

Online Review Characteristics and Information Asymmetry

Is it easy to switch between Online Shopping sites? A Case Study of Reviews from Amazon and Flipkart

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Abstract

Consumer characteristics and store attributes decide the store choice decision of consumers. To facilitate the switching process, physical formats create identical layout structures, shelf designs, staffing and billing desk. In similar lines, online stores also create features like similar website characteristics like the menu, creating shopping basket options, comparing product and billing process. Similar to Word-of-Mouth (WOM), online stores encourage and facilitate electronic Word-of-Mouth (eWOM) communications through Online Consumer Reviews (OCR) in their websites. Many online buyers use the reviews of others, social media content and blogs in their decision process. To understand the distribution characteristics of the online reviews, in this research work, we analyze the online review from Amazon and Flipkart for the masks and sanitizers. In a review, star rating, review length and helpfulness of a review are visual characteristics that communicate the content faster than words and no research works compare their variation between two online sellers. We prove that there are significant differences exist in the distribution of review characteristics between the online retailers' reviews. Two websites reviews vary in terms of star rating, review length and helpfulness votes. There are variations between Amazon and Flipkart reviews in general, and differences are observed in their brands sold also. Since the review characteristics and their distributions are unknown, this information asymmetry creates constraints for store switching behavior of online consumers.

Keywords: COVID19, eWOM, Information Asymmetry, Online Consumer Reviews, Online Store Choice

1. Introduction

The pandemic virus spread COVID19 has created disasters around the globe. To protect the virus spread, many nations and governments insist their people use the mask and sanitizers. These products until March 2020, used by specialized user segments, suddenly have become mass-market consumption category. In India, there are legal amendments, like a penalty for non-compliance of usage of the products in common places. These developments have triggered a new set of manufacturers for the masks and sanitizers, retailers, online retailers and created new demand cycles for the products. In particular, measures like complete lockdown, ban on public transport and restriction of people movements create a dependency to source the products from online retail firms. In turn, Amazon and Flipkart, the major players of online retail business, have to depend upon a few reliable suppliers and manufacturers to get the products in stock. These developments lead to a research context, where the product category, brands and retailers are relatively new and a very little information is available about consumers' awareness level, product knowledge and attributes consider for purchase.

A literary work on classification by (Andersen & Philipsen, 1998) outline and redefine the characteristics of products as the Search-Experience-Credence goods (Gottschalk, 2018). The researchers argue that relevant attribute information for experience and credence goods are not available to the customers before the purchase (Girard and Dion, 2010). Masks and sanitizers fit into the definition of experience goods, where the product quality is possible to assess by the customers in their post-purchase stage (Swaminathan, J. Fox, and K. Reddy, 2001). The products are relatively new to the shopping basket of many consumers and consumers' identification and evaluation of product-related attributes is highly formative nature.

Various researchers address factors influencing the store choice of consumers. Predominantly the studies consider the brick-and-mortar formats and rarely the studies compare online formats or retailers. Store choice is influenced by shopping trip timing (Leszczyc,

Sinha and Timmermans, 2000), brand loyalty (Dawes and Magda Nencyz-Thiel, 2014), lifestyle factors and shopping motives (Jayasankara Prasad and Ramachandra Aryasri, 2010), in-store layouts and shelf designs (Elbers, 2016). In the technology era of business, retailers or manufacturers' websites, comparison websites, social media and blogs are modern sources of information and the online stores have become choice of not only information search but also, a source to buy.

In the monopolistic competitive structure of the online retail business in India, a few retailers dominate the competition. The online retailers present almost very similar product categories, brands, visuals, product specification and follow the same pricing policies of their competitors. Research work on signaling theory and cue theory suggests that producer or marketer's credibility or the reputation are capable of reducing the perceived risk, uncertainty and improve the validity of information signals (Helm and Mark, 2007). Researchers prove that due to risk, experience and credence goods have direct influence from eWOM (Chiu, Chen, Wang and Hsu, 2019). If the purchase situation is a 'straight re-buy', there is a lesser need for additional information by the consumers. Nevertheless, in situations like modified re-buy or new purchases, consumers seek an opinion from other buyers, online sources and retailer's website. Thus, while buying products like masks and sanitizers, which experience in nature, consumers' dependencies are higher on retailer's websites and reviews from other consumers.

