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Understanding Electronic Word-of-Mouth Helpfulness Using Review, Hotel, and Reviewer Characteristics

Sanchita Aggarwal [1] , Abhishek Tandon [1] , Sweta Yadav [1] , Anu G. Aggarwal [1]

1. Department of Operational Research, University of Delhi, New Delhi, IND

Corresponding author: Anu G. Aggarwal, anuagg17@gmail.com

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Abstract

A customer provides their feedback on the online platform through textual and numeric formats. The textual reviews are also known as electronic Word-of-Mouth (eWOM), which contain the elaborated experience of the customer. It enables potential customers in making informed decisions. These also act as tools for the service providers, by informing them about key areas of customer interest. Nowadays, eWOM has emerged as a business intelligence tool that enables optimum strategy making. eWOM helpfulness is important in choosing useful reviews from a corpus of humongous data available on the internet. In this study, we propose a framework to identify the impact of various characteristics related to the reviewer who posted the review, eWOM itself, and the hotel for which a review is posted on eWOM helpfulness. We used a dataset from Tripadvisor.com which contains 16699 reviews written by 1099 reviewers. Variables belonging to all three categories have been extracted and have been evaluated using econometric modeling and different machine learning techniques. The findings of this study report a positive significant relationship between hotel and reviewer features and eWOM helpfulness. It also reports that eWOM polarity and recency share a negative significant relationship with eWOM helpfulness. However, all other eWOM features have been reported to share a positive significant relationship with their helpfulness. We also discuss theoretical and practical implications of our research at the end.

Categories: Branding in tourism and hospitality, Mathematical programming, Sustainable Tourism and Hospitality Management
Keywords: ewom helpfulness, econometric modelling, machine learning, review features, reviewer features, hotel features

Introduction

In recent years, travel and tourism industry has exhibited significant growth in India. It is a famous destination for national as well as international tourists due to its richness of food, heritage, spiritual experiences, and ancient cultures. In India, a total of USD 231.6 bn contribution to GDP comes from the travel and tourism industry (TTI), of which over 40% comes from the hotel industry alone. The main factors behind this significant growth are modernization, connectivity, a relaxed visa regime on arrivals, and others. Along with these, some major attributes such as smartphones, affordable internet services, digitalized payment services, and social media facilitate the easy access of TTI for tourists. As the trend of social media grows, electronic Word-of-Mouth (eWOM) is the important source of information for consumers and firms in TTI. Travelers search for accommodations by going through different hotel booking websites and social media channels to check the first-hand experiences of fellow travelers (Yang et al., 2024). They rely more on the online user-generated word-of-mouth (WOM) due to its real, dynamic, and easily accessible nature.

In the past decades, eWOM has emerged as a primary business intelligence tool which facilitate the informed decision-making in various fields. Development of information and communication technology positively affected the broader growth of tourism and hospitality sector. The growing businesses of hotel industry widely depends on the customer eWOM and the website's friendly interface which makes them reliable (Li et al., 2024). Due to easy accessibility of websites, and low-cost internet services, the growth of eWOM is happening at an exponential pace. Customer encounter information in many reviews but struggle to identify the valuable and relevant eWOM. Islam et al. (Islam et al., 2024) studied the effect of eWOM written by previous travelers on the hotel booking intentions by taking the data of 218 surveys. In this case, review helpfulness play an important role in customer decision-making, and also the number of helpful votes affect the probability of spreading an eWOM (Kwok and Xie, 2016). So, it is crucial to know the important factors behind the helpfulness votes.

With the development of online booking websites such as Agoda.com, booking.com, Gobibo.com, TripAdvisor.com, Yelp.com, and others, consumers easily access the online reputation, experience related to any industry in digital world from any corner of the globe with the help of eWOM. The eWOM has different characteristics that impact customer behavior specially in the service/experience industry. A study

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in social media investigated the emotional intensity of negative eWOM on the perceived helpfulness (Chen and Zhang, 2022). Another study was conducted by taking the data of 8903 reviews written for 20 movies from Douban.com. They applied the logistic regression model and their findings indicated that review length and review rating impact the helpfulness votes (Luo et al., 2021). A study on movie reviewers characteristics suggested that reviewer experience and involvement positively impact the reviewer trustworthiness by using the regression modeling (Banerjee et al., 2017). In hospitality industry, Fang et al. (Fang et al., 2016) studied the impact of review characteristics such as readability, rating, sentiment, and reviewer rating on the helpfulness votes by applied the logit regression model.

