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Customer satisfaction scores: New models to estimate the number of fake reviews

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ABSTRACT

In this paper we develop new models for the distribution of customer satisfaction scores. This leads to new approaches for estimating the number of fake reviews in empirical data. Modifications of the basic model are presented that account for the propensity of extreme positive and negative reviews, and a potential lack of engagement on the part of reviewers. Further work to incorporate price and cultural effects is proposed.

1. Introduction

Online customer satisfaction data may variously drive sales, firm value and performance, and build customer satisfaction (Huang & Crotts, 2019). Though potential customers often make use of textual reviews the aggregation of ratings into a single number for each product or service constitutes an important filtering stage (Soifer et al., 2021). Hence, more principled modelling of customer satisfaction ratings is important in ensuring related decision making remains sound.

Baka (2016) recommends “systematic management of reputation” in relation to user-generated content. Fake reviews have emerged as a significant problem affecting ratings (Wu et al., 2020). The effect can be both positive and negative (Choi et al., 2017). The impact of fake reviews is substantial (Filleri et al., 2015; Martinez-Torres & Toral, 2019) and likely to grow further given recent developments in AI. Fake reviews, and the subsequent distrust caused, may damage all concerned (Akhtar et al., 2019). High stakes and excessive pressure may lead managers to manipulate ratings (Banerjee, 2022).

In this paper we develop new models for customer-satisfaction scores. Using an approach borrowed from physics (Visser, 2013) we build on a range of recent Tourism (Koo et al., 2017) and non-Tourism (Clauset et al., 2009) applications. We construct a baseline model that combines an elegant analytical framework with the empirically realistic feature that higher ratings are progressively more likely to occur (Hu et al., 2009). The number of fake reviews can then be identified as a departure from this baseline model. The model is first developed for longitudinal data constituting repeat observations from the same hotel. We then present a modification for cross-sectional data that provides a better description of empirical datasets on fake reviews (Gryka & Janicki, 2023). In a mathematical appendix at the end of this paper, we show that other forms of extreme behaviour that may artificially depress ratings can also be modelled. This includes a less-commonly observed under-reporting bias (Hu et al., 2009) and limited reviewer engagement.

The contribution of our paper is fourfold. Firstly, we provide foundational models of customer-satisfaction scores. These combine power-law type models (Clauset et al., 2009) with a widely documented participative bias known to affect ratings (Hu et al., 2009). Secondly, we develop principled models for the number of fake positive and fake negative reviews. If fake negative reviews occur, they are assumed to result in the lowest possible score of 1 being awarded with probability 1. If fake positive reviews occur, they are assumed to result in the highest possible score of U being awarded with probability 1. Some empirical support for this idea is presented in Section 2. If baseline model parameters are estimated from the distribution of ratings in the range $2 \leq x \leq U-1$, we can then reverse-engineer estimates of the number of fake positive and fake negative reviews and de-bias accordingly (Brint & Fry, 2021). Our focus on the ratings part of fake reviews thus serves as an important contrast with previous approaches that analyse individual review characteristics. In empirical applications the method can be shown to apply across both longitudinal and cross-sectional datasets. Thirdly, we apply our model, and proposed de-biasing method, to empirical hotel ratings data. Fourthly, motivated by punitive reviews in

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other contexts (Fry, 2024), we model alternative ways in which customer-satisfaction scores may be artificially lowered by extreme behaviours on the part of reviewers.

The layout of this paper is as follows. Section 2 develops a model for longitudinal data constituting repeat observations from the same hotel. Motivated by the cross-sectional nature of empirical datasets (Gryka & Janicki, 2023) Section 3 extends the model in Section 2 to cross-sectional data. Empirical applications are discussed in Section 4 (longitudinal data) and Section 5 (cross-sectional data). Section 6 concludes and discusses the opportunities for further research. A mathematical appendix exploring alternative ways of modelling extreme survey responses is contained at the end of the paper.

