The interactive effects of online reviews on the determinants of Swiss hotel performance: A neural network analysis

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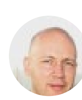
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The interactive effects of online reviews on the determinants of Swiss hotel performance: A neural network analysis

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HIGHLIGHTS

- We examine the determinants of Swiss hotel performance.
- We use an artificial neural network model to build on prior eWOM studies.
- Regional room star rating has a positive impact on RevPar.
- Room quality, regional review, hotel regional reputation negatively affect RevPar.
- Findings imply boundaries to reputational benefits for Swiss hotels.

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ABSTRACT

From a strategy perspective, the growth of social media accelerates the need for tourism organisations to constantly re-appraise their competitive strategies. This study contributes theoretically to the tourism performance literature by validating a new approach to examining the determinants of hotel performance. Drawing from and extending prior hotel determinants studies, this study uses artificial neural network model with ten input variables to investigate the relationships among user generated online reviews, hotel characteristics, and Revpar. The sample includes 235 Swiss hotels for the period 2008–2010, with 59,688 positive reviews from 69 online sources.

The empirical findings reveal four hidden nodes that have a significant impact on RevPar. Three of these have negative impacts: room quality, positive regional review, hotel regional reputation, and regional room star rating has a positive impact. Further, the findings imply that there may be boundaries to reputational benefits for Swiss hotels.

1. Introduction

Successful tourism organisations tend to focus attention on those factors that enhance performance, so that they can maintain sustainable long-term success. The deployment of assets, resources, processes, capabilities and competencies that collectively provide the tourism organisation its unique advantage remain the key components of a successful strategy. Although the strategy literature advocates a variety of universal rules and concepts to enhance performance (Phillips, Davies, & Moutinho, 2002), to date there has been a paucity of fresh approaches investigating the determinants of tourism performance.

The identification of new determinants of tourism performance remains one of the most critical activities for those concerned with the planning and management of tourism organisations. Today's tourism performance measurement approaches have to comprise financial and non-financial performance measures linked to business strategy (Vila, Costa, & Rovira, 2010). Moreover, technological turbulence in the external environment, market competition and more discerning customers make it a requirement that tourism organisations constantly re-appraise the effectiveness of their competitive strategies.

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The increasing use of social media in the tourism industry has resulted in electronic Word of Mouth (eWOM) reviews having a strong influence in consumer decision-making (Blal & Sturman, 2014). Moreover, the influence of the Internet has created the growth of new hospitality and tourism applications. A detailed analysis by Scaglione, Schegg, and Murphy (2009) of monthly revenue indicators of 147 Swiss hotels between 1992 and 2003 indicates that website adoption is positively related to performance. Their results suggest that the adoption of an innovation, i.e. the creation of a website, relates to a performance indicator – Revenue per Available Room (RevPar). Consequently, hoteliers are diverting increasing resources to efficiently aggregate, organise and manage their online reputations. When online reputations are effectively managed, hoteliers can perform better internal and external analyses of their operations. Monitoring can take place at the individual unit, brand and chain level.

User generated content (UGC) and in particular, online reviews have seen rapid growth in recent years. Interestingly, according to TripAdvisor (2014a) a significant proportion of its four million business and properties relates to accommodation with hotels, B&B and speciality lodging, accounting for 810,000 units. In February 2014, TripAdvisor (2014b) issued a press release announcing a UGC milestone making it the first travel site to offer consumers 150 millions reviews and opinions. The increase in online reviews echoes a similar pattern to the growth of hotel room bookings through e-distribution (O'Connor, 2008; Schegg & Scaglione, 2013; Toh, Raven, & DeKay, 2011). However, despite the achievement of the eWOM stream of research (Cantallops & Salvi, 2014), research can go further in providing broader insights of eWOM as a determinant of hotel performance.

This paper asserts that while eWOM research has enriched our knowledge of the impact on performance; it has not yet fully considered a comprehensive view of performance determinants. Previous eWOM performance studies assume a direct relationship between online consumer reviews and performance with studies deploying a bi-variate methodology (Anderson, 2012; Tuominen, 2011; Ye, Law, & Gu, 2009). While bi-variate approaches are important for articulating initial insights, the changing business dynamics necessitate broader insights into what underpins hotel performance. In addition, future eWOM performance research should focus on broader geographic areas and include different types of hotels (Levy, Duan, & Boo, 2013).

The motivation for our current work is to develop the notion of determinants of tourism performance. Specifically we draw from and extend prior works of Anderson (2012); Duverger (2013); Tuominen (2011) and Ye, Law, Gu, and Chen (2011). In this context, our study makes several contributions to the literature. The first is to comprehensively assess the impact of online reviews on RevPar across a single country, Switzerland, taking into account different locations, regions, types of hotels in terms of number of rooms and number of beds, and hotel quality. Second, our model proposes the utilisation of an aggregated evaluation score in order to evaluate UGC. The study uses the aggregated TrustYou (www.trustyou.com) score, a propriety measure based on reviews across 69 review and social media sites worldwide. By combining actual hotel performance data with hotel profile and UGC data, we contribute to the tourism literature in that we evaluate the relationship between the aggregated score and performance of a wide range of hotels. Third, methodologically, the study contributes to the existing tourism literature by validating a new approach to determine the relationship between user-generated online reviews and hotel performance. We propose Artificial Neural Network (ANN) as a method for analysing the determinants of hotel performance. ANNs do not require prior knowledge of the distribution, which make them particularly suitable for complex relationships. Finally, our findings make a meaningful theoretical and practical contribution to the Swiss hotel sector, which can help decision-makers enhance the level of economic and social benefits.

The structure of this paper is as follows. First, the concept of UGC and its use in the tourism industry are discussed. Second, UGC and tourism performance studies are reviewed. Third, ANNs are introduced followed by the method of the study. The background, sample, model and data analysis are presented. Finally, conclusions and implications are offered.

2. User generated content

In the past decade there has been growing interest in the application of social media to the hospitality and tourism domain. Much of this interest has arisen from the emergence of Web 2.0, which has resulted in numerous UGC websites capturing online reviews, online recommendations, or online opinions shared by customers (Ayeh, Au, & Law, 2013; Cantallops & Salvi, 2014). Within the tourism industry, hotel businesses are probably most affected by UGC, which is shared on social networks, online travel communities, and review sites (Ayeh et al., 2013; Tuominen, 2011).

Nevertheless, due to the increasing number of platforms and online reviews there is now awareness among tourism managers that consumers' online reviews form a rich source of data. According to a SAS Institute Inc. study (McGuire, 2013), the bottom line is that driving revenue in the hospitality industry is no longer just about competing on price as consumers are clearly turning to UGC to inform their purchase decisions. Reviews as a resource can contribute to the effective management of the entire sector and to the achievement of competitive advantage of tourism businesses (Kim & Hardin, 2010; Leung, Law, van Hoof & Buhalis, 2013; Lu & Stepchenkova, 2012; Robson, Farshid, Bredican, & Humphrey, 2013). User generated reviews are a significant source of information for companies and the analysis of the information can facilitate improvement in the quality of the products/services, the identification of customer needs and the implementation of new marketing strategies (Jun, Vogt, & MacKay, 2010; Loureiro & Kastenholz, 2011; Yacouel & Fleischer, 2012).

