Influencing the Influencers: Analyzing Impact of Prior Review Sentiments on Product Reviews

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Abstract

Extant research has widely studied the impact of online product review on sales and most studies have found a significant impact of these reviews as an e-WOM tool. Given the importance of the online reviews, we study a hitherto understudied area of antecedents of sentiments in user reviews. We assess the impact of contagion effect of past review sentiments on reviewers' choice to write a review. We analyze the impact of emotional response of users while writing product reviews triggered by the appraisal response to prior online reviews. A short selection of reviews, which most e-commerce websites show, along with the numerical product rating (if any) could strongly bias the sentiments in a review being written under their influence. Through a mix of experimental methods and text analysis of online reviews, we find that review writers tend to veer towards extreme reviews in absence of any benchmark or prior reviews.

Keywords: Sentiment analysis, bandwagon effect, online product reviews, controlled experiment

1. Introduction

Digital economy has pushed a large part of our economic activity online. A large section of purchases for products ranging from soaps to electronic gadgets now take place online. The increasing reach of digital stores can be gauged from the fact that online shoppers in US spent $1611 per person in the year 2014 [1]. Due to the rising proliferation of online stores as a preferred shopping medium, online product reviews have also increased as a source of information to consumers [2]. Consumers use the product reviews found online, to complement their understanding of the product/service being offered, as an additional word-of-mouth feedback medium [2,3,4].

Most e-commerce websites have developed some kind of an online community feedback or review system where users of the products and services are encouraged to share their experiences. Even the earliest studies in the domain inform us about the managers' belief that such online community participation increases brand loyalty [5]. Some firms even go as far as to manipulate the product reviews to influence consumers' perception [6,7]. A host of studies conducted by researchers across disciplines like marketing and information systems have found evidence for impact of online reviews on either sales or the reputation of the product [2][4][8].

However, there remains a hitherto understudied area in the domain of online product reviews. Most of the research in the domain of online reviews assumes that reviews are dependent only on the users' personal experience. This, very strong assumption, questions multiple traits that psychologists have established about human biases [9]. We challenge this assumption in our study. Most e-commerce and online product review websites shows a selection of top rated or most helpful reviews. Theory of human biases suggests that readers could be biased from these as a stimulus when they are writing their own reviews. Sridhar & Srinivasan [10] in their work on reviews of hotel services on a third party website found evidence of social influence in writing reviews. While their work forms a first piece of literature in this domain, lack of experimental control and setting of a service domain in a third party website limits its applicability for managers as well as its theoretical understanding. To bridge this gap, we analyze prior reviews of a product as antecedent which, apart from the user experience itself, impact the strength of sentiments expressed in the product reviews.

To achieve this, we bring different strands of literature from Marketing, Information Systems and Organization Behavior together. We use ‘Emotion Appraisal Theory’ [11] as the theoretical lens to understand the behavioral aspect of review writing. We perform a two stage analysis in the study. In the first stage we analyze how the sentiments for different products vary over time, from inception to a later point. This is done through sentiment analysis of textual product reviews. We then proceed to assess the impact of bandwagon effect on reviewers' choice to write a review based on positive and negative sentiments triggered by the cognitive appraisal process of prior online reviews

Our study throws some really interesting preliminary results with huge theoretical and managerial implications. We find that in the online product review space negative emotions tend to be more subdued. Additionally our sentiment mining of review texts also tell us of the strong path dependence where the initial review sentiments gets amplified over a time period. Our experiments reveal the impact of the inherent biases in writing of the reviews. Through the ratings and reviews provided by our experiment subjects, we find that review writers tend to veer towards extreme reviews in absence of any benchmark or prior reviews. While this may be good for products which are of extremely high quality and inherently expect great consumer experience, but the strategy may not be great if some users have negative experience with the products. The treatment of subjects with different sets of reviews has considerable influence on the eventual review sentiment. Based on the findings of this study, marketing departments of online retailers can potentially influence the generative process of online reviews thereby producing the desired bandwagon effect in their favor.

2. Theory and Hypotheses

Word of mouth (WoM) has long been considered an important factor impacting sales of products, predating the advent of online shopping and review sharing websites [12]. The rise of multiple online platforms of commerce and sharing of views has led to development of research on the e-WoM phenomenon [13]. In our case we are using amazon’s reviews and similar experimental setup as it provides for direct impact reviews while also not being on producer’s website prevents it from being directly manipulated by the producer.