Machine learning models predict more accurately in the huge dataset. In the hospitality and tourism studies, many researchers and practitioners suggested that machine learning extracts hidden patterns and unveils new knowledge (Chen et al., 2012). A study on Amazon.com (Zhang et al., 2015) used the class probabilities and binary class classifiers to classify the reviews into helpful and non-helpful classification. Anh et al. (Anh et al., 2019) studied the helpfulness classification of camera and laptop review datasets of Amazon website through different machine learning (ML) methods.

Previous studies done using the review and reviewer characteristics provide the direction for this research. From these studies, we identify that none of the studies have analyzed the effect of polarity on eWOM helpfulness. Further, hotel ratings and reviewer badges are also among the unexplored variables in the context of eWOM helpfulness. Most of the prior studies have used the regression method for prediction of helpfulness votes. We extend the literature with some added characteristics and ML predictive models. In this study, we used a large dataset of eWOM written for hotels from TripAdvisor.com along with different characteristics of review, reviewer, and hotel. Therefore, we use the econometric as well as ML models. The following research objectives have been addressed in this study:

Objective One: Identify the eWOM characteristics that affect its helpfulness.

Objective Two: Identify the hotel characteristics that affect the helpfulness of eWOM.

Objective Three: Identify reviewer characteristics that affect the helpfulness of eWOM.

Objective Four: Find out which ML technique predicts the eWOM helpfulness accurately.

In the marketing literature, many researchers have inferred that length of eWOM significantly impacts the number of helpful votes it receives in different sectors (Fernandes et al., 2022). In the hospitality sector, some of the studies reported that the sentiment, readability, and recency of online reviews written for restaurants and hotels impact the customer's perceived helpfulness (Wang et al., 2019). Moreover, researchers have also conducted a deeper analysis of customer emotions and reported that on experience products such as hotels, human emotions such as pleasure, arousal and dominance strengthen the perceived helpfulness of reviews wherein arousal and dominance enhance the perceived helpfulness on the contrary pleasure emotion reduces it (Xu et al., 2025). Hence, we posit the following hypotheses:

H1: The length of the eWOM positively influence its helpfulness.

H2: The subjectivity of the eWOM positively influence its helpfulness.

H3: The polarity of the eWOM polarity negatively influence its helpfulness.

H4: The readability of the eWOM readability positively influence its helpfulness.

H5: The recency of the eWOM recency negatively influence its helpfulness.

Past studies belonging to the hotel literature found that the overall rating given by the travelers, by considering all the parameters of their stay experience, affects hotel performance (Kim et al., 2015). Hence, we propose the following hypothesis:

H6: Rating of hotel positively influences the helpfulness of eWOM.

Hospitality literature has recognized badge level as a determinant of reviewer expertise (Schuckert et al., 2016). Hu and others (Hu et al., 2020) explained trustworthiness of reviewers based on the total eWOM posted by them and their average helpful votes. Researchers have also established reviewer helpfulness and their badge levels which are awarded to acknowledge their contribution to the community, as indicators of reviewer credibility (Banerjee et al., 2017). Thus, we hypothesize the following:

H7: Helpfulness of reviewer positively influences helpfulness of eWOM.

H8: Reviewer badge positively influences the helpfulness of eWOM.

Figure 1 shows the conceptual framework of the research. Initially, we collect the dataset from TripAdvisor.com which is an online travel agency (OTA) website. Then, we extract the values of different eWOM, hotel, and reviewer features. Further, we formulate three models to study the impact of different sets of variables on eWOM helpfulness. Then, we use seven machine learning models namely, "Decision Tree (DT)", "k-Nearest Neighbour (KNN)", "Naïve Bayes (NB)", "Support Vector Machine (SVM)", "Random Forest (RF)" and "Artificial Neural Networks (ANN)", and "Recurrent Neural Networks (RNN)" to predict the model results.

