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Difference Analysis and Prediction of the Helpfulness in Online Reviews of Experience-based, Search-based, and Mixed-based Goods

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Abstract. Online reviews (ORs) have shown evidence to help consumers to reduce hesitation in the last stage of the purchase and has been also found that ORs help online businesses increase sales. However, ORs are increasing faster, becoming every time more robust with better ways and media to express useful and helpful information. Therefore, the way ORs help online business and consumers are constantly changing. Previous studies have intended to analyze helpfulness in different ways. However, they have not totally yet identified the most appropriate influence significance of the factors to test and predict the helpfulness of ORs due to the constant change and evolution of ORs in E-commerce platforms. I based this study on the economics of information, media richness, and negativity-bias theories, proposing a model that shows the influencing factors in the helpfulness of ORs (such as length, sentimental Analysis, score rating, number of images, video and published days). To find a closer optimal helpfulness analysis and prediction, a data set of 17,119 samples of three types of online goods have been extracted from different products on Amazon.com. For the analysis, we have considered employing a regression model to analyze the significance level of the factors in ORs for every type of online goods. The findings in this research prove that in fact there is a different perception of helpfulness for every type of good.

Keywords: Online reviews, Length, sentimental Analysis, score rating, Review helpfulness

1. Introduction

As much time pass online businesses and consumers have put more attention on ORs due to the popularity and the positive influence of ORs in purchase decisions. According to sources in 2016 more than 24,000 ORs were published every minute in online platforms, and in 2020 has shown that year by year the number of ORs submitted increase nearly 11% [1] ORs have a positive impact to reduce hesitation to take a final purchase decision through alternative and specific information which are the most important part when buying online goods [2-3]. Further, the Bright local's survey in 2020 found that 87% of consumer read products reviews and the time average that spend reading is 13 min and

45sec [4]. Previous researches have also caught attention in electronic word-of-mouth (eWOM), since it has a positive increment on online sales [5-7].Moreover, the impact of covid-19 in e-commerce has shown a peak on sales in online business from 10% to 50 %, and is expected to grow more in the following years. Therefore, ORs as a potential source of social influence, will be continuous analyze in the upcoming years.

E-commerce platforms such Amazon.com used to ask consumers if the review has been helpful for them, previous research has based their studies on analyzing such factors as the dependent variable. However, nowadays this platform lets customers judge the OR as an optional option to consider it helpful. An OR is considered helpful if the consumer after reading the review gets valuable information and assesses it as helpful, for some consumers find richer information is itself a source of pleasure [8]. As many votes of "helpful" an OR has, much helpful it is. Moreover, a review with higher votes is usually stuck in upper positions, as a consequence more people can read it.

There are three main products types that can be found on e-commerce websites: experience goods (EG), search goods (SG) and credence goods (CG) and these types have different helpfulness in consumers' perceptions. It was categorized by [9] and has been used by many previous researchers such [10-11]. Search-based goods are products that can be evaluated for their features and characteristics, these types of products can be evaluated before consumers buy the product or consume it such as cameras, and laptops. Experience-based goods are products that can be evaluated during their consumption such as books, and video games. Also, some previous research has shown that there are some products that possess both search and experience-based characteristics and they are considered mixed goods (MG) such as bag packs [12]. Due to the complexity of analysis and quantity of reviews, this study has not considered credence goods.

Within the context of an online review, there are many factors that are fundamental to the helpfulness and credibility in the consumer perception. One factor that essentially affects is the sentiment polarity it possesses. Sentiment analysis measures the polarity and identified the positive, negative and neutrality in the review context [13]. There are two common techniques to measure the polarity of word-level sentiment analysis: supervised learning and unsupervised learning which are based on a lexicon-based approach [14]. This study analyzes reviews based on the buyer's opinion or sentiment expresses that differ from different persons and unlabeled data set. In that case, unsupervised learning is more useful. To determine the polarity in this study will be using the library VADER by a python use a dictionary based on an opinion lexicon.

