The Impact of Social Media on Lodging Performance

by Chris K. Anderson

ABOUT THE AUTHOR

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EXECUTIVE SUMMARY

Social media has been touted as having an increasingly important role in many aspects of the hospitality industry, including guest satisfaction and process improvement. However, one of the more intriguing aspects of social media is their potential to move markets by driving consumers' purchasing patterns and influencing lodging performance. In the absence of a comprehensive attempt to quantify the impact of social media upon lodging performance as measured by bookings, occupancy, and revenue, this report uses the unique position of Cornell's Center for Hospitality Research to combine data from three CHR research partners (ReviewPro, STR, and Travelocity), and two other data providers (comScore and TripAdvisor) in a first attempt at determining ROI for social-media efforts. The analysis finds the following. First, the percentage of consumers consulting reviews at TripAdvisor prior to booking a hotel room has steadily increased over time, as has the number of reviews they are reading prior to making their hotel choice. Second, transactional data from Travelocity illustrate that if a hotel increases its review scores by 1 point on a 5-point scale (e.g., from 3.3 to 4.3), the hotel can increase its price by 11.2 percent and still maintain the same occupancy or market share. Third, to measure the impact of user reviews on hotel pricing power, consumer demand, and revenue performance the study uses matched-sample data from ReviewPRO and STR. By matching ReviewPRO's Global Review IndexTM with STR's hotel sales and revenue data, a regression analysis finds that a 1-percent increase in a hotel's online reputation score leads up to a 0.89-percent increase in price as measured by the hotel's average daily rate (ADR). Similarly this 1-percent increase in reputation also leads to an occupancy increase of up to 0.54 percent. Finally, this 1-percent reputation improvement leads up to a 1.42-percent increase in revenue per available room (RevPAR).

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Hotel industry executives and managers have seen much anecdotal evidence that social media influence guests' booking behavior—and thereby rate and occupancy. However, so far I am aware of no comprehensive analysis of the extent to which social media postings move markets. The cooperation of three Cornell Center for Hospitality Research partners makes such an analysis possible, as presented in this report. Those partners, ReviewPro, STR, and Travelocity, make data available on a non-disclosure basis for aggregate analysis, in this case, an estimate of return on investment for social-media activities. For this report, comScore and TripAdvisor also provided data.

EXHIBIT 1

Factors in hotel selection

Guest Experience Factors	51%
Location	48%
Price	42%
Loyalty Program Points	18%
Promotions	16%
Amenities	8%
Convention	8%
Green Program	1%

Study by Market Metrix. *Hotel & Motel Management*, January 13, 2010.

In this CHR Report, I analyze the effect of social media upon consumers' purchase decisions and hotels' top-line performance. Using online consumer panel data from comScore, the study illustrates the upstream impact of TripAdvisor on online hotel reservations. In this portion of the study, I show that the percentage of consumers consulting reviews at TripAdvisor prior to booking a hotel room has steadily increased over time, as has the number of reviews they are reading prior to making their hotel choice. Using transactional data from Travelocity, I illustrate the impact of user reviews upon consumers' hotel choice at the time of purchase. Data from purchased and non-purchased hotels illustrate that if a hotel increases its review scores by 1 point on a 5-point scale (e.g., from 3.3 to 4.3), the hotel can increase price by 11.2 percent and still maintain the same occupancy or market share. Last I measure the impact of user reviews on hotel pricing power, consumer demand, and revenue performance using matched-sample data from ReviewPRO and STR. By matching ReviewPRO's Global Review IndexTM with STR's hotel sales and revenue data, I estimate the impact of hotels' online reputation in social-media channels upon hotel performance. I demonstrate that a 1-percent increase in a hotel's online reputation score leads up to a 0.89-percent increase in price as measured by the hotel's average daily rate (ADR). Similarly this 1-percent increase in reputation also leads to demand creation with up to a 0.54-percent increase in occupancy. Finally, this 1-percent reputation improvement leads up to a 1.42-percent increase in revenue per available room (RevPAR).

