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Examining Hedonic and Utilitarian Values' Effect on Ratings Based on Reviews

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Abstract

Over the past years, with the growth of e-commerce, online reviews have become an important mean for companies to observe consumer purchase behavior. Previous research suggests that there are two motivators behind the consumer purchase behavior; hedonic gratification and utilitarian reasons. In light of this, the hedonic and utilitarian values within the reviews and their effect on ratings was explored. Hedonic purchase behavior relates to the emotional and sensuous aspects of products, accompanied by a joyful and fun shopping experience. On the other hand, utilitarian purchase behavior is related with efficiency, functionality and rationality, in which the completion of the shopping task is crucial. Thus, the research aimed to provide insight for companies, regarding the different aspects their products have, as well as how they are perceived in the eyes of the consumer. What differentiates this paper from previous research is that, the products selected, a toothpaste and an athletic shoe, are perceived as both highly utilitarian and highly hedonic, preventing bias that could've occurred due to the products' own attributes. The reviews are scraped from Amazon.com and Latent Dirichlet Allocation, an unsupervised model designed to find latent topics within a corpus, is done to identify the topics among the reviews. After naming and classifying these topics as either hedonic or utilitarian, logistic regression was used to see whether these topics make the rating go higher or lower. The analysis showed that; for the toothpaste, the changing of the formula had the highest impact by decreasing the probability of getting high ratings and for the athletic shoe, fast delivery had the highest impact by increasing the probability of getting high ratings. Finally, as a managerial implication it was concluded that, to increase ratings; a single utilitarian aspect or multiple hedonic aspects of the products should be looked upon.

Table of Contents

1. Introduction ... 4
2. Theoretical Framework ... 8
2.1 Online Reviews and Ratings ... 8
2.2 Hedonic Values ... 9
2.3 Utilitarian Values ... 12
2.4 Measurement of Values ... 13
2.5 Product Selection ... 15
3 Data ... 17
3.1 Data Description ... 17
3.2 Pre-processing & Visualization ... 18
4 Methods ... 22
4.1 Latent Dirichlet Allocation (LDA) ... 22
4.2 Logistic Regression ... 25
5 Results ... 26
5.1 Toothpaste Data ... 26
5.1.1 Hedonic Topics ... 28
5.2.2 Utilitarian Topics ... 30
5.2 Athletic Shoe Data ... 32
5.2.1 Hedonic Topics ... 34
5.2.2 Utilitarian Topics ... 36
5.3 Regression Results ... 38
6 Conclusion ... 41
7 References ... 44

1. Introduction

With the Covid-19 pandemic effecting the everyday life of people in areas such as working and travelling (Deloitte, 2021) another area that was hit was physical shops, for retail sales, that required the customer to be physically present during the sale. Stores had to close down across the world as a measure of lockdown protocols for safety reasons concerning the customers and the shop employees. These stores would range from the smallest of shops (e.g. 22% of small and medium businesses closed in February 2021 in the US (Sundaram, 2021)) to large fast food chains (10% of all restaurants closed in the US with Subway closing 1557 stores followed by Dunkin Donuts with 559 (Meisenzahl, 2021)) and large scale electronic stores (e.g. Apple closed all of its retail stores outside China temporarily (Chan, 2020)). With shops being unable to provide service to customers on a physical basis, shop owners and managers switched their focus on to their online shops. We mentioned that stores had to be closed due to lockdown protocol but also people had to stay at home in quarantine in order to be safe. With 8.300 stores closed in the US alone in August 2020 (Peterson, 2020) and 12.200 by the end of the year (Wahba, 2021), combined with consumers staying at home due to lockdown regulations and curfews led to an increase in online e-commerce's share of global retail trade from 14% in 2019 to 17% in 2020 (UNCTAD, 2021).

In recent years, global e-commerce sales have been increasing year by year. Forecasts show that the same growth trend that occurred between 2017 to 2021, will continue until 2023 (Chaffey, 2021). According to OECD (2020), reports suggest that there has been a shift in demand from retail to e-commerce in 2020 as online sales increased by 14.8% in the United States and 30% in Europe compared to the previous year. This resulting shift from retail to e-commerce is likely to be significant across other countries. With sales increasing year by year, the number of product reviews written by the happy and unhappy consumers also increases.

For companies, online product reviews are an important mean for receiving and providing feedback concerning the products and services (Felbermayr, 2016). Product reviews could help the company by finding out what is wrong with the product, how to improve it, and what the general consensus about the product is. As it stands, understanding the consumers is a crucial issue in order to develop the best product or service (Özdağoğlu, 2018). According to Maurer

(2011), online reviews are a potential channel to articulate problems since the barriers to complain are very low. In addition, online reviews can be done in any time and any place, making it convenient for the consumers. Another aspect of online reviews is that; they can be helpful. Consumers express their pre and post purchase experiences and give recommendations to help other interested consumers make better purchase decisions (Muralidharan, 2017). With consumers not having a chance to examine a product in a real life setting due to the pandemic, other reviews of consumers were crucial, as they were the only information along with the product description. With the expansion of e-commerce, the number of reviews expanded as well. Consumer web blogs, social networks and review sections in product websites provided opportunities for consumers to share their shopping experience (Özdağoğlu, 2018). Data collected from the reviews accompanied by ratings play an important part in the growing online sales industry. From a business perspective, allowing companies to explore the reviews of the products helps them better understand the behavior of their customers. Martinez-Lopez (2014), touches on this topic and states that companies should be aware of consumers' motivations in the consumption process as motivations are important to identify consumer behavior.

Regarding consumer motivations, Batra and Ahtola (1991), states that the two basic reasons behind consumer purchases, are "(1) consummatory affective (hedonic) gratification (from sensory attributes), and (2) instrumental, utilitarian reasons" (Batra, 1991). For example, a consumer may want to purchase a car but they may have certain preferences regarding the attributes of the car. They may seek better mileage and a large trunk which are utilitarian values, or they may seek a sporty design and shiny rims which are hedonic values. Research suggests that consumer choices are driven by utilitarian and hedonic considerations (Batra and Ahtola 1991; Voss, Holbrook and Hirschman 1982; Dhar and Wertenbroch 2000). To elaborate, a brief introduction to utilitarian and hedonic consumer behavior and motivations as well as utilitarian and hedonic products is given below.

Utilitarian consumer behavior can be simply put as a "getting things done" behavior. This means that consumers are task oriented, efficient and rational (Anderson et al., 2014). Imagine a consumer parking their car, heading to the store that sells the specific product they are looking for, purchasing it and returning back to the car immediately. The consumer's behavior in the example can be seen as completing the intended goal of purchasing an item without delay. In relation to this example, Babin, Darden and Griffin (2003) states that “utilitarian value may be most relevant in explaining shopping trips described by consumers as ‘an errand’ or ‘work’ where they are happy simply to get through it all.” Another aspect of utilitarianism can be found in products. Utilitarian products are products that are mainly used for their specific purpose, making them “necessary, functional and practical” (Jingyi et al., 2016).

Hedonic consumer behavior, on the other hand, relates to the multisensory, fantasy and emotive aspects of one’s experience with products (Hirschman & Holbrook, 1982). Hedonic consumption is more entwined with the joyful and fun experience of shopping. Instead of the previous example for utilitarian consumer behavior, imagine another consumer parking their car, heading out to look at different stores, with no particular goal of purchase, enjoying the hours they spent while looking around. In this regard, Anderson et al. (2014) stated that “consumers desire entertainment and consider the purchasing process an enjoyable experience in which completing the transaction is not required.” Hedonic products, on the other hand, are products that help satisfy the consumers sensations and also give an emotional aspect to the product. Voss & Spangenberg, Grohmann (Voss et al., 2003) stated that the hedonic dimension results from the sensations from the experience of using the product. An in-depth look into both subjects can be found in the theoretical framework part of this study.

So far, the increase and importance of online product reviews following the rise of e-commerce have been discussed. It was important to touch on those topics as they will be used as a source to understand consumer behavior and purchase experience and the rating they give. In order to better understand consumer behavior, two concepts were introduced: Hedonic and utilitarian values, which are drivers of consumer behavior (Batra & Ahtola, 1991). Using online product reviews written by consumers, the consumer shopping experience can be investigated. In this sense, hedonic and utilitarian values, mentioned as drivers for behavior, are used as a tool to classify the consumer behavior as either hedonic or utilitarian. This classification provides information on how consumers perceive a product on a 1-5 Star scale. Whether consumers focus on a product due to its utility or the feelings it conveys could help provide companies a better understanding of their products and the consumers behavior.

To understand consumer perceptions towards a product, the reviews that are written by the consumer must be analyzed. In order to analyze reviews, one must know that the reviews are text based data, and hence text analytics must be used. Özdağoğlu (2018) indicates that a large volume of data from consumers can be collected in free-text or structured forms. In addition, she stated that consumer reviews can be considered a digital VoC (Voice of the Customer), and advanced data analysis methods can be applied to mine hidden patterns for reaching the corresponding customer wants and needs (Özdağoğlu, 2018). One method in particular, is topic-modelling. Topic-modelling is a text-mining technique used to explore hidden patterns in a collection of documents. The aim of topic-modelling is to group similar documents within the same cluster. Among topic-modelling methods, Latent Dirichlet Allocation (LDA) is used to categorize reviews under particular topics and generate representative samples for each topic (Özdağoğlu, 2018). Therefore, by using LDA, the aim is to uncover topics among reviews that can be related to utilitarian and hedonic values. However, currently there isn't a "guide" that can be used for this separation in topic modelling. In light of this, studies and previous research, including a two dimensional hedonic-utilitarian scale (HED/UT) developed by Voss, Spangenberg & Grohmann (2003) will be used as a reference (Babin et al., 1994; Batra and Ahtola, 1991; Voss et al., 2003). This research tries to answer the following question:

To what extent does utilitarian and hedonic values, as observed in topics in online product reviews, effect product ratings?

The contribution of this research to the existing literature is that, to the authors knowledge, there hasn't been a research on hedonic and utilitarian values found in online product reviews by using topic modeling and the relation of these topics to the review ratings. With respect to this, this research aims to provide information on consumers' shopping experience by looking at products that have high utilitarian and high hedonic values (Toothpaste and Athletic Shoe). As it stands, focusing on products with both values is crucial. Previous research either used products that are hedonic (high on hedonic values and low on utilitarian values) and utilitarian (high on utilitarian and low on hedonic value) to create a scale (Batra and Ahtola, 1991; Voss et al, 2003; Dhar and Wertenbroch, 2000) or compare products that are hedonic to utilitarian (Lim and Ang, 2008; Baltas et al., 2016; Micu and Coulter, 2012; Okada, 2005). This research aims to fill the gap in literature by examining products that have high utilitarian and high hedonic values.

As of January 2021, the number of active internet users is approximately 4.66 billion (Statista, 2021a). Among these users, a whopping estimated 2.14 billion people are shopping online in 2021 (Oberlo, 2021a). One of the largest online stores, Amazon.com (Oberlo, 2021b), has 753 million unique monthly visitors as of December 2020 (Statista, 2021b). On top of that, in 2014, Amazon.com had a total of 1.2 million reviews among all products with 510.434 distinct reviewers (Woolf, 2014). This research is relevant because the collected data (product reviews) is scraped from one of the most used websites. From a consumer perspective, reading other reviews help obtain knowledge about the product and is of crucial importance towards the perception of the product. This research can help companies to look into different aspects of their products and to better understand how each is perceived. From a managerial stand point, understanding these different aspects can help managers position their goods and services in the most suitable way (Nili, 2013).

2. Theoretical Framework

In this section, prior literature about the current research will be evaluated. While relating previous literature to the research, hypotheses are presented in order to help answer the research question. First, online reviews are discussed. Following that, hedonic and utilitarian values are explained in detail with aspects such as consumer behavior and products. How these values are measured are explained in the measurement part and the importance of product selection is presented in detail. Lastly, how the thesis shapes up is explained at the end.

2.1 Online Reviews and Ratings

Online reviews have become an important part of the consumers' decision journey. According to McKinsey (2009), consumer decision journey is made up of 4 phases: the initial consideration, active evaluation, closure as a moment of purchase and post purchase experience. Online reviews come into the picture in the second and fourth phase. The second phase is about information gathering and evaluation of the consumers' wants and needs. Online reviews provide information about the products for the consumers who didn't purchase the product yet, but is seeking information. The fourth phase is about the post-purchase experience. The consumer builds up expectations to inform the next in-line for the decision journey from their experience with the product. In both phases online reviews have a role to inform and give information regarding the product and the purchase experience. Regarding this idea, Park (2007) expresses that online reviews have two goals, an informant and a recommender. As an informant, it provides user-oriented product information, while as a recommender, it provides recommendations by previous consumers in the form of electronic word-of-mouth (Park et al., 2007).

Product ratings that are used in this study are based on a 5-star rating in which the stars are ordinal and the higher star rating given indicates higher consumer satisfaction with the products. Product ratings are formed by the overall satisfaction the consumer experiences; as a result, they express this by giving one of the 5 ratings: Very poor, poor, fair, good, very good (Likert 1932). In this research, reviews that have 1, 2, and 3 star ratings are considered as low (negative) ratings, and reviews that have 4 and 5 star ratings associated with them are considered high (positive) ratings. Another important detail to mention is the review valence. According to Cheung (2009), there are 3 major categories of review valence that product reviews can be classified in: Positive (one-sided), negative (one-sided) and neutral (two-sided). One sided reviews consist of features that are either as positive or as negative. Two sided reviews, on the other hand are more balanced, explaining the positive features of the product as well as the negative features consumers encountered. In this research the review valence is not considered due to the fact that ratings are of central focus. A review with a 5-star rating may be two-sided but the consumer deemed the product 5-star worthy and thus the review will only be considered having a high (positive) rating.