There are a vast number of factors of an OR that determine helpfulness. Those factors that have been found most useful by previous studies in ORs are the length and the score rating [15-16]. The review length is one of the factors that has a direct relationship with the information, when an OR is longer, more information can be found. However, some contributors have found that when the review is very long it loses helpfulness, and when it is very short, they are much less helpful, concluding that the online reviews with moderate length are the most useful for consumers such in the study by [17]. According to the bias negativity theory [18], buyers who dislike the obtained product tends to write longer reviews and also is expected to judge something strongly, intelligence and expert than positive or moderate reviewers. Therefore, the review length is a fundamental factor that helps consumers to make a purchase decision. The other important factor is based in terms of how buyers judge or score the online product, the score rating express how people judge the product by giving stars and the score is usually rated from 1 to 5 stars in online platforms. Extreme rating show how positively or negatively has impacted the online product to the buyer. In the study by [19] found that positive score rating is less helpful than negative rating, and this is because people that has had bad experience with the product tend to be sincerer and judge stronger. Another important factor that has been recently studied is the influence of images and videos in the helpfulness perception for online reviews [12], this factor has become more fluent on websites since e-commerce platforms allow consumers to post heavier online reviews. Images and videos are richer visual and/or auditory information that can support to the consumer to concrete the final purchase decision.

2. Literature review

Extant literature has shown that factors such length, rating, images, sentimental analysis in ORs have a positive influence in the helpfulness. Those previous literatures have significantly contributed to other researches, but still some unexplored things. For example, one research has found that product types moderate the effect of review extremity, and got that for experience goods extreme rating are less helpful than moderates rating [10]. However, due to the time of the research, they have not considered such factors as images or/and videos in an OR, and it's compressible because in that period there was not too much interest to submit an OR. Another research did an experimental laboratory in a university using students as participants, the research found was that video-based online reviews are more useful, persuasive and helpful than text-based online reviews [12]. However, this experiment is very limited because of the interpretivism method they used, and not a general extent of data.

To understand the OR helpfulness, a big number of researchers has made different types of contribution having all of them the same objective in analyzing the independent variable "helpfulness". Some researchers have focused the analysis on unique types of goods such as books or devices of ORs on platforms like Amazon.com, Aliexpress.com [10] [20] and others analyzing the study of services such as hotel booking and restaurant ORs on online websites such TripAdvisor.com, Yelp.com [21] [15] [22]. On the other hand, just a few researchers have analyzed the difference among types of goods either by product or service, or the SAC categorization (Search, Experience and credence goods). Therefore, the outcomes of previous research obtained have positively contributed to understanding more how important are ORs for online sales and increasing the attention of the participants.

2.1. Structural and Semantic features information

Previous studies have focused in the analysis on structural and semantic features to identify helpful reviews for online consumers. The review length is view as one of the most essential structural features of ORs. Researches have illustrated that the length of the review contributes to the helpfulness perception, when the review contains more words is preview that has more valuable information [23-25]. However, the findings by [26] set that exceed of number of words can diminish the helpfulness perception. The moderation of review length has a relationship with the polarity, other researchers has found that negative reviews are mostly long and more helpful than positive reviews, the researches based their results supported by the bias-negatively theory that established that people judge better and strongly when something affects them negatively [27]. The influence of rating score in the helpfulness has also been carefully studied, and there are studies that support that review score has a positive influence when they are extremely rated [28]. But, other studies say that moderate rating is more helpful than extreme rating for products like books [29]. In the context of semantic features, the polarity of the review has indicated that there is a relationship between the online review and its sentiment [29]. Another study of semantic features by [23], established that negativity tends to have more value information that positives due to people criticize something stronger when they don't like or affect them directly.

2.2. Visual and auditory information

In Recent Years There are a few researches that have studied the influence of images and videos to online review and found it as important factor such [30]. The outcomes of those studies are based on the Media Richness theory by [31-32] that describes as the ability of get information to change understanding within a time interval. Also, established that the ability to transmit needed information in a better media can be perceived as more helpful. The study by [12] compares the difference between the textual information and visual/auditory information suggesting that the visual/auditory information could be the next generation of perceived helpfulness in ORs. Therefore, a better media for getting information can enhance cognition for consumers [33] [3].

