Segmenting Reviewers Based on Reviewer and Review Characteristics

Himanshu Sharma, University of Delhi, India
Anu G. Aggarwal, University of Delhi, India*

https://orcid.org/0000-0001-5448-9540

ABSTRACT

Being experiential commodities, it becomes difficult to make any judgment about hotels or attractions before their utilization. This is where the reviews provided by guests/tourists play an influential role. Therefore, it becomes imperative to study in-depth characteristics of reviewers through which such valuable information is diffused, and also classifying them into various categories based on it. This study adopts a two-stage methodology to segment reviewers based on the reviewer as well as review characteristics. In the first stage, factors that help in evaluating a reviewer are formulated using factor analysis. Later on, cluster analysis is performed for the segmentation of reviewers. Finally, the obtained reviewers’ segments are validated using external validation methods. The study comes up with various implications that could be profitable for business managers in selecting the reviewer community.

KEYWORDS

Cluster Analysis, Experience, Expertise, Factor Analysis, Identity Disclosure, Review Characteristics, Reviewer Segmentation, TripAdvisor

1. INTRODUCTION

Due to the digitalization of businesses, the firms allow customers to express their experience concerning the product or service on their web platforms in terms of feedback termed electronic word-of-mouth (EWOM). These EWOMs can influence the buying behaviour of customers, as potential customers look out for reviews related to the product/service before making the final purchase decision (Banerjee, Bhattacharyya, & Bose, 2017). This is particularly true for experience goods or services, the response for which cannot be attained before its usage. Appreciating the utilization of EWOM by various platforms, the role of the review poster (reviewer) has turned out to be indispensable. This is because prospective customers consider this raw information provided by such reviewers as trustworthy and credible in comparison to those provided by companies or third-party travel agents (Craciun & Moore, 2019). These reviewers help the service providers by raising voices against their bad practices and applauding the good ones (Chua & Banerjee, 2015).

Keeping in mind the trustworthiness or credibility of the reviewers, it becomes necessary for websites to keep these reviewers attached within their community. Not all reviewers have equal contributions since feedback provided by them is a generous task and there is no return for their
inputs (Liang, Schuckert, Law, & Chen, 2017). Extrinsic motivation can be provided by organizations which may be some monetary incentives (Meng, Webster, & Butler, 2013). Monetary incentives in return for a review might look like a bribe and so firms have started emphasizing on providing non-monetary rewards in the form of badges or labels (Antin & Churchill, 2011). Therefore, this study aims to segment reviewers into a badge hierarchy, based on review as well as reviewer characteristics. The reviewers are evaluated based on review characteristics such as review length, sentiment, and readability; while the reviewer characteristics considered are number of cities visited, miles travelled, years of membership, number of helpful votes, age, location, gender, total reviews posted, and total photos posted.

This type of appreciation will encourage new reviewers as well as maintain activeness among the existing ones (Schuckert, Liu, & Law, 2016). Many websites have already started working on this, for example, TripAdvisor gives five badge categories in terms of the level of contribution; Yelp provides an elite badge reflecting the competency and expertise of reviewers; Amazon utilizes the top 10,000 reviewers badge to reward outstanding reviewers. However, the premise underlining the qualifications for providing the badge/medal is the same. In some question-answer platforms, the medals are provided based on the acknowledgments received by the responder, similarly, websites allot labels/badges based on the volume of reviews posted by them (Meng et al., 2013). This is the motivation behind proposing the present study. This is important as reviewers with higher badge levels are asserted to be more trustworthy and credible sources as compared to ones with lower badge levels (X. Liu, Schuckert, & Law, 2018). So, this becomes important from both the customers’ and firms’ end as feedback provided by such sources will influence the sales, price, revenue, and loyalty of both the stakeholders (Casalo, Flavian, Guinaliu, & Ekinci, 2015; Chen, Liu, & Chang, 2013; Schuckert, Liu, & Law, 2015).

For this, the study considers a couple of research questions: Which factors determine the quality and excellence of the reviewers, and how the reviewer community can be segmented based on these factors? To tackle these research questions, the study adopts a two-stage process combining factor and cluster analysis. This type of methodology has been adopted by earlier researchers and proves to be a better segmentation approach in comparison to direct clustering (Kamata & Misui, 2015; Kucukusta & Denizci Guillet, 2016). Firstly, on the collected data, exploratory factor analysis (EFA) is performed to get the factors concerned for studying the behaviour of a reviewer. Reviewer evaluation consists of many factors. However, it is difficult to isolate each characteristic and factor and to use these for segmentation purposes. Factor analysis helps to derive the factors for ease of interpretation. These factors are used for the clustering process. Under clustering, hierarchical clustering is initially performed to obtain the number of clusters that should be built. Finally, k-means clustering is performed to get the clusters representing the badge level equivalent of the reviewers. Overall, the key objective of the study is to come out with various implications for practitioners in judging the value of review writers. Moreover, research findings provide the ideation of how each segment of the reviewer community should be identified and managed. The remaining paper is organized as follows: the relevant literature is provided in Section 2; Section 3 provides the research methodology and data description; the detailed data analysis is presented in Section 4; discussions based on the obtained results along with their implications are provided in Section 5; lastly Section 6 concludes the study and suggests the scope for future works.

2. LITERATURE REVIEW

Extant researchers have started emphasising the inclusion of reviewer characteristics while satisfying their objectives such as review helpfulness, trustworthiness, or credibility. In a study, review helpfulness was determined using reviewer characteristics as one of the determinants (Otterbacher, 2009). The items such as real name, entropy, perplexity, volume, and helpful votes were combined as “reviewer reputation”. Another study by Ghose and Ipeirotis (2010) considered the role of reviewer history
(past helpful votes and volume) and personal characteristics (real name, nickname, hobbies, location, and interests) on the helpfulness of reviews. Filieri (2015) talked about the significance of source credibility on review helpfulness, where the credibility construct was a combination of experience, expertise, and reliability. In another study, user experience and proficiency were found to be related to perceived trust in a travel website (Filieri, Alguezau, & McLeay, 2015). Z. Liu and Park (2015) stated that review characteristics (valence, length, readability) and reviewer characteristics (personal identity, reputation, and expertise) lead to the usefulness of reviews.