The Theory of Planned Behavior proposed by (Ajzen, 1991) pointed out that behavioral intention and behavioral control are predictors of behavioral achievement. Theory of Planned Behavior interpreted that attitude and subjective norms of engaging in an action influence intention of people (George, 2004). Moreover, Theory of Planned Behavior finds it relevance in Internet Purchase Behavior and online purchases. In purchase decision process, a buyer searches information (intention) and aware of sources, product attributes, retailers attributes (control) to arrive decision (achievement). However, reviewers can effectively use the information from alternate sources,

only if the information available is similar, identical, superior or complementary.

Unless the distribution of various review characteristics is well known, reviewers cannot use an alternate source of information in the decision process. To address this research gap, we compare the online reviews of Amazon and Flipkart and establish the distribution characteristics of online reviews. We analyze review characteristics like star rating, review length and helpful votes that are 'visual' in nature. Finally, we show how the information asymmetry present in the search attributes, affect E-retail store choice decisions.

2. Review of Earlier Studies

Word-of-Mouth communication (WOM) and electronic-WOM (eWOM) play a significant role in recommendation-based heuristics and hybrid decision processes (Chatterjee, 2001). In general, information search theories suggest a common process, which includes stages like need identification, decision to use, source selection, collection, interpretation and use of the information (Kundu, 2017). Research work on channel choice behavior proves the influence of offline channel's service quality and performance levels on choosing the online channels (Yang, Lu and Chau, 2013). However, the determinants of an online retailer as a shopping destination or the role of online reviews on store choices are found a place in the retail researches.

Design of the webpage and navigation are the key drivers of success for the online retail stores (Wu and Tsai, 2017). Moreover, online retailers need specialized skills to acquire and maintain customers' preferences and handle privacy, security risks related to the reviews they post online (Ayanso, Lertwachara and Thongpapanl, 2010) in addition to ensure availability of required information to reviewers.

To facilitate any new buyers, purchase process, many offline stores create similar layout structures and identical shelf locations for various products. In parallel, online firms create identical menu structure, product grouping and online customer review templates. If we

consider online review characteristics of Amazon and Flipkart, both the firms provide almost similar features in the consumer's review template except few fields, which are unique in the review forms (See Appendix-1). Fields like profile image, user profile and comment for review are unique in Amazon, whereas, fields like review location and not helpful reviews are unique in Flipkart reviews.

Among many review characteristics, star rating (a visual with star symbol), review length (long reviews or short) and helpfulness of the review (number of votes, represented by thumbs-up symbol) strike any reviewers attention and we operationalize them as 'visual' review characteristics for our study purpose. This study specifically tests the following hypotheses on e-retailer brands and their relationships with various review characteristics that are 'visual' in a review.

3. Hypotheses for the Study

3.1 Star Rating

Almost all the product or service websites provide a provision of registering a consumer opinion in a numeric rating scale, ranging from one to five. Known as star rating, it conveys a glimpse of the review content in one go to the reviewer. Various studies have addressed the significance of star rating; its influences on consumer purchase process (Wang, Cunningham and Eastin, 2015), association with product liking (Moe and Trusov, 2011), sales volume (Chiu et al., 2019); (Arbelles, Berry and Theyyil, 2020) and post-purchase satisfaction level (Chua and Banerjee, 2016). Even though this numeric summary provides signals faster than the content itself, extreme review ratings are considered as less helpful in the consumer's decision process (Mudambi and Schuff, 2010b).

Review length is another visual message characteristic that influences a reviewer's decision process. A study on review length proves that 3 to 5 lines as, ideal review length (Hernandez-Ortega, 2020). Another study finding shows that longer reviews are associated with high-ranked reviewers (Baek, Ahn and Choi, 2012). Researchers prove that review length affects perceived

helpfulness (Ryan and Alexander, 2010) and the utility of the review (Heng, Gao, Jiang and Chen, 2018).

Helpfulness votes of a review are another parameter that improves the credibility of an online review. Online retailers make efforts to bring down the expectation-performance gap of online sources in the purchase decision process by adding the source credibility and trustworthiness of a reviewer in the online review templates (Mumuni, Lancendorfer, O'Reilly and MacMillan, 2019). Firms are also encouraging a customer to provide testimonial and referrals in the online review system (Anastasiu and Dospinescu, 2019) thereby involving him in the information search process. To identify and use helpfulness review in the search process, firms hire people to create interactive online product review systems (Lin, Bruning and Swarna, 2018).

