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Do Customers Perceive Reviews as Manipulated? A Warranting Theory Perspective

(Full Paper)

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ABSTRACT

Online customer reviews proved to have an influence on customer's purchase. However, most online reviews don't always prove effective in guiding the purchase process, because of fake reviews. While e-commerce platforms do tend to incorporate ways to counter review manipulation, customer perception on review quality is more important. In this study we aim to understand the impression mechanism of online reviews. Using warranting theory, as theoretical lens we found that textual and review characteristics play a crucial role in forming an impression amongst the customers. Further, research suggest that higher contamination of reviews influence customers to perceive reviews less authentic.

Keywords: online reviews, perceived manipulation, warranting theory, e-commerce platforms, fake reviews.

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INTRODUCTION

Dear Customer,

Thank you for your purchase! Hope you like the new case! Could you please give 5-star positive review? That'll be helpful to other customers. Much appreciated!!

This is the personalized hand-written note received by a customer who purchased MacBook Air 11-inch hard case from Amazon. With the prevalence of online reviews, these days sellers are incorporating various manipulating techniques such as positive reinforcement (which includes offering money, gifts, praise, and personalized messages) to fetch positive reviews from the customers. Such luring appeals often influence customers leave a review of higher rating than they actually intend to (Aral, 2014). Apart from manipulating customers, sellers are asking their friends and family to leave high product ratings and reviews. Furthermore, they themselves are making purchases from their own business so as to get a *certified (or verified) buyer* badge, thereby rating and reviewing their own product. In 2017, the news website Quartz highlighted that nearly two-thirds of the customers experienced a significant variation in product review and product, which is making them distrust the reviews present on the website. All these techniques adopted by sellers to generate reviews can be viewed under umbrella term- *review manipulation*.

Review manipulation basically involves injection of either fake positive reviews for themselves or fake negative reviews for their competitors (Hu *et al.*, 2012). Zhang *et al.* (2016) define fake reviews as *deceptive reviews provided with an intention to mislead customers in their purchase decision making, often by reviewers with little or no actual experience with the products or services being reviewed. Fake reviews can be either unwarranted positive reviews aiming to promote a product or unjustified false negative comments on competing products in order to damage their reputation* (p.457). Enormous volume and anonymity make it easy for sellers to manipulate/corrupt the information flow through online reviews by adding biased contents. Many anecdotal evidences in the recent past provides evidence for review manipulation. For instance, Samsung was alleged to have hired students to post negative comments about mobile phones made by HTC (Zhang *et al.*, 2016); professional marketers were hired to promote and post positive reviews for new albums (Mayzlin, 2006); booksellers and publishers were discovered to write reviews for their own book on Amazon (Hu *et al.*, 2012). In 2013, nineteen companies based in New York were charged hefty penalties for writing fake online reviews in United States. These companies were found to have bombarded a number of customer review sites such as Yelp.com and CitySearch.com (Zhang *et al.*, 2016). Although research has been conducted on the impact of such strategic manipulation (e.g., posting praising reviews, hiring influencers) on information quality and firms' payoff (Dellarocas, 2006), literature remains silent on how customers perceive such manipulation.

Studies in Information Systems (IS) (e.g., Hu *et al.*, 2012; Luca & Zervas, 2016) have established a systematic relationship between the review manipulation probability and financial variables – predominantly 'sales'. Luca and Zervas (2016) found that a one-star increase in rating leads to more than a 5% increase in sales for independent businesses. With the review manipulation prevalent, research has also examined the characteristics of fake reviews. For instance, Ong, Mannino, and Gregg (2014) explored linguistic characteristics of fake reviews by comparing shill reviews with genuine reviews; where shill reviews were generated by hiring people from Amazon Mechanical Turk and the reviews available on the internet were treated as genuine reviews. On comparison, both the reviews differed in terms of informativeness, product usage experience, and readability. Although, a number of studies have

examined the characteristics of fake reviews (see Jindal & Liu, 2008; Kumar *et al.*, 2018; Mukherjee, Liu, & Glance, 2012) which is well documented at the review or reviewer’s level, no consensus has been arrived if characteristics of manipulated reviews listed by the literature are identified as manipulated by customers as well. Customer’s perception of a review ultimately shapes perception about their behavior intention well as about the trustworthiness of a platform (Zhang *et al.*, 2016).

From a customer’s perspective there are four possibilities of review classification. However, all these four possibilities influence his/her impression towards reviews as well as behavioral intention towards platform differently (see Table 1). If a review in actual is genuine and customer also perceives it as genuine (Category I), then in this case reputation for the platform as well as sellers increases, or the trust remains intact. In category II, if a review is perceived fake, whereas in actual it is genuine it would affect both the platform as well as sellers in terms of their popularity and sales respectively. Even a single review perceived fake has potential to damage the platform’s reputation, making them bear high costs. Similarly, category III depicts the condition when customer perceives fake review as genuine. In this case there are two sub-conditions:

1. *When seller fakes positive reviews:* Extreme positive review will make customers chose the product, but the main issue arises when the product is delivered to the customer. The probable variation between the actual product delivered and reviews makes customer suffer by making them put more effort in filing complaint and tracking package. Further, platforms incur higher cost in terms of delivery and packaging of the return products.
2. *When seller’s competitor fakes negative reviews:* Here, the ultimate damage is done to the seller as customers might not opt for the product yielding lesser sales. However, this is not going to the customer altogether.

Next is category IV where customer presumes fake review as a fake. This will affect a customer’s trust towards the platform and further leading to the customer migration from one platform to another. In general, a study by Jin Ma and Lee (2014) found that consumer’s trust towards reviews decreases when made aware about sellers’ involvement in review content manipulation.

Table 1: Customer’s perception map and its consequences to platforms and sellers.

Perceived Actual	Genuine	Fake
Genuine	True Positive (Category I) <i>Increases reputation of both platforms and sellers</i>	False Negative (Category II) <i>Affects platform and sellers in terms of popularity and sales</i>
Fake	False Positive (Category III) <i>When sellers fake positive review: Platforms incur higher cost in terms of delivery and packaging and customer follow-up</i>	True Negative (Category IV) <i>Decreases trust towards the platform and leading to customer migration and loss of market share</i>

In summary, as platforms are the face for the customers any action taken by sellers will ultimately affect platforms who have to bear the cost. Hence, looking at the damages perceived review manipulation by customers have on platforms this study poses two fundamental questions:

RQ1: Do customers perceive reviews as manipulated?

RQ2: What factors form the customer’s impression of a review? And through what mechanism these factors shape customer’s impression of reviews?

We examine these questions from the lens of warranting theory according to which greater the perceived manipulation in the content by the customers, lesser would be its perceived authenticity (Walther *et al.*, 2009). This suggests that higher the manipulation done by the firms more likely its reputation and brand image is at stake. From the business perspective answer to the above questions are important for understanding their customers and ultimately findings of the study can be implemented for developing an automated system for filtering out perceived fake reviews.

These research questions remain largely unexplored. Research on online reviews till date has focused on understanding the impact of review characteristics (numerical rating, review length) and sentiment of review on perceived helpfulness of reviews (Ho, Wu, & Tan, 2017). Review characteristics might determine why some reviews get higher up-votes over other reviews, but with the prevalence of review manipulation across the globe intensifies the consumer’s concern regarding authenticity of online reviews. Since, customer’s knowledge on manipulation influences their purchase intention (Jin Ma & Lee, 2014). Hence, in this study we try to understand how individual reviews are evaluated by the customer. We argue that it is the characteristics of a review that shapes the consumer’s perception towards the ethical norms and values of the platform.