2.2 Hedonic Values

Hedonic values referred to in this paper encompass hedonic aspects of the shopping experience and consumer behavior. Throughout literature hedonic aspects are explored in a multitude of ways, hence, in this paper, to refer to all of these aspects at once the term hedonic values is used. In this section, these aspects are individually explored. Hirschman and Holbrook (1982) introduced the term hedonic consumption, as it refers to consumers' multisensory images, fantasies and emotional arousal in using of products. This may also be referred to as hedonic response as well. They further emphasize that by using a hedonic consumption perspective, products are viewed not as objective entities but rather subjective symbols. This creates the symbolism aspect of hedonic values. Additionally, researchers aren't concerned with what the product is, but with what it represents (Hirschman, 1982). In another paper published by Holbrook and Hirschman (1982), they indicate that, in some cases the symbolic role is especially rich and salient; they mentioned that entertainment, the arts, and leisure activities encompass symbolic aspects of consumption behavior. In the same paper, Holbrook and Hirschman (1982), indicate that pleasure oriented consumption raises three methodological issues. Firstly, measures for hedonic responses should be improved, so that "pleasure" is constituted in a valid definition. Secondly, problems of reliability and validity occur due to hedonic responses being unusually susceptible to fluctuations across situations. Lastly, using sensation seeking to explain sensory-emotive phenomena is difficult (Holbrook, 1982). An example for the above mentioned issues can be seen with the product Coca-Cola. Regarding the product, Çal and Adams (2014) state that "even though the product may be largely conceived as a utilitarian product, in the sense of having characteristics such as a thirst quencher and accompaniment at meals, the product also reflects some hedonic characteristics with regards to the pleasure it may arouse, status symbols and symbolic meanings it may represent such as being cool, western, and accessible."

Another aspect of hedonic values is the playful and enjoyment aspect. This is seen in the shopping experience as consumers with hedonic consumer behaviors tend to enjoy the time they spend on shopping as it gives them pleasure. Scarpi (2012), defines Hedonism as "the festive, ludic or even epicurean side of shopping; its related to fun and playfulness rather than to task completion, and thus it reflects the experiential side of shopping, comprising pleasure, curiosity, fantasy, escapism and fun." As an example for this, Scarpi mentions that consumers who shop online and have a hedonic attitude can get an added value as they can listen to music, watch videos, have a personalized experience while browsing through huge array of products (Scarpi, 2012). In the offline environment, where consumers shop at physical retailers, consumers have the benefit of approaching a salesperson or a clerk for more information about product. According to Haas and Kenning (2014), hedonic value while consulting a salesperson relates to the shoppers' affective response to a target (e.g. liking a salesperson). They also emphasize that the more shoppers are motivated by the enjoyment of the shopping process, the more they will value such hedonic returns expected from consultations, and thus the greater the shoppers' motivation to consult with a salesperson (Haas, 2014). In another study by Ozturk (2016), which explored the role of utilitarian and hedonic values on users' continued usage related to mobile hotel booking (MHB), found out that "MHB systems should include entertainment-oriented activities, such as animated images and tools with appealing visual layouts. Adding fun components to the mobile app is another way to maximize users' hedonic value perceptions."

Another fun component in the shopping experience is the hunt for a good bargain. Anderson (2014) states that “bargain perceptions as a hedonic motivation may reflect retailers’ approach of ‘gamifying’ the experience of attaining coupons and bargains inclusive of coupon websites that evoke an innate bargain hunting environment.” Additionally, Babin (1994), states that the hunt for a good bargain and finding products for really cheap or at a good deal motivates bargain perception without the need of a task-oriented purchase. Consequently, Babin (1994) identified bargain perception as a hedonic value along with Arnold and Reynolds (2003) who used the phrase “thrill of the chase” while doing so.

Hedonic values are also associated with the need to justify a purchase. According to Okada (2005), it is more difficult to justify spending on hedonic goods because there is a sense of guilt associated with it and its benefits are more difficult to quantify. Since hedonic goods deliver benefits primarily in the form of experiential enjoyment, it may be more difficult to evaluate and quantify (Okada, 2005). This can be further explained by Bazerman, Tenbrunsel, and Wade-Benzoni (1998), as they suggest that affective preferences (“wants”) and cognitive or reasoned preferences (“shoulds”) that underlie consumer choice can be distinguished. Hedonic value items are likely to be subject to want preferences (Dhar & Wertenbroch, 2000). As hedonic value items are related to the consumers’ want preferences, it becomes clear that hedonic consumer behavior also encompasses unplanned and impromptu purchases. According to Scarpi (2012), hedonic consumers spend more money and buy more items compared to the utilitarian consumers because they indulge in many unplanned purchases. Ultimately, we can assume that purchases made with hedonic purchase behavior leads to guilt, which leads to lower rated product reviews. On the other hand, it was discussed that hedonic consumptions’ playful and joyful aspects result in a more positive shopping experience for the consumer. In order to see the effect of hedonic values, the following hypothesis is tested to see if the hedonic scores are associated with high or low ratings. The hedonic score of a review is obtained by the sum of the probabilities of the hedonic topics occurring within the review. The resulting score is the probability of a review being hedonic.

H1: Hedonic scores are not associated with product ratings.

2.3 Utilitarian Values

Utilitarian values referred to in this paper encompass the utilitarian aspects of the shopping experience, consumer behavior and the utilitarian products. The very first and systematic look upon utilitarianism was done by philosopher Jeremy Bentham in 1789 in his book “Introduction to the Principles of Morals and Legislation”. However, the birth of utilitarianism showed a more philosophical side instead of its multidisciplinary aspect today. Investigation of the hedonic and utilitarian components of attitude has been suggested in diverse disciplines such as sociology, psychology, and economics. (Voss et al. 2003). Bentham (1789) explained utility as “property in any object, whereby it tends to produce benefit, advantage, pleasure, good, or happiness or to prevent the happening of mischief, pain, evil, or unhappiness to the party whose interest is considered.” This was followed almost 100 years later by work from John Stuart Mill in his book “Utilitarianism” as he explained utility as, the Greatest Happiness Principle, “that actions are right in proportion as they tend to promote happiness, wrong as they tend to produce the reverse of happiness. By happiness is intended pleasure, and the absence of pain; by unhappiness, pain, and the privation of pleasure.” (Mill, 1863). However, in consumer research, the modern use of the word utilitarianism is linguistically distinct from its past namesake. According to Babin et al, (1994), Bentham’s notion of utilitarianism is equated closely with modern notions of hedonism and Mill’s utilitarianism also reflects a hedonic component and in general equates utility with happiness.

Back to the modern take on utilitarian values, Batra et al (1991) describes utilitarian consumer behavior as task-related and rational. A utilitarian outcome comes from the sense of accomplishing an intended goal. Finishing the intended shopping task is the peak of the utilitarian shopping values. Whether the task is completed in a fastidious and efficient way can increase the utilitarian aspect of the shopping value. The purchase act itself can elicit a utilitarian response, arising from the shopping tasks successful culmination (Babin et al., 1994). However, some researchers state that a purchase is not a necessary precursor of utilitarian shopping value as utilitarian result may result from a customer collecting information out of necessity (Bloch, 1983). In either case, one common ground is that the task that is set in the consumers’ mind is completed. Whether this is a purchase or collecting information doesn’t matter. According to Scarpi (2012) “if convenience is the main benefit expected from shoppers online, then the internet may best suit utilitarian consumers, who perceive the act of shopping as a necessary task to be performed as quickly as possible.” This further illustrates that utilitarian shopping values often thrive from fast and efficient task completion.

Another aspect of utilitarian values are the products. Utilitarian products are ones whose consumption is more cognitively driven, instrumental, and goal oriented and accomplishes a functional or practical task (Strahilevitz & Myers, 1998). Throughout previous researches, multiple utilitarian products were used in the studies which included items such as; a bar of soap, dish detergents, glue stick, fork, paper towels (Micu & Coulter, 2012; Dhar & Wertenbroch, 2000; Lim & Ang, 2008; Baltas et al., 2016). For utilitarian products, primarily functional and instrumental aspects stand out. This leads to the purchase of utilitarian products easier to justify (Okada, 2005). With easily justified purchases that are functional, task-oriented and simply useful, it is expected that the topics classified as utilitarian are associated with higher ratings. The utilitarian score of a review is obtained by the sum of the probabilities of the utilitarian topics occurring within the review. The resulting score is the probability of a review being utilitarian. Thus the following hypothesis is proposed:

H2: Utilitarian scores are associated with higher ratings.

2.4 Measurement of Values

A clear cut and strict evaluation of hedonism and utilitarianism cannot be made as it is fairly subjective and forever changing. One product may be completely utilitarian according to one individual, but completely hedonic according to another individual. For example, imagine two people A and B: A purchases a t-shirt, from a music band they like with the bands’ logo/group members etc. on it. For A, this t-shirt symbolizes their love and bond for the band and has sentimental value. For B, a person who has not even heard of the band, this t-shirt possesses no sentimental value and at most possesses some utilitarian value that comes from the t-shirts ability to keep B warm. Obviously the same product has different valuation for different people since they have subjective opinions and in measuring these values, this has to be taken into account. This causes a major impediment as capturing both dimensions with a reliable and valid measurement instrument is difficult (Voss et al., 2003). That being said, the scales created to measure hedonic and utilitarian values are formed with the opinions of people. Additionally, each scale created throughout literature have either used different methods or used similar methods but with different samples.

Batra and Ahtola (1991) created one of the first measurement scales used in the study of utilitarian and hedonic dimensions. While developing the scale they used the semantic differentials (SD) identified by Osgood et al. (1967), which displayed adequate reliability, convergent validity, discriminant validity and nomological validity. (Batra, 1991). Their work consisted of 16 7-point evaluative SD items with 59 respondents rating 4 arbitrary selected brands (Batra, 1991). An exploratory common factor analysis for the four brands were conducted and in all cases resulted with a two-factor structure. Batra and Ahtola (1991) states that one of the factors were labeled as hedonic and was "loaded heavily on pleasant-unpleasant, agreeable-disagreeable, nice-awful, and similar items" whereas the second factor was labeled as utilitarian and was "loaded heavily on useful-useless, beneficial-harmful, important-unimportant and similar items." Ultimately, confirmatory factor analysis was conducted to see convergent and discriminant validity to the 3 highest loaded items in the previous analysis.

In Babin, Darden and Griffin's (1994) study, the initial scales are formulated by two focus groups consisting of 6 and 8 people consecutively that had to evaluate an activity's worth. Following this, 71 scale items were generated from the focus groups and past literature. Three college professors evaluated the items and 5 items were considered through majority votes and 48 items were considered for the research through unanimity. 125 undergraduate students then rated each item on a five-point Likert scale. For dimensionality and item reduction, principal component analysis was used for the 53 items, resulting in the first two factor explaining 21% and 14% of the variance consecutively. The initial PCA was rotated using an oblique technique to examine factor structure and 20 items comprising the first two factors remained for further analysis. Lastly, confirmatory factor analyses were done validating the scale (Babin et al. 1994).

Lastly, Voss, Spangenberg and Grohmann's (2003) criticized Batra and Ahtola for "the inability to account for relevant theoretical concepts within a nomological framework" (Voss et al., 2003) which includes aspects like involvement. Hence Voss et al. (2003) created an updated version of Batra and Ahtola's work. An initial pool of adjective pairs from published literature and a pretest of students and professionals was generated. 608 students rated brands on the 27, 7-point SD items (Voss et al., 2003). For the psychometric analysis, they conducted a principal components exploratory factor analysis and assessed internal consistency. This resulted in 3 SD's (hedonic/not hedonic, utilitarian/not utilitarian, convenient/not convenient) being deleted and leaving 12 adjective pairs for both hedonic and utilitarian dimensions of product attitude. Unidimensionality was assessed by using confirmatory factor analysis as the items loaded as predicted and minimal cross –loading occurred for both brand names and product categories. After that, to reduce the scales, a new group of 400 students were used on the 24 adjective pairs. With the scales reduced, Voss et al. (2003), conducted discriminant validity, predictive validity and finally nomological validity to create the 10-item HED/UT scale. The HED/UT scale is comprised of 5 adjective pairs for hedonic and 5 adjective pairs for utilitarian items. These adjectives help guide the decision making of classifying the topics of LDA as hedonic and utilitarian.

