GOOD FOOD, CLEAN ROOMS AND FRIENDLY STAFF: IMPLICATIONS OF USER-GENERATED CONTENT FOR SLOVENIAN SKIING, SEA AND SPA HOTELS' MANAGEMENT

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Abstract. *The paper studies user-generated evaluations of hotels in three types of destinations in Slovenia (skiing, sea and spa). Using a broad dataset of user-generated evaluations for 28 different hotels and a combination of text mining and standard statistical methods we show how this data provides rich decision-making information. Although numerical evaluations of different destination types can hardly be directly compared due to different guest structure, the results show that guests in general evaluate in their texts primarily the "basics" (room, food/drink, staff). Using a combination of sentiment and novel aspect-based sentiment, hotels can monitor their competitiveness in time, across different types or brands, and use content analysis to further determine sources of competitive advantages in order to enhance performance. The article is the first comprehensive evaluation of Slovenian tourism using on-line peer reviews and provides a toolkit for similar applied analyses.*

Keywords: *tourism, Slovenia, user-generated content, computational linguistics*

1 INTRODUCTION

Slovenia is a small, but geographically very diverse country at the top end of the Mediterranean Sea, at the south-eastern rib of the Alps and western part of the Pannonia Plain. Consequently, the country offers diverse tourist experiences, including seaside, spa and skiing resorts. The tourism industry has traditionally contributed a significant share to GDP and employment. In 2014, for example, the tourism sector in Slovenia directly contributed 3.5% to GDP, while the estimated total contribution was even 12% (WTTC, 2015).

The sector, as well as many other end-consumer sectors, has become increasingly affected by the on-line content. Especially the analysis of peer-generated reviews has been gaining in importance, caused by the technological developments that led to the surging importance of social media and other (especially user-generated) content. Peer evaluation is becoming an important segment of services offered by the Internet, especially in tourism. According to the research by Bassig (2013) over 90 percent of potential tourists rely on one of the popular on-line reviews sites, while Munar and Ooi

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(2012) say that in fact a “virtual tourism culture” is emerging. On-line reviews help the individual form a “tourist destination/facility image”, which is extremely important in the selection process (Wilson et al., 2012), which in turn implies that it is important for both consumers as well as destination management (Bucur, 2015; Chen et al., 2012). They allow the potential consumers to obtain a better image of the “product” before actually deciding on a purchase, thereby stimulating a more rational choice. Jacobsen (2015) adds that reviews improve the match between the potential buyers and the services or products sold. But, more importantly, they serve the suppliers as well. They can help the sellers improve their product/service to match it better to the desires based on the observed criticism (Amarouche et al., 2015; Chen et al., 2012; Gandomi & Haider, 2015; He et al., 2013).

The purpose of this paper is to investigate the perceived qualities of three basic types of Slovenian tourist facilities as seen through the user-generated content on one of the major travel review websites. Combining most recent text mining techniques with standard statistical methods, we examine: how a specific type of facility (sea, spa, ski) is seen and evaluated by tourists, which aspects tourists appreciate and which not and what are the differences between destination types, and what decision-making implications such comparisons and data analyses provide. The analysis relies on a broad dataset of user-generated content for 28 Slovenian hotels, which in total comprised 243 thousand words.

This research makes several contributions to the field. It first extends the knowledge of the nature and qualities of Slovenian tourist facilities. To the best of our knowledge, this is the first such study of Slovenian tourism at large. The paper also extends at the moment not yet broad (text-mining based) empirical research in the field (e.g. Godnov & Redek, 2016b; Jeong & Mindy Jeon, 2008; Memarzadeh & Chang, 2015), adding to the analysis, also very novel aspect analysis. Although the use of on-line content in tourism research, including on-line reviews has been increasing fast, many studies at the moment rely on a smaller reviews sample (e.g. Jeong & Mindy Jeon, 2008) and many also rely on more rudimentary text analysis approaches. This paper also offers an overview of methodology that can be applied in actual business intelligence analysis. Finally, the paper adds to the knowledge of the importance of data analysis in business research, which is developing extremely fast (e.g. Raimbault et al., 2014; Wachsmuth et al., 2014; Williams, 2016).

In the next part, the paper first provides theoretical background by studying the role of user-generated content for travel decision-making and the implications for businesses. Then, Slovenian tourist sector is briefly presented to provide a frame to the analysis. This is followed by the research goals, data and methodology. The results, discussion with implications and limitations follow after that. The paper ends with conclusions.

2 THEORETICAL BACKGROUND

This paper investigates the role of user-generated content for understanding the consumer decision-making (guests’ expectations) and the implications for businesses on the example of Slovenian hotel facilities from ski, spa and sea resorts. In continuing, first a theoretical background is provided, linking user-generated content to consumer-expectations and decision-making, followed by a brief presentation of tourism in Slovenia.

2.1 The role of user-generated content in consumer decision-making and its impact on businesses

Travel decision-making is similar to other consumer-decision making processes. It contains several steps (Mathieson and Wall, 1982). First, one feels the need/desire to travel. Next, information collection and evaluation begins, which is followed by a decision to travel, preparation for travel, which includes studying available information about possible destinations, and the travel itself. The process ends by travel evaluation and satisfaction evaluation and today increasingly also by sharing and influencing (Mathieson and Wall, (1982); Torben, 2013; Bjork and Jansson, 2008) .

The process of **data collection and analysis** for **travel decision-making** is extensive (Bjork and Jansson, 2008). In tourism, TripAdvisor, Booking and Expedia dominate and offer a wide range of different information. For example, on June 23rd, 2015 TripAdvisor reported to offer more than 200 million reviews, while Booking offered access and reservation (with at least some reviews included) for more than 677 thousand locations. The on-line (especially user-generated) contents in various forms (reviews, photos, videos, blogs, etc.) are important for consumers in their own decision-making as well as for other consumers, where others' experiences act as influencers. Consequently, also for hospitality businesses (for details see e.g. Leung, Law, Van Hoof and Buhalis, 2013).

When **customers are deciding on a product**, they are increasingly influenced by other people's opinion – today primarily by the e-word of mouth (Z. Zhang, Ye, Law, & Li, 2010; Ye, Law, & Gu, 2009). According to Lee, Law and Murphy (2011) on-line reviews make decision-making easier. Potential travellers value these comments not only because of detailed textual evaluations, but since they are often perceived as more trust-worthy and are thereby even more influential (see e.g. Gretzel, Yoo, & Purifoy, 2007). Lee et al. (2011) also find that people perceive reviewers who travel more, post reviews more actively, belong to a specific group, or give lower hotel ratings as being more trustworthy. Gretzel and Yoo (2008) showed that reviews were used to inform accommodation decisions, but not to choose location. Also, women and younger people relied more on the reviews. Simms and Gretzel (2013) showed that the use of social media is stronger in case of first-time travel to a certain location, for women and younger people. The content of reviews is very important, it matters, whether one reads 'excellent' or just 'good' and decision-making often relies heavily on the negative experiences (Memarzadeh & Chang, 2015; Stepchenkova & Mills, 2010)

As user-generated content impacts on the decisions of (potential) guests, **it is extremely important for businesses as well as a source of business intelligence** (Dolk & Granat, 2012; Ghose & Ipeirotis, 2009, Zhang et al., 2012). For example, Gémar & Jiménez-Quintero (2015) stress that by studying social media, firms transform text into information and obtain knowledge both about themselves as well as their competitors.

Often, colloquial evidence suggests that if you are not as a supplier present on Booking or TripAdvisor, you as a hospitality business "do not exist". Having a post on one of the major travel review websites is a signal by itself. Not being present makes it much more difficult to be noticed (see e.g. Ye, Law, Gu, & Chen, 2011). Listing a facility (for example a restaurant) on one of the major websites does in fact boost its sales. Miguens et al. (2008) claim that TripAdvisor co-creates both the single operator/supplier as well as the destination as a whole. Similarly, Lackermair et al. (2013) show that already the existence of a rating and review system is taken as a positive signal of the quality on the side of consumers. As discussed, user-generated content will either encourage or discourage individuals from deciding on a specific location.

