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REVIEWS AS A POWERFUL MARKETING TOOL: PROFILING REVIEW READERS IN TOURISM SERVICES

Zuzana KVÍTKOVÁ – Martin VAŠKO – Alžběta ZÍKOVÁ

ABSTRACT:
This study investigates the heterogeneity of online review readers in the tourism sector by developing a comprehensive typology based on empirical data. The main aim of this study is to create a typology of review readers. The research aims at providing a deeper insight into the profiles of the review readers and evaluating the impact of reading the review in different segments. Utilising a data-driven segmentation approach, the authors analysed 2,525 valid questionnaire responses collected from European consumers, primarily in the Czech Republic and Slovakia. Through hierarchical and K-means cluster analyses, ANOVA and discriminant analysis, four distinct segments of review readers were identified and validated: Enthusiasts (41%), who heavily rely on reviews for travel decisions; Pragmatists (34%), who consult reviews for practical and financial reasons; Observers (10%), influenced by social context and trends; and Uninfluenceable Readers (14%), who largely disregard reviews. Profiling revealed that while socio-demographic factors such as age, education, and income are related to segment membership, their influence is generally weak compared to behavioural patterns. The findings fill a gap in the literature by offering a nuanced understanding of review readers, with implications for targeted reputation management, tailored marketing communication and platform selection.

KEY WORDS:
communication, cluster analysis, reputation, reviews, segmentation, tourism

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1 Introduction

Nowadays, eWom is an integral part of marketing communication, and is a factor of image creation affecting brand attitude, and is a significant predictor of purchase intentions (Alrwashdeh et al., 2019; Devianti & Irwansyah, 2020; Ismagilova et al., 2020). EWom is part of interactive communication (Liu & Jayawardhena, 2023). Two-way communication is a crucial benefit of eWom and communication managers should pay attention to the platforms. However, the response rate and the activity of companies still remain rather low.

EWom changes the character of marketing communication towards authenticity (Bharti et al., 2024). Through this eWom is a powerful communication tool for specialised topics, aims and groups. The promotion of sustainable tourism in Bangladesh is strongly influenced by online reviews, social media recommendations, travel blog content, and so on (Rahman & Mia, 2025). In some cases, community-based reviews are an effective way of communication (Wanigapura et al., 2025).

In tourism, the eWom plays an even more important role in the decision-making process as the amount of money that is going to be spent is a substantial part of the budget. The accelerated digitalisation of tourism in the last decade significantly changed consumers' positions. They quickly became highly informed tourists that are exceedingly oriented in offers. Word-of-mouth (WOM) is one of the most powerful factors affecting consumer behaviour (Daugherty & Hoffman, 2013) and its evolution into electronic world-of-mouth (eWOM) brought a revolution in information exchange and flow. User-generated content UGC (e.g., blogs, reviews) and eWOM is a key source of information for customers and is a vitally important source of value to entrepreneurs (Nam et al., 2020).

Review systems, offered by OTAs as an integral part of their applications (e.g., Booking.com), or offering information as stand-alone platforms (e.g., TripAdvisor, Yelp), dominate amongst these electronic sources. These review platforms are an important tool for companies and are a useful source of information for quality management, and serve as a customer satisfaction indicator. It enables companies to control and manage their reputation (Lai & To, 2015). The positive reviews represent an opportunity to gain new customers, skip ahead of competitors, and improve financial performance.

This study will approach the topic from the review readers' perspective. The main research question is whether there are identifiable segments with similar characteristics and what those characteristics are. As this research is part of the broader research topic of online reputation management, we see evidence in literature that the readers are different, using different platforms and having different approaches to the reviews. However, the overall description of the review readers is missing, and this study aims to fill this knowledge gap. The main aim of this study is to create a typology of review readers using clustering methods. The research aims at providing a deeper insight into the profiles of the review readers and at evaluating the impact of reading the reviews on different segments. First, the study presents approaches to segmentation, the relevant segmentation criteria, the differences between travellers, review writers, and readers in order to identify potential differences. Second, the methodology is described, and the results are presented. In the end, managerial implications, conclusions, and limitations are discussed.

2 Literature Review

Segmentation itself is a key factor in effective marketing and marketing communication (Wind & Bell, 2008). The division of the market allows targeted communication (and other parts of the marketing mix) that best suits the segments.