The significance of online reputation implies that its management should be seen as a strategic issue, and the links between the management of reputation and financial performance explored (Davies, Chun, & Kamin, 2010). Yet, research on the impact of user generated online reviews on business activities has focussed on sales and bookings (e.g. Ye et al., 2009 and Ye et al., 2011) and to a lesser extent on the impact on financial performance. Within the tourism literature, research on this relationship seems to be scarce and Tuominen (2011) argues that the issue of the impact of online consumer generated reviews on the performance of hospitality businesses has been overlooked previously. Ye et al. (2011) state that the influence of user-generated online reviews is largely unknown in the tourism industry.

2.1. User generated content and performance

Within the tourism context, researchers such as Dickinger and Mazanec (2008), Ye et al. (2009, 2011) analysed the impact of online reviews on hotel bookings and found that positive reviews can significantly increase the number of bookings and that the variance or polarity of eWOM for the reviews of a hotel had a negative impact on the amount of online sales. Cantallops and Salvi (2014) and Ye et al. (2011) call for more research into the relationship between online reviews and business performance arguing that this relationship has not been explored in great detail. The lack of attention might be explained by the fact that obtaining actual business performance data matched to the online reviews for businesses is difficult and therefore, studies such as Ghose and Ipeirotis (2006), Chevalier and Mayzlin (2006), Ye et al. (2009, 2011) investigated the relationship using proxies for hotel room sales or booking data.

Among the few studies that exist for the tourism industry Tuominen (2011) attempted to investigate the impact of eWOM on hotel profitability (measured as RevPar and occupancy rate) by analysing online information such as the amount of reviews and the average ratings provided by customers on one particular evaluation platform. Although Tuominen's (2011) research involved a limited number of destinations and a handful of hotels, he found a positive relationship between the number of reviews written and the performance of a hotel. By combining ReviewPRO's Global Review IndexTM with Smith Travel Research's hotel sales and revenue data, Anderson (2012) assessed the impact of social media on hotel performance and found that an improvement in a hotel's online reputation score leads to an occupancy increase and an increase in RevPar. More recently, Nieto, Hernandez-Maestro, and Munoz-Gallego (2014) analysed the effect of marketing decisions by Spanish rural lodging establishments on eWOM and the effects of eWOM on business performance (measured as the owner's perceptions). They found that customer ratings and the number of reviews positively influenced the perceived satisfaction, profitability and market perceptions.

In the absence of a comprehensive attempt to quantify the impact of online reputation on tourism business performance, this study aims to contribute to knowledge. It extends existing research which has so far tended to be based on proxies for business performance, or tested with a limited range of destinations (e.g. Ye et al., 2009; Tuominen, 2011; Anderson, 2012; Nieto et al. 2014). Our model proposes the utilisation of an aggregated evaluation score (TrustYou) in order to evaluate consumer-generated online reviews. By using actual Swiss performance data we contribute to the tourism literature in that we analyse the aggregated online review scores with traditional determinants of hotel performance. Findings are expected to make a meaningful contribution to the strategic management of hotel businesses by providing information on the relevance and importance of online reviews for organisations' performance. Methodologically, we contribute by proposing a new method (ANN) for analysing the determinants of hotel performance in order to gain in-depth knowledge about these relationships. The following section provides a background to ANN and considers applications in consumer behaviour and tourism.

3. Artificial neural networks

The origin of an ANN is embedded in physiology and psychology. The aim is to work with a direct analogy of the human brain as a set of interconnected processing units, usually called nodes, neurons or cells operating in parallel. Thus, the ANN reproduces the network of neurons, and carries out the lower level computational actions (as opposed to the high level cognitive operations) in the human brain. More explicitly, ANNs are pattern recognition algorithms that capture relevant features from a set of inputs and map them to outputs (Bishop, 1995; Swingler, 1996). A neuron executes two operations on the receiving values; the first, called “combination function”, consists of summing its inputs weighted by the correspondent links of the neuron. The second, called “activation function”, applies a function to the value obtained in the former operation and produces the output of the neuron. The activation function is sometimes called the “squashing function”, as it limits the amplitude range of the output signal to some finite value. The activation function can be classified into three groups: (1) Threshold, (2) Piecewise-linear, and (3) Sigmoid (S-shaped) function. In general, the form of activation function, used in the construction of an artificial neural network, is the Sigmoid function (Haykin, 2008). In their ANN model, Phillips, Davies, and Moutinho (1999) use the Sigmoid function to model the threshold effect, which can range input values from one to zero. They also mention that for small inputs the function slopes sharply, but as inputs increase the differential impact becomes progressively lower. Also, the Sigmoid Function is a bounded non-decreasing and nonlinear function, which exhibits smoothness and asymptotic properties. In particular, this function has the ability to find patterns of non-linearity which other traditional statistical methods such as multiple regression analysis cannot model (DeTienne, DeTienne, & Joshi, 2003).

The most common architecture within the realm of ANNs is feedforward networks (Bentz & Merunka, 2000; Cardoso, Almeida, Dias, & Coelho, 2008; Gan, Limsombunchai, Clemes, & Weng, 2005; Gronholdt & Martensen, 2005; Phillips, Davies, & Moutinho, 2001; Phillips et al., 2002; Vellido, Lisboa, & Meehan, 2000). In Phillips et al. (2001), the revision of neural networks application in marketing problems clearly sustains that feedforward networks outperform other statistical and optimisation methods. The Backpropagation (BP) algorithm is the preferred supervised learning rule for the training of this computer modelling approach. The literature corroborates that many ANN applications were developed using this technique. When dealing with complex problems, we can observe a slow convergence and long training times. Therefore, other methods are proposed in order to increase its speed of convergence as well as the capacity of generalisation of the resultant network. Lopes and Ribeiro (2003) presented a new learning process called Multiple Backpropagation (MBP), and a new neural network topology: a Multiple Feedforward (MFF) network.

