MKTG4501 ADVANCED STUDY IN MARKETING REPORT

Helpfulness of online reviews

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Table of Contents

1. Research Overview

Over the last 10 years there has been a steep shift in our shopping behaviour, we are able to shop across product categories and stores through the ease of a few tabs on our phone. This is possible through the highly competitive e-commence environment, which can offer both large established brands as well as local or personal business a chance to reach their consumer base. Unlike a traditional shopping scenario such as a shopping complex or a brick-and-mortar store choice, time constraints and accessibility are no longer a problem faced by the consumers.

In this online shopping scenario, we longer rely on feedback from peers or information from the store employees or extended marketing campaigns. But we rely on a word of mouth in the form of online reviews. These reviews are left by a user on the product. May it be a window shopper, a verified purchase, or a product expert. We refer to the reviews when we look confirm the product attributes listed, user sentiment while using the product and comparison with other products in the same category. All patrons of the e-commerce website can leave reviews, this can lead to an extensive collection of reviews discussing different aspects of the products listed. The sheer number of reviews can be overwhelming and often confuses or steers the consumers away from their purchasing intentions. This phenomenon is known as the information overload. It is detrimental to e-commerce platforms as it decreases their retention of the consumers and a fall in revenues. To counter this problem e-commerce giants such as Amazon have produced a system to sort online reviews based on a helpfulness rating. Every "helpfulness" rating tag is rated by the fellow patrons who found it was important to their decision making in their product consideration. A higher helpfulness rating means the e-commerce lists the review is at the top right after the product description. However, there is a major problem with this helpfulness rating system.

Random Brainwaves

Poor battery life, probably best to hook up external charger while using

Reviewed in Canada on 16 December 2018

Style: HERO7 Silver | **Verified Purchase**

The new gopros are like iphones, can't change the battery. The gopro loses battery life while not turned on. Takes a long time to charge. If it turns on when charging, it uses power faster than its charging.

34 people found this helpful

Report abuse

Figure 1: Online review 1

Marc Chabot

Hero7 Silver Fails to satisfy but for the most Basic features

Reviewed in Canada on 28 February 2019

Style: HERO7 Silver | **Verified Purchase**

The only thing I liked about this camera is the new voice command features and the vibration stabilization is good. Several sports require two hands and using these two feature are great. I have been buying GoPro since the Hero4. This camera has less ability than my old 4. Regardless of the spot meter lock feature it is almost impossible to get the proper exposure straight out requiring way too much post production. The creek has frozen at least once EVERY time I have used the camera. The wifi burns through the battery like fire through dry kindling. I have to hard reboot this thing every time the screen freezes to be able to control any features. Gone are all the ability to modify how this camera captures everything. Even the timelaspe frame capture is hard set. GoPro has decided that if you want anything other than the most basic point and shoot, you need to buy the Black. If customer service can I will be begging for them to replace this first ever bad experience I have had with GoPro with the Black.

23 people found this helpful

Report abuse

Figure 2: Online review 2

Looking at a comparison of two online reviews for a GoPro camera, we can observe online review 1 has a greater helpfulness rating compared to the online review 2. Online review 2 has a much more in-depth comparison of the product attributes, includes sentiment of the product, and use scenario is listed. The online review 1 has a higher helpfulness rating as it was left at an earlier date compared to online review 2. It has had more time to interact with the patrons of the e-commerce platform and hence is able to receive a higher helpfulness rating compared to a more recent in-depth review. This system of sorting online reviews based on helpfulness rating only relies on the time related variables and disregards other key features of the online review such as information depth, whether a product expert has left it etc. This report explored this gap identified. To design a more comprehensive system of sorting online reviews to address the problem of information overload, while considering all relevant factors of an online review which leads us to the research question.

Which factor/factors are considered most important to establish helpfulness for a consumer in the online shopping scenario?

