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Impact of Review, Reviewer, and Hotel Characteristics on eWOM Helpfulness: An Empirical Study

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Abstract

Electronic Word of Mouth (eWOM) has been gaining popularity for its numerous benefits and ability to be applied in various fields. It helps consumers make informed decisions and aids service providers in delivering an enhanced service or product. Despite all these benefits, dealing with the huge amounts of eWOM is a consistent problem. eWOM helpfulness comes in handy to address this issue. In this study, we utilize 16,699 hotel-related eWOM written by 1,099 reviewers which are collected from TripAdvisor.com. Our main objective is to analyze which factors impact eWOM helpfulness and how. For this purpose, eight unique variables belonging to three different categories are selected (eWOM length, eWOM subjectivity, eWOM polarity, eWOM readability, eWOM recency, hotel rating, reviewer badge, and reviewer helpfulness) and are analyzed using econometric modelling. Our findings show that hotel rating as well as reviewer badge and helpfulness enjoy a positive significant relationship with eWOM helpfulness. It also suggests that eWOM length, readability, and subjectivity positively influence eWOM helpfulness though eWOM polarity and recency are found to have an inverse relationship with the helpfulness of eWOM. Thus, our study reports that review, hotel, and reviewer characteristics impact eWOM helpfulness in different ways. This study is summarized with a discussion of theoretical and practical implications.

Keywords: eWOM helpfulness, review parameters, reviewer parameters, hotel parameters, econometric modelling

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Introduction

In this ever-evolving world, the digital revolution has enabled the sharing of one's personal experiences and opinions about anything with a lot of people at the same time. Digitalization has also impacted businesses by providing them with the benefits of cost-effectiveness, no geographical limitations, and ease of use. The tourism industry along with many other service sector industries is increasingly converting their businesses from offline to online mode which provides an opportunity for the customer to avail all the travel agency services on the online platform from the comfort of their home. Since travel and hospitality are experience goods, reviews written by previous travelers are of utmost importance. Studies have shown that eWOM significantly impacts the booking intentions of customers (Tsao et al., 2015).

With more and more customers reaping the benefits of eWOM, a lot more travelers are willing to share their experiences and opinions with fellow travelers on Online Travel Agency (OTA) websites. This results in the generation of a huge amount of eWOM data daily which has become the ultimate source of information for both practitioners and customers reviews contain abundant information about the likes and dislikes of the customer which can be used by industry personnel for analyzing their services. Potential travelers can obtain unfiltered, raw opinions about a place or hotel property from eWOM to make well-informed booking decisions (Cantallops & Salvi, 2014; Ghose & Ipeirotis, 2010). However, it is an appalling task to go through such a huge database in stipulated periods. To simplify this, OTAs applied the concept of "helpfulness of a review" which is measured as the total count of helpful votes obtained by a review from the readers (Cao et al., 2011).

Many of the past studies have examined the contribution of eWOM characteristics on eWOM helpfulness. Chua & Banerjee (2016) studied the impact of customer sentiments contained in a review on the review's helpfulness. Korfiatis et al. (2012) investigated the effect review length, ratings, and readability have on the helpfulness of reviews. Another study conducted by Tandon et al. (2021) analyzed the impact review recency had on the helpfulness of eWOM along with some moderating parameters. Lately, analysts have also examined the effect of reviewer attributes such as gender, expertise, age, contribution level, etc. on review helpfulness (Srivastava & Kalro, 2019). A study conducted by Craciun et al. (2020) talks about the influence of emotion-related gender stereotypes on the perceived helpfulness of the review and the reviewer's credibility.

However, none of the above studies have discussed the impact of review, reviewer, and hotel characteristics on the review helpfulness at the same time. In this study, we examine the influence of review length, subjectivity, polarity, readability, and recency on the eWOM helpfulness. We also discuss the impact of hotel ratings (given by the customer) on the helpfulness of eWOM. We use reviewer helpfulness i.e., the total helpful votes received by a reviewer along with the badge number and study their effect on eWOM helpfulness. This set of parameters chosen by the authors is exclusive to our research. Therefore, in this paper, we aim to tackle the following research questions:

RQ1: Which review characteristics impact the eWOM helpfulness and how?

RQ2: Which hotel characteristics impact the eWOM helpfulness and how?

RQ3: Which reviewer characteristics impact the eWOM helpfulness and how?