There are several approaches to segmentation depending on the purpose. The most used ones are Value-Based Segmentation, Behavioural Segmentation, Propensity-Based Segmentation, Loyalty Segmentation, Socio-demographic and Life-Stage Segmentation, and Needs/Attitudinal-Based Segmentation (Tsiptsis & Chorianopoulos, 2011). For companies, the financial perspective and effective use of the resources are crucial. Customer Value Matrix (Marcus, 1998) can divide the customers according to their worth for the company (a store in this case). Marcus argues in his study that the Customer Value Matrix is more suitable for local stores than for large chains. An extension of customer value is the concept of Customer Lifetime Value (CLV). To keep, care for and satisfy the most valuable customers is a very logical strategy. Finding the most valuable segment is not so simple; however, in tourism it is very beneficial (Webb et al., 2022). The models usually consider past behaviour but ignore some aspects like the defection of customers (Hwang et al., 2004). The recency, frequency, and monetary value (RFM) segmentation model brings the aspect of time into the model (Pradhan, 2021).

Behavioural segmentation is useful for persona creation (An et al., 2018) and relevant for hotels. Loyalty, frequency of accommodation, and spendings on additional services are important inputs for revenue management. Working with different segments can have an impact on occupancy (Ahmad et al., 2011). In tourism, segmentation is extremely important as the situation complexity and variety of needs (also different for each person in different situations) and possibilities are enormous. For marketing, benefit segmentation is useful and used (Perera et al., 2020), especially when preparing sales arguments for marketing communication (Nduna & Van Zyl, 2020). Thanks to understanding the needs, motivation, and sources of satisfaction, the companies and destinations can prepare specific products for the individual segments (Konu et al., 2011; Noor Zatul Iffah et al., 2021), in this case, activity-based segmentation is appropriate (Eusébio et al., 2017). Another relevant segmentation criterion is the purpose of the trip and destination type (Schewe & Calantone, 2016), and motivation (Rid et al., 2014; Guttentag et al., 2018; Lee & Kim, 2023). For tourism, expenditure segmentation is also highly relevant, however, underutilised (Vinnciombe & Sou, 2014) and in some situations, territorial segmentation can be beneficial (Simancas Cruz et al., 2022). Sometimes the content or sentiment of reviews is used for segmentation (Nessel et al., 2021; Jardim & Mora, 2022; Shu et al., 2023).

A segmentation of resort visitors found four clusters with different resort selections, satisfaction, opinion, and preferences. From a socio-demographical point of view, life cycle, education, and age were decisive factors, and gender was not (Inbakaran & Jackson, 2005). Recent years have brought fast progress in technology and self-check-in, technology-equipped rooms, online communication, and similar innovations can divide the market in other ways than the usual approach. Whereas at the beginning of this century, ICT was still not a common criterion for segmentation (Antti Pesonen, 2013), the relevance of bringing technology into segmentation is confirmed by concurrent and later research (Victorino et al., 2009; Nica et al., 2019). Another research article segmenting Airbnb users and non-users emphasises the relevance of age, income, gender, and education for being in a particular segment (Angelovska et al., 2021).

Taking a look into reputation and reviews, the reviewers can be analysed from several aspects of their lives and behaviour. The researchers found differences in reviews and ratings concerning culture, language, geographical distance, and travellers' preferences (Antonio et al., 2018; Ahani et al., 2019; Phillips et al., 2019; Li et al., 2020). One of the most important aspects of segmentation is the motivation for writing reviews (Gonçalves et al., 2018; Mladenovic et al., 2019).

The authors mainly approach the reviews in order to find the preferences of writers, current quality issues, correlations between the evaluated categories, effects on hotel performance, etc. The readers are less researched, and the questions focus on the booking intention, effect of the reviews on decision making process, or question of adoption of the information.

The motives for reading differ for the individual readers (Hennig-Thurau et al., 2003). The most important are (1) risk reduction, (2) reduction of search time, (3) dissonance reduction, and (4) group influence. Based on the values and current situation, the customer perceives risk in functional areas (quality of the service), social (family and friends), financial (price), and physical areas (bodily harm). The motive for reducing time is very relevant nowadays. Finding the proper product brings two kinds of costs: internal and external (Smith et al., 1999). Internal costs are mainly represented by mental effort; external are opportunity costs for the time and monetary costs of obtaining the information. These costs lead to the effort to reduce the time of the search. Time pressure for the reader is given by the general perception of lack of time. Dissonance reduction is well applicable to tourism as a motive for reading reviews. Sweeney et al. (2000) explain the conditions when dissonance may be aroused and all of them are applied to leisure travel – the traveller invests a substantial amount of money or psychological cost into the choice, the decision is voluntary, and it is usually irrevocable (or for a certain level of costs).