2.3. Types of goods

Extant literature has found that various factors of online review have a different level of significance that influence the helpfulness perception for different types of goods. The analysis that contrasts the consumer perception of helpfulness between product types (search and experience goods) was studied by [11] [34], their findings show that the helpfulness determinants for Search goods have a different level of significance than Experience goods. However, the data used in those studies have not been enough and one of their limitations suggests incrementing the data. Another research support that some online products have a mixed behavior. The study extends the classification of the SEC goods finding some online goods with search and experience goods characteristics, the study used an interpretivism experiment in a university using students as participants [12]. While a few product types' research examples are potentially relevant to understanding the usefulness of reviews, the search, experience goods paradigm has proven particularly helpful in explaining online shopping behavior.

Compared to other studies such as shown in Figure 1, the proposed study will use a longer and more comprehensive database with a variety of products retrieved from amazon.com for each type of product. Moreover, for the analysis of polarity, the VADER library in python has shown better results when analyzing contexts based on opinions. Contrasting with previous studies, most of them have used sentiment analysis based on searching for repeated words. Therefore, shows limitations when calculating polarity. This is because when writing an OR there is no order and no unique structure, which has complicated previous studies. Furthermore, other researchers have not focused on how useful visual and auditory information are for ORs. Nowadays buyers tend to upload more complete reviews due to the fact that the society in electronic commerce is becoming more and more popular, also every year more online business encourage buyers to write better

ORs through offers and discounts. For this reason, more customers tend to spend their time uploading reviews with images and videos, apart from the fact that online platforms also provide better benefits for buyers who write more useful reviews. So, based on the previous information, previous researches differ outcomes can differ with recently studies.

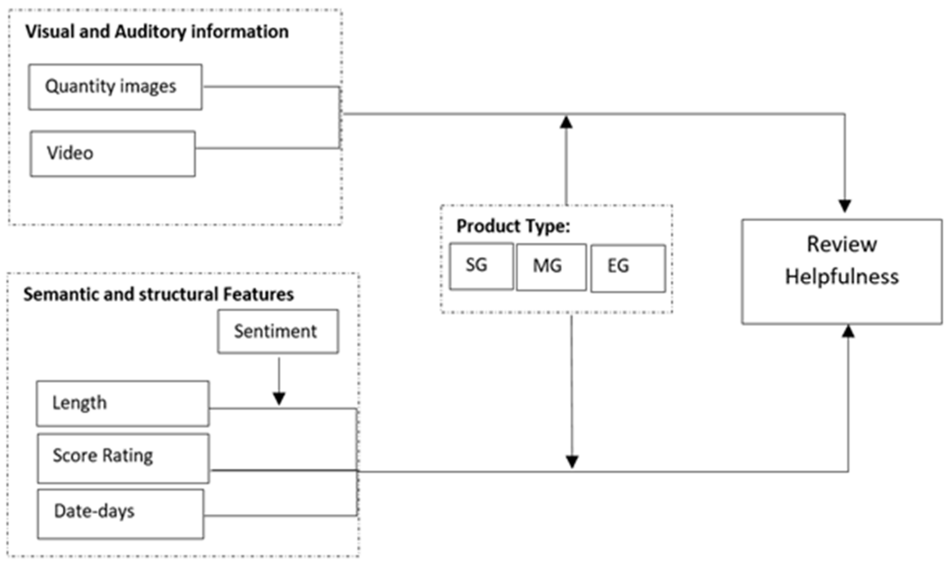
Table 1: Summary of contributions by previous researches