Yoo, Lee, Gretzel, and Fesenmaier (2009) stated that the qualities of reviewer that leads to trust in their content are perceived trustworthiness (honest, sincere, unbiased, and considerate,) and perceived expertise (experience, knowledge, and information). Another study mentioned the importance of the reviewer’s trustworthiness, usefulness, attractiveness, and writing style on EWOM credibility (Teng, Wei Khong, Wei Goh, & Yee Loong Chong, 2014). Manuela López and Maria Sicilia (2014) stated the control of reviewer credibility (expertise and trustworthiness), valence, and volume on the influential impact of EWOM. In another study by them, the influential impact was dependent on reviewer trustworthiness (Manuela López & Maria Sicilia, 2014). The EWOM adoption intention is affected by the inclusion of reviewer credibility which comprises trustworthiness (experience) and expertise (knowledge, usefulness) (Hussain, Ahmed, Jafar, Rabnawaz, & Jianzhou, 2017). Another study confronted the role of central (length, relevance, factual) and peripheral (expertise, experience, reliability) cues on information diagnosticity (Filieri, Hofacker, & Alguezau, 2018).

Source credibility was considered a key determinant of EWOM credibility (Cheung, Luo, Sia, & Chen, 2009). The source credibility construct is built-up of good, reputable, and trustworthy reviewers, who also talk about the product/service. Another study emphasized the role of personal identifying information (such as name, state, gender, date of trip) of the reviewers on the credibility of reviews (Xie, Miao, Kuo, & Lee, 2011). Park, Xiang, Josiam, and Kim (2014) combined personal information (location, interest) and review characteristics for determining reviewer credibility. Another study depicted the review credibility using source credibility (expertise and trustworthiness) along with the quality of messages (Shan, 2016). Fang, Ye, Kucukusta, and Law (2016) also succeeded in proving the impact of review (length, readability, ratings) as well as reviewer (helpful votes, total reviews, historical rating) characteristics on the helpfulness of reviews.

2.1 Reviewer Badge-Related Studies

Several researchers report that the free public service of posting travel experiences is purely for seeking reputation along with gaining experience and expertise (Goes, Guo, & Lin, 2016; X. Liu, Schuchert, & Law, 2016). This concept comes under status-seeking theory stating that “status is designed to improve an actor’s standing in a group, and is therefore judged by the degree to which associated activities result in increasing prestige, honour, or deference” (Congleton, 1989). Therefore, status-seeking is focused on self-image formation, gaining public recognition, and outclassing others. This phenomenon can be motivated through external means such as economic and social advantage or they could be motivated through internal means such as psychological and emotional values (Jin, Li, & Wu, 2011). These days, various sites are providing some sort of badges as a proxy for rewards for consistently and efficiently writing reviews. This covers the psychological aspect of internal motivation.

The pioneering study that discussed the importance of incentivising the reviewers who post on the website of a firm was conducted by Lampel and Bhalla (2007). According to them, altruism, status-seeking, and reciprocity are the key determinants of a reviewer, who provides useful information to prospective customers. The study was able to prove its assumptions through quantitative analysis performed using regression. After providing the mathematical justification, it led to the chain of studies focusing on the badge/label of review writers. A theoretical view regarding the impact of social factors such as reputation, affirmation, identification, instruction, and goal setting on badges or rewards in an online framework was done by Antin and Churchill (2011). The study succeeded in pointing out a psychological outlook of review posters, however, no empirical justification was provided to them.
Meng et al. (2013) performed a theoretical study on the social question-answer (SQA) platform to determine the importance of badges provided to the responders. The study considered the role of various motivational variables namely need, affection, reputation, and obligation. Even though the study presents the motivational factors for reviewers, a numerical justification was still lacking. Another study was conducted considering badges as an incentivisation tool (Anderson, Huttenlocher, Kleinberg, & Leskovec, 2013). The objective of their study was to design an optimization model utilizing the Markov decision process by considering the incentive effect as a utility function. The badge system of the Stack Overflow QA site was used to determine the factors that lead to more participation as well as how badges should be distributed to stimulate user behaviours. The empirical findings were relevant but such a mathematical model resulted to be costly and difficult to be comprehended by the business managers.

Another study encouraged the role of the gamification mechanism in a hierarchical badge allocation system (Cavusoglu, Li, & Huang, 2015). Again, using Stack Overflow QA data, it was inferred that the badge's value along with gamification phenomena effectively increases the voluntary participation of users. Propensity score matching and t-test validated the underlying theory. A goal-setting theory-based model for incentive hierarchy was developed to determine the user behaviour as his badge level increases (Goes et al., 2016). Taking a QA site, a relative distance measure-based function (taking a reference point as the goal) was constructed to test the hypotheses. The research findings showed that users make effort before reaching a certain badge level, and after reaching the topmost level, their effort declines. However, his study focused only on QA platforms and like.