Group influence is the willingness to comply with the peer group, and many people are influenced by group opinion (Lee et al., 2011). The influence of community and social environment can affect the approach and usage of reviews. The literature identifies also social reassurance as a motive (Kim et al., 2011).

The effect of positive and negative reviews has proved to be different (Park & Nicolau, 2015) and the literature confirms even a different effect of positive and negative reviews on the booking intention of different groups of customers (Tsao et al., 2015). The research found differences between the genders regarding reading online reviews (Kim et al., 2011).

It also matters where the reviews are being read. Tourism is a complex phenomenon, and tourists typically undertake a complicated decision-making process (although there are exceptions). Even if there is no obvious reason, the platforms and users of the platforms differ. The authors found differences in terms of information quality between TripAdvisor, Expedia, and Yelp (Xiang et al., 2017), with the choice of the review platform being influenced by emotions (Yan et al., 2018). Expedia contained many empty reviews, and the length of the review was the shortest; it was also perceived as the least useful. Yelp, on the other hand, seemed to attract unsatisfied and complaining customers and had the highest share of reviews with negative sentiment and the lowest rating amongst the platforms. Also rating scales and calculations can give different impressions to the readers on different platforms (Martin-Fuentes et al., 2020).

The usefulness of the review is the key factor in adopting the information. Based on the information adoption model, the research also confirmed that information adoption is influenced by argument quality credibility of the message (Chong et al., 2018) and credibility of the source (Zhang et al., 2014). The attitude of the readers to the reviews in general, explicitly whether they perceive the reviews as useful or not, determines to a certain level their behavioural responses (Akhtar et al., 2019; Oliveira et al., 2020).

There were few studies offering the tourists segmentation involving online reviews. The studies of Hernández-Méndez et al. (2013) and Nessel et al. (2021) include reviews in a certain way into their analysis. However, the role of reading the reviews is not a decisive criterion.

Potential customers and their approach and attitude to reviews are worth researching in more detail. The literature provides enough evidence that individual review readers differ in many ways, but the complex typology and segmentation are missing. This study aims to fill this knowledge gap by assuming that:

H1: There are identifiable segments with similar behavioural patterns but still significantly different from each other.

H2: The cluster (segment) members are similar in terms of socio-economic and demographic characteristics and travel habits.

Confirming or rejecting these two hypotheses will lead to answering the main research question regarding if there are identifiable segments with similar characteristics and what the characteristics are. The clusters are identified, profiled, and described. In this study, we adopt a data-driven approach to segmentation and bring new insight to the review readers' typology, their characteristics, and behavioural patterns.

3 Methodology and Data

The research aims to provide a deeper insight into the profiles of review readers and evaluate the impact of reading reviews in different segments. The framework of segmentation is based on the literature and is presented in Figure 1.