User-generated content can also be efficiently used in analysing the qualities of one's services or products and can serve as input for business intelligence– the information can help understand the guests and their needs, can help improve the services as it identifies the aspects users are less satisfied with or tailor the services/facilities to guests' expectations. As such, it can improve the competitiveness of a location, destination, facility (Anderson & Narus, 1998; Enright, 2005; Gémar & Jiménez-Quintero, 2015).

The literature has already confirmed the impact of ratings with purchases as well as sales for consumer goods (Archak et al., 2007, for sales; Chevalier & Mayzlin, 2006, for consumer purchasing decision-making). Sales in general are improved with satisfied consumers. The guests' satisfaction in the hospitality sector is determined by a number of factors, where the basic facilities (room, hotel characteristics), friendliness, location are among the most important (Han & Hyun, 2018; Prud'homme & Raymond, 2013; Radojevic et al., 2015).

This paper aims to contribute to the debate by studying user-generated content, i.e. the information that the reviewers provide in their texts in order to investigate the potential benefits of a broader, comparative approach, such as is the example of Slovenian ski, spa and sea hotels.

2.2 Slovenian tourism overview

Slovenia has several important tourist regions. The most important are the Coastal-Karst region, representing 21% of all 122 thousand tourist beds in the country, closely followed by the Alpine Gorenjska region (known primarily for skiing) with just below 21%. The tourist sector is also well developed in Savinjska, Goriska, and Central Slovenia; each of them adding another 10% to tourist facilities. Generally, the majority of Slovenian tourist accommodation are hotels (40%), 20% camping sites and around 40% all other facilities (mostly private accommodation) (SORS, 2015).

Due to its diverse geographical, cultural, and historical aspects, Slovenia offers a number of attractive arrangements that appeal to many domestic and foreign guests. Foreign guests traditionally dominate; in 2013 for example, they represented 62% of total 9.5 million of tourist stays (overnight stays), the rest being domestic guests. All of them of course travelled for private as well as business purposes. Recently, due to the economic crisis impact at home, the number of domestic tourists has declined by close to 9%, but the number of foreign tourists has increased, thus, in total, the number of tourists (calculated in overnight stays) has increased by approximately 3% (SORS, 2015).

The structure of guests has changed slightly in the past years. Among foreign guests there have been many more guests from overseas countries, such as Korea, Brazil, and China. In total, between 2008 and 2013 their number increased by up to 230 percent (the initial values being really low, ranging between 5 and 10 thousand overnight stays). Generally, the guests from Italy, Austria and Germany altogether represent 24% of all overnight stays, while Italian, German, Russian, Austrian, Dutch, British, Croatian, Serbian and domestic guests in total represent roughly 75% of all guests (SORS, 2015).

The guests choose different locations. The majority travel to the seaside dominated

Coastal-Karst region (21%), closely followed by the skiing dominated Gorenjska region (19%) and the more spa tourism oriented Savinjska (15%) and Pomurska region (9%). Of course, central Slovenia, also due to its capital city of Ljubljana, receives a lot of tourists as well, in total 11% (SORS, 2015).

2.3 Research questions

Slovenian tourism supply is very diverse, but the three mentioned above (seaside, spa and skiing resorts) form the pillar of Slovenian tourism. The purpose of this article is to investigate the image that the potential travellers can obtain from on-line content about Slovenian tourist destinations (spa, seaside and ski resorts). To do that, we investigate in detail the comparative ranking of the three locations and assess comparative advantages and disadvantages of each of the tourist regions using on-line reviews. In brief, we investigate:

1. What the general tourists' satisfaction with Slovenian facilities is and how skiing, seaside and spa resorts differ from the perspective of user satisfaction? What are the differences based on different measures of satisfaction? How can this information be used in a comparative manner as source of business intelligence?
2. Which aspects of tourist destination are most important to tourists (and most discussed) and how the three types of tourist destinations differ in these aspects? Do the tourists evaluate (care about) very similar things regardless of the differences between the locations or do they have a much different focus depending on the chosen location?
3. How could the data be used in consumer-decision making and in business intelligence at large? Could some aspects be defined as general source of advantage or should a comparative analysis be focused on a specific facility type or resort type? What are the difficulties when comparing different types of destinations?

3 METHODOLOGY AND DATA

In order to answer the research questions, we rely on the most recent methods in text mining. In continuation, we briefly explain each method and present the data.

3.1 Methodology

The first goal is to assess general satisfaction with a specific location. To do that, we assess the location (seaside, ski or spa) by using the user-generated numerical evaluation. The travel reviews site enables the users to numerically evaluate every facility on a scale from 1 to 5. The travellers also provide textual reviews, which are even more relevant to a potential traveller. We assess the level of satisfaction using also textual reviews with the sentiment analysis. **Sentiment analysis** or **opinion mining** is based on evaluation of the words in the sentence (Bollen et al., 2011; Cambria et al., 2013; Liu, 2012; Pang & Lee, 2008). Each word is given a numerical value depending on its position in a lexicon. The earliest sentiment analysis relied on evaluating each word either as positive (1), neutral (0) or negative (-1) (e.g. Hu & Liu, 2004). The most recent methods rely on modern lexicons (e.g. ANEW, AFINN, etc.) and scale words between -5 and 5. In the analysis we rely on the very popular AFINN lexicon (Nielsen, 2011, scale -5 to 5) as well as the basic Hu and Liu (2004, scale -1, 0, 1) methodology to also illustrate the differences arising due to the choice of methodology.

The sentiment reveals what "emotion" the potential traveller or a reader of the review obtains via the text. Namely, as Table 1 shows, numerical evaluation is too short to provide any detail. This comparison is relevant, since the potential consumer is primarily interested in the details, which, in the second case, actually provide an overall negative sentiment. While the numeric ranking is very positive, the reviewer is in fact quite critical (as evident from the example relying AFINN sentiment). Nevertheless, it is the criticism that will have a much larger impact on the potential traveller and, consequently, the hotel management should take the sentiment of the reviews into consideration as well. To confirm the importance of the sentiment analysis, we also check for the strengths of the relationship between numerical rating and sentiment score.

In hospitality in general, the satisfaction of guests is the most important determinant of the perceived quality. In tourism, as was indicated by previous research (e.g. Bahtar & Muda, 2016; Godnov & Redek, 2016) specific characteristics or services or infrastructure (restraurants, staff, bed, etc.) and their aspects (food, frienliness, etc.) are important for consumers. To evalute the satisfaction with these specific aspects, which are the most important determinants of satisfaction in the hospitality industry, we also used **aspect-based sentiment analysis**. Aspect-based sentiment analysis is a two step procedure. In the first step relevant terms are identified (describing specific aspect, e.g. restaurant) in sentences. In the second stage, polarity of each aspect is studied at sentence level. For tourism and hospitality, Aylien software offers a pre-defined set of aspect categories (e.g. food, cleanliness, friendliness - for restaurants). These are identified and then based on the sentiment of words related to the aspects. Each of the aspects is evaluated as positive, negative or neutral (Saujanya and Satyendra, 2018).