Thus, earlier studies have brought out the significance of various visual review characteristics. However, all the researches consider the context of a regular buying decision process. Unless the distribution of star rating, review length and helpfulness votes are 'similar', 'identical' between two retailers, a reviewer cannot use the information in his decision process. However, no research works in the past address variation in the star rating, review length and helpfulness votes between two online retailers. Thus, to understand the distribution of select 'visual' review characteristics and the variation across e-retailers and brands sold by them, we propose the following hypotheses.

H_1 : Online retailer brands and online review characteristics ('visual') are independent of each other.

The hypothesis H_1 is tested for a set of 'visual' review characteristics like 'star rating (H_{11})', 'review length (H_{12})' and 'helpfulness of a review (H_{13})'.

Further, to understand the association between e-retailer brands and their review characteristics, we compare the review characteristics across the e-retailer brands and brands sold by them [exclusive brand and common brand]. The following hypothesis H_2 is tested again for the set of review characteristics that are 'visual' in a review.

H_2 : Online review characteristics ('visual') are varying significantly across the online retail brands and brand sold by them.

The hypothesis H_2 is tested for a set of 'visual' review characteristics like 'star rating (H_{21})', 'review length (H_{22})' and 'helpfulness of a review (H_{23})'.

4. Methodology

To compare online review characteristics of the products, we use sample reviews from Amazon and Flipkart websites. For the analysis purpose, we consider the reviews of experience category products masks and sanitizers from March 2020 to June 2020, posted from India. Out of the 34263 sample reviews taken for the study, 67% of the reviews (23092 reviews) are from Flipkart and the remaining 33% of reviews are (11171 reviews) from Amazon. Various brands related information is summarized in Table 1.

To understand how online consumers, review characteristics vary between Amazon and Flipkart, we collect online reviews of various brands of Mask and Sanitizers. The brands sold are further classified as exclusive and common; for example, in Table 1, 'Dettol' is sold only in Flipkart whereas 'boroplus' only in Amazon and few brands like 'Dabur' by both the players. In particular, we analyze variations in the star rating, review length and helpfulness votes for the reviews between online retailers (Amazon and Flipkart) and brands sold by them (common brands and exclusive brands). Hence, this study can be considered as a descriptive research work (Cooper and Schindler, 2002).

4.1 Pre-processing the Data

Preprocessing of the text data is the starting point of any text analysis procedure. Through the R-Programming and the R-studio, we use plugins like 'wordcloud', 'wordcloud2' and 'tm' and 'gsub' command to preprocess the data. As per the earlier literature guidelines, the preprocessing is done (Al-Otaibi et al., 2018; Gaikar and Marakarkandy, 2015). In this stage, various tasks like the removal of punctuations, special characters in a review, numbers and symbols, lowercasing

Table 1. Reviews of exclusive and common brands used in the study

Brands sold exclusively by the E-retailers		Brands commonly sold by the E-retailers
Flipkart	Amazon	
Asian, Dettol, Flipkart, Godrej, Jokot, Peter_England, Phour, Venus, Wildcraft	Arniv, big_tree, bodyguard, boroplus, mediweave, mirah, onroad, oriley, oromask, scott, solimo, urbangabru, xtore	Dabur, Himalaya, Lifebuoy, Mediker, Savlon,

Table 2. Test of independence for star rating and E-retail brands

		1 2	Star Rating of the review				Total	
			3	4	5			
E-retailer	Flipkart	Count	2554	899	2097	4778	12764	23092
		% within E-retailer	11.1%	3.9%	9.1%	20.7%	55.3%	100.0%
	Amazon	Count	2928	745	979	1738	4781	11171
		% within E-retailer	26.2%	6.7%	8.8%	15.6%	42.8%	100.0%
Total		Count	5482	1644	3076	6516	17545	34263
% within E-retailer			16.0%	4.8%	9.0%	19.0%	51.2%	100.0%

Pearson Chi-Square = 1535.051 [DF=4, Sig. = 0.000]

the words, removal of stem words and blank spaces are carried out. Then for each review, we counted the number of words in the review and added them back to the dataset for further analyses.

It is well-known fact that www.amazon.in and Flipkart gives the flexibility in filling the feedbacks, where, all the fields are not mandatorily to be filled by the reviewers, except star rating. Hence, in some places, the sample sizes would be varying from the total reviews collected. For example, the helpful field not filled by all the reviewers and, only 10% of the reviews received at least one vote for helpfulness component in a review.

