,013

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0144
95% CI for difference:  (-0,0543; 0,0255)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,99  P-Value = 0,331  DF = 37
```

of errors / # of words



Descriptive Statistics: № of errors / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of errors / № of word	N	24	0,00368	0,01043	0,00000	0,00000	0,00000	0,00000
	Y	16	0,00330	0,00903	0,00000	0,00000	0,00000	0,00000

Variable	HELPFUL?	Maximum
№ of errors / № of word	N	0,04167
	Y	0,02778

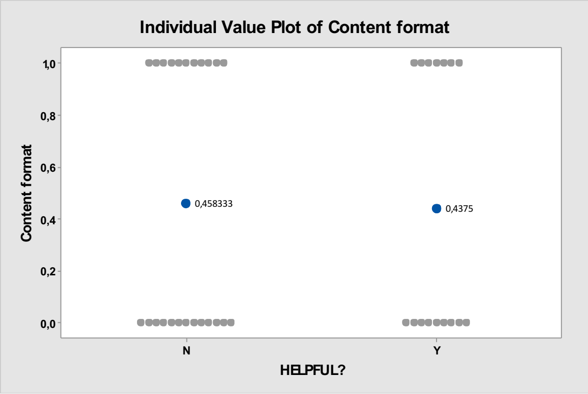
Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

Two-sample T for № of errors / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	24	0,0037	0,0104	0,0021
Y	16	0,00330	0,00903	0,0023

```
Difference = μ (N) - μ (Y)
Estimate for difference:  0,00038
95% CI for difference:  (-0,00592; 0,00668)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,49  P-Value = 0,145  DF = 35
```

Content format



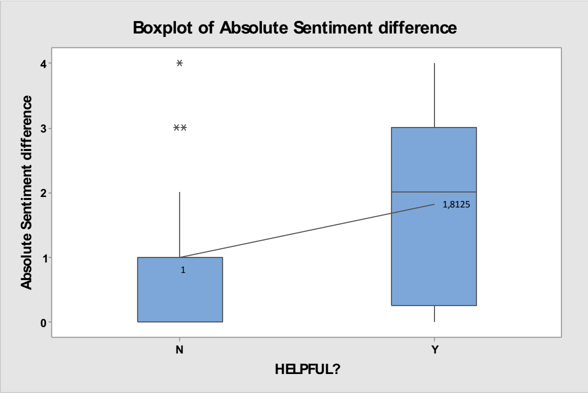
Descriptive Statistics: Content format

```
Variable        HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
Content format  N         24  0,458  0,509    0,000  0,000   0,000  1,000    1,000
                Y         16  0,438  0,512    0,000  0,000   0,000  1,000    1,000
```

Two-Sample T-Test and CI: Content format; HELPFUL?

```
Two-sample T for Content format

HELPFUL?   N   Mean  StDev  SE Mean
N         24  0,458  0,509     0,10
Y         16  0,438  0,512     0,13


Difference = μ (N) - μ (Y)
Estimate for difference:  0,021
95% CI for difference:  (-0,315; 0,357)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,10  P-Value = 0,924  DF = 32
```

Absolute sentiment difference



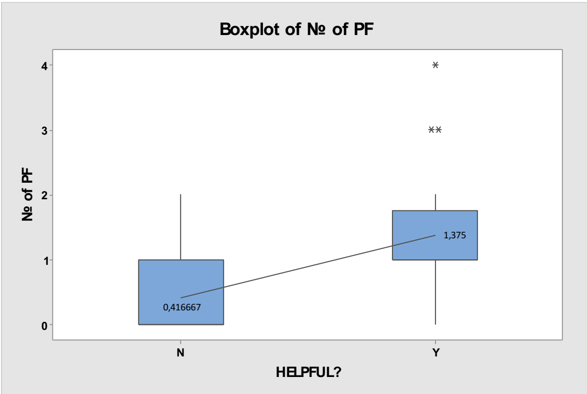
Descriptive Statistics: Absolute Sentiment difference

```
Variable                HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
Absolute Sentiment diffe N         24  1,000  1,103    0,000  0,000   1,000  1,000    4,000
                        Y         16  1,813  1,377    0,000  0,250   2,000  3,000    4,000
```

Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

```
Two-sample T for Absolute Sentiment difference

HELPFUL?   N  Mean  StDev  SE Mean
N         24  1,00   1,10     0,23
Y         16  1,81   1,38     0,34


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,813
95% CI for difference:  (-1,657; 0,032)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,99  P-Value = 0,057  DF = 27
```

of PF



Descriptive Statistics: № of PF

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of PF	N	24	0,417	0,654	0,000	0,000	0,000	1,000	2,000
	Y	16	1,375	1,088	0,000	1,000	1,000	1,750	4,000

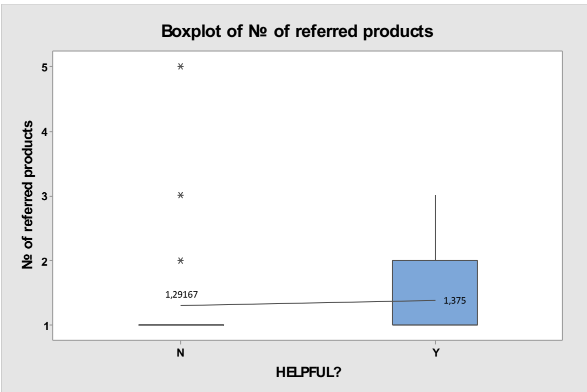
Two-Sample T-Test and CI: № of PF; HELPFUL?

Two-sample T for № of PF

HELPFUL?	N	Mean	StDev	SE Mean
N	24	0,417	0,654	0,13
Y	16	1,38	1,09	0,27

Difference = μ (N) - μ (Y)
Estimate for difference: -0,958
95% CI for difference: (-1,587; -0,330)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,18 P-Value = 0,004 DF = 22

of referred products



Descriptive Statistics: № of referred products

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of referred products	N	24	1,292	0,908	1,000	1,000	1,000	1,000	5,000
	Y	16	1,375	0,619	1,000	1,000	1,000	2,000	3,000

Two-Sample T-Test and CI: № of referred products; HELPFUL?

Two-sample T for № of referred products

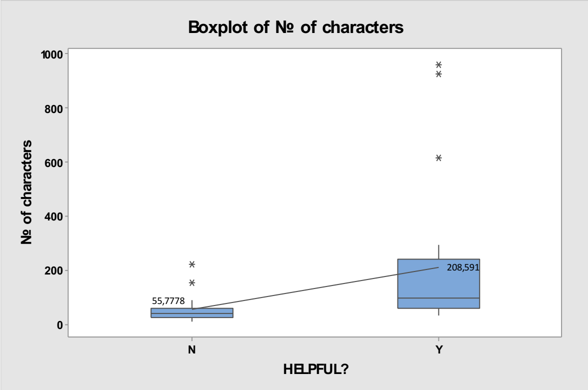
HELPFUL?	N	Mean	StDev	SE Mean
N	24	1,292	0,908	0,19
Y	16	1,375	0,619	0,15

Difference = μ (N) - μ (Y)
Estimate for difference: -0,083
95% CI for difference: (-0,573; 0,406)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,37 P-Value = 0,717 DF = 37

E.2 Facebook reviews

F1: Customer Attributes

of characters



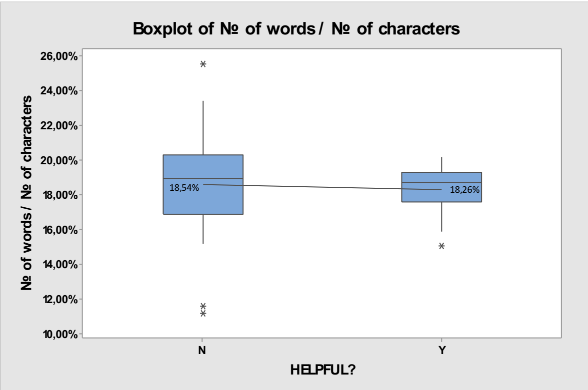
Descriptive Statistics: № of characters

```
Variable         HELPFUL?   N   Mean  StDev  Minimum    Q1  Median     Q3  Maximum
№ of characters  N         18   55,8   53,4      9,0  25,8    39,5   59,8    221,0
                 Y         22  208,6  270,5     32,0  56,5    97,0  237,8    959,0
```

Two-Sample T-Test and CI: № of characters; HELPFUL?

```
Two-sample T for № of characters

                               SE
HELPFUL?   N  Mean  StDev  Mean
N         18  55,8   53,4    13
Y         22   209    271    58


Difference = μ (N) - μ (Y)
Estimate for difference:  -152,8
95% CI for difference:  (-275,2; -30,4)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,59  P-Value = 0,017  DF = 22
```

of words / # of characters



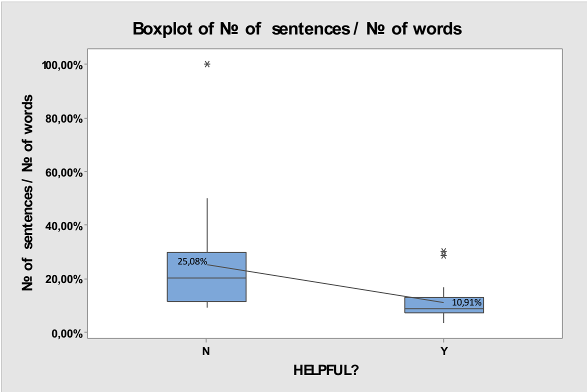
Descriptive Statistics: № of words / № of characters

```
Variable                  HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of words / № of charac  N         18  0,18540  0,03602  0,11111  0,16857  0,18922  0,20288
                          Y         22  0,18262  0,01367  0,15000  0,17572  0,18661  0,19276

Variable                  HELPFUL?  Maximum
№ of words / № of charac  N         0,25532
                          Y         0,20130
```

Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

```
Two-sample T for № of words / № of characters

HELPFUL?   N    Mean   StDev  SE Mean
N         18  0,1854  0,0360   0,0085
Y         22  0,1826  0,0137   0,0029