This research is the first to perform an assessment of the influence of social media upon hotel performance by illustrating the increasing role of social media in the research phase and how this ultimately leads to hotel pricing power and revenue generation. This is a step beyond earlier efforts that focused more on the use of social media rather than its impact on performance.[1] Similar to the early days of electronic distribution,[2] social media and user-generated content are of increasing importance in the eyes of hospitality companies as consumers become more engaged across numerous platforms during the decision process. One of the aims of this study is to help shed light on why some hotel companies are able to achieve price and occupancy premiums in this new environment.[3]

User Generated Content During Consumers' Hotel Search

TripAdvisor is by far the dominant source for online reviews in the hospitality space, with more than 75 million reviews generated by some 32 million users.[4] In terms of the hotel choice process, as reported by Market Metrix,[5] the tipping point came in 2010, as shown in Exhibit 1. At this point, the guest experience mentioned in customer reviews became the dominant factor in hotel selection, with 51 percent of survey respondents indicating they factored

[1] Rohit Verma and Ken McGill, "Travel Industry Benchmarking: Marketing ROI, Opportunities, and Challenges in Online and Social Media Channels for Destination and Marketing Firms," *Cornell Hospitality Report*, Center for Hospitality Research, Vol. 11 No. 9 (2011).

[2] Judy Siguaw and Bill Carroll, "Evolution in Electronic Distribution: Effects on Hotels and Intermediaries," *Cornell Hospitality Report*, Cornell Center for Hospitality, Vol. 3 No 5 (2005).

[3] Cathy A. Enz, Linda Canina, and Mark Lomanno, Competitive Hotel Pricing in Uncertain Times," *Cornell Hospitality Report*, Center for Hospitality Research, Vol. 9 No. 10 (2010).

[4] TripAdvisor.com, viewed October 2012.

[5] Jonathan Barsky and Lenny Nash, "What Is More Important than Location in Selecting a Hotel?," *Hotel & Motel Management*, January 13, 2010 (www.marketmetrix.com/en/default.aspx?s=research&p=MoreImportantThanLocation).
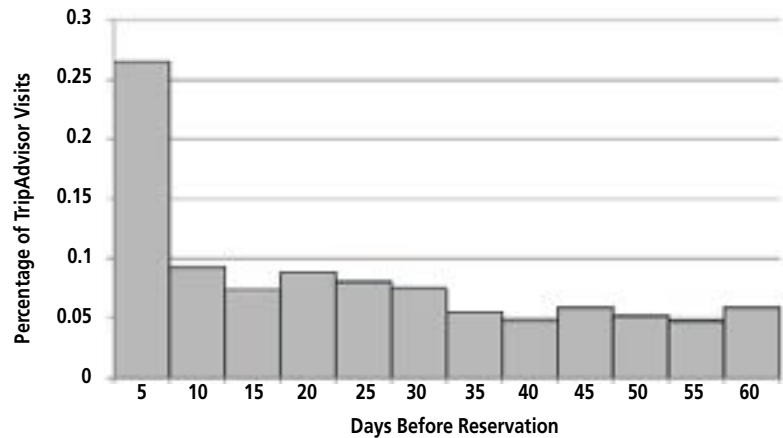
EXHIBIT 2

TripAdvisor visitation prior to Brand.com booking

Year	% of Brand.com visiting TripAdvisor	Visits per reservation	Pages per visit	Time per visit (minutes)
2008	28%	3.71	6.89	4.52
2009	26%	3.78	6.19	4.27
2010	36%	4.72	5.51	3.44

EXHIBIT 3

Distribution of when guests visit TripAdvisor.com

guest experience factors into their hotel selection decision. Given TripAdvisor's dominance in the generation of user reviews I focused on how often consumers consult TripAdvisor prior to booking a room using publicly available data from comScore.

TripAdvisor Traffic Prior to Brand.com Reservation

Using online consumer panel data from comScore I tracked TripAdvisor.com utilization during consumers' hotel research phase. The comScore panel measures how consumers behave in the digital environment, specifically their internet browsing, buying, and other activity. The firm does this by continuously measuring the online site visits made by approximately 2 million worldwide consumers.

This comScore dataset consists of 1,720 purchase events (hotel reservations) at InterContinental Hotels Group's HolidayInn.com site during nine months: June, July, and August of 2008, 2009, and 2010. This is an example of a brand's website that has come to be generically known as Brand.com. Owing to the nature of the comScore data I have all travel-related website visits (e.g., TripAdvisor.com, Orbitz.com, LasVegas.com) and travel-related searches (i.e., Google, Yahoo, and Bing) for 60 days prior to each of these reservations. Thus I can track the clickstream where consumers

went online prior to making a reservation at the suppliers' Brand.com website, and determine what sort of travel-related research they performed. As one would expect; consumers who make reservations online also spend a great deal of time online researching those transactions.