2.5 Product Selection

Product selection is one of the most crucial difference this paper makes when examining hedonic and utilitarian values. Unlike many authors' work (Micu & Caulter 2012; Baltas et al. 2017; Lim & Ang 2008; Dhar & Wertenbroch 2000), this research does not use products that are solely hedonic and utilitarian. According to Hirschman and Holbrook (1982), prior research focused on products where "a priori one might anticipate that the assumptions and propositions it advanced would most likely be found valid." For example, for utilitarian products a washing machine would be best predicted and explained using the expectancy-value formulation of the traditional multi-attribute attitude model. Likewise, researchers examining hedonic consumptions often played it safe by selecting "emotion laden, subjectively-experienced products such as ballet, music and theater" (Hirschman, 1982). This research, instead, uses products that are both highly hedonic and highly utilitarian. They are selected as such because in this research, the goal is to find how much effect does each topic have on a product. The two products that are used in this research are a toothpaste and an athletic shoe. The toothpaste was used in the studies by Batra and Ahtola (1991), indicating the two bases of evaluation, referring to utilitarian dimension of instrumentality and hedonic dimension measuring the experiential affect associated with the object, may not be salient; some product categories, brands and behaviors may be more positively evaluated on one dimension than another, and different objects should differ predictably in the extent to which overall attitudes towards them are hedonic or utilitarian. The toothpaste in this situation was given as an example due to its utilitarian aspect of preventing cavities and the hedonic aspect of providing pleasure from its taste (Baltas et al., 2016). For this research, a Colgate brand toothpaste was selected which comes in a 4-pack and its main attribute is that it whitens teeth. The second product, is Nike brand athletic shoes, which was also used in the work of Voss, Spangenberg and Grohmann (2003). They used the Hedonic/Utilitarian scale (HED/UT scale) and updated after Batra and Ahtola's (1991) work and in both measurement methods athletic shoes were confirmed to be highly hedonic and highly utilitarian on their quadrant map. In another study to extend predictive validity, Voss et al. (2003) used the 4 athletic shoe brands, resulting in the brands "Keds" and "Reebok" being both highly utilitarian and highly hedonic. However, brands such as "Adidas" and "Nike" were considered to be proportionally higher when it came to their HED/UT scale. That being the case, Nike was selected to be the brand of the athletic shoe in this research.

From this point onward, the next section explores the data of the research, how it was collected and prepared for analysis. The following section, explains the methodology that is used; how Latent Dirichlet Allocation extracts topics from reviews and how and when logistic regression is used. Section 5 contains the results of the LDA and includes the process of labeling the topics as either hedonic or utilitarian. In addition, it contains the results of the logistic regression, in which, the high and low ratings are regressed on the topics. Ultimately, the sixth section evaluates the results, discusses the managerial implications and explains the limitations and how they can be improved in future research.

3 Data

3.1 Data Description

The dataset in this research were scraped by the author from the relevant product review pages on Amazon.com. Two products were selected, a Colgate brand toothpaste and a Nike brand athletic shoe. The reviews were taken from the product page, sorted from newest to oldest and all reviews posted on the website were scraped at that moment (June 4th, 2021). As a result, a total of 1467 and 5000 reviews were scraped for the toothpaste and the athletic shoe respectively. In the toothpaste data, the 1467 reviews generated 36868 words in total with 3285 of them being unique words. For the athletic shoe data, the 5000 reviews generated 110500 words in total with 5393 of them being unique words. An in-depth view to the data can be found under Table 1. Within the customer reviews, there exists two different languages, English and Spanish. A total of 155 Spanish reviews were translated to English via Google Translate. It is aim that all reviews are considered in the research as removing the Spanish reviews could've caused inaccurate results. The reviews range from December 13th, 2018 to June 1st, 2021 for the toothpaste and a much larger period of time from October 18th, 2011 to June 1st, 2021 for the athletic shoe. Lastly, the star ratings for the toothpaste can be seen in Figure 1 with 167 1-star, 50 2-star, 57 3-star, 157 4-star, and 1063 5-star reviews. For the athletic shoe, 354 1-star, 212 2-star, 297 3-star, 672 4-star, and 3465 5-star reviews were obtained and is shown in Figure 1 as well. The following variables can be found in the dataset:

- **User Name:** The consumers' online ID that is found on Amazon.com
- **Review Location:** The country the review was written
- **Review Date:** Indicates the date that the review has been posted on the website. Contains the day, month and year.
- **Product Rating:** The consumers' valuation of the product based on a 1-5 scale using stars. The higher the rating is the better valuation it is.
- **Review:** Contains the consumers' review of the product as a text format.

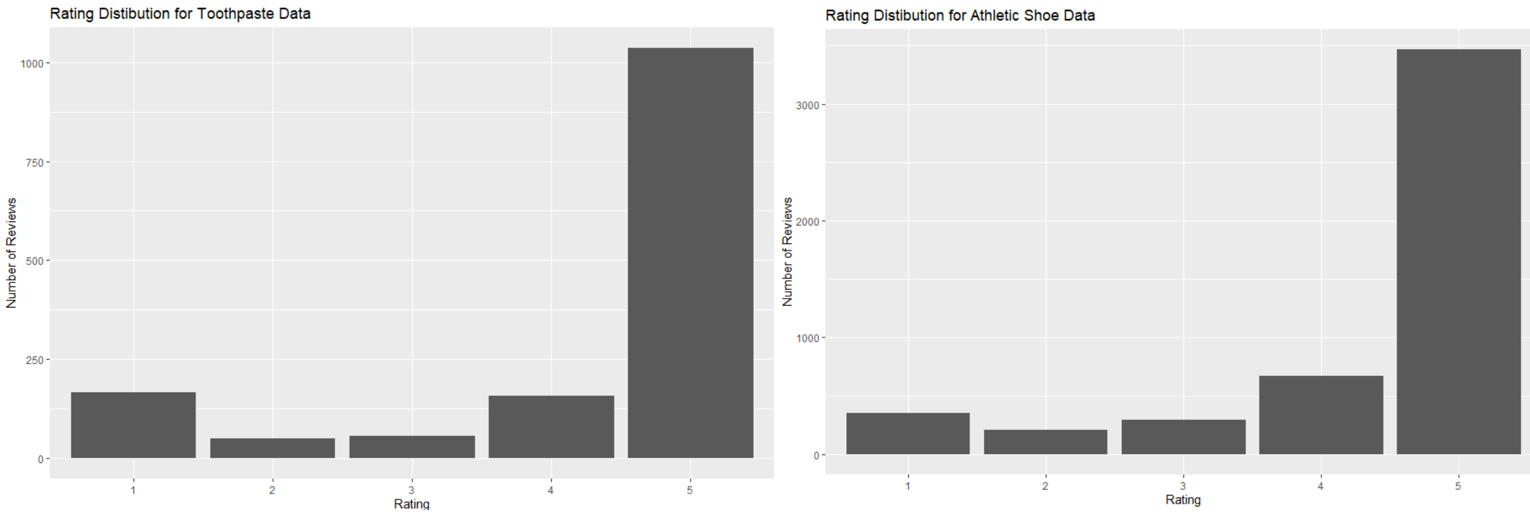

Figure 1 Toothpaste and Athletic Shoe Ratings

3.2 Pre-processing & Visualization

So as to achieve visualizations and analysis, pre-processing must be applied on the data. Pre-processing, can be generalized as the few steps that needs to be done before analyzing data. Removing stop words and stemming the words are two of the most used methods. In the data the first thing that was done was to set the encoding to UTF-8, “an encoding system used for representing text encoded using the Unicode standard” (Ushey, 2018), which allows characters of all languages to be encoded. After that, every character was turned into lowercase preventing same words appearing more than once. The emoticons (emoji’s and other special characters) used in the reviews were analyzed by turning them into the word representations. Lastly, certain symbols and punctuations are removed.

	Toothpaste Data	Athletic Shoe Data
Number of Reviews	1467	5000
Number of Words	36868	110500
Number of Unique Words	3285	5393
Number of Words Without Stop Words	13652	40342
Number of Unique Words Without Stop Words	2774	4812
Number of Words After Stemming and Without Stop Words	13652	40342
Number of Unique Words After Stemming and Without Stop Words	2185	3651

Table 1 Data Summary

In Table 1, results of these processes up until now can be observed. After removing stop words, the total number of words in the toothpaste dataset reduced from 36868 to 13652. The number of unique words, on the other hand, decreased by 511, meaning 511 unique stop words were removed. Stemming was applied and the number of unique words without stop words decreased from 2774 to 2185 meaning that 589 words were combined into words with a similar root. An example can be the words “feel” and “feels”, where the word “feels” loses the “s” with stemming and combines with the word “feel”. The athletic shoe data saw a similar decrease as the number of words decreased from 110500 to 40342 after stop words were removed, simultaneously decreasing the number of unique words by 581. Stemming was applied to the remaining words, causing the number of unique words to drop from 4812 to 3651 as 1161 words were combined into words with a similar root. The top 25 most frequent words for both datasets can be seen in Figures 2 and 3.

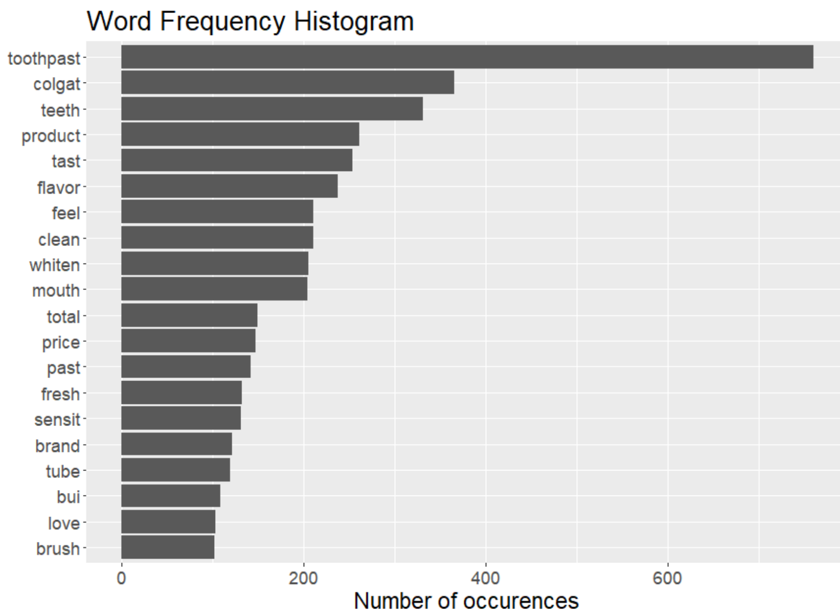

Figure 2 Toothpaste Data Word Frequency Histogram After Stemming

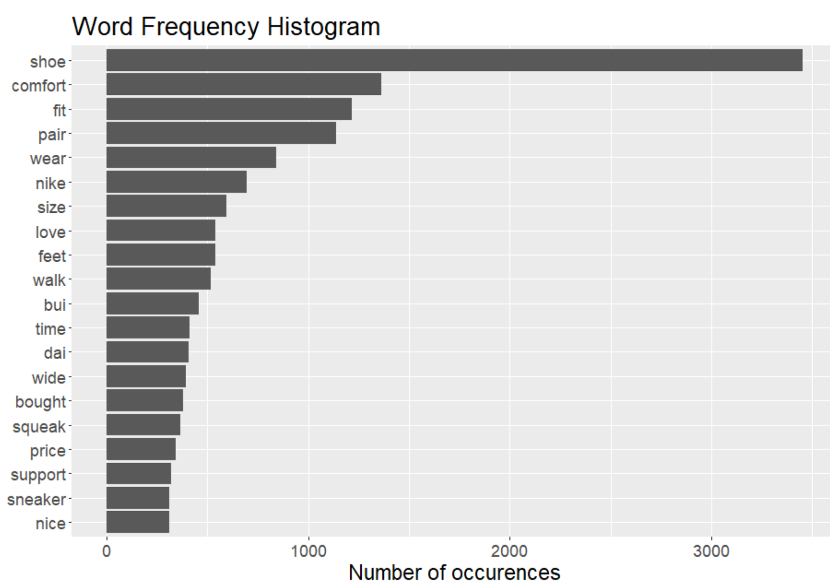

Figure 3 Athletic Shoe Data Word Frequency Histogram After Stemming

In Figure 2, with the data being stemmed and cleaned, the most relevant words can be seen in the visualization. The word “toothpast” is the most frequent word in the reviews with more than 700 occurrences but it is not informative. Although the dataset contains a small number of reviews, word occurrences over 200 still give a lot of information. Words such as “tast”, “flavor”, “feel”, “whiten” are very informative about the consumers’ experience and issues with the product. In Figure 3, the top 25 most frequent words for the athletic shoes can be observed. Similar to the word “toothpast”, the most frequent word in the athletic shoe dataset is also highly uninformative as it is “shoe”. Both words are removed for further analysis to take place. With a larger dataset than the toothpaste data, yet still relatively small, words that occur over 1000 times give an informative view of what the consumers talk about. Words such as “comfort” and “fit” demonstrates how consumers value their comfort and care about the shoes fit to their feet.

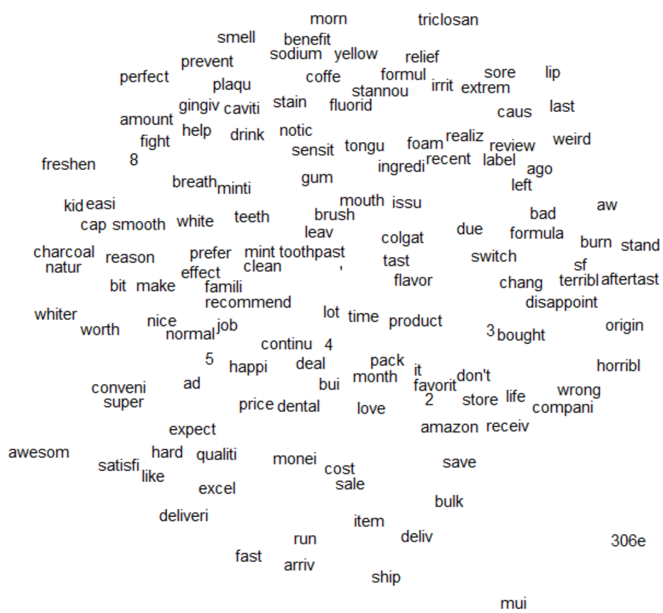

Figure 4 MDS Map for Toothpaste Data

To look at the reviews even more in depth, Multidimensional Scaling plots were created to see how the words co-occur together in the reviews. In Figure 4, the MDS map of the toothpaste data can be observed. Here, the words are placed according to how much they occur together in reviews and even according to how close they are in a text. Words that are placed closer to each other on the map are words that have a high co-occurrence in reviews. This allows a more insightful look into the data. On the middle right side, words such as “bad”, “formula”, “change”, “switch”, “terrible”, “aftertaste”, “disappoint” occur as stemmed and very close to each other.