Research has established reviews impact the sales of the product being reviewed both positively as well as negatively. This has been found to be true in case of experience products like movies and books [15] as well as more utilitarian products [16]. This line of research has been taken forward to understand the exact factors leading to higher impact of the online reviews. Li & Hitt [8] took the line of research further and studied the information content of the reviews and its efficacy in communicating the message. Extant research has also established the role of credibility [17], emotional content [18], single sentiment primacy [19] which makes an online review impactful for the readers. These lines of research come from almost all contemporary management fields like behavioral sciences, marketing, information systems and strategy, and have attempted to demystify various factors leading impact of online product reviews

An interesting aspect that a thorough review of literature of the field informs us is that there has been a very limited research to answer a fundamental question related to the reviews themselves. This question is regarding the origin of the reviews’ sentiments. In most of the research related to online product/service reviews, the unstated assumption, that review sentiments are dependent on the experience of the user is always present. While there is no denying the fact that users personal experience of the product/service, whether good or bad, is poured in the reviews that the said user writes for their experience with the product/service. However, the fact is that sentiments are the manifestations of the emotions that humans have [7][20]. And defining emotions in line with the dominant psychology research as " … *intense, relatively short-term affective reactions to a specific environmental stimulus [21]* '[22], we find that emotions may be heavily dependent on different kinds of environmental stimuli. Humans are extremely sensitive to emotions and biases [9] and hence it would be erroneous to assume that the reviews being written by a user online reflect just her personal experience of the product. In this study, we fall back on the appraisal theories to see how users respond to the stimuli to form their opinions and emotional responses that they put forward as their review of the product.

2.1. Appraisal Theories – Social and Emotional

We view the phenomenon of writing product reviews from the perspective of appraisal theories. Appraisal theories – social and emotional- have had a huge impact in interpreting and understanding how we respond to various stimuli. Research in the domain of social appraisal has found that humans typically tend to conform to the dominant view in a social setting [23]. This is to identify with certain social groups or to be seen as a part of a majority. Ability to be identified as an outlier acts as the main motivation for people to adapt their views to conform to social norms. The central tenant of social appraisal, thus, informs us that people tend to weigh their response to stimuli not from their personal perspective but from the perspective of their standing in a social setting. Sridhar and Srinivasan [10] look the concept of social influence and social appraisal and performed first (to the best of our understanding) study on social behavior of product reviews.

However, the pressure to conform is expected to be far lesser in an online space because of lack of any dominant group to identify with or fear of being singled out [24,25]. This was expected to lead to truer responses on online platforms as compared to offline platforms where social influence was proven to be very strong (Davenport, 2002). However, as Sridhar and Srinivasan's [10] work found, even in online setting social influence impacts seems to be driving people's review.

While social appraisal theory tends to talk of human response to stimuli being dependent on a person's social setting, another stream of literature talks about another kind of appraisal- "The Emotional Appraisal". It informs us that over time humans may respond to different or same stimuli in different way [11]. If we assume that the emotional responses produced by users while writing online reviews are impacted by some kind of stimuli, the first such stimuli has to be the prior online reviews themselves.

It would be the strength of prior sentiments along with the social setting being visible from the past reviews that would influence the user's own emotional response. Research has established that prior reviews evokes a sense of familiarity with a product leading to increase or decrease in sales of the product under study [15,16]. However, while during the sales of product, a user would be more open to reviews and would respond just to the reviews; while writing a review the impact would be interacting with user's own experience as well as their inherent biases.

