Online Consumer Reviews at the Long Tail

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Keywords: Long tail, online consumer reviews, niche products, WOM

Abstract

This research aims to understand how consumer reviews can help the products at the long tail of the distribution curve. Long-tail products are those large number of niche products that sell in small number compared to the few main-stream products that sell in large numbers. Research shows despite the Pareto principle, long-tail products cumulatively can give tough competition to the main-streams for the profitability of a retail chain. We know, reviews impact the sales of a product through its various dimensions like valence, volume, quality, length etc. We want to find if the same applies for long-tails as well. If not, then how long-tails can take the advantage of reviews like the main-streams do? These two product categories essentially target different consumers. Long-tails suit consumers with more niche preferences whereas main-streams are more inclined towards hedonism and general preferences. We believe this changed consumer behavior should reflect in the reviews as well. Incidentally, statistical tests reveal reviews for the long-tails differ significantly from those of the main-streams. With methods of text analytics, we also find reviews for the long-tails tend to be more detailed and descriptive while containing more number of topics. Then we find, among the various dimensions, long-tail consumers are motivated by review quality and not by review length, valence or volume.

Online Consumer Reviews at the Long Tail

Introduction

The emergence of Web 2.0 and ecommerce have fundamentally altered the sales and distribution of products with the creation of infinite inventory for the online retailers or e-tailors. Hence for obvious reasons the offerings of Amazon.com, Netflix, iTunes etc. surpasses that of any brick and mortar store by many times. The internet has led the discovery of the niche products easier than ever before. The Pareto Principle says, the sales are concentrated with the superstars or the block-busters (top 20% or so). Though this still prevails in the online markets (Brynjolfsson et al. 2010b, Duan et al. 2009), however a new reality is slowly emerging. The distribution of sales is getting flatter by the day and the lesser-knowns are gaining larger market share. These previously untapped niche products constitute the long-tail phenomenon (Anderson 2004, 2006, 2009). The phenomenon has been applied and explored by many researchers to investigate the change in demand distributions within spans of time (Brynjolfsson et al. 2010a, Elberse and Oberholzer-Gee 2008). The distinct characteristics of this long-tail market are: (a) these products appeal to a select few meaning a vast majority are the misses and (b) these niches in aggregate amount to a sizable proportion of the total sales. Evidences show that 30% of Amazon.com offerings and 25% of that of Netflix's are not available with the largest brick and mortar stores (Anderson 2006). And this is growing by the day (Elberse 2008).

Again, in the internet domain. online consumer reviews (OCR) have been the forefront of research for quite some time. This is because OCR impacts product sales (Godes and Mayzlin 2004, Duan et al. 2005) and plays a crucial role in consumer decision-making process (Dellarocas et al. 2007, Dhar & Chang 2009). Approximately, 80% of the consumers who are planning for an online a purchase, would prefer to know the reviews before making the decision (Infogroup 2009). At times, consumers are willing to pay even 20% higher price for 5-star rated offerings when compares to others (ComScore 2007).

When we think of OCR for the long-tail, we know those reviews are being generated by a different set of consumers who have niche preferences. These consumers are generally high-involvement consumers. Since long-tails, by definition are hidden in the clutter, thus one has to make some effort to discover those. Hence users of long-tail seems to be more aware of their needs and are more particular about their product choices. We believe, the reviews for the long-tail products would contain certain other dimensions not found or are distinct from the reviews written for the main-stream products.

With the help of internet, as more and more niches get discovered, in aggregate their contribution to sales would rise (according to the long tail characteristics). Hence it is in the interest of the businesses to understand how they can tap the power of OCR for these niches, in order to give them the right exposure. Managers can then make the required changes in their OCR strategies for the niches. This article also aims to enrich the nascent literature on consumer behavior for the long-tail.

