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The Impact of Message Content And Descriptive Features On Review Helpfulness: An Empirical Study

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Abstract

The way reviews are written can affect the consumer's perception of information helpfulness.Two people may convey the same information in two different ways and hence changing the way they are perceived by others. The major influences are in message content and descriptive features. The proposed paper exhibits a study that uses reviews from Amazon India. The intention behind the research is to identify the change in the helpfulness of review with the variation in message content and the descriptive features. This could further help predict the helpfulness of review if the descriptive and message content is known. The methodology in the paper incorporates a regression model which includes the review rating, review length, review valence, number of First-person singular pronouns, number of First-person plural pronouns, number of second-person plural pronouns, number of third-person plural pronouns and affect. These are the descriptive features and the message content considered. From the study, it was clear that review helpfulness is influenced by the message content and descriptive features. This may not immediately contribute to short-term sales performance but will increase customer satisfaction and lead to long-term firm value

Keywords: *Descriptive features, Message content, Amazon reviews, Regression, Text - Mining)*

1. Introduction

The experience of other people and what they think about a product are important sources of information for many consumers. This makes WOM marketing one of the most important forms of marketing.

The internet is one of the most transformative technologies and this development of the last decade has dramatically changed the conventional ways of sharing information. This is one major factor that has led to the digital platform economy where companies like Google, Facebook, and Amazon have reshaped the entire market space thereby changing the way business is being done. As a result, there were changes in marketing practices also. Consequently, word of mouth has now got an electronic element (eWOM).

eWOM is defined as “any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet” (Hennig-Thurau, 2003). Even when eWOM is defined as the electronic element of WOM, they essentially have some crucial differences. Some of them include the variation in credibility, privacy, diffusion speed, and accessibility. eWOM will have lower credibility as most of the reviews we see are from unknown sources. The privacy is also limited as the information is readily available over a connected network. The speed at which eWOM spreads in comparison to the traditional word of mouth is very high. Moreover, these messages are available at any time and space. The author very rightly quoted “the analysis of the review showed that these two concepts – WOM and eWOM – while seemingly the same, are at the same time very different” These differentiating features creates a difference in the way WOM is perceived and eventually they influence the buying behaviour [1].

eWOM has some unique characteristics as well. Some of them include enhanced volume, dispersion, persistence, observability and community engagement. It is also observed that there is an increased dependence on EWOM. The factors that contribute to this increased dependency include reduced search efforts, reduced risk, and social assurance[2].

In today's scenario, the amount of data shared in the form of review makingis huge and it one major source of eWOM. Hence an important area of study is the factors of an online review that influences the buying behaviour of customers[3, 4]. Some of them include the impact of information usefulness, quality, credibility, and attitude. A review is considered to be useful if the available information enhances his/her performance. The usefulness of a review will lead to information adoption, and this will further lead to a purchase intension. Anyone can post an online review. Hence the reviews with higher quality have a positive impact on the purchase intentions of customers. The reviews of users with higher credibility will also demonstrate more positive impacts on purchase behaviour. The attitude in which each of these reviews is perceived by customers will vary and this factor also has an influence on the buying behaviour and purchase intentions[5].

The helpfulness of a review is one such factor that stimulates customer purchase intention. The helpfulness of a review is directly related to the diagnosticity of the review for a customer. If more customers find the review helpful, the helpfulness of the review increases[6][7]. Helpfulness of reviews and the customer purchase intension are closely related and this feature of an online needs to studied further. Online customer reviews have a major impact on customers buying intension. The accumulation of reviews for each product makes it difficult for a customer to go through all the reviews. Hence it is a necessity to filter the ‘helpful’ reviews from all the available reviews.

The mental model theory suggests that individuals understand discourse by constructing mental models of the described situation [8]. This emphasis on the fact that each person perceives a message differently. There is also a possibility that two messages with the same content but conveyed differently will also have different perceptions[9, 10].