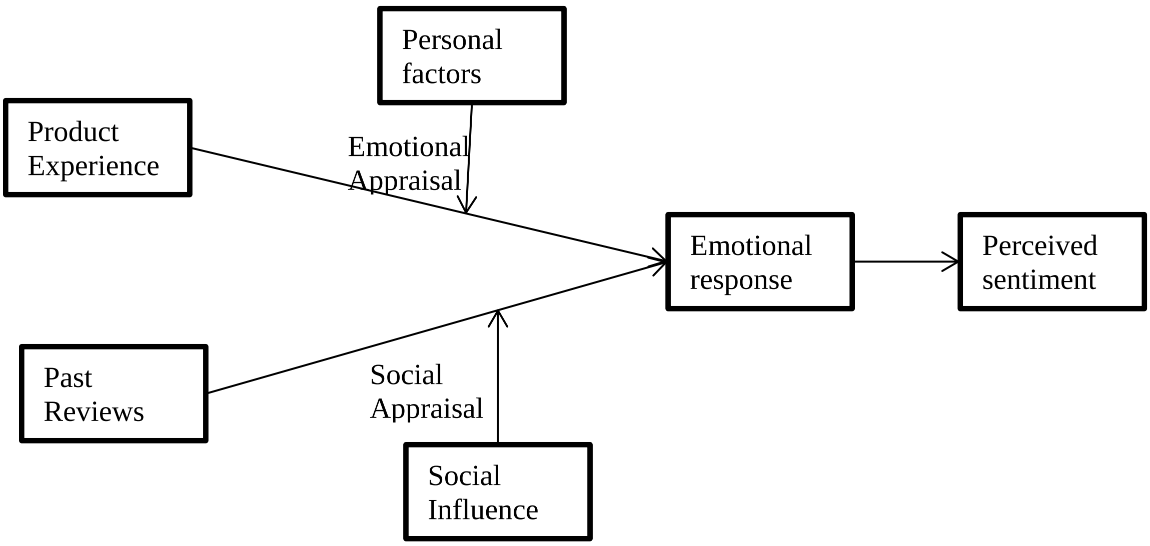

Fig 1 *Theoretical Model*[1]

Decision-making in the context of this paper revolves around an individual's choice of how to respond based on his/her reading of the preceding online reviews. We assess the impact of emotions generated by appraising a series of online reviews rather than relying on one's own experience of using a certain product. This reliance on others opinions through reading online reviews and the emotions appraised therefrom is termed as 'contagion effect' in psychology and organization behavior literature. In particular, 'emotional contagion' is defined as "a process in which a person or group influences the emotions or behavior of another person or group through the conscious or unconscious induction of emotion states and behavioral attitudes" [27, pp:50].

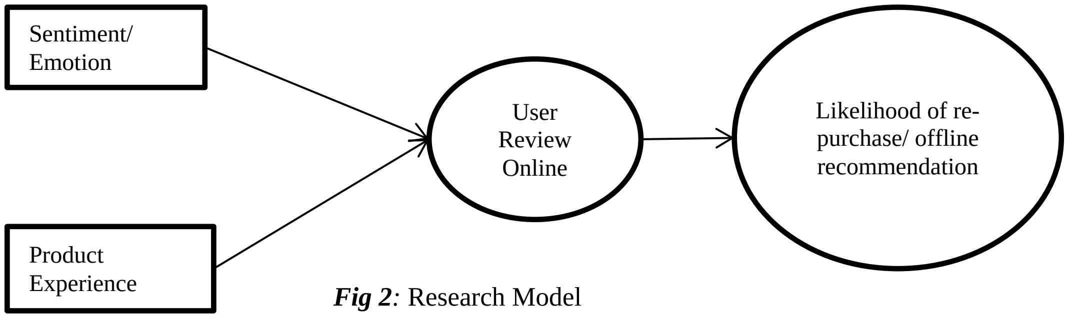

***Fig 2**:* Research Model

Hence we propose our research question in the form of following null and alternate hypothesis

H_0: Product reviews for any product are unbiased and not dependent on past product reviews written.

H_a: Product reviews depend on past reviews written for the product and are hence Path dependent

We also extend the analysis further to form the complete link between purchase, product experience, review in online circumstances and review in offline circumstances. Figure 2 illustrates the research model

2.2. Reinforcing Social Contagion Stimuli

The first effect that we intend to study is the reinforcing social contagion which could be represented as strong reinforcing sentiments being shown by a large and dominant group of individuals. A user's response to such stimuli may depend on their personal biases which would determine their willingness to be either be a part of the dominant group or assert their independence and opposition to the dominant group [22].