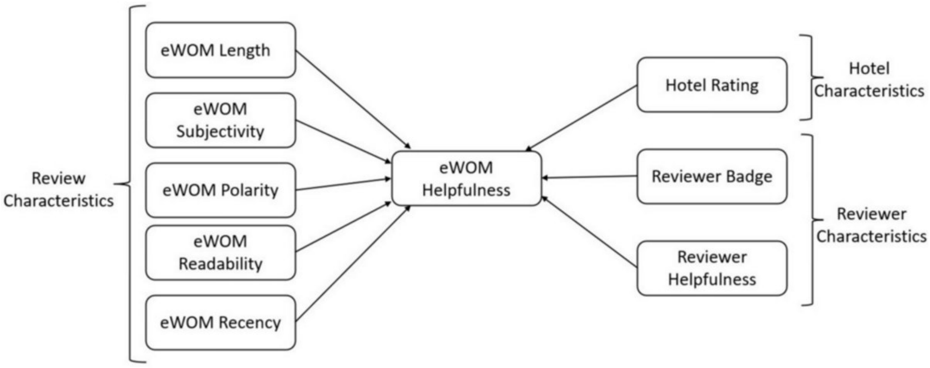

FIGURE 1: Conceptual model

eWOM, electronic Word-of-Mouth

Research Method

Data collection

For this study, we have used the TripAdvisor.com dataset which is divided into two files (Roshchina et al., 2015). One of the files contains review data fields such as “username”, “review type”, “date”, “review title”, “review text”, “rating”, and “helpfulness votes”. The second file contains data pertaining to reviewers such as “username”, “age range”, “gender”, “location”, “reviewer badge” and “total helpful votes” for each reviewer. Out of approximately 32k review entries, we shortlisted reviews pertaining to hotels only. First, we removed all the entries with any missing values of “username”, “date”, “review text”, “rating”, “helpful votes”, “reviewer badge”, and “total helpful votes”. Then, we removed all the entries where the language of textual review was non-English. Further, we applied basic steps of text pre-processing to get a clean dataset. For this, initially we removed any URL present in the data as that is not required in this study. Then we converted all the uppercase alphabets to lowercase and numbers into alphabetic numbering. Further, we removed punctuations, special characters, stop words, and extra white spaces from the reviews. Then we ran the code for word tokenization, and stemming which clubbed all the variants of a word to the root word. Together, these steps transformed the unstructured review texts into a corpus of 16353 filtered reviews and 1087 reviewer related fields which are free of any noise and unwanted information for further illustration of the model.

Characteristics extraction and econometric model formulation

This study has eWOM helpfulness as the response variable, which is the count of helpful votes of an eWOM. In addition, there are eight independent variables which are "length", "subjectivity", "polarity", "readability", and "recency" of the eWOM; "helpfulness votes" received by the reviewer on all reviews written by them, "reviewer badge" along with "hotel rating". eWOM length (E_Len) has been calculated as the count of characters in an eWOM. eWOM readability (E_Read) has been calculated using the FKGL score due to its efficiency with textual data (Kincaid et al., 1975). FKGL includes numerous features to deal with the eWOM hospitality text, it includes total words, total syllables, and total sentences for calculating the review comprehensibility. Particularly in the hospitality industry, FKGL helps to tailor the customer response, identify the difference between simpler or detailed review, consistent or broken reviews, and ease of understanding. The review characteristics, which include, length, subjectivity (E_Subj), polarity (E_Pol), and readability, have been extracted using python programming. Values of eWOM helpfulness (E_Help), helpfulness votes of reviewer (R_Help), and hotel rating (H_Rate) have been directly taken from the data itself and eWOM recency (E_Rec) which is the difference of "review posting" and "extraction dates" has been extracted using MS Excel. Table 1 shown the features list and their descriptions. Reviewer badge (R_Badge) is the star badge assigned by TripAdvisor.com to their reviewers for acknowledging their contribution to the community by considering the total number of eWOM posted by reviewers and helpful votes received on them. There are a total of five badges: “Top-contributor” (50+ reviews), “Seniorcontributor” (21-49 reviews), “Contributor” (11-20 reviews), “Senior-reviewer” (Six-Ten reviews), and “Reviewer” (Three-Five reviews).

Variables	Code	Description
eWOM Helpfulness	E_Help	eWOM helpfulness is the sum of upvotes obtained on an eWOM
eWOM Length	E_Len	eWOM length is the total number of characters of an eWOM
eWOM Subjectivity	E_Subj	eWOM subjectivity measures the extent of opinion of an eWOM
eWOM Polarity	E_Polr	eWOM Polarity measures the emotional strength of an eWOM
eWOM Readability	E_Read	eWOM Readability measures the comprehensibility of text
eWOM Recency	E_Rec	eWOM Recency is measured in number of days calculated by subtracting the eWOM post-date from crawl date
Hotel Ratings	H_Rate	It is the rating provided by each customer to the hotel
Reviewer Badge	R_Badge	It is a range of five badges given by OTA platforms to the reviewers
Reviewer Helpfulness	R_Help	It is the count of upvotes gained by all the eWOMs posted by a reviewer

TABLE 1: Variable descriptions

Based on the above discussed variables, we have formulated three different econometric models. In model I, we have taken the eWOM variables as independent variables (given in Equation 1). In the model II, both review variables and hotel rating act as the independent variables (Equation 2). In model III, we consider the effect of all the features on helpfulness of eWOM (given in Equation 3).