5. Results

To test the hypothesis-1 (H_1) on the association between review characteristics and online retail brands, we use Chi-square test of independence and the results summarized in Table 2 conclude that Star rating and E-retail brands are dependent upon each other [$\chi^2 = 1535.051$, Sig. = 0.000] and, there is support for the hypothesis H_{11} .

Again, to test the hypothesis-1 (H_1) on the association between review characteristics and online retail brands, we use Chi-square test of independence and the results given in Table 3, conclude that Review length and E-retail brands are dependent upon each other

($\chi^2 = 2195.054$, Sig. = 0.000) and there is support for the hypothesis H_{12} .

In addition, to test the hypothesis-1 (H_1) on review characteristics and online retail brands, we use Chi-square test of independence and the results provided in Table 4, conclude that Helpfulness of reviews and E-retail brands are dependent upon each other ($\chi^2 = 1637.602$, Sig. = 0.000) and there is support for the hypothesis H_{13} .

From the specific hypotheses results of H_{11} , H_{12} and H_{13} , it is clear that online review characteristics and e-retailer brands are dependent upon each other and there is a support for the hypothesis H_1 .

To test the hypothesis H_2 on the review characteristics across the e-retailer brands and brands sold by them, we use a 2 X 2 Univariate Factorial ANOVA. We consider star ratings of the reviews as a dependent variable, E-retailers (Amazon vs. Flipkart), Brands sold (Exclusive brands vs. Common brands) as the factor variables.

The result of Univariate Factorial ANOVA given in Table 5 & Table 6 shows that the main effects (E-retailer and Brands) are significant and their interaction effect (E-retailer X Brands) is significant. Thus, there is a support for the hypothesis (H_{21}) that the star ratings of

Table 3. Test of independence for review length rating and E-retail brands

Less than 5 Words 5-10 Words			Review Length			Total
			More than 10 Words			
E-retailer	Flipkart	Count	17455	3319	2318	23092
		% within E-retailer	75.6%	14.4%	10.0%	100.0%
	Amazon	Count	5860	2246	3065	11171
		% within E-retailer	52.5%	20.1%	27.4%	100.0%
Total		Count	23315	5565	5383	34263
% within E-retailer		68.0%	16.2%	15.7%	100.0%	

Pearson Chi-Square = 2195.054 [DF = 2, Sig. = 0.000]

Table 4. Test of independence for helpfulness of reviews and E-retail brands

No Votes Up to 10 Votes			Helpfulness of a review			Total
			More than 10 Votes			
E-retailer	Flipkart	Count	22139	821	132	23092
		% within E-retailer	95.9%	3.6%	0.6%	100.0%
	Amazon	Count	9280	1723	168	11171
		% within E-retailer	83.1%	15.4%	1.5%	100.0%
Total		Count	31419	2544	300	34263
% within E-retailer		91.7%	7.4%	0.9%	100.0%	

Pearson Chi-Square = 1637.602 [DF = 2, Sig. = 0.000]

Table 5. Mean star rating across E-retailers and brands sold

E-retailer	Brands	Mean Star Rating	Std. Deviation of Star Rating	Number of reviews
Flipkart	Common Brands	4.3926	1.05718	14697
	Exclusive Brands	3.4565	1.55408	8395
	Total	4.0523	1.33867	23092
Amazon	Common Brands	3.8704	1.51836	4737
	Exclusive Brands	3.0895	1.70771	6434
	Total	3.4206	1.67510	11171
Total	Common Brands	4.2653	1.20719	19434
	Exclusive Brands	3.2973	1.63263	14829
	Total	3.8463	1.48667	34263

Table 6. Summary of tests of between-subjects effects (Star Rating)

Source of variation for Star Rating	F Ratio (Sig.)	Hypothesis Result
Main Effects		
E-retailer	736.968 (0.000)	H₂₁ is supported
Brands	2748.101 (0.000)	
Interaction Effect		
E-retailer * Brands	2748.101 (0.000)	

the reviews vary across E-retailers and Brand Sold by the retailers.

Again, to test the hypothesis H₂ on the review characteristics across the e-retailer brands and brands sold by them, we use a 2 X 2 Univariate Factorial ANOVA. We consider Length of the reviews as a dependent variable, E-retailers (Amazon vs. Flipkart), Brands sold (Exclusive brands vs. Common brands) as the factor variables.

