Understanding Low Review Ratings in Online Communities: A Personality Based Approach

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Abstract. Online communities like Yelp thrive when users participate actively by writing good and useful reviews. While useful reviews are needed to keep the community active, understanding the users who post low rated and unhelpful reviews is also important, so that developers can implement persuasive strategies targeted at this group of users. In this paper, we identify those users who post low rated, unhelpful reviews and their personality types in Yelp using the Linguistic Inquiry and Word Count (LIWC) tool. The result of the analysis reveals that users who post unhelpful reviews are mostly of the personality type *neuroticism*. Using partial least squares structural equation modelling, we further explored the susceptibility of the different personality groups of users to *rewards* as a means of influencing them to write more useful reviews. Our results show that only the users that are high is *extraversion* who post unhelpful reviews are susceptible to *rewards*. This result demonstrates that rewards might not be persuasive to most of the Yelp users who post unhelpful reviews, hence the use of other persuasive strategies should be explored to influence users to post helpful reviews. The result of this study can be helpful to developers and stakeholders of online communities in implementing personalized influence strategies that work.

Keywords: Online communities; reviews; rewards; personality

1 Introduction

Over the past decade, there has been an increase in online communities (such as Yelp.com) that provide review and rating information about businesses that customers have come to rely on [4]. The ratings and reviews provided on Yelp have been shown to have a direct impact on the revenue of businesses, with an increase in Yelp ratings resulting in an increase in revenue [11], [4]. The quality of reviews play a huge role on the possible influence such reviews have on customers [16]. High quality positive or negative reviews are more helpful to customers than low quality reviews, hence persuading customers to post quality reviews is important to businesses. Although communities like Yelp include tips on how to write useful reviews, not all reviewers adhere to these tips, thus some reviewers write reviews that are not helpful to other customers.

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It is therefore important to identify who these users are that continuously post unhelpful reviews and explore means through which they can be influenced to post helpful reviews. Thus, this paper aims to 1) identify the personality type of uses who post unhelpful reviews and 2) explore their susceptibility to *rewards* as a form of persuasive strategy.

The use of a person's personality as a means of influencing a target behavior has been explored in various sectors such as health [13] and marketing [17]. A person's personality includes the notable features, characteristics or qualities that form their distinctive characteristic [12]. There are various models that classify people based on their personality traits, with people in each group having a high tendency to behave in a particular way under certain situations. One such model is the Big Five Model which describes a person's personality using five dimensions: *openness to experience, conscientiousness, extraversion, agreeableness* and *neuroticism* [5]. In this paper, we identify the personality of users who often post unhelpful reviews using the Big Five Model. We chose this model because it has been studied extensively in several domains including health [13], marketing [8]and social networks [1].

In order to identify users who often post reviews that are not useful to the Yelp community, we used the dataset available from the Yelp challenge of 2017[1]. We selected users that have posted at least two reviews with ratings less than 3 (out of 5) and which other users have not complimented for being useful (useful vote = 0). We then applied the Linguistic Inquiry and Word Count (LIWC) [14] tool which classifies users into the five dimensions of the Big Five Model. We were able to identify the five personality types of the Big Five Model.

To determine the susceptibility of the various personalities identified to *rewards* as a means of influencing them to post helpful reviews, we developed and tested a structural model using Partial Least Squares-Structural Equation Modelling (PLS-SEM). The result of this analysis suggests that of the five personality types in the dataset, only the users who score high in *extraversion* are likely influenced by *rewards*. These users form a small fraction of the community (based on the dataset we worked with), hence, *rewards* might not influence users who write unhelpful reviews to write better reviews.

The results of this paper can provide useful insights in designing persuasive strategies that work in online communities.

2 Related Work

2.1 Yelp

Yelp[2] is an online community that helps people locate businesses such as restaurants and hotels within a geographical location. Yelp thrives on user generated reviews and ratings which are written by patrons of such businesses. Yelp rewards its members who write good reviews and are active in the community with the *Elite status*. Members of

[1] https://www.yelp.com/dataset_challenge
[2] www.yelp.com

the community can rate reviews on a scale of 0 to 5 stars. In addition, they can complement reviews by voting them as being *useful*, *funny* or *cool* on a scale of 0 to 5. The more stars and compliments a user gets for his/her reviews, the higher the chances he/she has of being rewarded with the *Elite status*.

Reviews in online communities such as Yelp is currently an active research area. Luca [11] in his study of Yelp explored the effect of consumer reviews on the revenue of businesses. Their study suggests that an increase in a restaurant's rating on Yelp results in an increase in the business' revenue. Luca concluded that online consumer reviews in Yelp are an alternative to traditional reputation systems. Huang et al. [7] studied customers' reviews to determine what the customers expect from various businesses. They explored restaurant reviews to identify what hidden topics customers discuss that can be useful to restaurant owners in improving their ratings on Yelp.