Factor Determinant	Definition	Prior finding	Researchers
Review Length	Review length, review depth, word count, review quantity	The review length (short, moderate and long) influence in the helpfulness for different types of goods and/or services	[35] [36] [25] [37]
Review rating	Star rating, extreme rating	Extreme reviews are more helpful to consumers when reviews are long and accompanied by the reviewers' photos.	[38] [10]
Polarity	Sentimental Analysis: positive, negative and neutral reviews content. Review compound polarity. sentiment score	Review polarity affects helpfulness depending on the sentiment it has, moreover some of them suggest that negative reviews are more helpful than positive or moderate reviews.	[39] [26]
Country/Culture	Reviews from different countries, length, rating	Customers from individualistic cultures are more likely to post reviews, and their reviews are longer.	[40] [41]
Sentiment	semantic measure of review helpfulness, Information entropy	The results show that semantic Measure behaves more as theory suggests that it should than the current vote-up/ vote-down based measures do.	[42]
Profile image in Online reviews	Review attributes: profile image/image type	Have shown that the presence of reviewer profile image enhances consumer's perceived value of an online review.	[43]

Readership	ORs from amazon: Longevity, helpfulness, readership, polarity	Measures the readership and the helpfulness of ORs in amazon.com	[44]
Linguistic Features	Linguistic categories: Adjectives, state verbs, State Actions verbs, Interpretive actions verbs, and descriptive actions	The linguistic category features were found to be effective in predicting helpfulness of experience goods.	[45]

3. Research model and hypothesis

For the adaptability of the research, the model in Figure 1 illustrates two important groups of factors that determine the helpfulness of ORs. These are the visual and auditory information, and the semantic and structural features information. Since the differences in the nature of information seeking in search, experience and mixed goods, this model addresses the research objectives, and integrate the previous mention theories (economics of information, media richness and negativity-bias theories) to explain the influence of those factors with the dependent variable "helpfulness" of ORs.



Note: SG: Search Goods, EG: Experience Goods, MG: Mixed Goods
Figure 1: Research Model

For the fact that Search goods Mixed goods are evaluating for the features and characteristics it possesses, and also that the consumer can easily get information in the product's description and characteristics; Therefore, images or videos can support that information and/or contrast it with other information already obtained [12]. Moreover, supported for the Media Richness theory by [31] [32] videos and/or images are medias where someone can easily observe and get information, the visual and/or auditory information can facilitate, complement and satisfied the shopper information seeking [46] for search and mixed goods. For this reason, the first proposed hypothesis is:

H1: Visual and auditory information has a positive influence in the helpfulness for Search goods and mixed goods than experience goods.

In the case of experience goods, they can be assessed after and during its consumption, and the satisfaction experience can be different and often depend of the consumer's point of view of the product that they have purchased. Thus, those online reviews can differ easily by the experience obtained in the perspective of the information. So, images and videos may not be significantly helpful because they cannot give to the reader the complement of the information seeking, and for this type of good because of the increment of information technology, the overabundance of information has been more problematic than the lack of information [47]. Furthermore, due to there are different opinions of the buyers when writing reviews, the consumers can find ORs which are much longer, well expressed, clearly and usually contradictory more helpful than ORs that are short, where these short ORs can be mostly found in the category of Search goods [10] and now more often showing images and/or videos. Thus, I hypothesized that:

H2: Length of the online review has a positive influence in the helpfulness for Experience good than Mixed and search goods.

An OR published during a lot of time has more probability to be read it by the consumers. As higher is the time or longevity posted of the ORs in the platform is also more probable to get helpful votes [44]. Moreover, this type of factor can show the same positive influence to every type of products and goods in the platform because most platforms such amazon will not show the newest reviews first in the review section and it makes new ORs less probable to get helpful votes. So, the next hypothesis to be test is:

H3: The time of the OR published (date-days) influence in the helpfulness of the online review for Search, Experience and Mixed Goods.