The summary result of Univariate Factorial ANOVA given in Table 7 & Table 8 shows that the main effects (E-retailer and Brands) are significant and their interaction effect (E-retailer X Brands) is significant. Thus, there is a support for the hypothesis (H₂₂) that the review length varies across E-retailers and Brand Sold by them.

To test the hypothesis H₂ on the review characteristics across the e-retailer brands and brands sold by them, we use a 2 X 2 Univariate Factorial ANOVA. We

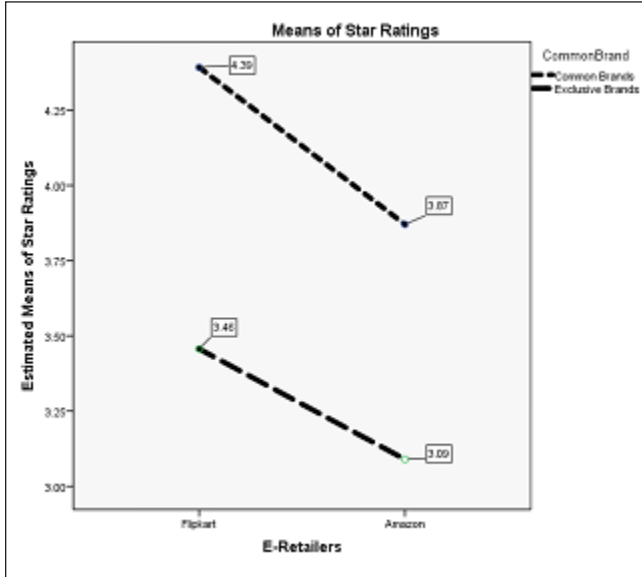


Figure 1. Star rating variation for E-retailers and brands sold.

Source: Primary data

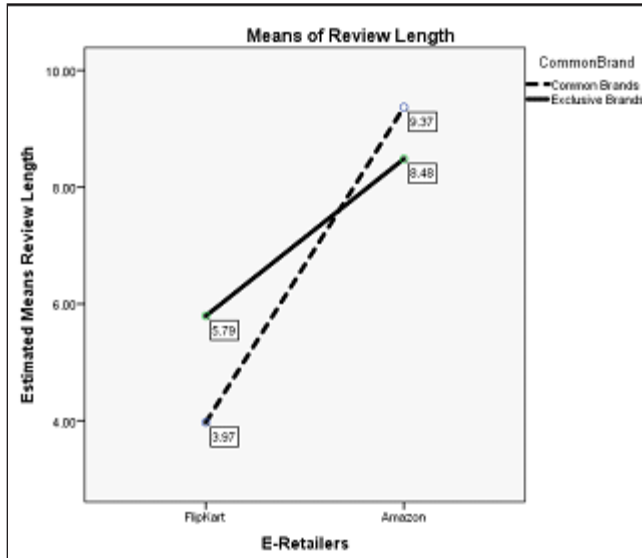


Figure 2. Review length variation for E-retailers and brands sold.

Source: Primary data

consider helpful votes in a review as a dependent variable, E-retailers (Amazon vs. Flipkart), Brands sold (Exclusive brands vs. Common brands) as the factor variables. We consider only the reviews, which received at least one helpful vote for this analysis.

The result of Univariate Factorial ANOVA given in Table 9 & Table 10 shows that the main effect

Table 7. Mean review length across E-retailers and brands sold

E-retailer	Brands	Mean review length	Std. Deviation of review length	Number of reviews
Flipkart	Common Brands	3.9722	4.85161	14697
	Exclusive Brands	5.7948	6.75021	8395
	Total	4.6348	5.68445	23092
Amazon	Common Brands	9.3662	11.92931	4719
	Exclusive Brands	8.4824	9.58584	6420
	Total	8.8568	10.65028	11139
Total	Common Brands	5.2832	7.59948	19416
	Exclusive Brands	6.9594	8.21025	14815
	Total	6.0087	7.91322	34231

Table 8. Summary of tests of between-subjects effects (review length)

Source of variation for Review Length	F Ratio (Sig.)	Hypothesis Result
Main Effects		
E-retailer	2025.007(0.000)	H₂₂ is supported
Brands	27.323 (0.000)	
Interaction Effect		
E-retailer * Brands	227.084 (0.000)	