Research Purpose

Research shows that the consumers who look for niches, search differently than consumers who look for the block-busters. This is because the characteristics of the long-tail consumers are different. Long-tail and main-stream products cater to two different set of consumers. Long-tail consumers are willing to spend more time in the internet (Elberse 2008) to find the product of their choice. They search in detail and in most cases, are also aware of the offerings that might suit their purpose. They do not follow the crowd as in the case of the block-busters (hedonism), rather they prefer the exact offering of their choice (utilitarian). This changed behavior of the long-tail consumers has led us to the assume that the reviews generated by them would also be different. There has been a lot of studies on consumer reviews including its antecedents and precedents, however existing literature provide little or no clue in this regard.

The purpose of this paper is to understand if the reviews for long-tails are different in characteristics from that of the main-stream products. If yes, then how these reviews are different? It seems logical to assume there would be differences as the consumers of these two categories search differently and consumer differently. Hence their tastes are different and we feel this should reflect in their reviews. This understanding has immense potential. One direct impact would be for the managers managing the long-tails to use the OCR to its advantage.

Research Question(s)

Here we narrow down the research problem to specific question(s) that we seek to answer through our research. Existing research tells us, reviews are characterized through many dimensions like valence, volume, review length, review quality etc. Valence deals with the preferences that are being carried in the review. This can be positive, neutral or a mix of positive and negative. In the context of OCR, the valence is the star (numerical) rating that the users provide for the offerings from the providers. On the other hand, the volume refers to the total number of reviews generated irrespective of their preferences. This paper aims *to see whether the various review dimensions (volume, valence, length and quality) changes in case of niches vis-à-vis the main-streams.*

To answer this question, we have approached in two stages. In the *first stage*, we begin with a preliminary analysis. The purpose of this preliminary analysis is to ascertain if our assumptions are correct or if we are heading towards the right direction. Once this is ascertained, then in the *second stage*, we review the literature, propose hypotheses and conduct the research.

In the preliminary analysis, we present two main stream products from different categories along with their two long-tail counterparts. We then analyze their reviews in terms of the content. We then try to understand, if there are any visible differences between the reviews for those products. When we observe the differences between the reviews, we proceed to explain and develop hypothesis in the later stage.

In the *second stage*, we look into the literature, propose formal hypotheses, conduct experiment and provide suggestions to businesses. We approach this stage in three phases: *first*, we seek to know what constitute the long-tail reviews. Here we outline the characteristics of long-tail reviews. *Second*, we try to find out why the reviews for the long-tail are different from the reviews for the main-stream products. *Third*, we provide a few suggestions to businesses on motivating consumers to incorporate those elements while writing reviews for long-tail. This would help other long-tail consumers who are reading the reviews to evaluate products for probable purchases.

Definition and Preliminary Studies

Collins English Dictionary describe “long tail” as a noun (long tail 2019) with the definition “*the segment of a market representing the large number of products that sell in small quantities, considered by some to be of greater financial value than the few products that sell in very large quantities*”. The phrase essentially comes from Statistics where the “long-tail distribution” means a very large number of occurrences far from the head and thus the tail is very long. In business, the idea as made famous by Chis Andersen in his 2004 article in the Wired magazine (Anderson, 2004). Andersen shows us there is every kind of option within a long tail. Thus, in absolute numbers, the main-streams are few in compared to the long-tails. The long-tail caters to all tastes of all kinds which the main streams are not essentially targeting. Each of these products has few users, but when put together, these number of users surpass their main-stream counterparts. Hence, the contribution of long-tail in the business is of significance. During the yester years, there was a problem of inventory for the brick and mortar stores. The stores were not able to hold this high number of products and thus were not able to cater to all the tastes. However, with the modern internet, the concept of infinite inventory has kicked in. The present-day e-commerce websites find it much easier to display a large inventory of products. This in turn has helped the consumers who now can search for the specific products that suites their specific requirement. One example can be a slim grey external SATA hard drive of memory 2 TB with USB 3.0 support weighing less than 150 gm which is compatible to both PC and Mac. This is in contrast with just a Seagate 2 TB external hard drive. The former is an example of long-tail search. The same is true for any other products like a movie, or a gadget or a book and so on.