Theoretical development and empirical testing in this area are still scant. Thus, on the theoretical front we make four key contributions to the literature. First, we extend the line of research proposed by Ho, Wu, and Tan (2017) by examining an important issue of customer perception in understanding review manipulation. Second, we develop and test the research model to predict the performance of online reviews. Although previous studies have measured the review performance through perceived helpfulness, we argue that latter might not be a good predictor of review performance. Third, we contribute to the online ethics and business literature by identifying the information cues that shapes an impression of a reviews. On practice front we contribute by informing platforms regarding the areas they should address to avoid such perception of manipulation among customers.

The rest of the paper is organized as follows. In the next section, we examine the literature on review manipulation as well as discuss the theoretical lens to examine review manipulation. In the third section, we present our research model and related hypothesis. In the fourth section, we present our data collection procedure to test these hypotheses. In the fifth section, we present the analysis of our data. In the sixth section, we discuss our research findings and present the implications of our research to theory and practice. Finally, we conclude with the limitations of our study.

LITERATURE REVIEW AND THEORETICAL BACKGROUND

Research on Online Reviews

Online customer reviews can be defined as *peer-generated product evaluations posted on a company or third-party website* (Mudambi & Schuff, 2010). Let us first understand the review generation mechanism and the role of different stakeholders in review generation. Reviewers are the ones who evaluate the product with an intention to share their opinion after its usage. Apart from providing textual review of the product, they also provide a numerical rating (usually varying from 1 to 5, where 1 means lowest and 5 means highest) about the product. These star ratings numerically depict individuals’ experience with the product. In other words, textual review and star-ratings are the two review-components provided by the reviewers. Figure 1 depicts a typical review.



Figure 1. Sample of customer review from Flipkart.com (Source :<https://www.flipkart.com>)

The product (or service) for which a reviewer posts a review is known as the bystander (Luca & Zervas, 2016). On the review platforms, such as Trip Advisor, Amazon and Zomato, people leave reviews for the product or the sellers. Upon receiving the review, these platforms now add further components to these reviews namely – review date, badge and reviewer name. Some platforms also rank reviewers and/or provide badges (such as top 500 reviewer, certified buyer, generic reviewer name in case not mentioned by the reviewer) to increase the perceived authenticity of the review. Other potential customers who visit these platforms to understand more about the product (apart from the information provided in the product description) through other’s experience can vote a review by giving a thumbs-up or thumbs-down. For example, Amazon asks people: “Was this review helpful? Yes or No” or as in Figure 1 – the likes and dislikes. This helpful vote count reflects other potential customers’ view towards a review.

Thus, different stakeholders are involved with a single review– (a) reviewer who writes a review, (b) bystander who are the subjects of a review being written, (c) platforms who posts the reviews on their website, (d) customers (or readers) who reacts towards a review by participation in voting, (e) other customers whose read reviews to make a purchase decision.

Studies on online reviews have primarily focused on two units of analysis, namely, reviewers and readers. Studies using reviewers as unit of analysis focus on understanding the motivation behind people writing reviews. Previous studies (e.g. Wang, 2010; Zhang *et al.*, 2015) have used the construct *online review authorship* to understand the factors which motivate people to write. A number of studies (e.g. Zhang *et al.*, 2015) found social factors as having significant influence on authorship of online reviews. Wang (2010) observed that people tend to write a greater number of reviews and prefer giving less extreme star ratings in order to establish a social image. This implies that there is an audience effect which shapes user’s writing behavior. Moreover, people naturally tend to prefer giving ratings from 3 to 4 stars. Basically, content shared/ created by people has a social exchange value of generating reciprocity (Fehr, Kirchsteiger, & Riedl, 1998). That means, if I like your content, you will like mine. Most of the platforms, such as Zomato and Amazon, enable establishment of follower-following relationship. Goes, Lin, and Au Yeng (2014) examined such relationships and demonstrated that people on attaining substantial number of followers begin to review product more objectively, induce less focus on negativity and valence variance. Further studies have also identified content’s affective characteristics (Berger & Milkman,

2012) as well as individual traits (Mowen, Park, & Zablah, 2007) as antecedents motivating people to contribute to the content creation.

While studies using readers as unit of analysis seek to find the drivers that motivate people to read (or consume) online reviews: (a) information acquisition mainly in case of pre- or post- purchase decisions (Goldsmith & Horowitz, 2006) (b) risk reduction (Kim, Mattila, & Baloglu, 2011) (c) seek social assurance (Bailey, 2005) (d) enact negativity bias (O'Reilly & Marx, 2011). Drawing on similar lines, previous studies have also explored the context using different perspective, such as examining the factors that influence people to judge the informational value of the reviews (Weiss, Lurie, & MacInnis, 2008), information quality (Kane & Ransbotham, 2016), and helpfulness (Mudambi & Schuff, 2010). The question of what makes a review helpful has received much scholarly attention in e-commerce and information systems literature. Mudambi and Schuff (2010) found that star-rating and number of words present in a review are strong predictors of helpfulness of a review for the readers. Liu and Karahanna (2017) also found that review characteristics of online reviews shape customers' perception about their helpfulness.

In summary, the textual characteristics and review characteristics of an online review shape the readers (or consumers) perception of helpfulness. We define textual characteristics of a review as the semantic and stylistic features of the review (Cao, Duan, & Gan, 2011) which are related to a reviewer's writing style. Review characteristics, on the other hand, are defined as the basic characteristics of a review (such as star rating, review posting time, total up-votes) which can be observed easily (Cao, Duan, & Gan, 2011). Research on review manipulation (e.g. Hu *et al.*, 2012; Mayzlin, Dover, & Chevalier, 2014) have found evidence of manipulation of reviews by different stakeholders. Mowen, Park, and Zablah (2007) found that review quality and quantity frames people's purchase intention. However, with review manipulation, bystanders, sellers, and paid reviewers try to manipulate customer's intention by injecting fake positive for themselves as well as fake negative review for their competitors. Additionally, a study by Wan and Nakayama (2014) found that review helpfulness count for the reviews on the platforms are inflated. This suggests that the results of studies that have examined the relationship between various review characteristics and their perceived helpfulness could be biased. Most of these studies have also assumed that a higher utility perception of a review affects consumer trust and product sales (Mudambi & Schuff, 2010). However, as per Wan and Nakayama (2014) manipulation might backfire this assumption of increase in product sales. Thus, building on the study by Wan and Nakayama (2014), we try to understand how consumers perceive reviews with possible review manipulation (Hu *et al.*, 2012) on online business platforms. We use warranting theory as the theoretical lens to examine the phenomenon of review manipulation as discussed below.

Warranting Theory

Walther and Parks (2002) proposed warranting theory to theorize the phenomenon of impression management. Using the context of social networking sites (e.g. Facebook) they tried to understand the phenomenon of why experiences vary when people meet offline for the first time, after they have already met online. They suggested that this variation is a function of potential for anonymity which leads to the discrepancy in the outcome of experience. Researchers have applied warranting theory to understand how people assess an information and how does this assessment shape impressions in various context, such as social networking sites (Fox, Warber, & Makstaller, 2013), online dating sites (Ellison, Heino, & Gibbs, 2006) and online rating systems (Flanagin & Metzger, 2013). Most of these studies have found source of information to be an important predictor of information control.

