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CLUSTERING CONSUMER PROFILES IN PEER-TO-PEER TRAVEL ACCOMMODATION

Vuk Jovanović*[1], Nikola Zornić[1], Aleksandar Marković[1]
[1]University of Belgrade – Faculty of Organizational Sciences, Jove Ilića 154, Belgrade, Serbia
*Vuk Jovanović, e-mail: jvuk039@gmail.com

Abstract: *The sharing economy has significantly transformed the tourism landscape, introducing peer-to-peer accommodation platforms that have reshaped market dynamics and consumer behaviors. This study analyzes the socio-economic impact of these platforms on tourism. Employing a dataset from a survey of 344 respondents, we conducted a cluster analysis to identify distinct user profiles and their preferences. The analysis reveals two primary user clusters: 'Experienced Sharers' and 'Guided Novices', differentiated by their familiarity with and usage of sharing platforms. Key factors influencing user choices include personal experience, knowledge of shared accommodations, and socio-economic indicators such as city size and monthly income. Our findings underscore the dual impact of peer-to-peer accommodation: while it offers economic opportunities and diverse choices for consumers, it also presents challenges in terms of privacy concerns and the quality of service.*

Keywords*: sharing economy, peer-to-peer accommodation, cluster analysis*

1. INTRODUCTION

The sharing economy, driven by advanced technology, allows individuals to make use of otherwise wasted physical assets through peer-to-peer platforms, which have become vital for sharing information and trading goods and services (Lee, 2020).

The rise of sharing economy platforms has reshaped tourism and hospitality, presenting challenges and opportunities. The sharing economy provides many benefits to both sides, from service providers engaging in entrepreneurship and earning additional income to users of these services getting the chance to use something much lower price. Although the sharing economy impacts various industries, its most significant and most noticeable effect is on tourism (Alrawadieh & Alrawadieh, 2018). Particularly in the tourism and hospitality industry, accommodation-sharing platforms have significantly altered the market landscape (Song et al., 2020).

Sharing accommodation (SA), also known as peer-to-peer accommodation, home sharing, or short-term rentals, has emerged as a significant component of the sharing economy. These platforms enable individuals to derive economic and social value from underutilized properties (La et al., 2021). On the demand side, accommodation sharing has streamlined communication between users and service providers, with mobile platforms offering diverse content and information channels tailored to tourists' needs (Song et al., 2020).

The rise of platforms like Airbnb, Uber, and Lyft has significantly transformed the landscape of the tourism industry, achieving substantial market share (Zervas et al., 2017; Zhang et al., 2022). Scholars have noted that expanding these tourism platforms reshapes the industry and influences tourist decision-making processes. Factors such as destination choices, travel frequency, duration of stays, and the range of tourism activities are being impacted. Airbnb emerged as a prominent sharing accommodation platform within the tourism sector (Jung et al., 2021).

In Serbia, the utilization of accommodation-sharing platforms such as Airbnb is on the rise, providing travelers with lodging options and hosts the opportunity to rent out their spaces. Comprehending user experiences is essential to fully grasp the advantages, disadvantages, and potential opportunities associated with such platforms and identify the critical factors contributing to their success. By exploring factors such as users' education levels, the status of their properties, and the nature of their travel, we can gain valuable insights into their preferences and concerns when selecting accommodation. Additionally, examining aspects like safety, pricing, amenities, and users' intentions for future usage is imperative for effectively tailoring services and enhancing overall user satisfaction (Au-Yong et al., 2019; Kurisu et al., 2021).

In this paper, clustering analysis is conducted on a dataset gathered through a survey involving over 400 participants. To ensure a comprehensive examination of opinions, specific questions were excluded from further analysis, allowing us to capture insights from all respondents, regardless of their prior usage of sharing accommodation platforms. While a small percentage of participants were excluded due to being outliers, the overall impact on the dataset was minimal. The primary objective of this research is to uncover distinct clusters within the dataset and identify attributes that exhibit the most significant variations among them. These insights are intended to inform further analyses, particularly in marketing and promotion strategies. By understanding the factors of greatest concern, desire, and importance to users, accommodation owners can better tailor their offerings and services to meet the needs of their target audience effectively.

The paper is organized as follows: After an introduction to peer-to-peer accommodation and the broader concept of the sharing economy, section 2 presents the methodology used to examine survey data. Section 3 provides the results of the cluster analysis. Finally, section 4 presents conclusions and visions for future research.

2. METHODOLOGY

The data analyzed in this paper was gathered using a survey conducted among students born between 1993 and 2003. At the outset, the dataset comprised 419 respondents. The survey was completed by 32% of males and 68% of females.

The computed Cronbach's alpha coefficient of 0.753 suggests a reasonably high level of internal consistency among the items within survey. This indicates that the items are sufficiently correlated, demonstrating reliability in measuring the underlying construct or constructs of interest.