3.1. Use of artificial neural networks in marketing and tourism

ANNs have been successfully applied in a broad range of domains including classification, data mining, optimisation and time series prediction. Since the mid-nineties, they have also been applied to marketing problems, such as modelling consumer responses to market stimuli (Curry & Moutinho, 1993), in direct marketing (Venugopal & Baets, 1994), market segmentation (Bloom, 2005), predicting consumer choice (West, Brockett, & Golden, 1997), examining the usefulness of perceived risk theory to understand consumers' behaviour in the package holiday (Mitchell, Davies, Moutinho, & Vassos, 1999), new product development (Thieme, Song, & Calantone, 2000), marketing strategy (Li, 2000), sales forecasting (Kuo, 2001), market segmentation (Boone & Roehm, 2002), assessing the impact of market-focused and price-based strategies on performance (Phillips et al., 2002), modelling the effect of market orientation on firm performance (Silva, Moutinho, Coelho, & Marques, 2009) and predicting share market price (Khan, Alin, & Hussain, 2011). Benefits over traditional statistical methods (DeTienne et al., 2003) include enthusiasm of researchers in using the methodology for predicting and explaining problems in several research areas. This is not only in the domain of consumer behaviour, but also in the tourism marketing and management areas. Consequently, the number of studies employing artificial neural networks has increased considerably.

A majority of the research studies on tourism employing ANNs use them to forecast tourism demand time series. Palmer, Montano, and Sese (2006), for example, used ANNs to predict tourist expenditure in the Balearic Islands and pointed out that they are effective and flexible instruments for forecasting in tourism. In addition, Du, Guo, and Wang (2007) presenting a prediction on room occupancy rate, showed that the neural model outperforms other traditional statistical techniques. Moutinho, Huang, Yu, and Chen (2008), using neural networks, investigated the determinants of Mainland Chinese arrivals to Taiwan and forecasted corresponding tourism demand. As neural networks are adequate in handling non-linear data, without making a priori assumptions about the specific nature of relationships between inputs and outputs, Huang, Moutinho, and Yu (2007) offered an application of the neural network based fuzzy time series model to forecast international tourist arrivals to Taiwan.

Despite several studies using ANN, this modelling approach remains scarce beyond tourism forecasting. An exception is Tsaur, Chiu and Huang's (2002) study, which investigated the determinants of business travellers' loyalty toward international hotels. They compared the results of ANNs with those of logistic regression models and concluded that ANNs outperform regression models. ANNs were also used for market segmentation in tourism literature, and their performance was shown to be satisfactory (Bloom, 2005; Mazanec, 1992). Recently, they have been used to identify critical service attributes by considering their non-linear effects on overall customer satisfaction (Deng & Pei, 2009; Mikulic & Prebezac, 2012).

4. Case study

4.1. Background

Switzerland is an example of a mature Western tourist destination, a pioneer in Alpine tourism since the second part of the 19th century with a well-established infrastructure of hotels, vacation rentals, railways and cable-cars. Travel and tourism (domestic and international tourists) are still among Switzerland's most important economic activities. From a total revenue of CHF 35.5 billion in 2010, 18 billion (51%) came from tourist accommodation, F&B or transportation (Swiss Tourism Federation, 2011). The expenditure of foreign guests has the same effect on the balance of payments of Switzerland as the export of goods and services with approximately 6% of Switzerland's export revenue deriving from the tourism sector (Swiss Tourism Federation, 2011).

In the 1950s, Switzerland was a top tourist destination worldwide in terms of volume, but the Swiss hotel industry has been experiencing stagnation for the last 40 years (Sund, 2006). This can be measured in terms of arrivals, overnight stays and number of firms, which is declining steadily, from 8145 in 1974 (Sund, 2006) to 5257 in 2012 (Swiss Tourism Federation, 2013). Output in terms of overnights reached a first peak in 1972 with over 35 million room nights and stagnated since then with room nights varying between 30 and 35 million (Sund, 2006). The most recent evolution of the Swiss hotel industry since 2000 is still characterised by quite large variations on the demand side. After a lull between 2002 and 2003 (32 million room nights) the sector reached an all-time high of over 37 million in 2008. This positive evolution was mainly boosted by the dynamics of the Swiss cities (business tourism). With the economic crises in Europe the Swiss tourism sector saw a decline in demand and room nights decreased to below 35 million in 2012 (Swiss Tourism Federation, 2013).

This downturn was more pronounced in the alpine leisure resorts compared to the dynamic markets in the urban centres. These regional variations in performance of the hotel sector can have different explanations; differences in market position and structure of the offer as well as the competitive strengths are just some of the reasons. The sector is dominated by small and medium-sized properties scattered throughout the country, operating with small marketing budgets and an infrastructure which is often lacking and/or out of date (Kanton Wallis, 2013), especially in the low to mid-scale market which accounts for a very large part of the sector (Swiss Tourism Federation, 2013). The country represents therefore an interesting and rich “laboratory” for a wide-scale analysis of hotel performance determinants.

4.2. Sample

The sample consists of 235 hotels operating in Switzerland for the three-year period 2008–2010. The user generated online review scores were made available by the company TrustYou, which has developed a semantic search engine for online evaluations. TrustYou aggregates customer online generated reviews for all Swiss hotels, and in 2010 included 69 evaluation platforms, such as TripAdvisor, HolidayCheck and booking.com. Hotel characteristics and performance data were provided by the major stakeholders of the sector: Swiss Federal Statistical Office, Switzerland Tourism and hotelleriesuisse, which is the major trade organisation for the hotel industry. Table 1 provides a summary of the sample dataset.

According to the Swiss Tourism Federation (2010), there were 128,865 rooms and 245,251 beds available in Switzerland, so our sample represents 10.4% of rooms and 9.4% of beds. In our sample, we had no hotels of one star quality, but only 2% of the Swiss hotel sector are rated as one star. Two limiting factors reduced the sample size. First getting hold of hotel RevPar data for 2008, 2009 and 2010 together with the TrustYou and hotel characteristics was challenging. In addition, the Swiss Tourism Federation has problems of incomplete data by reporting 4827 open establishments (in terms of being open for trading) out of 5477 surveyed hotels for 2010. In addition (see Table 2), only 41.3% (being 1995/4827) properties were given a category (star rating) with 338 being of no stars. The sample of 235 hotels represents 11.8% of the Swiss hotel industry. Table 3 compares RevPar by star rating for both samples. The under representation of one star hotels increase the average RevPar. Fig. 1 compares the performance of both samples by star rating, RevPar and room size.

4.3. Explanatory data analysis

The variables included in the research were provided by TrustYou (see Table 4). The selected variables are representative of what is required for hoteliers to perform benchmarking. These were corresponding to the following explanatory variables: Canton, Touristic Region, Stars, Quality Label, Number of Rooms, Number of Beds, TrustYou Scores, Number of Sources for Reviews, Number of Reviews and Percentage of Positive Comments. The last four of the 10 input variables listed above relate to online reviews, which is a salient contribution to the academic literature. More specifically there are four types of input variables – location (Canton and Touristic Region), positioning (Stars and Quality Label), infrastructure (Number of Rooms and Number of Beds) and customer review (TrustYou Scores, Number of Sources for Reviews, Number of Reviews and Percentage of Positive Comments). Previous eWOM studies have used revenue per available room (Revpar) (Anderson, 2012; Blal & Sturman, 2014; Scaglione et al., 2009), which is the leading hotel performance metric. As the TrustYou data contained

Table 1
Summary of dataset.