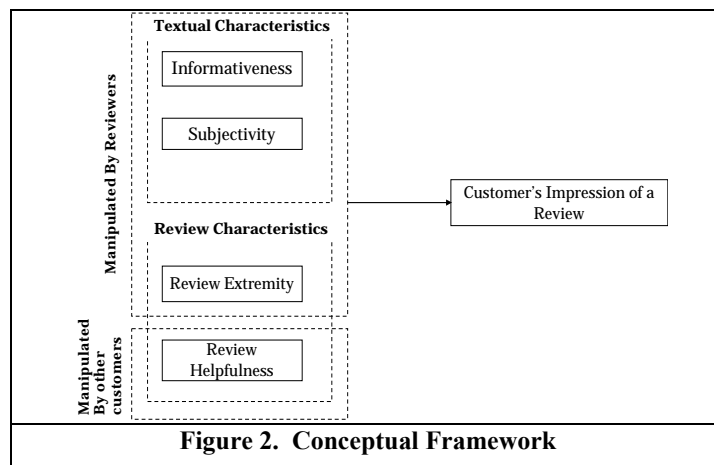
The term *warrant* in the warranting theory refers "to any cue that authenticates and legitimizes an online-presentation" (DeAndrea, 2014, p.187) and *warranting* refers to the process of validation. For e.g. Willemsen, Neijens, and Bronner (2012) claims that people labelled as experts are considered people with greater expertise over self-claimed experts in an online-community because, "...their status as experts is warranted by others" (p.23). As per DeAndrea's (2014), warranting theory proposes a psychological construct that reflects "perceptions about the extent to which information is immune to manipulation by the source it describes" (p.187). In other words, people attach credence to the information, if it is perceived to be unaltered by the target body to whom the information refers (DeAndrea, 2014). Warrants that are extremely difficult to manipulate by the user are considered high on warranting value, whereas those warrants that are easily manipulatable have a low warranting value. Warrants with low warranting value are considered questionable and perceived to be less authentic. Perceptions of the information controllability and the way it influences the perception is the core tenet of warranting theory. In summary, the warranting principle theorizes that *the lesser an information is perceived to be controllable by the person to whom it refers, the greater will be the weight it will carry in shaping impressions* (DeAndrea, 2014, p.188)

Applying this argument to the context of online reviews, the components of reviews (such as review text, review star rating, up-vote, downvote, reviewer name, and the reviewer badge) have higher probability of being subjected to manipulation. Out of these components, review text and star-rating are easily subjected to manipulation by reviewers. If a reviewer is paid, or is writing to seek social acceptance from others, then in both these cases the likelihood of information being subjected to manipulation is high. However, in the former case of the review being paid, the information controllability is also very high. Paid reviews and socially accepted (aka most helpful reviews) reviews are most likely to be extremely high rated reviews if meant to enhance the brand perception and visibility. While if the reviews are paid to tarnish the image of competitors, they are more likely to be extremely negatively rated (1 star). In summary, reviewers can manipulate the textual characteristics of the review, namely informativeness and writing style by

incorporating more stylistic characteristics. Moreover, reviewers can also manipulate review characteristics, such as review extremity (i.e. star rating).

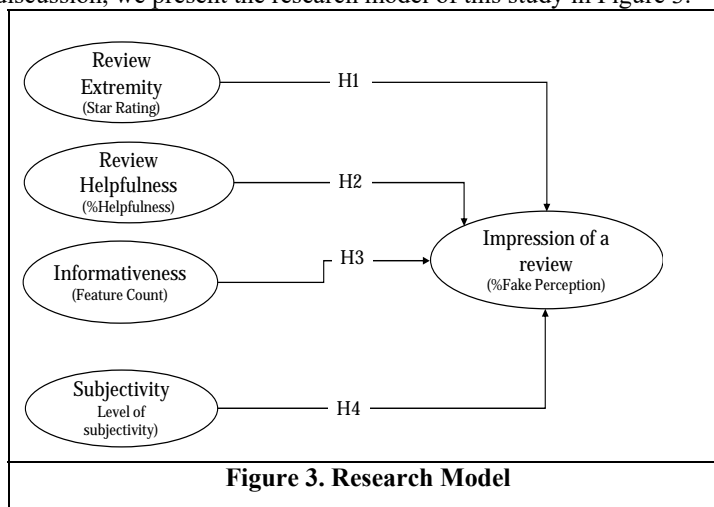
The information on up-votes and down-votes received by a review is provided by other customers who are neither involved in writing a review nor are related to the target body or bystander. Following warranting theory, information which is provided by the third-party about a target is perceived as more authentic, as it is difficult to control what others post or vote online (Walther *et al.*, 2009). As the number of likes and dislikes received by a review cannot be controlled by the target body, their authenticity is high because peer generated cues are more authentic than self-claims (Willemsen, Neijens, & Bronner, 2012). However, these can also be manipulated, when a large number of customers randomly provide up-votes to a product because of the herding effect leading to inflated reviews (Wan & Nakayama, 2014). Based on the discussion and extant literature, it is evident that review characteristics and textual characteristics can be manipulated by the target body as well as other customers.

E-commerce platforms initially created a section called *Customer Reviews* so as to allow customers co-create value with them (Prahalad & Ramaswamy, 2003). This section helped other customers create an impression of a product leading to a wiser purchase decision. However, with adulteration of reviews (both in terms of quality and quantity) due to manipulation, the impression of a review formed in a consumer's mind is hazy. As per the theory of selective attention, people selectively process the information as per their processing capability (Treisman, 1969). When a person receives cluttered information, human mind selectively chooses lesser information to process. Likewise, in the case of online reviews, customers selectively look at few reviews by applying sort and filters such as "Most positive", "Critical ones", "Top rating", "Most helpful" etc. These processing style varies from customer to customer. On these selected reviews customers then look for warrants (or cues) which help shape the perception of warranting value and ultimately the impression of a review. Figure 2 depicts the conceptual framework for this study.



HYPOTHESIS DEVELOPMENT

Based on the aforementioned discussion, we present the research model of this study in Figure 3.



Review Characteristics

According to the theory of selective attention, people read reviews selectively as reading all the reviews for a product is time consuming and a tedious job. On selection of reviews, consumers look for informational cues (or warrants) (DeAndrea, 2014) that help them authenticate the review. Star rating along with the review helpfulness is the first warrant people look for while selecting the review. Focusing on star ratings, e-commerce sites, such as Amazon and Flipkart, have a filter to view only specific star rating reviews or the most helpful reviews first. Further Amazon classifies the reviews as favorable (includes 5-star reviews) and critical (includes 1-star reviews) based on the star rating. Literature defines star-rating as review extremity which is the extent to which review is positive or negative (Mudambi & Schuff, 2010). Review extremity usually varies on a continuum from 1 to 5, where 1 means extremely negative and 5 means extremely positive rating for the review.