I focused on TripAdvisor reviews in this study. For a more generalized look at online behavior, please see my CHR Report, "Search, OTAs, and Online Booking: An Expanded Analysis of the Billboard Effect."[6] Exhibit 2 summarizes TripAdvisor behavior of guests who book directly at the Brand.com website. As shown, an increasing proportion of guests over the three years are visiting TripAdvisor prior to booking with the hotel directly. Not only is the fraction of consumers increasing, but those consumers that do visit are visiting more often (that is, visits per reservation are increasing) and they view more pages overall (although pages per visit and time per visit dropped slightly). I believe the drop in time per visit may be due to a more efficient TripAdvisor experience and faster connections (and computers) or simply the increase in consumers' search abilities.

Exhibit 3 summarizes customer activity in terms of when they visit TripAdvisor prior to booking their hotel at

[6] C.K. Anderson, "Search, OTAs, and Online Booking: An Expanded Analysis of the Billboard Effect," Center For Hospitality Research Report, Vol 11 No 8 (2011).

EXHIBIT 4

Logistic regression results: position, reviewer score, number of reviews, and relative room price

	Parameter Estimates*	Odds Ratio
Position	-0.1218	0.885
User review score	0.133	1.142
Number of reviews	0.0025	1.002
Relative price	-1.192	0.304

*All significant at 0.001 level.

the hotel's website. A little more than one-fourth (26.5%) of TripAdvisor visits occur in the last five days prior to the reservation, with the remaining three-quarters roughly equally spread out over the other 55 days. This may be an indication of how guests' research intensifies just prior to making the purchase decision. The close proximity (to the purchase) of consumer visitation to TripAdvisor perhaps indicates that user reviews are some of the final and potentially pivotal criteria in the hotel selection process.

Point of Purchase Impact

Moving away from Brand.com, let's look at the impact of user reviews at a different point of purchase, in this case, at an online travel agency. I analyzed the impact of user reviews at Travelocity.com upon the purchases made through that site. The data consist of 13,341 reservations made during July 2012 in nine major U.S. cities.[7] For each of these 13 thousand-plus reservations, I have information (as provided by a typical OTA display) for the property purchased, as well as all other properties not purchased on the final page the customer looked at prior to selecting the property in question.

Using these data we can gain insight into some of the key attributes that drive hotel selection decisions. Specifically, I estimate the probability a customer would purchase a given hotel as a function of price, user review ratings, and the number of user reviews. Because the outcome variable is binary (1 or 0; 1 for purchase, 0 for non-purchase), regular linear regression can't be used to estimate the impacts of these attributes upon the purchase decision. However, logistic regression can be applied. Using logistic regression I model the probability that a customer would purchase a listed hotel given its attributes (e.g., price, star rating). The logistic regression model given here:

$$\text{Probability of Purchase} \mid X = \frac{e^{\alpha+\beta X}}{1+e^{\alpha+\beta X}}$$

is similar to linear regression where outcomes are modeled as a function of a constant (α) and some attributes (X), which are weighted by parameters (β) modified with the use of Euler's number or e, a mathematical constant equal to about 2.71828. Please contact me if you would like a discussion of the technical issues behind why we need such a model. For this purpose, what is important to realize is that the βs in logistic regression, as in regular regression, indicate the impact of the attribute upon the outcome.

Exhibit 4 summarizes parameter estimates from a logistic regression model of purchase decisions. To account for the hotel's position on the screen, I added a variable, Position, to the independent variables. Position describes the placement of the hotel in the list of hotels (e.g., 1st, 2nd, or 3rd, from the top and so forth). Position takes values of 1-25 with 1 being the top position and 25 at the bottom of the list. Owing to the differences in prices across chain scales I use a relative price measure. The Price variable is a hotel's price divided by the average price of all same star hotels co-listed with the subject hotel. I also control for chain scale by adding an indicator variable for each star level. Of particular interest are the remaining two variables, review scores and review volume and their impacts upon price. Using the regression I estimate how much higher the hotel could price if it had better review scores.