Table 9. Mean votes per review across E-retailers and brands sold

E-retailer	Brands	Mean votes per review	Std. Deviation of votes in review	Number of reviews
Flipkart	Common Brands	8.5992	31.83102	484
	Exclusive Brands	8.5096	40.70094	469
	Total	8.5551	36.44752	953
Amazon	Common Brands	5.0793	12.40883	618
	Exclusive Brands	5.7038	21.51318	1273
	Total	5.4997	19.02200	1891
Total	Common Brands	6.6252	23.10483	1102
	Exclusive Brands	6.4592	28.01774	1742
	Total	6.5236	26.21942	2844

Table 10. Summary of tests of between-subjects effects (helpful votes per review)

Source of variation for Helpful Votes	F Ratio (Sig.)	Hypothesis Result
Main Effects		
E-retailer	8.834 (0.003)	H₂₃ is partially supported
Brands	0.063 (0.802)	
Interaction Effect		
E-retailer * Brands	0.113 (0.737)	

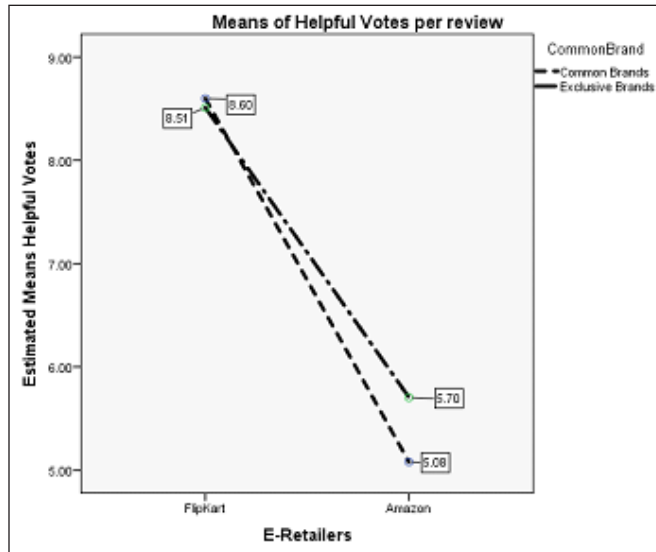


Figure 3. Helpfulness vote's variation for E-retailers and brands sold.

Source: Primary data

'E-retailer' is a significant one and the main effect of Brands and their interaction effect (E-retailer X Brands) are not significant. Thus, there is partial support for the hypothesis (H_{23}) that the mean helpful votes per review vary across E-retailers and brand sold by them.

From the specific hypotheses results of H_{21} , H_{22} and H_{23} , it is clear that online review characteristics are varying across e-retailer brands and brands sold by them. Thus, there is partial support for the hypothesis H_2 .

6. Discussion

WOM communications predominantly consider personal sources only. Based on the closeness with a personal source, the information is classified as weak or strong. However, this feature is not directly available to the internet forums (Chatterjee, 2001). To overcome this issue, the consumer often gives higher importance to product websites and E-retailer's sources. Researchers prove that firms can be benefited by effectively managing buyer-created information in their product websites (Chen and Xie, 2008). In line with the views, Amazon and Flipkart allow users to generate reviews and feedbacks from their post-purchase consumption. In this research work, we

compare and show variation in online consumer review characteristics of two product websites.

From the comparisons of Amazon and Flipkart reviews, it is evident that star rating, review length and helpful votes of the reviews vary between the e-retailers. The cross-tabulation on these results further support that if a consumer switches from Flipkart to Amazon website, 1. The likelihood of seeing lower star-rated reviews are higher than Flipkart; 2. The likelihood of seeing longer reviews are higher than Flipkart and 3. The likelihood of seeing reviews with helpful votes are more in number for Amazon reviews. The results clearly have brought out the systematic variation on the reviews posted between Amazon and Flipkart. Thus, unless the consumers have distribution characteristics of reviews, it is not easy to compare the product or brand reviews from two different sellers or switching from one seller to another.

Another significant dimension, we consider in our research, is the role of brands sold by them. Few brands are available in the shelves of both the retailers (common brands) whereas, another set of brands are unique to a specific retailer (exclusive brands). Further analyses on review characteristics across the e-retailer brands and brands sold by them provide evidence that the means of star rating, review length and helpful votes of the reviews are varying significantly across e-retailers and brands sold by them.