Difference = μ (N) - μ (Y)
Estimate for difference:  0,00279
95% CI for difference:  (-0,01588; 0,02145)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,25  P-Value = 0,808  DF = 21
```

of sentences / # of words



Descriptive Statistics: № of sentences / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of sentences / № of w	N	18	0,2508	0,2155	0,0909	0,1141	0,2000	0,2976
	Y	22	0,1091	0,0689	0,0339	0,0702	0,0858	0,1271

Variable	HELPFUL?	Maximum
№ of sentences / № of w	N	1,0000
	Y	0,3000

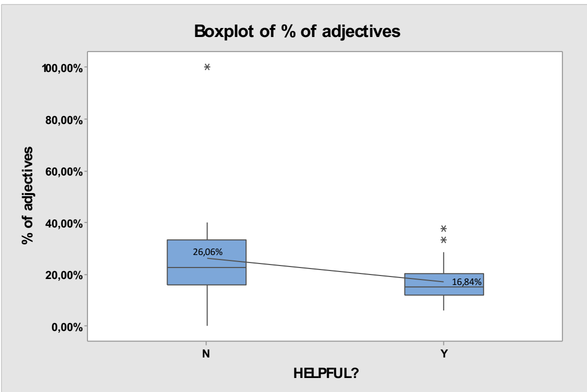
Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

Two-sample T for № of sentences / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,251	0,215	0,051
Y	22	0,1091	0,0689	0,015

Difference = μ (N) - μ (Y)
Estimate for difference: 0,1417
95% CI for difference: (0,0310; 0,2523)
T-Test of difference = 0,005 (vs ≠): T-Value = 2,59 P-Value = 0,018 DF = 19

% of adjectives



Descriptive Statistics: % of adjectives

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adjectives	N	18	0,2606	0,2165	0,0000	0,1595	0,2250	0,3333	1,0000
	Y	22	0,1684	0,0832	0,0591	0,1176	0,1484	0,2000	0,3750

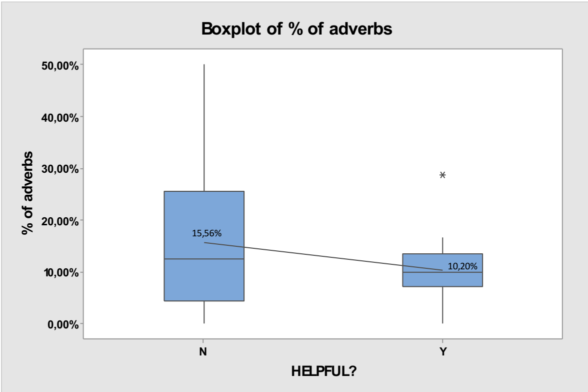
Two-Sample T-Test and CI: % of adjectives; HELPFUL?

Two-sample T for % of adjectives

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,261	0,217	0,051
Y	22	0,1684	0,0832	0,018

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0922
95% CI for difference: (-0,0202; 0,2046)
T-Test of difference = 0,005 (vs ≠): T-Value = 1,61 P-Value = 0,121 DF = 21

% of adverbs



Descriptive Statistics: % of adverbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adverbs	N	18	0,1556	0,1447	0,0000	0,0441	0,1250	0,2557	0,5000
	Y	22	0,1020	0,0593	0,0000	0,0702	0,0990	0,1338	0,2857

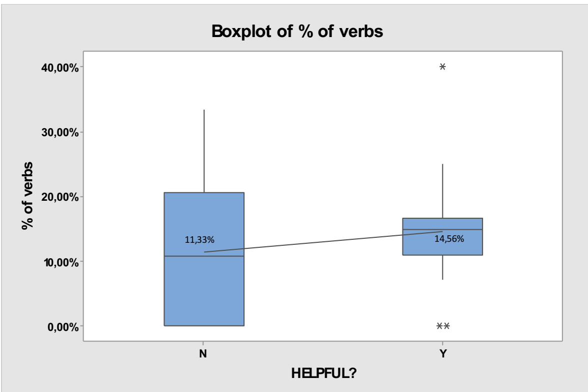
Two-Sample T-Test and CI: % of adverbs; HELPFUL?

Two-sample T for % of adverbs

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,156	0,145	0,034
Y	22	0,1020	0,0593	0,013

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0536
95% CI for difference: (-0,0220; 0,1292)
T-Test of difference = 0,005 (vs ≠): T-Value = 1,34 P-Value = 0,196 DF = 21

% of verbs



Descriptive Statistics: % of verbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of verbs	N	18	0,1133	0,1065	0,0000	0,0000	0,1080	0,2056	0,3333
	Y	22	0,1456	0,0805	0,0000	0,1083	0,1488	0,1667	0,4000

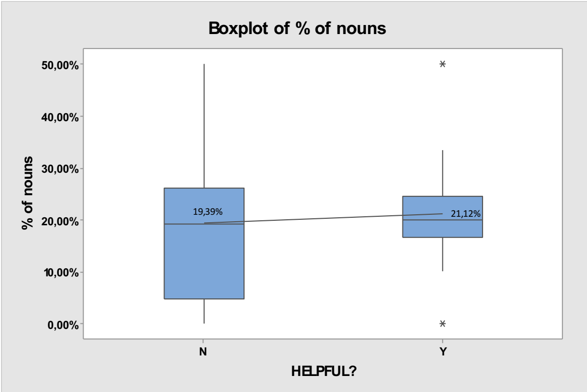
Two-Sample T-Test and CI: % of verbs; HELPFUL?

Two-sample T for % of verbs

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,113	0,106	0,025
Y	22	0,1456	0,0805	0,017

Difference = μ (N) - μ (Y)
Estimate for difference: -0,0322
95% CI for difference: (-0,0943; 0,0298)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,22 P-Value = 0,230 DF = 31

% of nouns



Descriptive Statistics: % of nouns

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of nouns	N	18	0,1939	0,1511	0,0000	0,0469	0,1909	0,2610	0,5000
	Y	22	0,2112	0,0938	0,0000	0,1667	0,2000	0,2449	0,5000

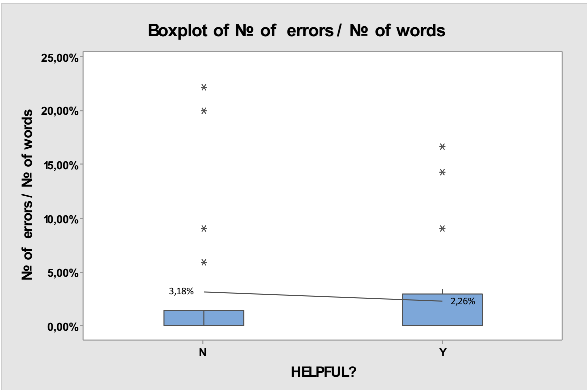
Two-Sample T-Test and CI: % of nouns; HELPFUL?

Two-sample T for % of nouns

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,194	0,151	0,036
Y	22	0,2112	0,0938	0,020

Difference = μ (N) - μ (Y)
Estimate for difference: -0,0174
95% CI for difference: (-0,1011; 0,0664)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,55 P-Value = 0,588 DF = 27

of errors / # of words



Descriptive Statistics: № of errors / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of errors / № of word	N	18	0,0318	0,0698	0,0000	0,0000	0,0000	0,0147
	Y	22	0,0226	0,0480	0,0000	0,0000	0,0000	0,0298

Variable	HELPFUL?	Maximum
№ of errors / № of word	N	0,2222
	Y	0,1667

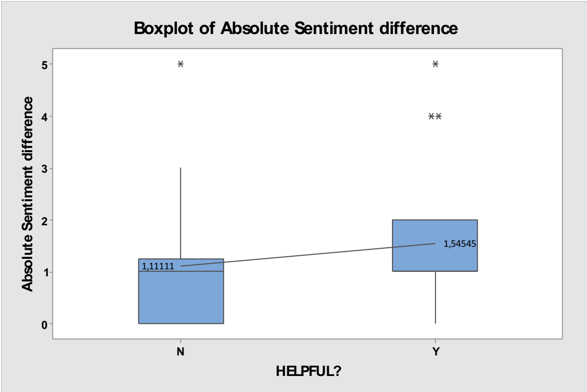
Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

Two-sample T for № of errors / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,0318	0,0698	0,016
Y	22	0,0226	0,0480	0,010

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0092
95% CI for difference: (-0,0304; 0,0489)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,22 P-Value = 0,829 DF = 29

Absolute sentiment difference



Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	18	1,111	1,367	0,000	0,000	1,000	1,250	5,000
	Y	22	1,545	1,299	0,000	1,000	1,000	2,000	5,000

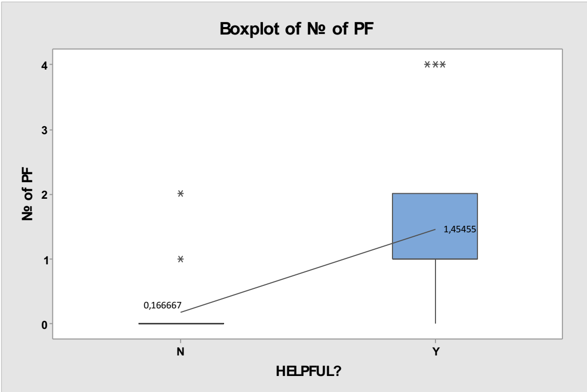
Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

Two-sample T for Absolute Sentiment difference

HELPFUL?	N	Mean	StDev	SE Mean
N	18	1,11	1,37	0,32
Y	22	1,55	1,30	0,28

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,434
95% CI for difference:  (-1,297; 0,428)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,03  P-Value = 0,308  DF = 35
```

of PF



Descriptive Statistics: № of PF

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of PF	N	18	0,167	0,514	0,000	0,000	0,000	0,000	2,000
	Y	22	1,455	1,184	0,000	1,000	1,000	2,000	4,000

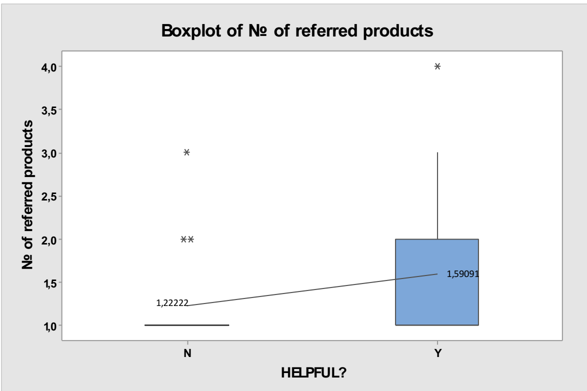
Two-Sample T-Test and CI: № of PF; HELPFUL?

Two-sample T for № of PF

HELPFUL?	N	Mean	StDev	SE Mean
N	18	0,167	0,514	0,12
Y	22	1,45	1,18	0,25

Difference = μ (N) - μ (Y)
Estimate for difference: -1,288
95% CI for difference: (-1,861; -0,715)
T-Test of difference = 0,005 (vs ≠): T-Value = -4,62 P-Value = 0,000 DF = 29

of referred products



Descriptive Statistics: № of referred products

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of referred products	N	18	1,222	0,548	1,000	1,000	1,000	1,000	3,000
	Y	22	1,591	0,796	1,000	1,000	1,000	2,000	4,000

Two-Sample T-Test and CI: № of referred products; HELPFUL?

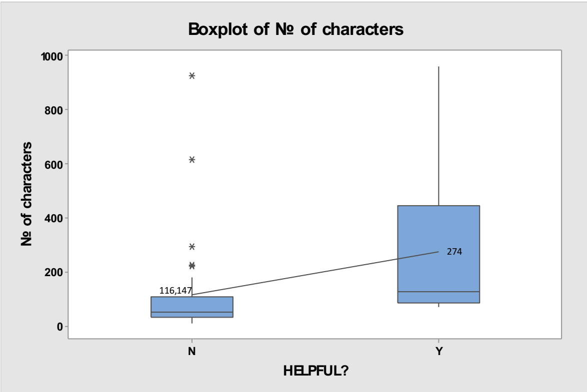
Two-sample T for № of referred products

HELPFUL?	N	Mean	StDev	SE Mean
N	18	1,222	0,548	0,13
Y	22	1,591	0,796	0,17

Difference = μ (N) - μ (Y)
Estimate for difference: -0,369
95% CI for difference: (-0,801; 0,064)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,75 P-Value = 0,088 DF = 37

F3: Customer evaluation (competitors)

of characters



Two-Sample T-Test and CI: № of characters; HELPFUL?

Two-sample T for № of characters

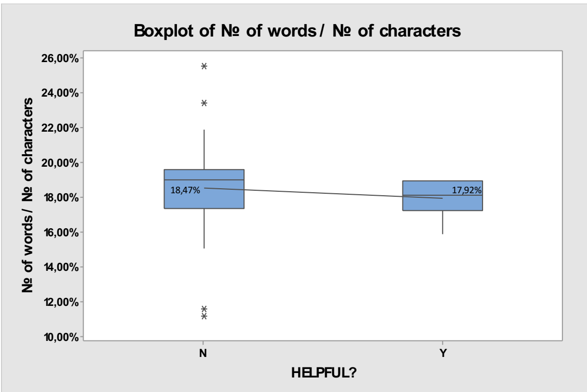
HELPFUL?	N	Mean	StDev	SE Mean
N	34	116	183	31
Y	6	274	344	140

Difference = μ (N) - μ (Y)
Estimate for difference: -158
95% CI for difference: (-527; 212)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,10 P-Value = 0,322 DF = 5

Descriptive Statistics: № of characters

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of characters	N	34	116,1	182,5	9,0	32,8	49,5	106,3	924,0
	Y	6	274	344	68	85	127	445	959

of words / # of characters



Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

Two-sample T for № of words / № of characters

HELPFUL?	N	Mean	StDev	SE Mean
N	34	0,1847	0,0277	0,0047
Y	6	0,1792	0,0114	0,0047

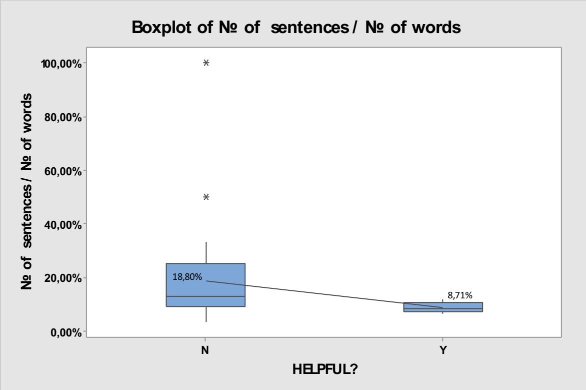
Difference = μ (N) - μ (Y)
Estimate for difference: 0,00548
95% CI for difference: (-0,00855; 0,01951)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,07 P-Value = 0,944 DF = 17

Descriptive Statistics: № of words / № of characters

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of words / № of charac	N	34	0,18469	0,02767	0,11111	0,17296	0,18980	0,19564
	Y	6	0,17921	0,01141	0,15842	0,17196	0,18098	0,18905

Variable	HELPFUL?	Maximum
№ of words / № of charac	N	0,25532
	Y	0,18954

of sentences / # of words



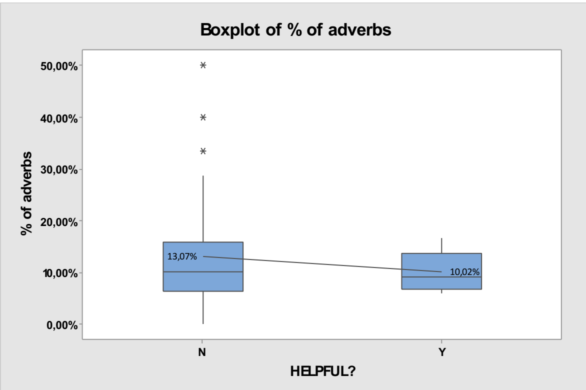
Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

```
Two-sample T for № of  sentences / № of words

HELPFUL?   N    Mean   StDev  SE Mean
N         34   0,188   0,177    0,030
Y          6  0,0871  0,0201   0,0082


Difference = μ (N) - μ (Y)
Estimate for difference:  0,1008
95% CI for difference:  (0,0370; 0,1646)
T-Test of difference = 0,005 (vs ≠): T-Value = 3,05  P-Value = 0,004  DF = 36
```