From this, it can be stated that the formula of the toothpaste was changed and it gave a terrible aftertaste to the disappointed consumer. In the middle part, words and numbers such as “deal”, “pack”, “4”, “buy”, “price” can be seen clustered together. This can be interpreted as the 4-pack deal in which the toothpaste is sold in.

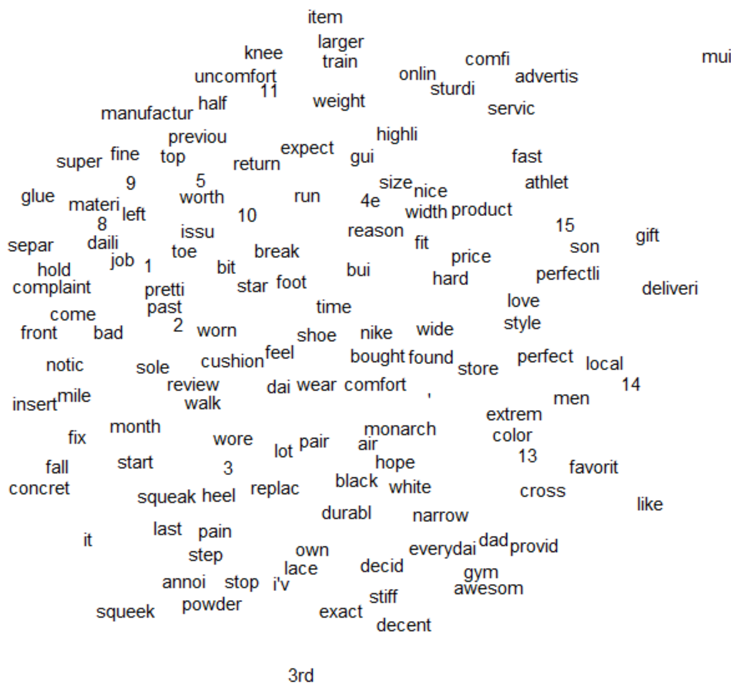

Figure 5 MDS Map for Athletic Shoe Data

In Figure 5, the MDS map for the athletic shoe data can be observed. On the bottom left side, words such as “squeak”, “annoy”, “step”, “heel” can be seen close to each other. From this, it can be stated that the heel part of the shoe makes annoying squeaky noises. On the bottom right part of the map words such as “black”, “white”, “durable”, “narrow”, “own”, “lace”, “decide” occur. These words give information of the colors of the shoe, how one might use their own laces, and the shoes aspects being narrow and durable.

4 Methods

In this section the methods that are used in the research are introduced. Besides this, how the methods are integrated to the research is also explained. Firstly, Latent Dirichlet Allocation (LDA) is introduced as the main topic modelling method. After this, in order to answer the hypotheses that were developed throughout the Theoretical Framework, generalized linear model is defined.

4.1 Latent Dirichlet Allocation (LDA)

To identify the topics within the corpus Latent Dirichlet Allocation (LDA) was selected among the topic modelling methods. Before getting into LDA, some basic notations and terminology must be introduced, allowing the method to be easily followed. Although these terminologies were mentioned in the Data section, a precise definition of them will be given. According to Blei, Ng & Jordan (2003);

- A *word* is the basic unit of discrete data, defined to be an item from a vocabulary indexed by {1, …, *V}*.
- A *document* is a sequence of *N* words denoted by **w** = (w_1, w_2, …, w_N), where w_n is the *n*th word in a sequence.
- A topic is a distribution over a fixed vocabulary of terms.
- A *corpus* is a collection of *M* documents denoted by *D* = {$\boldsymbol{w}_1$, $\boldsymbol{w}_2$, …, $\boldsymbol{w}_N$}.

Now that the terminologies are clear, LDA can be explained. According to Blei (2003), "LDA is a generative probabilistic model of a corpus. The basic idea is that, documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words." Mixture models need to be considered in order to capture the exchangeability of both words and documents. LDA is applied in areas like information retrieval and text category for its flexibilities and completeness (Xu, 2013). In this study, LDA is used to find topics within the online product reviews of a toothpaste and an athletic shoe. "In LDA, the observed data are the words of each document and the hidden variables represent the latent topical structure, i.e., the topics themselves and how each document exhibits them" (Blei, 2009). That being said, Blei (2009), states that LDA assumes the following for each document **w** in a corpus *D*:

1. For each topic,
    a) Draw a distribution over words $\vec{\beta}_k$ ~ Dir_K(η).
2. For each document,
    a) Draw a vector of topic proportions $\vec{\theta}_d$ ~ $Dir_V(\vec{a})$.
    b) For each word,
        i. Draw a topic assignment $Z_{d,n}$ ~ Mult($\vec{\theta}_d$), $Z_{d,n} \in \{1, \ldots, K\}$.
        ii. Draw a word $W_{d,n}$~ Mult($\vec{\beta}_{Z,d,n}$), $W_{d,n} \in \{1, \ldots, Z\}$.

Initially, the number of topics associated within a document is assumed a priori and is denoted with *K*. These *K* topics are associated with a collection, and that each document exhibits these topics with different proportions (Blei, 2009). According to Blei's (2009) notations *K* is the specified number of topics, *V* is the size of the vocabulary, ergo the number of words, $\vec{a}$ is a positive *K*-vector and η a scalar. Although Blei's 2003 research showed the distribution of words with a Poisson distribution, it was suggested that Poisson isn't really necessary and it converted into Dirichlet in the 2009 research. That being said, the $Dir_V(\vec{a})$ denotes a *V*-dimensional Dirichlet with vector parameter $\vec{a}$, whereas Dir_K(η) denotes a *K*-dimensional symmetric Dirichlet with scalar parameter η (Blei, 2009). The Dirichlet distribution is an exponential family distribution over the simplex of positive vectors that sum to one (Blei, 2009). The Dirichlet has the probability density:

$$p(\theta|\vec{a}) = \frac{\Gamma\left(\sum_i a_i\right)}{\prod_i \Gamma(a_i)} \prod_i \theta_i^{a_i - 1} \tag{1.1}$$

where the parameter a is a k-vector with components $a_i > 0$, and $\Gamma(x)$ is the Gamma function, a function that can be thought of as a real-valued extension of the factorial function (Blei, 2009). A better representation for LDA can be found in Figure 6.

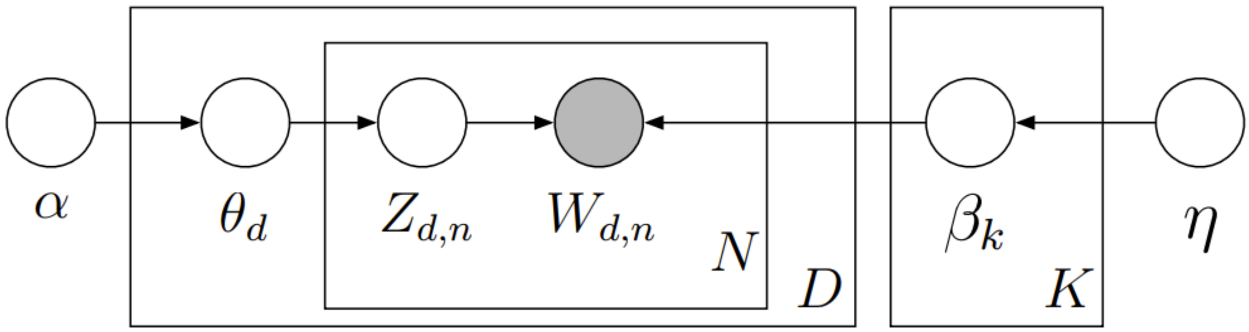

Figure 6 Graphical Model Representation of LDA

Here, the nodes denote random variables, the shaded node ($W_{d,n}$) denotes observed random variables, the unshaded nodes denote hidden random variables and the rectangles denote replication (Blei, 2009). The hidden random variables, in this case, are the topics $\vec{\beta}_{1:K}$, the per-document topic proportions $\vec{\theta}_{1:D}$, and lastly the per-word topic assignments $Z_{1:D,1:N}$ (Blei, 2009). These allow the documents to contain more than one topics. Similar to this, some terms may be placed under different topics due to the soft-clustering aspect of LDA. Basically, a word in the end is generated by one single topic, but a term can correspond to multiple topics. Blei (2009) adds that the hidden topic decomposition of a particular corpus arises from the corresponding *posterior distribution* of the hidden variables given the *D* observed documents $\vec{w}_{1:D}$,

$$(1.2)\ \ p\left(\vec{\theta}_{1:D}, Z_{1:D,1:N}, \vec{\beta}_{1:K} \,\middle|\, \vec{w}_{1:D}, \alpha, \eta\right) = \frac{p\left(\vec{\theta}_{1:D}, Z_{1:D,1:N}, \vec{\beta}_{1:K} \,\middle|\, \vec{w}_{1:D}, \alpha, \eta\right)}{\int_{\vec{\beta}_{1:K}} \int_{\vec{\theta}_{1:D}} \sum_{\vec{Z}} p\left(\vec{\theta}_{1:D}, Z_{1:D,1:N}, \vec{\beta}_{1:K} \,\middle|\, \vec{w}_{1:D}, \alpha, \eta\right)}$$

This process above is the generative process of LDA and the posterior can be thought of as the reverse of this process. In generative form the probability distribution generates the topic probabilities which generates the topics and then generates words. However, in the estimation process, the words are the only thing that is observed, this is the cleaned data that was obtained, and the topics are the things that is estimated. As an estimation technique Gibbs sampling is used. Gibbs sampling is a form of Markov chain Monte Carlo, which is easy to implement and provides a relatively efficient method of extracting a set of topics from a large corpus (Stevyers, 2006). Stevyers (2006) explained how the sampling occurs as follows; “Gibbs sampling simulates a high-dimensional distribution by sampling on lower-dimensional subsets of variables where each subset is conditioned on the value of all others. The sampling is done sequentially and proceeds until the sampled values approximate the target distribution." As it stands, in this study Gibbs sampling is used to obtain an approximate distribution of the topic scores.

4.2 Logistic Regression

Logistic regression is used to see how the topics found previously, in the above mentioned method, effect the ratings. In this model, the dependent variable falls into one of two categories. This could be yes or no, high or low, and such. Instead of modeling Y directly, logistic regression models the probability that Y belongs to one of the two categories (James, 2015). $p(X)$ is modeled to give outputs between 0 and 1 for all values of X. Hence, the logistic function is as such:

$$p(X) = \frac{e^{\beta_0 + \beta_1 X_1}}{1 + e^{\beta_0 + \beta_1 X_1}} \tag{2.1}$$

For low X values, the right hand side of the equation is always close to, but never below zero, meaning it will always have very small probabilities. The same goes for high X values as it will never be above one, yet always close to it. As a result, this function produces a S-shaped curve from 0 to 1, including both numbers. After manipulation to the equation (2.1), it is established that:

$$\frac{p(X)}{1-p(X)} = e^{\beta_0 + \beta_1 X_1} \tag{2.2}$$

The left hand-side of the equation is called the "odds" and can take on any value between 0 and ∞ (James, 2015). When the odds values are close to zero they indicate very low probabilities of the desired outcome of the dependent variable occurring, whereas when the odds values are close to infinity, this indicates very high probabilities of the desired outcome of the dependent variable occurring. After taking the logarithm of both sides, the following is obtained:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X_1 \tag{2.3}$$

The left hand-side of the equation is what is known as logit or log-odds. It can be observed that the logistic regression model in (2.1) has a logit that is linear in X (James, 2015). In this model, increasing X by one unit changes the log-odds by β_1, or equivalently, it multiplies the odds by

e^{β_1} (James, 2015). Since the relationship between $p(X)$ and X isn't a straight line, β_1 does not correspond to the change in $p(X)$ associated with a one-unit increase in X (James, 2015). James (2015) also states that how much $p(X)$ changes, due to a one-unit increase in X depends on the current value of X. If β_1 is positive, increasing X will be associated with increasing $p(X)$. Likewise, if β_1 is negative, then increasing X will be associated with decreasing $p(X)$. The coefficients β_0 and β_1 in (2.1) are unknown and must be estimated based on the available training data, hence maximum likelihood is used to estimate β_0 and β_1 such that the predicted probability $\hat{p}(x_i)$ of high and low ratings, using (2.1), corresponds as closely as possible to the reviews' observed rating (James, 2015). In other words, we try to find β_0 and β_1 such that plugging these estimates into the model for $p(X)$, given in (2.1), yields a number close to one for all reviews which has high ratings, and a number close to zero for all reviews which don't (James, 2015).

5 Results

5.1 Toothpaste Data

It is important to note that the topics found and labelled in this section are based on the authors inference based on the previous research done on hedonic and utilitarian values. The first task is to identify the number of topics. Before the first task, both datasets are split into 80% training and 20% validation data and use perplexity to measure the performance. Perplexity is a measure of how easy a probability distribution is to predict (Mcaffrey, 2016). According to Blei (2003), perplexity is algebraically equivalent to the inverse of the geometric mean per-word likelihood. A lower perplexity score indicates better generalization performance (Blei, 2003). To test the performance, the number of topics were tested from 10 to 50 in a sequence of 5 topics (10, 15, 20, …, 50) and in a sequence of 2 topics (10, 12, 14, …, 50). The better performing model, the model with the lowest perplexity would be selected. These numbers were selected to prevent overfitting. For a sequence of 5 topics, the optimal number of topics were found to be 15 with the validation perplexity resulted with 450.214. However, testing the number of topics in a sequence of 2 resulted with 16 topics and a validation perplexity of 445.3581. Thus 16 topics were selected as the validation data, the data used to give an estimate of the model fit, performed the lowest perplexity at that point (Figure 7).