The breakthrough study considering the reviewer badge, under the hospitality sector was proposed by Schuckert et al. (2016). A correlation-based study was conducted on TripAdvisor data collected from various regions of Hong Kong to study the relationship between reviewer badges, extreme ratings, and helpful votes. The analysis showed that reviewers with higher-level badges prefer moderate ratings over extreme. However, the study lacked the vital personal characteristics of a reviewer, which can influence such relationships. Another study was performed to check the relationship between badge level, review quality, and extreme ratings (X. Liu et al., 2016). TripAdvisor data was used to check the stated hypotheses. A regression model was proposed comprising badge level as the independent variable whilst review extremity and helpfulness were taken as the dependent variables. The results showed that reviewers with higher badge levels are less likely to give extreme ratings and also the quality of reviews lowers due to the law of diminishing marginal utility. Thus, the study succeeded in providing a quantitative justification for the assumptions, but still the role of other reviewer characteristics was missing.

Another research was conducted to study the utilitarian behaviour and knowledge growth of a reviewer by considering the badge level as one of the explanatory variables (X. Liu et al., 2018). TripAdvisor data was used to validate the stated hypotheses through regression models. The results showed that lower badge reviewers post reviews with fewer words (utilitarian) and that as the badge level increases the knowledge level and experience of the reviewer increases. The review characteristics included were “number of words” and “comprehensibility”. Their study lacked the role of reviewer identity characteristics and was left for prospects.

Overall, previous studies talked about four pillars while including reviewers in their research framework namely expertise, experience, identity disclosure, and the characteristics of reviews posted by them. Expertise means “the extent to which the reviewer is capable of providing correct information”. Researchers submit that reviews posted by experts are treated to be more helpful in comparison to less expert reviewers (Banerjee et al., 2017). The extent of knowledge and information present in a review posted by an expert will in turn create an intention to book. Expertness can be judged based on the number of feedbacks posted and their helpfulness. However, the photos attached to the review also demarcate a reviewer’s expertise (Yang, Shin, Joun, & Koo, 2017). Experience represents “how long the reviewer has been writing reviews for a particular platform”. It is believed that experienced reviewers play the role of opinion leaders for potential guests, and thus the feedback
Experience has been measured in terms of the destinations travelled, geographical area covered, and finally the years of association. When a reviewer discloses his personal information through his profile, then the skeptical nature of the content is resolved as the readers are confirmed about the credibility of the writer (Kusumasondjaja, Shank, & Marchegiani, 2012). Disclosing their identity in the form of the real name, location, age, gender, hobbies, etc. is believed to be helpful by the readers and in turn, increases trust towards that reviewer. Finally, the last aspect looks at the type of reviews posted by the reviewer. Past studies quote that lengthy and readable reviews along with positive sentiment are helpful to potential customers and enhance their booking intention (Chua & Banerjee, 2016). The present study utilizes these pillars for segmenting the reviewer set available here.

2.2 Segmentation Studies in Hospitality Sector

Segmentation is a topic of interest in recent studies in the hospitality and tourism sector. Segmentation means dividing a huge heterogeneous population into homogenous subgroups called clusters based on the unique characteristics shared within the group (J. Liu, Liao, Huang, & Liao, 2019). Previous studies have segmented spa hotels, hotel chains, travellers, and markets based on demographic characteristics, benefit variables, motivation variables, pricing, and many more (Chen et al., 2013; Cho, Bonn, & Brymer, 2017; Denizci Guillet & Kucukusta, 2016; Guo, Ling, Yang, Li, & Liang, 2013; Guttentag, Smith, Potwarka, & Havitz, 2018; J. Pesonen, Laukkanen, & Komppula, 2011; Schuckert et al., 2015; Shani, Wang, Hutchinson, & Lai, 2010). A list of past studies that have performed segmentation under the hospitality and tourism sector is provided in Table 1.

Table 1. Segmentation Studies in Hospitality and Tourism

| Author(s) | Segmentation of | Based on |
|-----------|-----------------|----------|
| Shani et al. (2010) | Golf travellers | Travel expenditure |
| Koh, Jung-Eun Yoo, and Boger Jr (2010) | Spa-goers | Benefit variables |
| Voorhees, McCall, and Calantone (2011) | Hotel customers | Demographic and spending patterns |
| J. Pesonen et al. (2011) | Wellbeing tourists | Benefit variables |
| J. A. Pesonen (2012) | Rural tourists | Push and pull motivations |
| Chen et al. (2013) | Older visitors | Customer service variables |
| Guo et al. (2013) | Hotel rooms | Occupancy rate, price, and profit |
| Díaz and Koutra (2013) | Hotel chains | Website persuasiveness |
| Rondan-Cataluña and Rosa-Diaz (2014) | Hotel clients | Pricing variables |
| Legohérel, Hsu, and Daucé (2015) | International tourists | Variety-seeking variables |
| Schuckert et al. (2015) | Online reviews | Language groups |
| Denizci Guillet and Kucukusta (2016) | Spa market | Customer preference |
| Dryglas and Salamaga (2017) | Health tourists | Destination attributes |
| Cho et al. (2017) | Wine tourist markets | Preference and intention variables |
| Guttentag et al. (2018) | Airbnb tourists | Motivation variables |
| Ahani, Nilashi, Ibrahim, Sanzogni, and Weaven (2019) | Spa hotels | Online reviews and ratings |
| Aakash and Jaiswal (2020) | Reviewer community | Reviewer’s frequency, helpfulness, and recency |
2.3 Research Gap

In the vein of the above discussions, we observe a few research gaps that are handled here:

- Much of the earlier badge-related studies considered the data of QA platforms and majorly provides a qualitative study to satisfy the assumptions. Also, the studies considering EWOM characteristics for studying the role of the reviewer badge are scant. This study attempts to make another valuable contribution to the literature by taking into consideration the role of EWOM.
- Previous reviewer badge-related studies have considered review quality and valence of the reviewer’s experience. They lacked the significance of the reviewer’s identity characteristics and his expertise in helping readers. This study considers all the variables (review as well as reviewer related) necessary for evaluating a reviewer simultaneously.
- Segmentation studies exist in hospitality and tourism literature considering spa hotels or various types of tourists. This study aims to segment the reviewer community.
- The badge-related studies considering EWOM utilized the data of hospitality only. This paper tries to cover a broader aspect by considering a dataset related to reviewer postings concerning hotels, restaurants, and attractions.