Descriptive Statistics: № of sentences / № of words

```
Variable                  HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  sentences / № of w  N         34   0,1880   0,1770   0,0339   0,0902   0,1292   0,2500
                          Y          6  0,08714  0,02007  0,06250  0,07134  0,08248  0,10700

Variable                  HELPFUL?  Maximum
№ of  sentences / № of w  N          1,0000
                          Y         0,11765
```

% of adjectives



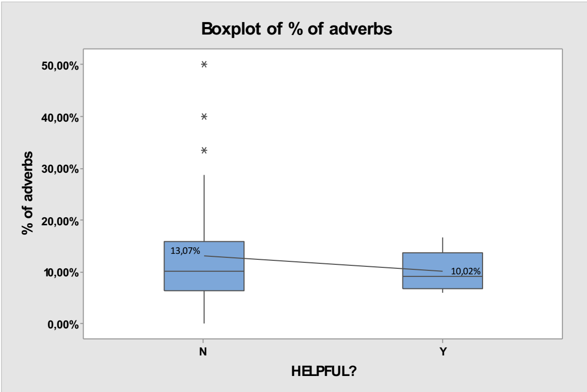
Two-Sample T-Test and CI: % of adjectives; HELPFUL?

```
Two-sample T for % of adjectives

HELPFUL?   N    Mean   StDev  SE Mean
N         34   0,219   0,171    0,029
Y          6  0,1606  0,0914    0,037


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0580
95% CI for difference:  (-0,0455; 0,1615)
T-Test of difference = 0,005 (vs ≠): T-Value = 1,12  P-Value = 0,286  DF = 12
```

Descriptive Statistics: % of adjectives

```
Variable         HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of adjectives  N         34  0,2186  0,1712   0,0000  0,1294  0,1818  0,2857   1,0000
                 Y          6  0,1606  0,0914   0,0686  0,1090  0,1315  0,2157   0,3333
```

% of adverbs



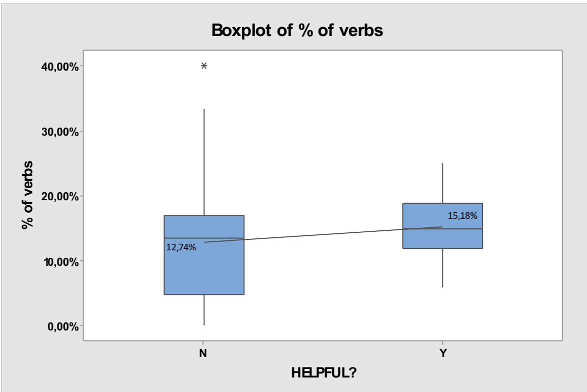
Two-Sample T-Test and CI: % of adverbs; HELPFUL?

```
Two-sample T for % of adverbs

HELPFUL?   N    Mean   StDev  SE Mean
N         34   0,131   0,116    0,020
Y          6  0,1002  0,0403    0,016


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0304
95% CI for difference:  (-0,0232; 0,0840)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,98  P-Value = 0,336  DF = 22
```

Descriptive Statistics: % of adverbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adverbs	N	34	0,1307	0,1161	0,0000	0,0639	0,1000	0,1571	0,5000
	Y	6	0,1002	0,0403	0,0588	0,0664	0,0910	0,1354	0,1667

% of verbs



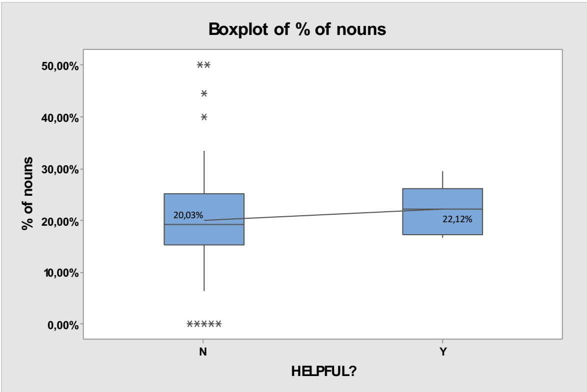
Two-Sample T-Test and CI: % of verbs; HELPFUL?

```
Two-sample T for % of verbs

HELPFUL?   N    Mean   StDev  SE Mean
N         34  0,1274  0,0981    0,017
Y          6  0,1518  0,0613    0,025


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0243
95% CI for difference:  (-0,0915; 0,0429)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,97  P-Value = 0,354  DF = 10
```

Descriptive Statistics: % of verbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of verbs	N	34	0,1274	0,0981	0,0000	0,0469	0,1342	0,1691	0,4000
	Y	6	0,1518	0,0613	0,0588	0,1182	0,1486	0,1875	0,2500

% of nouns



Two-Sample T-Test and CI: % of nouns; HELPFUL?

Two-sample T for % of nouns

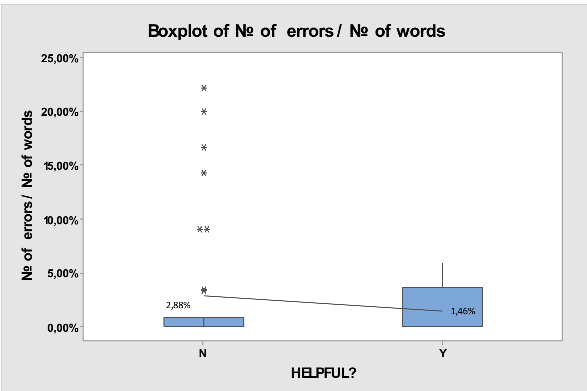
HELPFUL?	N	Mean	StDev	SE Mean
N	34	0,200	0,130	0,022
Y	6	0,2212	0,0493	0,020

Difference = μ (N) - μ (Y)
Estimate for difference: -0,0209
95% CI for difference: (-0,0837; 0,0418)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,86 P-Value = 0,399 DF = 20

Descriptive Statistics: % of nouns

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of nouns	N	34	0,2003	0,1304	0,0000	0,1526	0,1909	0,2500	0,5000
	Y	6	0,2212	0,0493	0,1667	0,1710	0,2220	0,2610	0,2941

of errors / # of words



Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

Two-sample T for № of errors / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	34	0,0288	0,0623	0,011
Y	6	0,0146	0,0245	0,010

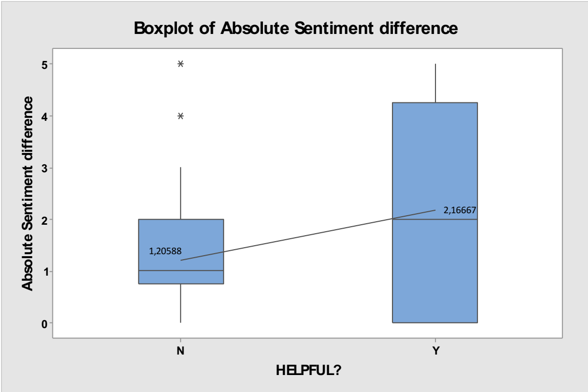
Difference = μ (N) - μ (Y)
Estimate for difference: 0,0143
95% CI for difference: (-0,0164; 0,0449)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,63 P-Value = 0,534 DF = 19

Descriptive Statistics: № of errors / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of errors / № of word	N	34	0,0288	0,0623	0,0000	0,0000	0,0000	0,0083
	Y	6	0,0146	0,0245	0,0000	0,0000	0,0000	0,0361

Variable	HELPFUL?	Maximum
№ of errors / № of word	N	0,2222
	Y	0,0588

Absolute sentiment difference



Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	34	1,206	1,122	0,000	0,750	1,000	2,000	5,000
	Y	6	2,167	2,137	0,000	0,000	2,000	4,250	5,000

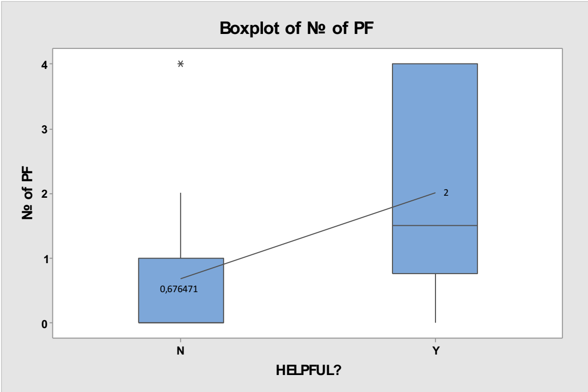
Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

Two-sample T for Absolute Sentiment difference

HELPFUL?	N	Mean	StDev	SE Mean
N	34	1,21	1,12	0,19
Y	6	2,17	2,14	0,87

Difference = µ (N) - µ (Y)
Estimate for difference: -0,961
95% CI for difference: (-3,257; 1,336)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,08 P-Value = 0,329 DF = 5

of PF



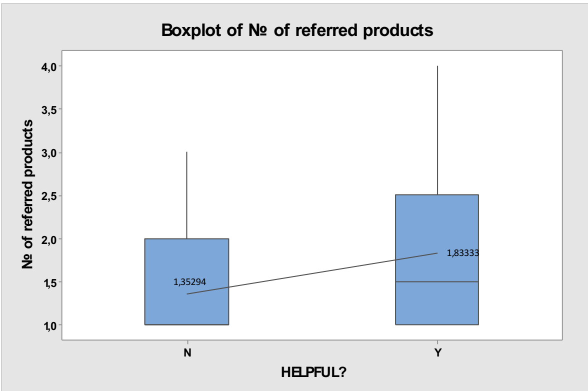
Two-Sample T-Test and CI: № of PF; HELPFUL?

```
Two-sample T for № of PF

HELPFUL?   N   Mean  StDev  SE Mean
N         34  0,676  0,912     0,16
Y          6   2,00   1,67     0,68


Difference = μ (N) - μ (Y)
Estimate for difference:  -1,324
95% CI for difference:  (-3,125; 0,478)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,90  P-Value = 0,117  DF = 5
```

Descriptive Statistics: № of PF

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of PF	N	34	0,676	0,912	0,000	0,000	0,000	1,000	4,000
	Y	6	2,000	1,673	0,000	0,750	1,500	4,000	4,000

of referred products



Two-Sample T-Test and CI: № of referred products; HELPFUL?

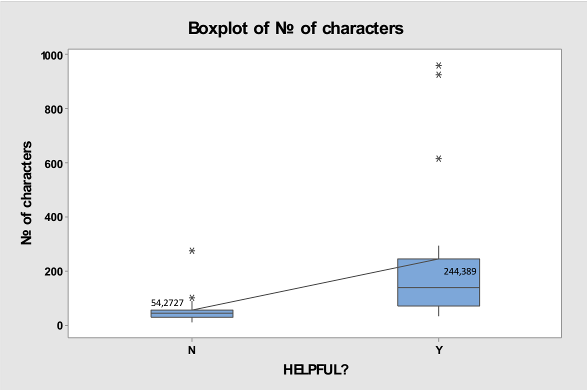
```
Two-sample T for № of referred products

HELPFUL?   N   Mean  StDev  SE Mean
N         34  1,353  0,597     0,10
Y          6   1,83   1,17     0,48


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,480
95% CI for difference:  (-1,735; 0,774)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,99  P-Value = 0,366  DF = 5
```

Descriptive Statistics: № of referred products

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of referred products	N	34	1,353	0,597	1,000	1,000	1,000	2,000	3,000
	Y	6	1,833	1,169	1,000	1,000	1,500	2,500	4,000

F4: Engineering characteristics and/or product targets related

of characters



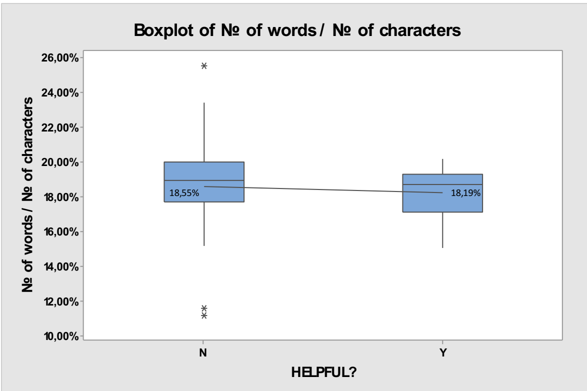
Two-Sample T-Test and CI: № of characters; HELPFUL?

```
Two-sample T for № of characters

                                SE
HELPFUL?   N  Mean  StDev  Mean
N         22  54,3   54,1    12
Y         18   244    287    68


Difference = μ (N) - μ (Y)
Estimate for difference:  -190,1
95% CI for difference:  (-334,7; -45,5)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,77  P-Value = 0,013  DF = 17
```