If a consumer switches from Flipkart to Amazon website, the likelihood is more to see 1. Comments with lower star ratings, 2. Comments of common brands sold getting lower star ratings and 3. Comments of its exclusive brands also get lower star ratings. Thus, Flipkart reviews receive a higher star rating than Amazon reviews. We have observed this systematic variation between Amazon and Flipkart reviews.

As far as review length is concerned, if a consumer switches from Flipkart to Amazon website, the likelihood is more to see 1. Longer comments, 2. Longer comments for common brands sold and 3. Longer comments for its exclusive brands. Thus, Flipkart reviews will be shorter than Amazon reviews.

Again, this is another systematic variation between Amazon and Flipkart reviews.

By combining the results on review length and star rating, we have noticed that our results are different from an earlier work, where the researchers claim that longer reviews are positive and higher star rated (Korfiatis, García-Bariocanal and Sánchez-Alonso, 2012). 5% of Flipkart reviews and 17% of Amazon reviews have received helpfulness votes. Among the helpful reviews, however, the mean number of votes per review is higher for Flipkart than Amazon.

By combining the review length and helpfulness results, we have noticed that our study findings are in line with an earlier study, where the researchers concluded that lengthier reviews are more helpful than shorter reviews, which is true in the case of Amazon reviews (Mudambi and Schuff, 2010a)

Thus, the marketers have to address a key concern on the review characteristic. Researchers show that voluminous data available from online sources has a dysfunctional effect of creating confusion rather than providing clarity to the customers (Sturiale and Scuderi, 2013); (Baek et al., 2012). It is an important task for the firms to eliminate this confusion. Moreover, the consumers need credible and valuable online reviews, that create a positive attitude, which in turn, influence the purchase decision process (Mumuni et al., 2019).

7. Managerial Implications

The e-retailers should come up with strategies to reduce such asymmetry in such a way to make it useful for the new buyers or buyers who plan to switch. Firms are already providing information characteristics like more helpful review and ranking of the reviewers, in addition to sorting facilities of reviews based on star rating, most recent and helpfulness. If needed, more information metrics for review characteristics can be added to the website dashboards. Due to COVID19 impact, more number of new customers is visiting the sites for the first time and, they rely on reviews and try to make their purchase decisions based on reviews

shared by the customers as directional views for their purchase decisions.

Researchers prove that if reviews contain information related to product quality, the likelihoods are higher for the review to receive helpfulness votes (Singh et al., 2016). However, a significant review characteristic, the helpfulness of a review, reflected by the number of votes, are very less in number for Flipkart. Research results show product quality and price influence the buyers to post online reviews of the products (Duan, Gu and Whinston, 2008). Hence, Flipkart may encourage consumers to provide reviews based on product attributes.

In the eWOM context, the consumers express their service quality satisfaction through star ratings (Park and Nicolau, 2015). More number of lower started reviews in Amazon may create a negative impression for the first time user, even though information theory on rational consumers suggests that they will give more weightage to negative information than positive to reduce risk of losses (Hong, Xu, Wang and Fan, 2017). To overcome this issue, Amazon may think of classifying the reviews as 'service performance' and 'product-related' so that its brand equity is not hit by the poor performance of a product or brand. Since Amazon receives more number of helpful votes for its reviews, they should add further details like the product category, reviewer's expertise and review sidedness for its reviews to enhance their helpfulness review mechanism (Ming-Yi Chen, 2016).

8. Conclusion

Comparison of e-retailers' online reviews and its research, managerial implications are less researched in the past. A research finding on review characteristics suggests that about-to-buy shoppers look for positive reviews as an affirmation to their decisions and the retailers should ensure access of such positive reviews (Ong, 2011). In general, the consumers would like to create channel synergies between the retailers rather than dissynergies, so that they can use them as complementary (Yang et al., 2013). Particularly, this strategy would provide better outcomes, when a

preferred product or brand is not available with one retailer. Periods of lockdown, restriction of shopping timings, the consumers prefer to choose alternate channels. However, to rely on his decision to use a retailer, he needs overall review characteristics of online retailers to evaluate them. Unfortunately, product websites, review blogs or social media platforms do not provide insights on the distribution of review characteristics.

In this study, we have brought out the distribution characteristics of Amazon and Flipkart reviews. In particular, we showed how the distribution of star rating varies from one retail to another. For example, due to non-availability of mask or sanitizer, if the buyer moves from Flipkart to Amazon, he would likely to see more number of negative reviews for the product. We further proved that both the retailers sell the brand, still, the buyer is likely to see a number of negative ratings for the products in Amazon.

