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Segmenting an Online Reviewer Community: Empirical Detection and Comparison of Reviewer Clusters

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Abstract

Online review communities thrive on contributions from different reviewers, who exhibit a varying range of community behavior. However, no attempt has been made in the IS literature to cluster behavioral patterns across a reviewer population. In this paper, we segment the reviewers of a popular review site (Yelp) using two-step cluster analysis based on four key attributes (reviewer involvement, sociability, experience, and review quality), resulting in three distinct reviewer segments - Enthusiasts, Adepts, and Amateurs. We also compare the propensity of receiving community recognition across these segments. We find that the Enthusiasts, who show high involvement and sociability, are the most recognized. Surprisingly, the Adepts, who are high on review quality, are the least recognized. The study is a novel attempt on reviewer segmentation and provides valuable insights to the community managers to customize strategies to increase productivity of different segments.

Keywords Online reviewer segments, online recognition, cluster analysis, reviewer characteristics, Yelp

1 INTRODUCTION

With the proliferation of internet, online communities for sharing consumer reviews and opinions are becoming increasingly important to influence purchase decisions for various products and services. Research has found that consumers tend to rely on the word-of-mouth shared by peers more than the information shared by marketers and advertisers (Bickart and Schindler 2001). With the growing importance of electronic word-of-mouth, online reviewer communities encourage their members to contribute more and write better quality reviews by implementing reputation systems such badges, titles, etc., or by offering rewards such as discounts, gift vouchers, etc. Intrinsic motivation (altruism, knowledge self-efficacy, gratification derived from helping others) along with extrinsic motivation (rewards and reputation) drive individuals to contribute reviews on such review sites. Presently, millions of online reviewers are actively involved in providing reviews on various platforms. Review site Yelp.com had over 1 million active reviewers generating a total of 121 million reviews on local businesses at the end of year 2016[1]. Such large pool of online reviewers is constituted of individuals who may differ on several aspects, such as, their experience in writing reviews, level of involvement demonstrated, attitude of community commitment, etc. For example, some reviewers may post frequently, while some may be quite passive members who rarely share any review. Review quality is also expected to differ from one reviewer to another. Moreover, not all of them enjoy equal popularity (friends and followers) among the community members. Hence it can be stated that in an online review community, each reviewer demonstrates certain characteristics and thus plays a specific social role which in turn leads to the community forming certain perceptions about the reviewer.

Extant literature pertaining to online reviewers predominantly investigated the influence of various reviewer characteristics on review helpfulness (Fang et al. 2016; Hu et al. 2008; Lee & Shin 2014). Some studies have tried to identify influential reviewers in a community based on their profiles and observable online behavior (Ku et al. 2012; Li et al. 2010). However, while identifying influential reviewers may help community managers incentivize few exceptional individuals to contribute more, this endeavour does not capture the entire value that could be derived from a systematic segmentation of the entire population of reviewers. It is well established in literature that end-user segmentation has proved to add significant value in creating user-centric system design and promoting better management of system usage (Kramer et al. 2000). Hence, we expect that systematically categorizing all active reviewers in an online community into few key segments would help in discovering the dominant characteristics, behaviors, strengths, weaknesses, etc. of each segment which could lead to better strategies in managing such huge reviewer base.

Segmentation of markets has always been an important area of research in management for decades. Segmentation of new age technology adopters (e.g. mobile Internet services users) has been a recent development (Hamka et al. 2014; Okazaki 2006). Few works on segmentation have extended to the Web 2.0 context which include identifying various social roles in online discussion forums and profiling of users on social networking sites like Facebook (van Dam and Van de Velden 2015). Majority of the profiling work has been done with the objective of better customer relationship management and target marketing, e.g. recognising passive observers in online forums and incentivising them to contribute or advertising effectively to Facebook users based on their segment. However, despite a lot of research on online reviews, to the best of our knowledge, segmentation of online reviewers is an area which has never been looked into.