Model-I

$$E\_Help = \beta_0 + \beta_1 * \ln(E\_Len) + \beta_2 * E\_Read + \beta_3 * E\_Subj + \beta_4 * E\_Pol + \beta_5 * \ln(E\_Rec) + \varepsilon \quad (1)$$

Model-II

$$E\_Help = \beta_0 + \beta_1 * \ln(E\_Len) + \beta_2 * E\_Read + \beta_3 * E\_Subj + \beta_4 * E\_Pol + \beta_5 * \ln(E\_Rec) + \beta_6 * H\_Rate + \varepsilon \quad (2)$$

Model-III

$$E\_Help = \beta_0 + \beta_1 * \ln(E\_Len) + \beta_2 * E\_Read + \beta_3 * E\_Subj + \beta_4 * E\_Pol + \beta_5 * \ln(E\_Rec) + \beta_6 * H\_Rate + \beta_7 * R\_Badge + \beta_8 * R\_Help + \varepsilon \quad (3)$$

Performance evaluation of predictive models

For the binary prediction of eWOM helpfulness, we use seven predictive techniques, which are KNN, DT, NB, SVM, RF, ANN, and RNN. eWOM helpfulness acts as the predicted variable and the rest of the features act as predictor variables. eWOM has been categorized into helpful and non-helpful based on a threshold value. Due to the continuous nature of dependent variable, reviews have been categorized using mean value of helpfulness score. eWOM with helpfulness score above mean score has been categorized as helpful and the rest as non-helpful (Aakash and Aggarwal, 2020). To validate the predictive models, we used 10-fold cross-validation technique. In this validation, data have been divided into 10 equal parts where 9 parts have been used for training purpose, and 1 part for testing. This process has been repeated 10 times where each time the training data changes (Aakash A and Aggarwal AG, 2020).

Results

We used two methods to assess the effect of eWOM, reviewer, and hotel features on the helpfulness of eWOM. Firstly, we analyzed the impact through econometric modeling. Then, we used the machine learning classifiers for eWOM helpfulness predication.

Econometric modeling results

The results of the econometric modeling are shown in Table 2. The hypotheses H1, H2, and H4 are significant, which represent that length, subjectivity and, readability of eWOM positively influence the eWOM helpfulness in all the three models. However, the polarity and recency negatively influence the helpfulness of eWOM, thus accepting hypotheses 3 and 5. This means that older reviews and reviews which contain extreme emotions have been deemed as non-helpful. The numeric rating of hotel has been found to significantly impact the helpfulness of eWOM, thus, supporting H6. The hypotheses H7 and H8 are also supported which means that the reviewer badge and reviewer helpful votes positively influences the eWOM helpfulness. This implies that reviews written by reputed reviewers are found to be more helpful. It is evident from Table 2 that the adjusted R^2 value, which indicates the goodness of fit of the models, is highest for model III (0.750), in our research proving it to be the best performing model. These results indicate that all the selected features affect the helpfulness of eWOM, and thus can aid strategic decision-making.

Independent Variable	β Coefficient (Std. Error)		
	Model I	Model II	Model III
ln(E_Len)	.747*(.015)	.715*(.017)	.684*(.020)
E_Subj	.007**(.002)	.006**(.002)	.006**(.002)
E_Pol	-.462*(.034)	-.428**(.005)	-.458**(.003)
E_Read	.012**(.004)	.012**(.004)	.010**(.004)
ln(E_Rec)	-.054*(.022)	-.065*(.023)	-.075*(.023)
H_Rate		.085*(.023)	.074*(.023)
R_Badge		.063*(.026)	.007***(.001)
R_Help			.063***(.026)
Adjusted R^2	.7490	.7492	.7502

TABLE 2: Estimation results

Note: Significance Level: ***p < 0.001; **p < 0.01; *p < 0.05.