Swiss hotel data	
Number of Cantons	26
Number of Regions	13
Number of Hotels	235
Number of Rooms	13,363
Number of Beds	23,082
Number of Positive Reviews	59,688
Total Number of Reviews	74,025

Table 2
Number of hotels participating and Swiss average (2010).

Category	No. of hotels in sample		No. of hotels in Switzerland	
1 star	0	0%	39	2%
2 Star	38	16%	239	12%
3 Star	82	35%	884	44%
4 Star	67	29%	413	21%
5 Star	24	10%	82	4%
No category	24	10%	338	17%
Total	235	100%	1995	100%
No information			2833	
Swiss Total			4827	

Table 3
RevPar for hotels in the sample and Swiss totals by star rating (2010).

Category	RevPar of sample CHF	RevPar of Swiss hotels CHF
1 star	0	86
2 Star	67	68
3 Star	79	85.6
4 Star	117.7	128.2
5 Star	283.2	284.3
Average RevPar	112.3	103.4

RevPar data it was decided that the hotel performance would be measured by revenue per available room (RevPar).

Table 5 presents descriptive statistics for the sample of 235 hotels. The mean and median for Rooms, Beds, TrustYou scores, Reviews and Av RevPar illustrate the discrepancy in size and performance within the sample. The mean of the Canton and Region do not mean much as they are qualitative scores. Tables 6 and 7 provide an illustration of the observations of canton and region. Only the Jura canton was not represented, and all regions were represented within the sample. Overall, there is considerable diversity in the hotels in the sample, evidenced by the representation of cantons and regions.

On average, hotels in the sample have a star rating of just over three stars, so we were dealing with a mid-range hotel on average. The TrustYou score, and Percentage of Positive Comments display a negative skewness, while Rooms, Beds, Number of Reviews and RevPar have positive skewness in excess of 2.358. The positive skew on Rooms and Beds suggests that the larger hotels pull the distribution up, which is evidenced by the discrepancy between the mean and median measures in relation to Rooms and Beds. The mean and median for the Number of Reviews vary considerably being 315 and 192 respectively and together with a high standard deviation of 357.431 show that values are spread over a broad range. We can see that 80% of the reviews are positive, on average

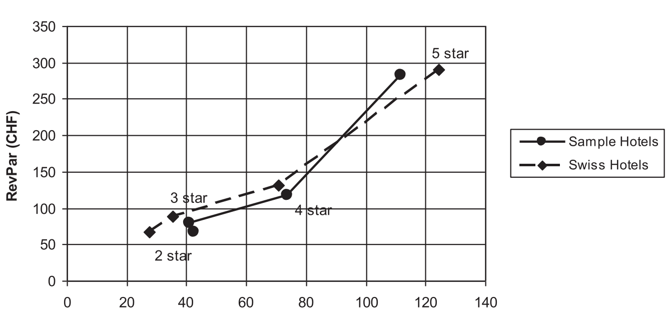

Fig. 1. Comparison between sample and Swiss hotel sample, average hotel room size by RevPar.

Table 4
Explanation of labels/variables.

Term	Label in Text	Operationalisation
Canton	Canton	Aargau, Appenzell Innerrhoden, Appenzell Ausserrhoden, Basel-Countryside, Basel-City, Bern, Fribourg, Geneva, Glarus, Graubünden, Jura, Lucerne, Neuchâtel, Nidwalden, Obwalden, St. Gallen, Schaffhausen, Solothurn, Schwyz, Thurgau, Ticino, Uri, Vaud, Valais, Zug, Zurich
Region	Region	Basel- Region, Berner Oberland, Fribourg – Region, Geneva- Region, Geneva–Lake District, Graubuenden, Neuenburg, East-Switzerland, Swiss- Mittelland, Tessin, Wallis, Central Switzerland, Zurich (Region),
ScoCat_T	Stars	Number of stars, 0–5 stars
Qual_Label	Quality Label	Swiss internal Quality Management Evaluation Label, Levels 1–3
Rooms	No of Rooms	Number of Rooms
Beds	No of Beds	Number of Beds
Scores	TrustYou Score	Proprietary score (not the average) provided by company, based on 69 evaluation platforms such as booking.com, Tripadvisor.com
Number of Sources	No of Sources	Number of online sources (max. 69 evaluation platforms)
Number of Reviews	No of Reviews	Number of online reviews from max. 69 evaluation platforms
Percentage of Positive Reviews	Percentage of Positive Reviews	Number of positive reviews/total number of reviews
RevPar	RevPar	Average for 2008, 2009 & 2010

and the median is close to this figure. This illustrates that we have a clustered distribution, as the standard deviation is small. The sample does not fit the Gaussian distribution of 0 in terms of Kurtosis. Rooms, Beds, Number of Reviews and Average RevPar have Kurtosis in excess of 6.656 with Rooms peaking at 18.575. Collectively, the analysis reveals that the distribution of data is unsymmetrical.

4.4. Multiple regression analysis

Multiple regression is a statistical technique that enables comparison between a continuous dependent variable and two or more continuous or discrete independent variables. The technique has been used in prior tourism related studies for comparison with ANN (Bloom, 2004; Burger, Dohnal, Kathrada, & Law, 2001). Thus, the inclusion in this study is to compare its effectiveness against neural networks as both are essentially interpolating tools (Burger et al., 2001).

The multiple regression equation is: $y = f(x_n)$

The independent variables are defined in Table 4. The dataset is used to build the multiple regression model. Using SPSS V20 the results of the multiple regression are shown in Table 8. The hotel performance determinants model accounts for 39.3% of RevPar variance. On average from the standard error of the estimate, our estimates for RevPar will be wrong by 65.615, which is not a trivial amount given the mean value of 112.280 for RevPar.

The Revpar is predicted to increase 122.240 when the percentage of positive comments goes up by one, and with the exception of number of sources (up by 1.199) increase by less than one. However, these multiple regression results from the Swiss panel data have a relatively low adjusted R^2 of 0.366, together with a large standard error of the estimate of 65.615. The results show that only 37% of the variation in RevPar is explained with these variables. Seven out of the ten variables are not significant, but for the purposes of this study we wish to obtain greater insight into the dataset. The neural

Table 5
Descriptive statistics.

	Canton	Region	Stars	Qual_Label	Rooms	Beds	Score	No_Sources	No_Reviews	%_Pos_Rev	Av_RevPar
Mean	15.153	7.851	3.021	2.634	56.864	98.221	73.248	15.409	315.000	0.800	112.280
Median	16.000	8.000	3.000	2.000	40.000	70.000	84.333	14.000	192.000	0.807	89.014
Std dev	8.311	3.763	1.335	1.010	56.978	86.593	24.623	7.014	357.431	0.083	82.409
Skewness	−0.161	−0.248	−0.822	1.237	3.458	2.493	−1.075	0.817	2.433	−0.684	2.358
Kurtosis	−1.537	−1.181	0.374	0.415	18.575	9.498	−0.470	0.715	7.488	1.330	6.656

Table 6
Frequency by canton.