Given the managerial need and the corresponding dearth of systematic effort to profile online reviewers we intend to take up the following research question:

What are the specific segments of reviewers found in an online review community?

Once we identify the key reviewer segments, we could further probe to find out the dominant traits of each reviewer segment. It would also be interesting to inquire if an online community prefers one segment over the other when it comes to granting community recognition or virtual rewards. These lead to the follow-up questions:

What are some of the dominant traits that reviewers of each segment display? Does likelihood of receiving community recognition differ across the reviewer segments? Which category of reviewers is more likely to gain recognition, and which one is the least recognized?

[1] https://www.statista.com/statistics/278032/cumulative-number-of-reviews-submitted-to-yelp/; accessed on July 2017.

We attempt to answer these questions by empirically identifying few key segments in an actual online reviewer community based on various reviewer characteristics. Utilizing data from the popular review website Yelp.com we segment its existing reviewers using cluster analysis into the *Amateurs*, *Enthusiasts*, and *Adepts*, named based on their distinct traits. Yelp also provides community recognition to selected reviewers every year by conferring them with ‘Elite’ title based on their contribution and community behavior. An illustration of a typical reviewer profile in Yelp.com with various reviewer characteristics is shown is Appendix 1. To investigate the social perception of community towards different segments, we also compare the segments on their propensities to be declared as ‘Elite’. The identification of the key characteristics of the most recognized and unrecognized segments provides interesting insights into what attributes are preferred and what are neglected by the community members and managers.

There are several implications of this work on academicians and practitioners. First, being the first study to attempt profiling of reviewers, it not only extends the literature on online reviewers and communities, but also paves way for similar research in other platforms and contexts to form more generic segmentation models. Second, the differences among the segments lead to interesting follow-up questions for academicians with respect to the various differentiating factors (psychological, social, etc.) and theoretical explanations. Third, segmentation of reviewers with differences in key characteristics provide critical and more organized insights to the community managers and website administrators. It gives them the freedom to adopt a differentiated strategic framework tailor-made to maximize the contributions made by each segment, instead of applying a one-size-fits-all strategy to the entire community. Fourth, by comparing the segments based on their propensity to become recognized reviewers, community managers could learn more about the effectiveness of their existing recognition system in place. For instance, our results showed that the *Adepts* segment of reviewers in Yelp who are high-quality writers did not get due recognition in line with their contribution.

2 LITERATURE REVIEW

Existing literature on online reviewers predominantly focuses on the impact of certain characteristics of the reviewers on the evaluation of reviews they write. Connors et al. (2011) found that reviewer characteristics are important antecedent of perceived helpfulness of reviews, and also that the reviews written by self-declared experts are considered to be more helpful than others. Another study established that reviewer reputation and exposure significantly influence consumers’ evaluation of online reviews and in turn affect purchase intention (Hu et al. 2008). It is also found that reviewer engagement characteristics, such as reputation, commitment, and current activity are key determining factors of the helpfulness of their reviews (Ngo-Ye. et al. 2014). (Banerjee et al. 2017) found a positive moderating effect of reviewer trustworthiness on the relationship between online reputation of a business and business sales. In the same study, they also identified six reviewer characteristics responsible for significantly influencing reviewer trustworthiness.

Only a few studies have ever attempted to understand reviewer activities and classify them based on their online profiles and community conduct. For example, Ku et al. (2012) simply distinguished reviewers into high reputation and low reputation based on their web-trust network on an online opinion site. However, no existing work has been done in clustering online reviewers based on several other important traits, such as, quantity and quality of contribution, experience in writing, polarity of their reviews, etc. It is noteworthy that extant literature records work on segmentation and role identification of users for various online communities such as Q&A and discussion forums. For instance, ethnographic studies of content interaction and investigation into structural and behavioral cues of users were carried out to identify various social roles in online discussion forums (Marcoccia 2004; Turner et al. 2005). Some of the social roles emerged through this processes are: local experts, fans, answer people, trolls, etc. (Welser et al. 2007). Similarly, user profiling has been conducted for social networking sites, such as Facebook, through analysing their non-reactive data (click-stream, IP address, likes etc.) and reactive data (name, gender, location etc.) (van Dam and Van de Velden 2015). In this study, we extend the work of segmentation and profiling in the context of online reviewers.