When the user's experience is positive, the reinforcing social contagion stimuli would be to have positive reviews being accorded to the product. In case of such a stimulus, prior research has shown that the most expected response is to dissociate with the dominant view [22]. This is done to show one's refinement or better taste or evolution over the dominant group [28]. Since criticism has long been considered the domain of experts, such a behavior is typical of users who want to be seen as experts [28].

[1] Personal factors include the emotional appraisal mechanisms like connectedness to the product, brand preference, familiarity etc.

H1: Positive social contagion stimulus for positive user experience would decrease the positivity of sentiment and rating for the product

Similarly for negative user experience, based on prior research in the field of human behavior, there is a reason to believe that the negative emotions would be exaggerated [18]. This is expected to happen as it not only strengthens user's standing as an expert or a critic but also pitches the user in conformism with the dominant view [18]. Hence we hypothesize

H2: Negative social contagion stimulus for negative user experience would increase the negativity of the sentiment and rating for product

2.3. Contradicting Social Contagion Stimuli

The second case is where the dominant social belief is in direct contradiction to a user's experience. For instance, when the user's experience is good but the dominant view of the product is extremely bad or vice versa. Since the most attractive human tendency is to act as a critic [29], theory suggests that the user would most likely gravitate towards negative sentiment.

It is easy to see this for a positive experience, where user's sentiments are expected to be subdued by the dominant negative sentiments. Decrease of positivity in the user's response would be a natural reaction to such a stimuli as it would increase the social conformism of the user and also increase the expert perception. Hence we hypothesize

H3: Negative social contagion stimulus for positive user experience would decrease the positivity of the sentiment and rating for product

Similarly for positive stimulus during negative experience, there is a reason to believe that social appraisal would lead the user to temper their negative sentiments. In dominant positive sentiments, a negative review might cast the user as an outlier and not a critic. Being a social outcast is something, humans inherently resist [23]. Conformism is a response to avoid being the odd one out [23][29]. Although the user's experiences are negative, the emotional response of the user would be far tempered in this case. Hence we hypothesize

H4: Positive social contagion stimulus for negative user experience would increase the positivity of the sentiment and rating for product

3. Research Method

The research method for any particular research is determined by the research question at hand. The complexity of our research question leads us to a multi method approach. Multi-method research allows for a research question to be examined from multiple perspectives and provides depth that single methods based research works do not allow [30,31]. Mingers [30] has specifically called for multi-method research in information systems domain to build strong and comprehensive theories. In this paper, we have used sentiment analysis along with controlled experiment to answer different aspects of the research question. Figure 3 shows the complete research process in the study with the aim of each phase mentioned.