Two reviews with the same content can be perceived differently by customers. For example “This mobile was a bad decision. The quality of the mobile is not worth the money” and “I regret buying this mobile. I got a mobile of very poor quality and the mobile is not new” are statements with very similar content but are reviews that have chances to be perceived differently. Thereby changing the helpfulness of each review. The most prominent difference in these reviews is that one uses first-person singular pronouns (FPSP), while the other does not. This study evaluates how the presence of FPSP moderates the helpfulness of a review[11].

2. Literature Review

A. eWOM

Word of mouth marketing is essentially one of the most powerful tools of marketing as it directly involves the customers. Some of the key motivators of the word of mouth that were identified by Ditcher in 1966 were of three categories[12].

1. The satisfaction of emotional needs: self-involvement and perceived product involvement

2.Message involvement- talk simulated because of the way the product is presented.

3.Other involvement- say need to give the person receiving the WOM proper information.

eWOM is defined as “any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet”[13]. eWOM, in other words, can be defined as the electronic element of WOM. But they still essentially have some crucial differences. Some of them include the variation in credibility, privacy, diffusion speed, and accessibility. Even when there are differences the motivations of WOM remain the same.

B. Review Helpfulness

With the growth of the internet, WOM has also taken its electronic form namely eWOM. In today's scenario, there is a huge amount of data shared in the form of review making it one major source of eWOM. A single product may have thousands of reviews which makes it difficult for a potential customer to go through all the reviews. Hence the most valid reviews have to be selected from the larger set of reviews. One parameter that helps to categorize these reviews is the review helpfulness[14].

“Helpfulness of a review is a reflection of its diagnosticity in the consumer’s decision-making process” [6][15].Hence the perceived helpfulness of an online review is not always linked to increasing the sales of a product. It rather focuses on creating value to the customers by providing them with useful information from past purchases. There are many factors identified that influence the helpfulness of a review of which the message content and descriptive features are of prime importance. The descriptive features considered include the length, rating valence and extremity of reviews. As stated reviews with very similar content may also be perceived differently. One reason for this could be the variation in linguistic content like the first person singular pronouns in reviews[11][16].

C. Message Content and Descriptive Features

The characteristics of a review can be classified into two major categories. The descriptive features and message content. The descriptive features of review include the length, rating valence and extremity of reviews. The message content of the review includes the usage of FPSP and its affect[11].

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The length of a review is defined as the total number of words in a review. The valence of a review is identified using the rating in a review and a review is called an extreme review if the rating is 1 to 5 on a scale of 1 to 5. The effect of FPSP is measured by taking the ratio of FPSP to the total number of words in a review. The affect of a review can be measured using LIFW dictionary.

D. Filtering of Fake Reviews

There is an increasing dependency on online reviews. This has caused an increase in fake reviews that would eventually manipulate the perception of customers. Hence it is a necessity to remove the fake reviews before the analysis is done. Some of the existent methods for fake reviews detection include[17][18]

1. Content-based spam filtering
2. Spam filtering based on behaviour
3. product information based spam detection
4. Spammer groups detection

E. The Impact of Message Content and Descriptive Features On Review Helpfulness

There are different ways in which a reviewer chooses to convey his information. One major difference could be the use of linguistic terms in the review. Consider a review which has an FPSP. Such reviews have a tendency to be related to the person who has written the review rather than the product. The more the presence of first-person singular pronouns the more the reviews will be related to the reviewer [17].The use of FPSP can also decrease the perceived relevance of a review. The presence of FPSP suggests that there will exist information subjectivity and could be a personal experience or opinion. Hence the presence of FPSP negatively influences a review [19]

H1: The presence of FPSP negatively influences the helpfulness of a review.

Message content also has an influence on how the information will be perceived. The parameters considered to evaluate message content include review length, extremity and the review rating.[20]

Review length has to positively influence the perceived helpfulness of a review. This is because longer reviews[6]provide detailed descriptions and more information about the product[21]. It could even decrease the negative influence that could be generated due to the presence of FPSP. But there is a chance that reviewers may not completely go through the content of the review and there is also a chance that these reviews are skipped [22].