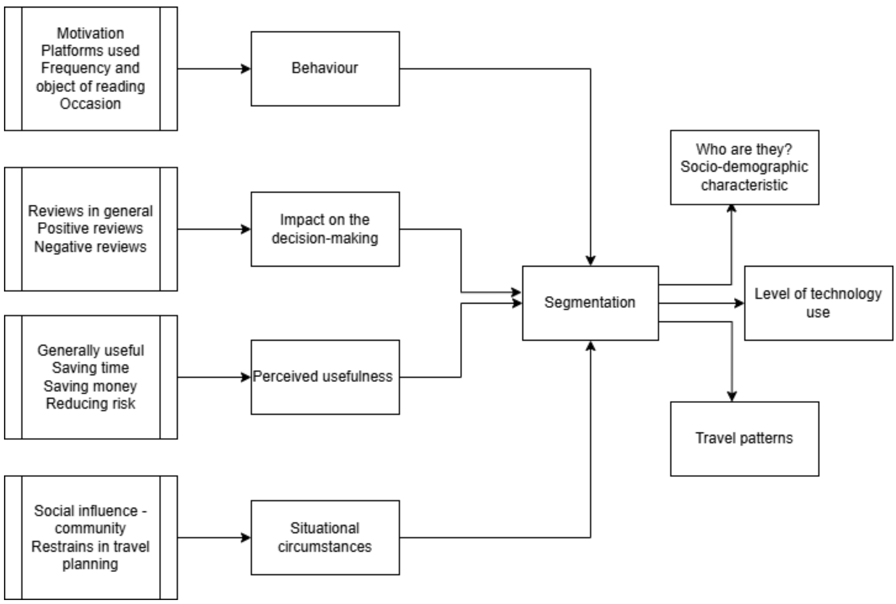

Figure 1: Segmentation framework
Source: Own processing, 2025

The study is on data-driven segmentation, and therefore is exploratory in nature (Dolnicar, 2019) and according to Dolnicar (2006), consists of steps that are necessary for the quality of the solution. These steps include (1) the sampling stage; (2) the data pre-processing stage; (3) the segmentation stage; and (4) the validation stage. This study combines these stages with stage (5) – profiling of clusters. This approach, combining traditional segmentation, validation, and profiling, using multivariate statistical methods (two-step cluster analysis, discriminant analysis), represents an advanced approach, as it is not limited to merely one of the methods. The two-step analysis is typical for tourism segmentation (Torkzadeh et al., 2021). On the contrary, it proposes a methodology that, supported by complementary techniques, allows us to reach a very detailed market differentiation (Correia et al., 2008). The statistical procedures were carried out for this study using the Statistical Package for Social Sciences (SPSS).

Sampling

To analyse the review readers, a questionnaire was prepared based on the literature review and identification of potential differences. The data was collected between October 2021 and February 2022 in the Czech Republic and Slovakia and also contain answers from other nations (6% of all responses). From the overall perspective, the respondents represent European consumers. Using electronic distribution, altogether 2,993 answers were collected. The data was checked for completeness and unusual responses, and 468 answers were excluded due to missing values. The analysis is based on 2,525 valid questionnaires.

Data Pre-processing

The data pre-processing combines a check for missing values and unusual observations, and in the segmentation studies factor analysis (FA). FA aims to reduce the number of variables that are used for the next stage and to find latent factors. This study omitted FA for the reasons that Dolnicar (2003) explains in her study. The two main reasons are that there can be much information lost after the use of the FA and that segments are constructed in a space other than what was initially chosen.

Segmentation

The segmentation was based on 45 statements using a Likert scale with answers 1-7. In the first step, to find the optimal number of clusters, 5% of respondents were randomly selected and with the help of Ward's linkage method with the squared Euclidean distance, it was determined that 4 clusters would be optimal. Ward's linkage method with the squared Euclidean distance is the most used technique amongst linkage methods (Dolnicar, 2003). In the second step, the K-means cluster analysis for all responses for 4 clusters was applied, where cases were grouped into the cluster closest to the centre. K-means is the most used technique amongst partitioning clustering methods (Dolnicar, 2006).

Validation

The validation combines univariate (analysis of variance, ANOVA) and multivariate approaches (discriminant analysis, DA). To identify the differences in data structure between the clusters, ANOVA tests for each of the questions (variable) were carried out. However, these tests should be used only for descriptive purposes and not to test the hypothesis that the cluster means are equal, because the clusters have been made to maximise the differences between cases in clusters.

The DA was based on a set of quantitative explanatory variables (45 questions) that explained the cluster membership. The aim was to test whether the clusters (or groups) are statistically significantly different for all variables together. Since there is a four-group model, three discriminant functions were calculated to discriminate between the four groups. The prior probabilities were based on the size of each group. The quality of classification was confirmed by the resubstitution and cross-validation approach. This type of stability test was proposed by Dolnicar (2003) who summarised 243 publications in the area of business administration where data-driven segments were identified.

Profiling

For the profiling of groups (segments), each cluster was cross-tabulated with characterising variables such as visitors' socio-economic profiles and behavioural variables regarding their travel habits. These relationships were checked for statistical significance using chi-squared tests and ANOVA according to the variable type, and the strength of the relationships was measured by Cramer's V. Profiling (external validation) of segments, by identifying in which personal characteristics segments differ significantly, and is based on the methodology by Dolnicar (2008).

4 Results

The analysis is based on 2,525 valid questionnaires. The sample consists of 34% men, 64% women, and 2% who did not wish to respond. The average age is 30.22 years (std. dev. 13.48). The distribution of education and income level is in Table 1.

Table 1: The highest level of education and income group

Highest Level of Education	Valid Percent	Income Group	Valid Percent
Elementary	5.08	Under Average	12.22
Vocational	7.55	Average	68.51
High School	56.70	Above Average	17.07
University / College	30.67	Highly Above Average	2.19

Source: Own processing, 2025

The characteristics of each variable were calculated. The means for the data set vary between 1.35 and 5.35 and the standard deviation vary between 1.02 and 2.17.

The Segmentation

After the hierarchical cluster analysis for the randomly-chosen 5% of responses, four clusters were found to be optimal for segmentation. K-means clustering divided all responses into these four clusters. The four groups are statistically significantly different in means according to the one-way ANOVA for each variable (H1). The following figures show differences based on the means of the following characteristics: motivation (Figure 2), occasions, frequency, and object of reviews (Figure 3), used platforms (Figure 4), impact on decision-making (Figure 5), perceived usefulness (Figure 6), and social influence and restraints in travel planning (Figure 7).