To address this research question, comprehensive research was conducted with comprised of collecting data to first, measure the attitudinal preferences of a varied sample of e-commerce consumers through Likert scales. Second, observing their changes in behaviours when places in a hypothetical online shopping scenario. The use of a survey, a discrete choice experiment along descriptive statistics and cutting-edge predictive analytics through R programming software is used to address this question. Finally, the report will outline recommendation for e-commerce platforms, when applied will help increase consumer retention rates, build a loyal consumer base and consumers acting on their purchasing intentions in the online shopping scenario.

2. Sample Characteristics

A survey collection method for applied to randomly selected subjects. It consists of 4 parts. The introduction and the purpose of the study to give an introduction of the topis and importance of the study, then either a Likert scale or a discrete choice modelling experiment based on a randomised model. Finally, demographic data was collected which was able to give information if the data collected was representative of the benchmark set. The target population for this study is very diverse. Past studies tell us it is very hard to distinguish the online shoppers based on a specific demographic or a characteristic. When comparing the demographics, 78% of both males and females consider online reviews, the comparison between the age categories also shows the same comparison. 79% of the population in the age category 19-34 years old have the, 80% of the population in the in the age group 35-54 years also consider the online reviews before their purchases (Freddie, 2020). The statistic does not vary when comparing the number of users in the 54-80 years old category either. Finally, 78% of the users who consider online reviews are also social media users. Therefore, the sampling plan will look to gain a varied sample of data across age categories (19-34, 35-54, 55-80), with varied gender representation and who are avid social media users (Freddie, 2020). Considering this variation in the demographic features convince sampling was applied, firstly due to budgetary constraints of the project and secondly, no specific targets or restrictions had to be set based on the type of data collected. The only guideline was to generate results from a varied subjects based on the different demographic characteristics.

The survey managed to get 34 responses, which is sufficient data set for the regression model, factor analysis and discrete-choice model planned to be run for analysis. From the data, 67% of the subjects were males, 30% females and 3% did not disclose their gender. When considering age 65% of the subjects were in the 20-29 years age category 14% in the 30-39 years age category and finally, 21% in the 50 or above years old age category. The representation of the populations states the highest number of participants resided in Singapore (15), followed by Australia (6) and then closely by India (5). With representation from Japan (1), China (1) and United States (2) as well. Electronic gadgets, Clothes and apparel, Groceries and food items and sport equipment were the categories most popular when looking at online reviews before purchasing. Finally, 80% of the survey participants compared online reviews always or sometimes when shopping online. Comparing these with the benchmark set earlier, the survey results suggest varied responses were collected and data was suitable for further analysis as it is a good representation of the target populations selected.

To avoid the collection of biased data, several methods were employed. First, there was a randomization feature applied to the attitudinal measure and the decision-making scenario, this way subject was randomly assigned to these sections in the survey flow. Next, forced responses were added to both the Likert scale section and the decision-making scenario to gauge the most accurate difference between the altitudinal data collected. This allowed to measure if the attitudes towards the helpfulness of the online review changed when the participants were placed in a hypothetical scenario. Finally, before the analysis process 4 respondents were removed before the factor and regression analysis as they had incomplete values for the Likert scales. Similarly, 6 respondents were removed before the discrete choice modelling analysis due to incomplete values. The removal of these missing or incomplete values allowed to achieve consistency in the results and most accurate application of the statistical techniques applied.

3. Descriptive Results

A Likert scale was developed to obtain results of the attitudinal measures of the online reviews. Theory tells us three main aspects of the online review affect the online review helpfulness. Namely review related variables, reviewer related variables and time-related variables. Extensive research has been conducted to elaborate on how each of these factors will affect the online review helpfulness. These different elements of the online reviews were tested using a 5-point scale from strongly agree to strongly disagree. Each of the question tested the variables related to the three individual factors and understand if that contributed to the helpfulness of the online review.