Third, to further investigate the nature of facilities and the differences between them, we also conduct **topic analysis**. Several methods are used. First, the simplest, keywords and keywords-in-context methodology is used. According to the literature, keywords are primarily aimed at capturing the essential information in the text (Beliga et al., 2015; Feinerer et al., 2008; Gupta & Lehal, 2009, 2010; Zha, 2002). The text mining procedure is normally based on simple counting by relying on word stem and not on specific form. For example, *tourist* and *tourists* have the same stem and thus count as the same word. In addition, most common words (such as

Table 1: An example of evaluations with highly divergent numerical and sentiment evaluation: high numerical evaluation can be associated with a relatively negative sentiment in the review

Text	Numeric user evaluation	Sentiment as calculated from the review (AFINN)
I just returned from an absolutely amazing week at the ***. I have stayed at several luxury hotels and this hotel is truly one of the best….(continuing in the same positive manner)	5	81
Stayed there for 3 nights past week. Hotel is managed excellent. It is truly the best Slovenian hotel, but there are still things to be corrected: at breakfast we got dry croissants, there were tree leafs in the pool at same place for all 3 days, also some dirt around the pool-waiters at pool were slow as snails.	5	-4

Source: Authors.

and, *to*, *be*, etc.), which are, for the English language, in R statistical package "tm" known as "stop words", are excluded first.

But keywords analysis provides only a limited assessment of the topics that are being discussed in the text. To identify the main topics, we rely on topic modelling, which is one of the most recent and most advanced methods in text mining. We rely on an iterative Latent Dirichlet Allocation (LDA) procedure as an example of topic modelling (Chang, 2015). LDA is a probabilistic method that identifies a predetermined number of topics in the text and the words associated with each topic. Overall, the methods described will allow an extended overview of the information which users (both travellers and management) can extract from the text.

3.2 Data

In order to assess the nature of Slovenian tourism we investigate the user-generated textual reviews in combination with user-generated numerical rating. The analysis relies on a sample dataset of in total over 243 thousand words from 1,712 reviews of 28 different hotels on TripAdvisor. All hotels with reviews were included, but we decided to analyse only hotels and not apartments.[1] Out of the 1,712 available reviews, 847 referred to skiing resorts, 580 to seaside resorts and 285 to spa resorts. The hotels were sampled based on their importance: first all major resorts were included and then all most important providers (hotels), while small hotels with only few reviews were not included. Since the purpose of this analysis is not to evaluate specific hotels, names are not disclosed (Table A1 in the Appendix provides a structure of sample without names). Only reviews in English were considered.[2] The sample represents roughly 30% of all available reviews, where the percentage varies from roughly 25 to 50, depending on a hotel. The majority of reviews are from UK, Slovenia, Croatia, Italy, Serbia, Germany and other European countries, which in total comprised 70 % of all reviews. Given the guest structure in Slovenian tourism, this structure reflects well the dominance of domestic guests and those from nearby countries. Latest data shows that EU and domestic guests represented 76% of all guests (see SORS, 2015, for details). We are aware of the possibility of fake reviews in the literature, but, for several reasons, we believe that in the sample this is not a problem.[3]

[1] The decision to include only hotels was based on two considerations. Firstly, the hotels have more reviews. The fact that there are more reviews is largely important for the analysis itself, but it is also important from the perspective of the influence of potential fake reviews, which would have less impact on the overall results. Secondly, adding appartments or even camping sites would complicate the research because it would include into the sample facilities with very different amenities.

[2] Although the fit is not perfect, we felt that using automated language translation would be analytically bad due to both text style as well as different reliability of automated translation depending on original language (), despite the general/average increasing reliability of phrase based translation (e.g. O'Brien & Fiederer, 2009; Tillmann, 2003). The latter is, on the other hand, part of the estimation procedure in sentiment calculation. Using translations would, thus, lower the reliability of results. In addition, since this analysis includes the general picture and not specific hotel (guest structure differs significantly by hotel), we felt that using only English reviews was better than using translation.

[3] In the literature, the problem of fake reviews is also considered ((Bajaj et al., 2017; Filieri, 2016; Mathews Hunt, 2015) (Filieri et al., 2015). First of all, TripAdvisor itself filters out fraudulent reviews ("TripAdvisor's Review Moderation and Fraud Detection FAQ," 2018). Despite that, it is impossible to completely rule out possibility of fake reviews. Although the problem is relevant and it may tamper with the results, the size of the hotels and the number of reviews in total, in our sample, would lower the impact of any fake reviews. It is also easier to impact reviews in case of smaller hotels with smaller number of reviews. So far, for Slovenia, a case of review faking was not identified (or claimed). Also, potentially, it would be a problem for all providers, thus levelling the field of play. Furthermore, the criticism in some reviews at least as well as the lack of outliers speaks in favour of faking not being (significantly) important in the sample. Consequently, in the research we did not address this issue in more detail.

The data was collected in April 2015. Studies rely either on manual collection or automatic (see Johnson et al., 2012, for a discussion of options). In our case, reviews were gathered partially manually. Excel with special add-in for Excel, Power Query, was used as the primary tool, relying on hotel URL and parametrization of the query with pages' numbers in M language. After retrieving the data, Power Query's transformation tools were used to finalize the data for further analysis in R programing language. Data analysis was conducted using tm package (Feinerer et al., 2008) and LDA package (Chang, 2015). The whole aspect analysis was run in Aylien software.

On average, a review consisted of 141 words, with the shortest review comprising only 9 words and the longest 1,222 words.

4 RESULTS

Following the objectives outlined in the research questions, the purpose of the analysis is to (1) investigate general satisfaction with three types of resorts, determine user-identified qualities of different facilities, satisfaction and dissatisfaction with different aspects of tourist offer, and thereby identify comparative advantages and disadvantages of a location type and the general satisfaction with the specific type. We also (2) try to determine which aspects of tourist destination type are most important to tourists for each of the specific types and (3) what are the implications for decision-making, what are the difficulties when comparing different types of destinations and whether at least some aspects could be compared. Overall, answering these three questions will also allow us to provide insight into the perceived image of Slovenian tourism overall, as well as specific types of destinations.

4.1 General satisfaction with skiing, seaside and spa resorts

The travel reviews provide the user with a numerical and textual evaluation of the quality of a specific tourist destination. Moreover, the reviews address specific aspects (e.g. room, bed, etc.) that are most important to each guest.

Tourists evaluate each trip first by numerical ranking on a scale from 1 to 5. The potential travellers consequently obtain initial information from numerical rating, but then they also review textual evaluations, especially those having a very bad or a very good numerical evaluation (Memarzadeh & Chang, 2015; Stepchenkova & Mills, 2010). Table 2 provides summary statistics for numerical rating, followed by a summary or rating based on sentiment analysis of the text using different methods.

The results (Table 2) reveal that the users, using numerical evaluation on a scale from 1 to 5, rated the skiing resorts highest, with an average numerical evaluation of 4.41, followed by seaside resorts (4.14) and spa (3.99).

To further evaluate the perceived qualities of each of resort as "seen between the lines", sentiment analysis is calculated, using Hu-Liu and AFFINN method. Since the sentiment analysis evaluates the text, the relationship between the numerical evaluation and "what feeling the text portrays" may not be strong. Expectedly, it is not strong in our case (Figure 1).