The main-stream products are famous and hence can be easily pointed out. By definition, they are not hidden and thus don’t take much time and effort to discover. Hence consumers (both new and repeat) can find them easily. On the contrary, the consumers of long-tail understands and looks for exactly those products with specific parameters that they think would satisfy their needs. This is the reason they can find those products. Because of the high number in the long-tail, these products are hidden inside the clutter (Anderson 2006). It takes some amount of effort to search and find them. When consumers are willing to make the efforts, it shows they understand their products. We can also argue, long-tail consumers are more patient, as they have to scrape though a large number of options to find the exact one. The consumer might also be loyal to a particular product and is not willing to change brand. All these are pointing to the behavior of long-tail consumers. In the later section, we highlight in further detail the changed and distinct behavior of long-tail consumers.

When the long-tail consumers write reviews, we believe those would also be different. Long-tail consumers would look for specific information and their thoughts should reflect in the reviews. We believe these reviews would be detailed in nature. The reviews would also be a bit more technical. Hence the long-tail reviews might be lengthy compared to other reviews.

Here we set up a preliminary study to check our assumptions. The results of this study would be connected to the literature and this would help us developing the hypotheses.

For conducting the preliminary study, we chose two product categories. We then look for these products among the main-stream brands in the ecommerce websites. We selected the brand with the highest number of ratings and reviews and the brands which appear first (by relevance) in the e-commerce websites We then look at their reviews. After this, we found out their-long tail counterparts. We then analyzed those reviews.

We randomly selected two product categories – optical mouse (computer peripheral) and home television. To find realistic options, we then decided on few basic specifications which generally consumers look into before purchasing like the type etc. Computer mice are generally of two variant – wired and wireless. We decided on the wireless category. Home television needs more parameter to look for. Consumers generally look for the screen size and type as the prime parameter. We decided to go for 32 inches LED screen televisions. We searched for these items in the top e-commerce websites.

To maintain the diversity of the source, we decided to use both Amazon and Flipkart as the data source. These two are the largest online retailer in India with a valuation of 16 billion USD and 22 billion USD approx. respectively as of 2018 (Chanchani & Variyar 2018). We randomly assigned optical mouse to Amazon and home television to Flipkart website.

Preliminary Study 1

When we searched with the keyword “wireless optical mouse” in Amazon.in, the first product in the list was “Logitech M235 Wireless Mouse (Grey)”. This is when the list was sorted according to popularity (default settings). The most popular and relevant product would appear first. This particular product was also suggested by Amazon and was marked as “Amazon choice” (see the Table V in the Appendix for screen shots). This product also had the highest number of ratings and reviews by the consumers in that category. Hence this was an ideal choice for a main-stream product.

Now was the task to choose a long-tail product. For this we were looking for a product in the within the price range of the main-stream product. The product should also be highly rated indicating its high satisfaction among its users. However, the product should be used by a fraction of the consumers of the former product. Some of the products listed matched these criteria and we decided to choose “Abronix 2.4G Optical Wireless Mouse with 6 buttons Nano USB Receiver (Black).” In both the cases, we took the numbers of reviews as a proxy to the number of consumers.

We then analyze the reviews for these products and some striking features were observed. The reviews for the lesser known product are comparatively longer. The average word count for Logitech mouse is 14.23 and that of Abronix is 21.05. The median of the number of words in the reviews also varies by 100%. The median of the number of words for reviews of Logitech is 6, whereas that of Abronix is 12. Table I lists down the derails and our observations.