This paper is further formulated as follows: Section 2 details the literature on eWOM helpfulness along with the hypothesis developed for the proposed model. Section 3 discusses the research methodology used along with the data description. The results obtained by applying the techniques are presented in section 4. Findings are discussed and conclusion is drawn in section 5. Theoretical and practical implications are detailed in section 6. And the study is concluded with limitations and future scope.

Literature Review

eWOM helpfulness

To extract meaningful information from eWOM, many of the OTA websites like TripAdvisor.com provide their customers with an option to rate the usefulness of the review through which the customer can tell what they felt after reading that comment by either liking (helpful) or disliking (not helpful) the review. Review helpfulness (or eWOM helpfulness) has intrigued researchers in the past. A study conducted by López-López & Parra (2016) demonstrated that if a particular review is voted as "most helpful", and its valence is incongruent with the overall valence of the reviews, then that review considerably impacts the customer attitude towards the product. Ismagilova et al., (2020) examined in what way the contents of online reviews impact perceived helpfulness. They applied cognitive appraisal theory and attribution theory and discussed how different kinds of emotions impact both service and product review helpfulness. Filieri et al., (2021) found that in the case of extreme ratings, some of the product attributes discussed in customer reviews play a crucial role in determining the helpfulness of reviews. Thus, we can safely say that understanding the antecedents of eWOM helpfulness is of great importance to both service providers and service consumers. In this study, our basic aim is to study the effect of some eWOM characteristics, some hotel characteristics, and some reviewer characteristics on the helpfulness of review.

eWOM helpfulness and eWOM characteristics

An eWOM is basically nothing but a textual expression of the experience and the emotions associated with a service that the user availed. Any textual review comprises several characteristics associated with it. Review length is the total words contained in a review. It has been found to be of great importance for the assessment of review performance (Schindler & Bickart, 2012). Researchers have also argued that the review length positively impacts the purchase intention of the customer as it contains a detailed description of specific features (Banerjee et al., 2017). A longer review written by the consumer is believed to contain more information as compared to a shorter one. It also tends to be more persuasive as it contains multiple arguments (Schwenk, 1986).

To access the emotions of consumers contained in a review, concepts of subjectivity and polarity are used. The subjectivity of an eWOM is mainly associated with individual opinions, judgments, and emotions whereas the polarity of an eWOM is how positive, negative, or neutral the text is. Highly subjective eWOMs are more helpful by the researchers (Ghose & Ipeirotis, 2010). On the contrary, highly polar eWOM is extreme eWOM (i.e., extremely negative, or positive). Extremely positive reviews are often written in technical language and not in the common day-to-day “consumer language”. Therefore, it is very normal for the reader to assume that these reviews are written by the marketing team of the seller, or that of a competitor (in case of extremely negative reviews). In either of these cases, the probable customer perceives them to be unreliable (Filieri, 2016). Moreover, it is also noted that these sensational review comments gain limelight and lead to customer reactance, which results in unfavorable perceptions getting attached to the eWOM (Salehan & Kim, 2016). Such distrust and unreliability associated with extreme reviews lead to them being unhelpful (Chatterjee, 2020).

The readability of an eWOM is another key parameter that can impact the review’s helpfulness. Readability has been described as the ease with which a piece of text can be discerned by the reader on the basis of reviewer’s style of writing (Klare, 1974). Evaluation of the readability index is done on the basis of number of years in higher education and education grade level (Ghose & Ipeirotis, 2010). It is also a depiction of reviewer’s social status and hierarchy along with their education level (Tausczik & Pennebaker, 2010). Therefore, it can be inferred that eWOM having a higher readability index would be recognized as being more reliable in comparison to those with lower readability index. Also, with a better understanding of the review comment, more and more people would tend to read it and find it helpful (Fang et a., 2016).

Another key parameter of review helpfulness is the recency of the review. It depicts how old or recent the eWOM posted by previous travelers is. eWOM Recency is calculated from the posting date of the eWOM which tells its age (Xie et al., 2016). It is of great importance in influencing customer ratings (Wulff et al., 2015). Previous researchers have concluded that customers find recent reviews to be more helpful in comparison to the earlier ones (Otterbacher, 2009). Tandon et al. (2021) point out that recent eWOMs have comparatively higher chances of getting upvoted by peers. Not only this, but by virtue of Matthew's effect, they benefit in maintaining their ranking status (Wan, 2015). In accordance with the above discussion, we postulate the following hypotheses:

Hypothesis 1 (H1): eWOM length positively impacts the eWOM helpfulness.