Despite the ongoing research in online communities like Yelp, to the best of our knowledge, there has not been any work done on identifying users that post low rated reviews and the susceptibility of these users to rewards.

2.2 Personality Type; The Big Five Model

The Big Five model (also referred to as the Five-Factor Model) is a popular model that describes a person's personality using five dimensions: *openness to experience, conscientiousness, extraversion, agreeableness* and *neuroticism* [5]. These dimensions were derived from the analysis of common natural language terms people use to describe individual differences in themselves and others [9]. People with *extraversion* traits are talkative, energetic and assertive while those with *agreeableness* trait are co-operative, good-natures and can be trusted. *Conscientiousness* trait describes people that are dependable, responsible and orderly, while *neuroticism* characterizes people that are calm and are not easily upset. People with personality trait, *openness to experience*, are known to be imaginative, independent-minded and intellectual [9]. We used the Big Five Model because it has been used successfully in various domains including health [13], e-commerce [8] and online communities [1].

2.3 Linguistic Inquiry and Word Count (LIWC)

The Linguistic Inquiry and Word Count (LIWC) [14] tool reads text and determines what percentage of words in the text reflect personality, emotions, thinking styles and social concerns of the writer. LIWC works by calculating the percentage of given words that match its built-in dictionary of words. It assigns a percentage value for each personality type or trait such as *reward bias* or *thinking style.* The LIWC dictionary consists of about 6,400 words, word stems and emoticons. LIWC has been used extensively in analyzing users in social communities with success. Bazelli et al. [1] used the LIWC tool in exploring the personality of users in a popular question and answer social media, Stack Overflow. Their research suggests that top contributors in the community are extroverts. Romero et al. [15] also used the LIWC tool in their study of social networks.

The authors explored how the personality traits and behavior of decision makers in a large hedge fund change based on price shocks.

Based on the popularity and success of the LIWC tool as reported by other researchers, we chose to use it in this research.

3 Research Design and Methodology

This paper aims to 1) identify the personality type of uses who post unhelpful reviews and 2) explore their susceptibility to rewards as a form of persuasive strategy.

For this study, we used the dataset from the 2017 Yelp challenge[1]. In order to identify reviews that are not useful to the community, we used the ratings and "useful" compliments of the reviews. We selected users that wrote at least two reviews which met the following criteria:

- Reviews that were rated less than the median possible score, two out of five.
- Reviews that had a useful compliment of zero.

We did this because we hypothesize that a review that has a rather low rating and has not been voted or complimented as being *useful* by any member of the community is likely not a helpful review.

Of all the reviews in the dataset, only 78,240 reviews met this criteria written by 6,448 people. In order to have a lot of written text by the reviewer (which enhances the validity of the LIWC tool), we further excluded reviews that were shorter than 200 words. 6,249 reviews written by 2,154 users met this criteria. These reviews were explored in this paper.

4 Data Analysis And Result

To analyze our data, we used LIWC [14]. We used this tool because out of the existing tools and models for analyzing the Big Five Model's personality types, the LIWC tool has been widely used in various domains with success [1], [15]. Using the criteria described above in section 3, we extracted the user ids and text of the 6,249 reviews that met our set criteria in a CSV file. This formed the input to the LIWC tool. The LIWC tool reads text and determines what percentage of words in the text reflect personality, emotions, thinking styles and social concerns of the writer. LIWC works by calculating the percentage of given words that match its built-in dictionary of words. According to the Big 5, everyone exhibits some traits of all personality types, however one trait is more dominant than the others [5]. LIWC computes a value for each of the personality types (*openness, conscientiousness, extraversion, agreeableness* and *neuroticism)* for each user; the dominant trait for a user is the personality type with the highest value. The LIWC tool also computes a value for other traits such as *thinking style* and *reward bias.* We used the value for *reward bias* in evaluating users' susceptibility to rewards.

4.1 Result of LIWC analysis

The result of the analysis shows that there were more people who scored high on *neuroticism* compared to the other personality traits. Figure 1 shows the boxplot of the ranking of the five personality types.

In order to ensure that there are differences in the five personality types identified by the LIWC tool, we carried out an ANOVA with repeated measures test with a Greenhouse-Geisser correction. The result shows that the overall difference in the users based on the five personality types was statistically significantly different at $F(3.538, 22101.249) = 2914.798$, $p < 0.0005$). To further identify how each personality type differed, we carried out a pair wise comparison between the five personalities. Post hoc tests using the Bonferroni correction revealed that all but two of the personality types; *conscientiousness* and *openness* differed significantly. This shows that there is significant difference in users that possess personality types *agreeableness, extraversion* and *neuroticism*.