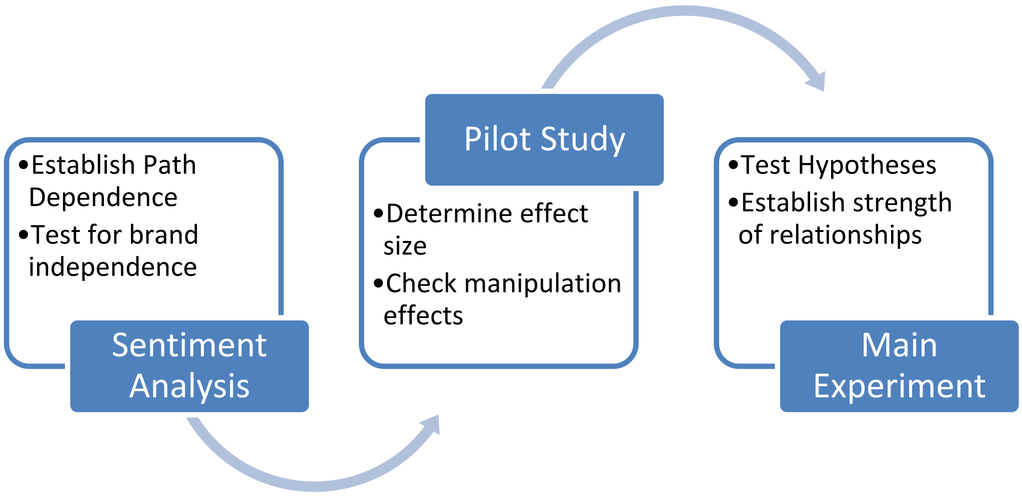

Fig. 3. Research method used in study as a process diagram

3.1. Sentiment Analysis

Sentiment analysis is a computational method to extract and establish the orientation (positive or negative) of author's attitude as expressed in the statements [20]. Sentiment analysis has long been used in information systems research to understand the message sender's emotions amongst other things [32.33]. We have used sentiment analysis in our research to perform the preliminary analysis for unearthing any pattern in reviewer sentiments on a product. To achieve this, we have scraped user review data from the launch of the product (first review on the product page) to the most current review at the time of conducting the data scraping. This allows us to see the change in sentiment of successive reviews for a specific product. This allowed us to map the change in review sentiments over time and understand if there exists links between prior review sentiments and the sentiments in new reviews being entered.

Since the product being used as experimental prop is a smartphone, we have stuck with the same product for data scraping and sentiment analysis. This ensures that different kind of user involvement of different products and its impact on the reviews is not reflected in our data allowing for consolidated understanding from two methods and data sources. Choice of a single product, smartphone in this case, removes biases due to differing user involvement in different products. We have performed the sentiment analysis on a single product but across different brands and price ranges. A common refrain amongst smartphone users is that people treat different brands/OS/price-range based smartphones differently. Performing a first level sentiment analysis over the complete a wide variety of smartphones checks for presence of such an effect.

Data was scraped from amazon.in, Amazon Inc.'s India subsidiary, which is one of the largest online e-commerce platforms in India as well as across the globe. We scraped data for different models/types and brands of mobile phone. This was done to ensure that brand specific factors like loyalty, consumer preferences could be averaged out. In total the data consisted of 50,487 reviews. For each product, we scraped reviews from the date of launch of the product on the platform till last available review (approximately January 2017).

For sentiment analysis, we have used lexicon based approach. In this approach, the algorithms extract lexicons and words used in the statement and detect positive or negative sentiments and its strength [20][34]. We have used the tool "SentiStrength" which uses human-designed lexicons for analysis of sentiments. The tool has been extensively used in past sentiment analysis based research [20][34]. Using the English language dictionary and lexicons in the tool, we computed the positive score as well as negative score for each review in our database. We also computed the overall sentiment of the review, where the sentiment polarity was computed as

$$\text{Polarity} = \text{sentistrength positive} + \text{sentistrength negative} \quad (1)$$

The range for sentistrength positive score ranges from 1 to 5 and denotes the strength of positive sentiments expressed in the statement and -1 to -5 for sentistrength negative showing strength of negative sentiments. We have computed all the three scores (sentistrength positive score, sentistrength negative score and polarity score) in a cumulative manner over the life period of the data collection period.

3.2. Experiment Design

Since the primary aim of this study is to find the impact of past reviews on the user behavior, experimental methods was deemed to be the most suitable for the purpose. Experimental research methods enable us to check human reactions to specified stimuli in a controlled environment [17]. For our experiment we used students, staff and faculty members of one of the premier most management institutes in India. For this particular study, the subjects do not have the typical student population drawbacks like being unaware of the environment. The subjects were well versed with online shopping and had used online shopping quite regularly.

We have used posttest-only control group design in a factorial design setting, since we had a multiple experimental conditions to manipulate. We dealt with 2 factors in the study. The first factor was user experience of the product which could be good or bad. The second factor was past reviews which could be positive or negative. The total number of conditions in the experiment was 6 (along with the 2 control cases) as explained in the table 1. Case no 1 and 4 act as the control cases. Table 1 also lists out the hypotheses that the theoretical background explained in the prior section has lead us to.

Table 1: Experimental conditions

Case No.	**User Experience** *2 levels- Good/Bad*	**Past reviews** *2 levels- Positive/Negative*	**Hypothesis**
1	Good	Not shown	Control
2	Good	Positive	H1
3	Good	Negative	H3
4	Bad	Not Shown	Control
5	Bad	Positive	H4
6	Bad	Negative	H2

4. Result and Analysis

To create the stimulus for the second factor i.e. past reviews, we used real reviews written by users on e-commerce platform for both positive and negative review cases. A set of more than 30 reviews were shown to diverse set of audience for human rating of the reviews. We have used human coding as a method of identifying credibility and sentiments instead of sentiment mining algorithm for analyzing the data related to the experiment. Human coded sentiments, although more costly in terms of both time and money, provide for better statistical rigor and triangulation as human coders allows for greater control of geography specific emotion and sentiment eliciting vocabulary [34]. Most sentiment mining algorithms still suffer from limitations of satire identification, complex emotion identification or regional slangs identification. For extremely large datasets, these may not as big a concern as the limitations are averaged out over large samples and additionally the cost of human coding is extremely huge.