Prior research has suggested that many bystanders try to manipulate reviews by posting fake positives for themselves and fake negatives for their competitors (Luca & Zervas, 2016; Mayzlin, Dover, & Chevalier, 2014). Further, Aral (2014) in his article mentioned a study by Hu, Zhang, and Pavlou (2009) who compared the rating behavior of students with that on Amazon. They found that students rating pattern followed a normal-distribution with a crest in middle over J-shaped distribution of Amazon. Students rated products moderately as 2, 3 or 4 stars over Amazon reviewers whose frequency for 5-star reviews doubled that of 1, 2, 3, or 4-star reviews. Social influence can be one of the reasons for higher extreme ratings. Aral (2014) mentions that “*I had thought the place deserved a three...Her review moved me. And I gave the place a four*” (p.47). On the contrary, Wang (2010) observed that people tend to write more reviews in (higher volume) and prefer giving lesser extreme ratings in order to establish a social image on the review platforms. From, these inconsistent results it can be inferred that reviewer controls star-rating irrespective of what incites it. The higher controlling power of review extremity makes its perceived warranting value low, leaving customers suspicious of its authenticity. Further, it is well known that platforms such as Amazon offer their products to the reviewers for getting it reviewed, and in return platform offers them hampers and gift vouchers. In such condition, it is less likely to remain unbiased and provide an honest review for the product. Hence, we hypothesize:

H1: Reviews with extreme star ratings are perceived less impressive than reviews with moderate ratings.

Next, warrant that people look at is review helpfulness. According to the warranting theory, content has a high warranting value, if it is less likely to be controlled or manipulated by the target body (Walther *et al.*, 2009). Review helpfulness is given by other potential customers, who up-vote/down-vote (or like/dislike) a review depending upon whether they perceive the review as helpful or otherwise in making their purchase decision. Moreover, the research suggests that as any content given by a third-party has no role in influencing the content it is perceived to be more authentic (Walther & Parks, 2002). For instance, claims made by friends on social-networking sites have been argued to create more impression than the self-made claims (Walther *et al.*, 2009). Therefore, we argue that if a review is perceived to be highly helpful by the large number of people, it is more likely that it will be perceived as authentic by the customers as well. Hence, we hypothesize:

H2: Higher review helpfulness count for a review is likely to impress customers more.

Textual Characteristics

Bond and DePaulo (2006) have found that people are able to detect deception in visible lies in comparison with audible lies. Due to lack of social cues in an e-commerce platform detection of fake content or paid reviews becomes difficult. But as per warranting theory claims made by people have an impact on warranting value of the information (Walther *et al.*, 2009). Self-generated claims are difficult to evaluate as even the sincere disclosers can be easily faked and disguised as unbiased reviewers. In an e-commerce platform, all the reviews are the self-generated claims made by reviewers making them susceptible to higher perceived manipulation. As per Walther and Park (2002) an information present on one's personal webpage has low warranting value as compared to the information about the same person present on a website operated by a third-party. Similarly, a photograph posted by an individual on their social media account has lesser warranting value than an online photograph clicked by a third person or a newspaper journalist. Photograph posted directly by an individual might be the results of the application of various camera filters. Similarly, the reviews are the results of the linguistic characteristics chosen by the reviewers.

In this study we focus on two basic linguistic characteristics namely – informativeness and subjectivity that have been considered by most of the literature in distinguishing genuine reviews from shill reviews. Linguistic characteristics are in the hands of reviewers who write reviews. Linguistic characteristics depicts the self-claims made by a reviewer, hence making it vulnerable to perceived manipulation. As discussed earlier, informativeness of a review refers to the amount of product-related information present in a review (Ong, Mannino, & Gregg, 2014). Prior research divides product information into two categories: official and unofficial. Ong, Mannino, and Gregg (2014) found that fake reviews discuss a greater number of product features than genuine reviews. Taking this as the basis, it can be argued that paid reviews, which are often lengthier, cover product features in a review more elaborately and thus are high on informativeness. While a genuine review often discusses only few features. This is also because a review is usually written by a reviewer within a week or two of the purchase and to mention all features elaborately is a daunting task. Most users focus on few features in their evaluation due to their cognitive inability to process all the features. On the other hand, many fake

reviews are also injected to increase the number of high rating reviews. Such reviews usually consist of a single word or a single phrase such as “*Good phone*”, “*Awesome*”, “*Excellent*” and are low on informativeness. They usually do not contain much information about product features and are written with an intention to increase the number of ratings and in turn product ratings. Thus, reviews that are very low or very high on informativeness are likely to be have high warranting value and are likely to be perceived as suspicious by customers.

H3: Reviews with moderate informativeness will be perceived more impressive over the reviews embedded with no or extreme informativeness.

Subjectivity is another measure to judge customer’s product usage experience (Ong, Mannino, & Gregg, 2014). Researchers have used subjectivity as a parameter to judge reviews’ perceived helpfulness and readership intention. Ong, Mannino, and Gregg (2014) found that in case of shill reviews percentage of usage of subjective sentences are lesser than in normal reviews. Using subjective sentences, customers describe unique experience with a product usage. With objective sentences customers list product description. The reviews loaded with objective sentences doesn’t give any crucial information which can influence customer’s purchase decision. Instead these reviews are injected as fake positive reviews so as to increase the visibility of the product on the platform. Most of these reviews rate different features of a product on a scale of ten. Ong, Mannino, and Gregg (2014) argue that reviews generated for the injection are mostly written by the customers who have never really used the product. In this case the reviews will have higher percentage of objective sentences over subjective sentences. This is because writing subjective sentences require writers to actually own and use the product for at least a few days, making such reviews less susceptible to suspicion, leading to the lower perceived warranting value.

H4: Reviews with higher level of subjectivity are perceived to be more impressive over reviews with lower level of subjectivity.

RESEARCH METHODOLOGY

Data Collection

We used mixed method approach in our study to collect the data. The unit of analysis in our study is a review. The data for main dependent variable (Impression of a review) was collected using an online survey developed using Qualtrics.com, an online survey site. The survey link was shared with the respondents using e-mail. Before sending the survey mail, we constructed the e-mail list of the respondents. We initially started with the post-graduate students of premium management institute of Central India. The institute on daily basis maintains a log of students who have received parcels from e-commerce sites. The log contains student’s name, order receive date, order source, receiving date, student’s enrolment number, and student’s e-mail address. Later, the authors shared survey link on their Facebook account and requested their friends who shop online to respond and shared survey with avid shoppers . Facebook platform was chosen to cover heterogenous customers. The respondents represent a mix of people from all over the country and also represent the sample for online shoppers.

The data for other variables was collected as objective data from Flipkart – a leading e-commerce platform in India – for all the mobile phones launched in India in 2017. The reason for selecting Flipkart and mobile phones was because almost 80% of the business of Flipkart comes from mobile phones and most of the big mobile giants (such as One Plus, Redmi, and Motorola) initially launched their phones exclusively on Flipkart. Further, the year 2017 in India witnessed rapid evolution in mobile technology. Before heading towards collection of reviews, we collected the product details (total ratings given to the product by the purchasers, total reviews received from the purchasers, product rating given by the Flipkart, and price of the product) of all the mobile phones available in Electronics Section on Flipkart. Later, we mapped their launch dates from Digits Magazine – a leading electronics magazine in the country.

On mapping the launch dates of all the mobile phones available on Flipkart at the time of data collection, we got 550 mobile phones that were launched in India in 2017. We further selected only those mobile phones which received more than 200 customer reviews. We were then left with 110 mobile phones. For each of these 110 mobile phones, we collected customer reviews from Flipkart. To build the customer reviews dataset, we wrote a R script to collect the data for each mobile phone. Flipkart has four filters on its customer reviews page namely- Most Helpful, Most Recent, Positive First, and Negative First. For each product, we collected reviews by applying each of these four filters so as to get an exhaustive set of customer reviews. We then removed duplicates, if any from the reviews dataset. The complete dataset thus consisted of 34,389 reviews. For each review we collected: (a) numerical star rating given by the reviewer to the product on the scale of 1 to 5 where 5 stands for highest rating, (b) review text, (c) title assigned to the review by the reviewer, (d) reviewer name (Flipkart tags anonymous reviews as Flipkart Customer), (e) buyer type (certified Buyer /Noncertified Buyer), (f) review date, (g) number of up-votes received by the review from other customers, and (h) number of down-votes received by the review from other customers.