After removing errors and outliers, the final count was 344 participants. Outliers were removed by first calculating the Z-scores for all data points. Rows with values exceeding three standard deviations from the mean were identified as outliers, and subsequently, these rows were excluded. Initially, there were 83 questions divided into distinct categories: Demographic Information; SA familiar; Respondents' concerns; Positive effects from SA; Recommendations; and Importance of reviews. However, this number was then reduced to 61 to accommodate users and non-users of sharing accommodation services. All the used attributes are presented in Table 1.

Table 1: Definition of the attributes used in the analysis

Attributes		**Definition**
Demographic	Gender	Male or female.
	Year of Birth	Year when the respondent was born.
	City Size	The size of the city the respondent is coming from.
	Region	The region of Serbia the respondent is coming from.
	Monthly Income	The income that the respondent is generating every month.
	Household Type	Type of the household where the respondent is living.
	Residential Type	Residential type where the respondent is living.
SA familiar	Prior Awareness	Respondent knowledge about sharing accommodation before the survey.
	Personal Experience	Does the respondent know anyone who bought shared accommodation?
	Personal Knowledge	Does the respondent know anyone who offered shared accommodation?
	Personal Usage	Has the respondent ever used shared accommodation services?
Respondents' concerns	Location Concern	Do location and surroundings of shared accommodation pose a threat?
	Provider Concern	Does the service provider of shared accommodation pose a threat?
	Co-tenant Concern	Other users with whom I share accommodation may pose a threat.
	Privacy Breach	Sharing accommodation platform may use my personal information.
	Provider Use	Service providers of shared accommodation could violate my privacy.
	Hidden Cameras	Privacy in shared accommodation can be compromised (e.g., cameras)
	Hidden Costs	Are respondents worried about hidden costs in shared accommodation?
	Higher Expense	Do respondents view shared accommodation as pricier than hotel stays?
	No Savings	Respondents believe shared accommodation will not offer savings.
	Quality - Price	Respondents expect a lower quality for the price of accommodation.
	Promised Quality	Respondents expect a lower than promised quality of accommodation.
	Communication Issues	Respondents believe that communication with the provider is complicated.
	Doubtful Responsiveness	Respondents believe that their complaints will not be respected.

Positive Effects from SA	Potential Earnings	Respondents believe they could earn money in shared accommodation.
	Financial Status	Respondents believe shared accommodation could boost financial status.
	Social Image	Respondents believe shared accommodation could improve social image.
	Community Recognition	Respondents see shared accommodation as earning social praise for supporting the local economy.
	Respect Gain	Respondents believe shared accommodation would earn them respect.
	Enhanced Reputation	Respondents believe sharing accommodation boosts reputation.
	Environmental Conservation	Respondents believe sharing accommodation saves natural resources.
	Sustainable Consumption	Respondents believe sharing accommodation is sustainable.
	Ecologically Friendly Behavior	Respondents believe sharing accommodation represents environmentally friendly behavior.
	Resource Inefficiency	Respondents believe sharing accommodation does not save resources.
	Enjoyable Experience	Respondents find participating in shared accommodation fun.
	Boring Experience	Respondents find participating in shared accommodation boring.
	New Experiences	Respondents see shared accommodation as providing new experiences.
	Trendy Experience	Respondents find participating in shared accommodation trendy.
	Complex Process	Respondents find participating in shared accommodation complicated.
	Senseless Endeavor	Respondents find participating in shared accommodation pointless.
Recommendations	Faculty Endorsement	Respondents would use shared accommodation if endorsed by faculty.
	Peer Influence	Respondents would use shared accommodation if other students used it.
	Friend Recommendation	Respondents will use shared accommodation if friends recommend it.
	Indirect Recommendation	Respondents will use shared accommodation if strangers recommend it.
	Family Recommendation	Respondents will use shared accommodation if their family recommends it.
	YouTube Recommendation	Respondents will use shared accommodation based on YouTube reviews.
	Social Media Recommendation	Respondents will use shared accommodation based on reviews on social media platforms.
Importance of reviews	Reviews	Before deciding on accommodation, the respondent checks reviews.
	Reviews Fraud	Online reviews assure the respondent that accommodation is legitimate.
	Review Anxiety	The respondent worries when they skip online reviews.
	Detailed Reviews	Detailed online reviews are crucial to the respondent.
	Photo Evidence	Attached images in online reviews are crucial to the respondent.
	Familiar Reviewers	Respondents prioritize online reviews from people they know.
	Unknown Reviewers	Respondents do not prioritize online reviews from people they know.
	Trusted Figures	Respondents do prioritize online reviews from well-known individuals.
	Abundant Reviews	Respondents prioritize accommodation with a high volume of reviews.
	High Ratings	Respondents prioritize accommodation that has a high rating.
	Provider Rating	Respondents prioritize accommodation with a provider with a high rating.
	Reviewer Profiles	Respondents prioritize checking profiles of people who left reviews.
	Live Experiences	Respondents prioritize reviews they hear in person rather than online.