The detailed methodology and description of the variables underlining this study are provided in the following section.

3. METHODOLOGY AND DATA

This study segments the reviewer community into reward categories using the reviewer as well as review characteristics. The review characteristics considered are review length, sentiment, and readability. The reviewer characteristics considered are the number of cities been, miles travelled, years of membership, number of helpful votes, age, location, gender, total reviews posted, and total photos posted. For this purpose, the study adopts a two-stage process. Firstly, the data is processed and combined under the above-mentioned heads, for all the unique reviewers. Then on the collected data, exploratory factor analysis (EFA) is performed to get the variables concerned for studying the behaviour of a reviewer. This behavioural categorization of the factors obtained is used for clustering. In specific, the factor scores generated are used for clustering reviewers and since they are restricted within specific limits, they discard the requirement of data normalization which is essential before applying clustering analysis. Under clustering, a hierarchical method is initially used to obtain the number of clusters that should be formed. Then k-means clustering is performed to get the clusters representing the badge level approximation for the reviewers. Clustering is performed using k-means as it is an unsupervised classification technique that provides good and reliable results. Also, the purpose here is not to compare various clustering algorithms (Knops, Maintz, Viergever, & Pluim, 2006). A flowchart representing these steps is provided in Figure 1. Since the study aims to gather in-depth knowledge about the characteristics of reviewers regarding the badge provided to them by the platform, the study uses external validation using ARI (adjusted rand index) and NMI (normalized mutual information) to compare the actual badge level with the ones obtained through clustering.

3.1 Data Collection

This paper utilizes the TripAdvisor dataset (Roshchina, Cardiff, & Rosso, 2015) as it is the largest social media platform concerning hospitality and tourism services consisting of more than 460 million reviews related to hotels, restaurants, and attractions (Ahani et al., 2019). The dataset contains two files where the first one has review variables such as username, the date on which the review was posted, review type (the posted review is for a restaurant, hotel, or attraction), review text, hotel rating, and total helpful votes. The second file contains reviewer variables such as username, gender, age
group, location, total reviews posted, total helpful votes, date of joining, number of cities been, miles travelled, date of the last contribution, photos posted, and reviewer badge. The time frame of all the information provided in the dataset is from November 2002 to January 2015. The dataset consists of information provided by reviewers coming from wide geographies such as the US, UK, China, New Zealand, Australia, and many other countries.

The purpose of this paper is to study in detail the qualities of reviewers that contribute to the hospitality and tourism industry. Therefore, those reviewers who provided feedback related to attractions, hotels, and restaurants were considered as the sampling units. This seems appropriate as the study is not focused on hotels or any particular destination, but on reviewers. Therefore, the two files were merged (using the inner join function in Python with the key variable as “username”) to get data for 69861 reviews posted by 1766 unique reviewers with complete information and not taking into consideration those reviewers for which some necessary information was missing such as helpful votes, username, age group, cities travelled, etc., on which the two-stage methodology (described in Figure 1) is applied.

3.2 Operationalization of Measures

From the review file, we calculate length, sentiment index, and readability index. Before proceeding with the major part of our data analysis, the data cleansing is performed that consists of several steps such as stop word removal, stemming, and tokenization. All the steps are similar to the ones described in Bharti and Singh (2015).
The number of characters represents the review length. These values were averaged reviewer-wise to get the average length for reviewers termed as AvgLength. That is, let $i$ denote an index for review and $j$ denote an index for the reviewer, then the average length of the reviews posted by a reviewer $j$ who has posted $n_j$ reviews are given as:

$$AvgLength_j = \frac{\sum_{i=1}^{n_j} (\text{review length})}{n_j}$$

In the absence of valence (star ratings), researchers suggest using review sentiment as its proxy (Chua & Banerjee, 2016). Review-wise sentiment values were obtained using the TextBlob package. The sentiment values are obtained from minus one to plus one, where the negative values imply “negative sentiment”, positive values represent “positive sentiment”, and the zero value represents “neutral sentiment”. Also, the extremity increases as the value approach one (or minus one). Again, the sentiment values were averaged reviewer-wise to generate AvgSentiment, i.e. for a particular reviewer $j$ the average sentiment is given as:

$$AvgSentiment_j = \frac{\sum_{i=1}^{n_j} (\text{review sentiment})}{n_j}$$

Gunning Fog index (GFI) was used to calculate the review readability values. Amidst various readability indices, GFI is preferred as it is based on the premise of the number of years of formal education required to understand any text at a first instant (Gunning, 1969). The GFI is calculated as:

$$[0.4 \times (\text{average sentence length} + \text{Hard words})]$$

where hard words means the number of words containing more than two syllables in a bunch of 100 words of a document (Fang et al., 2016). Below the index of 8, it is easily comprehensible for people having lower school grades, the value of 9-12 is for high school grades, 13-17 is for college level, and 17 above is for postgraduate level and higher (Wyliecomm, 2016). Here also we average the index values to get AvgReadability. Mathematically, for a reviewer $j$ the average readability is given as:

$$AvgReadability_j = \frac{\sum_{i=1}^{n_j} (\text{review readability})}{n_j}$$

From the reviewer file, we obtain age group, gender, total reviews posted, miles travelled, cities been, years of membership, and helpful votes. The total number of cities visited by the reviewer is termed as TotalCities. Total miles covered by the reviewer are termed TotalMile. The number of years of associating with the website is termed MembershipYears. The gender of the reviewer is represented as ReviewerGender, where females were quantified as 1 and males as 2. From the dataset, it is observed that 52.55% belonged to group 1 and the remaining in group 2. TripAdvisor provides five age groups to be selected by the reviewer. The age group 18 – 24 years were given 1, 25 – 34 years as 2, 35 – 49 years as 3, 50 – 64 years as 4, and lastly 65+ years as 5. It is observed that 2.49% of reviewers belong to category 1, 27.35% belong to category 2, 41.11% belong to category
3, 26.33% belonged to category 4, and the remaining belonged to category 5. The variable is termed ReviewerAge. The total number of reviews posted by the reviewer is denoted as TotalReviews while the total number of helpful votes received in return is termed as TotalHelpful. The number of photos posted by the reviewer is termed as TotalPhotos. Also, the location represents the reviewer’s hometown denoted as ReviewerLocation. It is also considered to be a categorical variable, where 1 represents that the location is provided by the reviewer while 0 gives the other case. It was observed that 97.62% of reviewers provided their location and the rest didn’t.

The description of the variables involved in the study is provided in Table 2 while their descriptive statistics are provided in Table 3.

The descriptive statistics show that a reviewer on average writes a review of 844 characters, with the lowest count being 132 characters. The reviewers tend to post reviews with positive polarity. The range of the readability of text posted by a reviewer is 17, with an average of 10 depicting that the text is comprehensible for a reader with a high school educational level. On average a reviewer visits 90 cities covering 119764 miles. Each reviewer on average is a part of the community for 5 years.

Table 2. Variable Description

| Variable name     | Variable description                                      |
|-------------------|-----------------------------------------------------------|
| AvgLength         | Average length of reviews posted by a reviewer.           |
| AvgSentiment      | Average sentiment index of the reviews posted by a reviewer. |
| AvgReadability    | Average readability index of the reviews posted by a reviewer. |
| TotalCities       | Count of visited cities by a reviewer.                   |
| TotalMile         | Count of miles covered by a reviewer.                    |
| MembershipYears   | Number of years of membership with the website.          |
| ReviewerGender    | Gender information was provided by the reviewer.         |
| ReviewerAge       | Age group of the reviewer.                               |
| TotalReviews      | Count of reviews published by the reviewer.              |
| TotalHelpful      | Count of helpful votes received by the reviewer.         |
| TotalPhotos       | Count of photos posted by the reviewer.                  |
| ReviewerLocation  | Location information was provided by the reviewer.       |

Table 3. Descriptive Analysis of Variables

| Variable        | Minimum | Maximum       | Mean   | Std. Deviation |
|-----------------|---------|---------------|--------|----------------|
| AvgLength       | 131.714 | 4717.777      | 843.580| 485.397        |
| AvgSentiment    | 0.014   | 0.607         | 0.253  | 0.073          |
| AvgReadability  | 4.422   | 21.531        | 10.772 | 4.836          |
| TotalCities     | 1       | 1456          | 90.793 | 134.917        |
| TotalMile       | 2       | 1655283       | 119764 | 165937.091     |
| MembershipYears | 0.030   | 12.255        | 5.442  | 2.270          |
| TotalReviews    | 5       | 795           | 39.577 | 50.885         |
| TotalHelpful    | 0       | 1726          | 37.489 | 76.533         |
| TotalPhotos     | 0       | 1823          | 16.288 | 83.776         |
39 reviews are posted on an average by a reviewer, have received 39 helpful votes approximately, and consist of 16 photos.

4. DATA ANALYSIS

After data preparation, we apply factor analysis and cluster analysis to obtain the appropriate segments.

4.1 Factor Analysis

EFA with principal component analysis under varimax rotation is applied to the obtained data for obtaining the factors that help in drawing judgments concerning the reviewers. The factors were obtained based on eigenvalue and factor loading. Factor loadings represent the degree of belongingness of a particular item to the factor and values between 0.4 and 1 are acceptable for analysis purposes (Sharma & Aggarwal, 2019). Factors with an eigenvalue greater than one and loading above 0.40 were considered for this study. Moreover, the Kaiser-Meyer-Olkin (KMO) value of 0.769 (any value between 0.5 – 1 is acceptable) and significant Bartlett’s Test of Sphericity \((p < .001)\) verified the usage of EFA on the present data. To check the internal consistency, Cronbach alpha (CA) is used. All the items had a CA value above the threshold value of 0.70 (Nunnally, 1978). Table 4 provides the EFA results.

The factor analysis resulted in four dimensions based on which the reviewers can be evaluated.

**Factor 1 - Expertise:** This factor explained about 28% of the variance in the data. It comprises three variables namely TotalReviews, TotalHelpful, and TotalPhotos. If a reviewer writes much feedback and it is liked by the reader (helpful), this shows the reviewer’s capability (expertness) in influencing potential customers (Reichelt, Sievert, & Jacob, 2014). Expertness is a reflection of the knowledge possessed by the reviewer along with providing information related to alternatives

| Factors                     | Loadings | CA  |
|-----------------------------|----------|-----|
| **Factor 1: Expertise**     |          |     |
| TotalReviews                | .842     | .729|
| TotalHelpful                | .901     | .789|
| TotalPhotos                 | .768     | .715|
| **Factor 2: Experience**    |          |     |
| TotalCities                 | .573     | .864|
| TotalMile                   | .488     | .849|
| MembershipYears             | .684     | .771|
| **Factor 3: Identity Disclosure** |      |   |
| ReviewerGender              | .694     | .865|
| ReviewerAge                 | .784     | .731|
| ReviewerLocation            | .811     | .744|
| **Factor 4: Review Characteristics** |         |   |
| AvgLength                   | .436     | .736|
| AvgSentiment                | .677     | .766|
| AvgReadability              | .629     | .704|
available. Reviews provided by such reviewers are well elaborated and reliable, and thus helpful for the readers (Huang, Chen, Yen, & Tran, 2015). Moreover, the reviewer’s expertise is portrayed by the proficiency with which he displays photographs related to the hotels along with his surroundings (Yang et al., 2017). Since the photos are always appealing to travellers, they help create booking intentions. Therefore, this factor has been named Expertise.