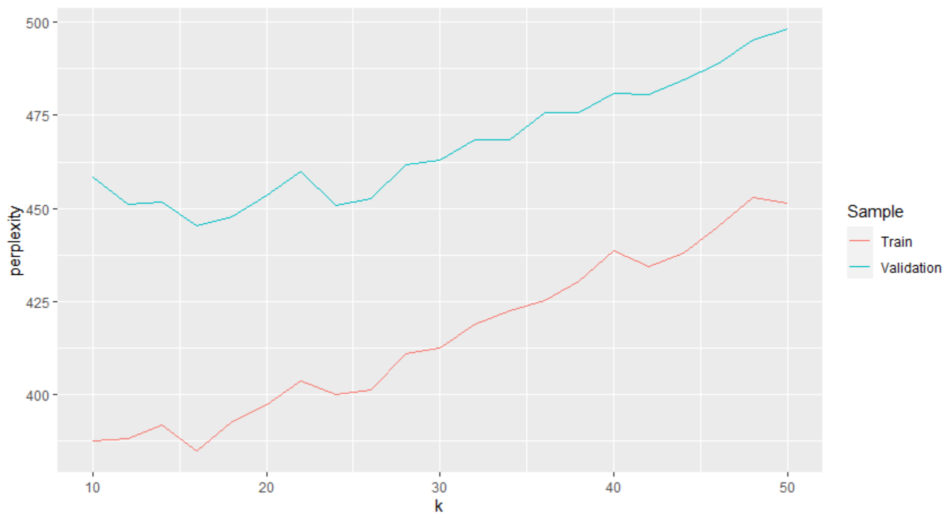

Figure 7 Toothpaste Data Number of Topics

After knowing the number of topics the topic sparsity is estimated. According to Naushan (2020), the α parameter will specify prior beliefs about topic sparsity and uniformity. A high α value assumes that documents are assumed to contain more topics. Essentially, this means that each document is likely to contain a mix of many topics and not a single topic specifically. Conversely, a low α value assumes that a document will contain a mixture of just a few or a single topic. When the value of α decreases, sparsity increases such that, when the distribution is sampled, most values will be zero or close to zero (Naushan, 2020). Gibbs sampling doesn't estimate the α and it is done by hand. The following result, shown below in Figure 8, shows the perplexity to the α value. Here the lowest value is at 0.2 and hence 0.2 is selected as the α.

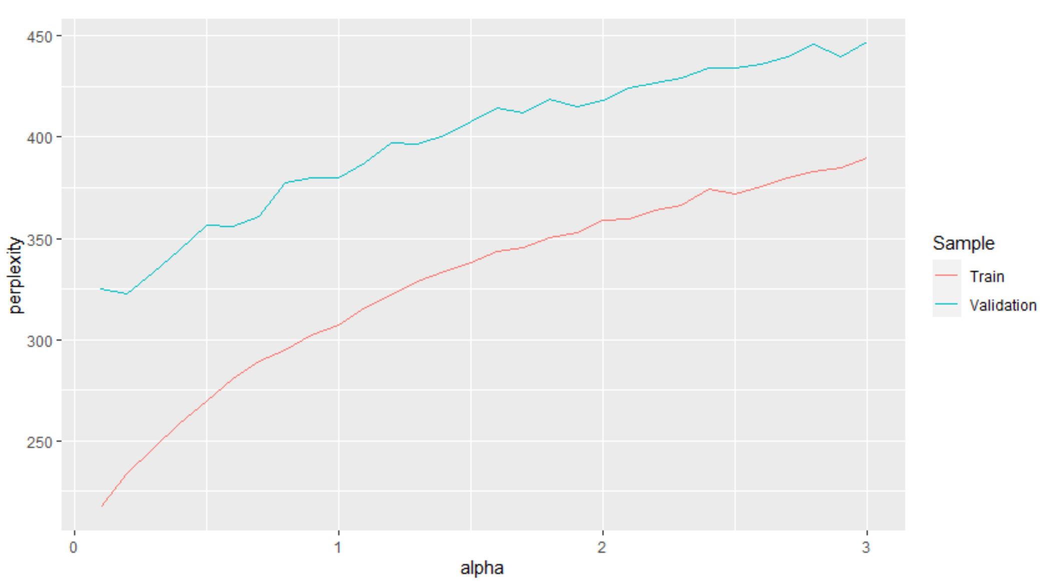

Figure 8 Toothpaste Data Alpha Prior

A brief summary of all the 16 topics found can be seen in Table 2 below. The topics have been re-ordered so that it is clear, leading to the first 8 topics being the hedonic topics and the remaining 8 comprising of utilitarian topics. An in-depth look into all the topics, and how they were labeled and classified can be found in sections 5.1.1 and 5.1.2.

Toothpaste Data Topics Summary					
Topic #	**Name**	**Class**	**Topic #**	**Name**	**Class**
Topic 1	Recommendation	Hedonic	Topic 9	Problems	Utilitarian
Topic 2	Change in Formula	Hedonic	Topic 10	Whitening	Utilitarian
Topic 3	Freshness	Hedonic	Topic 11	Product Price	Utilitarian
Topic 4	Preference	Hedonic	Topic 12	Packaging	Utilitarian
Topic 5	Long Lasting Effect	Hedonic	Topic 13	Product Box	Utilitarian
Topic 6	Minty Flavor	Hedonic	Topic 14	Protection	Utilitarian
Topic 7	Deal	Hedonic	Topic 15	Cleaning	Utilitarian
Topic 8	Improvements	Hedonic	Topic 16	Removal of Triclosan	Utilitarian

Table 2 Toothpaste Data Topics Summary

5.1.1 Hedonic Topics

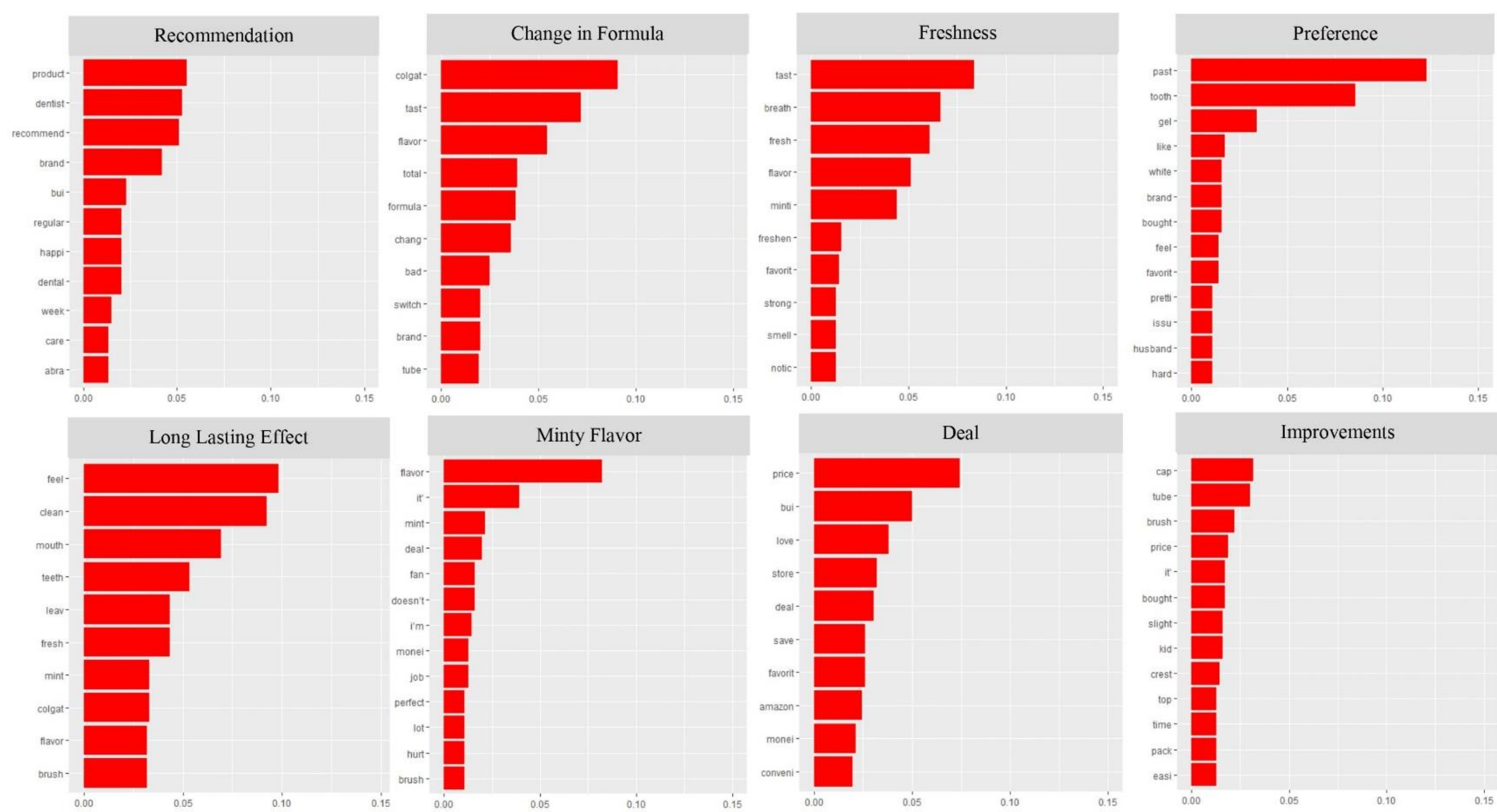

Figure 9 Toothpaste Data Hedonic Topics

With the number of topics selected (k=16) and the alpha value (α=0.2) chosen, topic modeling is performed. Figure 9 shows the first 8 topics, which represent the hedonic topics. Under each topic a bar graph of probabilities for each and every term is shown. These terms are sorted from highest probability to lowest. Starting off with the first topic, recommendation, a brief search of the terms was done in order to see the true picture. Following this, within the reviews, the terms “recommend”, “brand”, “product”, “dentist”, “dental” revealed that this topic is about dentists recommending the product/ the brand to the consumers. This led to the topic to be labeled as “Recommendation”. Research suggests that, consulting with salesperson increases the enjoyment of the shopping process for consumers (Haas, 2014). In line with this, Pöyry (2012) found that hedonic information search is positively related to eWOM usefulness, in which, hedonic information search leads a consumer to content that is perceived useful. In the case of a toothpaste, an expert’s, a dentist’s, opinion can be more trustworthy than a salesperson or electronic word-of-mouth. On the grounds of these research, a dentist’s recommendation can enhance a consumers shopping experience much like consultation with a salesperson and eWOM, the topic can hence be classified as hedonic. In the second topic, change in formula, the stemmed terms “tast”, “flavor”, “formula”, “chang”, “bad”, “switch” indicate that the toothpastes’ formula has been changed. This resulted in the change of the flavor as well, which ultimately left bad taste in the mouth. This clearly distinct topic is thus labeled as “Change in Formula” and can be marked as hedonic due to its effects on consumers’ sensory attributes. The third topic, labeled freshness, contains the terms “tast”, “breath”, “fresh”, “flavor” and “freshen”. This results from the sensation of freshness that occurs after cleaning one’s teeth and mouth. As freshness is a feeling and sensation that is felt by the consumer this topic is categorized as hedonic. The fourth topic, preference, is labeled due to the terms “past”, “tooth”, “gel”, “favorit”, and “bought”. After a deeper look into the reviews, it is concluded that consumers have preferences over whether the texture is a gel or a paste. Since a paste is thicker than a gel a different sensation occurs in the mouth. That being said, the sensations caused by this preference leads this topic to be hedonic.

The fifth topic, long lasting effect, contains the terms “feel”, “clean”, “mouth”, “teeth”, “leav”, “fresh” and “brush” that help label the topic. The main idea of this topic is that after brushing their teeth, the consumer is left with a feeling of freshness and cleanness in their mouth for a long time. This topic is hence classified as hedonic for the feeling conveyed, rather than how good the product cleans or freshens. The topic “Minty flavor” gets its name mainly from the terms “flavor”, “mint”. Since identifying a flavor is done with the five senses, in this case the tongue, this topic is classified as hedonic because of its sensuous properties. The topic “deal” is named after the terms “price”, “bui”, “store”, “deal”, “money”, “conveni”. The Theoretical Framework section goes into detail on why a deal or a bargain is hedonic and won’t be repeated here. The last hedonic topic is “improvements”. After a brief search of the terms “cap”, “tube”, “top” and “easy”, it is revealed that the cap (lid) of the tube has changed as it was a screw-on model previously, only to be a flip model in which the cap is intact with the tube, making it easier to open and close. This new and improved version led to the name “improvements”.