Data is analyzed using python packages pandas, collections, matplotlib and sklearn and aggregated results are presented.

3. RESULTS

Clustering was conducted using the k-means method. The first step in cluster analysis involves creating an elbow method graph and comparing it with the silhouette score. In our analysis, the elbow method clearly identifies a significant decrease in the silhouette score at 2 clusters, suggesting that this is the optimal number of clusters for our data. This point represents where the gain in homogeneity within the clusters no longer justifies the increase in the number of clusters (Shi et al., 2021). In the next step, we examined the silhouette score for various numbers of clusters. We have discovered once again that 2 clusters have the highest silhouette score.

Figure 1 contains a silhouette plot displaying the silhouette score of each instance within a cluster. The silhouette score ranges from -1 to 1, where 1 represents an instance entirely belonging to its cluster, 0 indicates that the instance lies between two clusters, and -1 signifies that the instance belongs to a neighboring cluster (Rousseeuw, 1987). It is evident from the plot that there were no negative silhouette scores.

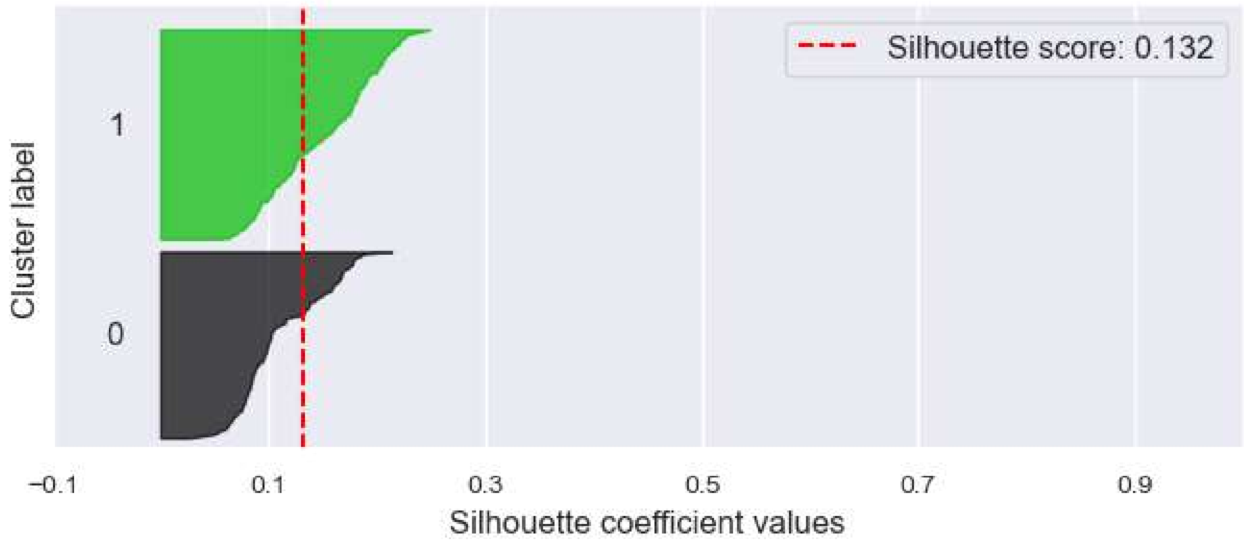

Figure 1: Silhouette Analysis

Cluster 0 contains 160 instances, while cluster 1 has 184 instances. In further analysis, cluster 0 is named *Experienced Sharers*, while cluster 1 is named *Guided Novices*. Besides determining the number of clusters, the correlation between attributes was assessed using Spearman because the data is not normally distributed. However, no significant correlation was observed, as the correlation coefficient does not exceed 0.2.