Hypothesis 2 (H2): eWOM subjectivity positively impacts the eWOM helpfulness.

Hypothesis 3 (H3): eWOM polarity negatively impacts the eWOM helpfulness.

Hypothesis 4 (H4): eWOM readability positively impacts the eWOM helpfulness.

Hypothesis 5 (H5): eWOM recency negatively impacts the eWOM helpfulness.

eWOM helpfulness and hotel characteristics

In the context of hospitality and tourism, hotel eWOM comprises of two main elements i.e., the textual review and the numerical rating. Numerical ratings given by travelers are of great importance affecting a lot many aspects. Terms like "hotel rating", "hotel segment", "hotel grading", and "hotel classification" have been conversely used to depict the distinguishing features of hotels in terms of their facility, price, and service levels (Cser & Ohuchi, 2008). Researchers have found that the different spoken languages of the customers affect the hotel rating provided to them (Liu et al., 2017). Rhee & Yang (2015) used overall hotel ratings given by travelers and their respective ratings on six hotel parameters ("room", "cleanliness", "service", "sleep quality", "location" and "value") to study how the importance of hotel characteristics differs concerning hotel classification. Another study conducted by Kim et al., (2015) revealed that overall hotel rating followed by a response to negative reviews is the most important predictor of hotel performance. Based on the above discussions, we posit the following hypothesis:

Hypothesis 6 (H6): hotel rating positively impacts the eWOM helpfulness.

eWOM helpfulness and reviewer characteristics

Reviewer is a key factor of eWOM as it is the reviewer who shares their experiences and opinions in the form of reviews which leads to the whole cycle of reviews posted, reviews read, and reviews' impact on the potential consumers, sales, customer satisfaction, etc. Not all travelers have the motivation to share their experiences online. It has already been confirmed that eWOM is a great information source for the assessment of hotel performance and guest satisfaction (Aakash et al., 2022). Thus, to sustain the current reviewers and simultaneously encourage new reviewers, OTA websites provide them with a badge which is an indicator of their contribution level (Bishop, 2007). A reviewer obtains different badges based on the count of reviews written and the total count of upvotes obtained by them. This indicates the authenticity and reliability of a reviewer and in turn that of the review posted by them (Willemsen et al., 2012).

Prior studies have found that reviewer rank (or badge) along with self-disclosed personal details significantly impact the determination of review helpfulness (Ghose & Ipeirotis, 2010). It has also been observed that customers inherently find reviews written by expert reviewers to be more helpful (Zhu et al., 2014). Another important reviewer characteristic is the reviewer helpfulness which is nothing but the total count of upvotes obtained on the eWOM written by them. Many researchers have studied the impact of reviewer helpfulness in different aspects. (Huang et al., 2015) examined the impact of quantitative parameters such as word count along with qualitative parameters like reviewer's impact, cumulative helpfulness, and experience on the helpfulness of the review. Ghose & Ipeirotis (2010) also observed that whenever there is an increase in the average helpfulness of a reviewer's previous reviews, it positively impacts the helpfulness of a review posted by them. Thus, considering the above discussion, we can hypothesize that:

Hypothesis 7 (H7): reviewer badge positively impacts the eWOM helpfulness.