Canton	Code	Frequency	Percent
Aargau	1	6	2.6
Appenzell Innerrhoden,	2	1	0.4
Appenzell Ausserrhoden,	3	3	1.3
Basel-Countryside,	4	32	13.6
Basel-City,	5	3	1.3
Bern,	6	7	3.0
Fribourg,	7	7	3.0
Geneva,	8	12	5.1
Glarus,	9	2	0.9
Graubünden,	10	22	9.4
Jura,	11	0	0.0
Lucerne,	12	11	4.7
Neuchâtel,	13	4	1.7
Nidwalden,	14	3	1.3
Obwalden,	15	3	1.3
St. Gallen,	16	3	1.3
Schaffhausen,	17	1	0.4
Solothurn,	18	3	1.3
Schwyz,	19	5	2.1
Thurgau,	20	7	3.0
Ticino,	21	26	11.1
Uri,	22	1	0.4
Vaud,	23	24	10.2
Valais,	24	21	8.9
Zug,	25	1	0.4
Zurich	26	27	11.5
Total		235	100

network approach is now employed to further analyse the Swiss hotel determinants model.

4.5. The ANN model

The TrustYou data had four categories: control data being property related data; hotel reviews; the TrustYou score; and RevPar. The explanatory variable selection for a non-linear method requires a protocol. In this study, many tests were conducted by varying the number of hidden layers and neurons to find the ANN that produces best generalisation for explanatory variables and RevPar. The predictive ability of the model was a priority, so threshold levels for each hidden layer were modelled by the Sigmoid Function, which was the nonlinear activation function. Bloom (2004) asserts that each input variable is scaled to primarily enable the network to learn the appropriate patterns. The Sigmoid Function, was highlighted by Phillips et al. (1999) in their ANN strategic planning-hotel performance study. The Sigmoid Function has the ability to scale panel data between 0 and 1. This enabled all the variables of our panel data to be used as inputs for the ANN. Our objective was to try several parameters and topologies in order to obtain a RMSE as small as possible, and to obtain a high goodness-of-fit coefficient. The hidden layers identified will be of interest to academics and practitioners, as they can be regarded as latent or unobservable variables, which when labelled by considering input and output variables will provide unique determinants of hotel performance. Fig. 2 shows this neural network architecture.

The data set of 235 examples was divided into a training set of 176 examples (75% of the sample) and a test set of 59 examples to validate the model. The presentation of the training patterns was in online mode and random. Several neural network architectures, including MFF were developed and trained with the supervised learning rule MBP. The optimal fit between inputs and outputs was achieved with a feedforward network with a single hidden layer of four neurons. This was thought to be a reasonable number of intermediate variables that could be identified and labelled. Increasing the number of hidden neurons beyond four did not improve predictions in any network topology, nor was there any advantage in increasing the number of hidden layers. The activation function used for the hidden and output neurons was the Sigmoid Function.

Different training configurations were tested with the MBP algorithm. Indeed, this supervised learning rule makes available a great diversity of training settings: namely, an adaptive learning rate and a momentum term (Lopes & Ribeiro, 2003). In this

Table 7
Frequency by region.

Region	Code	Frequency	Percent
Basel- Region,	1	10	4.3
Berner Oberland,	2	21	8.9
Fribourg – Region,	3	7	3.0
Geneva- Region,	4	12	5.1
Geneva–Lake District,	5	24	10.2
Graubuenden,	6	22	9.4
Neuenburg,	7	6	2.6
East- Switzerland,	8	18	7.7
Swiss- Mittelland,	9	17	7.2
Tessin,	10	26	11.1
Wallis,	11	21	8.9
Central Switzerland,	12	21	8.9
Zurich (Region),	13	30	12.8
Total		235	100

Table 8
Regression results (using OLS) Dependent variable: Revenue per available room.

Variable	Coefficient	(Standard error)
Canton	0.424	(0.674)
Region	−1.305	(1.486)
Stars	25.325***	(3.821)
Quality label	0.306	(4.540)
Rooms	0.041	(0.173)
Beds	0.091	(0.117)
Trust	0.446**	(0.204)
Source	1.199	(0.757)
Review	0.006	(0.012)
%Positive	122.240**	(54.706)
Constant	−123.413***	(47.314)
R-Squared	0.393	
Adjusted R-Squared	0.366	
Standard error of the estimate	65.615	
F-Statistic	14.510***	
Observations	235	

Stars denote level of significance as follows, *** if $p < 0.01$, ** if $p < 0.05$, * if $p < 0.1$.

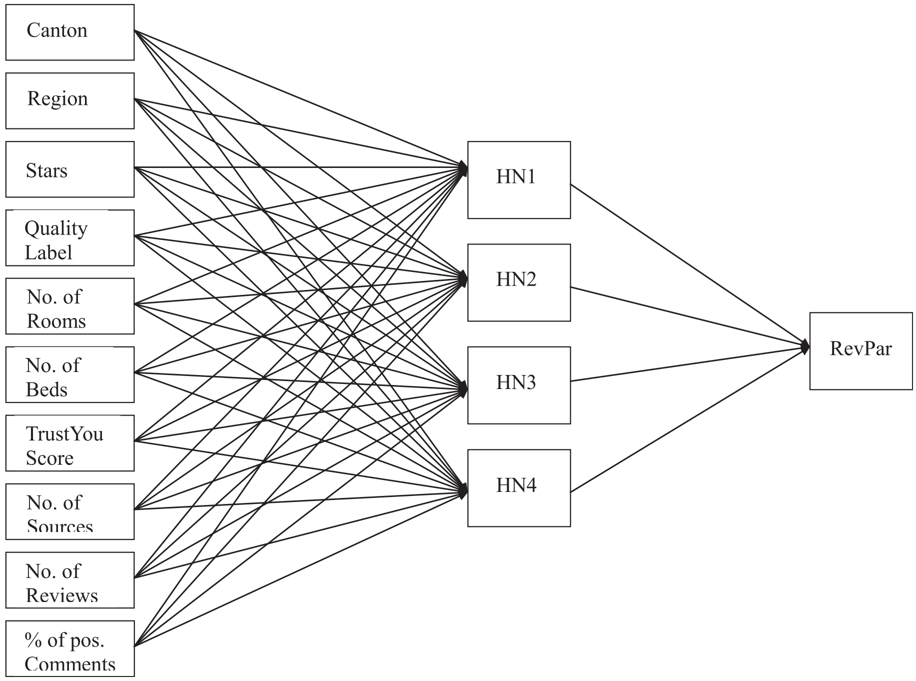

Fig. 2. Artificial Neural Network model.