To carry out the clustering activity, the key reviewer characteristics which factored into determining the clusters, were selected from the data available from a well-known review platform (Yelp.com). The factors were selected from the available fields in the data set with support from extant literature. Previous studies have identified the number of reviews as an important factor to predict review helpfulness (Liu, Z., Park 2015; Otterbacher 2009), and thus is an important reviewer characteristic. The total number of reviews written depicts a reviewer’s involvement with the platform and varies among reviewers based on their own motivation. Hence, we choose the aggregate number of reviews written by a reviewer as a factor of the profiling exercise. We also consider the total votes received by a reviewer for the contributed reviews as an important factor since it signals the overall impact of contribution. Reviewer experience on the platform is another important trait to be taken into account. Individuals may develop a psychological bond with a community after spending substantial time with it. Hence, the number of years on an online community might influence a reviewer's community commitment. Also, with many years of experience on a platform, reviewers tend to become more skilled and informed (Banerjee et al. 2017). The average number of helpful votes a reviewer received per review is a good indicator of her competence or effectiveness in writing reviews and is also considered to be an important trait (Ghose, A., Ipeirotis 2011). The number of friends and followers on the reviewer community which are measures of sociability and popularity, are also important identification attributes of a reviewer. (Liu, Z., Park 2015) confirmed the fact that friendliness of a reviewer is a determinant of review helpfulness, and hence, a key reviewer characteristic. In summary, the factors which were theoretically considered to be important for segmentation of reviewers are: number of reviews written, total votes received, years of experience on the review site, average number of votes received per review, number of friends, and number of followers. Though we admit the limitation of the factor list to be an unexhaustive one, these were the detected factors based on data availability, literature support and logical arguments as appropriate reviewer characteristics.

3 DATA AND ANALYSIS

3.1 Data Description

A dataset which was made publicly available by Yelp.com for a research competition was collected for our analysis. It consisted 2.2 million reviews of more than 77,000 local businesses in various cities of USA, UK, Canada, and Germany. Data on more than 525,000 reviewers who are part of Yelp was also published containing reviewer-specific attributes. For our analysis, we considered the reviewer dataset. We carried out preliminary data cleaning where we removed the outliers and records with missing values. Further we retained only those reviewer records which had at least one follower, one friend, and one year of experience in the platform resulting in 55,690 valid records. The data set was sufficiently large to perform data analytics techniques on it. It was a cross-sectional dataset containing variables with information about the reviewers aggregated over 12 years of time period (2004 – 2015). Among the variables, we used Number of followers, Number of reviews, Years of experience, Total votes per user, Average votes per user, and Number of friends as our input variables.

We also considered a factor called 'Reputation' which depicts the propensity of a reviewer being selected as 'Elite' in the community. It is the ratio between the number of years a reviewer had been selected as 'Elite' and the number of years she was active in the platform. In Yelp community reviewers who are nominated by themselves or by any other Yelp members get selected by the community managers at the starting of each year as 'Elite' based on their contribution and camaraderie in the community. The title, apart from recognition, provides opportunities to the reviewers to be invited in exclusive events organised by local businesses. Thus, it works as a reputation system as well as reward system, which could act as a source of extrinsic motivation for the reviewers. The rationale behind using propensity of being 'Elite' as the variable of interest is that considering only years of 'Elite' would have created bias towards the more experienced reviewers when comparing between the reviewer segments. The ones who joined the platform later would get lesser number of opportunities to be selected as 'Elite' than their experienced counterparts. Hence, propensity of receiving the title, represented by the variable 'Reputation' is a fair measure when it comes to comparing between reviewers having varying degree of experience in the community.