**Factor 2 - Experience:** This factor explained 18% of the variance in the data. The factor consists of three variables namely TotalCities, TotalMile, and MembershipYears. A reviewer’s experience is talked about in terms of the years of association with the community, the total cities he has explored, and how many miles he has covered in his activity period (Ghose & Ipeirotis, 2010). According to Fang et al. (2016), an experienced reviewer will discuss various geographies through his content and will also compare it with other destinations. Moreover, the more experience a reviewer has in publishing reviews, the more familiar he becomes with the aspects of good feedback (Huang et al., 2015). Since reviews provided by experienced reviewers are more rational and relevant, they help influence the booking intention. Thus, this justifies the title of this factor.

**Factor 3 - Identity Disclosure:** The factor explains 13% of the variance in the data. It includes ReviewerGender, ReviewerAge, and ReviewerLocation. When a reviewer provides his personal information, it instills a sense of realism in the reader about the feedback provided by him (Kusumasondjaja et al., 2012). This will lead the readers to consider the provided review seriously and also save the firm from allegations of providing fake reviews (Z. Liu & Park, 2015). Availability of socio-demographic and other personal information of the reviewer along with the posted review helps in creating a sense of similarity and relatedness amongst the readers and writer, and thus controls the buying intention of potential customers (Su et al., 2017). They also stated that if the personal and demographic characteristics of the reviewer are disclosed, it is taken positively by the reader and creates trustworthiness amongst them. This influences the perception of customers towards the product/service and amplifies purchase intent. Thus, this factor is appropriately stated.

**Factor 4 - Review Characteristics:** 9% of the variance in the data is explained by this factor. It includes AvgLength, AvgSentiment, and AvgReadability. This factor provides an overall evaluation of the quality of reviews posted by a reviewer by considering the length of reviews provided by him, the tone of his reviews, and the degree of comprehensibility of the reviews posted by him (Chua & Banerjee, 2016). It has been proved that lengthy reviews along with fewer grammatical errors are deemed to be useful for readers. Also, providing a consistent sentiment (emotion) through the text is important. Elaborate reviews discuss in detail the length of stay or travel along with the description of services provided, to explain the satisfaction/dissatisfaction level of the reviewer (Z. Liu & Park, 2015). Understandability is also an important aspect for measuring the quality of reviews and shows the extent to which the reader is ready to imbibe the information provided via EWOM (Fang et al., 2016). Moreover, they stated that the readers perceive the sentiment of the reviews precisely and judge the extremity hidden in them. This extremity can excite or disappoint the readers. Thus, the items fit the factor.

**4.2 Cluster Analysis**

The present study aims to segment the reviewer community based on factors evaluated through EFA. This objective is met with the usage of a cluster analysis approach. One of the major problems encountered while applying the analysis is determining how many clusters should be formed (Vavougios, Natsios, Pastaka, Zarogiannis, & Gourgoulianis, 2016). For this, cluster analysis is performed in two stages (Kucukusta & Denizci Guillet, 2016). The factor scores generated during the factor analysis approach are used as inputs. Since these scores already lie within a finite range, they discard the requirement of normalizing the data before the initiation of clustering. In the first stage, hierarchical cluster analysis (Ward’s method) is used to determine the number of clusters. Applying this dataset, we obtain the requirement of five clusters. Witnessing the criticality of the
number of clusters, the previous method is validated through the Elbow method. The pictorial representation (provided in Figure 2) verifies the utility of the five clusters. In the second stage, k-mean clustering (with \( k = 5 \)) is used to obtain the final clusters. This type of clustering is a distance-dependent algorithm and works on the resultant similarity between the objects. The k-mean clustering results are presented in Table 5, along with the ANOVA results depicting the significant difference between the clusters \( (p < .001) \).

Based on the pattern of mean score values, the clusters are named as follows. The naming of clusters is adopted from the concept of decision-making under groups (Atalay & Can, 2017).

**Cluster 1 - Beginner:** This cluster contains 186 reviewers. Under this cluster, the mean scores of all the four variables are less than 0.5 i.e. their contribution is low (Kamata & Misui, 2015). The cluster consists of reviewers who have less experience in writing reviews, their reviews’ quality is low, they do not disclose their identity on the platform, and have few reviews posted by them. Along with this, they get a few helpful votes and post a few photos of the destinations/hotels/attractions.

**Cluster 2 - Practitioner:** This cluster contains 212 reviewers. Under this cluster, the mean scores of all the factors are low except for ‘Identity Disclosure’ (mean=.544). It includes reviewers who have less experience in writing reviews, their review quality is somewhat low, and has a smaller

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**Table 5. Cluster Analysis Results representing Mean Scores**

| Factor                 | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 | F value |
|------------------------|-----------|-----------|-----------|-----------|-----------|---------|
| Expertise              | .350      | .450      | .461      | .478      | .547      | 4.233   |
| Experience             | .342      | .399      | .415      | .618      | .623      | 6.665   |
| Identity Disclosure    | .388      | .544      | .563      | .679      | .629      | 5.987   |
| Review Characteristic  | .360      | .404      | .720      | .772      | .716      | 6.129   |

**Figure 2. Elbow Method Result**

![Elbow Method Result](image)
number of helpful reviews. However, they have provided their personal information in their account. The mean values for all these factors are higher than those of Cluster 1.

**Cluster 3 - Proficient:** The cluster consists of 749 reviewers. The reviewers belonging to this cluster do not get a very high number of helpful votes in comparison to their review volume and have also not travelled much and do not have a very long association with the interface. However, their account details consist of their personal information (mean=.563) and the feedback provided by them is explanatory and readable (mean=.720). The mean values for all the factors are higher than those of Cluster 1 and 2 respectively.