Figure 2: Cluster centres for Behaviour – Motivation
Source: Own processing, 2025

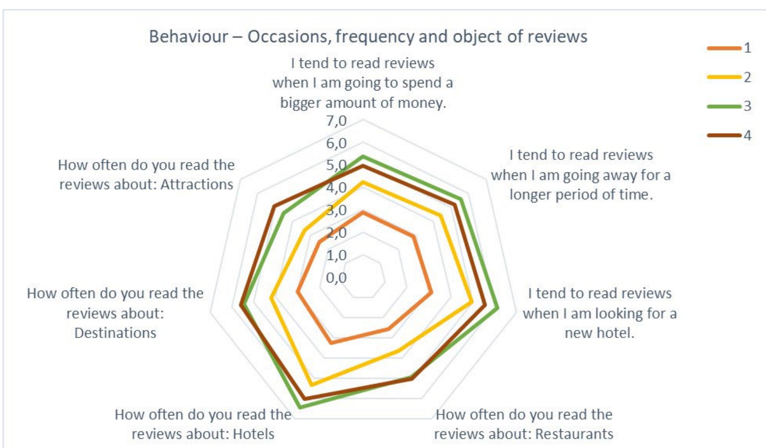

Figure 3: Cluster centres for Behaviour – Occasions, frequency and object of reviews
Source: Own processing, 2025

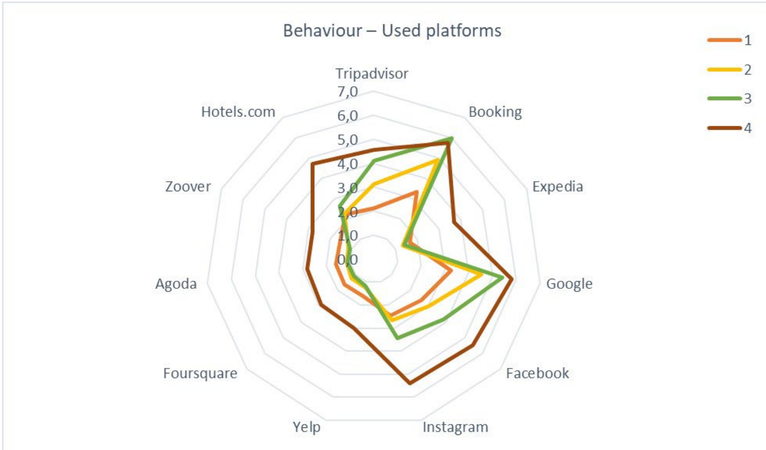

Figure 4: Cluster centres for Behaviour – Used platforms
Source: Own processing, 2025

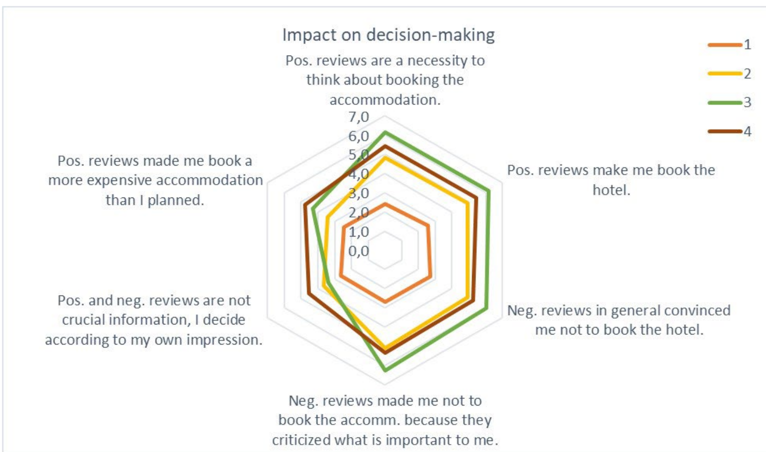

Figure 5: Cluster centres for Impact on decision-making
Source: Own processing, 2025