The rating was done by the coders for 2 items, the sentiment strength on a scale from positive to negative[2]; and sentiment credibility on a scale from most to least credible [17]. The rating for credibility helps to identify the most impactful reviews; as prior research has found that credibility of a review, whether the rating is positive or negative, has a huge impact

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[2] Likert scale with range from 1 to 5 where 1 denotes extremely negative and 5 denotes extremely positive review. A similar likert scale with range from 1 to 5 was used for credibility rating where 1 denoted minimum credibility and 5 denoted maximum credibility.

on how much credence readers give to the reviews they are reading [17][3]. The consistently positive 8 reviews with mean above 4 with standard deviation below 1 with a credibility rating of 3.5 and above were chosen for positive stimulus. The reviews with sentiment levels below 2 with credibility rating above 3.5 were chosen for negative stimulus. Therefore, for our experiments, we used only the reviews with extreme sentiment scores on each end with high credibility scores.

Since, no prior studies of similar nature were available to us, we conducted the pilot study with about 90 respondents to generate the effect sizes, and check for manipulation effects. For the pilot phase as well as for the proposed final experiment design, monetary incentive was provided to the subjects to generate true responses.

The effect size of positive past review reinforcement, negative past review reinforcement was computed based on the pilot study. The effect size was computed for both the numerical rating under the stimuli as well as the descriptive review provided by the subject (which was again manually coded by expert research assistant). Size of experimental sample for the main experiment for full factorial design was computed to be 242.

For the main experiment, subjects had a similar profile as the pilot (excluding the subjects who had participated in the pilot). Figure 4 shows the different stages of the experiment process. The subjects were asked demographic and control questions as a first stage. The control questions were to determine their awareness and expertise of the domain and establish their suitability as subjects for our case . We informed the subjects about the product under study i.e. a Smartphone by a dummy firm ‘Tokas”. The OS of the smartphone informed to be generic and was not explicitly intimated to the subjects. This was done to control for biases arising out of any specific android/iOS preferences that subjects may have.