Table 1 reports the descriptive statistics of the variables used in the processed dataset.

	Mean	SD	Min	Max
Number of Followers	2.04	1.94	1	23
Number of Reviews	45.02	46.49	3	284
Years of Experience	5.21	2.08	1	12
Total Votes per User	91.05	107.40	0	635
Average Votes per User	2.08	1.41	0.00	8.50
Number of Friends	7.19	9.35	1	49

Reputation	.03	.11	0	1

Table 1. Descriptive Statistics of the Variables Used

The aim of this work is to segregate the entire base of active reviewers into two or more distinct clusters based on their attributes. Further, we intend to compare the mean of ‘Reputation’ among the emerged clusters. The objective is to investigate whether reviewers in each cluster display significant difference in the propensity of becoming an ‘Elite’. We can further analyse the segment with the highest reputation and note their characteristics, which would reveal the combination of attributes appreciated by the community.

3.2 Dimension Reduction

In the first part of the analysis we reduced the dimensions using principal component analysis followed by varimax rotation. Initially we had six variables as inputs: Number of followers, Number of reviews, Years of experience, Total votes per user, Average votes per user, and Number of friends.

We observed that the Number of reviews, Total votes per user, and Number of followers loaded on a single factor, and thus were combined to create a single dimension called Reviewer involvement. This factor shows the extent to which a reviewer is involved in the online forum. The idea of member involvement in virtual communities is resonated in another study, where involvement is defined as member participation in the online community and communication with other members (Lin 2008). Hence, we may say that individuals who write more number of reviews and have many followers and hence receive more votes are usually much involved in the community. Remaining three factors were Number of friends, Years of experience, and Average votes received by each user. Each of these three factors is measurement of a particular quality of the reviewer. The number of friends is a measure of sociability of the reviewer (Banerjee et al. 2017). It shows the connectedness of an individual with the members of the online platform. Years of experience is a measure of the time a reviewer has been associated with the platform, which also reflects her engagement with the community. Finally, the average number of helpful votes received depicts the quality of a reviewer’s contribution (Otterbacher 2009). Hence, through dimension reduction, we were left with four factors: Reviewer Involvement, Number of friends, Years of experience and Average review votes received by the reviewer.

Table 2 shows the descriptive statistics of the final factors.

	Mean	SD	Min	Max
Reviewer Involvement	0.00	0.99	-1.79	7.01
Number of Friends	7.19	9.35	1	49
Years of Experience	5.21	2.08	1	12
Average Votes per Review	2.08	1.41	0.00	8.50

Table 2. Descriptive Statistics of the final factors

3.3 Two-step Cluster Analysis

Following the dimension reduction, we used two-step cluster analysis using the four identified factors. Cluster analysis has recently been applied to various contexts for segmenting internet-shoppers (Bhatnagar and Ghose 2004), cellular phone users, mobile internet users, etc. (Okazaki 2006). The appropriate number of clusters was determined using the silhouette method, which shows the quality of the clustering process. It is one of the popular techniques for selecting the optimum number of clusters based on comparison of cohesion and separation of the data points in a cluster (Rousseeuw 1987). After comparing different number of clusters on the cluster quality and ratio between the largest and the smallest cluster we found the most appropriate number of clusters to be three. Figure 1 shows the fair quality 3-cluster partition using the silhouette method with average silhouette width (ASW) more than 0.25. As cluster quality is a subjective measure the admissible value of ASW depends on the clustering context and data points available. An ASW more than 0.25 is an acceptable value of cluster quality for naturally occurring observations (Kaufman and Rousseeuw 1990). For three clusters, the ratio between the size of largest and smallest cluster is 1.80 which is also considered to be acceptable. Figure 2 displays the pie chart of each of the three cluster sizes.