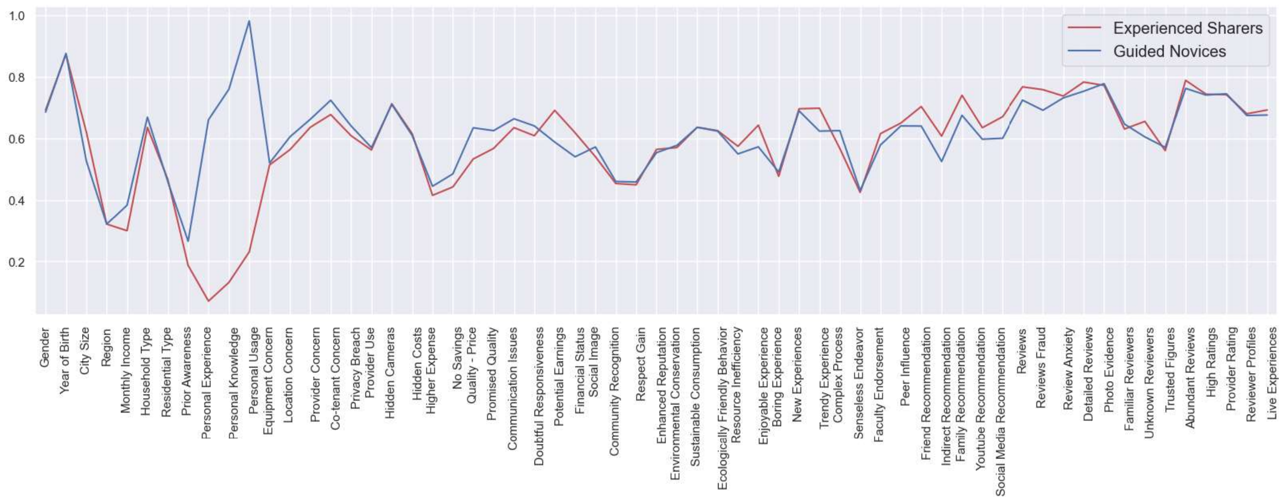

Figure 22: Line Graph – Clusters

It remains to analyze the line graph of clusters and normalized values for centroids (Figure 2). The most significant differences between these two clusters lie in the attributes *Personal Experience* and *Personal Knowledge*, which represent respondents' familiarity with knowing someone who offers or uses shared accommodation, and *Personal Usage*, which indicates whether respondents have previously used shared accommodation (Table 2).

These differences indicate that *Experienced Sharers* are much more familiar with sharing accommodation and have used it extensively. At the same time, are unfamiliar with and have not used it so far.

Furthermore, differences between clusters emerge, which are not as pronounced as the three previously mentioned. Noticeable distinctions lie in attributes such as *City Size*, *Monthly Income*, *Potential Earnings*, *Enjoyable Experience*, *Trendy Experience*, *Complex Process*, *Friend Recommendation*, *Indirect Recommendation*, *Family Recommendation*, *YouTube Recommendation*, and *Social Media Recommendation*.

Members of *Experienced Sharers* are from smaller cities, with higher monthly income, and they believe they can earn more by sharing accommodation than the members of *Guided Novices*.

Table 2: Most noticeable value differences

Variables	*Experienced Sharers*	*Guided Novices*
Personal Experience	0.668750	0.070652
Personal Knowledge	0.768750	0.130435
Personal Usage	0.981250	0.239130
City Size	0.612319	0.535417
Monthly Income	0.300272	0.382812
Potential Earnings	0.686141	0.592188
Enjoyable Experience	0.575000	0.639946
Trendy Experience	0.631250	0.690217
Complex Process	0.625000	0.567935
Friend Recommendation	0.647917	0.695652
Indirect Recommendation	0.528125	0.603261
Family Recommendation	0.681250	0.733696
YouTube Recommendation	0.598437	0.633152
Social Media Recommendation	0.598438	0.671196

It can also be noticed that members of *Guided Novices* have a better opinion on the process of sharing accommodation in general, where they believe that the process is more enjoyable and less complex than members of *Experienced Sharers*. One can guess that *Guided Novices* have great expectations from shared accommodation, as most of them haven't used it yet. Another evidence for this claim can be found in fact that they are more sensitive to recommendations, are more likely to consider using shared accommodation than members of *Experienced Sharers* cluster.

4. CONCLUSION

Our research employed a cluster analysis of data collected using a survey, revealing two distinct user groups: *Experienced Sharers* and *Guided Novices*. These findings highlight significant differences in usage patterns, familiarity, and socio-economic factors that influence user preferences and decision-making processes in the context of shared accommodation.

The rise of platforms like Airbnb has undoubtedly provided substantial benefits, such as increased income opportunities for hosts and more diverse lodging options for travelers. However, the analysis also exposes underlying challenges, including privacy concerns and potential disparities in service quality. Such issues necessitate targeted strategies to enhance user satisfaction and trust, which are crucial for the sustainable growth of sharing platforms.

Moreover, the distinctions between the two identified clusters suggest that tailored marketing strategies could be more effective than a one-size-fits-all approach. Marketing efforts should be designed to address each user group's specific needs and concerns, thereby improving engagement and optimizing the overall experience.

As peer-to-peer accommodation continues to evolve, ongoing research will be essential to track its impact on traditional hospitality sectors and regional economic development. Future studies could expand upon this work by exploring the long-term effects of the sharing economy on tourism, particularly in terms of economic sustainability and community relations.

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