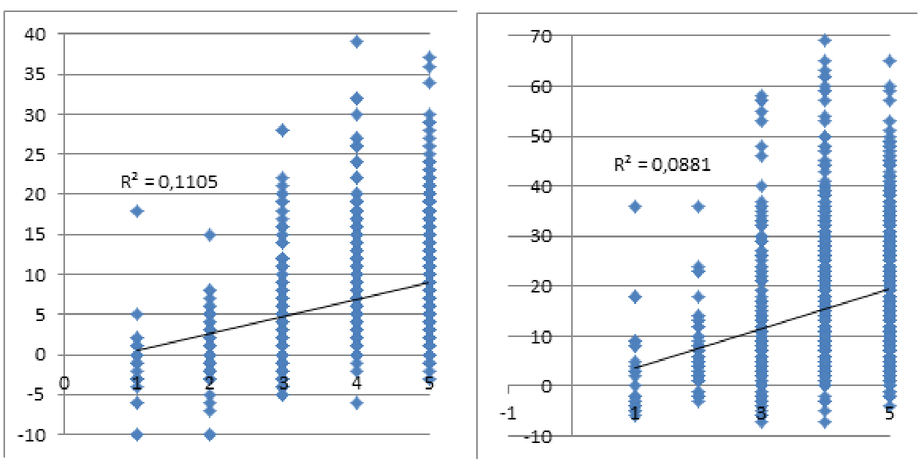
The correlation between sentiment value (for the entire sample) and numerical evaluation is very weak, on average around 0.3 (significant at $p<0.001$). The weak relationship is also evident from the scatterplot (Figure 1). Correlation between numerical evaluation and sentiments by type of resort is

*Table 2: Descriptive statistics for the numerical ratings and sentiment scores in the three types of Slovenian tourist destinations**

	Category	N of reviews	Minimum	Maximum	Mean	Std. deviation
Sea	Numerical rating	580	1	5	4.17	.953
	Hu-Liu sentiment		-11	36	6.67	5.534
	AFINN sentiment		-14.0	81.0	15.37	11.624
	AFINN per unit of numeric rating		-14.00	19.33	3.65	3.10696
	Hu-Liu per unit of numeric rating		-11.00	9.33	1.53	.06279
	No of words		15	1222	137.68	120.244
Ski	Numerical rating	847	1	5	4.41	.804
	Hu-Liu sentiment		-6	39	8.66	6.009
	AFINN sentiment		-7.0	77.0	18.90	12.323
	AFINN per unit of numeric rating		-3.00	36.00	4.34	3.15789
	Hu-Liu per unit of numeric rating		-3.00	18.00	1.97	1.52681
	No of words		9	1133	156.45	136.888
Spa	Numerical rating	285	1	5	3.99	1.036
	Hu-Liu sentiment		-10	24	5.15	4.945
	AFINN sentiment		-16.0	63.0	12.08	10.411
	AFINN per unit of numeric rating		-16.00	15.75	2.81	3.15638
	Hu-Liu per unit of numeric rating		-10.00	5.75	1.11	1.68618
	No of words		19	527	105.28	91.729

* *Hu-Liu refers to the calculation of sentiment based on the Hu_Liu approach, which rated words only as positive, negative of neutral. AFINN is an advanced method, ranking sentiment of words on a scale (-5,5).*
Source: Authors.

Figure 1: Scatterplot between the sentiment score (Hu-Li, left, AFINN right) on the vertical axis and numerical rating (1-5, horizontally); R^2 and linear trend added



Source: Authors.

the strongest in the case of spa hotels (0.45 for Hu-Liu sentiment and 0.38 for AFINN) and the weakest in the case of ski resorts (0.221 and 0.212 for the Hu-Liu and AFIN), while for sea resorts, the correlation was 0.36 and 0.30. In all cases, the relationship is significant at 0.01 level or more. This implies that the sentiment in fact is worth examining and does tell a partially different picture than numerical evaluation.

Regardless of the sentiment calculation method used, the *perceived* quality of the skiing resorts' hotels was highest (Table 1) (but note our discussion in continuing regarding problems when comparing different types). Further analysis reveals that the differences in the sentiment between groups are statistically highly significant. In both cases, the case of Hu-Liu sentiment method as well as AFINN method, ANOVA F value is significant at $p<0.001$. T-tests confirm also that the picture painted through the use of words in the reviews referring to skiing destinations is statistically significantly better than that for seaside and spa destinations (higher sentiment value), while seaside destinations are by sentiment value ranked higher than spa destinations. In all cases p values are <0.001.

The seeming void between the sentiment and numeric evaluation was further examined by calculating the sentiment per unit of numerical rating (ratio between sentiment and numeric evaluation). The results in fact show that the textual evaluations only strengthen the perceived quality differences between the locations. The ratio between the sentiment and numerical evaluation average was in fact lowest in case of spa resorts[4] (2.81 and 1.11 for AFINN and Hu-Liu sentiment), indicating lowest differences or variation.

The overall results imply that numerical grading captured the overall satisfaction in the case of spa resorts best or that the discrepancy between the numeric and "textual" evaluation was lowest. For example, per unit of numerical rating, the skiing resorts rank highest, considering both AFINN or Hu-Liu method, meaning that, for example, if a user wrote a text with a sentiment value of for example 18 and this is normalized against the user awarded numerical evaluation of 4 for the same resort, the skiing resorts on average obtained best textual reviews for the same numerical rate. So, if a spa destination obtained a numerical grade 5, on average the text would describe it in a much less favourable manner in comparison to a ski resort also evaluated with 5.

4.2 The perceived quality of hotel facilities and services and user satisfaction

Guests' satisfaction in the hospitality sector is determined by a number of factors, where the basic facilities (room, hotel characteristics), friendliness, and location are among the most important (Han & Hyun, 2018; Prud'homme & Raymond, 2013; Radojevic et al., 2015). Using several methods of content analysis (key-words extraction and LDA) and aspect-based sentiment analysis, we investigate whether this is true also in the sample and how satisfied users were with selected aspects.

When providing a review of the destination, the users normally speak about the package elements or the location in general that they care most about or is, in their opinion, the most relevant aspect of a tourist offer. This implies that the keywords analysis

4 The ratio was calculated as the ratio between a specific sentiment value and the average numerical evaluation for each type of destination, relying on data from Table 1. Average values were used as inputs. The results were 3.65 and 1.53 for the ratio between AFINN sentiments or Hu-Liu sentiment and the numerical evaluations average, 4.34 and 1.97 for ski resorts and 2.81 and 1.11 for spa resorts. In all cases, first the ratio between AFINN and numerical score is provided, followed by Hu-Liu-based ratio.

Table 4: Key-words analysis by tourist destination type: 15 most common words and associated relative frequency in percent**

	Sea side, N=79855		**Spa,** N=30531		**Skiing,** N=132982	
	Word	Frequency, %	Word	Frequency, %	Word	Frequency, %
1	hotel	1.77	hotel	0.28	hotel	1.52
2	room	1.19	good	0.16	good	0.64
3	good	0.50	pools	0.14	room	1.00
4	breakfast	0.44	food	0.10	food	0.48
5	nice	0.42	spa	0.10	staff	0.44
6	staff	0.40	nice	0.10	great	0.40
7	pool	0.38	room	0.17	ski	0.34
8	great	0.34	staff	0.09	nice	0.31
9	sea	0.30	great	0.08	pool	0.29
10	service	0.30	really	0.08	breakfast	0.29
11	beach	0.28	clean	0.08	clean	0.29
12	***	0.28	time	0.07	friendly	0.27
13	food	0.27	place	0.07	really	0.26
14	view	0.27	water	0.07	stayed	0.49
15	stayed	0.46	will	0.06	excellent	0.22

**N refers to total number of words in reviews pertaining to a specific type. (***) replaces a specific location's name or a city.*
Source: Authors.

would allow to identify the aspects the users wrote about most because they either liked or disliked something and to identify certain aspects as the most important determinant of a wholesome package or as important features to tourists.

The results (Table 4) show that in all cases the users care about more or less the same basic elements: hotel, room, food (breakfast) and staff. Results from Table 4 also show that the elements specific for a location are discussed: sea and beach for the seaside; water, spa and cleanliness for the spa; and skiing for the skiing resorts.