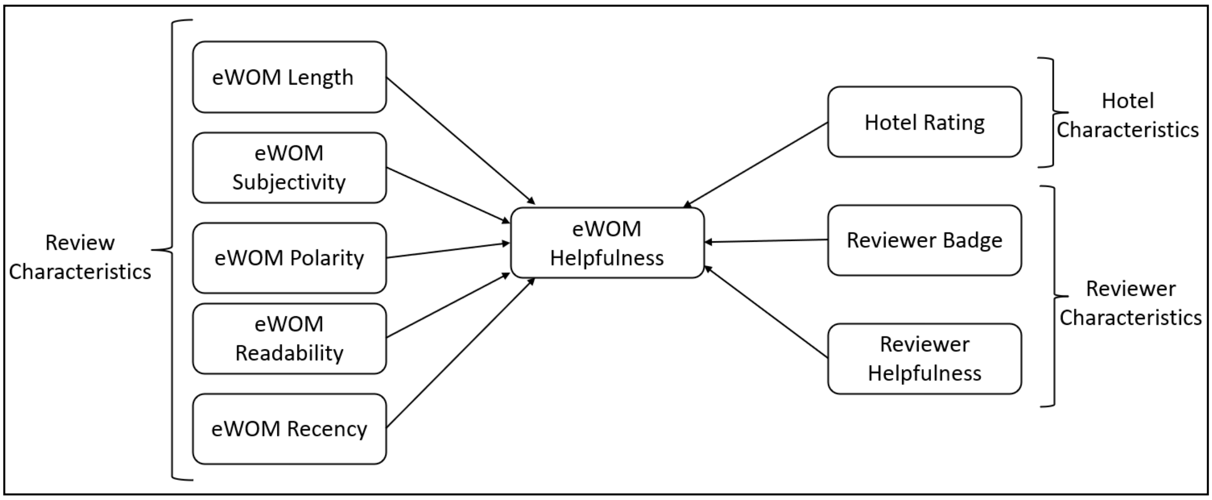
Hypothesis 8 (H8): reviewer helpfulness positively impacts the eWOM helpfulness.

Methodology

This study proposes to use econometric modelling for the identification of variables that impact the helpfulness of eWOM in the tourism and hospitality industry. Fig. 1 provides the proposed model for this study.

Figure 1.

Research Model



Data collection

This research uses a TripAdvisor.com dataset (Celli et al., 2014; Roshchina et al., 2015) which is one of the biggest and the most popular OTA websites. It provides its users with booking options for hotels, flights, cars, cruises, and restaurants. Along with that it also enables travelers to share and discuss their experiences on the travel forum. This dataset comprises two CSV files, one containing the review-related data fields such as “username”, “type” (i.e., hotels, restaurants, attractions), “date”, “review title”, “review text”, “rating” and “helpfulness votes”. The other file containing reviewer-related data fields such as “username”, “age range”, “gender”, “location”, “reviewer badge” and “total helpful votes” obtained by that user. The review file has a total of 32,580 reviews pertaining to hotels, restaurants, and attractions. Out of these only hotel reviews are selected. Also, the reviewer file contains the information of 7,034 reviewers. Out of these, only those reviewers are chosen who have written hotel reviews. Concerning each review, we select data for the field’s username, date, review text, rating, and helpfulness votes and w.r.t. each reviewer, we select data for the field’s username, reviewer badge, and total number of helpful votes. For the econometric modelling, we have a total of 16,699 reviews which are written by 1,099 reviewers.

Variables

This research used one dependent and eight independent variables which are discussed in Table 1. Among them, eWOM helpfulness, reviewer badge, reviewer helpfulness and hotel rating are directly taken from the dataset. Rev_badge, which is assigned by TripAdvisor.com to its customers, consists of 5 badges namely “Reviewer” (three-five reviews), “Senior Reviewer” (six-ten reviews), “Contributor” (eleven-twenty reviews), “Senior Contributor” (twenty-one-forty-nine reviews) and “Top Contributor” (50+ reviews) and is assigned on the basis of two criteria which are “number of reviews posted” and “total number of helpful votes received by a reviewer". R_help is the dependent variable used in this study. R_length is calculated as the count of total number of words contained in a review. For the calculation of R_recency, the difference between the review posting the date and data extraction date is calculated. The higher the difference, the older the review. For the research, ln(R_recency) and ln(R_length) are used.

Table 1.

Variable Description

Type	Features	Description
Dependent	Review Helpfulness (R_help)	Represents the total count of helpful votes obtained by an eWOM
Review	Length (R_length)	Represents the total count of words contained in an eWOM
	Subjectivity (R_subj)	Represents the amount of subjectiveness contained in an eWOM
	Polarity (R_pol)	Represents the degree of negativity/positivity of an eWOM
	Readability (R_read)	Represents how easy /hard an eWOM is to comprehend
	Recency (R_rec)	Represents the difference between eWOM posting and extracting date
Hotel	Ratings (H_rate)	Represents the numerical rating given to a hotel by the user
Reviewer	Badges (Rev_badge)	Represents the star badge assigned by the OTA website
	Helpfulness (Rev_Help)	Represents the total number of helpful votes obtained by that reviewer