Descriptive Statistics: № of characters

```
Variable         HELPFUL?   N   Mean  StDev  Minimum    Q1  Median     Q3  Maximum
№ of characters  N         22   54,3   54,1      9,0  26,0    42,5   53,5    273,0
                 Y         18  244,4  286,7     32,0  70,8   137,5  243,0    959,0
```

of words / # of characters



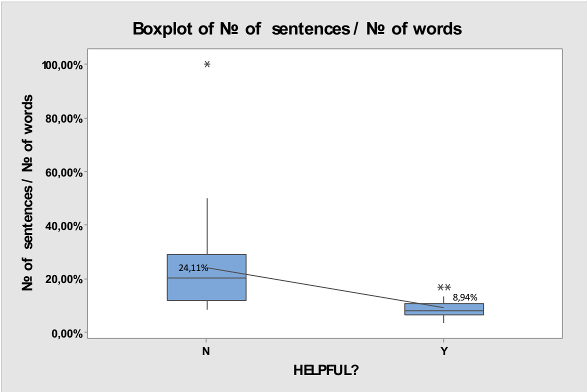
Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

```
Two-sample T for № of words / № of characters

HELPFUL?   N    Mean   StDev  SE Mean
N         22  0,1855  0,0326   0,0069
Y         18  0,1819  0,0146   0,0034


Difference = μ (N) - μ (Y)
Estimate for difference:  0,00362
95% CI for difference:  (-0,01222; 0,01946)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,18  P-Value = 0,860  DF = 30
```

Descriptive Statistics: № of words / № of characters

```
Variable                HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of words / № of charac  N       22  0,18550  0,03259  0,11111  0,17652  0,18927  0,20000
                          Y       18  0,18188  0,01460  0,15000  0,17109  0,18661  0,19276

Variable                HELPFUL?  Maximum
№ of words / № of charac  N       0,25532
                          Y       0,20130
```

of sentences / # of words



Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

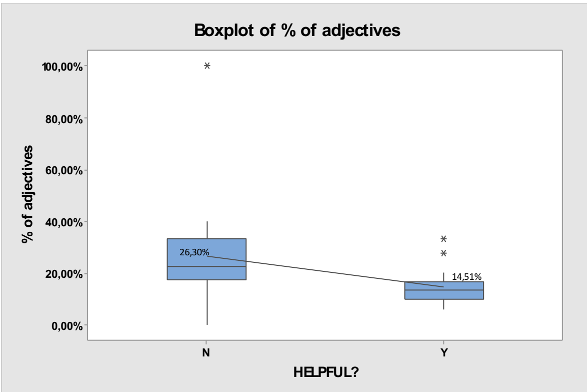
```
Two-sample T for № of  sentences / № of words

HELPFUL?  N     Mean   StDev  SE Mean
N        22    0,241   0,200    0,043
Y        18   0,0894  0,0375   0,0088


Difference = μ (N) - μ (Y)
Estimate for difference:  0,1517
95% CI for difference:  (0,0617; 0,2418)
T-Test of difference = 0,005 (vs ≠): T-Value = 3,38  P-Value = 0,003  DF = 22
```

Descriptive Statistics: № of sentences / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of sentences / № of w	N	22	0,2411	0,1995	0,0816	0,1160	0,2000	0,2893
	Y	18	0,08937	0,03748	0,03390	0,06563	0,08088	0,10536

Variable	HELPFUL?	Maximum
№ of sentences / № of w	N	1,0000
	Y	0,16667

% of adjectives



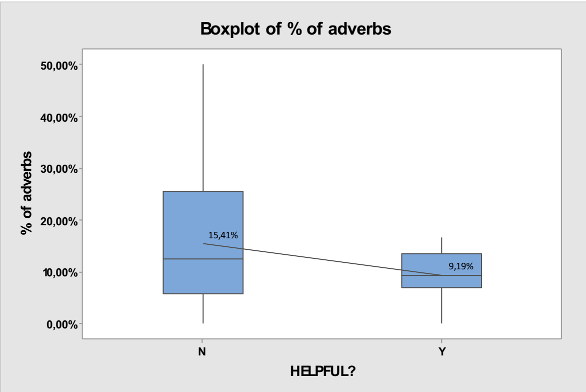
Two-Sample T-Test and CI: % of adjectives; HELPFUL?

```
Two-sample T for % of adjectives

HELPFUL?  N    Mean   StDev  SE Mean
N        22   0,263   0,196    0,042
Y        18  0,1451  0,0692    0,016


Difference = μ (N) - μ (Y)
Estimate for difference:  0,1179
95% CI for difference:  (0,0258; 0,2099)
T-Test of difference = 0,005 (vs ≠): T-Value = 2,52  P-Value = 0,018  DF = 27
```

Descriptive Statistics: % of adjectives

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adjectives	N	22	0,2630	0,1961	0,0000	0,1740	0,2250	0,3333	1,0000
	Y	18	0,1451	0,0692	0,0591	0,1000	0,1342	0,1667	0,3333

% of adverbs



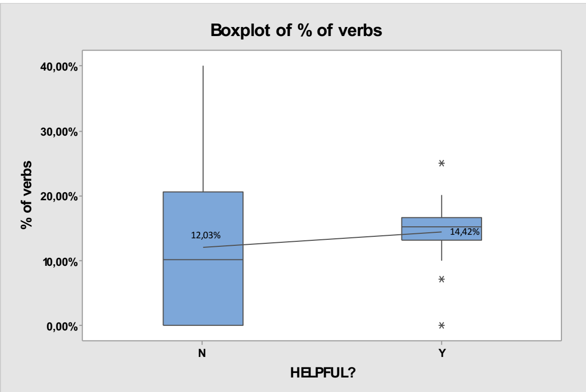
Descriptive Statistics: % of adverbs

```
Variable      HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of adverbs  N         22  0,1541  0,1351   0,0000  0,0580  0,1250  0,2557   0,5000
              Y         18  0,0919  0,0463   0,0000  0,0684  0,0931  0,1338   0,1667
```

Two-Sample T-Test and CI: % of adverbs; HELPFUL?

```
Two-sample T for % of adverbs

HELPFUL?   N    Mean   StDev  SE Mean
N         22   0,154   0,135    0,029
Y         18  0,0919  0,0463    0,011


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0623
95% CI for difference:  (-0,0010; 0,1256)
T-Test of difference = 0,005 (vs ≠): T-Value = 1,86  P-Value = 0,074  DF = 26
```

% of verbs



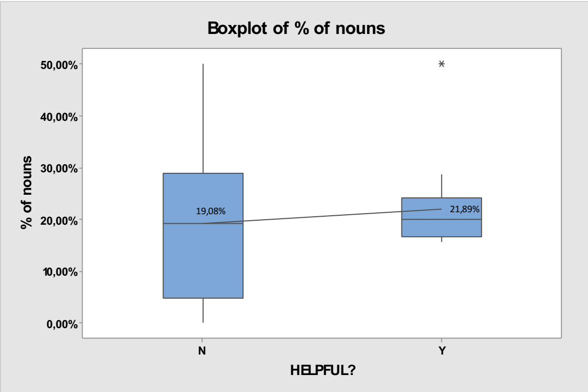
Descriptive Statistics: % of verbs

```
Variable    HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of verbs  N         22  0,1203  0,1170   0,0000  0,0000  0,1010  0,2056   0,4000
            Y         18  0,1442  0,0520   0,0000  0,1313  0,1522  0,1667   0,2500
```

Two-Sample T-Test and CI: % of verbs; HELPFUL?

```
Two-sample T for % of verbs

HELPFUL?   N    Mean   StDev  SE Mean
N         22   0,120   0,117    0,025
Y         18  0,1442  0,0520    0,012


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0239
95% CI for difference:  (-0,0807; 0,0329)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,04  P-Value = 0,307  DF = 30
```

% of nouns



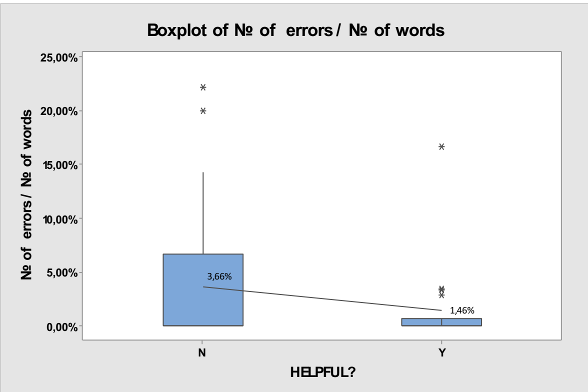
Two-Sample T-Test and CI: % of nouns; HELPFUL?

```
Two-sample T for % of nouns

HELPFUL?   N    Mean   StDev  SE Mean
N         22   0,191   0,148    0,032
Y         18  0,2189  0,0793    0,019


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0281
95% CI for difference:  (-0,1028; 0,0466)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,90  P-Value = 0,374  DF = 33
```

Descriptive Statistics: % of nouns

```
Variable    HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of nouns  N         22  0,1908  0,1481   0,0000  0,0469  0,1909  0,2878   0,5000
            Y         18  0,2189  0,0793   0,1559  0,1667  0,2000  0,2408   0,5000
```

of errors / # of words



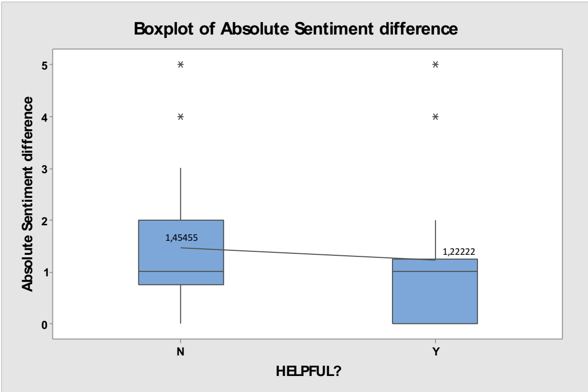
Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

```
Two-sample T for № of  errors / № of words

HELPFUL?   N    Mean   StDev  SE Mean
N         22  0,0366  0,0691    0,015
Y         18  0,0146  0,0399   0,0094


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0220
95% CI for difference:  (-0,0135; 0,0576)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,98  P-Value = 0,336  DF = 34
```

Descriptive Statistics: № of errors / № of words

```
Variable                 HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  errors / № of word N         22   0,0366   0,0691   0,0000   0,0000   0,0000   0,0668
                         Y         18  0,01458  0,03987  0,00000  0,00000  0,00000  0,00714

Variable                 HELPFUL?  Maximum
№ of  errors / № of word N          0,2222
                         Y         0,16667
```

Absolute sentiment difference



Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	22	1,455	1,335	0,000	0,750	1,000	2,000	5,000
	Y	18	1,222	1,353	0,000	0,000	1,000	1,250	5,000

Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

Two-sample T for Absolute Sentiment difference

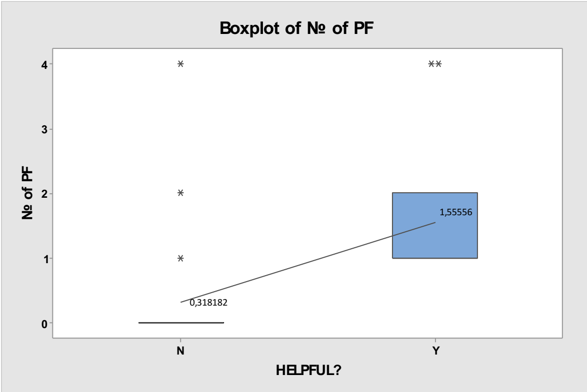
HELPFUL?	N	Mean	StDev	SE Mean
N	22	1,45	1,34	0,28
Y	18	1,22	1,35	0,32

Difference = μ (N) - μ (Y)
Estimate for difference: 0,232
95% CI for difference: (-0,635; 1,099)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,53 P-Value = 0,598 DF = 36

E.3 iMore Forum reviews

F1: Customer Attributes

of PF



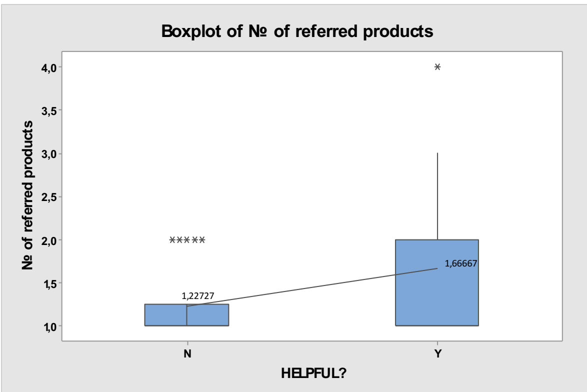
Descriptive Statistics: № of PF

```
Variable  HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
№ of PF   N         22  0,318  0,945    0,000  0,000   0,000  0,000    4,000
          Y         18  1,556  0,984    1,000  1,000   1,000  2,000    4,000
```