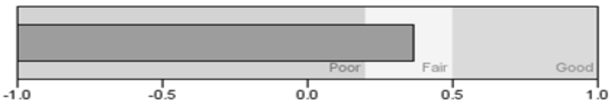

Figure 1: Cluster quality (number of clusters=3)

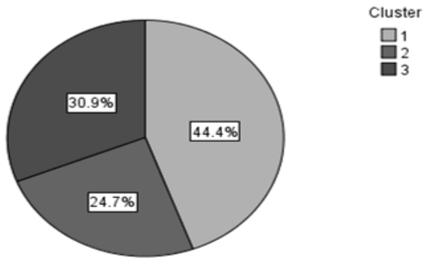

Figure 2: Cluster sizes

We used the two-step cluster analysis method provided by the statistical tool IBM SPSS Statistics. This is suitable for large datasets with natural groupings of observations which would not be apparent otherwise (Norusis 2008). This clustering algorithm proceeds in two steps: In the first step, the original dataset is divided into pre-clusters which are then used in the second step as inputs to hierarchical clustering. The exact distribution of 55690 records among the three clusters on executing the algorithm was found to be Cluster1 (24709), Cluster2 (13757) and Cluster3 (17224), as summarized in Fig.3.

Further we analysed the factors which helped in differentiating the segments using the cluster profiles generated by the tool. Table 3 shows the descriptive statistics of the centroids of the three identified clusters.

Cluster ID		Years of Experience	Average Votes per Review	Number of Friends	Reviewer Involvement
1	Mean	4.00	1.20	3.10	-0.42
	SD	1.58	0.60	3.321	0.44
	Min	1	0	1	-1.26
	Max	8	3.42	20	1.67
2	Mean	6.01	2.30	18.31	1.13
	SD	2.02	1.29	12.22	1.24
	Min	1	0	1	-1.58
	Max	12	8.50	49	7.01
3	Mean	6.32	3.17	4.17	-0.30
	SD	1.82	1.50	3.98	0.58
	Min	1	0	1	-1.79
	Max	12	8.50	25	1.87

Table 3. Summary Statistics of the Key Factors in Each Cluster

Comparing and analyzing the mean values of each of the key factors used for clustering, the three segments were classified as follows:

i. Cluster 1 comprised of the reviewers who were low on all the factors: reviewer involvement, number of friends, years of experience, and average helpfulness votes. This implies that they not only demonstrated lesser overall contribution to the community but also were the lowest in terms of the quality of reviews and also had the smallest social network compared to the other segments. But to be fair to this category, they did have lesser experience in the reviewer community as compared to others which could imply that they may still have been learning the ropes. Most of the reviewer population (44.4%) fell in this segment. Given their lack of experience and contribution quality, this segment of reviewers can be referred to as the '*Amateurs*'.

ii. Cluster 2 was formed with reviewers displaying the highest level of involvement and sociability (number of friends). Also, they were pretty experienced (although a bit less than the third cluster). But despite being extremely involved with the community, they were perceived to produce moderate quality of reviews based on the votes received per review. 24.7% reviewers belonged to this segment. Given that their overall distinguishing feature is an enthusiastic community involvement, this segment could be named as the '*Enthusiasts*'.

iii. Cluster 3 which had 30.9% of total observations was the one with the reviewers who were the most experienced as well as the most effective ones. They got the highest number of average helpful votes per review. However, they showed a significantly lower level of involvement and number of friends compared to the enthusiastic Cluster 2. Expertise in writing good quality reviews being their forte, this segment of reviewers could be named as the '*Adepts'*.