2. Modelling and estimating the number of fake reviews in longitudinal data

In this section we develop a model for longitudinal ratings data constituting repeat observations from the same hotel. The model is subsequently applied to empirical customer-satisfaction data in Section 4. The model is then adapted for different data types (Gryka & Janicki, 2023) in Section 3 leading to a further empirical application in Section 5.

Suppose that customer satisfaction scores are on the scale 1, 2, …, U with higher marks better. A typical value is $U = 5$ (Brint & Fry, 2021). Consider a discrete random variable X that takes values on 1, 2, …, U with $p_n = Pr(X = n)$. We follow a maximum entropy approach (Visser, 2013) that seeks to maximise the entropy given by $S = -\sum_{n=1}^{U} p_n \ln(p_n)$. The method of maximum entropy is an accepted way of constructing probability models based around the physical notion that in the longer term the statistical behaviour of a system will converge to the maximum entropy configuration (see e.g. Bishop, 2006).

Suppose as shown in equation (1), the expected value of the logarithm of X (the geometric mean) is constrained to be equal to μ_1:

$$E[\ln[X]] = \sum_{n=1}^{U} p_n \ln(n) = \mu_1. \tag{1}$$

This construction is both tractable and linked to a voluminous academic literature on service-quality index construction (Van Puyenbroeck & Rogge, 2017). To maximise the entropy, we maximise

$$-\sum_{n=1}^{U} p_n \ln(p_n) - \eta\left(\sum_{n=1}^{U} p_n - 1\right) + \alpha\left(\sum_{n=1}^{U} p_n \ln(n) - \mu_1\right). \tag{2}$$

in equation (2) η is a Lagrange multiplier ensuring the normalisation condition $\sum_{n=1}^{U} p_n = 1$ holds. Similarly, α is a Lagrange multiplier corresponding to the constraint (1). Equation (2) shows that the parameter α provides a "force" that ensures the constructed probability density exhibits a participative effect with high values progressively more likely provided $\alpha > 0$ (Hu et al., 2009). From a Tourism perspective α matches the high number of cases where expectations are met in theories such as the PZB service quality model (Parasuraman et al., 1985) and the expectation/disconfirmation model (Zhang et al., 2021). It follows that

$$-\ln(p_n) - 1 - \eta + \alpha \ln(n) = 0;\ \ln(p_n) = \alpha \ln(n) + C;\ p_n = An^{\alpha}, \tag{3}$$

where A is constant with respect to n. Equation (3) thus predicts that X should be power-law distributed with exponent $-\alpha$. A similar power law model used in Tourism applications is discussed in Koo et al. (2017). The distribution in (3) has probability mass function

$$Pr(X = n) = p_n = \frac{n^{\alpha}}{H_U(-\alpha)}, \tag{4}$$

where $H_U(z) = \sum_{n=1}^{U} n^{-z}$ is the Generalized Harmonic number (Visser, 2013).

Further

$$E[X] = \mu_1 = \frac{H_U(-\alpha - 1)}{H_U(-\alpha)}. \tag{5}$$

in the sequel we adapt the above model to estimate the number of fake positive and fake negative reviews. Suppose that with probability f_1 a respondent leaves a fake negative review resulting in a score of 1. Similarly, suppose that with probability f_U a respondent leaves a fake positive review resulting in a score of U. Some empirical support for this propensity of fake reviews to award the maximum rating of 5 is given in Table 1. With probability $1 - f_1 - f_U$ the reviewer is assumed to be fair and leaves a review according to the distribution in (4). Firstly, restricting to observed ratings in the body of the distribution $2 \le x_i \le U - 1$, we use equation (4) to estimate α by maximum likelihood. Next, we equate the observed proportion o_1 and o_U of scores equal to 1 and U respectively to their theoretical values:

$$\begin{aligned} &\text{Proportion of 1 scores} \quad f_1 + \frac{1 - f_1 - f_U}{H_U(-\alpha)} = o_1 \\ &\text{Proportion of U scores} \quad f_U + \frac{(1 - f_1 - f_U)U^{\alpha}}{H_U(-\alpha)} = o_U. \end{aligned} \tag{6}$$