The LIWC analysis on the data set also revealed two clusters of users who post reviews that are not useful. These are shown in figure 2.

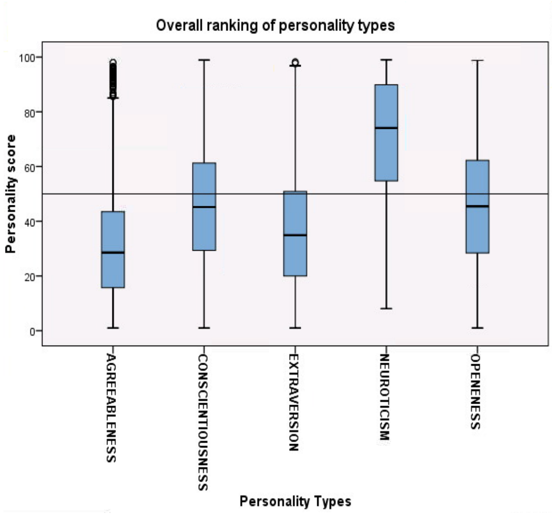

Figure 1. A boxplot showing the overall ranking of the personality types of users by LIWC. The horizontal line indicates a median ranking of 50 out of 100

Cluster1:

This cluster formed 52.46% of the users and is shown in blue color in figure 2. Users in this category can remain calm and cope with stressful or unpleasant situations. In addition, they are easy-going and relaxed. They take problems as they come, they are patient and slow to anger. They typically make others feel relaxed and comfortable. In terms of family orientation, they are not close with or focused on family. They place themselves over family and familial relationships.

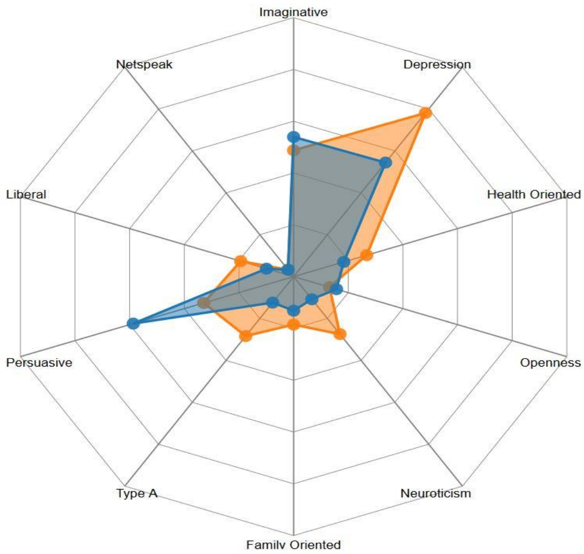

Figure 2. Clusters of users identified by LIWC tool

Cluster 2:

This cluster formed 47.54% of the users and is shown in orange color in figure 2. This set of users are closed-minded. They are generally conventional and may be perceived by others as stubborn. They are not close with or focused on family and they prioritize themselves and friends over their families. In addition, this group of users are likely to have a hard time experiencing enjoyment; they ruminate and may often experience stress. Furthermore, these users are likely to have difficulties controlling negative moods and may seem distant.

4.2 Susceptibility of personality types to rewards

Having identified the personality types of users who post unhelpful reviews, we explored the effect of *rewards* on these different personalities. Rewards have been identified as one way through which users can be motivated to participate in online communities [3], hence we explored the effect of rewards on each personality type. To do this, we developed and tested a structural model using Partial Least Squares – Structural Equation modelling (PLS-SEM) with the results of the personality types and susceptibility to *reward bias* derived from the LIWC tool. We used PLS-SEM because we wanted to measure the influence of the various personalities on *reward* as an influence strategy.

Path coefficients (β) and path significance (*p*) are important criteria in measuring the validity of relationships between variables in structural models [6]. While path coefficients measure how one variable influences another, path significance determines how significant (or not) that influence is [6]. The result of our model is shown in figure 3 with the individual path coefficients (β) and their corresponding level of significance (*p*) shown in brackets.

The result from the structural model reveals that the personalities of users in Yelp who post unhelpful reviews influence the persuasiveness of rewards. Our results suggest that rewards are likely to motivate behavior only from people who are high in *extraversion* ($\beta = 0.433$, $p<0.0001$) compared to the other personality types. Although the path significance between *neuroticism* and rewards is significant ($p<0.0001$), the path coefficient is however very low ($\beta = 0.102$) [18].