Previous analysis has showed that customers tend to mostly rated a product as extremely negative or positive (1 or 5 stars) [15] But in the research of [10] was found that ORs with moderate score rating are more helpful than others for products that are experience-based, and this is because for these products there are many opinions for one product among the reviewers. In the case of search goods the opinion of the product must have similar opinions among the others because they are judge before you buy the product. Moreover, until now have not been proved how the score influence in mixed goods but due the mixed goods tents to have the characteristics of a search goods we can assume that this type of goods can has outcomes similar to search goods. Follow the case, my next hypothesis is:

H4: The Score-rating in ORs has a positive influence in the helpfulness for Search and Mixed goods than Experience goods

The Theory of negativity-bias establishes that negative opinions or expressions can be more helpful than others (either positive or moderate). But since there is a better use of the media in ORs might be different from the results of previous researches. In the sentimental analysis, using the library VADER from python was obtained a better accuracy to test the polarity [48]. Consumer can classify online review as positive, neutral or negative (depending of its polarity). Based in the Negativity Bias theory and the study of previous studies [21] [18], establish that negativity tends to be more helpful than positive and neutral ORs, for experience goods that customers can judge the product during its consumption, also they can be more expressive and the consumers can have different critics about the product the theory can be supported. In the other hand, for Search goods we found that people opinion about the product are no so different, and this is because they can get the information of the product before buy it and even support the information with the visual and auditory information found it in the ORs. Therefore, for search goods is easier to get positive review than negative. Therefore, the next hypothesis is:

H5: Negative ORs are more helpful than positive and moderate for search, experience and mixed goods.

The length and the sentiment are variables the have shown influence in the helpfulness and might have relation between them. In experience goods mostly can be observer that reviews are longer and opinions tends to be more sentimental than other types [10]. The sentiment may influence vast more in longer than shorter ORs. As we know in Experience goods are much longer than the sentiment may show influence in the length, in this case if the review are short and inconsistent may cause the loss of emotion and sentiment such in search goods. Therefore, we can hypothesize that:

H6: Sentiment of ORs plays a significant moderating role on the relationship between Length of ORs and Helpfulness for experience goods.

Most of These hypotheses are supported by three theories, and is expressed in the proposed model, differing with other models suggested before, these hypotheses also update previous old models that has lost consistent due to the time and the evolution of ORs as important tool for purchase decisions. In addition, the recently Covid-19 has impulse more consumers to get into more in e-commerce tendency in consequence ORs also have vastly increased and paid more attention [49].

4. Methodology

4.1. Data collection

For this research, I collected ORs from different types of goods (SG, EG, MG), and products from Amazon.com to expand the data. The data collected prioritizes the ORs that the purchase has been confirmed, ORs without purchase confirmation must reduce the credibility for the buyers and might generate complexity for the analysis and prediction. Products such laptops, cameras and Macs were used to make the analysis for search goods as also previous researches has suggested it. In the case of experience goods were products such books, video-games and movies. And lastly for mixed goods, were use products such backpacks and suitcases. Further, the study just includes ORs that has been written in English. On the other hand, ORs written in other language weren't include because might cause negative influence in the analysis of the data and the sentimental analysis. For this research, I collected in total 17,119 ORs from the 3 types of good of goods, shows the details of the data.

After the data collection, ORs with less than 3 Helpful votes were eliminated from the analysis because as previous researches [6] and [44], authors argued that the analysis must consider reviews that assure number of votes.

For the data collection, a code in Python 3.9 was programmed by the author to crawl the necessary information of 238 products in amazon.com. Web crawling facilitated the data collection and can filter most possible inconvenient. Web crawler, can extract the information of every product using software named *spiders*. All the ORs were parsed and conditioned according to the priorities. For the analysis, we prioritize the following conditions to collect the factors of ORs as data-base:

Table 2: Information of data collected for SG, EG and MG

Type of Goods	Number of products	Number of ORs	Valid ORs	Product	References Research
SG	81 online products	5638	1530	Cameras, Laptops and Mac-books	[50]
EG	77 Online Products	5710	1526	Books, Video-games PS4 and PS5, music player	[10] [34]
MG	80 Online Products	5771	1020	Backpacks and Suitcases	[12] [51]