Two-Sample T-Test and CI: № of PF; HELPFUL?

```
Two-sample T for № of PF

HELPFUL?   N   Mean  StDev  SE Mean
N         22  0,318  0,945     0,20
Y         18  1,556  0,984     0,23


Difference = μ (N) - μ (Y)
Estimate for difference:  -1,237
95% CI for difference:  (-1,861; -0,614)
T-Test of difference = 0,005 (vs ≠): T-Value = -4,04  P-Value = 0,000  DF = 35
```

of referred products



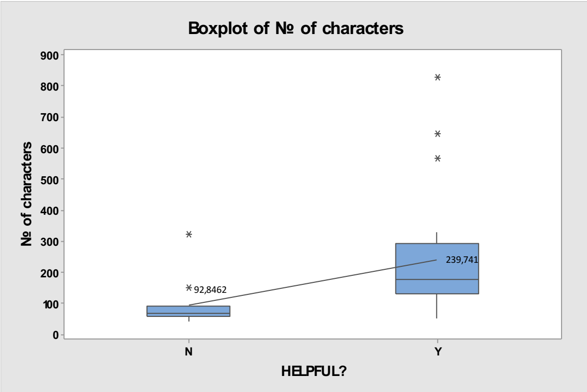
Descriptive Statistics: № of referred products

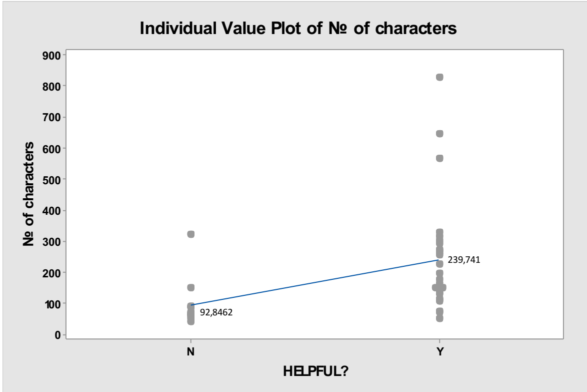
```
Variable                HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3
№ of referred products  N         22  1,2273  0,4289   1,0000  1,0000  1,0000  1,2500
                        Y         18   1,667   0,907    1,000   1,000   1,000   2,000

Variable                HELPFUL?  Maximum
№ of referred products  N          2,0000
                        Y           4,000
```

Two-Sample T-Test and CI: № of referred products; HELPFUL?

```
Two-sample T for № of referred products

HELPFUL?   N   Mean  StDev  SE Mean
N         22  1,227  0,429    0,091
Y         18  1,667  0,907     0,21


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,439
95% CI for difference:  (-0,921; 0,042)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,91  P-Value = 0,069  DF = 23
```

of characters





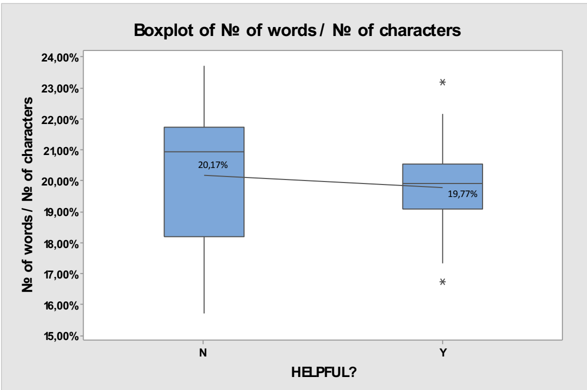
Descriptive Statistics: № of characters

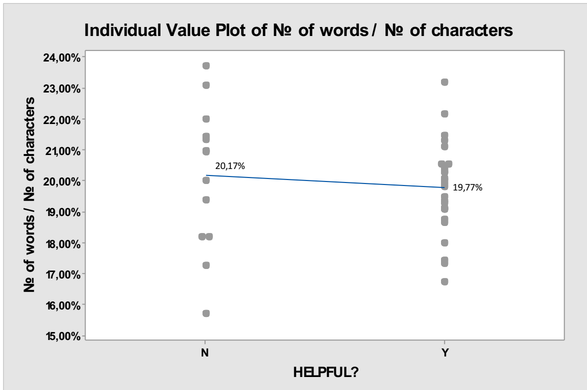
```
Variable          HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
№ of characters   N         13   92,8   73,4     42,0   58,5    66,0   89,5    320,0
                  Y         27  239,7  180,9     50,0  128,0   176,0  292,0    827,0
```

Two-Sample T-Test and CI: № of characters; HELPFUL?

```
Two-sample T for № of characters

                               SE
HELPFUL?   N  Mean  StDev  Mean
N         13  92,8   73,4    20
Y         27   240    181    35


Difference = µ (N) - µ (Y)
Estimate for difference:  -146,9
95% CI for difference:  (-228,6; -65,2)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,64  P-Value = 0,001  DF = 37
```

of words / # of characters





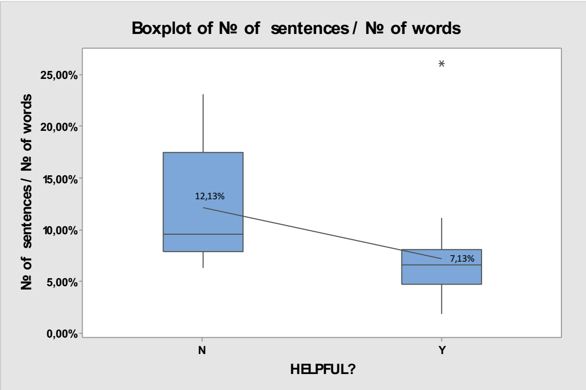
Descriptive Statistics: № of words / № of characters

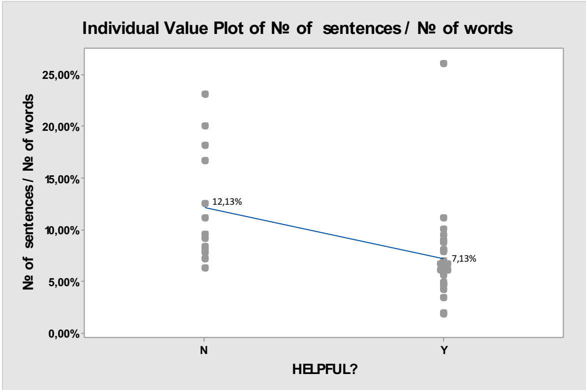
```
Variable                  HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of words / № of charac  N         13  0,20166  0,02338  0,15714  0,18182  0,20930  0,21714
                          Y         27  0,19767  0,01456  0,16729  0,19081  0,19922  0,20548

Variable                  HELPFUL?  Maximum
№ of words / № of charac  N         0,23729
                          Y         0,23188
```

Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

```
Two-sample T for № of words / № of characters

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,2017  0,0234   0,0065
Y         27  0,1977  0,0146   0,0028


Difference = µ (N) - µ (Y)
Estimate for difference:  0,00399
95% CI for difference:  (-0,01099; 0,01897)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,14  P-Value = 0,888  DF = 16
```

of sentences / # of words





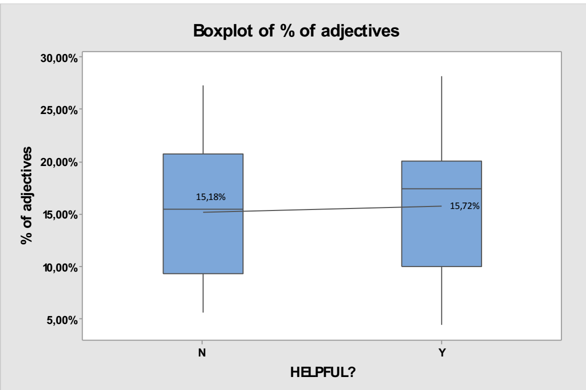
Descriptive Statistics: № of sentences / № of words

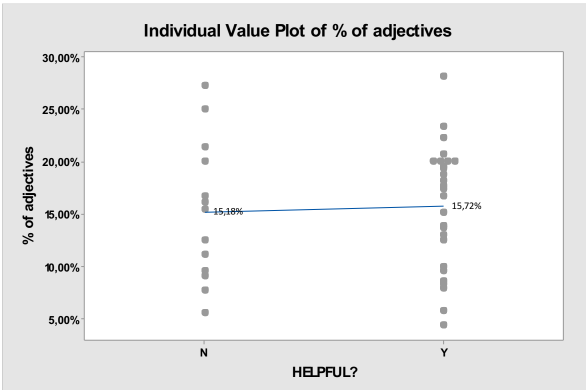
```
Variable              HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  sentences / № of w  N     13   0,1213   0,0552   0,0625   0,0788   0,0952   0,1742
                      Y         27  0,07126  0,04418  0,01754  0,04688  0,06522  0,08000

Variable              HELPFUL?  Maximum
№ of  sentences / № of w  N      0,2308
                      Y         0,26087
```

Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

```
Two-sample T for № of  sentences / № of words

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,1213  0,0552    0,015
Y         27  0,0713  0,0442   0,0085


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0500
95% CI for difference:  (0,0133; 0,0867)
T-Test of difference = 0,005 (vs ≠): T-Value = 2,57  P-Value = 0,019  DF = 19
```

% of adjectives





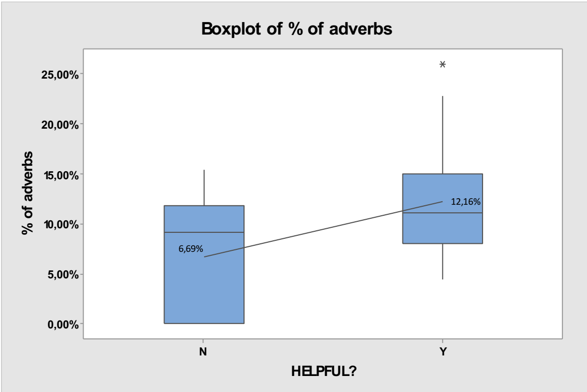
Descriptive Statistics: % of adjectives

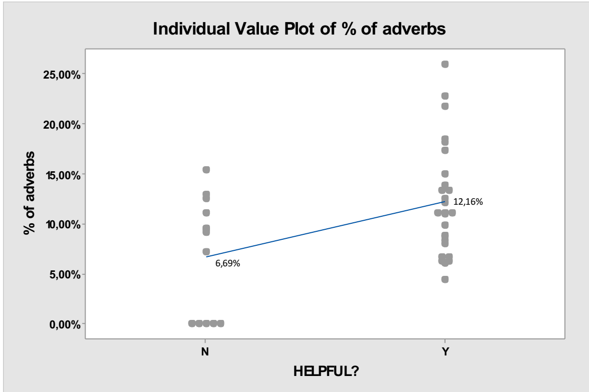
```
Variable         HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of adjectives  N         13  0,1518  0,0677   0,0556  0,0931  0,1538  0,2071   0,2727
                 Y         27  0,1572  0,0587   0,0435  0,1000  0,1739  0,2000   0,2813
```

Two-Sample T-Test and CI: % of adjectives; HELPFUL?

```
Two-sample T for % of adjectives

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,1518  0,0677    0,019
Y         27  0,1572  0,0587    0,011


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0054
95% CI for difference:  (-0,0511; 0,0403)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,47  P-Value = 0,640  DF = 20
```

% of adverbs





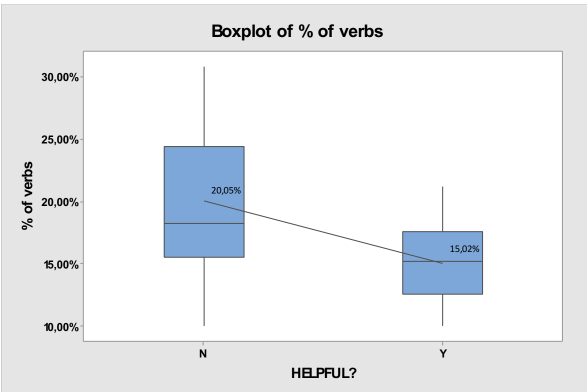
Descriptive Statistics: % of adverbs

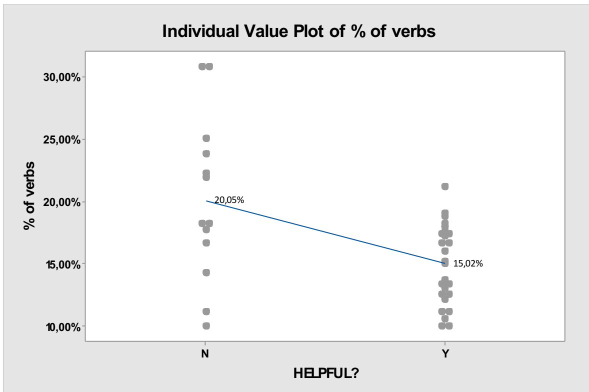
```
Variable      HELPFUL?  N    Mean    StDev   Minimum    Q1     Median    Q3    Maximum
% of adverbs  N         13   0,0669  0,0586   0,0000   0,0000  0,0909  0,1181   0,1538
              Y         27   0,1216  0,0556   0,0435   0,0800  0,1111  0,1500   0,2593
```

Two-Sample T-Test and CI: % of adverbs; HELPFUL?

```
Two-sample T for % of adverbs

HELPFUL?  N    Mean   StDev  SE Mean
N         13  0,0669  0,0586   0,016
Y         27  0,1216  0,0556   0,011


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0547
95% CI for difference:  (-0,0951; -0,0143)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,07  P-Value = 0,006  DF = 22
```