Questionnaire Design

Before the survey construction for the main study, we conducted an exploratory study. Initially, we interviewed around 20 online shoppers and asked their opinion on customer reviews available on the e-commerce platforms and their understanding on its

manipulation. We stopped at 20 respondents because of the theoretical saturation in their reply. These interviewees were representative of the population who shop online. Interviews gave us an insight that most people are aware of presence of fake reviews on e-commerce platform. So as to not fall into the trap of these fake reviews customers take some preventive measures. For instance, one of the interviewees say *“For electronic products I first prefer to do a thorough search even visit brick and mortar stores and check product reviews. Often I visit critical reviews first so as to check where exactly the problem lies.”* Another one states *“In case of apparels I can easily distinguish fake reviews. Most of the times reviews include alternate names to describe the cloth type mentioned in product information. After being deceived 2-3 times, I now pay enough attention to the review details especially the product details. I have also stopped purchasing products from the site which had disappointment earlier.”* Some customers look for the helpfulness count as an indicator to distinguish between reviews and mentions *“...say for example if one or two reviews have 100+ likes and others have just 2 or 3 that considerable difference helps me identify how the review is.”* In summary, most of the customers are aware of the review manipulation prevailing on e-commerce platforms and take necessary precautions in analyzing them. With this exploratory study, it was evident that review manipulation has a huge impact on customer’s purchase decision and influences trust towards an e-commerce site. Further, review characteristics play as deciders in predicting the quality of reviews.

Later, as per warranting principle information controllability is a crucial factor in accessing the warranting value. Thus, we then surveyed individuals on to catch the impression of a review. Alternatively, we also verified our qualitative findings using a quantitative survey. The instrument captures an individual’s understanding on review manipulation by asking them to rate their understanding on a scale of 1 to 7 from *Strongly Disagree* to *Strongly Agree*. We found that 65.34% customers believed that sellers of Flipkart have an ability to control the reviews that appear on the e-commerce platform. 81% further, marked in agreement that they think reviews are manipulated by the sellers. Only 35% people felt confident that reviews are actually written by the actual users of mobile phone. Thus, to further comprehend how reviews frame an impression on customers, we tested our research model as presented in Figure 3.

The main survey instrument for this study aims to capture the dependent variable – impression of an online review (fake/genuine). Each review was presented to the respondents requesting them to categorize 30 set of reviews into either fake or genuine. After collecting reviews, we created a survey instrument to capture customer’s impression of reviews by asking them to categorize reviews as fake or genuine. For survey instrument, we randomly selected 120 reviews from the review corpus of 34,389 reviews. We then divided these 120 reviews into 4 blocks containing 30 reviews each. Each block was evenly randomly presented to the survey participants such that each participant receives a block i.e. 30 reviews. Decision to keep a block of 30 reviews was made after interviewing few customers, who asserted that most of them read reviews up to 3 pages (each page contains 10 reviews on Flipkart and Amazon). One IS Professor and three IS scholars (also active online shoppers and mobile enthusiasts) reviewed the survey instrument. They were asked to share their feedback about the length of the instrument, content, and question ambiguity. Subsequently, the survey was presented online. Appendix A presents the snapshot of the survey instrument. Each review block was presented to an average of 50 respondents. Thus, combining responses for four blocks, we obtained a total of 246 responses. Table 2 presents the respondent characteristics. After removing the partial/incomplete responses, we were left with 202 usable responses.

Table 2. Descriptive Statistics of the Respondent’s Characteristics

Variable	Categories	Frequency (%)
Gender	Male	129 (63.8%)
	Female	73 (36%)
Age	Under 18	0 (0%)
	18-24	68 (33.6%)
	25-34	115 (56.9%)
	35-44	15 (7.4%)
	45-54	4 (1.9%)
	Above 55	0 (0%)
Education	Below high school	0 (0%)
	Graduate	58 (28.7%)
	Post-Graduate	108 (53.5%)
	PhD	16 (7.9%)
	Other Professional degree	20 (9.9%)
Online Shopping Frequency	Once a week	20(9.9%)
	Once a fortnight	28(14%)
	Once a month	105 (51.98%)
	Once a six month	49 (24.26%)
Last Purchase made using Online Reviews	This week	32 (15.84%)

	Last week	36 (17.82%)
	Last month	107 (52.97%)
	Don't consider online reviews	27 (13.36%)
<i>Total</i>		202 (100%)

Operationalization of Variables

We operationalized the explanatory variables included in the model using the reviews dataset collected from the Flipkart. We have review extremity, helpfulness, informativeness, subjectivity, and objectivity as the explanatory variables. First variable – review extremity (on a scale of 1 to 5) – was measured as the numerical star rating given by the reviewer (Mudambi & Schuff, 2010). Review extremity varies from 1 to 5, where 1 depicts low rating and 5 depicts highest rating. Helpfulness was measured as the percentage of people who found the review helpful (Mudambi & Schuff, 2010). The percentage helpfulness was calculated by dividing the total number of up-votes received by a review to the sum of total up-votes and total down-votes for a review.

For measuring informativeness, we examined each review for the number of product features of the mobile phone discussed in the review. Although, it was subject to author(s) judgment, it was quite objective as it was quite easy to decipher number of features about the mobile phone discussed in the review. The last explanatory variable, subjectivity level (Tan *et al.*, 2018) was dummy coded as low, medium, and high.

The dependent variable – Impression of an online review – was operationalized using the data collected through the survey instrument and was defined as the percentage of people who found the review fake. This was derived by dividing the number of people who voted a review as fake to the total number of people who voted for a particular review (both fake and genuine). Dependent variable varies between 0.0 and 1.0. Numerically, we operationalized an impression of a review in terms of percentage of people who find it fake. Higher is the fake perception percentage, less likely is the review going to form an impression amongst the customers. Table 3 describes the variables used in our study. The descriptive statistics of the variable are presented in Table 4.

Table 3. Variables and their operationalization

Construct	Variable	Operationalization
Impression of a review	Fake Perception %	Percentage of people who found the review <i>i</i> as fake
Review Extremity	Star Rating	Numerical star rating assigned with a review <i>i</i>
Review Helpfulness	Review Helpfulness %	Percentage of people who found the review <i>i</i> helpful
Informativeness	Feature Count	Number of product features mentioned in a review <i>i</i>
Subjectivity	Subjectivity level	Dummy coded as low, medium, and high

Table 4. Descriptive Statistics for the Sample

Variable	Mean	SD	Min, Max, Med.	N
Impression of a review	0.38	0.0167	0.03, 0.8, 0.39	120
Review Extremity	3.61	1.58	1, 5, 4	120
Review Helpfulness	0.602	0.311	0, 1, 0.71	120
Informativeness	2.425	3.663	0, 18, 1	120
Subjectivity				High (31), Low (60), Medium (29); Total 120

DATA ANALYSIS AND RESULTS

We used fractional logit model to analyze our research model due to the nature of the dependent variable (Papke & Wooldridge, 1996). The bounded nature of the dependent variable (impression of a review) makes this technique suitable. The variable in our case is bounded within 0 and 1. The main issue with using OLS, when the dependent variable is ratio, is that the predicted values can never be guaranteed to lie within unit interval (Papke & Wooldridge, 1996). Fractional logit model does not consider any structural assumption for prediction of the dependent variable. The main advantage of this statistical method is that it can also address the possibility of non-normal errors, heteroscedasticity, and non-linear errors, if any. Another reason which makes the model suitable for our data is that the predicted value of the dependent variable can also include 0 and 1, 0 when the review is considered entirely genuine by the customers and 1 when everyone who encounters the review regards it as fake.