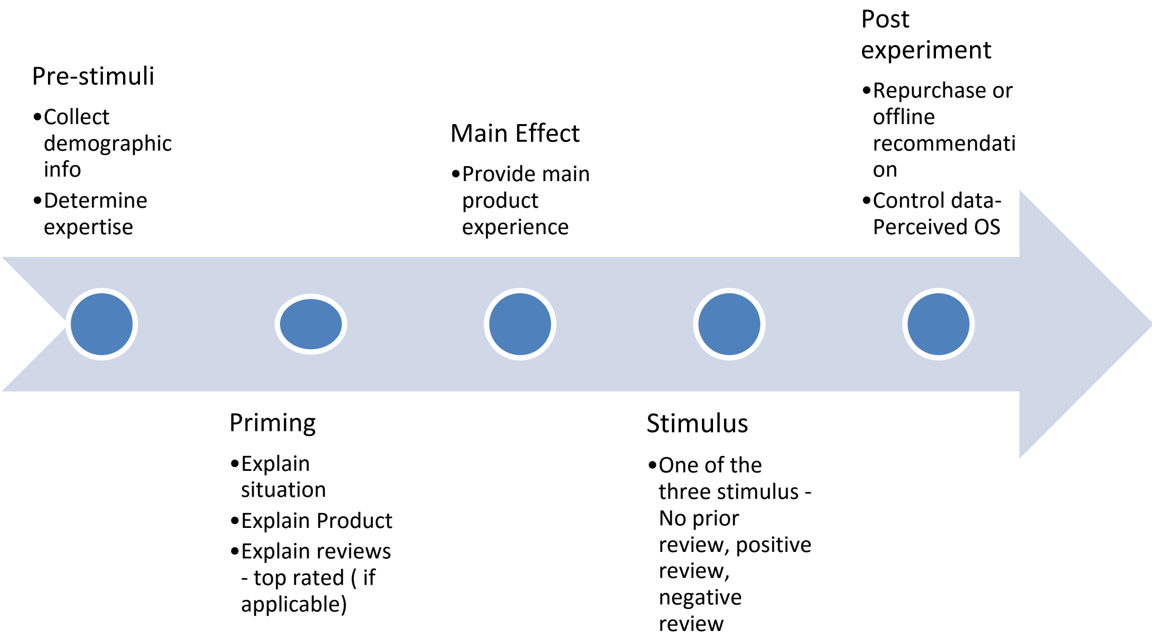

***Fig. 4**. Experiment setup*

In the next step subjects were exposed to the product i.e. “Tokas” mobile phone with randomized group of people getting the 2 levels of experience i.e. a good product and a bad product. Subsequently, the subjects were asked to write the reviews for the product. For the control groups where subjects were exposed to positive or negative prior reviews, subjects were explained that the reviews are top rated reviews so as to eliminate the temporal or recency biases. The reviews were collected in a google form document to eliminate and any e-commerce platform related biases were controlled. Providing a numerical rating for the

[3] To help the human coders understand and code credibility, the definition as well the different components which build up credibility, as explained in Cheung et al. (2012), was informed to the subjects.

product was mandatory for the subjects. However, providing a descriptive review was not mandatory. However we found that a majority of the population provided descriptive reviews. This might be the effect of experiment in a controlled setting where subjects felt the need to write review to justify their involvement. To ensure that no frivolous reviews were entered due to such a phenomenon, these reviews were also rated for credibility by a trained research assistant.

In the final step, we asked the subjects questions related to their willingness regarding repurchase intention and offline recommendation. As a control for biases related to OS of the phone, we also asked the subjects, their opinion on what they felt was the OS of the phone they reviewed.

We have completed one phase of analysis on online reviews as well as analysis on the pilot phase of the experiment. Table 2 shows the demographic information of experiment subject. As visible from the table, the distribution is balanced to a great extent across age groups and gender. The table also shows the familiarity of the subjects with the experimental condition i.e. online shopping.

Table 2 : Experiment subject demographics in the pilot phase

Past review writing experience	**No**		**Yes**		**Total**
Gender	**Female**	**Male**	**Female**	**Male**	
Online Usage					
Frequently (once a week or more)					
18-24	1	1	2	4	8
25-35	1	1	1	2	5
Total	2	2	3	6	13
Occasionally					
18-24	5	5		1	11
25-35	5	7	1	5	18
Total	10	12	1	6	29
Regularly (About once a month on average)					
18-24	4	6	3	6	19
25-35	3	10	4	12	29
Total	7	16	7	18	48
Grand Total	19	30	11	30	90

The analysis of the pilot survey data was performed in 2 steps. In step 1 the ratings entered by the users were analyzed using ANOVA method. The reviews written by the subjects were again coded by humans. Cohen's Kappa was used to ensure that the scoring scales between different human coders were not diverging. Due to paucity of space, we are not detailing the complete results of the pilot phase. However the main findings are summarized in the points below:

a) The effect size was very significant and strong for different user experience. Cohen's d was computed to be 0.9. This denotes that past experience was properly framed and presented

b) The effect size for past reviews was also significant and medium. Cohen's d was computed to be 0.4.

c) Preliminary analysis of the reviews and ratings given by the subjects also indicate that for bad user experience, reference point increases the review ratings. In absence of past reviews, users tend to give extremely bad reviews (ratings of 1 on a scale of 5). However the user ratings increase to 2 in the condition where prior reviews and ratings are provided, even if the prior ratings were bad (average past rating of 2 on a scale of 5, which was considered as a very bad product in the initial survey).

5. Limitation and Conclusion

The paper is limited with the choice of the experimental setup. To control for product level effects, we have used premium mobile phones for our study and the effect found in this study may not be same for different type of utilitarian or experiential products ranging from soaps to holidays. However, the premise of the current paper is very exciting and the initial results point to novel theoretical and managerial implications. This paper, to the best of our understanding, is the first work in attempting to analyze the drivers behind users review sentiments. This would enhance the managerial understanding on how to place and utilize past reviews for better marketing and e-wom based targeting for their products.

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