First, responses to the attitudinal responses on the review related factors were tested. Wu et al (2018) applied the dual process theory to give reason why online consumer relate review related factors to the online review helpfulness. The dual process theory tells us every message has informative and normative features. A message that can provide higher information and aligns with the general sentiment of the messages about an instance is considered more important in decision making scenarios. In the context of an online review the informative features discuss the abundance of information about the product, its use scenario sentiment and discussion of the product attributes, while the normative elements portray how closely the message either aligns itself with the general revie corpus or deviates from it. Wu et al (2018) inform us that a review that has more informative elements and coincides with the general sentiment of the product description is considered more helpfulness compared to a review that is less in-depth about the product attributes and deviates from the general sentiment about the product listed.

To test the responses to these review related questions, participants were tests on their attitudinal responses towards the presence of a helpfulness rating, review length and the presence of an extreme star rating. The results yield interesting responses that mostly align with past research, while some deviate from the past research. When asked if the presence of an extreme star rating affected their perception of the usefulness of the online review, the participants (n = 30), responded with a mean of 3.47. Research tells us, that a presence of an online review deems the review as being less helpfulness as the patrons of the website are looking for reviews that compare both the negative and the positive elements of any product. This study, however, presents the attitudinal response that the participants found reviews that have extreme star rating more helpful. Next, they were enquired on how the presence of the helpfulness rating present on the review affected their perception of the helpfulness of the review. Again, the participants responded with a high mean of (n=30) 3.97. The current online review systems apply the use of helpfulness rating therefore, the mean from the respondents confirms this behavior with the research. Finally, the respondents were asked if a longer in-depth review was considered when determining the helpfulness of the review. Research tells us that an in-depth review which compares specific information about the products attributes, sentiment and use scenario is considered more important than a review which fails to discuss it. The high mean of 4.17 (n=30) in this scenario confirms these attitudinal responses from the subject of this study. This further highlights the gap to consider the review depth to devise a more effective system of defining the helpfulness of the online reviews.

The next part of the survey involved discussing the reviewer related features of the online review and reflect on the attitudinal features that affect the helpfulness. Reviewer-related factors inform the users on the personal identifiers, whether the reviewer is a product expert and if the review is left from a user with a verifies purchase. Studies tell us signalling theory describe how these factors will contribute to the helpfulness of the review. This tells us that the reviews from personal identifiers are considered important, however reviews left from product experts are considered more helpful than the ones from a normal consumer purchase. The results from the participants reflect similar sentiments, the presence of a product expert presented a high mean of 4 (n=30) towards the helpfulness rating. The presence of a high number of reviews left the reviewer also reflected a high helpfulness rating with a mean of 3.69 (n=30). Interesting, the presence of personal identifiers such as name and age were considered more important than the expert rating with a mean of 3.89 (n=30). Research tells us that there are two ways in which a reviewer than reflect their expertise in the online scenario. First, by leaving a high number of reviews across that product category or by receiving an expert rating from the e-commerce platform. The responses towards the attitudinal confirm the same sentiments as reviewers from product expert and if they had left a high volume of reviews across the product category.

Finally, the attitudinal responses towards the time related variables were recorded. Namvar et al (2020), inform key attributes of the time related variables that explain the helpfulness of the online reviews. Frequency is a major factor that leads to the online review helpfulness, stating that the higher number of reviews present for the products will reflect a higher online review helpfulness for all the reviews presents. Attitudinal responses from the participants reflected similar sentiment, as the higher number of reviews present received a very high mean of 4.22 (n=30) leading to the helpfulness of the review. Next, participants were asked if an older review was considered more helpfulness than a recent one, interestingly, it had the lowest mean of 2.41 (n=30), as contributing to the helpfulness of the review. This highlights a major flaw with the current online review sorting system, the current methods list review that have a high helpfulness rating on top. The reviews that have had a longer time to interact with the patrons and have a greater traction will have a higher helpfulness rating. However, the attitudinal responses from the participants from this study also reflect that the recency of the review is not considered important to the helpfulness of the review. The next few sections of this study will help to establish the importance of the different factors of the online review and help to realise the hierarchy of the factors. This will then help to outline a more comprehensive method to contribute to the helpfulness of the online reviews.