Given the nature of logistic regression, the parameter estimates (the βs) are not as easily interpreted as in regular regression. Instead of using the parameter estimates, we focus on the odds ratio. The odds ratio represents the change in the odds of an option being chosen (in this case, that is the odds of the hotel being booked) given a one-unit change in the attribute. The odds are the probability of being selected divided by probability of not being selected ($\frac{P}{1-P}$). The Position value of 0.885 demonstrates the negative effect of being ever lower on the search results. If a hotel is listed at spot 2 versus 1 (or 10 versus 9) its odds of being selected decrease to 0.885 of the odds of being selected when in position 1. That equates to an 11.5-percent decrease in its chances for every notch it drops (all else being equal).

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[7] Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York, Orlando, and Phoenix.

The results of review scores move in the other direction. Using Travelocity's 5-point score for user reviews, the Review Score odds ratio means that increasing one point increases the odds of being selected by 14.2 percent Using the example of a hotel that goes from a review score of, say, 3.3 to one of 4.3, that property has increased its odds of being selected by 1.142 times the odds when its review score was 3.3. A similar result is found for Number of reviews. The 1.002 indicates that for each new review a hotel adds, it increases its odds of being selected increase by 1.002 or 0.2 percent.

It is a little harder to interpret the odds ratio of price in this equation because this variable is actually relative price. Price is perhaps best understood by combining the effects of price and review scores. Say that the average price of all competing hotels (those with the same star rating) that appear on the list page with our hotel was $100 and our hotel's price was $100. If we were to increase our review score from 3.3 to 4.3 we could increase our price about 11.2 percent and maintain the same probability of being selected. The positive effect of the review score change on the odds of being chosen would offset the presumably negative odds caused by a price increase.

Impact on Hotel Performance

Taking the analysis one step further, I analyze the effect of social presence on overall hotel performance, again using matched samples of performance data and online reputation data. Performance data are monthly revenue, demand, and supply data from STR for 2½ years (January 2010 through June 2012) for each subject property. I also compared each hotel with its specified list of competitors, to gain a sense of relative performance in an effort to control for seasonality. I have these data for 11 major markets (6 European and 5 North American cities).[8]

I use ReviewPro's Global Review Index (GRI) for the subject hotels as well as each hotel within its STR listed competitive set as a measure of online reputation. ReviewPro aggregates hundreds of millions of social media mentions, in over 35 languages, from Online Travel Agencies (OTAs), review websites and social media platforms. Their GRI is an aggregate online reputation score for an individual hotel, group of hotels, or chain. It is based on scores given by reviewers on major online review sites and online travel agencies (OTAs). The GRI is calculated by analyzing quantitative scores on these sites, using a proprietary algorithm.[9]

With this matched data set we look at the impact of GRI on three typical industry metrics: ADR (average daily rate),

occupancy, and RevPAR (revenue per available room). In all cases, I am using an index. Thus the measurements are the effect of GRI against a hotel's pricing power as measured by its ADR Index, which is a hotel's average daily rate divided by the average of its competitors' ADRs; the GRI's impact upon demand as measured by the occupancy index, and on overall performance as measured by GRI upon a RevPAR index. Likewise, the GRI Index is calculated as the subject hotel's GRI divided by the average GRI of its competitive set hotels. This GRI Index is the independent variable. Similar to many marketing actions (e.g., advertising and pricing) we can anticipate decreasing marginal returns.[10] That is, as the GRI score increases the additional impact upon performance decreases. To incorporate decreasing marginal returns, I use a multiplicative model of impact often referred to as a constant elasticity model. Using price and demand as an example I illustrate this approach as follows.

Price elasticity of demand is defined as the percentage change in demand for a given percentage change in price. So, for example, if price increased by 1 percent, and as a result demand fell 2 percent, then elasticity is -2 (-2%/1%). Price elasticity (ε) can be expressed as:

$$\varepsilon = \frac{\%\Delta Q}{\%\Delta P} = \frac{\partial Q}{\partial P}\frac{P}{Q}$$

where ε is the price elasticity, P is the price, and Q is the quantity demanded.