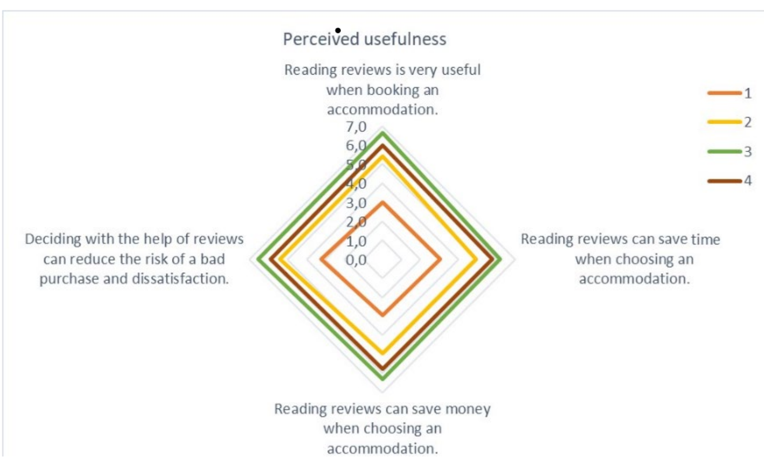

Figure 6: Cluster centres for Perceived usefulness
Source: Own processing, 2025

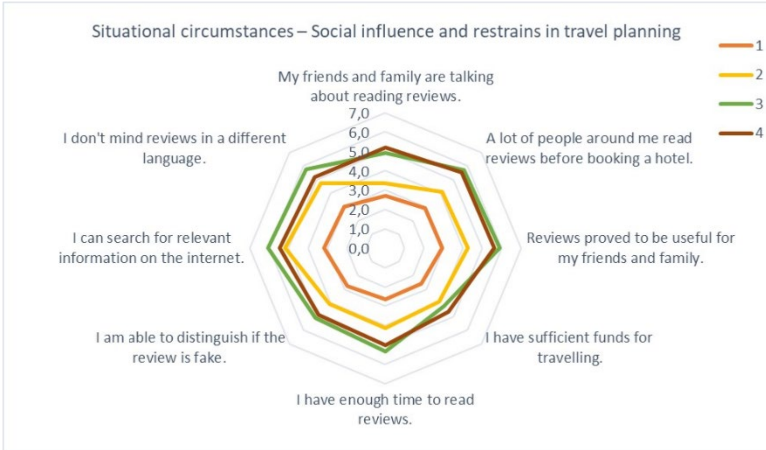

Figure 7: Cluster centres for Situational circumstances – Social influence and restrains in travel planning
Source: Own processing, 2025

The figures present the means in the clusters. All p-values of the F-tests, testing the hypothesis of equal expected values, are below 0,000. The variables describe the behaviour according to the segmentation framework suggested in Figure 1. After validation and profiling, the segments are described below.

Validation

The four clusters are statistically significantly different based on the significance tests of the functions. The classification results show that discrimination was successful from both approaches. Table 2 presents the discriminant analysis.

Table 2: Discriminant analysis tests

Test of Function(s)	Wilks's Lambda	Chi-square
1 through 3	,079	6335,925
2 through 3	,449	2002,225
3	,850	405,432

Source: Own processing, 2025

All 3 discrimination functions had p-values below 0,000. 93.0% of original grouped cases were correctly classified. 91.6% of cross-validated grouped cases were correctly classified. In cross-validation, each case is classified by the functions derived from all cases other than that case.

Profiling

The next step was profiling the segments. Each cluster was cross-tabulated with characterising variables such as visitors' socio-economic profiles and behavioural variables regarding their travel habits. The results are presented in Table 3.

Table 3: Socio-demographics and travel habits

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Sample	Cramer's V
Gender						
Male	32%	36%	28%	32%	32%	0.081
Female	64%	62%	71%	64%	66%	
Don't want to say	4%	2%	1%	3%	2%	
Highest Level of Education						
Elementary	9%	5%	4%	8%	5%	0.085
Vocational	10%	5%	4%	10%	6%	
High school	56%	56%	59%	54%	57%	
University / college	25%	33%	34%	28%	32%	
Income Group						
Under average	13%	14%	12%	6%	12%	0.069
Average	64%	69%	71%	70%	69%	
Above average	19%	14%	16%	22%	16%	
Highly above average	4%	2%	1%	2%	2%	
Technology Usage						
Basic	11%	8%	4%	6%	6%	0.078
Regular	48%	52%	48%	51%	50%	
Advanced	28%	31%	38%	35%	34%	
Very advanced	13%	9%	10%	8%	10%	
You Travel to ... Destination						
Always to the same	7%	2%	1%	3%	2%	0.087
Usually to the same	28%	25%	23%	25%	24%	
Usually to a new	46%	59%	59%	58%	57%	
Always to a new	20%	13%	17%	14%	16%	
4 or more months in advance	20%	15%	15%	20%	16%	0.071
2 – 4 months in advance	27%	29%	28%	30%	29%	
3 – 8 weeks in advance	25%	33%	33%	34%	32%	
1 – 14 days in advance	23%	21%	22%	13%	21%	
I make travel decisions during the trip	5%	2%	2%	2%	2%	
only a little (once/twice a year)	46%	50%	40%	41%	44%	0.072
occasionally (3 – 5 times a year)	42%	40%	50%	50%	46%	
very often (6 and more times a year)	12%	9%	10%	9%	10%	