framework, we use adaptive step sizes (being the increment u = 1.1, and the decrement d = 0.9) and the Moment Terms of the Main network and of the Space network were initialised with the same value of 0.05 decaying this 1% after each 1000 epochs different random initialisations for the weights were also tested. The interval [−1, 1] was considered to provide better results regarding the error function

$$E^p = \frac{1}{2}\sum_{o=1}^{N_o}\left(d_o^p - y_o^p\right)^2,$$

where N_o is the number of outputs, d_o^p and y_o^p are, respectively, the desired and the correspondent output of neuron o for pattern p. To attain robustness, the learning rate was further reduced by a factor of 0.5 each time the root mean square error (RMSE) increased more than 0.1% and is defined by

$$RMSE = \frac{1}{2}\sqrt{\frac{1}{N_p N_o}\sum_{p=1}^{N_p}\sum_{o=1}^{N_o}\left(d_o^p - y_o^p\right)^2},$$

where N_p represents the number of input patterns, increased more than 0.1%. The MBP algorithm performed thirty runs being the number of epochs confined to a maximum of 1,000,000 since beyond the threshold level no further improvement could be made to the quality of the network predictions. MFF were trained with the MBP, being the RMSE of 0.0150. The training performed 843,761 epochs from which any improvement in the generalisation capacity of network takes place.

5. Data analysis and discussion

Tables 9 and 10 show the weights of the network connections between the nodes as well as the contributions made by the explanatory variables. The contributory and inhibitory weights were within a range of [−33.042, 29.168]. The RMSE obtained for the test data was 0.0150. To evaluate the performance of the network, a goodness-of-fit coefficient was computed. The values were similar to the coefficients provided in multiple regression analysis, that is,

$$R2 = 1 - \frac{RMSE}{s_y^2} = 1 - \frac{0.015}{1072.971} = 1 - 0.0000139797457 \cong 0.99$$

where s_y^2 is the variance of the desired output for the test data. The R^2 value for RevPar was 0.99, so the neural network model explains 99% of the variance of the output variable. The values and signs (+or -) of the network connection weights between the input nodes and the hidden neurons are used to infer suitable intermediate attributes with which to label the hidden neurons. Moutinho, Davies, and Curry (1996) assert that this labelling has some element of subjectivity, but this is true of many causation models that attempt to explain attitudes or behaviour in terms of latent variables: for example, LISREL. Similarly, in factor analysis, the interpretation and labelling are subjective.

5.1. Inputs to hidden nodes

The resulting neural network topology derived from the study, reveal that the highest total contribution comes from Rooms (60.092) to the four neurons comprising the hidden layer. The second highest total contribution comes from Stars (54.882), with No. of Sources (42.338), Percentage of Positive Comments (39.794) and No. of Reviews (31.956) being third, fourth and fifth respectively. Canton (26.319), TrustYou Score (28.865), No. of Beds (29.625), Quality Label (29.93) and Touristic Region (30.103) were the five lowest of the ten input factors. Interestingly, the solution provided by the neural network topology reveals that the input factors 'Canton', 'TrustYou Score' and 'Number of Sources' make a negative contribution to all four hidden nodes. As the aim of ANN is to transform inputs into meaningful outputs the No. of Sources (42.338) appears to be significantly influential in terms of performance.

Table 9
Impacts of input nodes on hidden nodes from the hidden layer.

To the hidden layer	Bias	Canton	Region	Stars	Qual_Label	Rooms	Beds	Score	No_Sources	No_Reviews	%_Pos_Rev
1st neuron	8.529	−1.802	−0.303	−33.042	−14.634	14.073	−1.874	−10.9	−1.816	−24.624	−9.211
2nd neuron	−2.349	−4.693	10.357	−4.531	−9.301	−14.548	−16.497	−7.036	−24.44	0.405	19.542
3rd neuron	0.911	−1.433	3.426	8.083	2.544	−2.303	3.235	−9.145	−8.339	2.363	1.883
4th neuron	10.188	−18.391	16.017	9.223	−3.451	29.168	−8.019	−1.784	−7.743	−4.564	−9.158
Total contribution		26.319	30.103	54.882	29.930	60.092	29.625	28.865	42.338	31.956	39.794

Looking first at hidden node 1 (HN1), the most striking feature is that with one exception, Rooms (14.073), all of the input variables were negative and significant. The most inhibitory weights stemmed from Stars (−33.042), No. of Reviews (−24.624), Quality Label (−14.634), TrustYou Score (−10.900) and Percentage of Positive Comments (−9.211). These findings led us to label this neuron as "Room Quality". As the only contributory weight is Rooms (14.073), we can assume that the number of rooms is a key determinant of RevPar, but performance is hampered by many variables in the model. When considering the Swiss hotel business environment during the period of the study, which was in the mature/decline stage, a holistic vision is required. Factors which affect the intensity of competition in a mature/declining industry include height of exit barriers, level of fixed costs, and the commodity nature of the product. In the hotel business at the corporate level the brand can be a major differentiator, while at the hotel unit level the actual room is a key differentiator for the guest. So, the contributory weight of rooms provides support for such a view. However, those hotel managers that cope effectively with their strategic interdependencies such as strategic position, strategic choice, and action plans can benefit from higher levels of performance. In the context of HN1 the dependencies relate to those of strategic position and some consideration needs to be given to the competitive strategy, as well as the actual metrics. For example the results are based on the entire sample, which is heterogeneous. Thus, hotels in different Cantons and Regions within the same brand may be pursuing differing competitive strategies.

Fig. 1 shows the room size is related to star classification. In terms of number of rooms, four and five star hotels are significantly larger than two and three star hotels. Quality in terms of number of stars, number of reviews, quality labels, TrustYou scores really matters, with Stars (−33.042) and No. of Reviews (−24.624) being the two highest inhibitory weights in the whole of the neural network. This suggests that possessing a higher star rating and receiving many reviews does not automatically translate positively to RevPar. In fact, these latter two factors were found to somewhat hamper Room Quality. Although, hotel industry executives have much anecdotal evidence that social media influence guests' bookings and rate and occupancy (Anderson, 2012), there remains a paucity of evidence. Among the sample, guests may have prior expectations based on the star level of their hotel. As the RevPar for four and five star hotels are higher than for two and three star hotels, a guest booking a four or five star hotel may expect to see better reviews.