% of verbs





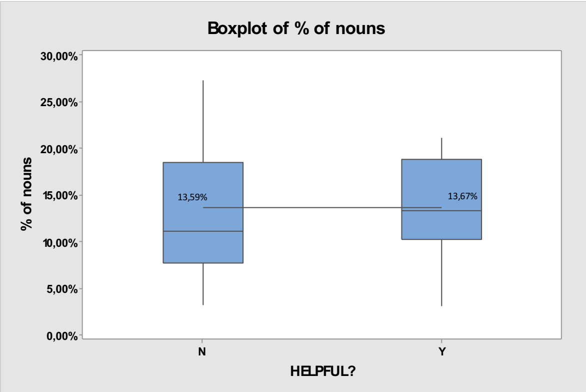
Descriptive Statistics: % of verbs

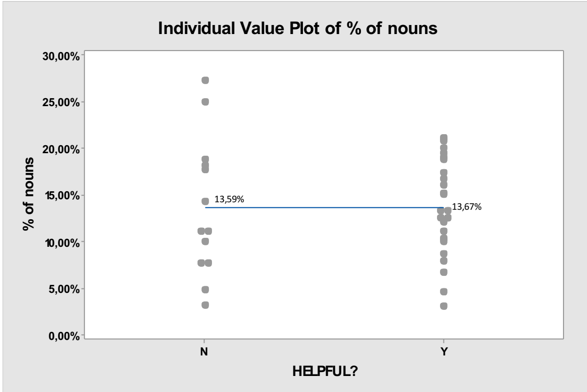
```
Variable    HELPFUL?  N     Mean     StDev   Minimum     Q1      Median      Q3     Maximum
% of verbs  N         13   0,2005   0,0655   0,1000   0,1548   0,1818   0,2440   0,3077
            Y         27   0,15017  0,03149  0,10000  0,12500  0,15152  0,17544  0,21154
```

Two-Sample T-Test and CI: % of verbs; HELPFUL?

```
Two-sample T for % of verbs

HELPFUL?  N    Mean   StDev  SE Mean
N         13  0,2005  0,0655   0,018
Y         27  0,1502  0,0315   0,0061


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0503
95% CI for difference:  (0,0092; 0,0914)
T-Test of difference = 0,005 (vs ≠): T-Value = 2,37  P-Value = 0,033  DF = 14
```

% of nouns





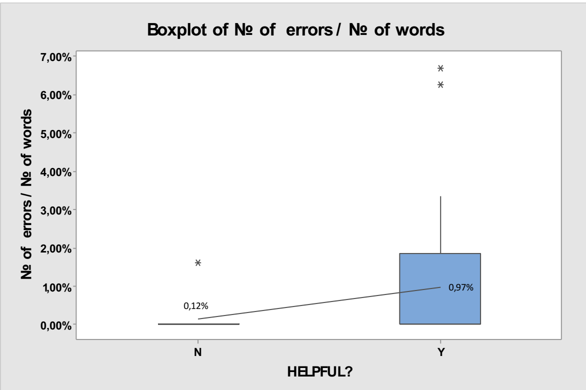
Descriptive Statistics: % of nouns

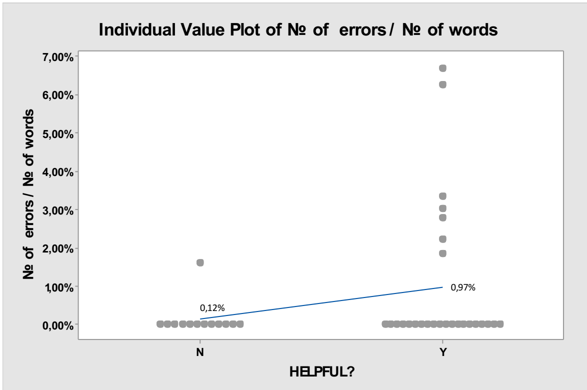
```
Variable    HELPFUL?   N    Mean    StDev  Minimum       Q1   Median       Q3  Maximum
% of nouns  N         13   0,1359   0,0744   0,0313   0,0769   0,1111   0,1847   0,2727
            Y         27  0,13668  0,05103  0,03030  0,10185  0,13333  0,18750  0,21154
```

Two-Sample T-Test and CI: % of nouns; HELPFUL?

```
Two-sample T for % of nouns

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,1359  0,0744    0,021
Y         27  0,1367  0,0510   0,0098


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0007
95% CI for difference:  (-0,0490; 0,0475)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,25  P-Value = 0,805  DF = 17
```

of errors / # of words





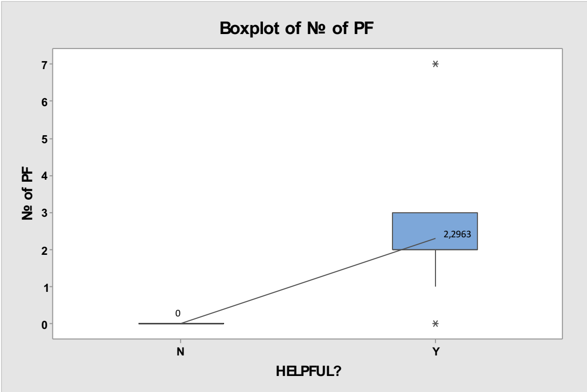
Descriptive Statistics: № of errors / № of words

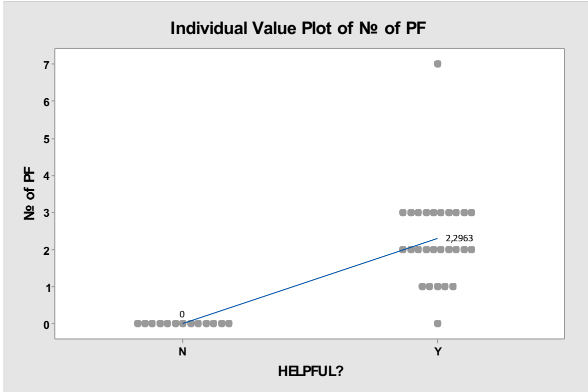
```
Variable                   HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  errors / № of word   N         13  0,00124  0,00447  0,00000  0,00000  0,00000  0,00000
                           Y         27  0,00968  0,01907  0,00000  0,00000  0,00000  0,01852

Variable                   HELPFUL?  Maximum
№ of  errors / № of word   N         0,01613
                           Y         0,06667
```

Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

```
Two-sample T for № of  errors / № of words

HELPFUL?   N     Mean    StDev  SE Mean
N         13  0,00124  0,00447   0,0012
Y         27   0,0097   0,0191   0,0037


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,00844
95% CI for difference:  (-0,01634; -0,00054)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,47  P-Value = 0,002  DF = 31
```

of PF





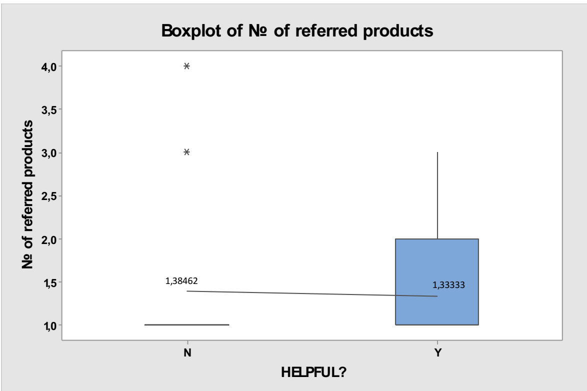
Descriptive Statistics: № of PF

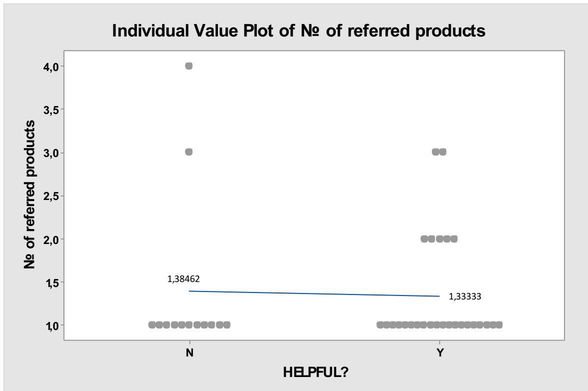
```
Variable  HELPFUL?   N      Mean     StDev   Minimum        Q1    Median        Q3   Maximum
№ of PF   N         13  0,000000  0,000000  0,000000  0,000000  0,000000  0,000000  0,000000
          Y         27     2,296     1,265     0,000     2,000     2,000     3,000     7,000
```

Two-Sample T-Test and CI: № of PF; HELPFUL?

```
Two-sample T for № of PF

HELPFUL?   N   Mean  StDev  SE Mean
N         13  0,077  0,277    0,077
Y         27   2,30   1,27     0,24


Difference = μ (N) - μ (Y)
Estimate for difference:  -2,219
95% CI for difference:  (-2,741; -1,698)
T-Test of difference = 0,005 (vs ≠): T-Value = -8,71  P-Value = 0,000  DF = 30
```

of referred products





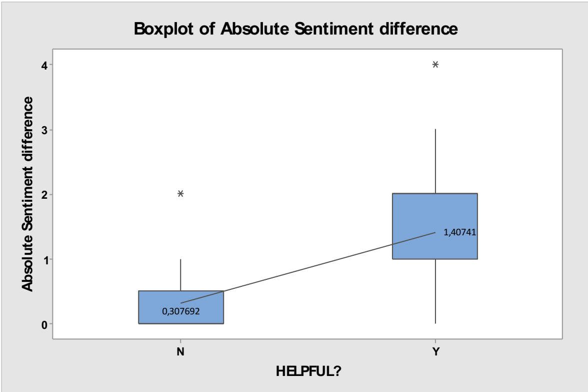
Descriptive Statistics: № of referred products

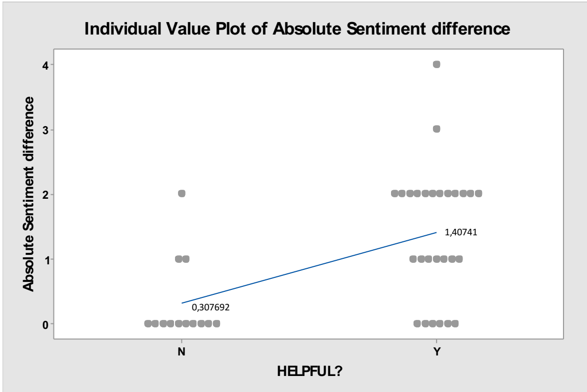
```
Variable                HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
№ of referred products  N         13  1,385  0,961    1,000  1,000   1,000  1,000    4,000
                        Y         27  1,333  0,620    1,000  1,000   1,000  2,000    3,000
```

Two-Sample T-Test and CI: № of referred products; HELPFUL?

```
Two-sample T for № of referred products

HELPFUL?   N   Mean  StDev  SE Mean
N         13  1,385  0,961     0,27
Y         27  1,333  0,620     0,12


Difference = μ (N) - μ (Y)
Estimate for difference:  0,051
95% CI for difference:  (-0,568; 0,670)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,16  P-Value = 0,876  DF = 16
```

Absolute sentiment difference





Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	13	0,308	0,630	0,000	0,000	0,000	0,500	2,000
	Y	27	1,407	1,010	0,000	1,000	2,000	2,000	4,000

Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

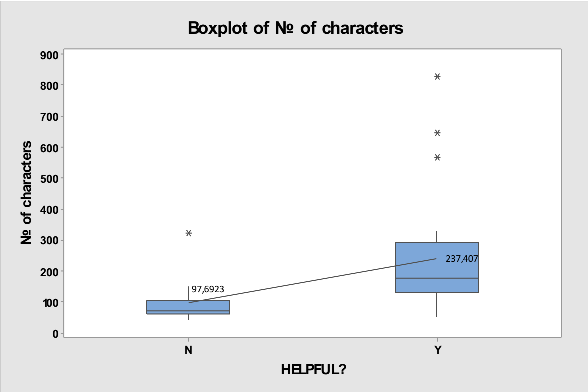
Two-sample T for Absolute Sentiment difference

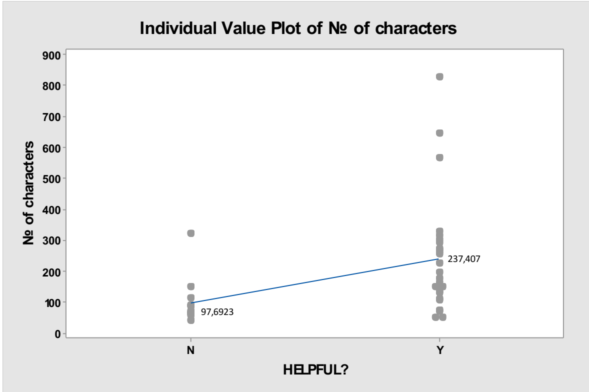
HELPFUL?	N	Mean	StDev	SE Mean
N	13	0,308	0,630	0,17
Y	27	1,41	1,01	0,19

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -1,100
95% CI for difference:  (-1,630; -0,569)
T-Test of difference = 0,005 (vs ≠): T-Value = -4,23  P-Value = 0,000  DF = 35
```

F4: Engineering characteristics and/or product targets related

of characters





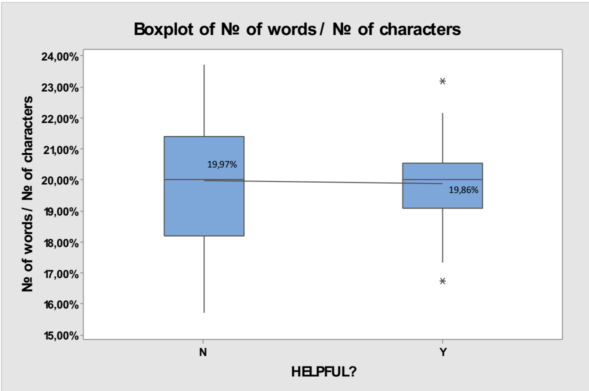
Descriptive Statistics: № of characters

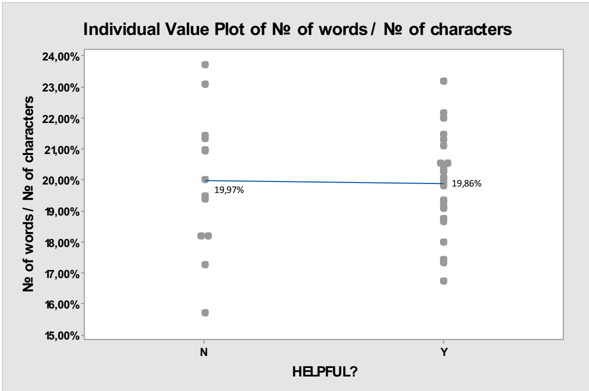
```
Variable         HELPFUL?   N   Mean  StDev  Minimum     Q1  Median     Q3  Maximum
№ of characters  N         13   97,7   72,4     42,0   60,5    70,0  102,0    320,0
                 Y         27  237,4  183,0     50,0  128,0   176,0  292,0    827,0
```

Two-Sample T-Test and CI: № of characters; HELPFUL?