H2 (a): Review length negatively influences the helpfulness of a review.

The review rating has an influence on customer perception of reviews. Reviews of extreme valence will have more visibility than the others. There is also a high chance that the lower extreme valences have a higher influence on the helpfulness of reviews[5, 23]

H2(b): Review valence influence the helpfulness of a review. The lower valence reviews will have a higher influence on the helpfulness of the review.

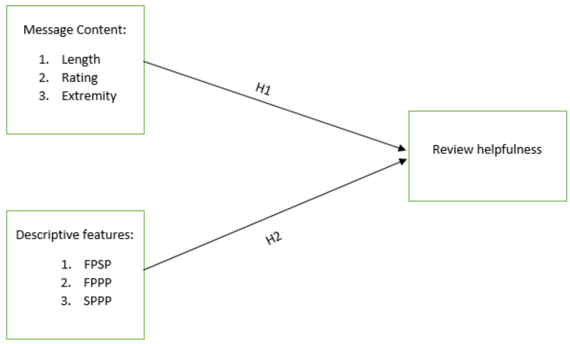

Figure 1: Research Framework: Influence of message content and descriptive features on review helpfulness

The influence of message content and FPSP were separately evaluated. The presence of FPSP in long reviews moderate the negative influence of FPSP in the review. Similarly, the effect of FPSP is dominant in lower valence reviews. Hence the FPSP moderates the influence of message content on review helpfulness

H3: FPSP moderates the influence of message content on review helpfulness.

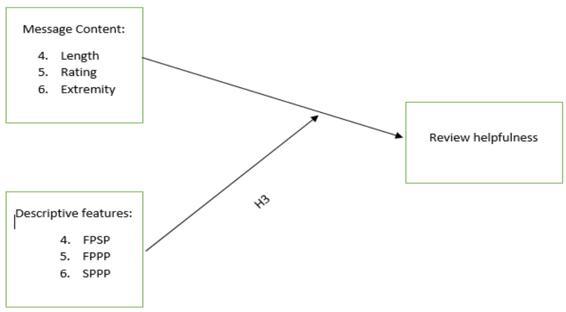

Figure 2: Research Framework: moderating effect of descriptive features on review helpfulness

3. Methodology

Online reviews for four product categories, including, Animal and pet supplies, electronics, Furniture, Media, Health and beauty, Home and garden, Office supplies, Office supplies electronics, and Toys & Games were collected from Amazon.in during the time period of 2014 to 2019. These products are widely purchased online and consumers heavily rely on product reviews in their decisions.Further, these products could be classified into two broad categories as durable and non-durable products[24].

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Figure 3 describes the Mean of the data. The data clearly depicts only 4 % of the total reviews were helpful. The average length of a review is 25 to 26 words. The average rating is 4.5 which means most of the reviews are positive. 70% of the reviews are extreme and most of them would be positive. Only 3 % of the length of the total reviews contain FPSP and the percentages of FPPP and SPPP are minimal.

	Mean
reviews.numHelpful	0.043659337
length	25.639325169
reviews.rating	4.513888399
extremity	0.736314545
fpspratio	0.037379147
fppratio	0.003475112
sppratio	0.005059764
tppratio	0.009166496

Figure 3: Mean

Figure 4 describes the standard deviation of the entire data. The variation in the helpfulness of a review is by 20%. This means approximately 20 to 25 % of the reviews were helpful. The average length of a review varies by 36 words making the usual range of length of a review 25 to 61 words. The review rating varies by at most .9 indicating most of the reviews fall from the neutral to the positive category.The variation in FPSP, FPPP, SPPP,TPPP are 4%,1%, 2% and 3% respectively.

	standard deviation
reviews.numHelpful	0.20433960
length	36.60142788
reviews.rating	0.93532539
extremity	0.44063850
fpspratio	0.04811778
fppratio	0.01576231
sppratio	0.02078585
tppratio	0.03472970