Hidden node two (HN2) has a split weighted impact from the input factors with seven negative and three positive impacts. Also, three contributory weights were opposite to HN1. The contributory weights of Percentage of Positive Comments (19.542), Region (10.357), and No. of Reviews (0.405) were opposite to their inhibitory weights in HN1 and impact HN2. The inhibitory weights of No. of Sources (−24.44), No. of Beds (−16.497), No. of Rooms (−14.548), Quality Label (−9.301), TrustYou Score (−7.036), Canton (−4.693) and Stars (−4.531) were found to somewhat significantly hamper "Positive Regional Reviews" being the label of HN2. The highest (negative) contribution comes from 'Number of Sources', which indicates that the number of online platforms used by customers to evaluate the hotel is significantly related to the hotel's performance. The inhibitory weights of No. of Beds (−16.497) and No. of Rooms (−14.548) suggest that hotel economy of scale benefits are not being obtained. During times of economic slowdown a fall in demand occurs, and this will reduce room revenue and occupancy levels i.e. RevPar. As described previously, the number of reviews does not automatically lead to higher levels of RevPar, and for HN2 the breadth of reviewers does not enhance RevPar.

Table 10
Impacts of hidden nodes on output nodes.

	Bias	HN1	HN2	HN3	HN4
RevPar	0.951	−5.038	−2.677	−29.22	4.959

Hidden node three (HN3) has a more evenly split weighted impact from the input factors; with six contributory weights: Stars (8.083), Region (3.426), Beds (3.235), Quality Labels (2.544), No. of Reviews (2.363), and Percentage of Positive Comments (1.883). Both TrustYou Score (−9.145), and No. of Sources (−8.339) are strong inhibitory weights in terms of negatively affecting HN3. No. of Rooms (−2.303) and Canton (−1.433) also have a negative impact. Collectively, we have labelled HN3 as "Hotel Regional Reputation". Since the input factors TrustYou Score and No. of Sources provide the highest contribution it could be argued that the overall TrustYou score, derived from the different sources is a significant performance driver. It appears that the quality of TrustYou score and possessing reviews from many sources inhibit Revpar. The ability to monitor reputation at the group, brand and unit level is a perquisite and a major thrust of this study. Each hotel general manager has to manage reviews proactively and systematically.

Three input factors are shown to have a positive impact on hidden node 4 (HN4). The highest contributory weight is Rooms (29.168). Interestingly, Region (16.017) and Stars (9.226) were the second and third highest contributory weights affecting HN4. Strong inhibitory weights of Canton (−18.391), Percentage of Positive Comments (−9.158), No. of Beds (−8.019), and No. of Sources (−7.743) negatively affect HN4. Taking into account these myriad impacts we have labelled HN4 as "Rooms and Regional Star Rating". Since the highest positive contribution derives from the Number of Rooms we could infer that those hotels with a larger number of rooms are more likely to achieve a higher RevPar. However, as discussed for the other hidden nodes the strong inhibitory weights will damper the RevPar. This reinforces the importance of key strategic interdependencies.

5.2. Hidden nodes to outputs

The empirical findings reveal four hidden nodes that have a significant impact on RevPar. Based on the differences in weights of each input factor on the hidden nodes, we can see that some combinations of factors are more likely to promote RevPar than others. A striking observation is the fact that HN1 – "Room Quality" (−5.038), HN2 – "Positive Regional Reviews" (−2.677), and HN3 – "Hotel Regional Reputation" (−29.22) have a significant negative impact on RevPar and that "Rooms and Regional Star Rating" (4.959) has a positive effect on RevPar. Hotel Regional Reputation is dominated by positioning/quality variables (Stars 8.083), and customer feedback variables (TrustYou −9.145 and No. of Sources −8.339). From a competitive strategy perspective, strategy as a position is an important component of our results. Hoteliers need to match their resources to the external environmental opportunities in order to gain a favourable position in the Swiss hotel industry compared with their competitors. At the country level the structure of the Swiss hotel sector with its cantons, regions, quality labels, and different size chains and units blur the lines between operational, business and corporate levels. Flexibility is needed in designing new strategies and to generate appropriate alternative decision options to cope within the Swiss hotel environment.

The model illustrates that on one hand a combination of hotel determinants can enhance RevPar, and another three combinations will hamper RevPar. The input factor of rooms has the highest contribution to each hidden node followed by the star rating, which to a large extent is an outcome of quality management and helps to manage guest expectations. We can state that the number of rooms is a crucial determinant of RevPar. This equates with the definition of RevPar, which is average daily rate multiplied by occupancy percentage. The number of rooms together with the effective use of technology should lower unit labour costs, distribution and marketing costs, while increasing sales and ultimately RevPar.

However, the neural network model shows how complex the relation is with the hidden node "Hotel Regional Reputation" (−29.22) needing to be very carefully managed. This reinforces the thrust of this study being the influence of UGC, and more specifically hotel related online reviews. Failure to adequately manage the TrustYou Score (−9.145) and the No. of Sources (−8.339) for a hotel can be significantly detrimental to hotel performance. Investing in positioning/quality variables such as Stars and Quality Label and managing bad reviews can enhance performance. However, if the location, positioning/quality, infrastructure, customer reviews are not in alignment, pursuing a strategy of lower prices or relying on possessing four or five stars will not overcome strategic and operational deficiencies. Also, possessing a poor reputation less than a hotel's competitive peer set will result in fewer customers willing to pay the full room rate.

5.3. Overall evaluation of multiple regression analysis and ANN

ANN approaches have been used to fit various performance models (Phillips et al., 1999, 2001; Tsaur et al., 2002), who used the back-propogation neural network model. Jost (1993) states that the back-propogation neural network can be liken to advanced multiple regression and cope with complex and non-linear data. The ability of the model to predict is usually represented by two indicators: prediction rate and goodness-of-fit, R^2. Bloom (2004) and Kim, Wei, and Ruys (2003) both use ANN to gain insights into market segmentation. Bloom (2004) concludes that BP was superior to that of multiple linear regression and logistic regression models, while Kim et al. (2003) stressed that ANN is particularly well suited for separating relevant structures from noisy data.

Multiple regression analysis and ANN were developed to validate a new approach to examine the determinants of Swiss hotel performance. The coefficient of multiple determination R^2 is 0.393; therefore 39.3% of the variation of RevPar is based on the ten input variables of our model. Moreover, the standard error of the estimate is 65.615, which is substantial and further restricts the predictive ability of the multiple regression equation. The ANN RMSE was 0.0150, and the coefficient of multiple determination, R^2 is 0.99; therefore 99% of the variation of RevPar is based on the ten input variables of our model. These ANN results are much stronger than for the multiple regression analysis, and are a much better predictive model of RevPar.

6. Discussion

Our findings not only underscore the importance of management attention to user-generated online reviews as identified for example by Chen and Huang (2013) and Loureiro and Kastenholz (2011), they also imply that hotel managers have to actively manage their online presence and be present on as many evaluation platforms as possible. Online reviews will continue to be at the forefront when customers plan their hotel booking, and their cumulative impact, as shown in our model, provides some guidance. Our results further indicate that positive reviews can contribute to hotels' financial performance and thereby we concur with studies that used proxies to measure companies' performance (e.g. Ye et al., 2011; Sparks & Browning, 2011; Yacouel & Fleischer, 2012; Ye et al., 2009). On that basis we argue that the Swiss hotels managers sampled in this study need to create identities that stimulate positive awareness at the local, regional, national and international level.