5.2.2 Utilitarian Topics

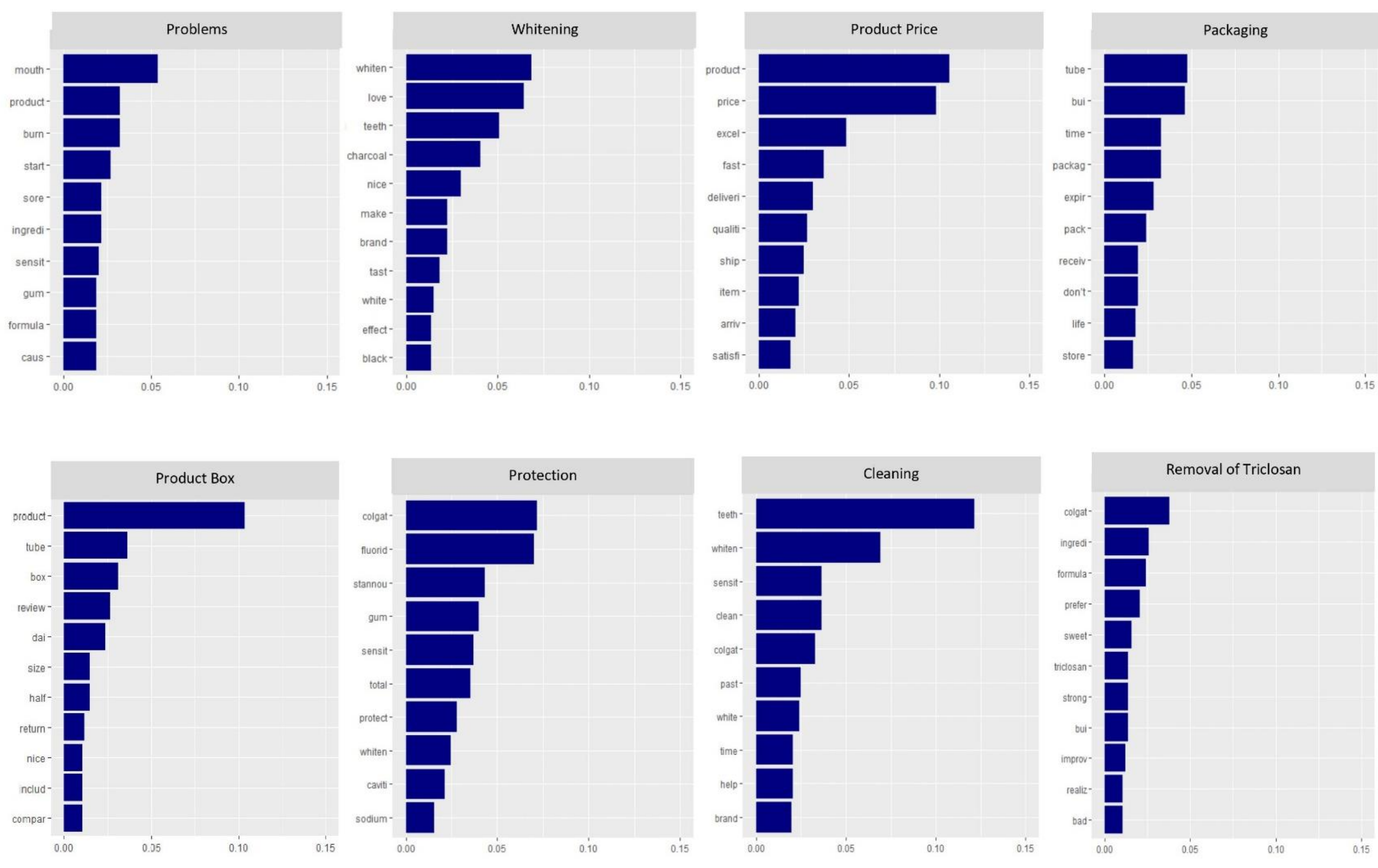

Figure 10 Toothpaste Data Utilitarian Topics

Figure 10 shows the remaining 8 topics, which are classified as utilitarian. The first topic, “Problems”, brings up the issues that the consumers have dealt with after using the product.

From the terms, “mouth”, “burn”, “start”, “sore”, “sensit”, “gum” and “caus”, problems relating to the mouth can be concluded. The gums face soreness and a burning sensation that was caused by the product. With this in mind, the topic is labeled “Problems” and is considered utilitarian due to the harmful and problematic (Voss et al., 2003) nature of the experience. The topic “Whitening” is labeled after the terms “charcoal”, “white”, “whiten”, “teeth”, “effect”. The term charcoal, referring to the charcoal powder, is part of the ingredients used in the toothpaste. Additionally, this powder is used for teeth whitening and the term “whiten” in the topic confirms this. With all the information in mind, this topic can be labeled as “Whitening” and can be classified as utilitarian, which was supported by Baltas’ (2016) work. The next topic, “Product price”, is labeled after the top two terms “product” and “price”. That being said, the other terms in the topic suggests fast shipment/delivery which leads to the same reasoning that utilitarian aspects are associated with efficiency. Hence the topic is classified as utilitarian. The following topic, “Packaging” has the terms “tube”, “time”, “packag”, “expir”, “pack”. Since the information that is displayed on the package, the expiration date/time, does not correspond to any sensation and in fact contains a lot of practical and helpful (Voss et al., 2003) information, it can be acknowledged that it is utilitarian. The subsequent topic, “Product box” contains the terms “product”, “tube”, “box”, “size”, “half”, “includ”, “compar”. Although it is similar to the previous topic, these terms refer to the box size rather than its packaging. This could be seen in the terms “box”, “size” and “half”. Additionally, the term “compar” could indicate that the box size decreased by half compared to the older model. All in all, this topic is categorized as utilitarian due to the functional and efficient (Voss et al., 2003) aspects of a smaller box size.

The sixth topic contains the terms “fluorid”, “stannous”, “tast”, “protect”, “caviti”, “total”, “gum”, “sodium” and “sensit”. From these terms, the naming for this topic can be derived as “Protection” due to the following reasons: Firstly, stannous fluoride is an anti-bacterial agent that’s clinically proven to be protective against gingivitis, plaque and tooth sensitivity (Crest, 2021; Biesbrock, 2019). Following this, protection against cavities and gum protection are also mentioned among the terms, backing up the naming process. This topic is considered as utilitarian due to one of the main functions of toothpaste is that it provides protection. Second to last, the topic “Cleaning” features terms such as “teeth”, “sensit”, “whiten”, “clean”, “help”. These terms are in line with the cleaning aspect of the toothpaste. Sensitive gums, stainless teeth and a clean breath can be examples for how these terms were used. Thus the label for this topic is

“Cleaning” and the topic is classified as utilitarian due to the helpful, effective and functional (Voss et al., 2003) aspects shown by the cleaning ability of the toothpaste. The last topic has quite compelling terms and after research its concluded that the topic should be labeled “Removal of Triclosan”. After researching the terms “ingredie”, “formula”, “triclosan”, “realiz”, “bad”, these terms can be connected to the fact that triclosan is an ingredient that leads to cancer (Dinwiddie, 2014) and was removed from the product. Since removing triclosan is healthier, this can be considered an improvement to the product. According to Voss et al. (2003), helpful and beneficial actions are considered utilitarian and hence this topic is considered utilitarian.

5.2 Athletic Shoe Data

Similar to the previous data, the data for athletic shoes is split into 80% training and 20% validation datasets. Once more, perplexity is used to measure the performance. Similar to the previous data, in order to prevent over-fitting, the number of topics were tested from 10 to 50 in a sequence of 5 topics (10, 15, 20, …, 50) and a sequence of 2 topics (10, 12, 14, …, 50). The better performing model was the sequence of 5 topics. This resulted in the selection of k=20 topics, with the validation perplexity of 365.7179. This could be seen in Figure 11, where the validation perplexity is at its lowest.

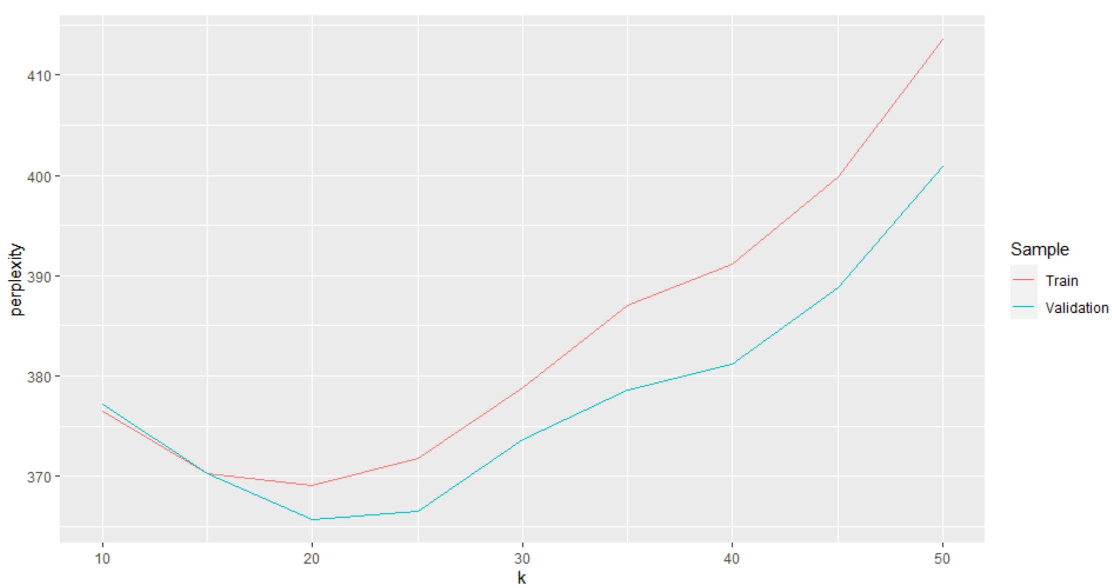

Figure 11 Athletic Shoe Data Number of Topics

The number of topics, k=20, helps find the topic sparsity. Just like in the previous data, topic sparsity is estimated by the Gibbs implementation, and is done manually. In Figure 12, the perplexity values of the α can be seen, and α is lowest at 0.1 with a validation perplexity of 253.5744.

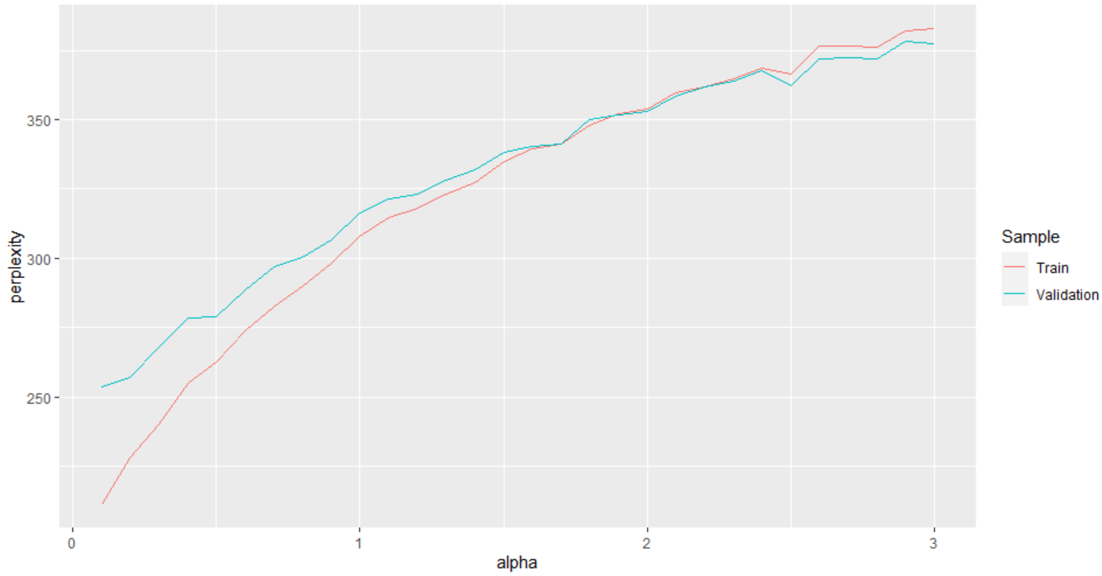

Figure 12 Athletic Shoe Data Alpha Prior

A brief summary of all the 20 topics found can be seen in Table 3 below. The topics have been re-ordered so that it is clear, leading to the first 10 topics being the hedonic topics and the remaining 10 comprising of utilitarian topics. An in-depth look into all the topics, and how they were labeled and classified can be found in sections 5.2.1 and 5.2.2.