(1) Purchase confirmation: All ORs must have been purchased confirmed because those ORs are more credible and trustful.
(2) Minimum ORs by product: Products with less than 20 [52], weren't considered in this research because cannot illustrate whether the high rating dispersion is at work.
(3) Quantity ORs by product: I extracted approximately 70 ORs randomly for every product to increase the significance of the research.
(4) ORs in English: All ORs must been written in English to avoid error in the sentimental Analysis using the library VADER in python.
(5) ORs with Content: ORs in blank weren't considered.
(6) Factors in ORs: Review Length, Review Rating, Sentimental Analysis, Quantity of images, whether there is video, helpfulness_2, Helpfulness Votes and Date-days (number of days since the OR was published).

4.2. Definition of variables

(1) Independent variables
we categorized the independent variables in two groups: the structural and semantic features information, and the visual and auditory information where are compounds by the length, review rating, date-days and the sentiment polarity for the first group and the quantity of images and video for the second group respectively.
(2) Dependent variable
For the dependent variable was consider 1 type for every ORs which was analyzed in base of total votes from other customers Helpfulness votes: The total number of votes that the OR has received until the date of the extraction
(3) Moderating variable
Sentiment is hired as moderator in our model. Sentiment analysis will carried out based on the sentiment dictionary. The three yield values -1, 0, and 1 refers to negatively-framed, neutrally-framed, and positively framed online reviews. In our model, the sentiment is supposed to play moderating role on the path between ORs Length and Review Helpfulness.

5. Data analysis and results

Firstly, the descriptive statistics was checked for every type of good (SG, EG and MG). This analysis helped to visualize and determine the direction of the research. As it can be observed in Table 3, we found an over dispersion due to the standard deviation (SD) is bigger than the mean for some variables including nonnegative and integer variables such Helpfulness Votes and Review Length. Therefore, the analysis must be adjusted using log-transformation [44] [53].

Table 3: Descriptive Analysis for SG, EG and MG

Variables	Search Goods Mean(Standard Deviation)	Experience Goods Mean(Standard Deviation)	Mixed Goods Mean(Standard Deviation)
ScoreRating	3.52 (1.6135)	2.861 (1.704)	3.704 (1.671)
Sentiment	0.418 (0.856)	0.063 (0.954)	0.508 (0.821)
Length	120.1 (134.7)	148.5 (174.5)	126.5 (103.8)
Images(number)	0.55 (1.183)	0.12 (0.6164)	0.549 (1.444)
ReviewVideos	0.051 (0.221)	0.002 (0.050)	0.015 (0.124)
HelpfulnessVotes	33.94 (77.71)	44.06 (102.9)	27.17 (105.2)
Visual&Auditory	0.2276 (0.419)	0.056 (0.238)	0.340 (0.474)
Date-Days	527.1 (373.6)	527.1 (454.1)	603.0 (480.3)

Note: Type of goods-Based Data-set Descriptive statistic; Sentiment analysis: -1, 0, and 1 reflecting Negatively-framed, Neutrally-framed or Positively-framed ORs respectively; Review rating: 1, 2, 3, 4 or 5; Review length and date-days: positive integer; Helpfulness Votes; Positive integer. Visual and Auditory; 0 and 1 reflecting is the review contents whether Images/Videos or neither respectively.

Moreover, in the descriptive analysis we can highlight some important points. As expected before, we can observe that for search goods and mixed good there are more ORs with videos and images than experience goods. For experience goods, the mean of the review length shows that ORs are mostly longer, and the quantity of images and videos are much less evident than the other types of goods.

For this research I considered to use the Negative Binomial regression to test our hypothesis because that model might follow this approach, and also to control the over dispersion in our variables. So, the equation 01 was proposed and tested for every type of good independently to analyze our hypotheses proposed previously.

$$
\begin{aligned}
log(HelpfulnessVotes)\% &\\
&= \beta 0 + \beta 1 log(Length) + \beta 2 log(Date - Days)\\
&+ \beta 3 log(Sentiment * Length) + \beta 4(Visual\&Auditory)\\
&+ \beta 5(Sentiment) + \beta 6(ScoreRating)
\end{aligned}
$$

Furthermore, we analyzed the correlation among the independent variables using the correlation matrix for the previous equation. Then, in table 4 we can observe high correlation among the independent variables for every type of good. Therefore, this analysis gave us more confident to proceed and implement the Negative binomial regression analysis.