Equation (6) can then be solved to give

$$\begin{aligned} f_1 &= \frac{o_1 H_U(-\alpha) + o_U - (U^{\alpha} o_1 + 1)}{H_U(-\alpha) - (U^{\alpha} + 1)} \\ f_U &= \frac{o_U H_U(-\alpha) - o_U - U^{\alpha} + U^{\alpha} o_1}{H_U(-\alpha) - (U^{\alpha} + 1)}. \end{aligned} \tag{7}$$

The values of f_1 and f_U thus obtained in (7) are the estimated proportions of fake negative and fake positive reviews.

3. Modelling and estimating the number of fake reviews in cross-sectional data

In this section we discuss the modelling of fake reviews in cross-sectional data. Such a construction tallies with the format of available datasets (Gryka & Janicki, 2023), leading directly to a further empirical application in Section 5. In the model in Section 2

$$Pr(X = n) = q_n \propto n^{\alpha}. \tag{8}$$

in equation (8) α corresponds to repeated ratings from the same hotel. Next, suppose that we have cross-sectional rather than longitudinal data. This situation is of practical interest since one of the few published datasets that identifies genuine and fake reviews is of this form (Gryka & Janicki, 2023). Suppose there is now only one observation per hotel. The parameter α in (8) now varies across the population. A convenient choice is a gamma distribution for α: $\alpha \sim \Gamma(\mu, \beta)$. This construction remains analytically tractable, ensures α remains non-negative and has the flexibility to model a range of different distributional shapes. If α is gamma distributed (8) should be replaced by

$$Pr(X = n) = q_n \propto \int_0^{\infty} \frac{n^{\alpha} \beta^{\mu} \alpha^{\mu-1} e^{-\beta\alpha}}{\Gamma(\mu)} d\alpha = \left(\frac{\beta}{\beta - \ln n}\right)^{\mu}. \tag{9}$$

The probability mass function then becomes

Table 1
Empirical distribution of survey ratings for online ratings identified as fakes in Gryka and Janicki (2023).

Rating	Probability
1	0.005
2	0.001
3	0.001
4	0.007
5	0.986

$$q_n = \frac{(\beta - \ln n)^{-\mu}}{\sum_{i=1}^{U} (\beta - \ln i)^{-\mu}}. \tag{10}$$

If we assume that fake negative and fake positive reviews occur in the same way as before equation (6) now becomes

$$\begin{array}{ll} \text{Proportion of 1 scores} & f_1 + (1 - f_1 - f_U) q_1 = o_1 \\ \text{Proportion of U scores} & f_U + (1 - f_1 - f_U) q_U = o_U. \end{array} \tag{11}$$

Equation (11) can then be solved to give

$$\begin{aligned} f_1 &= \frac{o_1 - q_1 - q_U o_1 + q_1 o_U}{1 - q_U - q_1} \\ f_U &= \frac{q_U o_1 + o_U - q_U - q_1 o_U}{1 - q_U - q_1}, \end{aligned} \tag{12}$$

where q_1 and q_U are given by equation (10).

4. Empirical application I: Sheffield hotels

In this section we estimate the proportion of fake positive and fake negative reviews in empirical data. We analyse the performance of hotels located in the Northern English city of Sheffield – known as a source of interesting operations-research questions (Fry & Binner, 2016). Results are shown in Table 2. Columns 2–5 list the observed data. Column 6 gives maximum likelihood estimates of α from data with the lowest possible values (1) and highest possible values (5) removed. These α values are then used in conjunction with equation (5) to compute average customer satisfaction scores – corrected for the presence of fake reviews (see Column 9). Columns 7–8 give the estimated number of fake negative and fake positive reviews obtained from equation (7).

Empirical results in Table 2 suggest that accounting for fake reviews can lead to notable increases in the average score received. A large proportion of the lowest scores received may be false negatives. Nonetheless there appear to be some cases where fake positive reviews may have artificially inflated observed scores.