If we propose decreasing marginal returns, a demand model might look like $Q=aP^b$. If we take the natural logarithm (the inverse of Euler's number) of each side of this equation we get a log-linear demand model of the following form:

$$lnQ = a + b \cdot lnP$$

where Q and P are defined as before, and a and b are parameters to be estimated. The log-linear demand function implies that the price elasticity of demand is constant:

$$\varepsilon = \frac{dlnQ}{dlnP} = b$$

Using data from over 50,000 monthly observations from the eleven global cities, we can look at the impact of GRI upon performance in this log linear framework where I model the impact of ln(GRI Index) upon ln(ADR Index), ln(Occupancy Index), and ln(RevPAR Index), using three log linear models. Exhibit 5 summarizes the elasticities for GRI upon these three performance metrics. The table indicates a stronger impact of GRI upon pricing power

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[8] Berlin, Chicago, London, Madrid, Miami, Milan, Los Angeles, New York, Prague, Rome, and San Francisco.

[9] More details on the Global Review Index can be found at www.reviewpro.com/product/global-review-index.

[10] For an example of the diminishing marginal returns principle, see: Joseph Thomas, "Linear Programming Models for Production-Advertising Decisions," Management Science, Vol. 17, No. 8 (April 1971), pp. B-474–B-484.

Exhibit 5

GRI elasticity

	Pricing Power (ADR)	Demand (Occupancy)	Performance (RevPAR)
All	0.80	0.20	0.96
Luxury	0.44	0.09	0.49
Upper Upscale	0.57	0.30	0.74
Upscale	0.67	0.19	0.83
Upper MidScale	0.74	0.42	1.13
MidScale	0.89	0.54	1.42

(ADR) than on demand (Occupancy). This indicates firms are pricing consistent with their value proposition. Better reviews lead to higher prices, while lower reviews force prices lower for hotels to achieve similar occupancies under both settings. As the impacts of GRI upon demand and pricing power are both positive, the impact upon performance or RevPAR is even stronger. The first row in Exhibit 5 looks at all chain scales together, with the subsequent rows looking at online reputation impact by chain scale. The table entries represent the percentage impact upon pricing, demand, and performance given a 1-percent change in online reputation as measured by GRI. Looking at the first row, a 1-percent increase in a hotel's GRI score, say from 80 to 80.8 aligns with a 0.96-percent increase in RevPAR. It is interesting to compare the RevPAR elasticity across chain scales, as the effect of online reputation is stronger for lower-end chain scales. Thus, the gain from online reputation improvement is much more profound for a midscale property (1.42%) than for a luxury hotel (.49%). Given the vast diversity of service levels in midscale hotels, would-be guests may experience more uncertainty in the level of service in lower chain scales. Thus, it makes sense that reviews in the form of the GRI have a much stronger effect on lower chain scales. The improvement in online reputation represented by a strong GRI reduces the level of service quality uncertainty in the eyes of consumers. As a result those highly rated firms have increased pricing power compared to those with lower ratings.

Summary

Hotel operators have suspected that the effect of social media and user generated content on hotel performance has been strengthening. This paper provides a numerical confirmation and estimate of those effects. Reviews and review sites continue to be in the forefront when consumers

are planning a hotel room purchase. Our comScore sample indicates that the percentage of consumers consulting online review sites prior to their purchase is increasing with time, and the number of visits per person also has grown noticeably. With regard to online reviews, TripAdvisor continues to play an increasing role in the eyes of consumers, and with its marketing options this site has the potential to affect hotel performance as it acts as a portal to brand sites. More generally, OTA reviews, their quality and numbers, lead to increased conversion rates and improved pricing power at the OTA, as evidenced by our investigation of transactions at Travelocity. Using logistic regression to model purchase incidence I estimate that a 1-point increase in user review score (on an OTA's 5-point scale) would allow a property to increase price by 11.2 percent and maintain the same purchase probability or market share. Last, the cumulative impact of user reviews across all channels shows a positive relationship with overall hotel performance. We see that improved online reputation, as measured by ReviewPRO's GRI, results in increased pricing power and occupancy for a hotel. The model estimates that a 1-percent increase in GRI leads to as much as a 0.89-percent increase in ADR, and a 0.54-percent increase in occupancy. Combining these effects, a 1-percent increase in GRI results in up to a 1.42-percent increase in RevPAR.

As a note of caution this study has focused on the impact of user generated content and hotel performance. Needless to say, many factors contribute to hotel performance that are not measured here. That said, these results are generalizable to the extent that the factors that are not measured are random across the firms in our samples. As I attempted to collect a sample across a wide spectrum locations, it is reasonable to say that these results do apply to hotels generally. ■

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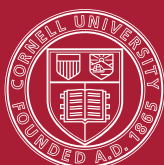
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