Latent Dirichlet Allocation method was applied next to further investigate the content of the texts (Table 5).[5] LDA summarizes clusters of words that appear together and, by doing so, it reveals both the topics and the contents of the discussion. In the cases of spa and skiing resorts, one topic (T1) is more general and refers to the hotel, room, food and staff, while the second captures the infrastructure that is typical for the location. In case of the seaside, the first and the second topic overlap, both dealing with the general elements. Besides nouns, adjectives, which were most commonly associated with nouns in a specific topic, are also presented. These

[5] For the LDA analysis, the number of topics must be predetermined by the analyst. Several topics were tested before we finally opted for two topics, which is also in line with the results of the keyword analysis. Namely, it showed that there are some general and some specific elements discussed by the users. Thus, if number two was chosen, the LDA iterative procedure was expected to identify these two topics and the most common words associated with each of the topics.

are generally positive and stem from good, nice, great to clean (which interestingly is related to spas, where cleanliness in even more important due to the structure and expectations of guests).

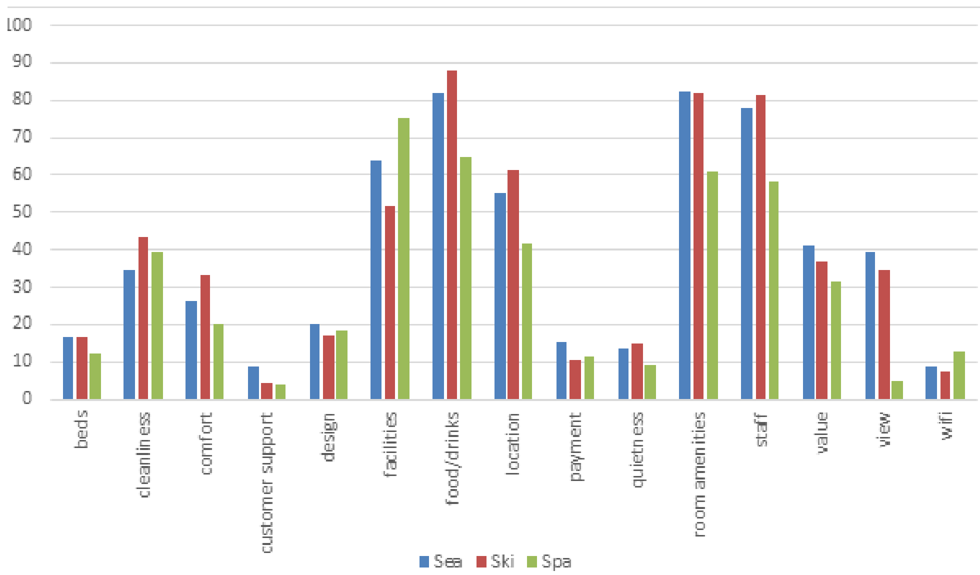
The satisfaction with specific elements of hotels was further examined with aspect-based sentiment analysis (entire table in Appendix, Table A2). Figure 2 presents the share of reviews which in the text addressed a significant aspect of hotels and evaluated it. The results show that guests most often evaluated food/drinks, followed by room amenities, staff and facilities. Roughly eighty percent of all reviewers (different by type

*Table 5: Latent Dirichlet Allocation results by destination type: most common words associated with each of the two topics for each location**

Sea		Spa		Ski	
T1	T2	T1	T2	T1	T2
hotel	room	hotel	pool	hotel	good
good	hotel	room	one	room	room
breakfast	one	good	can	stay	ski
stay	day	also	place	food	pool
nice	night	nice	sauna	staff	day
staff	time	stay	water	great	just
great	get	clean	restaurt	nice	one

**T denotes topic.*
Source: Authors.

Figure 2: The percent of all reviews, which in their evaluations evaluated specific aspects

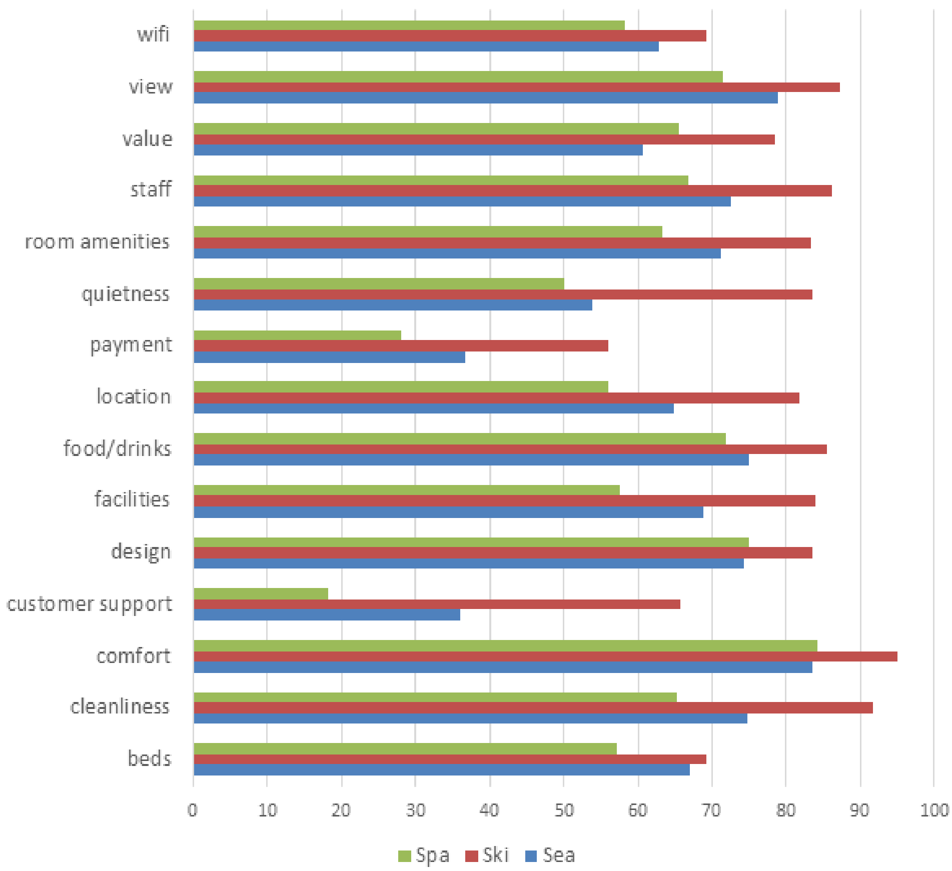


Source: Authors.

of resort) mentioned food/drinks, room and staff, which confirms the importance of these (basic) qualities of any hotel to a guest. This is in line with LDA results, which showed also these aspects to be most common among words. This implies that guests care most about these basic characteristics. However, it is important to mention that around 40% of guests spoke about cleanliness and view, and 40-60 % about the location.

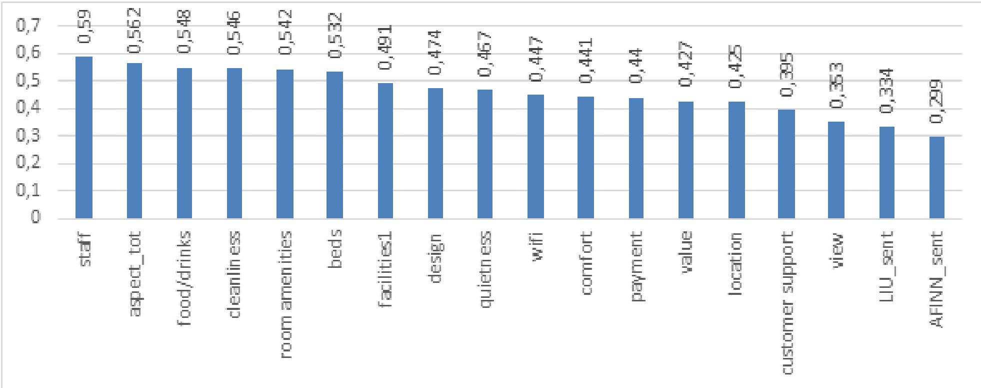
The reviews were on average most satisfied with the comfort, cleanliness and view (Figure 3). Interestingly, these aspects the guests are most satisfied with are not the aspects which are most commonly evaluated. It is true that the guests were satisfied with the aspects that are most important to them (food, location, room, staff). Interestingly, skiing resorts again stand out in terms of the percentage of positive evaluations.