In H1, we hypothesized that review extremity shapes impression of a review. We expect that reviews with extreme star ratings should be perceived as less authentic over reviews obtaining moderate ratings. Thus, we expect a non-linear relationship between review extremity and impression of a review and hence modelled the same by incorporating both linear (star rating) and quadratic term (star rating²). Further, we expect linear term to be negative and quadratic term to be positive, that is a U-shaped relation, implying that reviews with extreme star ratings would be perceived more fake (or less authenticity) than reviews which received moderate ratings. To test hypothesis H2, we include percentage of helpfulness. In H2, we expect that increase in review helpfulness decreases

perception of fakeness towards a review. For H3, we included number of product features mentioned in a particular review. Similar to review extremity, we expect informativeness to follow non-linear relationship with review impression, hence, we included both linear (feature count) and quadratic term (feature count²). We expect a U-shaped relationship with linear term to be positive and quadratic term to be negative implying, fake perception of a review decreases at a threshold point and then again increases with each additional product feature mentioned in a review. To test H4, we used dummy of subjectivity level. We expect that highly subjective reviews to decrease perception of a review being fake making it useful in product evaluation. Based on the explanation, the resulting non-linear model is

$$Fake\ Perception\% = G(\beta_1 + \beta_2(Star\ rating) + \beta_3(Star\ rating)^2 + \beta_4(Helpfulness\ Percent) + \beta_5(Feature\ Count) + \beta_6(Feature\ Count)^2 + \beta_7(Subjectivity\ Medium) + \beta_8(Subjectivity\ High)) \tag{1}$$

Where G(.) function satisfies 0 <G(z)<1 for all z belongs to real number. G(z) function guarantees that the predicted values lie within 0 and 1. G(z) can be any cumulative distribution function (Papke & Wooldridge, 1996), and we have used logistic functional model (Ramalho *et al.*, 2011). The results of estimating equation 1 are presented in Table 5. The statistical modeling was done using ‘R’ – an open source software for multiple statistical purposes.

Table 5. Fractional Logit Model Output

Fractional logit model Output				
DV: Fake Perception%				
Variable	Coefficient	Standard Error	t-value	Sig
Constant	1.266	0.279	4.538	0.000***
Star Rating	-1.512	0.228	-6.632	0.000***
(Star Rating) ²	0.263	0.0362	7.263	0.000***
Helpfulness %	-0.507	0.175	-2.891	0.004 ***
Feature Count	-0.0596	0.041	-1.429	0.153
(Feature Count) ²	0.008	0.002	3.360	0.001 ***
Subjectivity Medium	-0.055	0.143	-0.387	0.699
Subjectivity High	-0.345	0.146	-2.356	0.018 **
Observations	120			
R-squared	0.484			
RESET	0.288 (0.592)			

Value in parentheses in the RESET statistics are p-value; these are obtained from a chi-square distribution with two degrees-of-freedom. Note: p-value< ‘***’ 0.001; ‘**’ 0.01; ‘*’ 0.05; ‘.’ 0.1; ‘ ’ 1

All the variables are highly significant except the linear term of feature count and medium subjectivity level. The higher p-value of RESET statistics suggest that equation 1 has no misspecification (Papke & Wooldridge, 1996). This suggest that there is a non-linear relationship between both star rating (review extremity) & feature count (informativeness), and fake perception (review impression). The linear negative and quadratic terms being positive indicates our hypothesized U-shaped relationship of view extremity, and informativeness with the dependent variable. In case of non-linear econometric models, it is difficult to interpret the coefficients. However, the results in Table 4 inform the direction and statistical significance of the relationship between independent and dependent variables. Thus, from Table 4 it can be interpreted that increase in review and textual characteristics shapes negative impression of reviews in a consumer’s mind.

For interpreting the magnitude, literature suggests computation of average partial effects (APE) (Gallani, Krishnan, & Woolridge, 2015) . APE’s coefficients are interpreted similar to linear regression coefficients. As per Gallani, Krishnan, and Woolridge (2015) “calculation of APE involves computation of marginal effect at every observation, and then averaging the marginal effects across the range of the predictors” (p.18). Further, Gallani, Krishnan, and Woolridge (2015) states that “by calculating and interpreting APE’s, the researcher obtains useful information about the average magnitude of the causal relation, without compromising the non-linearity of the model and its enhanced fit characteristics compared to the linear ones” (p.18). Table 6 presents the APE results.

Table 6. Average Partial Effects

Average Partial Effects				
DV: Fake Perception%				
Variable	Coefficient	Standard Error	t-value	Sig
Star Rating	-0.3378	0.0486	-6.952	0.000***

(Star Rating) ²	0.0587	0.0077	7.671	0.000***
Helpfulness %	-0.1134	0.0392	-2.895	0.004 ***
Feature Count	-0.0133	0.0093	-1.433	0.152
(Feature Count) ²	0.0018	0.0005	3.402	0.001 ***
Subjectivity Medium	-0.0124	0.0320	-0.387	0.698
Subjectivity High	-0.0770	0.0326	-2.363	0.018 **

Table 6 shows negative sign in linear term and positive sign in quadratic term of star rating. These terms suggest a U-shaped relationship, implying that reviews with extreme star rating are quite likely to be less impressive than moderate reviews. In other words, with an increase in star rating, the fake perception and star rating graph decreases till a certain point and then increases thereafter, thus supporting hypothesis H1. It has to be noted that dependent variable -impression of a review measures fake perception percentage, which means the percentage of people who find a particular review to be fake. Higher value of fake perception implies lesser impressive (or authentic) review. In other words, review with extremely high ratings (5 star) and extreme low ratings (1star) are likely to be perceived less authentic than reviews with moderate ratings (2, 3 and 4 star). Results show that one percent increase in the count of review helpfulness decreases the fake perception percentage by 11.34%. Thus, reviews with higher review helpfulness percentage are perceived to be more impressive, supporting hypothesis H2. On examining the coefficients of informativeness, linear term feature count is insignificant, but the quadratic term of feature count appears as significant in the model. The negative and positive signs of linear and quadratic terms respectively suggest that a non-linear relationship exist between informativeness and fake perception percentage. This make reviews with moderate feature count more impressive, thus supporting hypothesis H3. Next, for subjectivity level, we have considered low subjectivity level as the base category. Thus, the coefficients on the two dummy variables measures a proportionate difference in impression relative to low subjectivity level. Variable subjectivity medium turned out to be insignificant, but subjectivity high comes significant. The coefficient of subjectivity medium suggests that highly subjective reviews decreases fake perception by 7.7% with respect to lower subjectivity level reviews. In other words, more people find lower subjective level reviews to be fake as compared to highly subjective reviews. In terms of impression, highly subjective reviews have 7.7% more likelihood to impress people over lower subjective reviews. This supports hypothesis H4. However, nothing can be inferred for reviews having mediocre subjectivity level.