Athletic Shoe Topics Summary					
Topic #	**Name**	**Class**	**Topic #**	**Name**	**Class**
Topic 1	Comfort	Hedonic	Topic 11	Amazon Purchase	Utilitarian
Topic 2	Squeak	Hedonic	Topic 12	Replacement Pair	Utilitarian
Topic 3	Colors	Hedonic	Topic 13	Size	Utilitarian
Topic 4	Recommendation	Hedonic	Topic 14	Leather Quality	Utilitarian
Topic 5	Tennis Shoe	Hedonic	Topic 15	Durability	Utilitarian
Topic 6	Gift	Hedonic	Topic 16	Fit	Utilitarian
Topic 7	Cross Trainer	Hedonic	Topic 17	Sole Issue	Utilitarian
Topic 8	Light Feel	Hedonic	Topic 18	Fast Delivery	Utilitarian
Topic 9	Support	Hedonic	Topic 19	Wideness	Utilitarian
Topic 10	Daily Walk	Hedonic	Topic 20	Toe Problem	Utilitarian

Table 3 Athletic Shoe Topics Summary

5.2.1 Hedonic Topics

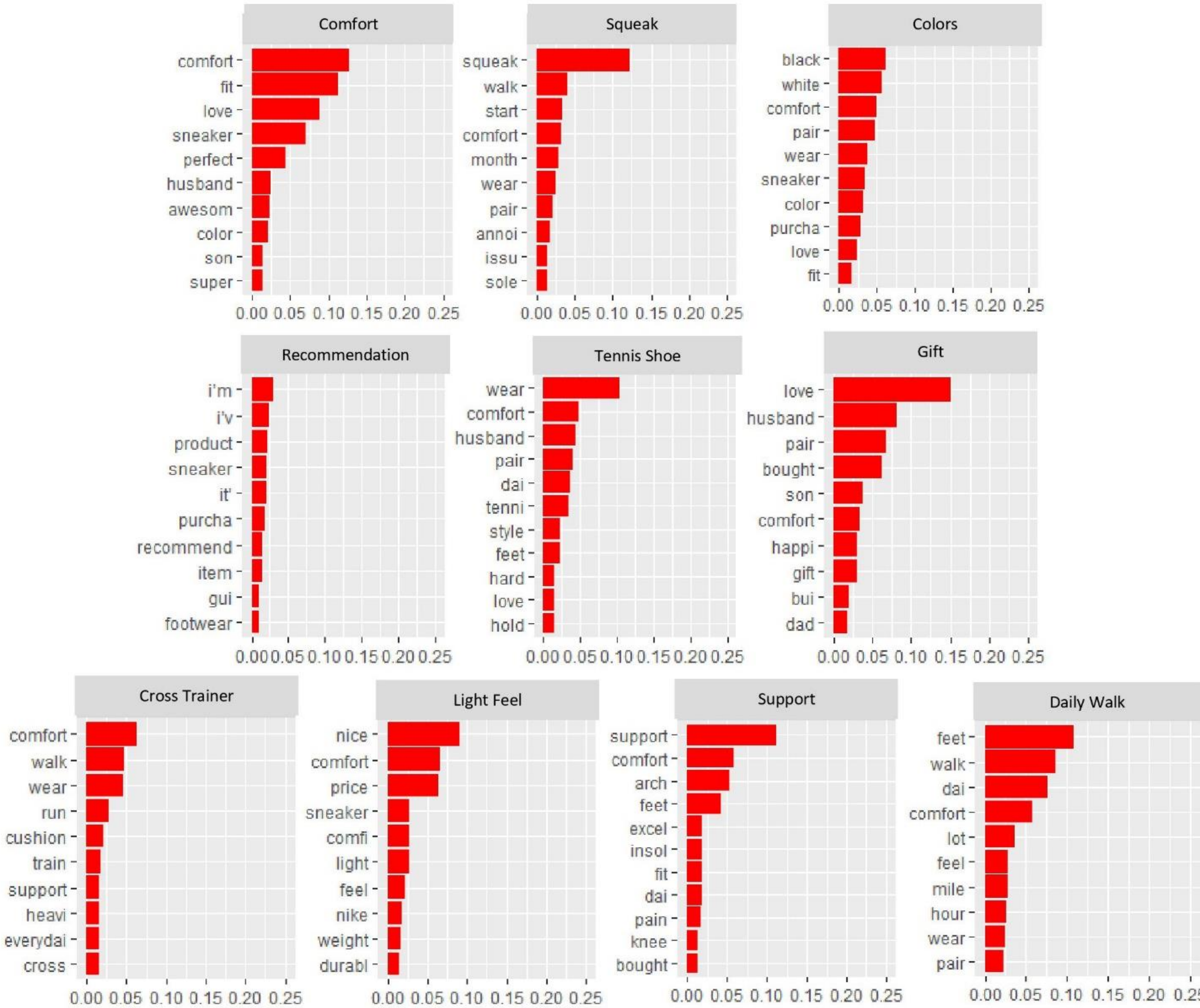

Figure 13 Athletic Shoe Data Hedonic Topics

The Latent Dirichlet Allocation was performed after the number of topics (k=20) and the alpha value (α=0.1) were found. In the first topic, the terms “comfort”, “fit” describe how well the shoe fits and how comfortable it is. According to Merriam-Webster’s (2021) definition, comfort, when used as a noun, is described as a satisfying or enjoyable experience. That being said, this topic is labeled “Comfort” and is classified as hedonic due to Voss et al. (2003) classifying enjoyment as hedonic as well. The second topic contains terms such as “squeak”, “walk”, “start”, “annoi” that expresses the consumers discomfort towards a squeaking noise. Thus, this topic is named as “Squeak” and due to the feeling of annoyance this topic is categorized as hedonic. The third topic, “colors”, the most outstanding terms are “black”, “white”, and “color”. These terms support the idea that the topic is about “Colors”. Additionally, Hirschmann (1982), confirms the categorization of colors as hedonic based on colors being a part of multisensory images.

Similar to the first topic of the toothpaste data, the fourth hedonic topic of the athletic shoe is also labeled “Recommendation”. However, only the terms “recommendation” and “gui” can be considered insightful. In addition to the initial reasoning behind recommendation being hedonic described in 5.1.1, “gui”, being the stemmed version of guilt, supports Okada’s (2005) study that hedonic purchases contain a sense of guilt. Thus, the topic is categorized as hedonic. The fifth topic includes the terms “wear”, “comfort”, “dai”, “tenni” and “style” and hence the topic is labeled as “Tennis Shoe”. Likewise, it is categorized as hedonic because of its contribution as a leisure activity, in addition to Voss et al.’s (2003) classification of fun and enjoyment aspects as hedonic. For the sixth topic, it is required to look at one specific term and build around it. It encases vague terms such as “love” and “happi” but also terms that convey a family, such as “husband”, “son” and “dad”. Lastly, the term “gift” is the main focus of this topic as it can be concluded that the pair of shoes were a gift for the family. Thus, the topic is labeled as “Gift” and is categorized as hedonic, based on Okada’s (2005) explanation of hedonic consumption and how gift giving is a part of this.

The last row of Figure 13 starts with the topic “Cross Trainer”. Similar to the “Tennis Shoe” topic, this topic is about the shoe is used for a leisure activity, that is cross training and is categorized as hedonic. This is inferred in the terms “walk”, “run”, “train”, “cross” and “everyday” as activities such as walking, running is done in some cross training exercises. The topic “Light Feel” is labeled after the terms “sneaker”, “light”, “feel” and “weight”. Although the shoe having light weight may seem like a utilitarian trait, the terms “comfort” and “comfi” support the idea that the shoe feels light rather than it is light weight. Ergo, the sensuous feel of lightness makes this topic hedonic. The penultimate hedonic topic is about “Support” based on the terms “support”, “comfort”, “arch”, “feet”, “insol”, “knee”, “pain”. The support the shoe provides for the feet is concluded to be not enough, as the term “pain” gives us insight of how the consumer feels. Likewise, the arch and insole are parts of a shoe and are mentioned due to lack of support in those parts. That being said, the topic “Support” is classified as hedonic. Lastly, the last hedonic topic has the terms “dai”, “walk”, “wear”, “lot”, “hour”, “mile”, “feet”.

These terms can be summed up as a “Daily walk”, where the consumer wears the shoes a lot, hours even, mile after mile. Hence, this leisure activity categorizes the topic as hedonic just like the previous leisure activities.

5.2.2 Utilitarian Topics

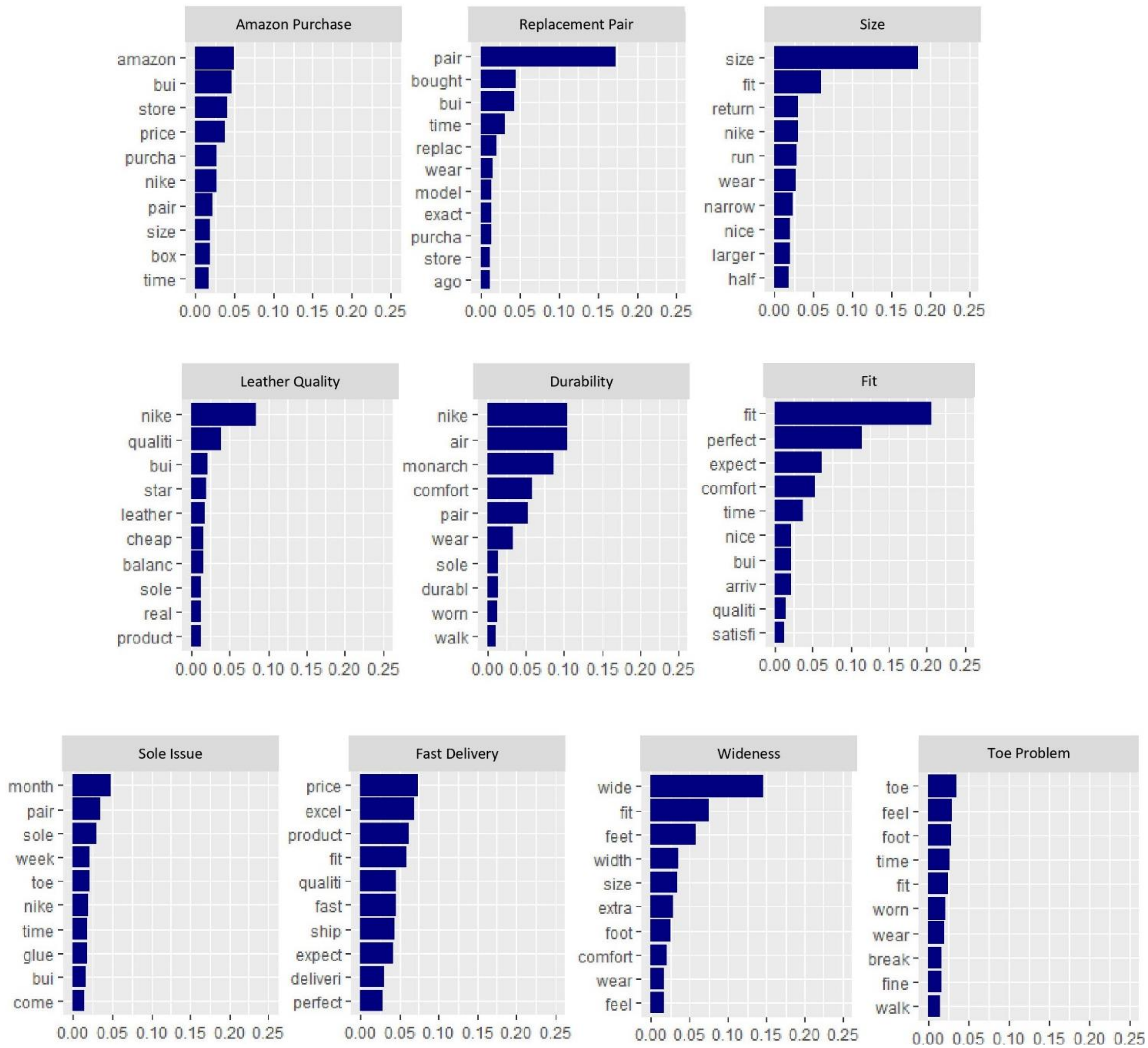

Figure 14 Athletic Shoe Data Utilitarian Topics

Figure 14 showcases the 10 utilitarian topics found. The first topic has very informative terms such as “amazon”, “store”, “price”, “purcha”, “bui” and “time”. It being self-explanatory, the topic is labeled “Amazon Purchase” and is classified as utilitarian. This is supported by the term “time” as it depicts efficiency as discussed by Babin et al. (1994) in the theoretical framework section. The second topic contains the terms “pair”, “bought”, “wear”, “time”, “replac”, “exact”, “model” and “ago”. A sentence comprised of all the mentioned terms would talk about how a pair that was bought, got wear and tear over time and is in need of a replacement. Additionally, it can be concluded that some consumers have bought the exact same pair a long time ago, hence the terms “exact”, “model”, “ago”. That being said, a suitable name for this topic is “Replacement” and is classified as utilitarian on the basis of practicality and functionality (Voss et al., 2003). The last topic of the first row is labeled as “Size” according to the terms “size”, “half”, “larger”, “fit”, “narrow”. Since the size of a shoe can vary as narrow, wide, and by number, this is part of its functionality and handiness. These two aspects are considered as utilitarian according to Voss et al. (2003), hence this topic is categorized as utilitarian.

The fourth topic is named as “Leather Quality” based on the terms “leather”, “cheap”, “real”, “qualiti”. These terms addresses whether the shoes leather is real or a cheap knock-off. The material of the shoe is instrumental and of utmost function as it forms the quality and determines the wear and tear as well as any water resistance. These attributes make the topic utilitarian. The fifth topic includes the name of the shoe model within the terms (“Nike Air Monarch”) as well as a key term such as “durabl”. Durability is a very important aspect of a shoe as it determines how long the shoe can be worn. The label is hence labeled as “Durability” and is classified as utilitarian because of its helpful, effective, and functional properties (Voss et al., 2003). The last topic of this row, “Fit”, encompasses the terms “fit”, “perfect”, “expect”, “comfort”, “qualiti”, “satisfi”. How well a shoe “fits” is beneficial (Voss et al., 2003) for the consumer, otherwise the consumer may have to return the product, get a different shoe size and go through all sorts of trouble. Hence, this topic is categorized as utilitarian.