Figure 3: Share of reviews that positively evaluated a specific aspect as percent of reviews that provided an evaluation of specific aspect (in %)



Source: Authors.

*Figure 4: Correlation between aspect evaluation and overall numerical rating (star rating)**



**(all coefficients were significant at p=0.05 or more)*
Source: Authors.

*Table 6: Correlation coefficients between aspect-based evaluation and overall rating **

Sea	Correlation	**Ski**	Correlation	**Spa**	Correlation
Beds	0,634	Food/drinks	0,521	Staff	0,684
Aspect_tot	0,619	Staff	0,517	Cleanliness	0,604
Comfort	0,616	Payment	0,481	Aspect_tot	0,587
Room amenities	0,604	Room amenities	0,458	Food/drinks	0,56
Staff	0,589	Aspect_tot	0,445	View	0,554
Food/drinks	0,547	Cleanliness	0,445	Facilities	0,543
Cleanliness	0,531	Beds	0,443	Wifi	0,537
Design	0,517	Value	0,409	Location	0,533
Facilities	0,516	Design	0,401	Beds	0,526
Wifi	0,495	Facilities	0,391	Design	0,51
Quietness	0,492	Wifi	0,356	Room amenities	0,483
View	0,434	Quietness	0,351	LIU_sentiment	0,455
Location	0,401	Location	0,344	Value	0,416
Value	0,401	Customer support	0,332	AFINN_sentiment	0,385
LIU_sentiment	0,358	Comfort	0,281	Payment	0,371
Payment	0,358	LIU_sentiment	0,224	Comfort	0,273
Customer support	0,354	AFINN_sentiment	0,215	Quietness	0,254
AFINN_sentiment	0,3	View	0,213	Customer support	0,222

**(all coefficients were significant at p=0.05 or more)*
Source: Authors.

Since the positive evaluations of the hotels should be linked to overall better evaluation, the aspect-based sentiment should be positively linked to overall sentiment and the numerical rating. To check that, we categorized aspect-based nominal sentiment values into numerical (1 for positive, 0 for neutral, -1 for negative) and checked the correlations. First, we summed up all aspects to get the overall "aspect-based sentiment score", but we also checked for links between evaluations of certain aspects and the overall evaluations.

The results show that the numerical rating is most strongly positively related to positive evaluation of staff, followed by food and drinks, cleanliness, room, and beds. In these cases, the relationships were stronger than 0.5.

We also checked for the possibly different importance of certain characteristics with regards to overall rating by different types of resorts (Table 6, details in table A3, Appendix).

The overall numerical (star) rating is quite differently "dependent" on satisfaction with selected aspects. At the sea-side, beds, comfort and rooms are most strongly correlated with overall rating. In the spas, staff and cleanliness are most important, while overall rating of skiing is most closely related to food and drink, as well as staff. The overall sentiment is relatively weakly related to the overall numerical rating. In fact, satisfaction with key aspects (*aspect_tot*) has a much stronger relationship to the overall numerical rating.

5 DISCUSSION

Table 7 summarizes the main results and offers implications followed by a discussion on limitations.

5.1 Discussion of results with implications

Overall satisfaction with hotels in different resort types. The results show that the overall satisfaction with all three types of resorts is relatively high, the highest satisfaction being expressed by the reviewers of the skiing resorts. Reviewers were, overall, satisfied with hotels in all three types of resorts. However, the numerical ratings, sentiment ratings as well as aspect-based ratings, showed that hotels in the skiing resorts were evaluated as the best. Since the structure of guests (reviewers) is not the same across different resort types, this result cannot be interpreted directly, claiming that ski resorts in Slovenia are better than other resort types. For example, Gustavo (2010) finds that spa tourists come to spa hotels for specific reasons, primarily stress relief, relaxation, improving physical and mental health. On the other hand, Konu et al. (2011) show that, for skiing resort, consumers are primarily segmented based on their skiing preferences (downhill, country, all-but-down and other slope characteristics), while passive tourists and relaxation seekers are a weaker group. The importance of skiing (and less of other characteristics of skiing resorts) is also confirmed by pricing elasticity estimation, where again the slopes are primarily important (Falk, 2008). On the other hand, sea-side resorts primarily attract people who seek relaxation, fun, sun, food and sea (McClearly & Weaver, 1991; Mikulić & Prebežac, 2011; Papathanassis, 2012). Therefore, direct comparison is not possible. Nonetheless, a trend study can provide very relevant information to management, as it allows an analysis of competitiveness, which is especially

Table 7: A summary of findings

	Methods	Results	Implications
(1) General satisfaction with three types of resorts, user-identified qualities of different facilities, satisfaction and dissatisfaction with different aspects of tourist offer, identify comparative advantages and disadvantages	Numerical rating Sentiment analysis Aspect-based sentiment analysis	Guests satisfied with all three types of resorts Users of ski resorts were most positive. Users generally evaluate all aspects well, but were most satisfied with comfort, food/drinks, staff, view, design. Differences between resort-type were identified.	Monitor the trends in the evaluations in time and also across potentially competitive types. Both numerical and sentiment-based evaluations should be studied. Improve quality, strengthen existing capacities (advantages). Identify weaknesses from text evaluations.
(2) Aspects, most important to tourists for each of the specific types	Key-words analysis Latent Dirichlet Allocation (LDA) Aspect-based sentiment	Most reviewers talk about the “basics” in their reviews (hotel, food, room, staff) Most often evaluated aspects are food/drinks, room, staff, facilities.	Focus on ensuring highest standards for the aspects that are most important to tourists. This is specific to resort type (guest structure and expectations). Strong investment into “basic” qualities related to overall rating (numeric).
(3) Learning from comparisons of different types of destinations and related difficulties	Sentiment analysis Key-words analysis Latent Dirichlet Allocation Aspect-based sentiment	Generally, ski resorts ranked highest in evaluations, but reviewers were not the same people.	Direct comparison of ratings and score not possible. But important to observe trends, especially when resort types (hotels) are substitutes.

important in cases where resort types can be (partial) substitutes. This is the case of spa and ski resorts in the winter (not for all guests, but definitely for some) and spa and sea-side in the summer (see Vivian, 2011).

Our results also show that there is a significant difference between the sentiment evaluation (as the reviewer portrays the qualities of the resort through the text) and the numerical evaluations. This supports the other findings in the literature, such as Lackermair et al. (2013).

With regards to the second research question, we were trying to assess the **comparative importance of different aspects of hotels’ infrastructure, characteristics and qualities** (e.g. food, rooms, staff, etc.) for the overall satisfaction of guests (and good reviews). The findings show that, in general, similar elements matter for all three types of resorts. These are food/drink, rooms, staff, facilities, but also location, cleanliness, view and value. These are the most often evaluated aspects in the reviews. The fact that these aspects are also those revealed through the content analysis (LDA) confirms, through a different methodology, the need for all types of resorts to invest into having »strong basics«. This is in line with findings from the literature (Han & Hyun, 2018; Prud'homme & Raymond, 2013; Radojevic et al., 2015). Having strong »basics« is also positively correlated with overall numerical rating (which is the first thing displayed and observed by potential guests on web-page) and can be expected to support long-run competitiveness of a hotel. Finally, quite importantly, especially in terms of staff, food and cleanliness (taking into consideration costly refurbishment) a lot can be done without significant cost.