DISCUSSIONS AND IMPLICATIONS

Discussion for Findings

The objective of this study was to examine the factors that led people to evaluate a review, something that all customers engage on a day-to-day basis on online platforms. Using warranting theory, we found that characteristics of a review and textual characteristics of a review play a role in shaping impression towards a review. All of our hypotheses are supported. The study is first of its kind that examines the antecedents of review impression in terms of review quality. Prior scholarship has confined their research on review valence in understanding customers' response towards review manipulation (Jin Ma & Lee, 2014). They found that, when informed of review manipulation customer's trust towards a review influences their purchase intention. Two insights were generated from this study. First, that customers understand review manipulation and heuristics shape an impression of a review. Second, we found that online review information and social cues shapes customer's perception in terms of its being fake. Further, using exploratory study we found that unnecessary manipulation of reviews makes review unattractive, and thereafter affects platforms in terms of website stickiness.

Our findings can also be explained by an alternative theory, i.e. elaboration-likelihood model (ELM) (Petty & Cacioppo, 1986). This theory is apt for understanding why some informational content is more persuasive over other. Theory suggests two distinctive routes to persuasion namely: central and peripheral. Under central route, persuasion occurs when a person thoughtfully ponders over the merits of the information presented in front in support of advocacy. Whereas, under peripheral route, persuasion results from simple cues, primarily due to the familiarity or association with them. It is the people's motivation and ability that influences route selection. Considering informativeness, and subjectivity level as central cues, and star rating and review helpfulness as peripheral cues. Depending on customer's motivation and their ability to comprehend people will chose either of the cues to make their decision. Our results show a consistent negative relation between both central and peripheral cues towards impression formation.

Implications for Theory and Practice

This study presents interesting implications for both theory and practice. Theoretically, we contribute in three ways. First, much of the literature pertaining to review manipulation has focused on its detection and later its impact on product sales (Hu *et al.*, 2012). Previous studies in both computer science and Information Systems have established that review manipulation is wide-spread amongst the sellers and is evident in the online platforms (Hu *et al.*, 2012; Luca & Zervas, 2016; Mayzlin, Dover, & Chevalier, 2014). Even the studies in computer science have focused on identification of review manipulation and built algorithms to identify fake reviews. While those studies which have focused on identification of fake reviews have considered reviewer characteristics, review characteristics, as well as product characteristics. However, none of the studies have incorporated customer's perception while studying review manipulation and its ultimate impact on review impression. Consumer perception of a review is more

important in influencing sales than the perception of the platform. The results of this study suggest that costumers' do understand the review manipulation and review characteristics (such as helpfulness, review extremity) and textual characteristics (such as informativeness and subjectivity) shape customer's impression towards a review. Secondly, we contribute to the literature by presenting review performance parameters. Earlier research has used review helpfulness as an ultimate measure of review performance (Mudambi & Schuff, 2010). However, Wan and Nakayama (2014) proposed the manipulation of review helpfulness count, suggesting inflated and biased results towards the most explored research question "what makes a review helpful?" Thus, we used review helpfulness as an antecedent in forming impression of a review. Thirdly, we contribute to the literature by identifying the cues which affect customer's perception to the increased review manipulation. We found that customers' use textual and review characteristics as signals to deal with review manipulation. We further contribute by establishing the relationship between these cues and customer's perception using warranting theory, thus furthering the frontiers of research on online manipulation.

This study also has interesting implication for practice. From the survey data it was evident that considerable number of customers regard review as fake, the fake perception- the dependent variable ranged from 0% to 80%. This suggests that about 80% people perceived a review as fake. This perception has a huge impact on platforms stickiness. Exploratory study pointed out that people have boycotted a platform, if they encountered mismatch between product description and product received. Additionally, Table 1 also mapped the consequences of customer's perception on attitude towards an e-commerce platform and sellers. We suggest e-commerce platforms to keep an eye on the online reviews posted on their platform. Apart from that, e-commerce platform can deal with fake reviews by introducing a *disputed flag* to highlight the authenticity of the review. This flag will alert the customers of the review's authenticity while they are reading the reviews. Also, they can highlight the paid reviews by introducing a badge, this will help customers decipher information appropriately.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

The objective of this study was to examine whether and how customer perceive online reviews as manipulated. To date, review manipulation has been studied from the firm's perspective and has not incorporated customer's perspective while studying review manipulation. Accordingly, we used mixed method approach to examine customer's impression towards an online review using interviews and survey. Overall, this paper contributes to the literature by conceptualizing customer's impression a review. The results of this study also present interesting insights into customer perception of online reviews as manipulated. Customers do perceive online reviews as manipulated as such perception is primarily driven by review extremity (star-rating) and informativeness (feature count), review helpfulness, and subjectivity. The results of this study reveal that even a slight manipulation of informational and social cues of a review drastically lowers the review impression.

The results of our study should be interpreted in the light of its limitations. First, we have confined the study only to a single product category (mobile phones). Thus, there is a risk with our findings in terms of generalizability. Future studies could confirm the results by using a sample of diverse product. Secondly, we have taken only 120 reviews out of 34, 389 reviews collected, and classified them as fake/genuine by the online shoppers. Although this number is small, and its representativeness may be questioned, we took measures so that this sample remains representative of the entire population. We used random sampling procedure for selecting these 120 reviews. Nonetheless, future studies may build a prediction model by classifying a larger sample as fake/ genuine using customer's perception and then using it as a training sample for classifying the rest of the population of reviews. This would give much better insight into what makes a review impressive. Third, there could be a moderating effect of product type (such as search goods, and experience goods) on shaping customer's perception, which can be considered in future studies along with other control variables (such as customer experience and profession). Fourth, qualitative research opens up further avenues to verify and bring stability to our results.

REFERENCES

- [1] Aral, S. (2014). The problem with online ratings. *MIT Sloan Management Review*, 55(2), 47.
- [2] Bailey, A.A. (2005). Consumer awareness and use of product review websites. *Journal of Interactive Advertising*, 6(1), 68–81.
- [3] Berger, J., & Milkman, K.L. (2012). What makes online content viral? *Journal of Marketing Research*, 49(2), 192–205.
- [4] Bond Jr, C.F., & DePaulo, B.M. (2006). Accuracy of deception judgments. *Personality and Social Psychology Review*, 10(3), 214–234.
- [5] Cao, Q., Duan, W., & Gan, Q. (2011). Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach. *Decision Support Systems*, 50(2), 511–521.
- [6] DeAndrea, D.C. (2014). Advancing warranting theory. *Communication Theory*, 24(2), 186–204.
- [7] Dellarocas, C. (2006). Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management Science*, 52(10), 1577–1593.
- [8] Ellison, N., Heino, R., & Gibbs, J. (2006). Managing impressions online: Self-presentation processes in the online dating environment. *Journal of Computer-Mediated Communication*, 11(2), 415–441.
- [9] Fehr, E., Kirchsteiger, G., & Riedl, A. (1998). Gift exchange and reciprocity in competitive experimental markets. *European Economic Review*, 42(1), 1–34.