Table I: Summary data for wireless optical mouse category		
Parameters	Logitech M235 Wireless Mouse (Grey) (Popular product)	Abronix 2.4G Optical Wireless Mouse with 6 buttons Nano USB Receiver (Black). (Lesser-known product)
Total Number of reviews (proxy for number of consumers)	10,030	111
Average Rating	4.4 out of 5	3.9 out of 5
Rating above 4 stars	79%	76%
Number of Reviews analyzed	78 (most recent as on 12-Feb 2018, 11:00 PM)	78* (most recent as on 12-Feb 2018, 11:00 PM)
Average number of words per review **	14.23	21.05
Median of number of words in the reviews **	6	12
Mode of number of words in the reviews **	4	4

Note: *Amazon does not distinguish between number of ratings and number of reviews (Flipkart does). Hence for Abronix, though it was showing 111 reviews, the total number of text reviews were 78. Rest were only star ratings without anything (text) written.

** Both Amazon and Flipkart show reviews with headings. Headings appear in bold font. The words for headings and texts are combined and then counted. For eg.

Heading – Good Product

Text – This product is really nice. I’m happy and satisfied.

Once we found out the fact that the reviews for the less popular product is longer (at least in this case), we are interested in finding the dynamics of these reviews. We decided to check the contents of the reviews to understand better. We assume that the detailed reviews should cover a number of aspects ranging from technical aspects to customer satisfaction and the like. To test this, we have taken the help of software VOSviewer (van Eck and Waltman, 2009) version 1.6.8. We create a network diagram of the review contents for both these products. This helps us to understand the number of different aspects these reviews contain. The network diagram is created with the words or group of words that appear 3 or more times among all the reviews. The software then created various clusters based on the frequencies of the words (or groups of words) found.

The network for Abronix is much denser (see Table II(B)). There are 17 minor clusters in total. These are the topics/words that the consumers are using frequently in their reviews. Out of these the software has created four major clusters (shown in different colors) which can be classified as: (a) money or value related (good product or great product at this price), (b) product feature (like buttons, additional buttons etc.) related, (c) product quality related (battery, nice quality etc.) and (d) customer satisfaction related (good mouse, worth etc.).

The network diagram for Logitec (Table II(B)) shows 8 mini clusters from which the software has created two major clusters – (a) product feature related (price, mouse etc.) and (b) product quality related (good product, nice product, battery etc.).

This clearly shows the reviews for Abronix are rich in content and consumers are talking about multiple dimensions highlighting why they feel the product is good.

Table II(A): Below is the network diagram for Logitec

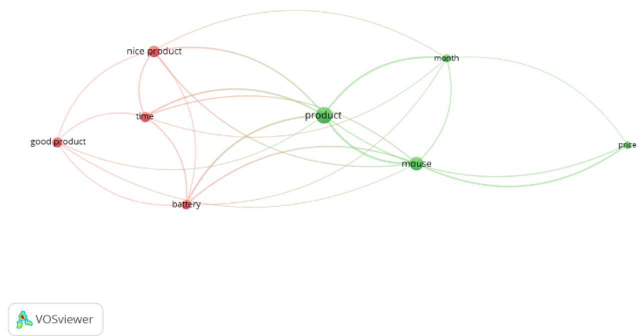
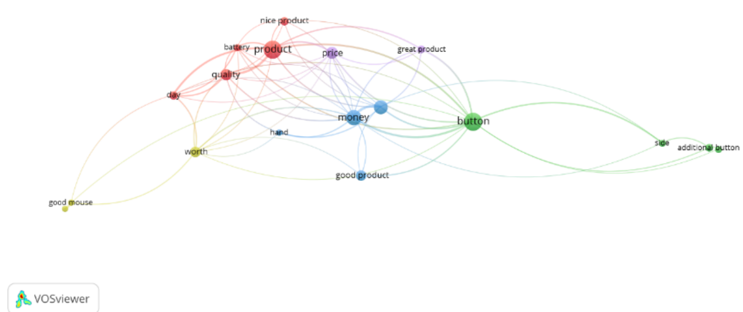


Table II(B): Below is the network diagram for Abronix



Preliminary Study 1I

In the second preliminary study we considered another set of products from a different category. We chose the category of home television. We also decided to change the online platform where to look for the product. The two largest ecommerce marketplaces in India are Amazon and Flipkart (Koetsier 2018). Since the last study was done using Amazon, we decided to go for Flipkart for this study. We assumed the consumer sentiments and the long-tail characteristics would be more or less equal in both these market places.