As shown also in the literature (Falk, 2008; Gustavo, 2010; Konu et al., 2011; McClearly & Weaver, 1991; Mikulić & Prebežac, 2011; Papathanassis, 2012) different types of resorts attract different segments of guests and their ranking of priorities is not the same. This adds another important implication for the management – the need to analyse the textual reviews to understand the expectations of their guests and adjust the services to their target segment. If guests chose the sea, but like swimming, can the guests swim in bad weather, is the beach equipped with the necessary infrastructure? In the spa (especially if guests substitute sea with spa), is the water warm and clean? Are the pools big enough? Similarly, in the skiing resorts alternative solutions for bad weather are also useful (pool, gym), however, skiing facilities should be of primary concern. Due to the vast availability of data, management can also study reviews of top providers, or providers in other countries that they either look up to, or consider their main competitors. Knowing and understanding the needs and desires of guests is one of the key aspects of success in the hospitality industry. This is especially due to an increase in the importance of data-driven decision-making and availability of data. Understanding different consumer segments, adjusting to their needs and relying on data to improve competitiveness has clearly become increasingly important (J. Anderson & Narus, 1998; Gursoy, 2018; He et al., 2013; Semerádová & Vávrová, 2016).

Our last research question addressed the **potential to compare directly the resorts**. As was shown in the discussion of the first two research questions, direct comparison is generally not possible between different types. It would also not be possible within the same type between different locations or within the same type and location, but it would be possible among hotels with different star ratings (3-star vs. 4 or 5-star hotel). They attract different consumers who have very different perception of quality (based on their expectations). Nonetheless, the results do stress a common trait – that basic services and infrastructure matter most and those should be managed with great care to retain competitiveness.

5.2 Contributions

The paper makes several contributions to the literature. The paper, first, represents an extension to the existing research about the use of travel reviews and the importance of studying several dimensions pertaining to text reviews (numerical or star evaluation, sentiment, content). This is a field that has been growing fast but is at the moment still offering many opportunities, primarily with regards to topic modelling. One of the few papers that use the recent topic modelling developments is Roseti, Fabio, Cao & Zanker (2016).

This paper extends the methodological debate and illustrates complementarities between established methods (such as sentiment analysis), the less-used content analysis and the novel aspect-based sentiment.

Consequently, the research directly contributes to the theoretical and sentiment-based empirical debate regarding the use of text mining in social media for competitive analysis (Gémar & Jiménez-Quintero, 2015). It directly contributes to the development of this debate in tourism, which was suggested already by Lau et al. (2005), as well as providing a tool-kit for further research on this debate.

The paper is also the first such analysis of Slovenian tourism which, hopefully, will on the one hand, stimulate the development of the field in the region and, on the other, become recognized as a tool that can be successfully applied in strategic planning as a tool for collecting information. This is especially relevant for countries where tourism is an important sector (such as neighbouring Croatia, Italy, and Austria).

5.3 Limitations and challenges for future work

The results do have some limitations, which are also challenges for future research. First of all, these results do not allow identification of competitive strengths or weaknesses of a specific destination (supplier, hotel). Aggregation by type of destination hid the individual specifics, but hotel level analysis was not a purpose of this study in any case. If the same approach were used at the level of a specific supplier, results would facilitate identification of comparative advantages or disadvantages, which represents one of the challenges for future research. In that case, the analysis and application of results to destination competitiveness models (e.g. Dwyer et al., 2004; Ritchie & Crouch, 2003) would be more important and more purposeful.

An additional challenge for future research is the relationship between the star (numerical) rating and the content (also revealed in the sentiment) and aspect-based sentiment. In our case, the relationship is positive, but not strong. As suggested by Lackermair et al. (2013), for product evaluations additional methods should be used. Furthermore, applying the tag approach, as suggested by Vig et al. (2012), could be useful for further research in the tourism sector.

For some small providers, only a few reviews are available, which is not enough for computational linguistics, and, consequently, the use of this methodology is limited. The small number of reviews also intensifies the problem of reliability (as discussed widely in Mayzlin et al., 2012) due to the potential problem of review manipulation. In a large number of reviews, this problem is minimized. An interesting challenge would be to analyse whether specific types/groups of hotels are on average more prone to faking reviews or encouraging customers to write (positive) reviews.

Another challenge is answering the strategic question of who the target consumers are currently and who the providers should target. If a selected group of reviewers is providing a significantly different picture, the differences should be examined and strategies adjusted, especially if this specific subset of customers represents an important target market.

Lastly, the comprehensive inclusion of user-generated reviews into the model of tourist destination competitiveness and among the indicators (for example into the existing OECD, 2013) represents another important challenge. But, at this stage, the diversity of the destinations and methodological challenges are still significant, requiring intense multidisciplinary approach.

6 CONCLUSION

User-generated content has been gaining in importance for decision-making in the tourism sector and the results of this analysis show that useful insights for both travellers, as well as management, can be obtained. This paper focused on possible implications for management, whereby the focus was not on a specific hotel, but rather on comparisons of hotels in different types of resorts. Although comparing ski and spa or spa and sea resorts might not seem sensible at first, it is relevant, since some of them are, in fact, substitutes. Moreover, understanding competition, and consumers' perceptions in general, will improve performance only if the data is used for improving aspects where competitive disadvantages are found.

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DOBRA HRANA, ČISTE SOBE I LJUBAZNO OSOBLJE: IMPLIKACIJE SADRŽAJA GENERIRANOG OD STRANE KORISNIKA ZA UPRAVLJANJE SLOVENSKIM HOTELIMA U SKIJAŠKIM, PRIMORSKIM I TOPLIČKIM DESTINACIJAMA

SAŽETAK

U ovom se radu analiziraju korisničke recenzije hotela u trima vrstama destinacija u Sloveniji (skijaškim, primorskim i topličkim). Korištenjem opsežnog skupa podataka korisničkih recenzija za 28 različitih hotela, koristeći kombinaciju kvalitativnog „data mining“-a i klasičnih statističkih metoda, pokazuje se da ovaj oblik podataka pruža bogatu podlogu informacija, relevantnih za odlučivanje. Iako se numeričke evaluacije različitih tipova destinacija ne mogu direktno uspoređivati, s obzirom na različitu strukturu gostiju, rezultati pokazuju da gosti, u načelu, vrednuju uglavnom „temelje“ usluge (sobu, hranu/piće, osoblje). Koristeći kombinaciju stavova gostiju i novih aspekata navedenih stavova, hoteli mogu u realnom vremenu analizirati svoju konkurentnost, uspoređivati različite tržišne marke i koristiti analizu sadržaja, da bi dalje utvrdili izvore konkurentske prednosti i unaprijedili svoje poslovne rezultate. Ova studija je prva sveobuhvatna analiza slovenskog turizma, uz pomoć on-line recenzija te pruža smjernice za daljnje srodne primijenjene analize.

APPENDIX

Table A1: Sample structure by the number of reviews per hotel and percent of all reviews (hotel names replaced by hotel 1 – hotel 28)

Type	Hotel code	Count of reviews	% of all reviews
Sea	Hotel 1	100	5,84
	Hotel 2	20	1,17
	Hotel 3	50	2,92
	Hotel 4	30	1,75
	Hotel 5	40	2,34
	Hotel 6	60	3,50
	Hotel 7	260	15,19
	Hotel 8	20	1,17
Skiing	Hotel 9	40	2,34
	Hotel 10	70	4,09
	Hotel 11	20	1,17
	Hotel 12	20	1,17
	Hotel 13	40	2,34
	Hotel 14	89	5,20
	Hotel 15	180	10,51
	Hotel 16	99	5,78
	Hotel 17	99	5,78
	Hotel 18	40	2,34
	Hotel 19	60	3,50
	Hotel 20	90	5,26
Spa	Hotel 21	50	2,92
	Hotel 22	20	1,17
	Hotel 23	50	2,92
	Hotel 24	30	1,75
	Hotel 25	18	1,05
	Hotel 26	49	2,86
	Hotel 27	48	2,80
	Hotel 28	20	1,17
	Total	1712	100,00