4. Modelling Results

a. Rating Scale Modelling

Once descriptive data about the variables was collected, it was important to run further statistical analysis to investigate the relationship between the variable of the reviews and show these affected the helpfulness of the online reviews. As mentioned above the variables that affect the helpfulness rating are divided into 3 main categories. All scales measured using a 5-point Likert scale model. For the reviewer related factors, the participants were asked if the presence of an “expert rating”, “multiple reviews across product categories” and finally the presence of the “personal identifiers” for the reviewers contributed to its helpfulness rating. For the review related variables, the participants were questioned if the presence of “extreme star rating”, “presence of helpfulness rating”, “longer in-depth review” and the “sentiment while product use” contributed to the helpfulness of the review. Finally, for the time related variables, variables were again collected on a three-point scale as the measure of “number of reviews left”, “recency” and “frequency” were measured as the function of helpfulness to the online review. Research in online reviews utilises a very different approach for data collection and analysis. Data about the reviews is easily available through e-commerce websites such as Amazon, this data is rich in content, high structured in term of the 3 factors mentioned above which can be easily used for either predictive analysis through regression or factor analysis. This study, however, uses a novel approach to data collection by forming question on a Likert scale to collect the attitudinal responses and their contribution to the helpfulness of the online review. Questions were constructed from scratch as no prior research has outlined the definition of the helpfulness or the usefulness of the online review. This may outline issues regarding the validity and the reliability of the model which will be discussed in the later sections of this report.

First a factor analysis was run to assess how well the data reproduces an expected structure of inter-item correlations for questions measuring the various dimensions of different latent variables. The latent variables in this study being the 3 factors of the review. The high KMO value of 0.923 suggests the data is suitable for exploratory factor analysis. Furthermore, the significant ($p < 0.001$) sphericity value of X^2 (45) 1751.180 from the Bartlett's test of sphericity proves the patterned relationship between the variables (see table 1). However, a major data error was presented when we looked to further elaborate through the pattern matrix to reduce the variable into 3 different factors.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.923
Bartlett's Test of Sphericity	Approx. Chi-Square	1751.180
	df	45
	Sig.	.000

Table 1: KMO and Bartlett's test of sphericity

The data is highly correlated and it difficult to distinguish between the three factors and the explanation towards the variance explained by the model towards the helpfulness of the online review (see table 2).

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Component	Total	% Of Variance	Cumulative %	Total	% Of Variance	Cumulative %	Total
1	9.989	99.89	99.89	9.989	99.89	99.89	9.989
2	0.003	0.03	99.92	0.003	0.03	99.92	0.003
3	0.002	0.02	99.94	0.002	0.02	99.94	0.003
4	0.002	0.017	99.958				
5	0.001	0.013	99.97				
6	0.001	0.009	99.979				
7	0.001	0.009	99.988				
8	0.001	0.006	99.995				
9	0	0.004	99.998				
10	0	0.002	100				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Table 2: Variance breakdown for with Eigenvalues (n = 30)

The eigenvalues were higher than one for only one factor, at the same time the first factor cumulatively explained 99.9% of the total variance. An initial model was run with no specifications on the number of factors to be extracted, in this scenario the model only produced one factor with the Eigen value of greater than 1. This did not change when the factor analysis was forced to run with 3 factors to be extracted based on the theory and research on factors affecting the online review helpfulness.

Careful consideration of the factor matrix and comparison of the pattern matrix revealed this was because of the high correlation between the each of the variables that were measured through the questionnaire. This highlights the flaw with the reliability of the model as it has high correlation within group, but also within the groups. Due to this error the factor analysis was unable to display three different factors and group the variables into distinct groups in the pattern matrix.

There are several reasons that may have led to the following error in the data analysis for the factor analysis. First, would be the absence of reliable constructs that could have been researched through the survey. As stated earlier, this is novel to data collection in the field of online reviews. Prior research, in this field relies on secondary data that is already segregated into the variables tested for this research. Therefore, there is no need to introduce questions to collect the primary data which was case in this study. Due to the absence of reliable testing model, questions were designed based on the judgement of the researcher. Upon further investigation, we learned the questionnaire tested both concepts on the usefulness and the helpfulness of the online reviews. This might have either confused the user of the outcome variable for each variable. The participants might also have same definition of the usefulness and the helpfulness of the online review which would have led to similar attitudinal responses when comparing the variables under the different categories.