Source: Own processing, 2025

All p-values are below 0,000. Four groups are characterised by seven socio-demographic indicators and travel habits. For each pair (cluster membership and one socio-demographic indicator) the Pearson chi-square test of independence was calculated. All these 7 socio-demographic indicators are statistically significantly related to the cluster membership; therefore, the values of socio-demographic indicators influence cluster membership. The relationship of each pair is weak; the maximum value of Cramer's V is only 0,087. Average age is in Table 4 and is between 28 and 30 years.

Table 4: Average age

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Age	30.83	30.00	28.23	28.45

Source: Own processing, 2025

P-value is 0,001. ANOVA was used for age and cluster membership; the relationship is statistically significant, and the mean age is different in all four groups, but the relationship is weak (the determination ratio is only 0.007 with a maximum of 1).

5 Discussion

The statistical analysis revealed four clusters of review readers. For the research results, the segments were named (1) Uninfluenceable Readers, (2) Pragmatists, (3) Enthusiasts, and (4) Observers. This relates to H2.

Uninfluenceable Readers (14%)

This cluster states that they are reading reviews, but their approach is very reserved. They have the lowest scores in most of the aspects of behaviour researched. If they read reviews, it is mostly about hotels, and they use Booking.com and Google. Even if they read reviews rather rarely, they partially admit that reviews could reduce the risk of bad purchases and dissatisfaction, but they are not really convinced about this. They tend to read reviews in case of booking a new hotel but still very rarely in comparison to other segments. Positive reviews are not a precondition for booking a hotel and they mostly decide according to their impression. From the socio-demographic and travelling point of view, it seems that there are two subsegments – some of the characteristics are in extreme positions. The members of this segment tend to make reservations four or more months in advance or at the last moment (on-site or maximum two weeks in advance). They see themselves mostly as basic technology users but also the characteristic "very advanced user" is slightly above the average of the sample. Uninfluenceable readers tend to travel to the same destination or always to a new one. The segment tends to group people with lower education but above average or even highly above average income. They might be successful craftsmen, or small-sized entrepreneurs, but this is only a guess. To point out the main characteristic of the Uninfluenceable Readers – they read reviews probably by chance and do not pay much attention to them.

Pragmatists (34%)

The pragmatic segment approaches reviews realistically. In most of the measured statements they are slightly below average but considering that value 4 is the neutral position, their attitude to reviews is positive in all aspects. They mostly read reviews to prevent disappointment regarding quality, and they use reviews because they can make the decision easier. Money is important to them in several ways. Their funds for travelling are limited. They read reviews to prevent wasting money and at the same time, to achieve a good price/quality ratio. Negative reviews are more influential than positive ones, which is in line with price/quality efficiency. Pragmatists do not allow reviews to lead them to a more expensive hotel. Like the other segments, they use mostly Booking.com and Google and most often read reviews about hotels. They think reviews are very helpful when booking a hotel and that reviews can reduce the risk of bad purchases and dissatisfaction. This pragmatic approach is slightly more typical for men. The members of the segment tend to have average or below average income and see themselves as basic or regular technology users. They usually travel only a little (once/twice a year). To point out the main characteristic of the segment – they read reviews as part of a rational decision-making process to use their money efficiently.

Enthusiasts (41%)

This segment depends on reading reviews with their travel decisions, and reviews are the "holy grail" for them. We can say that they do not decide on travelling without reading the reviews. They read them to avoid quality issues, save money and time, and check the location. They are very strongly influenced by reviews in their decisions. The effect of positive reviews is slightly stronger than that of negative ones. They let themselves be convinced to book a hotel with good reviews, and even a more expensive hotel can be booked. On half of the occasions, they use TripAdvisor, quite often Google, and almost always Booking.com. They practically always read reviews about hotels when going somewhere and often also about destinations and restaurants. They perceive reviews as very useful, and their peers and family read reviews as well. They do not mind reading reviews in other languages, and they think they can search for information on the Internet. This behaviour seems to be typical rather for women, and the members tend to have higher education levels (high school or university/college). This segment groups advanced technology users at the expense of regular and basic users. They travel occasionally or very often and the tendency to travel to new destinations prevails. To point out the main characteristic of the segment – reviews are everything when travelling.