Figure 4: Standard Deviation

Multicollinearity is a condition that occurs when independent variables of a regression model are correlated. Multicollinearity between independent variables should not exist as it alters the results of a regression model[16].The correlation between all the independent makes it evident that all independent are not related.

	reviews.numHelpful	length	reviews.rating	extremity	fpspratio	fppratio	sppratio	tppratio
reviews.numHelpful	1.00	0.22	-0.02	-0.03	0.05	-0.01	0.02	-0.05
length	0.22	1.00	-0.12	-0.09	0.11	0.04	0.07	-0.03
reviews.rating	-0.02	-0.12	1.00	0.54	0.00	0.01	-0.01	-0.03
extremity	-0.03	-0.09	0.54	1.00	0.00	0.01	-0.02	-0.01
fpspratio	0.05	0.11	0.00	0.00	1.00	-0.08	-0.09	-0.05
fppratio	-0.01	0.04	0.01	0.01	-0.08	1.00	-0.03	-0.01
sppratio	0.02	0.07	-0.01	-0.02	-0.09	-0.03	1.00	-0.02
tppratio	-0.05	-0.03	-0.03	-0.01	-0.05	-0.01	-0.02	1.00

Figure 5: Correlation Matrix

The regression analysis is done for analyzing three areas

1. The impact of message content and descriptive features on review helpfulness.
2. The moderating effect of descriptive features on review helpfulness.
3. The variation in the impact of message content and descriptive features with the variation in product categories.

The figure below summaries the regression model that studies the impact of message content and descriptive features on review helpfulness

```
Call:
glm(formula = reviews.numHelpful ~ ., family = binomial("logit"),
    data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.4533  -0.3011  -0.2674  -0.2244   2.8626

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)     -3.8273157  0.1693674 -22.598  < 2e-16 ***
length           0.0154914  0.0006891  22.481  < 2e-16 ***
reviews.rating   0.0295404  0.0402350   0.734   0.4628
extremity       -0.1448561  0.0853388  -1.697   0.0896 .
fpspratio        4.3259165  0.6428890   6.729 1.71e-11 ***
fppratio        -3.3104253  2.6195869  -1.264   0.2063
sppratio         2.1666540  1.5695862   1.380   0.1675
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

Figure 6: Regression analysis results 1

The model clearly indicates the major factors influencing the helpfulness of a review are the review length and the presence of FPSP. It is clear from the model that longer reviews do increase the helpfulness of a review. The presence of FPSP does also hasa positive effect on the reviews. The next most influencing factor is the review extremity. Review extremity has a negative influence on the review helpfulness and more positive reviews are regarded to be less helpful than the negative ones [25].

Figure 7 summaries the regression model that studies the moderating effect of descriptive features on review helpfulness.

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```
Call:
glm(formula = reviews.numHelpful ~ ., family = binomial("logit"),
    data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.4332  -0.2894  -0.2457  -0.2131   2.8251

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)    -3.715e+00  1.913e-01 -19.424   <2e-16 ***
length          1.754e-02  1.178e-03  14.892   <2e-16 ***
reviews.rating  1.795e-02  4.651e-02   0.386   0.6996
extremity      -3.412e-01  1.075e-01  -3.175   0.0015 **
fpspratio       1.577e+00  8.695e-01   1.814   0.0697 .
fpppratio      -1.758e+00  2.498e+00  -0.704   0.4815
sppppratio      1.827e+00  1.594e+00   1.146   0.2516
fpsplength     -3.026e-04  2.458e-05 -12.311   <2e-16 ***
fpspating       1.176e-02  6.564e-03   1.792   0.0732 .
fpspextremity   3.869e-02  2.548e-02   1.518   0.1290
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

Figure 7: Regression analysis results 2

The above table shows a regression analysis considering descriptive features as the mediating variables for review helpfulness. The results indicate that the most influencing factors of review helpfulness are length and FPSP*length. This indicates that the longer reviews are considered to be more helpful, but longer reviews with more FPSP negatively influence the helpfulness of a review. The next most influencing factor is the review extremity. Review extremity has a negative influence on the review helpfulness and more positive reviews are regarded to be less helpful than the negative ones

Figure 8 summaries the regression model that the variation in review helpfulness with product categories (considering only the product category: Electronics)