```
Two-sample T for № of characters

                            SE
HELPFUL?   N  Mean  StDev  Mean
N         13  97,7   72,4    20
Y         27   237    183    35


Difference = μ (N) - μ (Y)
Estimate for difference:  -139,7
95% CI for difference:  (-221,9; -57,6)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,45  P-Value = 0,001  DF = 37
```

of words / # of characters





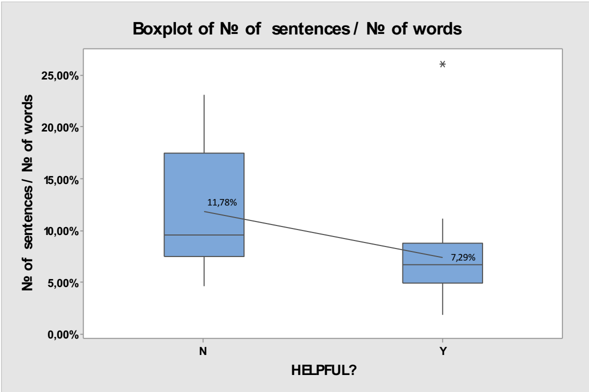
Descriptive Statistics: № of words / № of characters

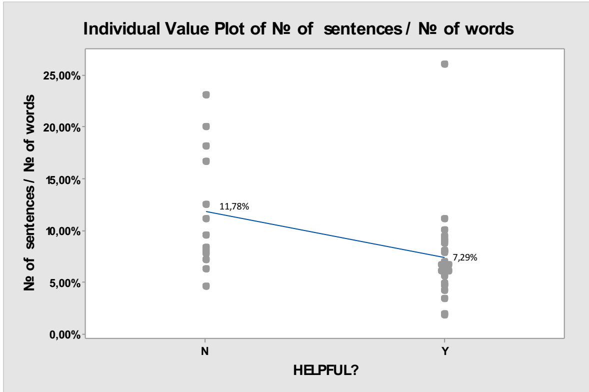
```
Variable                  HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of words / № of charac  N         13  0,19971  0,02277  0,15714  0,18182  0,20000  0,21381
                          Y         27  0,19861  0,01516  0,16729  0,19081  0,20000  0,20548

Variable                  HELPFUL?  Maximum
№ of words / № of charac  N         0,23729
                          Y         0,23188
```

Two-Sample T-Test and CI: № of words / № of characters; HELPFUL?

```
Two-sample T for № of words / № of characters

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,1997  0,0228   0,0063
Y         27  0,1986  0,0152   0,0029


Difference = μ (N) - μ (Y)
Estimate for difference:  0,00111
95% CI for difference:  (-0,01357; 0,01579)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,56  P-Value = 0,583  DF = 17
```

of sentences / # of words





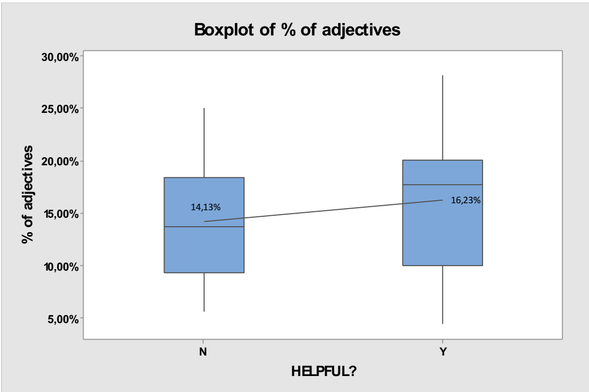
Descriptive Statistics: № of sentences / № of words

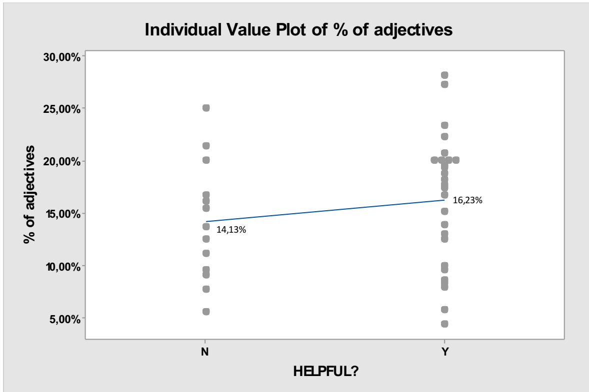
```
Variable                   HELPFUL?   N     Mean    StDev  Minimum       Q1   Median       Q3
№ of  sentences / № of w   N         13   0,1178   0,0587   0,0455   0,0742   0,0952   0,1742
                           Y         27  0,07295  0,04402  0,01754  0,04861  0,06667  0,08696

Variable                   HELPFUL?  Maximum
№ of  sentences / № of w   N          0,2308
                           Y         0,26087
```

Two-Sample T-Test and CI: № of sentences / № of words; HELPFUL?

```
Two-sample T for № of  sentences / № of words

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,1178  0,0587    0,016
Y         27  0,0729  0,0440   0,0085


Difference = μ (N) - μ (Y)
Estimate for difference:  0,0448
95% CI for difference:  (0,0063; 0,0834)
T-Test of difference = 0,005 (vs ≠): T-Value = 2,17  P-Value = 0,044  DF = 18
```

% of adjectives





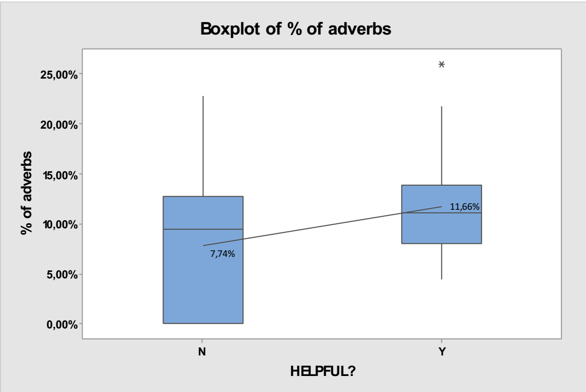
Descriptive Statistics: % of adjectives

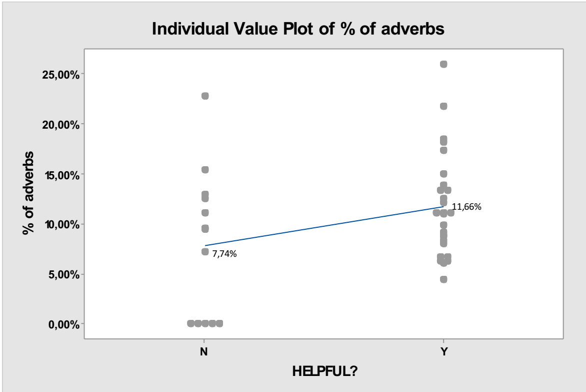
```
Variable         HELPFUL?   N    Mean   StDev  Minimum      Q1  Median      Q3  Maximum
% of adjectives  N         13  0,1413  0,0571   0,0556  0,0931  0,1364  0,1833   0,2500
                 Y         27  0,1623  0,0625   0,0435  0,1000  0,1765  0,2000   0,2813
```

Two-Sample T-Test and CI: % of adjectives; HELPFUL?

```
Two-sample T for % of adjectives

HELPFUL?   N    Mean   StDev  SE Mean
N         13  0,1413  0,0571    0,016
Y         27  0,1623  0,0625    0,012


Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0209
95% CI for difference:  (-0,0619; 0,0200)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,30  P-Value = 0,204  DF = 25
```

% of adverbs





Descriptive Statistics: % of adverbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of adverbs	N	13	0,0774	0,0736	0,0000	0,0000	0,0938	0,1270	0,2273
	Y	27	0,11659	0,05168	0,04348	0,08000	0,11111	0,13793	0,25926

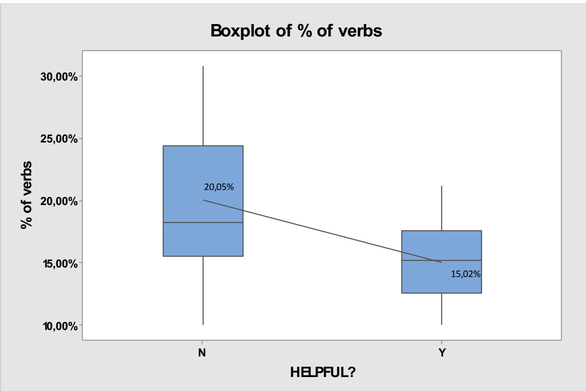
Two-Sample T-Test and CI: % of adverbs; HELPFUL?

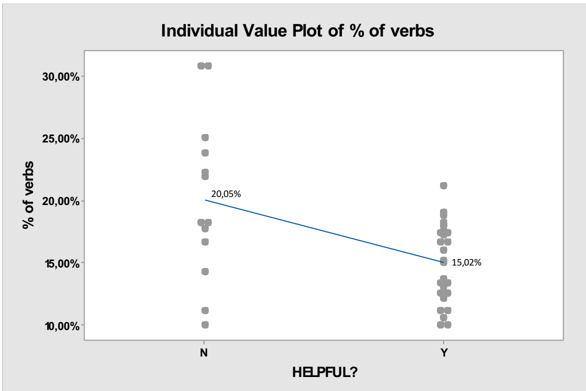
Two-sample T for % of adverbs

HELPFUL?	N	Mean	StDev	SE Mean
N	13	0,0774	0,0736	0,020
Y	27	0,1166	0,0517	0,0099

Difference = μ (N) - μ (Y)
Estimate for difference: -0,0392
95% CI for difference: (-0,0870; 0,0087)
T-Test of difference = 0,005 (vs ≠): T-Value = -1,95 P-Value = 0,068 DF = 17

% of verbs





Descriptive Statistics: % of verbs

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of verbs	N	13	0,2005	0,0655	0,1000	0,1548	0,1818	0,2440	0,3077
	Y	27	0,15017	0,03149	0,10000	0,12500	0,15152	0,17544	0,21154

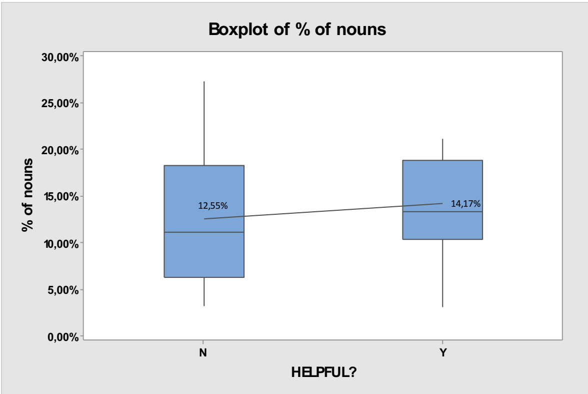
Two-Sample T-Test and CI: % of verbs; HELPFUL?

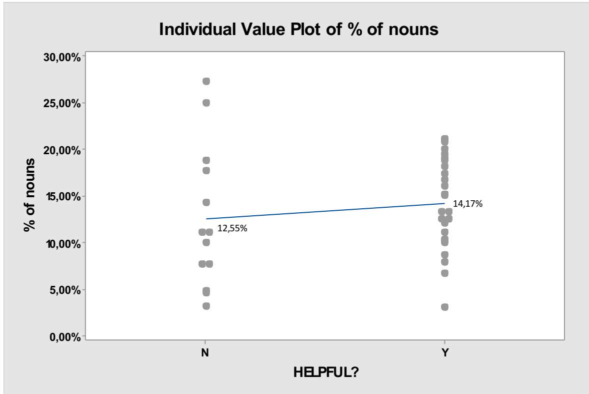
Two-sample T for % of verbs

HELPFUL?	N	Mean	StDev	SE Mean
N	13	0,2005	0,0655	0,018
Y	27	0,1502	0,0315	0,0061

Difference = μ (N) - μ (Y)
Estimate for difference: 0,0503
95% CI for difference: (0,0092; 0,0914)
T-Test of difference = 0,005 (vs ≠): T-Value = 2,37 P-Value = 0,033 DF = 14

% of nouns





Descriptive Statistics: % of nouns

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
% of nouns	N	13	0,1255	0,0770	0,0313	0,0623	0,1111	0,1825	0,2727
	Y	27	0,14174	0,04833	0,03030	0,10345	0,13333	0,18750	0,21154

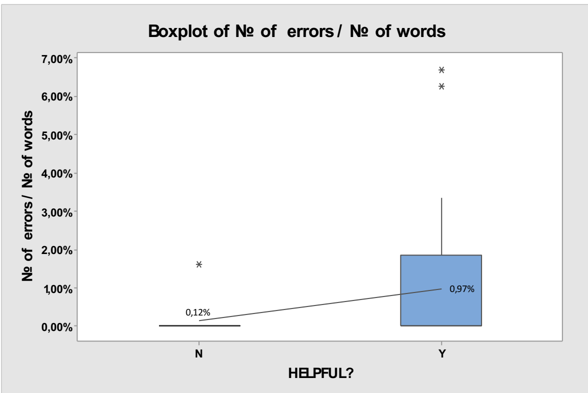
Two-Sample T-Test and CI: % of nouns; HELPFUL?

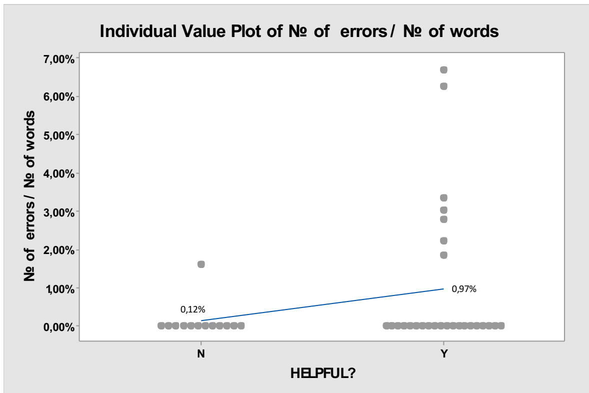
Two-sample T for % of nouns

HELPFUL?	N	Mean	StDev	SE Mean
N	13	0,1255	0,0770	0,021
Y	27	0,1417	0,0483	0,0093

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,0163
95% CI for difference:  (-0,0657; 0,0331)
T-Test of difference = 0,005 (vs ≠): T-Value = -0,91  P-Value = 0,375  DF = 16
```