In order to look for a parameter to search for the home television, we decided on the screen size. Screen size is one of the most important factors to decide on home television sets. Once the parameter is decided, now is the time to decide on the parameter value. The Hindu published an article (Nandana 2018) stating that 85% of Indians purchased televisions with screen size ranging from 32 to 43 inches. We thus, zeroed in the 32-inch screen size.

When we looked into the Flipkart database for TV sets with 32 inches screen size, the first one that appeared in the result is “Mi LED TV 4A 80 cm (32)”. This is when the data was sorted based on popularity (the default settings). It seems this TV (henceforth Mi TV) is the most popular one in the category. Unlike Amazon, Flipkart gives the number of star-ratings for the products and the number of reviews differently. The total number of ratings for the TV is 1,72,692 and the total number of reviews is 25,710 (see Table __ in Appendix). It is obvious that all consumers, who had rated the TV, did not commented as reviews. The Mi TV has a 4.4 stars average rating out of 5 stars. This product is a clear main-stream choice. Hence, we analyzed the reviews for the Mi TV.

The next task is to find out a high-ranking television (as per stars), but which is not as popular as the Mi TV. Also, the specifications should be more or less similar to that of the Mi TV. While looking for possible options, we out a product by TCL met our criteria. The full name of the TV displayed as “iFFALCON by TCL F2 80 cms (32 inch) HD ready LED smart TV (32F2)” (hence forth TCL TV). Our previous model Mi TV was also HD ready and was a smart TV. The TCL TV has a high rating of 4.1 stars out of 5 stars. The total number of rating for it is 3,083 where the total number of reviews is 806. This is a long-tail product.

We now analyze the reviews for both these TV sets. Table III, below contains the summary of the reviews and the ratings that we studied. In order to maintain a similarity with our previous study, we took the most recent 78 reviews for our analysis. Here also, we found the same trend from our last study for long-tail reviews. The reviews for the long-tail (TCL TV) product tends to be longer, though the difference is not as high as in our previous study. The average number of words in the reviews for TCL TV is 47.78, whereas that of Mi TV is 45.65. The median for the number of words in the review for TCL TV is 26 whereas the same for the Mi TV is 16. The mode for the number of words for the reviews in case of TCL TV is 15, where as the same in case of the Mi TV is 6.

Table III: Summary data for 32 inches LED home television category		
Parameters	Mi LED Smart TV 4A 80 cm (32) (Popular product)	iFFALCON by TCL F2 80cm (32 inch) HD Ready LED Smart TV (Lesser-known product)
Total Number of ratings & reviews (proxy for number of consumers)	1,72,692 ratings & 25,710 reviews	3,683 ratings & 806 reviews
Average Rating	4.4 out of 5	4.1 out of 5
Rating above 4 stars	86%	83.5%
Number of Reviews analyzed	78 (most recent as on 12-Feb 2018, 11:00 PM)	78* (most recent as on 12-Feb 2018, 11:00 PM)
Average number of words per review **	45.65	47.78
Median of number of words in the reviews **	16	26
Mode of number of words in the reviews **	6	15
Note: *Amazon does not distinguish between number of ratings and number of reviews (Flipkart does). ** Both Amazon and Flipkart show reviews with headings. Headings appear in bold font. The words for headings and texts are combined and then counted. For eg. Heading – Good Product Text – This product is really nice. I'm happy and satisfied.		