Readability of a review and review length affect the helpfulness of a review (Singh et al., 2016). In our research, we have proved that shorter reviews are often found in Flipkart than Amazon and in turn, Amazon has more helpful votes than Flipkart. This is true for even the brands common to both the retailers. If it is a new buy or modified re-buy, the reviews Amazon will provide more insights than shorter reviews of Flipkart.

Researchers on helpfulness of online review established that a retail site with more helpful reviews give better value to the consumers (Mudambi and Schuff, 2010c). A research work on predicting helpfulness of the review shows that star rating is significant determiner for certain product categories (Singh et al., 2016). One-star and two-star rated reviews contain more of negative words and sentiments and considered as helpful reviews than a 4-star or 5-star rated reviews (Reddy, Kumar, Keshav, Prasad and Agarwal, 2017). This research work findings complement the findings of earlier studies; even though Amazon reviews' mean star rating is lower than Flipkart, relatively a large proportion of customers have registered Amazon reviews are helpful. This is again, a complex information presentation by the online reviewers. Unless the consumers fully aware

of the distribution characteristics of helpful votes and star rating, it will create constraints to use information from an alternate channel.

We have also proved that the review characteristics are varying for the brands commonly sold by both the retailers. If it is an exclusive brand, it has lower mean star rating than brands commonly sold. Hence, it is clearly established that the consumers shift from one e-retailer to another involve voluminous information processing.

9. Limitations and Future Research Directions

The products like masks and sanitizers are recent entry to mass-market consumption. Until March 2020, specialized user segments post most of the reviews and suddenly from March 2020, common people purchase the products and posting reviews online. Experience goods attributes are difficult to evaluate even in the post-consumption stage and for many consumers, even attribute related information might not be available for comparisons. Thus, consumers might have posted reviews based on their preliminary evaluations. The firms generally restrict demographic details and, hence we did not analyze the role of demographic details and their influence on the visual characteristics of online reviews.

In the current research, we consider the products from credence category alone; a betweenness comparison of online retailers across the category of goods (search or experience or credence) will bring further insights on review characteristics. By including the mood of the consumers, future researches can bring temporal variables influence in the reviews. From the profile of the users, it is possible to identify consumer-buying segments and review characteristics may be analyzed across the buyer segments.

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Appendix -1

Online Reviews of Amazon & Flipkart

Must buy!

I really love the camera, though I would have loved a telephoto lens. The super steady OIS works like a charm.

I have been using MI A1 with Android One platform before, I find it a bit hard to find the settings options in S10 lite and mostly resort to Google search figure out the settings.

The phone is fast. Great display.

The included case won't keep the dust-out and will require regular cleaning or will damage the phone's outer layer.

The fingerprint scanner is small and not so accurate...

[READ MORE](#)

RAGESH TR Certified Buyer, Kakkianur 4 months ago

1431 likes 204 replies

That display !!!

Reviewed in India on 9 March 2019

Colour: Black | Size name: 128 GB | Style name: with No Cost EMI / Additional Exchange Offers | **Verified Purchase**

So happy to get my pre ordered S10. So far I'm impressed with most part. The display is unimaginably awesome, and pics dont do justice.

409 people found this helpful

[Helpful](#) | [1 Comment](#) | [Report abuse](#)

The No Nonsense Device.

Reviewed in India on 18 March 2019

Colour: Prism Blue | Size name: 128 GB | Style name: with No Cost EMI / Additional Exchange Offers

Hi, this is going to be a long-detailed review...So make yourself comfortable, relax and Let's begin.

I got this device on 6th March from flipkart, pre booked on 21st Feb itself. Probably one of the early recipients of this device. Then why did I take such long to post this review?

Because I didn't want to post an incomplete review for the sake of likes and views. I want my review to help average consumer to make his decision as this is an expensive device.

I'll start with Pro's of device, because why not? Everyone likes to hear good thing first, right? I'll spare your time with specs as you have already seen the specs sheet anyways. This is going to be a real life review.

1. Dynamic AMOLED Screen: Sure, the dynamic term is marketing strategy, but you know that Samsung is the best display manufacturer and this device is no exception. I am amazed with the quality of the screen, the colour reproduction, the lowest and maximum brightness. Everything is top notch.

Oh, and speaking of notches, I'll always prefer the punch hole cut out over the hideous long notches. It's simply less intrusive in my opinion.