To improve the survey design and increase the validity and the reliability of the model step can be taken to first define the concepts of the online reviews. The current reliability matrix shows a Cronbach alpha of 1 (n=30), further depicts the high correlation within the variables. This might result in different level of agreement towards the helpfulness of the online reviews across the 3 factors. Next, due to the budgetary and time constraints of the project it was not possible to collect data from a larger audience. Given more time and resources, a larger target population can be studied to explain the variance towards the three factors of the online review.

Reliability Statistics

Cronbach's Alpha	N of Items
1.000	4

Table 3: Reliability analysis of review related features n=30

Despite, the unreliable factor analysis we can still create composite variables to be used to create a regression model. The use of the regression analysis will enable to set predictive evaluation for the factors affect the helpfulness of the online review. This will help to create a hierarchy of importance of the factors which can be either emphasized or ignored when designed a method of sort the online reviews. Despite not being able to differentiate on the three factors based and form the composite scores based on the data in the results, Past research shows the presence of 3 main categories that can be used to analysis the regression model. Table 4 depicts the composites and the variables that contribute to each of them.

Factors	Variables
Reviewer related	Expert rating
	Personal identifies
	Number of reviews left
Review related	Extreme star rating
	In depth
	Sentiment
	Helpfulness rating
Time related	Recency
	Frequency
	Number of reviews left

Table 4:Summary of variables used for regression.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000[a]	1.000	1.000	.436

a. Predictors: (Constant), Time Variables, Reviewer Variables, Review Variables

b. N = 30

c. Dependent variable: Helpfulness rating presence on a review

Table 5: Model summary regression model

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19965.024	3	6655.008	34956.107	.000*
	Residual	5.711	30	.190		
	Total	19970.735	33			

a. Dependent Variable: if it has a "helpfulness" rating, reviewed by fellow users

b. Predictors: (Constant), Time Variables, Reviewer Variables, Review Variables

c. N = 30

d. *Values significant at p < 0.001

Table 6: Model significance ANOVA table

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.120	.083		1.440	.160
	Reviewer Variables	.163	.101	.162	1.607	.119
	Review Variables	.916	.124	.915	7.409	.000*
	Time Variables	-.078	.104	-.077	-.747	.461

a. Dependent Variable: if it has a "helpfulness" rating, reviewed by fellow users.