3.4 Segment Comparison: One-way ANOVA

Following the clustering exercise, we compared the three segments of reviewers in terms of their propensity to gain community recognition. Essentially, using one-way ANOVA we investigated whether the variable 'Reputation' differed across groups. An important assumption of ANOVA is the homogeneous variances of the outcome variable(s) for all the groups. To test whether variances of the three groups were significantly different we executed the Levene's test of homogeneity of variance. With a significant p-value ($p<0.05$) the assumption was violated in our case. Hence, for the main ANOVA we inspected Brown-Forsythe and Welch test results to accommodate the heterogeneity of variances. Table 4 reports the results of one-way ANOVA, whereas Table 5 reports the results from Brown-Forsythe and Welch tests. There was a significant effect of reviewer segment on the propensity to become 'Elite', $F(2, 55687) = 1593.48$, $p<0.001$. Brown-Forsythe and Welch F-ratio also suggested that variable Reputation differed significantly across reviewer segments. Hence it can be concluded that not only the reviewer characteristics vary across the three segments, the perception of community towards the reviewers varies as well.

Outcome variable: Reputation					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	39.09	2	19.55	1593.48	.000
Within Groups	683.10	55687	.01		
Total	722.19	55689			

Table 4. ANOVA Results

	Statistic	df1	df2	Sig.
Welch	981.24	2	29658.34	.000
Brown-Forsythe	1385.87	2	26613.61	.000

Table 5. Robustness Test for Comparison of Means

In order to understand how exactly community recognition differs across the three segments, we conducted a post-hoc test for pairwise comparison of means of our outcome variable. Since we had unequal variances as well as unequal sample sizes we used Games-Howell test and Gabriel's test respectively. Both the tests reported significant differences in mean of the dependent variable between any pair of clusters. Appendix 2 shows the results of Games-Howell test. Table 6 depicts the summary statistics of the outcome variable (Reputation) for each cluster. Figure 3 plots the error bar chart for reputation mean by segments, which visually depicts the comparison between groups. From the table and the plot, it is clear that our variable of interest, 'Reputation' is highest for the 'Enthusiasts' with a mean of 0.077. It means that reviewers who are high on community involvement and sociability turned out to be the most appreciated ones by the community and had the highest probability of being selected as 'Elite'. The remaining two clusters showed significantly low value for Reputation. Surprisingly, the 'Adepts' who are the best in writing quality reviews fared low on Reputation compared to the other two groups. This indicates that the recognition system in the review community recognizes the individuals with higher quantity of reviews, involvement and camaraderie as valuable contributors, however, often ignores the reviewers with high quality reviews as their dominant trait.

Cluster	Mean	SD	Min	Max	N
1. Amateurs	.018	.10	0	1.00	24709
2. Enthusiasts	.077	.16	0	1.00	13757
3. Adepts	.012	.06	0	1.00	17224

Table 6. Summary Statistics of Outcome Variable (Reputation)

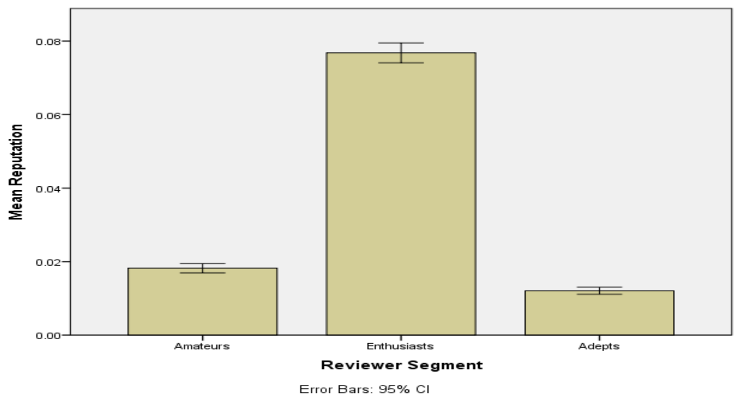

Figure 3: Error bar chart for outcome variable (Reputation)