5. Empirical application II: fake reviews

In this section we compare our model in Section 3 with an empirical dataset containing an estimated 13.55% fake reviews (Gryka & Janicki, 2023). Using the method in Section 3 we estimate the proportion of fake reviews to be 23.32% with an associated 95% confidence interval of (1.54–30.25%). This suggests there is a significant number, up to around 30%, of fake reviews in the sample. Without accounting for the cross-sectional nature of the data the model in Section 2 over-estimates 37.77% fake reviews in the sample. This means that when applied to an empirical dataset the cross-sectional model can both lead to marked improvements over a purely longitudinal model and a reasonable estimate of the number of fake reviews. Whilst the point estimate is roughly 10% too high the historically observed 13.55% lies within the constructed 95% confidence interval.

6. Conclusions

In this paper we develop new models for customer satisfaction scores. The approach leads to new ways of estimating the number of fake reviews from empirical data (Choi et al., 2017; Wu et al., 2020) and adjusting accordingly. Our distributional approach to estimating the number of fake reviews complements previous methods based on an analysis of reviewer details and review content. Suggested modifications to our baseline model are also proposed that explicitly account for extreme responses and lack of reviewer engagement. Further theoretical modelling of fake reviews may also be possible given interesting and freely available datasets in Gryka and Janicki (2023) and Salminen et al. (2022). In Section 5 an empirical application to the dataset in Gryka and Janicki (2023) suggests our model produces reasonable estimates of the number of fake reviews.

From a theoretical perspective all models developed here reconstruct the negative skew typically associated with customer satisfaction scores (Peterson & Wilson, 1992). Model development based around the

Table 2
Ratings for Sheffield hotels and suggested correction based on estimated numbers of fake negative and fake positive reviews.

Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8	Col. 9
Hotel	**n**	p_1	p_5	**Average score**	$\widehat{\alpha}$	f_1	f_5	**Corrected average**
Mercure St Paul's Hotel	3300	0.038	0.517	4.183	2.536	0.031	0.044	4.245
Novotel Centre	1949	0.048	0.348	3.887	2.345	0.034	0.000	4.196
Jurys Inn	3776	0.026	0.490	4.203	2.988	0.021	0.000	4.349
Premier Inn Centre (Angel Street)	1715	0.027	0.507	4.230	3.076	0.023	0.000	4.367
Leopold Hotel	1469	0.025	0.450	4.163	3.172	0.021	0.000	4.385
Hampton by Hilton	1800	0.026	0.509	4.274	3.767	0.024	0.000	4.486
Premier Inn Centre (St Mary's Gate)	1725	0.016	0.570	4.376	3.632	0.014	0.000	4.465
Premier Inn (Arena)	1041	0.022	0.608	4.389	3.116	0.019	0.121	4.374
Mercure Kenwood Hall & Spa	2039	0.098	0.243	3.478	1.323	0.048	0.000	3.828
Crowne Plaza Royal Victoria	1457	0.036	0.424	4.027	2.287	0.023	0.000	4.178
Ibis City	856	0.043	0.280	3.833	2.737	0.034	0.000	4.294
DoubleTree Sheffield Park	2070	0.049	0.410	4.016	2.790	0.042	0.000	4.306
Halifax Hall	968	0.019	0.539	4.292	2.980	0.014	0.000	4.347
Travelodge Central	956	0.052	0.414	3.997	2.591	0.043	0.000	4.259
Hotel Ibis Budget Arena	1138	0.109	0.221	3.420	1.373	0.061	0.000	3.850
Travelodge Meadowhall	1080	0.057	0.538	4.144	2.170	0.046	0.164	4.144
The Garrison Hotel	1007	0.036	0.508	4.214	3.155	0.032	0.000	4.382
Premier Inn Meadowhall Hotel	1327	0.032	0.520	4.234	3.070	0.028	0.000	4.365
Best Western Cutlers Hall	383	0.115	0.188	3.298	0.988	0.036	0.000	3.660
Travelodge Richmond	298	0.050	0.517	4.141	2.327	0.040	0.092	4.190
Brocco on the Park	322	0.006	0.770	4.606	1.602	0.000	0.607	3.947
Wilson Carlile Centre	105	0.029	0.495	4.143	2.086	0.014	0.070	4.118
easyHotel City Centre	317	0.082	0.533	4.117	2.877	0.077	0.068	4.325
The Florentine	336	0.042	0.491	4.122	2.286	0.030	0.040	4.178
Sleep Sheffield	118	0.220	0.220	3.271	2.341	0.208	0.000	4.194