Table 4: Correlation matrix of between SG, EG and MG

Variable-SG	ScoreRating	Sentiment	Length	Visual&Auditory	Date-Days
1.ScoreRating-SG	1				
2.Sentiment-SG	.737**	1			
3.Length-SG	.034*	.86**	1		
4.visual&auditory-SG	.084**	.064*	.130**	1	
5.Date-Days-SG	0.018	0.002	0.068**	.020	1
Variable-EG	**ScoreRating**	**Sentiment**	**Length**	**Visual&Auditory**	**Date-Days**
1.ScoreRating-EG	1				
2.Sentiment-EG	.631**	1			
3.Length-EG	.030*	.016	1		
4.visual&auditory-EG	-0.038**	-0.009	.058**	1	
5.Date-Days-EG	.107**	.107**	.119**	-.008	1
Variable-MG	**ScoreRating**	**Sentiment**	**Length**	**Visual&Auditory**	**Date-Days**
1.ScoreRating-MG	1				
2.Sentiment-MG	.681**	1			
3.Length-MG	.021	.095**	1		
4.visual&auditory-MG	-.104**	-.070**	.122**	1	
5.Date-Days-MG	-.011	-.023	.277**	.035**	1

** Correlation is significant at the 0.001 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

After the descriptive and the correlation matrix analyses, we conducted the testing of our hypothesis. The regression analysis for our equation were significant with at $p<0.001$ for every type of product. I also checked the good of fitness to make sure if the over dispersion was controlled and make sure the negative binomial was the right choice. The good of fitness was 1.165 for search good, 1.197 for experience goods and 1.177 for mixed good. The results of good of fitness make sure that our analysis using negative binomial regression was the correct choice for our research equation.

Regression results are shown in Table 5. It shows that for the relation between the visual and auditory information and the helpfulness is significant positive (B=0.532, P<0.000) for Search goods, positive but no significant (B=0.036, P<0.905) for experience goods and (B<0.186, P<0.016) positive and significant for mixed goods then, the hypothesis H1 clearly supported. For our second hypothesis H2, the results of the relation between the length of the OR and the helpfulness shows that is significance and barely positive (B<0.077, p<0.017) for search goods, significance and positive (B=0.168, p<0.000) for experience goods and no significance and barely positive (B=0.045, p<0.370) for mixed goods. Thus, the H2 is slightly supported. The outcomes between the number of days since the OR was published and the helpfulness for every type of goods shows to be strong significant and positive (B=0.576, p<0.000), (B=0.319, p<0.000) and (B=0.218, p<0.000) for search, experience and mixed goods respectively supporting strongly our H3. The results between the Rating and the helpfulness to be positive and significance (B=0.290, <0.000) for Search goods, barely positive and no significance (B<0.014, p<0.108) for Experience goods and positive and significance (B=0.325, p<0.000) for Mixed goods to conclude supporting H4. For the results between the sentiment and the helpfulness the results were based in a categorical way where was found that in fact negative reviews are mostly helpful than positive and neutral (For Sentiment = -1, B=0.739, p<0.036; Sentiment = 0, B=-0.461, p<0.038 both with respect to sentiment =0) for Search goods; (For Sentiment = -1, B=1.325, p<0.000; Sentiment = 0, B=-0.410, p<0.041 both with respect to sentiment =0) for Experience goods and (For Sentiment = -1, B=0.322, p<0.540; Sentiment = 0, B=-0.026, p<0.937 both with respect to sentiment =0) for Mixed good, showing that H5 is semi-supported because has not shown significance for Mixed goods. For the last hypothesis, the relationship between the influence of the sentiment in the length of the review with the helpfulness was found that is just supported for experiences Goods (B=0.078, p<0.01), in the case of Search and Mixed Goods the relationship was found that is not significant (B=-0.008, p<0.806), (B=-0.040, p<0.470) respectively. So, finally the last hypothesis H6 is supported.