Predictive modeling results

Table 3 provides the accuracy percentage of different predictive models. From the table, the best accuracy of model III is given by RNN (80.57%), followed by RF (80.54%). Also, for all the models, RNN gives the highest accuracy. Therefore, RNN predicts eWOM helpfulness better than the rest of the techniques because RNN has the ability to retain previous valuable information (in the hidden layer) and features hierarchy patterns; it scales better for large and complex datasets.

Techniques	Model I (%)	Model II (%)	Model III (%)
KNN	68.922	69.461	70.808
DT	77.824	78.038	78.803
ANN	79.042	79.82	80.389
RF	80	80.209	80.539
SVM	78.653	78.832	79.223
NB	77.879	78.683	79.072
RNN	80.09	80.659	80.569

TABLE 3: Predictive modeling results for different classifiers

DT, Decision Tree; KNN, k-Nearest Neighbour; NB, Naïve Bayes; SVM, Support Vector Machine; RF, Random Forest; ANN, Artificial Neural Networks; RNN, Recurrent Neural Networks

Figure *2* illustrates the accuracy percentage of all three models as performed by different classifiers. When comparing Model I and Model II, it can be observed that there is a slight change in accuracy for DT, RF, SVM, and RNN while the accuracies of KNN, ANN, and NB show better improvements. Similarly, while comparing Model II and Model III, it can be observed that there is a slight change in accuracy for RF, SVM, and NB while the accuracies of KNN, DT, ANN, and RNN show better improvements. Overall, the accuracies of Model III are better than the other two models through all the techniques. This demonstrates that eWOM helpfulness is best predicted through a combination of eWOM, hotel, and reviewer features.

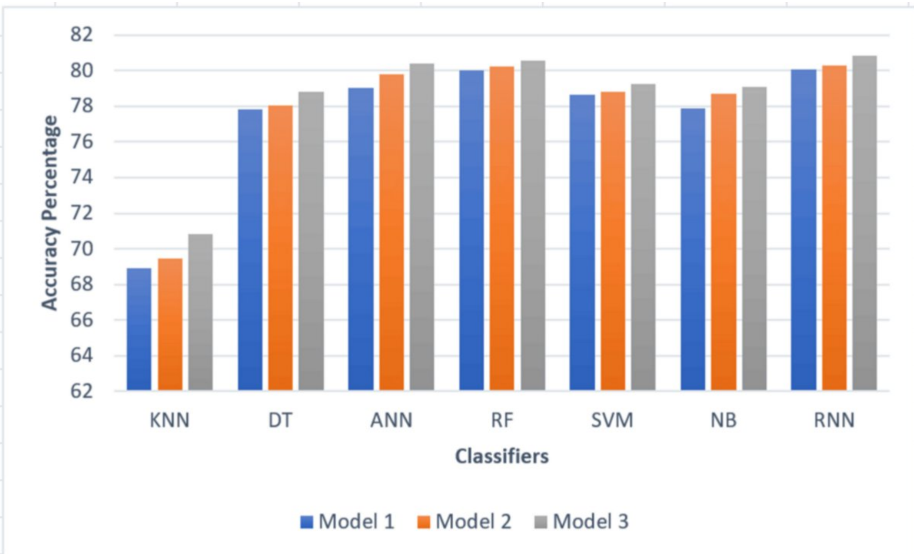

FIGURE 2: Accuracy of predictive classifiers for different models

Comparison of econometric and machine learning results

In this section, we analyze the results of two different techniques i.e. econometric modeling and ML. In regression, we evaluated the impact of eWOM features on helpfulness of eWOM through Model I. Model II analyzed the impact of hotel and eWOM features followed by a combination of all eight features in Model III. The findings revealed that the performance accuracy of Model III is (Adjusted R^2 = 75.02%) better than the other two models. Predictive modeling provides similar results, where Model III performs better than the other two models for all the techniques.

Discussion

According to the econometric results, hypotheses H1-H5 are significant with the helpfulness votes. So, in accordance with our first objective, we found that review characteristics such as length, subjectivity, polarity, readability, and recency influence the helpful votes. Now, if we look at the results of our study, H1 is found to be significant which means review length positively influences the helpful votes. This result is consistent with prior studies (Román et al., 2024). Also, H2 and H3 are found to be significant which is supported by the previous research. We also found that readability influences helpful votes (H4) positively which is in accordance with a prior study done on online reviews related to restaurant experiences (Liu and Park, 2015). H5 has also been found to be significant which suggests a negative influence of recency on review helpful votes, as is proven by Aakash and Jaiswal (Aakash and Jaiswal, 2020). As for the second objective of our study, we found that hotel ratings significantly impact eWOM helpfulness. As for the third objective, the findings of this research concluded that reviewer characteristics, which are its badge and helpfulness votes, significantly impact the helpful votes.