**Cluster 4 - Expert:** This subgroup of reviewers counts 489 members. Reviewers belonging to this cluster have low helpful votes in comparison to the total volume (mean=.478). These feedback writers provide their personal details on the platform, have a decent amount of experience in posting reviews, and the reviews provided by them are easily understood by a reader. However, mean values for all the factors are higher than those of the previous cluster respectively.

**Cluster 5 - Master:** This cluster consists of 130 reviewers who intensively write reviews that are treated as helpful by readers, have explored many cities and are strongly associated with the website for years, provide informative and easily readable reviews, and also provide their personal details while creating the account on the website. This can be inferred by observing that the mean values for the factors are quite high (more than 0.5), in comparison to that of the rest of the clusters formulated.

### 4.3 Cluster Validation

After obtaining the clusters, the next objective becomes to validate whether the clusters formed are appropriate or not. This can be done in the absence of labelled data (internal validation) or under the presence of available labelled data (external validation). For internal validation, we use ANOVA to check the difference between the mean values of cluster membership degrees. The ANOVA results are provided in Table 6. From the table, it is observed that all the clusters are different at a 5% level of significance.

The reviewer batch is the reward system used by TripAdvisor to provide non-monetary incentives to its reviewers, the data for which is available to us. TripAdvisor provides its reviewers with a star badge built on a 1-5 scale based on the contributions made by them as well as the helpful votes received by them in return (Schuckert et al., 2015). The five badges are displayed on the thumbnail profile next to the reviews and termed Reviewer (3-5 reviews), Senior Reviewer (6-10 reviews), Contributor (11-20 reviews), Senior Contributor (21-49 reviews), and Top Contributor (50+ reviews). Using the unlabelled data, clustering analysis is performed to obtain independent segments of reviewers. The next task is to compare this rating with those provided by the website (actual). External validation is used as a performance measure of the clustering algorithm against a true structure that is already known in advance (Luna-Romera, Martínez-Ballesteros, García-Gutiérrez, & Riquelme, 2019).

**Table 6. ANOVA Result**

| Factor          | Cluster          | Error            | F-value | Significance |
|-----------------|------------------|------------------|---------|--------------|
|                 | Mean square      | Degrees of freedom | Mean square | Degrees of freedom |
| Expertise       | 0.541            | 4                | 0.001   | 1761         | 555.342 | 0.000 |
| Experience      | 1.466            | 4                | 0.003   | 1761         | 454.139 | 0.000 |
| Identity Disclosure | 4.581      | 4                | 0.007   | 1761         | 635.792 | 0.000 |
| Review Characteristic | 0.608        | 4                | 0.004   | 1761         | 168.738 | 0.000 |
To check such type of clustering performance, researchers suggest the use of adjusted rand index (ARI) and normalized mutual information (NMI). ARI makes use of similarity between variables and it is assumed that the closer is the value to one, the better is the performance results (Zhang, Wong, & Shen, 2012). On the other hand, NMI is an entropy-based approach and falls in the range of zero to one and the closer is the value to one the less is the variation between actual and predicted clusters (Amelio & Pizzuti, 2017). The value obtained for the ARI metric is 0.861 while that for NMI is 0.913. This states that we have succeeded in obtaining approximately true labels for the reviewers.

5. DISCUSSIONS AND IMPLICATIONS

The objective of the study is to segment the reviewer community by clustering them based on characteristics or factors that judge a reviewer. TripAdvisor dataset was used for this purpose. Firstly, EFA is applied to determine the factors that provide judgment about any reviewer. Overall, four key factors were obtained namely expertise, experience, identity disclosure, and review characteristics. Previous studies comprehensively talk about these broad factors while considering the role of reviewers (Banerjee et al., 2017; Chua & Banerjee, 2015, 2016; Fang et al., 2016; Filieri et al., 2018). Taking forward these factors for clustering resulted in five clusters namely beginner, practitioner, proficient, expert, and master.

5.1 Theoretical Implications

The first cluster had low mean score values for all four factors. This is consistent with the previous studies (Anderson et al., 2013; Meng et al., 2013; Schuckert et al., 2016). A low value for expertise implies that the reviewer has just joined the community and so has not written many reviews and this newness has restricted his tally of helpful votes as there are a lot of things he might not be aware of that a reader expects (X. Liu et al., 2018). He also needs to understand the role of posting photos related to the hotel or restaurant in the trust generation of the reader. A low score for experience is trivial in this scenario. As he is new so he might not have travelled much or explored many cities (Schuckert et al., 2016). Also, the membership years will be fewer. This type of reviewer category might be reluctant in providing their personal details such as gender, age, and location; as well as mention them in their website account (Meng et al., 2013). This is where they fail to have the trust of the readers. Moreover, unaware of the importance of lengthy reviews, the sentiment carried through the messages, and the understandability of the textual message decreases their mean score value for review characteristics (X. Liu et al., 2016).

The second cluster had a low mean score for all the factors except for identity disclosure. Though the higher mean values in comparison to the “beginners” signify that the review volume has increased along with the number of helpful votes as the activity period is increasing. However, it is still not up to the mark. Even though the reviewers have started providing their personal details, as observed through high mean score values (Kim, Mattila, & Baloglu, 2011), but still they don’t provide hotel or restaurant-related photos. This is signified by a low score for expertise. Also, with time the reviewers are exploring more cities and covering many more miles, but still, they are not efficient enough (Lee, Law, & Murphy, 2011). Thus, the mean value for experience is low. Also, low review characteristic scores imply that there is still scope for improvement in the way of proving textual comments.