Further, subjectivity, polarity, and readability indices associated with the review text were calculated. As for the readability index, a lot of many techniques have been mentioned in the literature like The Gunning-Fox Index (FOG), Flesch-Kincaid Grade Level (FKGL), Automated Readability Index (ARI), etc. Text readability is calculated to access the educational level and amount of effort required to fathom a piece of text (Zakaluk & Samuels, 1988). In this paper, we use the FKGL method introduced by Kincaid et al. (1975) for the calculation of R_read because it considers various inbuilt text features such as the total count of words, syllables, and sentences to estimate the comprehensibility associated with each eWOM. FKGL can be calculated as:

$$FKGL = 0.39\left(\frac{count\ of\ words}{count\ of\ sentences}\right) + 11.8\left(\frac{count\ of\ sentences}{count\ of\ words}\right) - 15.59 \quad (1)$$

To understand the FKGL score, it is pointed out that if $90 \leq score < 100$, eWOM is "very easy to comprehend", if $80 \leq score < 90$, eWOM is "easy to comprehend", and if $70 \leq score < 80$, eWOM is "quite easy to comprehend". Further, if $60 \leq score < 70$, eWOM is said to be "easily readable and comprehend", if $50 \leq score < 60$, eWOM is said to be "quite hard to comprehend", if $30 \leq score < 50$, eWOM is said to be "hard to comprehend", and if $0 \leq score\ < 30$, eWOM is said to be "very hard to comprehend".

Research Model

For this research, we scrutinized three types of variables that may impact the helpfulness of an eWOM. Among these, one of the sets comprises review characteristics, one of the hotel characteristics, and one of the reviewer characteristics. We formulated three models for the same. In Model I, we consider five independent variables that depict eWOM attributes and study their linear relationship with the R_help. Model II includes another variable depicting hotel attributes in Model I as shown in equation (3). In Model III, we further add reviewer-related variables along with review and hotel variables to study their combined impact on R_help as shown in equation (4). In all of the models, another variable ε is added to include all the uncontrollable environmental factors (Ye et al., 2011).

Model-I

$$R\_help = \beta_0 + \beta_1 * \ln(R\_length) + \beta_2 * R\_read + \beta_3 * R\_subj + \beta_4 * R\_pol + \beta_5 * \ln(R\_rec) + \varepsilon \quad (2)$$

Model-II

$$R\_help = \beta_0 + \beta_1 * ln(R\_length) + \beta_2 * R\_read + \beta_3 * R\_subj + \beta_4 * R\_pol + \beta_5 * ln(R\_rec) + \beta_6 * H\_rate + \varepsilon \quad (3)$$

Model-III

$$R_{help} = \beta_0 + \beta_1 * \ln\left(R_{length}\right) + \beta_2 * R_{read} + \beta_3 * R_{subj} + \beta_4 * R_{pol} + \beta_5 * \ln(R_{rec}) + \beta_6 * H_{rate} + \beta_7 * Rev_{badge} + \beta_8 * Rev_{help} + \varepsilon \quad (4)$$

Results

Descriptive statistics for all the variables are presented in Table 2. Now, before moving forward, we need to check for the presence of multicollinearity among independent variables. Researchers suggest two major techniques for the same i.e., Variance Inflation Factor (VIF) and Tolerance (Banerjee et al., 2017). To negate the presence of multicollinearity among variables, the VIF value should be less than 10 and the tolerance should be more than 0.1 (Thompson et al., 2017). Table 3 contains the multicollinearity results for all the independent variables. None of the parameters violates the conditions and thus we can vouch for the absence of multicollinearity among our independent variables.

Table 2.

Descriptive Statistics

Variable	Std. Dev.	Mean	Min	Max
R_length	189.057	165.2276	1	2992
R_subj	25.9523	15.34577	0	100
R_pol	0.407924	0.244571	-0.89564	2
R_read	8.917005	6.304087	0.3	99.6
R_rec	1289.92	840.2087	2	4732
H_rate	3.966764	1.005511	1	5
Rev_badge	4.145637	0.900812	0	5
Rev_help	53.94197	69.79661	0	1468

The regression results of the above-formulated models are shown in Table 4. From the results it can be observed that R_length, R_subj, and R_read are positively associated with R_help in all the models, thus supporting H1, H2, and H4. In confirmation of these hypotheses, we can say that a highly subjective lengthy review is found to be more helpful to the customers. If we talk about readability, in accordance with what we discussed earlier, it can be said that a review with a high readability index is easier for the user to understand and thus becomes more appealing (or helpful). We also observe that review recency and polarity are negatively associated with the eWOM helpfulness thus supporting H3 and H5. This shows that the latest reviews are found to be more helpful in comparison to the older ones. It can also be inferred that a highly polar review leads to a sense of doubt among customers as extreme hatred or praise for something is not easily trusted.