4 DISCUSSION AND IMPLICATIONS

Based on the clustering of online reviewers in a review community (Yelp) we identified three distinct segments of reviewers (*Amateurs, Enthusiasts* and *Adepts*) with each segment displaying certain dominant behaviors. While Amateurs were mostly slackers who were relatively new to the community, the Enthusiasts and Adepts were experienced members with the former focusing more on amount of involvement and sociability, and the later focusing on writing good quality reviews which were more useful to the readers. The significant differences in reviewer characteristics and behaviors among the three segments challenge the implicit assumptions of homogeneity made by most studies on online reviews and reviewers. Taking the means of certain reviewer characteristics for the entire population may not always serve the research purpose because of the vast internal differences. Even for community managers, the segmented analysis may provide more practical insights than an overall population analysis which may get biased by the majority segment (Amateurs, in this case). It may be noted that while it is probable that the exact segmentation may not hold true for other online reviewer communities, a general overarching 3-segment pattern can be expected that some reviewers would focus on quantity, some on quality, and some on neither. Future research can look deeper into this proposition and can form theoretical models to explain such differentiated behaviors in social contexts.

Yelp has been recognizing the contributors by conferring a few chosen ones among them an 'Elite' status at the beginning of each year, the objective of which is to acknowledge their community participation and motivate them to contribute in better ways. By comparing the three segments in their propensity of being tagged as 'Elite', we found that the community highly recognized the Enthusiasts, the ones showing the highest level of involvement and sociability, which signals a greater importance of these two reviewer characteristics in affecting community perceptions. However, the more experienced Adepts who contributed lesser quantity, but higher quality of reviews showed a much lower propensity of being recognized which implies a limitation of the recognition system in the community to acknowledge good quality reviewers. While encouraging involvement and camaraderie is crucial for attracting more number of reviews and stronger social exchange on the platform, the community managers or the platform administrators should also appreciate the reviewers who might not be the most frequent ones, but the ones who write the most impactful reviews. Leaving out the Adepts while conferring the title might demotivate them to participate and eventually erode the value they bring to the platform. In further injury to the prestige of the Adepts, we also found a counter-intuitive insight that even the Amateurs had higher propensity of being recognized than them. One possible explanation that we could think of is that the community managers might be trying to entice and motivate the Amateurs to contribute more by providing recognition even to lesser deserving candidates. Overall, we found it very insightful to get such interesting outcomes just by segmenting the online reviewer community and comparing them on various individual behaviors and social perception.

This study has several important academic and managerial implications. First, to the best of our knowledge this is the first attempt to profile online reviewers and identify their key social roles. We broadly distinguish online reviewers as the *Amateurs* (new and less committed in the community), *Enthusiasts* (highly involved and social reviewers) and *Adepts* (experienced reviewers high on contribution quality). While the profiling is made for the Yelp reviewers, the study could also be adopted for other online review platforms. Further studies could lead to confirmations of these segments in other contexts, or to identification of other segments with different key characteristics. Second, we identify the key factors used as inputs in the segmentation process using principal component analysis. Future works could use these factors for classification of online reviewers. We only took the behavioral characteristics of the reviewers available online, however, it could be readily extended using reviewer demographic characteristics as well, subject to availability of data. Third, the study shows the distribution of reviewers among the clusters. It is seen that the highest percentage of reviewers are '*Amateurs*' with the lowest level of involvement, contribution quality and sociability. The direct implication for the platform administrators is to target these reviewers and incentivize them to be more active. Also, they could customize their guidelines for different segments to encourage certain behaviors. For example, the *Adepts* are high quality writers but are infrequent and less involved. The administrator might incentivize them to post reviews more frequently or make more social connections in the community. Fourth, this research acts as a caution to the online community regarding the recognition systems they implement. Online communities might fail to recognize deserving contributors. In this case, the reviewer segment providing the most number of helpful reviews is under-recognized which could be a potential source of demotivation to the members. Community managers should devise robust recognition systems and be careful in rewarding the 'Elite' title so that they do not overlook the deserving participants.

5 CONCLUSION

This paper is the first to attempt segmentation of online reviewers based on their observable characteristics. Using data from Yelp.com, we first applied dimension reduction to isolate four primary factors (involvement, experience, quality, sociability) among several reviewer characteristics which were suitable as inputs to next step of cluster analysis. Three clusters were identified to be displaying significantly different behaviors, namely - *Amateurs, Enthusiasts* and *Adepts*. Further on comparing their propensity of being recognized by the community, we found that the *Enthusiasts* were considered by far the best among the three segments, thus implying much greater importance of review quantity over quality.