On a broader dimension, these observations have significant academic and practical implications. Even before the economic recession of 2008, the Swiss hotel industry had been in decline for more than four decades (Sund, 2006). This highlights the complications created by the product and industry life cycles. In addition to practitioners having to develop strategies in a mature environment that involve declining sales and industry shakeout, the Swiss hotel industry will experience geographical concentration. All these factors combined will and have created the need for urgent regional policies. Michael Porter's (1998) cluster theory is apt. Sund (2006) also highlights signs of agglomeration or concentration around key locations. These key locations are around cities, business/leisure, easy transportation access and airports.

Sainaghi (2011) notes that prior studies investigating the determinants of performance have numerous applications in the tourism sector and, in particular in the hospitality sector. This corresponds with Romero and Tejada (2011) who observe that the hotel sector plays an important role in most destinations and is usually the focus of tourism related studies. Hotels with a focus on enhancing performance and value creation need to improve decision-making that will lead to improved resource allocation and a reduction in unforeseen/redundant activities. Sustaining high levels of performance over the long-term depends upon a hotel's ability to develop a clear and real-time understanding: of its drivers of performance; the impact of these drivers and the potential timing, magnitude and possible inherent risks.

Our results demonstrate that effective utilisation and management of tangible and intangible resources can contribute to RevPar. Successful hotels will be those who possess a bundle of resources that are aligned with and support the strategic objective. From our sample, we can observe that competitiveness in the Swiss hotel industry depends increasingly on UGC than just hotel profile. 'Rooms' was the highest total contribution of the neural network topology. However, size alone was not found to be a contributor to RevPar, investing in positioning/quality variables can enhance performance. By adequately managing performance driving variables, such as those included in this study, hotels can achieve higher organisational value. Therefore, researchers and practitioners will find it increasingly important to understand the value of quality enhancing variables (resources) and to find ways of capturing them in performance models (Saldamli, 2008).

7. Conclusions and implications

Our study makes several contributions to the tourism performance literature. First, Cantallops and Salvi (2014) highlight that the impacts of prior eWOM studies can be direct and indirect and analysed from both the consumer perspective and the company perspective. This study adds a potential third dimension of country perspective. This latter perspective can aid setting the policy agenda of those individuals and organisations responsible for tourism. As Cantallops and Salvi (2014) state, the tourism industry needs to embrace eWOM, and within the tourism industry, hotels and restaurants are probably the most affected. The potential of social media and in particular UGC to affect markets by driving consumer choice can have a discriminating effect on tourism performance. At the country level the economic effects of tourism can be considerable. For example, according to the Swiss Tourism Federation (2010), tourism (CHF 15.6bn) ranks fourth in terms of export revenues, after chemical industry (CHF 75.9bn); metal and machine industry (CHF 63.6bn) and watch making industry (CHF 16.2bn). Accommodation accounts for the lion's share of tourism value added, and tourism employs 144,800 full-time employees (Swiss Tourism Federation, 2010).

Second, Anderson (2012) draws attention to the lack of comprehensive attempts to quantify the impact of social media on hotel performance. A major theoretical contribution relates to the robust model of determinants of Swiss hotel performance. We observe that previous eWOM tourism studies assume a direct relationship between online consumer content, online reviews and tourism performance with empirical studies adopting a bi-variate methodology. This study uses ANN, which goes beyond linear and bi-variate investigations, and provides evidence to suggest that online reviews together with traditional hotel characteristics should be considered as salient determinants of hotel performance.

Third, our model proposes the utilisation of an aggregated evaluation score in order to evaluate UGC. The aggregated TrustYou score used in this study is a propriety measure based on 69 review and social media sites worldwide. By combining actual hotel performance data we contribute to the tourism literature in that we evaluate the relationship between the aggregated score and performance of a wide range of hotels.

Fourth, using ANN our study identifies the hidden nodes – HN2 – "Positive Regional Reviews" (−2.677), HN3 – "Hotel Regional Reputation" (−29.22) and HN4 – "Rooms and Regional Star Rating" (4.959) that are the key mediating variables in our Swiss hotel performance model. These observations echo the changes that have taken place within the Swiss hotel industry. During the industry life cycle phases of maturity and decline, innovation is crucial. HN1 "Room Quality" (−5.038) shows that in addition to being in the best locations, a failure to demonstrate innovation in room quality will hamper RevPar. Managers should place some emphasis on HN3-"Hotel Regional Reputation" (−29.22). Growth in room sales will slow down in a mature industry, which can eventually lead to the less efficient hotels exiting the industry. A hotel's reputation is a crucial strategic asset. The emergence of online reputation presents numerous opportunities and threats to the manager, and needs to be managed effectively. Yet, fully controlling or managing this asset often forms a major challenge for organisations since reputation, like other intangibles, is a non-physical resource for which a monetary value cannot be easily found and over whose development the organisation has only partly control (Roos, Pike, & Fernstroem, 2005). Martín de Castro, López Sáez, and Navas López (2004) recommend that building corporate reputation requires information management, reducing customers' efforts to collate information and making it easier to contact. Online reviews are highly important sources of information and can crucially shape the reputation of tourism enterprises. Arguably, our results illustrate the need for Swiss tourism policy makers to understand the impact of online presence on hotels' reputation. Dealing with increasing numbers of online rating sites, this study provides scope for managers to apply semantic web searching techniques. We suggest that an online reputational management system is used to actively monitor and provide timely feedback to customers. Levy et al. (2013) advocate such approach.

Despite the significant contribution that this study makes to both theory and practice, there are a number of limitations that we recognise. First, the study uses data from a time period that is likely to have been impacted by the global economic crisis. The three-year period of the study 2008–2010 captured the most challenging years for the global tourism industry. During this period significant numbers of hotels were buckling under debt, and with RevPar being an indicator determined by occupancy times average daily rate, maintaining and enhancing RevPar was a vital strategic objective. Therefore, the relationship between performance determinants and financial performance was severely affected. Therefore, we recommend that future research replicates the study by using data from a different time period say 2011, 2012 and 2013 and in other geographic contexts to test the generalisability of our findings. Second, although our sample is of sufficient size it was drawn from a single market and merely represents about 12% of hotels in that market. This again might hamper the generalisability of our results. Notwithstanding the difficulties of obtaining a larger sample in terms hotel profile and performance data, future research should tackle this challenge. Our study focused on the output variable of RevPar, which despite being a key indicator for hotels, only focuses on room revenue. Future research may focus on other strategic objectives as key indicators, or select a number of output variables that encapsulate a hotel managers' aspiration beyond room revenue.

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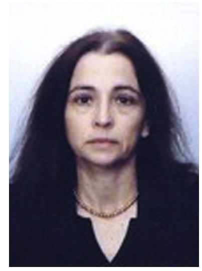

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