Observers (10%)

Observers are a small segment of review readers that have a positive approach to reviews but their motivation to read them in comparison to Enthusiasts is a bit vague. They read reviews to avoid disappointment with quality and to avoid wasting time, however, their responses do not score very highly. Most of the numbers are similar to Pragmatists. A relatively more important factor is being part of the modern community in comparison to Pragmatists. It seems that their motivation is to keep up with the trends. Reviews are only one of the parts of the overall picture for decision-making, the reviews are not crucial information. On the other hand, if they find useful information, they let themselves be carried away; positive reviews are slightly more influential. Positive reviews are a necessity for booking a hotel and positive reviews can convince them to book a hotel or an even more expensive hotel. The platforms used confirm the community's importance. Observers read reviews, not only on the traditional Booking.com and Google, but also on social media – Facebook and Instagram. TripAdvisor is most often used by this segment, and this is the only segment using Hotels.com. Extensive usage of these platforms speaks for their motivation in keeping up and being informed. They perceive the reviews as very useful in general; their attitude is positive (even if their motivation to read them is weaker), their friends and family have a positive attitude. The members of the segment tend to read reviews when going to a new hotel or for a longer time. Observers have rather lower education and average or above average income. They plan their holiday well in advance, travel rather occasionally and slightly prefer going to the same destination. To point out the main characteristic of the segment – community, peers, and being informed is important but their own impression is above all.

6 Conclusion

Literature confirms the importance of reviews; however, the influence does not have the same strength. The analysis identified four segments of review readers with different impacts and styles of using reviews. This confirms the assumption that review readers are not a homogeneous group but create clusters with significant common patterns. The largest group (41%) has the most positive attitude to reviews and is also the most affected segment, therefore was named Enthusiasts. The second largest cluster (34%) are Pragmatists, who read reviews for practical reasons. The two smaller groups are Observers (10%) and Uninfluenceable Readers (14%). Observers are influenced by their social group and seek information as part of the bigger picture. The latter more or less ignores reviews and does not read them intentionally with any particular motivation.

The previous research revealed that the motives for reading reviews in the literature are different (Lee et al., 2011) for individual persons, and this study confirmed that the differences are significant between readers. The most important reason to read reviews, in general, is to avoid disappointment and quality issues, and to make the decision easier, which is in line with other research (Hennig-Thurau et al., 2003) and dominates in all clusters. The groups differ in terms of the impact of reviews on real decision-making and in their reactions to positive and negative reviews. Whereas Park and Nicolau (2015) found that negative reviews are more influential, we found a segment that is rather open to positive reviews (which does not mean they are not affected by negative ones at all). Review platforms are technology-based applications and in accordance with the literature (Victorino et al., 2009; Nica et al., 2019) it was assumed that the level of technology usage can play a role in segmentation. Statistical tests confirmed the importance of technological knowledge. In line with other research, to belong to a segment, age was a significant characteristic in this study but not a determining one.

In this study, the customer segments are based on the approach to reviews; in some studies, they use reviews to cluster users (Jardim & Mora, 2022; Nessel et al., 2021). Although Nessel's approach and source of data was different, we can find similarity with our results – "quality-seekers" are similar to Enthusiasts and "bargain-seekers" are similar to Pragmatists. The percentage representation is similar (45 vs. 41% and 35 vs. 34%) as well. The research confirms the importance of eWom and its role in marketing communication. The effect is not only in the decision-making process but also in creating the whole image of the company and industry overview by the readers.

The research has certain limitations. First, the data was collected with an online questionnaire, so we have information only on what people think they do or what motivates them. The data was collected in Eastern European countries where the price-sensitive group can be larger than in Western Europe or America. The sample is also not gender-balanced. The analysis identified four clusters, however, socio-demographical analysis revealed that at least one segment is not homogeneous in this respect but is homogeneous in its approach to reviews. Future research can focus on users of specific platforms or distinguish between readers of hotel reviews and restaurant reviews, as these two occasions are different in terms of frequency of consumption and expenditures and other factors can play a role.

The contribution of the research is both academic and managerial. The complex typology of review readers was missing in the academic body of knowledge, and this study filled the knowledge gap. The practical implication is mainly in the information for hotel and destination managers – different groups read reviews with different motivations and with different effects on their behaviour. Delivery of the right information, in the right form and on the right platform is necessary for successful communication and reputation management.

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