The proposed method of clustering reviewers based on data obtained from a particular review site (Yelp) limits its generalizability. In future, the study could be extended for other online review sites and a generalized framework could be developed to identify social roles for online reviewers. Also, the factors used for clustering do not constitute exhaustive list of possible reviewer characteristics. Several other variables such as reviewer demographic data can complement the existing factors. Further, only cross-sectional cluster analysis could be carried out with the available data. This limits our capability to understand the mechanism behind formation of these clusters and to investigate whether they vary over time. It might also be possible that some reviewers assume different social roles at different points of time. Future studies may look into the effect of time on cluster formation and evolution in this context.

The study makes several academic contributions to the literature of online reviews and communities; and also highlights to the community managers the need for having different strategies tailored for making the multiple segments more productive. We hope that this study paves way for further research on segmentation and comparison of online user communities in different contexts.

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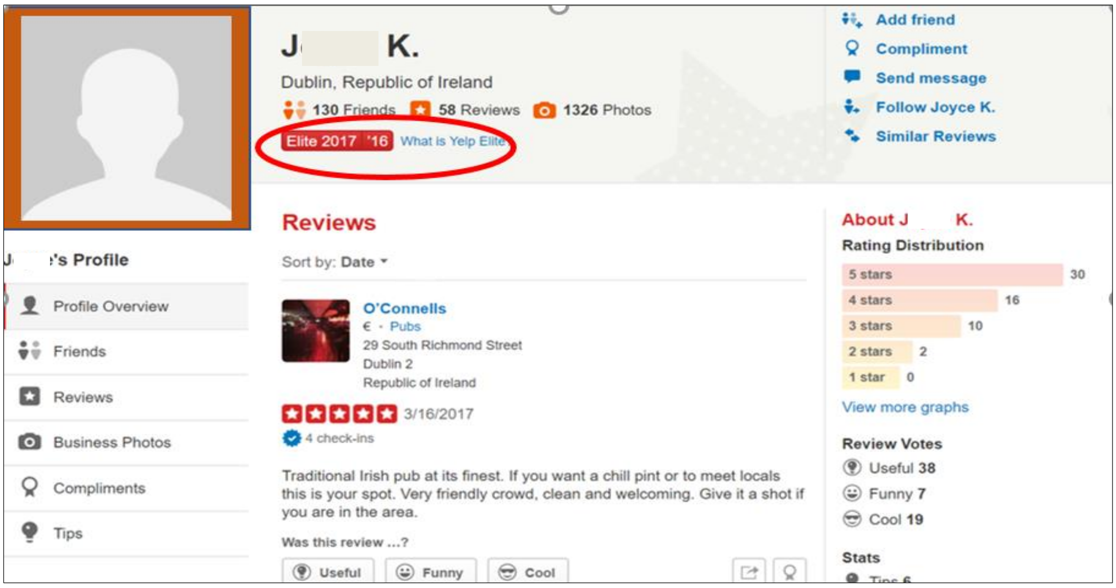
APPENDIX 1

An illustration of reviewer profile in Yelp.com



APPENDIX 2

Pairwise comparisons of Reputation among three clusters

Outcome Variable: Reputation

	(I)Cluster Number	(J)Cluster Number	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Games-Howell	1	2	-.05861*	.00152	.000	-.0622	-.0550
		3	.00614*	.00081	.000	.0042	.0080
	2	1	.05861*	.00152	.000	.0550	.0622
		3	.06475*	.00146	.000	.0613	.0682
	3	1	-.00614*	.00081	.000	-.0080	-.0042
		2	-.06475*	.00146	.000	-.0682	-.0613

*. The mean difference is significant at the 0.05 level.

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