```
Call:
glm(formula = reviews.numHelpful ~ ., family = binomial("logit"),
    data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.3511  -0.3727  -0.3332  -0.3159   2.7608

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)    -2.0579499  0.1978173 -10.403  < 2e-16 ***
length          0.0164723  0.0008712  18.908  < 2e-16 ***
reviews.rating -0.2885335  0.0465067  -6.204  5.5e-10 ***
extremity       0.2974988  0.0938022   3.172  0.00152 **
fpspratio       0.6784803  0.8285955   0.819  0.41288
fpppratio      -5.7124909  2.8073800  -2.035  0.04187 *
sppppratio      0.8675300  2.2546040   0.385  0.70040
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

Figure 8: Regression analysis results 3

The regression in the above two cases considered all the product categories. This analysis considers only product category at a time. The regression analysis the review helpfulness for the purchase of electronic products. These are mostly durable products and hence may have a different influence on review helpfulness. It is clear from the model that longer reviews do increase the helpfulness of a review. Review ratings negatively influence the helpfulness of a review. Hence positive reviews may not be helpful reviews. The extremity of a review also has a positive influence on the helpfulness of a review. Hence reviews with 5-star and 1-star ratings will be more helpful[26].

4. Results and Discussions

A. Results

The major influencers of review helpfulness were identified by analyzing three situations

1. The impact of message content and descriptive features on review helpfulness.
2. The moderating effect of descriptive features on review helpfulness.
3. The variation in the impact of message content and descriptive features with the variation in product categories.

The most dominant descriptive feature that influences review helpfulness is the presence of FPSP. There is a positive influence for the presence of FPSP on review helpfulness and hence as the number of FPSP in a review increases with respect to a fixed review length the helpfulness of the review increases.

The most influential message content is the review length. Review length has a positive influence on review helpfulness. The longer the review the more helpful is the review. This is because there is a chance of detailed explanation regarding the product features and their experiences.

On considering FPSP as a moderating variable, it was clear that longer reviews with a high count of FPSP had a negative influence on review helpfulness. This could be because longer reviews with more of FPSP could be viewed as personal experiences of the person who has written the review rather than the product. Hence it would be treated as a personal comment rather than a general one

Although the factors that influence the helpfulness of a review broadly remains the same, they may be subject to small variations. In the case of a product category that has more durable products (Electronics) apart from the length and presence of FPSP, some dominant features were the review rating and its extremity. The customers would consider the rating of a product more seriously when it a durable product. This could be the reason why review rating and its extremity were strong influencers in the Electronics category.

B. Suggestions

The impact of descriptive features and message content on review helpfulness is evident in the results. But identifying whether these reviews are fake is not is a necessity. The increasing dependency on online reviews has caused an increase in fake reviews that would eventually manipulate the perception of customers. Hence it is a necessity to remove the fake reviews before the analysis is done

5. Conclusion

The study is based on 28,000 reviews from Amazon which were posted during the time period of 2014 to 2019. It also covers 9 primary categories of products namely Animal and pet supplies, electronics, Furniture, Media, Health and beauty, Home and garden, Office supplies, Office supplies electronics, and Toys & Games. The research contributes to the theoretical development in three research namely

1. The impact of message content and descriptive features on review helpfulness
2. The moderating effect of descriptive features on review helpfulness
3. The variation in the impact of message content and descriptive features with the variation in product categories.

This study provides several managerial implications. First, it draws the attention of marketing managers to the importance of information value and helpfulness. In addition, linguistic categories can be effective in predicting the helpfulness of online reviews. The results provide strong evidence for the impact of one type of function words, FPSP, on consumer comprehension and perception of review helpfulness. The results also prove that variation on the factors that influence review helpfulness also varies with the type of product.

The model can be further improved by eliminating the fake reviews before the analysis.

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