On comparing predictive results of all machine learning techniques, the results indicate that RNN performs better than all the other techniques. RNN provides the prediction based on the forward as well as backward iteration, due to which it outperforms others and thus fulfils objective four. This study provides insights on how eWOM affects the customer's mindset about the firm. A lengthy, subjective, eWOM which contains sentiment polarity, is easily comprehensible, and not very old achieves more helpful votes than a short, emotionless, difficult to understand, and older review. A large number of helpful votes achieved by an eWOM indicates that the review is found useful by the potential customers. In addition, hotel rating, reviewer badge, and helpful votes along with other eWOM characteristics increase the prediction power of the eWOM helpfulness model. In conclusion, we conclude that the ML models have better prediction power than the econometric model. So, our study suggests that the firms should opt for ML tools for the prediction in hospitality industry.

Conclusions

As technology and digitization boom, they have led to a complete change in business dynamics. With the ease of internet, it has become easier for people to share their opinions on online platforms, making eWOM an important intelligence tool largely impacting businesses. With increasing eWOM, it becomes important to analyze their effectiveness. In this research, we investigated how reviewer and review features, along with hotel rating, affect eWOM helpfulness. To do so, we formulated three models where model one studies the effect of eWOM features on the helpfulness of eWOM. Second model evaluates the combined effect of eWOM features and hotel ratings and model three evaluates the impact of eight features belonging to eWOM, hotel, and reviewer categories. Estimation results of the models show that the impact of independent variables improves with each model, thus validating the addition of variables. Further, we performed predictive modeling for binary prediction of eWOM helpfulness using various techniques like ANN, Random Forest, SVM, KNN, RNN, NB, and Decision Trees. In predictive modeling, RNN provides the best results for all three models with an accuracy of 80.57% for Model III. Thus, RNN has a better ability to handle large, complex and high-dimensional datasets. It has also been observed that all the techniques show that the proposed models are satisfactorily accurate.

Our statistical analysis is based on 16699 online reviews of hotels. The developed econometric model shows goodness of fit improvement from 0.749 to 0.7520. On applying ML predictive algorithms on the same models, the resultant accuracy of the models comes out to be 0.689 and 0.8057. Hence, this research contributes by connecting ML and econometric modeling in the hospitality industry. This work has contributed to the knowledge expansion of hospitality literature by analyzing the factors affecting eWOM helpfulness. Researchers in the past have used traditional statistical techniques, whereas we used a combination of econometric modeling and machine learning techniques to predict the helpfulness of eWOM. Although, in this digital world, there are numerous OTA websites, but used the dataset from TripAdvisor.com due to its popularity among the masses. This study helps in understanding what different factors govern the helpfulness of a review. This provides insightful information on the parameters that differentiate a few eWOM from the humungous reviews pouring online on a daily basis. The findings of this study also enable industry personnel in creating policies and formulating strategies. This study has few limitations. First, we have used a dataset of ~17k reviews from TripAdvisor.com. It is the most trusted and widely used OTA website, thus has been selected for this study. However, the eWOM may suffer from some biased due to human nature. Thus, for properly generalizing the results, this study can be extended on datasets of different magnitudes from other OTA websites which can then be compared and provide a deep understanding of factors affecting eWOM helpfulness. Second, we used eight features to study their impact on eWOM helpfulness, several other parameters can also be explored to enhance the literature. Third, combinations of different techniques can be used for further research in this area. Finally, in the future, authors can use hybrid neural network techniques, which may offer better prediction performance.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Anu G. Aggarwal, Abhishek Tandon, Sanchita Aggarwal

Acquisition, analysis, or interpretation of data: Anu G. Aggarwal, Sanchita Aggarwal, Sweta Yadav

Critical review of the manuscript for important intellectual content: Anu G. Aggarwal, Abhishek Tandon

Supervision: Anu G. Aggarwal, Abhishek Tandon

Drafting of the manuscript: Sanchita Aggarwal, Sweta Yadav

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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