b. N = 30

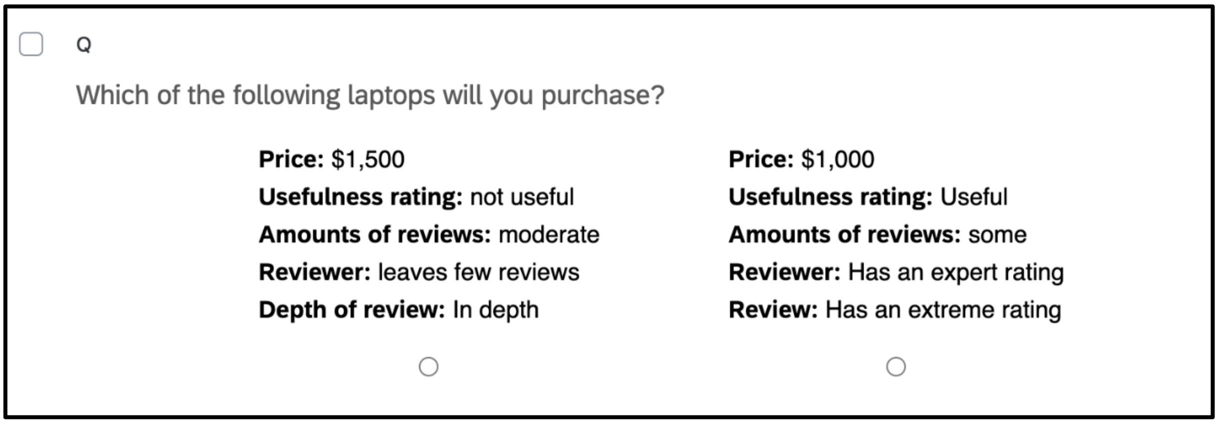
c. *Values significant at p < 0.001

Table 7: Factor Coefficients table

Overall, the model is significant (*F = 34956.107, df = 3,33, p < 0.001)* the R^2 indicates 100% of the of the variation in the dependent variable i.e., the presence of the helpfulness rating on an online review. Furthermore, analysis of the coefficients tells us the only the review related variables had a significant value to the change in the helpfulness rating of the online review. A 1-unit change in the review-related variables leads to 0.915 increase in the helpfulness of the online review (*t = 7.409, p < 0.001).* Both values are measured on a 5-point scale. Both the reviewer-related (*t = 1.607, p > 0.05)* and time related variables (*t = -0.747, p > 0.05)* are not considered to have significant relationship to the helpfulness rating of the online review. This further emphasizes the importance to develop a review sorting system using review related features such as the review depth or the presence of use scenario over using time related variable to give explanation for the same.

b. Choice Modelling

Moving on, once the attitudinal responses were recorded and explain the participants were also question based on a choice modelling scenario. The choice modelling scenario will help to explain if the descriptive attitudes and regression statistics are in line with the participants when placed in a hypothetical shopping scenario. Consistency between the two approaches will confirm if the consumers reflect similar attitudinal responses when placed in a hypothetical shopping scenario or consider other factors more important to their purchases. The online shopping scenario involved the purchase of a laptop online on an e-commerce platform. At the shopping scenario the subjects were introduced to 2 online shopping choices, each choice had 5 factors to inform the participants either about the product attribute namely price and the Online- review related features where 4 factors were measured with different number of levels for each. At the beginning of the survey each participant had received information of the different factor of an online review to avoid confusion. They were again informed about each level of the different factors to provided background before starting the decision-making process between 16 choice sets. Figure 3 depicts an example of a choice set for the participants.


Q

Which of the following laptops will you purchase?

Price: $1,500	**Price:** $1,000
Usefulness rating: not useful	**Usefulness rating:** Useful
Amounts of reviews: moderate	**Amounts of reviews:** some
Reviewer: leaves few reviews	**Reviewer:** Has an expert rating
Depth of review: In depth	**Review:** Has an extreme rating

Figure 3: Example of a choice set

Unlike the factor or the regression analysis price was also considered in this for the choicer-set analysis. This, orthogonal main effects plan (OMEP) survey design 0 helped to create many choice responses form a limited number of participants. Price comprised of 4 levels at $500, $1000, $1500, and $2000. Research suggest that price is a major driver of the perception of quality for use product such as laptops. They give the consumer gets a message about the quality of the product. Next factor was the usefulness rating, just as the consumers would observe in an online shopping scenario this was displayed as a 2 levels factor with a “usefulness” and “not useful” rating. Next, the number of reviews left was considered a 4 levelled factor, it was rated as the of the most important factors in the in time related variables hence was an important factor for the choice set analysis. The 4 levels were “Moderate", "Lots", "Some", "Very few". The penultimate factor was a 4 levelled factor to measure the reviewer related variables. The two ways in which reviewers can impose their expertise in the online shopping scenario is by leaving a lot of reviews in a particular product category or getting their account verified from the e-commerce platform. Therefore, the first 2 levels of this factor displayed if the reviewer had a “Expert rating” or had “No expert rating. The next two levels displayed if the reviewer left “lots of reviews” or “very few reviews” in the product category. Finally, the review related variables were considered. This factor comprised of 4 levels as well, "In depth", "Sentiment included", "Helpfulness rating", "Extreme star rating". Like the 4 levels in the attitudinal measures this factor had 4 levels in this decision-making scenario as well to observe if these attitudes were consistent when placed in the scenario.