Now once the summary has been analyzed for the reviews. We now look into the details of the contents. We again used the VOSviewer software (van Eck and Waltman, 2009) version 1.6.8 for the network analysis. Like our previous study, we decided to check for the words that appeared 3 or more times in all the reviews. The software then creates a network visualization with the word frequencies and association among them.

For the Mi TV, the software created seven major clusters where the nodes are colored differently (see Table IV (A) below). These clusters are: (a) money/worth related, (b) purchase related, (c) product quality related (sound, nice etc.), (d) e-commerce service related (fast delivery, installation etc.), (e) Issue related (problem, failure etc.), (f) software or app related (apps etc.) and (g) product type related (smart tv etc.).

For the TCL TV, the software has created six clusters (see Table IV (B) below) which are: (a) money/worth related, (b) software or apps related (Appstore, YouTube etc.), (c) e-commerce service related (time, service, day etc.), (d) product type related (smart tv, option etc.), (e) product features related (wall mount, sound etc.) and (f) the keyword "product" itself. It seems consumers are using the keyword multiple times in their reviews.

The striking feature for the network diagram for TCL TV is that the clusters contains many distinct sub clusters. The number of sub clusters are way more that in case of the Mi TV. The network is highly dispersed compared to the Mi TV network diagram. This means consumers are mentioning many different aspects of the TCL TV in their reviews. For e.g., if we take the software or apps, the different sub clusters are: (a) YouTube, (b) phone, (c) Appstore, (d) music, (e) video, (f) sound system, (g) picture and (h) good product. This high number of sub clusters can be found across all the clusters for the TCL TV. This is a clear indication that the consumers are reviewing about the technicalities and are talking about many different aspects of the product.

Table IV (A): Below is the network diagram for Mi TV

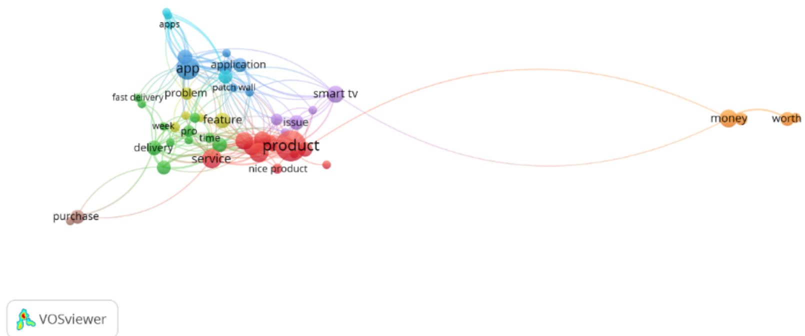
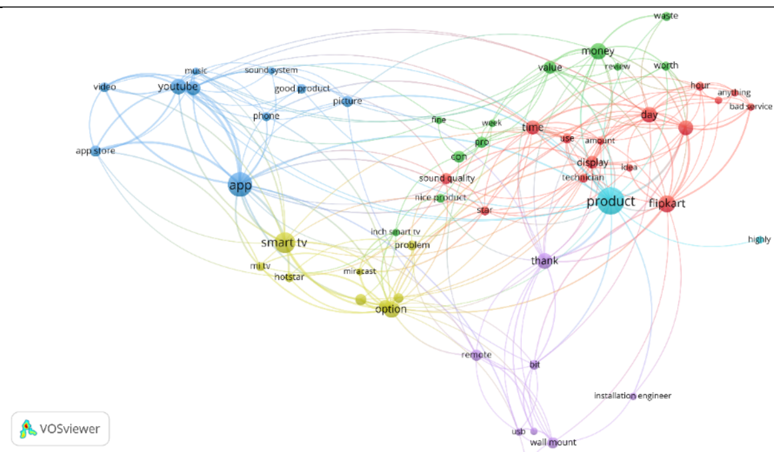


Table IV (B): Below is the network diagram for TCL TV



Search Behavior in the Long-Tail

Elberse (2008) stated that consumers with large capacity for content prefer niche products and they generally settle for long-tail. This is in line with the argument that searching for long-tail itself takes an amount of effort. Hence the consumer, who is motivated to invest an increased amount of time and effort to search for a particular product, he or she must have a higher awareness about his needs. Since he has already made an increased effort while searching, he would try to make sure of the utility received once he discovers the product. Overall, as an information gathering option, searching is a more expensive option for the consumers (Nelson, 1970). Existing research tells that when a consumer stops searching for a product, it means he has found products with higher utility than that he is or was getting (Stigler 1961, 1962, Moorthy et al. 1997).