The seventh topic of Figure 14 consists of the terms “month”, “pair”, “sole”, “week”, “time”, “glue”. It can be concluded that the sole of the shoe had some problems after only a month/week. Additionally, glue was needed to repair the shoe, stick it back into place. The problematic nature thus classifies this topic as utilitarian and the topic is named as “Sole issue”. Moving onto the next topic, “Fast Delivery” is named due to the terms “excel”, “fast”, “ship”, “expect”, “deliveri”. In the Theoretical Framework, the importance of efficiency was discussed under Utilitarian Values. Fast delivery is a prime example for fast and efficient task completion, hence is categorized as utilitarian. The second to last topic, “Wideness” contains the terms “wide”, “fit”, “feet”, “width”, “size” and “extra” are terms that lead to the conclusion that, the topic is about the “Wideness” of the shoe. In fact, the shoe itself has multiple different versions listed, under the size button on Amazon, which includes the option “wide”. Wide shoes differ from regular shoes as they are specially made for people with wide feet. This brings a functionality to the shoe as well as a necessity for people with wide feet. This feature lines up with Voss et al.’s (2003) initial scales and thus this topic is categorized as utilitarian. Lastly, the tenth utilitarian topic of the dataset contains the terms “toe”, “foot”, “wear”, “break”, “worn”, “walk”. After a brief search through the reviews, a problem with the inside of the shoe is apparent. This is supported by this topic as the inside, front, and top-part of the shoe seem to be of significance, merged with the term “wear” which might point to wear and tear. All of this combined with the term “toe” suggests that there is a problem with the toe area of the shoe and is labeled accordingly: “Toe Problem”. Much like Topic 7’s “Sole Issue”, this topic is categorized as utilitarian due the harmful and problematic (Voss et al., 2003) nature of the toe problem. This concludes the topics of both datasets, their labeling and categorization into hedonic and utilitarian values, the reasoning behind the naming and the categorization.

5.3 Regression Results

Logistic regression is done with the binary dependent variables being the rating being low or high (high=1, low=0) and the independent variables being the 16 topics for the toothpaste data and the 20 topics for the athletic shoe data. The regression was conducted for each of the products. The insignificant variables were removed from the model and the regression was conducted again until all of the variables were significant. The tables below show the findings of the final model for both products.

Class	Coefficients:	Estimate	Std. Error	Z Value	Pr (>|z|)	
	(Intercept)	2.8314	0.1879	15.072	< 2e-16	***
Utilitarian	Problems	-5.4172	1.1505	-4.709	2.49e-06	***
Hedonic	Change in Formula	-9.4925	0.9695	-9.791	<2e-16	***
Utilitarian	Packaging	-4.0840	1.0751	-3.799	0.000145	***
Significance codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05					AIC: 575.81	

Table 4 Toothpaste Data Logistic Regression Final Model

Table 4 contains the logistic regression results for the toothpaste data. For the intercept, the interpretation is that the probability of getting high ratings when all other variables are zero is

0.94. This means that if none of the topics are mentioned in a newly written review, then the probability of getting a high rating is 0.94. For the intercept, this is calculated with $e^{\beta}/(1 + e^{\beta})$. On the other hand, for a unit change in the topic "Problems", then the probability of getting higher ratings controlling for all the other variables would decrease by 99.55%. The unit mentioned here is the probability of that specific topic occurring in a review. A unit change, hence, would mean that the probability of the topic occurring in a review goes up by 1. This occurs if new and additional reviews contain that topic in them. The topic "Problems", is a utilitarian topic that is about the soreness and burning problems the consumers deal with, so if the probability of these problems being mentioned in a review goes up by 1, then that would lead to the probability of getting higher ratings to reduce by 99.55%. This number is found is by the formula e^{β} discussed in the Methods section for positive coefficients but 1-e^{β} for negative coefficients. The hedonic topic "Change in Formula", also has negative effect on the probability of getting higher ratings as a unit increase for the topic reduces the probability of getting high ratings by 99.99%. This means that if a consumer notices that the formula has changed and mentions it in the review, then it is almost guaranteed to have a lower rating. In the event of the company changing their formula once again and it being disliked by consumers has a high chance of not getting a high rating from the consumers. So they must make sure that the new formula has a better taste. The last significant variable, the utilitarian topic "Packaging" has a negative coefficient just like the other topics. Likewise, a unit increase decreases the probability of a higher rating by 98.31%. That being said, for the toothpaste data, the change in the formula has the highest impact on the probability of getting a higher rating, as it reduces it by 99.99%. This is followed by the soreness and burning problems and packaging respectively.

Class	Coefficients:	Estimate	Std. Error	Z Value	Pr (>|z|)	
	(Intercept)	-1.9941	0.2171	-9.185	< 2e-16	***
Utilitarian	Amazon Purchase	3.0612	0.5460	5.607	2.06e-08	***
Utilitarian	Replacement Pair	2.9541	0.5124	5.765	8.18e-09	***
Hedonic	Comfort	7.8486	0.9198	8.533	< 2e-16	***
Utilitarian	Size	1.3338	0.4128	3.231	0.00123	**

Hedonic	Colors	5.8713	0.7921	7.412	1.24e-13	***
Hedonic	Recommendation	3.1775	0.6784	4.684	2.82e-06	***
Hedonic	Tennis Shoe	6.7333	0.8159	8.253	<2e-16	***
Utilitarian	Durability	3.6880	0.5703	6.467	1.00e-10	***
Utilitarian	Fit	6.6580	0.7497	8.881	<2e-16	***
Hedonic	Gift	6.9742	0.8104	8.605	<2e-16	***
Hedonic	Cross Trainer	4.9891	0.6528	7.642	2.14e-14	***
Hedonic	Light Feel	5.7061	0.7481	7.627	2.40e-14	***
Utilitarian	Sole Issue	-1.3850	0.4620	-2.998	0.00272	**
Utilitarian	Fast Delivery	8.1057	0.9133	8.876	<2e-16	***
Utilitarian	Wideness	2.9250	0.4717	6.201	5.61e-10	***
Hedonic	Support	5.7207	0.7187	7.960	1.73e-15	***
Hedonic	Daily Walk	3.9953	0.5172	7.725	1.12e-14	***
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05					AIC: 2115.7	

Table 5 Athletic Shoe Data Logistic Regression Final Model

Table 5 shows the results for the logistic regression for the athletic shoe data. For the intercept, there is a negative coefficient and the interpretation is that the probability of getting high ratings when all other variables are zero is 0.11982. For a unit increase in the probability of the utilitarian topic "Amazon Purchase" being mentioned in a review, there is a 21.35 times greater likelihood of getting higher ratings controlling for all the other variables. This likelihood for the hedonic topic "Replacement Pair", there is a 19.18 times greater likelihood of getting higher ratings for a unit increase, controlled for all the other variables. For an increase of 1 unit of the probability of "Comfort" being mentioned in a review, the odds of high ratings are multiplied by 2562.62. The odds of high ratings are multiplied by 3.79, for the utilitarian topic "Size". There is a 35370% increase in the probability of getting higher ratings, or equivalently 354.70 times greater likelihood for every unit change in the hedonic topic "Colors". For the hedonic topic "Recommendation", there is a 23.98 greater likelihood of getting a higher rating for every unit increase in its probability. An increase of 1 unit for the "Tennis Shoe" topic, multiplies the odds of higher ratings by 839.91. For the utilitarian topic "Durability", an increase of one unit would multiply the odds of higher ratings by 39.96.

A unit increase in the topic "Fit", is associated with a 778.99 times greater likelihood of getting higher ratings, holding all variables constant. For the hedonic topic "Gift", an increase of 1 unit multiplies the odds of higher ratings by 1068.70. An increase of 1 unit for "Cross Trrainer", multiplies the odds of higher ratings by 146.80. For "Light Feel", there is a 300.69 times greater likelihood of getting a higher rating for every unit increase. For the utilitarian topic

“Sole Issue”, the coefficient is negative. This means that, when the unit increase by 1, then that would lead to the probability of getting higher ratings to reduce by 74.96%. The utilitarian topic “Fast Delivery”, has the highest impact on rating. There is a 3313.30 times greater likelihood of getting higher ratings for a unit increase, controlled for all the other variables. Subsequently, an increase of 1 unit, multiplies the odds ratio of higher ratings by 18.63 for the topic “Wideness”. The penultimate topic “Support”, has a 305.11 times greater likelihood of getting high ratings. Lastly, there is a 54.34 times greater likelihood of getting a higher rating for every unit increase in the topic “Daily Walk”. With these results in mind, it can be worked out that “Fast Delivery” has the highest impact on the probability of getting a higher rating, followed by “Comfort”, “Gift” and “Tennis Shoe” respectively.

The hypotheses that were formulated in the Theoretical Framework are tested. For the first hypothesis, a t-test was conducted between the hedonic scores of high ratings and low ratings and this resulted in a t-score of 1.1624 and a p-value of 0.2464 for the toothpaste data. Since the p-value is more than 0.05, the null hypothesis is failed to rejected, meaning there isn’t an association between hedonic scores and product ratings. For the athletic shoe data, this isn’t the case, as the t-score is -8.6257 and the p-value is 2.2e-16 and the hypothesis is rejected. This means that hedonic scores are associated with ratings. For the second hypothesis, a one-tailed t-test was conducted. For the toothpaste data the test resulted in a t-score of -1.1624 and a p-value of 0.8768, meaning we fail to reject the hypothesis. This means that utilitarian scores are associated with higher ratings. However, for the athletic shoe data this was not the case. With a t-score of 8.6257 and a p-value of 2.2e-16, the hypothesis was rejected. Meaning the utilitarian scores aren’t related to high ratings in the athletic shoe.

6 Conclusion

In this study, the goal was to see the effect of hedonic and utilitarian values on product ratings. First, these two concepts were introduced, followed by the product selection criteria. The products were selected based on their high hedonic and high utilitarian values to eliminate bias towards one of the two values. Following this selection, both products reviews and ratings were scraped from Amazon.com. To achieve this goal, topic modelling was applied to the reviews, resulting in 16 and 20 topics for the toothpaste and athletic shoe, respectively. After, a subjective classification of these topics into hedonic and utilitarian both of the products ended up having equal amount of hedonic and utilitarian topics. That is 8 hedonic and 8 utilitarian topics for the toothpaste and 10 hedonic and 10 utilitarian topics for the athletic shoe. Lastly, logistic regression was conducted using high and low ratings as the dependent variables and the topics as the independent variables. The effect on ratings were measured by an increase of one unit to the topic probability of the document. For the toothpaste data, 3 topics were found to be significant, with 2 of them being utilitarian and 1 of them hedonic. Additionally, all three topics' coefficients were negative. A hedonic topic, the change in the formula, had the highest impact by making the probability of getting a lower rating, higher. For the athletic shoe data, 17 topics were significant with 8 of them being utilitarian and 9 of them being hedonic. Based on these two datasets, it is safe to say that the total number of significant topics are equal in terms of being hedonic and utilitarian. In line with having more hedonic topics, the top 5 topics with the highest impact consists of 2 utilitarian topics and 3 hedonic topics for the athletic shoe data. Additionally, a utilitarian topic, fast delivery, had the highest impact on ratings. Thus, it can be concluded that, although there were more hedonic topics that were significant, the highest impact on ratings came from a utilitarian topic in the athletic shoe data. The first hypothesis tried to find if the hedonic scores are equally distributed between low and high ratings. For the toothpaste, the hypothesis was failed to rejected, thus meaning that there wasn't an association between hedonic scores and ratings. However, for the athletic shoe, hedonic scores were associated with high ratings as the null hypothesis was rejected. Finally, the second hypothesis tried to find if utilitarian scores were associated with high ratings, in which resulted with the toothpaste being associated with high ratings and the athletic shoe not being associated.

From a managerial standpoint, this study could help companies better understand what makes their products better rated. The results showed that, a utilitarian aspect caused the highest increase in the likelihood of high ratings. If companies focus on one aspect to increase user ratings, then it should be something that is utilitarian. However, it was also observed that quantity-wise, hedonic topics were more impactful in the top 5 topics. If companies want to improve the rating of their products by implementing multiple improving changes, such as making a shoe comfier and adding more color options, then focusing on hedonic aspects are a better choice. It is also important to note that 3 negative coefficients came from utilitarian traits and 1 from a hedonic trait. Although this study did not look into what attributes are most liked about the product, for example the previous formula and the taste of the toothpaste, this shows that companies should be aware of what the consumers like and don't try to fix what is not broken. Lastly, knowing what aspects makes the rating increase is key for the marketing strategy. For the toothpaste, knowing what decreases the probability of getting high ratings is the same for knowing how to increase the probability of getting high ratings. Firstly, the problems that are caused by the toothpaste should be looked upon and researched in order to prevent it. If the reason for these problems are also related with the change in the formula then, they should try and improve the formula, making it healthier and less problematic, while also changing the flavor back to the initial one that consumers liked. Additionally, the packaging should be improved, Colgate should get in touch with Amazon and to make sure that the products are delivered to the consumer, before the product is expired. For the athletic shoe, fast delivery had the highest impact so that should be kept at a steady level, if not improved. Moreover, marketing the product as "The best gift of the holiday season", referring to the topic "Gift", or marketing it with a tennis player wearing it, referring to the "Tennis Shoe" topic, could be an important addition and diversity to the marketing mix.

During this study, a few obstacles were encountered. The first limitation was that the number of reviews could have been higher. Although the toothpaste had around 50.000 ratings, it also only had 1467 reviews. The same can be said about the athletic shoe with around 20.000 ratings and 5.000 reviews, yet having a better review-to-rating turnover compared to the toothpaste. For future studies, different products with more reviews could be more helpful in terms of getting a better understanding of the effects. Additionally, as the reviews were taken from Amazon.com, a more product oriented website may have contained more reviews, such as collecting the toothpaste reviews from a dental website, to prevent the effect Amazon has on the rating of the product. Another limitation faced was the language barrier. A small proportion of the reviews were Spanish; those reviews were translated yet they might have suffered some context being lost in translation. For any future study, multiple different reviews, from multiple different countries can be obtained and be analyzed with a native speaker in order to observe the effect of culture on the forming of topics and their effects on rating.

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