Table 3.

Multicollinearity results

Variable	VIF	Tolerance
R_length	1.052104	0.950477
R_subj	1.318208	0.758605
R_pol	1.138710	0.878187
R_read	1.004220	0.995798
R_rec	1.097777	0.910932
H_rate	1.117548	0.894816
Rev_badge	1.326807	0.753689
Rev_help	1.258092	0.794855

From model II and III results, we find that H_rate, Rev_badge, and Rev_help are positively associated with eWOM helpfulness thus lending support to H6, H7, and H8. From this, we can pre-suppose that an eWOM written by a reputed contributor of travel reviews who is already a trusted personality in the community is more helpful. Hotel rating is also found to significantly impact the helpfulness of reviews however, on observing the adjusted R^2 value of model I and II, we can see that it does not impact the goodness of fit of the model. From Table 4, we can see that all three models have high adjusted R^2 values which represent an appreciable amount of goodness of fit in these models. It can also be noted that model III has the highest adjusted R^2 value thus supporting that review, hotel, and reviewer parameters combined significantly impact eWOM helpfulness.

Table 4.

Econometric Modelling Results

Independent Variable	Hypothesis	Standardized Coefficient (Standard Error)		
		Model-I	Model-II	Model-III
Ln(R_length)	H1	0.7479^{***} (0.015)	0.7150^{***} (0.017)	0.6849^{***} (0.020)
R_subj	H2	0.0076^{***} (0.002)	0.0069^{***} (0.002)	0.0063^{***} (0.002)
R_pol	H3	-0.5292^{***} (0.094)	-0.6625^{***} (0.101)	-0.6386^{***} (0.101)
R_read	H4	0.0128^{**} (0.004)	0.0121^{*} (0.004)	0.0109^{*} (0.004)
Ln(R_rec)	H5	-0.0548^{*} (0.022)	-0.0659^{*} (0.023)	-0.0759^{*} (0.023)

H_rate	H6		0.0854*** (0.023)	0.0742*(0.023)
Rev_badge	H7			0.0633*(0.026)
Rev_help	H8			0.0007*(0.000)
Adj. R-squared		**0.749**	**0.749**	**0.750**

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

Conclusion

This study focused on observing and explaining the effects of qualitative and quantitative parameters on eWOM helpfulness. Based on the data from a popular and renowned OTA website, we used econometric modelling to explain how different variables impact review helpfulness. Some previous studies have worked on extracting latent parameters from customer reviews like length, readability, sentiment, recency, etc., and studied their impact on review helpfulness (Ghose & Ipeirotis, 2010; Schindler & Bickart, 2012; Tandon et al., 2021). Few other studies also examined the effect of certain reviewer attributes like age, experience, impact, gender, etc., on the helpfulness of reviews (Huang et al., 2015; Karimi & Wang, 2017). A handful of researchers have also tried to demonstrate the significance of hotel rating on eWOM helpfulness (Cser & Ohuchi, 2008; Rhee & Yang, 2015).

In this research, we have chosen a unique combination of certain parameters of review, hotel, and reviewer categories. A study was done by Yang et al. (2017) analyzing the combined impact of review parameters (like rating, length, and photo) and reviewers' parameters (like location, level, and helpful votes) on review helpfulness. Another research done by Huang et al. (2015) investigated the combined effect of quantitative parameters (word count) and qualitative parameters (product rating, reviewer’s cumulative helpfulness, impact, and experience) on the helpfulness of reviews. However, in the sub-category of hospitality and tourism, no study in the past has evaluated the contribution of this amalgamation of parameters on eWOM helpfulness. An array of experiments and findings of this research backs up our contribution to the literature.

Based on previous literature eight hypotheses were proposed (H1, H2, till H8) in this paper. Three econometric models were projected incorporating all the hypotheses. In the first model, we analyzed the impact of review variables on the helpfulness of reviews. In the second model, hotel variables were added to the model and their combined impact was studied. Finally, reviewer variables were added to the amalgamation and the combined impact of all three types of characteristics was studied. The world-renowned travel website TripAdvisor.com was selected for this study and 16,699 hotel-related reviews were used for the analysis. These reviews were written by 1,099 customers whose profile data was extracted for the research. If we observe the model results, we can see that they show better goodness of fit from 0.749 to 0.750. However, it was also observed that there was no change from model I to II which concludes that the hotel variable that was added to the model is significant but does not impact the goodness of fit.