Once the data was collected from each respondent, they were through analysis in the R software to study the behavioural choices of the participants. Unlike, traditional choice-set questionnaire, the participants did not have the opportunity to pick the no choice option, because we wanted to observe the decision criteria each participant picked. The participants would consider each level that are important to them as they complete the choice-sets, they could either take an approach aligning with the price or the different factors that contribute to the helpfulness of the online review. Unlike the Likert scales used earlier, this method helped to irradicate any bias such the positivity bias where the participants might select an extreme high value consistency (for example “strongly agree”). Furthermore, it helped to remove bias that could come from between person scale use differences. This could be due to the subjective definitions of the different scales.

For the study, a long format data structure was included to learn the decision-making strategies of the participants. In this step a no choice example was also added. Which meant for each participant provided 3 choice making scenario for each of the 16 choice sets, a cumulative 48 instances for each participant. Due to this ability of the model 1344 instances were collected from the eligible 28 respondents for the decision-making scenario. A logistic regression was then run to analyse the decision-making criterion of the participants. A major concern of the model is the left-right bias, whereby the participants will consistently make the decision in one side of the choice set. Our results, however, has the left side being chosen 49% of the time and the right side being chosen 51% of the time. This confirms the respondents took enough consideration time for each instance as varied results were produced. Good survey design along with the randomization element of the OMEP model were able to ensure the variation in the data.

The model had a log-like hood value of -430.34. Price had the highest level of significance at (10.22, $p < 0.001$) with a positive estimate of the helpfulness rating. This suggests people preferred a laptop that was more expensive. This was an interesting insight which suggest the increase in price had a higher chance of the consumer picking the product. This could be explained as price being marked a symbol of quality and the higher price would have swayed to a higher perception of the product quality. The next most significant factor was the usefulness rating (-1.92, $p < 0.05$). The usefulness rating had a negative coefficient which meant it was not considered when the participants looked the factors that define the helpfulness of the review. This was a big contrast from the results in the attitudinal responses of the participants, The presence of the helpfulness rating had contributed very highly to the perception of the helpfulness of an online review. However, when placed in a decision-making scenario with other factors also listed participants showed a difference in their action. Finally, Time related variables are also seen to be approaching significance (1.60, $p<0.10$). This confirms the attitudinal responses left by the participants. In both the attitudinal and the decision-making scenarios, the higher number of reviews contributing to the review frequency were regarded when considering the helpfulness of the online review. The reviewer-related variables (1.23, $p > 0.1$) and the review-related variables (0.47, $p > 0.1$) failed to show any significance in choice sets. Unlike the Likert scales we understand that review related feature does not play an important role when the consumer is placed in a scenario when they have decided between the other variable of the product attribute (i.e., price) and the helpfulness was considered as a combination of absence of the usefulness ration and the presence of time related variables.

Coefficients	Z- values
Price	10.22***
Usefulness rating:	-1.9058*
Time variable:	1.6001**.**
Reviewer Variables:	1.2392
Review Variables:	0.4712

Log likelihood of model = -430.34. Unless stated coefficients are not significant at the P < 0.01 level.
*** p < 0.001
*p < 0.05
. p < 0.10

Table 8: Coefficient's regression model initial model

Once data was analysed based on the regression elements dummy variables were assigned based to create a hierarchy of the element for each of the factors which the participants included in their decision-making criteria. A list of models, with the dummy variable used and the log likelihood values is displayed below.