- [10] Flanagin, A.J., & Metzger, M.J. (2013). Trusting expert-versus user-generated ratings online: The role of information volume, valence, and consumer characteristics. *Computers in Human Behavior*, 29(4), 1626–1634.
- [11] Fox, J., Warber, K.M., & Makstaller, D.C. (2013). The role of Facebook in romantic relationship development: An exploration of Knapp's relational stage model. *Journal of Social and Personal Relationships*, 30(6), 771–794.
- [12] Gallani, S., Krishnan, R., & Wooldridge, J.M. (2015). *Applications of fractional response model to the study of bounded dependent variables in accounting research*. Harvard Business School Accounting & Management Unit Working Paper No. 16-016, Harvard Business School, Boston.
- [13] Goes, P.B., Lin, M., & Au Yeung, C. (2014). "Popularity effect" in user-generated content: Evidence from online product reviews. *Information Systems Research*, 25(2), 222–238.
- [14] Goldsmith, R.E., & Horowitz, D. (2006). Measuring motivations for online opinion seeking. *Journal of Interactive Advertising*, 6(2), 2–14.
- [15] Ho, Y.C., Wu, J., & Tan, Y. (2017). Disconfirmation effect on online rating behavior: A structural model. *Information Systems Research*, 28(3), 626–642.
- [16] Hu, N., Bose, I., Koh, N.S., & Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems*, 52(3), 674–684.
- [17] Hu, N., Zhang, J., & Pavlou, P.A. (2009). Overcoming the J-shaped distribution of product reviews. *Communications of the ACM*, 52(10), 144–147.
- [18] Jin Ma, Y., & Lee, H.H. (2014). Consumer responses toward online review manipulation. *Journal of Research in Interactive Marketing*, 8(3), 224–244.
- [19] Jindal, N., & Liu, B. (2008). Opinion spam and analysis. *Proceedings of the 2008 International Conference on Web Search and Data Mining* (pp. 219–230). WSDM, Palo Alto, California, USA, February 11-12.
- [20] Kane, G.C., & Ransbotham, S. (2016). Research note—content and collaboration: an affiliation network approach to information quality in online peer production communities. *Information Systems Research*, 27(2), 424–439.
- [21] Kim, E.E.K., Mattila, A.S., & Baloglu, S. (2011). Effects of gender and expertise on consumers' motivation to read online hotel reviews. *Cornell Hospitality Quarterly*, 52(4), 399–406.
- [22] Kumar, N., Venugopal, D., Qiu, L., & Kumar, S. (2018). Detecting review manipulation on online platforms with hierarchical supervised learning. *Journal of Management Information Systems*, 35(1), 350–380.
- [23] Liu, Q.B., & Karahanna, E. (2017). The dark side of reviews: The swaying effects of online product reviews on attribute preference construction. *MIS Quarterly*, 41(2), 427–448.
- [24] Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science*, 62(12), 3412–3427.
- [25] Mayzlin, D. (2006). Promotional chat on the Internet. *Marketing Science*, 25(2), 155–163.
- [26] Mayzlin, D., Dover, Y., & Chevalier, J. (2014). Promotional reviews: An empirical investigation of online review manipulation. *The American Economic Review*, 104(8), 2421–2455.
- [27] Mowen, J.C., Park, S., & Zablah, A. (2007). Toward a theory of motivation and personality with application to word-of-mouth communications. *Journal of Business Research*, 60(6), 590–596.
- [28] Mudambi, S.M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly*, 185–200.
- [29] Mukherjee, A., Liu, B., & Glance, N. (2012). Spotting fake reviewer groups in consumer reviews. *Proceedings of the 21st International Conference on World Wide Web* (pp. 191–200). WWW, Lyon, France, April 16–20.
- [30] O'Reilly, K., & Marx, S. (2011). How young, technical consumers assess online WOM credibility. *Qualitative Market Research: An International Journal*, 14(4), 330–359.
- [31] Ong, T., Mannino, M., & Gregg, D. (2014). Linguistic characteristics of shill reviews. *Electronic Commerce Research and Applications*, 13(2), 69–78.
- [32] Papke, L.E., & Wooldridge, J.M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11(6), 619–632.
- [33] Petty, R.E., & Cacioppo, J.T. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, 19, 123–205.
- [34] Prahalad, C.K., & Ramaswamy, V. (2003). The new frontier of experience innovation. *MIT Sloan Management Review*, 44(4), 12–18.
- [35] Ramalho, E. A., Ramalho, J.J.S., & Murteira, J.M.R. (2011). Alternative estimating and testing empirical strategies for fractional regression models. *Journal of Economic Surveys*, 25(1), 19–68.
- [36] Tan, H., Lv, X., Liu, X., & Gursoy, D. (2018). Evaluation nudge: Effect of evaluation mode of online customer reviews on consumers' preferences. *Tourism Management*, 65, 29–40.
- [37] Treisman, A.M. (1969). Strategies and models of selective attention. *Psychological Review*, 76(3), 282.
- [38] Walther, J.B., & Parks, M.R. (2002). Cues filtered out, cues filtered in. *Handbook of Interpersonal Communication*, 3, 529–563.
- [39] Walther, J.B., Van Der Heide, B., Hamel, L.M., & Shulman, H.C. (2009). Self-generated versus other-generated statements

- and impressions in computer-mediated communication: A test of warranting theory using Facebook. *Communication Research*, 36(2), 229–253.
- [40] Wan, Y., & Nakayama, M. (2014). The reliability of online review helpfulness. *Journal of Electronic Commerce Research*, 15(3), 179.
- [41] Wang, Z. (2010). Anonymity, social image, and the competition for volunteers: a case study of the online market for reviews. *The BE Journal of Economic Analysis & Policy*, 10(1), 1-35.
- [42] Weiss, A.M., Lurie, N.H., & MacInnis, D.J. (2008). Listening to strangers: whose responses are valuable, how valuable are they, and why? *Journal of Marketing Research*, 45(4), 425–436.
- [43] Willemsen, L.M., Neijens, P.C., & Bronner, F. (2012). The ironic effect of source identification on the perceived credibility of online product reviewers. *Journal of Computer-Mediated Communication*, 18(1), 16–31.
- [44] Zhang, D., Zhou, L., Kehoe, J.L., & Kilic, I.Y. (2016). What online reviewer behaviors really matter? Effects of verbal and nonverbal behaviors on detection of fake online reviews. *Journal of Management Information Systems*, 33(2), 456–481.
- [45] Zhang, H., Lu, Y., Wang, B., & Wu, S. (2015). The impacts of technological environments and co-creation experiences on customer participation. *Information & Management*, 52(4), 468–482.

APPENDIX A: Screenshot of Survey Instrument

This survey aims to understand customer's perception of online reviews. In this survey, we request you to classify following set of mobile reviews from Flipkart into **FAKE and GENUINE reviews**. By the term fake reviews, we mean

- A. The reviews that are written by an individual with little or almost no experience of the product usage;
- B. Paid reviews
- C. Reviews that are written with an intention to increase product's visibility or damage image.

The survey's responses will be used only for research purposes.

Thanks in advance for sparing your time and efforts

Please classify the following review as per your perception as FAKE or GENUINE

5 Star : Terrific

To order this phone in flash sale -> use a laptop/ pc with a high speed internet connection (strongly recommend) -> be at the site at 11:50 and log in your ID and save your address :- when the clock turns to 11:56 .. reload the page continuously untill you get the buy now option :- now not wasting time place order very fast or else it will be sold out :- choose COD (recommend because other options take much time) Note :- i myself has ordered two redmi note 4 (a gray and a black) Thank you for reading this

Likes Received : 330 | Dislikes Received : 196

MohdAmair Sohail | Certified Buyer | 08-Mar-17

- FAKE
- GENUINE