Searching requires an effort in deciding the product features to search for. This requires consumers to decide the search parameters to be used. In order to make the search efficient, consumers need to possess knowledge about the product or the offering. Consumers who are aware of the product features, pay more attention to the product attributes during their search (Brucks 1985). Consumes who give high importance to products and are highly involved in the product selection, generally perceive higher attribution differences than their counterparts (Howard and Sheth 1969). When consumers are highly involved in the product purchase process, he is likely to spend more time in searching in order to ensure right product selection (Belk and Clarke 1978).

We believe, because of this higher involvement, long-tail consumers are more aware of the products attributes and thus would evaluate them more critically. When these consumers write and post their reviews, there is a high chance that those reviews would reflect their high degree of awareness and involvement with the products. Hence the reviews should contain detailed description highlighting the views or opinions. These reviews should not just spread the message of "good or bad" to the other consumers. Rather they would try to explain and argue while also educating the other consumers. Hence, we propose:

Proposition 1: Reviews for long-tail products are more detailed, more informative and of higher technical nature than the reviews for the main-stream products.

Changed Behavior: How the OCR impacts in the Long-Tail?

OCR Volume

If we take a quote from Liu (2006, p 77), "*[the] greater the volume of WOM, the more likely a consumer will be able to hear about a product. Not surprisingly, greater awareness tends to generate* *greater sales".* Here WOM stands for Word of Mouth and the online reviews are a type of electronic WOM (Godes and Mayzlin 2004). Different previous studies have shown the volume to be corelated with consumer behavior and also to market outcomes (Anderson and Salisbury 2003, Bowman and Narayandas 2001). The volume helps in creating the 'buzz' for the offering as it can spread further leading to greater awareness. Higher number of reviews indicates higher number of users and thus gives an impression that the product is tried and tested.

However, for the long-tail consumers, we believe this volume of reviews would not matter much. The long-tail consumers are self-motivated and would not require the audience's cheer for selecting their products. These consumers not looking at the main-stream, itself is a testimony that they are aware of their needs and are willing to evaluate other products based on their attributes. These consumers are willing to take more risk in uncharted territories. These high involved consumers are willing to evaluate an offering based on their knowledge and accumulated information rather than going by the number of reviews or say number of 5-stars. These consumers may be among the handful others (may be a few thousands) who are opting for a particular long-tail offering. Hence, we propose:

Proposition 2: OCR volume is not an important factor for consumer motivation for long-tail offerings.

OCR Valence

Valence deals with the preferences that are being carried in the review information. This can be positive, neutral or a mix of positive and negative. In the context of OCR, the WOM valence is the star (numerical) rating that the users provide for the offerings from the providers. Research has already found valence of reviews to be positively related with sales (Li and Hitt 2008; Chevalier and Mayzlin 2006). Research talks about both conformity and negativity bias in connection to the impact of the valence of the reviews. Conformity bias (Klayman and Ha 1987; Chevalier and Mayzil 2006) happens when consumers look for affirmative evidence supporting their product choice. Whereas negativity bias (Mizerski 1982; Cui et al. 2012), suggests negative reviews have more impact than positive reviews when the consumers are neutral. These biases happen when the consumer is not in the possession enough information to be sure if the current offering can fulfill his needs. The impact of review valence should come down when the consumers are aware of the product attributes in detail. Here we propose, because of their enhanced product related knowledge, the long-tail consumers would not be influenced by the valence. Long-tail consumers have no need to get influenced by the positive/negative reviews as he understands requirements are unique and thus the offering which might not suite others' need, might suite his needs. This is extremely true for certain genres of movies, songs, books etc. Thus,