Model	Dummy variable	Log Likelihood
1	-	- 430.34
2	a. Not useful b. Time relates variable: very few reviews left. c. Reviewer relates variable: no expert rating. d. Review related variable: sentiment included	- 426.27
3	e. Not usefulness f. Time related variable: very few reviews left. g. Reviewer-related variables: Expert rating h. Reviewer-related variable: Depth of the review	- 425.06

Table 9: Summary of Log-likelihood values of test model

Model 3 was chosen as the most appropriate model as it had the lowest log likelihood value (425.05). It informs us that the participants consider a review with a usefulness rating over that is missing the rating (2.35. p <0.05), next some numbers of reviews are picked most often compared to other levels of the time-related variables. The significance value for this relationship was approaching significance (1.80, p < 0.1). Finally, the exclusions of sentiment in the reviews were preferred over depth of review related factors. This relationship was also approaching significance (-1.66, p < 0.1). An in-depth review was considered most important over all the other levels of the review related features.

Coefficients	Z- values
Price	10.17 ***
Usefulness rating: Useful	2.35 *
Time variable: Moderate	-0.32
Time variable: Lots	0.88
Time variables: Some	1.80**.**
Reviewer Variables: No expert	1.03
Reviewer Variables: Leaves lot of reviews	0.01
Reviewer Variables: Leaves few reviews	0.96
Review Variables: Sentiment included	-1.66**.**
Review Variables: Helpfulness rating	-1.61
Review Variables: Extreme star rating	-0.42

Table 10: Final model summary with categorical dummy variables

Log likelihood of model = 425.06. Unless stated coefficients are not significant at the P < 0.01 level.
*** p < 0.001
*p < 0.05
. p < 0.10

5. Recommendations

Based on the attitudinal responses, decision making scenarios and the statistical analysis here are some key recommendations to consider for e-commerce platforms when designing a more appropriate sorting system.

1. Both the attitudinal measure and hypothetical online shopping scenario tell us the review related factors are considered most important during the purchasing decision. Comparing the descriptive results, we understood that the gap that lies in the current sorting systems. Patrons consider recency as the least important feature to correlate to the helpfulness rating of the online review. While the depth of the online review was considered the most important. This was then confirmed by the regression model which had the most significant rating when comparing the review related features of the helpfulness. It was further noticed in the logistics regression model which showed the importance of the review depth on the helpfulness rating when comparing the other variables of the review related variables as well. E-commerce platforms such as amazon should look to develop standards for each product based on comparison of the depth through comparing reviews of the whole review corpus under any product. This method would also include the consideration that the online shoppers find reviews generally helpful if there are a lot of reviews left under any specific product.

2. The use of review related variables to define the create a comprehensive model for the helpful of the review will lead to a loyal customer base acting on their purchase intention. This study shows that filtering them in terms of review related features will yield a much better interaction with the website and therefore a greater chance of the consumer acting on their purchasing intention in the online shopping scenario. This method will help the E-commerce platforms to sort out reviews that are spam, not in-depth or deviating from the general sentiment of the reviews listed. The use of such sorting techniques will also encourage a healthy online review culture among the consumers on the platforms. Reviewers who look to gain higher expert ratings on the e-commerce platforms will leave more in-depth reviews to be displayed as the most relevant reviews. We understand the significance of the most relevant comment or search item in this digital age, organizations will

pay up to $50-$60 per click to be the top displayed item on search engines. Since these reviews will no longer be displayed at the top or the most relevant review, consumers will gain higher confidence in the e-commerce platform to aid their purchasing intention. These sorting systems should be developed by using data analysis techniques through word association and clustering to compare the whole review corpus under any product.

3. This study price is still the most important consideration when buying products online. While a lower price can provide competitive advantage, The higher price adheres to the perception of quality in the mind of the consumers. Especially in electronic gadget buying scenarios. The majority of the participants in this study 40% consider online reviews when buying electronic gadgets online. Therefore, e-commerce websites should look to promote high quality in their products listed online as consumers will not deviate from their purchasing intention due to the higher price.

As an E-commerce website online review has been very fruitful to provide information and help the consumers in scenarios where it is physically impossible to compare product attributes. This study shows a clear hierarchy when it comes to the consideration of the online review factors when consumers shop online. Review related variables more specifically in-depth reviews that describe and compare the product attributes are considered the most important, followed by the comparison of the time related variables i.e., frequency of the reviews over the recency and finally reviewer related variables are considered.

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