maximum-entropy approach (Visser, 2013) is also interesting. It remains to incorporate price (Alexakis et al., 2021) and cultural variables (Huang & Crotts, 2019) alongside aspects of customer segmentation (Kirilenko et al., 2019; Wang et al., 2020). Our aim is that better theory leads to better benchmarking of observed customer-satisfaction scores (Brint & Fry, 2021).

There is a need for fairer performance management of surveys and customer-satisfaction scores (Fry, 2024). Fake reviews, and the subsequent distrust caused, may damage innocent bystanders (Akhtar et al., 2019). The proportion of fake reviews is already substantial with previous estimates ranging from 10% (Hu et al., 2012) to 33% (Saleh-Esfahani & Ozturk, 2018). This is likely to have grown further, particularly with recent developments in AI. Detailed measures to increase the trustworthiness of travel websites are discussed in Ahmad and Sun (2018). In response social media platforms have tried to identify fake reviewers. However, Banerjee (2022) notes that contextual nuances may limit the effectiveness of such algorithms. Moreover, the prevalence of fake reviews also necessitates critical thinking on the part of readers of reviews (Banerjee, 2022). This paper provides a different approach to detecting and removing fake reviews. Modelling the distribution of non-fake reviews allows the validity of the overall rating for a product or service to be assessed, and a potential correction to be applied. Consequently, this research is a valuable addition for those combatting fake reviews. It also allows third parties to produce corrected ratings without needing the reviewers' details. Ultimately, managers should not need to be drawn into review manipulation (Banerjee, 2022).

Several limitations of this research should be acknowledged. Firstly, the empirical evidence on fake reviews is scant though recent publicly available datasets are provided by Gryka and Janicki (2023) and Salminen et al. (2022). There is therefore a need for further empirical analysis of fake reviews including diagnostic testing of models developed in this paper. Secondly, more work needs to be done to establish the true level of applicability of models developed in this paper. An early empirical application in Section 4 showcases the kinds of benchmarking analysis that may ultimately be possible. A further empirical application in Section 5 gives a reasonable estimate of the number of fake reviews in the limited empirical data that is available. Appropriate benchmarking of customer satisfaction data remains an interesting and important practical problem in its own right (Brint & Fry, 2021; Fry, 2024). Thirdly, models presented in this paper provide a rather narrow description of the kinds of fake reviews and extreme behavior that can affect ratings – albeit one that is motivated by the limited empirical evidence available (Gryka & Janicki, 2023). Alternative ways of modeling extreme behavior on the part of online reviewers are outlined in the Appendix. There is a lot of scope for further model development and empirical testing on this theme.

Impact

Review websites play a very important role when people are choosing hotels. Poor ratings may thus threaten a hotel's viability. Consequently, the presence of fake ratings is a significant concern that is likely to only increase with time. Research on countering this problem has focussed on examining the reviewer's details and the content of the review. The paper takes a complementary approach by concentrating on the ratings to derive the expected distribution for the ratings. Once hotel ratings are calibrated to this distribution a correction can subsequently be applied to a hotel's overall rating to account for the presence of fake reviews. Therefore, the paper provides a novel tool that adds to the suite of measures for highlighting suspicious ratings and removing their effects. Hence, results in this paper are important in monitoring the validity of ratings both for hotels and for websites that provide hotel satisfaction ratings.