Table A2: Results of aspect analysis

		Sea		**Ski**		**Spa**	
Aspect	**Evaluation**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Beds	Not evaluated	483	83	707	83	250	88
	Negative	29	30	35	25	14	40
	Neutral	3	3	8	6	1	3
	Positive	65	67	97	69	20	57
Cleanliness	Not evaluated	379	65	480	57	173	61
	Negative	45	22	21	6	34	30
	Neutral	6	3	10	3	5	4
	Positive	150	75	336	92	73	65
Comfort	Not evaluated	428	74	565	67	228	80
	Negative	23	15	7	2	9	16
	Neutral	2	1	7	2	0	0
	Positive	127	84	268	95	48	84
Customer support	Not evaluated	530	91	809	96	274	96
	Negative	32	64	13	34	9	82
	Neutral		0		0		0
	Positive	18	36	25	66	2	18
Design	Not evaluated	463	80	702	83	233	82
	Negative	25	21	20	14	10	19
	Neutral	5	4	4	3	3	6
	Positive	87	74	121	83	39	75
Facilities	Not evaluated	209	36	408	48	71	25
	Negative	93	25	56	13	75	35
	Neutral	23	6	14	3	16	7
	Positive	255	69	369	84	123	57
Food/drinks	Not evaluated	106	18	102	12	100	35
	Negative	83	18	83	11	43	23
	Neutral	36	8	25	3	9	5
	Positive	355	75	637	86	133	72
Location	Not evaluated	261	45	328	39	167	59
	Negative	82	26	70	13	43	36
	Neutral	30	9	25	5	9	8
	Positive	207	65	424	82	66	56
Payment	Not evaluated	490	84	756	89	253	89
	Negative	52	58	35	38	22	69
	Neutral	5	6	5	5	1	3
	Positive	33	37	51	56	9	28
Quietness	Not evaluated	502	87	720	85	259	91
	Negative	36	46	16	13	11	42
	Neutral	0	0	5	4	2	8
	Positive	42	54	106	83	13	50

Room amenities	Not evaluated	103	18	152	18	111	39
	Negative	107	22	71	10	49	28
	Neutral	30	6	45	6	15	9
	Positive	340	71	579	83	110	63
Staff	Not evaluated	127	22	156	18	119	42
	Negative	96	21	67	10	46	28
	Neutral	28	6	28	4	9	5
	Positive	329	73	596	86	111	67
Value	Not evaluated	341	59	535	63	195	68
	Negative	72	30	42	13	20	22
	Neutral	22	9	25	8	11	12
	Positive	145	61	245	79	59	66
View	Not evaluated	352	61	555	66	271	95
	Negative	33	14	23	8	3	21
	Neutral	15	7	14	5	1	7
	Positive	180	79	255	87	10	71
Wifi	Not evaluated	529	91	782	92	249	87
	Negative	13	25	15	23	11	31
	Neutral	6	12	5	8	4	11
	Positive	32	63	45	69	21	58

Table A3: Correlations between aspect-based sentiment value (converted into numerical), overall sentiment and rating

		Sea			**Ski**			**Spa**		
		LIU_ sentiment	AFINN_ senti.	Numeric rating	LIU_ sentiment	AFINN_ sent.	Numeric rating	LIU_ sentiment	AFINN_ sent.	Numeric rating
LIU_ sentiment	Correlation		,888**	,358**	1	,884**	,224**	1	,902**	,455**
	Sig. (2-tailed)		0,000	0,000		0,000	0,000		0,000	0,000
	N	580	580	580	847	847	847	285	285	285
AFINN_ sentiment	Correlation	,888**		,300**	,884**	1	,215**	,902**	1	,385**
	Sig. (2-tailed)	0,000		0,000	0,000		0,000	0,000		0,000
	N	580	580	580	847	847	847	285	285	285
Ocena	Correlation	,358**	,300**		,224**	,215**	1	,455**	,385**	1
	Sig. (2-tailed)	0,000	0,000		0,000	0,000		0,000	0,000	
	N	580	580	580	847	847	847	285	285	285
Aspect_tot	Correlation	**,540****	**,482****	**,619****	**,545****	**,483****	**,445****	**,617****	**,528****	**,587****
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	580	580	580	847	847	847	285	285	285
Beds	Correlation	,386**	,238*	,634**	,176*	0,076	,443**	0,246	0,277	,526**
	Sig. (2-tailed)	0,000	0,019	0,000	0,037	0,370	0,000	0,155	0,107	0,001
	N	97	97	97	140	140	140	35	35	35

Cleanliness	Correlation	,292**	,270**	,531**	,197**	,143**	,445**	,559**	,442**	,604**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,006	0,000	0,000	0,000	0,000
	N	201	201	201	367	367	367	112	112	112
Comfort	Correlation	,362**	,243**	,616**	0,060	0,027	,281**	0,180	0,194	,273*
	Sig. (2-tailed)	0,000	0,003	0,000	0,312	0,646	0,000	0,180	0,147	0,040
	N	152	152	152	282	282	282	57	57	57
Customer support	Correlation	,292*	,288*	,354*	0,051	0,032	,332*	0,167	-0,020	0,222
	Sig. (2-tailed)	0,040	0,043	0,012	0,759	0,848	0,042	0,624	0,952	0,511
	N	50	50	50	38	38	38	11	11	11
Design	Correlation	,398**	,335**	,517**	,199*	0,138	,401**	0,194	0,023	,510**
	Sig. (2-tailed)	0,000	0,000	0,000	0,016	0,099	0,000	0,168	0,874	0,000
	N	117	117	117	145	145	145	52	52	52
Facilities	Correlation	,270**	,303**	,516**	,191**	,176**	,391**	,402**	,331**	,543**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	371	371	371	439	439	439	214	214	214
Food/drinks	Correlation	,324**	,289**	,547**	,297**	,271**	,521**	,376**	,296**	,560**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	474	474	474	745	745	745	185	185	185
Location	Correlation	,344**	,302**	,401**	,219**	,214**	,344**	,470**	,438**	,533**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	319	319	319	519	519	519	118	118	118
Payment	Correlation	,269*	,277**	,358**	0,206	0,102	,481**	0,336	0,274	,371*
	Sig. (2-tailed)	0,011	0,008	0,001	0,050	0,335	0,000	0,060	0,130	0,037
	N	90	90	90	91	91	91	32	32	32
Quietness	Correlation	,366**	,266*	,492**	0,160	0,126	,351**	,448*	0,271	0,254
	Sig. (2-tailed)	0,001	0,019	0,000	0,073	0,158	0,000	0,022	0,181	0,211
	N	78	78	78	127	127	127	26	26	26
Room amenities	Correlation	,355**	,332**	,604**	,186**	,140**	,458**	,414**	,345**	,483**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	477	477	477	695	695	695	174	174	174
Staff	Correlation	,347**	,266**	,589**	,173**	,171**	,517**	,515**	,456**	,684**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	453	453	453	691	691	691	166	166	166
Value	Correlation	,352**	,313**	,401**	,168**	,151**	,409**	,313**	,276**	,416**
	Sig. (2-tailed)	0,000	0,000	0,000	0,003	0,008	0,000	0,003	0,009	0,000
	N	239	239	239	312	312	312	90	90	90
View	Correlation	,216**	,253**	,434**	,146*	0,083	,213**	,639*	0,496	,554*
	Sig. (2-tailed)	0,001	0,000	0,000	0,013	0,155	0,000	0,014	0,071	0,040
	N	228	228	228	292	292	292	14	14	14
Wifi	Correlation	,435**	0,269	,495**	,281*	0,195	,356**	0,233	0,188	,537**
	Sig. (2-tailed)	0,001	0,056	0,000	0,023	0,120	0,004	0,171	0,271	0,001
	N	51	51	51	65	65	65	36	36	36