In conclusion for most of the hypothesis tested, at exception of H2 that is barely support, are supported in this research.

6. Discussions

The findings were based in the investigation of the effect of two important groups, and the helpfulness of online reviews in amazon.com. Results show that in fact there are significance different perception among the products types. Also, we can highlight some points in this analysis, the first is the quantity of images and videos (visual and auditory information) have been increasing and been posted in ORs for Search and Mixed goods that now more researches can consider on investigate this effect for other platforms or broader studies. The second point rely in the sentiment analysis, indeed this factor has significance relation with the length of the review for experience goods. However, due to the library VADER that was used in this research for find the polarity of the sentiment of the online review, cannot rely for some sarcasm comments in reviews and it must be improve. The sarcasm can be harmful in the process of the sentiment analysis but can be improved in futures researches with better sentiment analysis skills or methods. In general this study has expanded a broader information and updated the field of the helpfulness in online reviews for amazon.com.

An expected finding was the relationship between the number of days since the online review was published (Date-days) with the helpfulness, it has been found significant positive between those variables for every type of good. In conclusion that indeed online reviews that have more time published are more helpful and easy to be perceived for consumers. Even though Amazon.com has an option in the platform to show newest review first, it has not affected in the perception of the helpfulness for older online reviews. Finally this findings can help online business vendors to implement better strategies to satisfy shoppers and reduce hesitation and make faster decisions when buying goods.

Table 5: Negative binomial regression for Search, Experience and Mixed Goods

Votes Helpfulness	Search Goods			Votes Helpfulness	Experience Goods			Votes Helpfulness	Mixed Goods		
	B	**Wald Chi-Square**	**Sig.**		**B**	**Wald Chi-Square**	**Sig.**		**B**	**Wald Chi-Square**	**Sig.**
Visual&Auditory	.532	51.251	.000	**Visual&Auditory**	.036	0.074	.740	**Visual&Auditory**	.186	5.800	.016
Length	.077	5.664	.017	**Length**	.168	31.219	.000	**Length**	.045	0.780	.370
Date-Days	.583	153.962	.000	**Date-Days**	.311	58.149	.000	**Date-Days**	.256	33.139	.000
ScoreRating	.290	61.212	.000	**ScoreRating**	.014	2.586	.108	**ScoreRating**	.325	60.306	.000
[Sentiment = -1]	.739	4.393	.036	**[Sentiment = -1]**	1.325	18.682	.000	**[Sentiment = -1]**	.322	0.375	.540
[Sentiment = 0]	-.461	4.304	.038	**[Sentiment = 0]**	.410	4.181	.041	**[Sentiment = 0]**	-.026	0.007	.937
[Sentiment = 1]	0			**[Sentiment = 1]**	0a			**[Sentiment = 1]**	0		
Sentiment* Length	-.008	.060	.806	**Sentiment* Length**	.078	6.360	.012	**Sentiment* Length**	-.040	0.523	.470

7. Limitations and futures research

Most of the previous research has studied online reviews helpfulness when Amazon.com used to provide the number of readers that provided votes of helpfulness with the total votes for every online review. However, this information is not provided anymore so, this study has put a proof this limitation and other researches can also support this test and upgrade the research field. Another important limitation of this research can be also of products from different industries to evaluate and support our findings. Moreover, limitations in our independent variables, is the general source of factors use in this research. Posteriors researches can make more specific and expand the number of factors such the gender or the product target (whether the product is for kids, young or older persons). Limitations in the sentiment analysis can be extended because of the lack of cultural and different language data analysis. This research has just considered online reviews written in English, in consequence, the analysis can be generalize for a wide complete population, and futures researchers can consider extending this analysis considering more language and cultural emotion analysis.

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