We reported that eWOM length, readability, and subjectivity positively affect the eWOM helpfulness. This shows that people find a highly subjective drawn-out review to be more helpful as it contains more details and opinions about the product or service. We can also infer that a more readable review that is easy to read and understand reaches more people. We also reported a negative significant impact of review polarity and recency on eWOM helpfulness. It accounts for the fact that extremely positive or extremely negative reviews do not earn much of the reader's trust. They assume them to be written either by the company's well-wishers or competitors. A negative relationship with review recency also shows that more recent reviews have a higher appeal to customers in comparison to older reviews. We also reported a significant positive relationship between hotel rating and review helpfulness. However, our results show that it fails to improve the goodness of fit of the model. In the end, we studied the impact of reviewer badge and reviewer helpfulness (calculated from the helpful votes received by a reviewer) combined with review and hotel parameters on the eWOM helpfulness. We present a positive significant impact of both the variables on the helpfulness which can be encoded to the understanding that eWOM written by a reviewer who has attained a reputation in the travel community is found to be trusted more by the readers. We also reached the understanding that to better discern what affects the helpfulness of reviews, a combined analysis of all the affecting parameters gives better results.

Implications

The prevailing research makes several theoretical and practical implications that are useful for the service providers of the industry and enhances the literature as well. Prior studies have focused on miscellaneous contributions of eWOM on a variety of customer behaviors like purchase intention, etc. (Ye et al., 2011). This research aims to analyze the impact of certain review, hotel, and reviewer characteristics on eWOM helpfulness. Talking about theoretical implications, first, we can say that the econometric modelling method used in this study to conduct the research explains why a particular review is more helpful than the other one. Second, this paper is among the very few ones that have combined aspects regarding all three fields (namely review, hotel, and reviewer) to find out what enhances eWOM helpfulness. Third, this study contributes to the literature as the thoughtfully picked combination of variables is unique and has not been explored in the history of the tourism and hospitality industry. This research also provides some practical or managerial implications. First, we found that lengthy reviews which are easy to understand are more helpful to people. Thus, hoteliers should keep an eye on such reviews to know what the customers found appealing and what disgusted them.

Second, since recently posted reviews are more helpful, hoteliers should encourage more and more travelers to share their experiences either by providing them some incentives or rewards for posting the review. Third, our study also implied that hotel rating positively affects eWOM helpfulness, thus practitioners should focus on improving their ratings by providing better services, ambiance, and overall holiday experience. They can also strive to introduce something unique like some dish or event, or activity etc. from time to time to maintain a spark of uncertain newness among the customers which will lure more travelers. This will also help them with improving their sales and thus market reputation and annual turnovers. Fourth, since prospective customers have limited patience and time, they only tend to go through the most helpful reviews to decide whether to opt for this hotel or not. Thus, the managerial team should assign designated personnel to reply to the helpful reviews. Fifth, a reputed, well-recognized reviewer has been found to write more helpful reviews. Thus, such contributors should be provided with some incentives as a token of appreciation which will encourage more and more customers to write reviews. Our findings also have implications for OTA websites like TripAdvisor.com, as these results can help them identify helpful eWOM which they can segregate and show to the customer at the top. This could save the user from information overload and the hefty task of scanning a huge pile of reviews. Easy availability of the required information will encourage the user to visit more often and will increase the number of customers on that OTA website.

Limitations and Future Scope

This study has a few limitations which are mainly due to the following reasons. First, the data set used in this research is taken from TripAdvisor.com, in future studies datasets from a different OTA website can be used to conduct the research. Datasets from several travel websites can be taken together as well to conduct a more in-depth study. Second, we use only hotel-related reviews in this paper. In the future, researchers can extend this study to different domains by using reviews of restaurants, flights, etc. Third, we have done econometric modelling in this paper to study the impact of various parameters on eWOM helpfulness. It can be extended by involving machine learning in the future to study the drivers of eWOM helpfulness. A comparative study of both techniques can also be conducted to analyze which technique provides better results. Fourth, a different set of variables can be explored to study their impact on the helpfulness of customer reviews.

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Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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