Proposition 3: OCR valence is not an important factor for consumer motivation for long-tail offerings

OCR Length

Consumers of long-tail gives importance to details. By definition, they are looking at the long-tail since they have niche preferences. This means consumers are looking for specifics or may be multiple specific information that suits his/her needs. We believe the same would be reflected when he is reading the reviews. While evaluating a long-tail, the consumer would focus on the detail and would be interested in the technical aspects of what the other consumers think about the product. The consumer would be expecting others to share their experiences on the usefulness or with the faults, if any. He understands that other consumers who have looked for such products, also have niche interests. Hence, consumers when reading reviews for the long-tail, expects a detailed perspective. They know that these are not main-stream products and are thus looking for specific information. We think that length of the review is an important criterion for consumer motivation in the long-tail. Hence,

Proposition 4: OCR length is an important factor for consumer motivation for long-tail offerings.

OCR Quality

The quality of a review is the strength of persuasion that it displays. The quality is being measured by various parameters like the relevance of the review, its comprehensiveness, the timing of the review and how accurate is the information it is providing s (Cheung & Thadani, 2012). Existing research (Park et al. 2007, Cheung et al. 2008) tells us that review quality is important for online consumers as high-quality reviews have a greater impact on consumers purchase decision. We believe the same would be specifically true for the long-tail consumers. While evaluating a product, long-tail consumers would be looking for sufficient fact-based evidences which are relevant for the product. We think the review quality is crucial for consumer motivation at the long-tail.

Proposition 5: OCR quality is an important factor for consumer motivation for long-tail offerings.

Conclusion, Implication and Scope for Future Research

This study confirms that consumers looking for long-tail products search differently from consumers of main-stream products. This is because long tail products are hidden from the clutter by definition. Andersen (2004) had proposed the term long tail. These are the products that satisfy consumers with niche preferences. Hence, they are hit with few consumers. Because of this, the sales of individual long tails are not much when compared to the main-stream products. The main-stream products are hit with many consumers having a wide range of preferences. However, Andersen (2004) observed that cumulatively the sales of long tail products can give close competition to that of the main-streams. The sale of long-tail never goes to zero and hence the graph keeps on going. We see, that consumers looking for long tail products, invest more time and effort in searching them. These consumers are also aware of their need and hence they are willing to make the extra effort to find the product. These are also evident in the reviews written by the long tail consumers. The reviews for the long tail are generally lengthier and are technically more informative. These reviews cover a lot of topics when compared to the reviews of the main stream products. We know reviews impacts consumer decision though its various dimensions like review length, valence, quality etc. However, long tail consumers are unlikely to get motivated by the length or valence of the review. Our study shows that long tail consumers would be motivated the by the quality of the reviews.

This study adds to the literature of consumer behavior related to the long tail products. Managers in charge of the long tail products can also benefit from this study. Managers can use this understating to promote products at the long tail. They would find that the general conceptions about the quantity and positivity of reviews would not be effective for consumer motivation in the long tail. Managers should concentrate on the review quality to boost the consumer reach for the long tail.

Like other studies, this research also has got few limitations. There are also opportunities for future researchers in this study. We have studied the consumer electronics category and we have focused on two product categories. It would be interesting to see if the same observations can be drawn from other product or services categories, say for e.g. movies or hotel industry. In tourism industry there are travelers who looks for obscure locations. Those can be considered as long tail offerings for tourist places. Future researchers can also try to develop a model for consumer motivation for the long tail products and services.

Appendix

Table V (A): The Logitech mouse and Mi TV appearing as the first choice

Table V (B): Number of reviews for the computer mouse category

Table V (C): Number of reviews for the home television category

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