of errors / # of words





Descriptive Statistics: № of errors / № of words

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3
№ of errors / № of word	N	13	0,00124	0,00447	0,00000	0,00000	0,00000	0,00000
	Y	27	0,00968	0,01907	0,00000	0,00000	0,00000	0,01852

Variable	HELPFUL?	Maximum
№ of errors / № of word	N	0,01613
	Y	0,06667

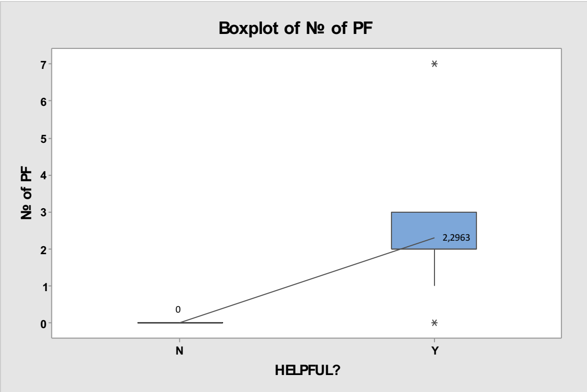
Two-Sample T-Test and CI: № of errors / № of words; HELPFUL?

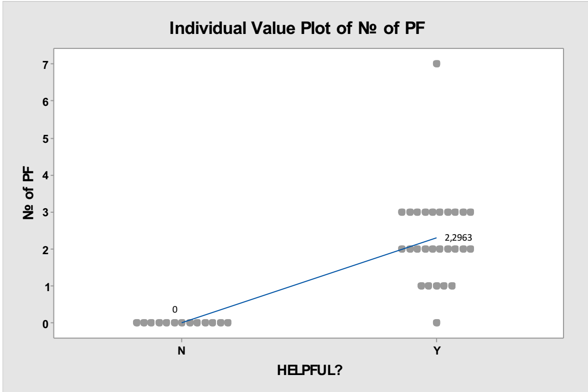
Two-sample T for № of errors / № of words

HELPFUL?	N	Mean	StDev	SE Mean
N	13	0,00124	0,00447	0,0012
Y	27	0,0097	0,0191	0,0037

```
Difference = μ (N) - μ (Y)
Estimate for difference:  -0,00844
95% CI for difference:  (-0,01634; -0,00054)
T-Test of difference = 0,005 (vs ≠): T-Value = -3,47  P-Value = 0,002  DF = 31
```

of PF





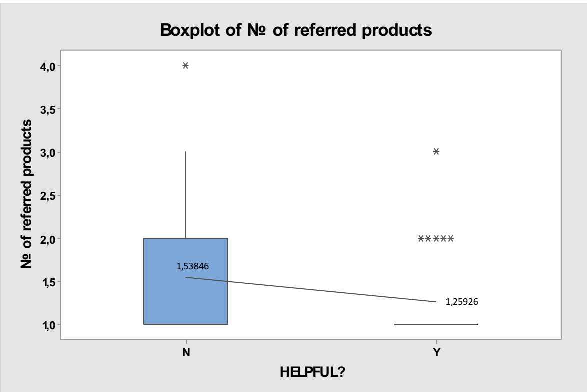
Descriptive Statistics: № of PF

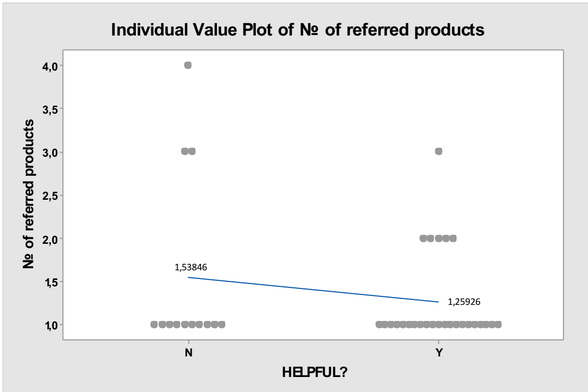
Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of PF	N	13	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000	0,000000
	Y	27	2,296	1,265	0,000	2,000	2,000	3,000	7,000

Two-Sample T-Test and CI: № of PF; HELPFUL?

```
Two-sample T for № of PF

HELPFUL?   N   Mean  StDev  SE Mean
N         13  0,077  0,277    0,077
Y         27   2,30   1,27     0,24


Difference = μ (N) - μ (Y)
Estimate for difference:  -2,219
95% CI for difference:  (-2,741; -1,698)
T-Test of difference = 0,005 (vs ≠): T-Value = -8,71  P-Value = 0,000  DF = 30
```

of referred products





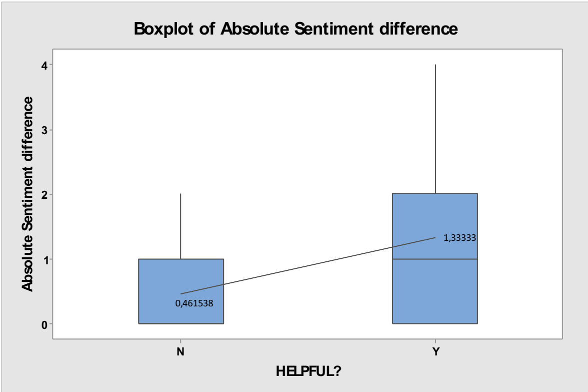
Descriptive Statistics: № of referred products

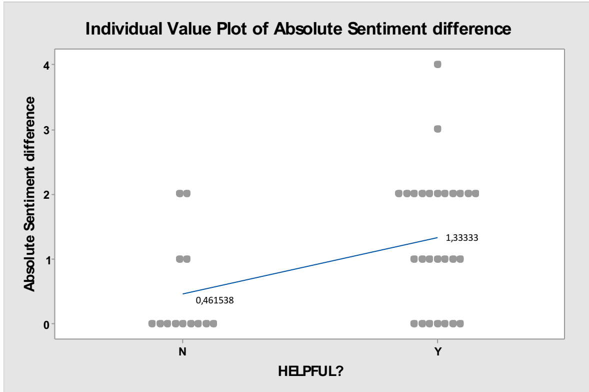
Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
№ of referred products	N	13	1,538	1,050	1,000	1,000	1,000	2,000	4,000
	Y	27	1,259	0,526	1,000	1,000	1,000	1,000	3,000

Two-Sample T-Test and CI: № of referred products; HELPFUL?

```
Two-sample T for № of referred products

HELPFUL?   N   Mean  StDev  SE Mean
N         13   1,54   1,05     0,29
Y         27  1,259  0,526     0,10


Difference = μ (N) - μ (Y)
Estimate for difference:  0,279
95% CI for difference:  (-0,382; 0,940)
T-Test of difference = 0,005 (vs ≠): T-Value = 0,89  P-Value = 0,389  DF = 14
```

Absolute sentiment difference





Descriptive Statistics: Absolute Sentiment difference

Variable	HELPFUL?	N	Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Absolute Sentiment diffe	N	13	0,462	0,776	0,000	0,000	0,000	1,000	2,000
	Y	27	1,333	1,038	0,000	0,000	1,000	2,000	4,000

Two-Sample T-Test and CI: Absolute Sentiment difference; HELPFUL?

Two-sample T for Absolute Sentiment difference

HELPFUL?	N	Mean	StDev	SE Mean
N	13	0,462	0,776	0,22
Y	27	1,33	1,04	0,20

Difference = μ (N) - μ (Y)
Estimate for difference: -0,872
95% CI for difference: (-1,472; -0,272)
T-Test of difference = 0,005 (vs ≠): T-Value = -2,99 P-Value = 0,006 DF = 30

Appendix F: Variable results

Seventh appendix includes the tables with the relation between analyzed variables and HoQ required information factors for each SM source.

	QFD variables					
	R1	R2	R3	R4	R5	R6
Variable	Customer attributes	Customer attributes importance	Customer evaluation (competitors)	Engineering characteristics	Correlation matrix	Relationship matrix
# of characters	1	0	0	1	0	0
# of words / # of characters	0	0	0	0	0	0
# of sentences / # of words	0	0	0	0	0	0
% of adjectives	0	0	0	0	0	0
% of adverbs	1	0	0	0	0	0
% of verbs	1	0	0	0	0	0
% of nouns	0	0	0	0	0	0
# of errors / # of words	1	0	0	0	0	0
Content format	0	0	0	0	0	0
Absolute sentiment difference	1	0	0	0	0	0
# of PF	1	0	0	1	0	0
# of referred products	0	0	0	0	0	0

Table F.1. Significant variables for HOQ construction for Twitter reviews

	QFD variables					
	R1	R2	R3	R4	R5	R6
Variable	Customer attributes	Customer attributes importance	Customer evaluation (competitors)	Engineering characteristics	Correlation matrix	Relationship matrix
# of characters	1	0	0	1	0	0
# of words / # of characters	0	0	0	0	0	0
# of sentences / # of words	1	0	1	1	0	0
% of adjectives	0	0	0	1	0	0
% of adverbs	0	0	0	0	0	0
% of verbs	0	0	0	0	0	0
% of nouns	0	0	0	0	0	0
# of errors / # of words	0	0	0	0	0	0
Content format	0	0	0	0	0	0
Absolute sentiment difference	0	0	0	0	0	0
# of PF	1	0	0	1	0	0
# of referred products	0	0	0	0	0	0

Table F.2. Significant variables for HOQ construction for Facebook reviews

	QFD variables					
	R1	R2	R3	R4	R5	R6
Variable	Customer attributes	Customer attributes importance	Customer evaluation (competitors)	Engineering characteristics	Correlation matrix	Relationship matrix
# of characters	1	0	0	1	0	0
# of words / # of characters	0	0	0	0	0	0
# of sentences / # of words	1	0	0	1	0	0
% of adjectives	0	0	0	0	0	0
% of adverbs	1	0	0	0	0	0
% of verbs	1	0	0	1	0	0
% of nouns	0	0	0	0	0	0
# of errors / # of words	1	0	0	1	0	0
Content format	-	-	-	-	-	-
Absolute sentiment difference	1	0	0	1	0	0
# of PF	1	0	0	1	0	0
# of referred products	0	0	0	0	0	0

Table F.3. Significant variables for HOQ construction for Forum reviews