CRediT authorship contribution statement

John Fry: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Andrew Brint:** Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis, Data curation, Conceptualization.

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Appendix. Other distributional models for customer satisfaction scores

In this section we develop two related models to provide a more nuanced description of extreme survey responses compared to Section 2. The first model reconstructs a J-distribution shape reported in Hu et al. (2009). The second model is a special case of the first model but may be both more interpretable and easier to practically implement.

Suppose that with probability p respondents are participative in nature with their behaviour described by the distribution in (4). With probability $1-p$ respondents are extreme and instead their responses follow a U-shaped distribution which encourages extreme responses. This corresponds to an under-reporting bias in online customer satisfaction ratings (Hu et al., 2009). The effect can be constructed by introducing the constraint

$$E\ln\left|x-\frac{U+1}{2}\right| = c_1. \tag{13}$$

The value of c_1 describes the amount of concentration in the tails of the distribution. Let $g_n = Pr(X=n)$. If an individual conducts an extreme review entropy the following entropy functional is maximised:

$$-\sum_{n=1}^{U} g_n\ln(g_n) - \eta\left(\sum_{n=1}^{U} g_n - 1\right) + \beta\left(\sum_{n=1}^{U} g_n\ln\left|n-\frac{U+1}{2}\right| - c_1\right). \tag{14}$$

in equation (14) the parameter β is a force encouraging extreme ratings either side of the median value. From a Tourism perspective β corresponds to cases where expectations are not met in theories such as the PZB service quality model (Parasuraman et al., 1985) and the expectation/disconfirmation model (Zhang et al., 2021). Similar to the above, the solution to (14) becomes

$$-\ln(g_n) - 1 - \eta + \beta\ln\left|n-\frac{U+1}{2}\right|;\ \ln(g_n) = \beta\ln\left|n-\frac{U+1}{2}\right|;\ g_n = D\left|n-\frac{U+1}{2}\right|^{\beta}.$$

This leads to:

$$Pr(X=n) = g_n = \begin{cases} \dfrac{\left|n - \frac{U+1}{2}\right|^{\beta}}{2^{1-\beta}\sum_{i=1}^{U-1/2}(2i)^{\beta}} & U \text{ odd.} \\ \\ \dfrac{\left|n - \frac{U+1}{2}\right|^{\beta}}{2^{1-\beta}\sum_{i=1}^{U/2}(2i-1)^{\beta}} & U \text{ even.} \end{cases} \tag{15}$$

in this case the probability mass function for the observed score can now be written

$$Pr(X=n) = pp_n + (1-p)g_n. \tag{16}$$

An interesting special case of the above occurs when the parameter $\beta = 0$ in (14), leading to $g_n = 1/U$. In this case

$$Pr(X=n) = pp_n + \frac{(1-p)}{U}. \tag{17}$$

The distribution in (17) is easier to practically implement and has the interesting interpretation (Fry, 2024) that obtaining high customer satisfaction scores and informative feedback both require active participation on the part of reviewers.

References

Ahmad, W., & Sun, J. (2018). Modelling consumer distrust of online hotel reviews. *International Journal of Hospitality Management, 71*, 77–90.

Akhtar, N., Ahmad, W., Siddiqi, U. I., & Akhtar, M. N. (2019). Predictors and outcomes of consumer deception in hotel reviews: The roles of reviewer type and attribution of service failure. *Journal of Hospitality and Tourism Management, 39*, 65–75.

Alexakis, C., Dowling, M., Pappas, V., Ramachandiran, M., & Skalves, F. (2021). Do hotel financial factors influence satisfaction? *Annals of Tourism Research, 90*, Article 103128.

Baka, V. (2016). The becoming of user-generated reviews: Looking at the past to understand the future of managing reputation in the travel sector. *Tourism Management, 53*, 148–162.

Banerjee, S. (2022). Exaggeration in fake vs. authentic online reviews for luxury and budget hotels. *International Journal of Information Management, 62*, Article 102416.

Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

Brint, A., & Fry, J. (2021). Regional bias when benchmarking services using customer satisfaction scores. *Total Quality Management and Business Excellence, 32*, 344–358.

Choi, S., Mattila, A. S., Van Hoof, H. B., & Quadri-Felitti, D. (2017). The role of power and incentives in introducing fake reviews in the tourism industry. *Journal of Travel Research, 56*, 975–987.

Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-law distributions in empirical data. *SIAM Review, 51*, 661–703.

Filleri, R., Alguezzaui, S., & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management, 51*, 174–185.

Fry, J. M. (2024). Revisiting student evaluation of teaching during the pandemic. *Applied Economics Letters, 31*, 1259–1263.

Fry, J., & Binner, J. (2016). Elementary modelling and behavioural analysis for emergency evacuations using Social Media. *European Journal of Operational Research, 249*, 1014–1023.

Gryka, P., & Janicki, A. (2023). Detecting fake reviews in Google maps – a case study. *Applied Sciences, 13*, 6331.

Hu, N., Bose, I., Koh, N. S., & Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability and sentiments. *Decision Support Systems, 52*, 674–684.

Hu, N., Zhang, J., & Pavlou, P. (2009). Overcoming the J-shaped distribution of product reviews. *Communications of the ACM, 52*, 144–147.

Huang, S., & Crotts, J. (2019). Relationship between Hofstede's cultural dimensions and tourist satisfaction: A cross-country cross-sample examination. *Tourism Management, 72*, 232–241.

Kirilenko, A. P., Stepchenkova, S. O., & Hernandez, J. M. (2019). Comparative clustering of destination attractions for different origin markets with network and spatial analyses of online reviews. *Tourism Management, 72*, 400–410.

Koo, T. T. R., Lau, P.-L., & Dwyer, L. (2017). The geographic dispersal of visitors: Insights from the power law. *Journal of Travel Research, 56*, 108–121.

Martinez-Torres, M. R., & Toral, S. L. (2019). A machine learning approach for the identification of the deceptive reviews in the hospitality sector using unique attributes and sentiment orientation. *Tourism Management, 75*, 393–403.

Parasuraman, A., Zeitharnl, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing, 49*, 41–50.

Peterson, R. A., & Wilson, W. R. (1992). Measuring customer satisfaction: Fact and artifact. *Journal of the Academy of Marketing Science, 20*, 61–71.

Saleh-Esfahani, S., & Ozturk, A. B. (2018). Negative reviews, formation, spread and halt of opportunistic behaviour. *International Journal of Hospitality Management, 74*, 138–146.

Salminen, J., Kandpal, C., Kamel, A. M., Jung, S.-G., & Jansen, B. J. (2022). Creating and detecting fake reviews of online products. *Journal of Retailing and Consumer Services, 64*, Article 102771.

Soifer, I., Choi, E.-K., & Lee, E. (2021). Do hotel attributes and amenities affect online user ratings differently across Hotel Star ratings? *Journal of Quality Assurance in Hospitality & Tourism, 22*, 539–560.

Van Puyenbroeck, T., & Rogge, N. (2017). Geometric mean quantity index number with benefit-of-the-doubt weights. *European Journal of Operational Research, 256*, 1004–1014.

Visser, M. (2013). Zipf's law, power laws and maximum entropy. *New Journal of Physics, 15*, Article 043021.

Wang, L., Wang, X., Peng, J., & Wang, J. (2020). The differences in hotel selection among various types of travellers: A comparative analysis with a useful bounded rationality behavioural decision-support model. *Tourism Management, 76*, Article 103961.

Wu, Y., Ngai, E. W. T., Wu, P., & Wu, C. (2020). Fake online reviews: Literature review, synthesis and directions for future research. *Decision Support Systems, 132*, Article 113280.

Zhang, J., Chen, W., Petrovsky, N., & Walker, R. M. (2021). The expectancy-disconfirmation model and citizen satisfaction with public services: A meta analysis and an agenda for best practice. *Public Administration Review, 82*, 147–159.

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