For the third cluster, the mean score values are higher for identity disclosure and review characteristics, while it is low for expertise and experience. These reviewers have provided their personal details on the website (Kim et al., 2011). In addition to this, they have started learning the art of writing easily readable and understandable reviews with important details (X. Liu et al., 2016). Again, the review volume has increased but still, the count of helpful votes is not commendable. Moreover, the years of association and cities explored are still lacking as compared to the average score value.
The fourth cluster corresponds to expert reviewers. Reviewers belonging to this cluster are treated as trustworthy as they provide their personal details on the website. They have already passed the stage of learning to write attractive reviews, with positive sentiment toward the hotel or restaurant, along with readable and understandable content (Banerjee et al., 2017; Reichelt et al., 2014). This reviewer subgroup has been successful in providing more volume of reviews as well as more photos underlining the review to create a sense of trust and authenticity among the potential customers (Schuckert et al., 2016). However, they are in the process of gathering the necessary experience by travelling to many cities and various geographical locations and have sufficient years of association with the website.

The fifth cluster consists of those reviewers who have achieved high ratings for all four factors. This means the reviewers in this cluster have posted remarkable reviews and have also received a sufficient number of helpful votes in return (X. Liu, Zhang, Law, & Zhang, 2019). They are also enthusiasts in displaying photos of the hotels/restaurants about which the comment is being provided. They provide their personal information and hence creating a sense of trust and credibility among readers (Sailer, Hense, Mayr, & Mandl, 2017). Also, these reviewers have learned how to write textual comments with minimal grammatical errors, of sufficient length containing all the vital details, and express sentiments concerning the hotel/restaurant being reviewed (X. Liu et al., 2016, 2018). Having reached this level, firms must try to make the reviewers loyal as these reviewers have a potential influence on the purchasing intention of customers as they have generated a sense of trust and credibility in them. These reviewers are valuable assets for the firm and help in increasing its potential sale or profitability (Goes et al., 2016; J. Liu et al., 2019; X. Liu et al., 2016, 2018; Schuckert et al., 2016). They have mean values higher than all the previous clusters but it can be noticed that the rate of increment is low. This is because after reaching the highest level of badge level hierarchy, the motivation for posting more relevant reviews, getting helpful votes, providing good quality reviews, and many more characteristics are stagnant (X. Liu et al., 2018).

5.2 Practical Implications

Along with the theoretical implications, some aspects can be valuable to practitioners. The study will help the hoteliers in keeping a check on regular review posters and introduce some reward system like those introduced by TripAdvisor or Yelp, to glorify their emotional and social status quo among the netizens. Online marketers must try to create an environment that is friendly for a newcomer (“Reviewer”) and also encourage them to post reviews and spend more time on their website. However, site owners should keep a check on these “beginners” as they may just keep on posting reviews (increase volume) to obtain higher badge levels and payoff it with quality text. This brings another key point that sites like TripAdvisor should also consider another review as well as reviewer characteristics to allocate a justified badge level rather than the one based on the number of reviews posted and helpful votes received in return. This will decrease biases in their rating system. Since not all reviewers are equal in terms of their knowledge and status, it is the responsibility of the managers to invest in their lacking areas to generate value for the firm. To improve the quality of reviews, online marketers can provide some sort of spell-checker to help the reviewers during their initial phase. Also, managers should provide support for travelling to many more cities and exploring their knowledge. Moreover, the marketers must emphasize supporting reviewers in generating trust and helpful votes by posting reviews covering diversified regions. The target of the managers should be that the reviewers belonging to the “Master” category must be made to stick to the site and motivate to keep providing efficient feedback. This can be done by allocating some type of incentives parallel to the concept of “loyalty points” introduced in product marketing. Under this, managers can provide free travel tickets, free stays, and many more such luxuries without any cost.
6. CONCLUSION AND FUTURE SCOPE

The experiential nature of the hospitality industry makes it difficult for customers to judge the value and cost of utilization beforehand. This is where the importance of reviews or feedback provided by guests arises. Not every review poster (reviewer) is capable enough to influence the purchase decision of potential customers. Therefore, websites must take the initiative of identifying capable reviewers who can act as opinion leaders, and incentivise, or reward them to encourage loyalty to their website. Recently, many sites have started grading reviewers with badges and rewards as a return for their commitment. This paper aims to segment the reviewer community based on their badge level using reviewer and review characteristics. The review characteristics considered are review length, sentiment, and readability, while the reviewer characteristics considered are number of cities been, miles travelled, years of membership, number of helpful votes, age, location, gender, total reviews posted, total photos posted. TripAdvisor data consisting of 1766 unique reviewers cumulating to 69861 reviews was accessed for the study purpose. A two-stage methodology was adopted wherein factor analysis was initially used to combine the key factors that judge a reviewer, then using these factors a hierarchical clustering analysis was performed to obtain the number of clusters to be formed, and finally k-mean clustering was applied to obtain the reviewer segments. The result findings showed that as the level of badge increases, the contribution towards each factor increases in parallel.

There are certain limitations in this study that provide a scope for future research. The data are taken from a social media website (TripAdvisor) and so the findings cannot be generalized to all sectors and also internationally. Future studies may consider other domains for studying the impact of badge level on the reviewer’s intention to write more reviews. In addition to the above point, another limitation of the present study is that it is based on a single dataset. Researchers can conduct studies based on other datasets in the hospitality and tourism sector and compare the inferences. Moreover, this study considers only the external characteristics of the reviewers; however, the internal traits such as humor or verbosity are neglected and can be considered by future studies. A factor-cluster-based approach is adopted in this study. Machine learning-based segmentation approaches can be applied in the future. The present study can be further extended in the future to include the concept of gamification. Also, future studies can adopt text analytics to explore the in-depth nature of reviewers and also find the determinants that lead to their success.

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