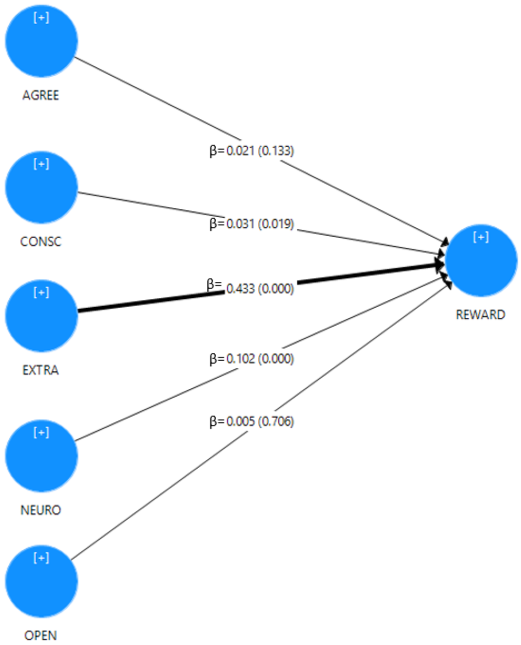

Figure 3. PLS-SEM model structure showing path significance and *p*-values shown in brackets. AGREE=Agreeableness, CONSC= Conscientiousness, EXTRA= Extraversion, NEURO= Neuroticism, OPEN=Openness to experience.

5 Discussion and Limitation

Because reviews are important in online communities like Yelp, it is important to encourage users to post useful reviews that are helpful to the community. This paper aims to identify users who post unhelpful reviews and the possibility of influencing them to post useful reviews using rewards. To do this, we identified the personality type of users who post unhelpful reviews using the LIWC tool. Our analysis suggests that users who post unhelpful reviews are those with the personality type *neuroticism* (figure 1). People who score high on this personality type are typically moody, usually anxious, depressed and lonely [5]. We further investigated the effect of the various personality types on rewards as a means of influencing change in users. The result of the structural modelling we carried out suggests that only users with personality type *extraversion* are significantly influenced by reward, but these users form only a small fraction of the total users who post unhelpful reviews (see figure 1). Therefore, one can conclude that the use of rewards does not influence participation of users that post unhelpful reviews in Yelp. This is because most unhelpful users score high on *neuroticism*, however, rewards influence mostly those who score high on *extraversion* and these users are few.

While research shows that online communities like Yelp offer incentives and rewards to influence participation, the approach commonly used seems to be a one size fits all method [3]. Our results suggest that because users have diverse personality types and these different personality types are influenced by rewards differently, personalizing rewards to an individual's personality type (instead of a one-size-fits-all method) or user characteristics (as described in figure 2) might be a better approach to influencing users to write useful reviews in Yelp.

Personalization using personality types has been successful in several domains like health [2] and e-commerce [10], hence online community developers and stakeholders should consider personalization of influence strategies when persuading users to contribute to the community.

Our research is limited in a few ways. The result of our personality test is based solely on the LIWC tool. We are confident with the result of this tool because it has been used extensively in various domains with success [1], [15]. We however plan to compare the results of the LIWC tool to other existing tools that identify personality through text. Another limitation is the dataset. We used existing data provided by Yelp which might represent only a fraction of Yelp users. We however believe that the approach presented in this paper can be applied to any online community.

6 Conclusion

Online communities like Yelp depend on its users to actively participate in the network by writing useful reviews. However, not all users do so. The aim of this paper is to identify the personality type of users who post low rated and unhelpful reviews and determine the susceptibility of the various personality types to rewards as an influence strategy to encourage the posting of useful reviews. We identify the personality types and reward bias of users using the Linguistic Inquiry and Word Count (LIWC) tool. The result of our analysis reveals that users who post unhelpful reviews are mostly of the personality type *neuroticism*. We further explored the susceptibility of the different personality groups of users to rewards as a means of influencing them to write useful reviews. Our results show that only the users that are high in *extraversion* who post unhelpful reviews are susceptible to rewards. This result demonstrates that rewards might not be persuasive to most of the Yelp users who post unhelpful reviews, hence other persuasive strategies should be explored to influence users to post helpful reviews. The result of this study could be helpful to developers and stakeholders of online communities.

In the future, we plan on comparing the result of the personality types determined by the LIWC to other existing tools to determine the validity of the LIWC. In addition, we will also explore what persuasive strategies can be implemented in Yelp for the users that scored high in *neuroticism* since they are not influenced by rewards.

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