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CUSTOMER PERCEPTIONS OF MODERN TECHNOLOGY INTEGRATION IN THE HOSPITALITY INDUSTRY

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The hospitality and tourism industry has changed significantly through the use of modern technologies, both for travellers and service providers. Digitalisation, AI capabilities, IoT, and mobile technologies have enabled a personalised booking, travel, and accommodation experience that provides travellers with timely and useful suggestions, information, and assistance. They have also opened up new opportunities for marketing and customer engagement, providing advanced analytics that enable the hospitality industry to reach a wider audience and deliver tailored offers and services. The objective of this study is to investigate users' attitudes towards the use of modern technologies, their willingness to disclose their private data in order to receive personalised content through digital communication, their perception of the benefits of personalised content, and the impact on their purchase intentions. The influence of gender and level of education on the responses to the survey and the possibility of forming groups in relation to the respondents' profiles were analysed in more detail. The methods used in this study were a survey, k-means clustering, one-way ANOVA and a two-sample t-test. A questionnaire with 15 statements was used, and 217 responses were collected. User behaviour was segmented using the k-means clustering method, resulting in two homogeneous clusters indicating two main user attitudes. A two-sample t-test was conducted to analyse whether there were significant differences between the responses of the different gender groups and between the different education groups. The results showed significant differences in both groups for several questions, as shown in the Results and Discussion section.

Keywords: *hospitality and tourism industry; modern technologies; customer experience; two-sample t-test; k-means clustering.*

1. Introduction

Digital tourism and hospitality encompass the use of technology to enhance the travel experience during the stay, but also before and after the trip (Verhun et al., 2022). The integration

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of technology has become increasingly important for the hotel industry to fulfil customer demands and expectations. Hotels are utilising artificial intelligence, mobile technologies, digital communication and other tools to improve their operations and provide a better experience for their guests.

Hotels are using technologies such as augmented reality, virtual reality, and robotics to offer their guests new and distinctive experiences (Elziny & Mohamed, 2021; D'souza et al., 2023) as they, especially business travellers and younger generations, place great value on the latest technologies in hotels. According to (Feng et al., 2022; Stringam & Gerdes, 2021) hotels can now offer faster, more convenient and comfortable customer service thanks to technological improvements. In order to reduce the number of physical touchpoints and improve guest safety, hotels are also focusing on the introduction of contactless solutions as technology develops. Digital keys and mobile check-in are becoming more common, allowing guests to skip the front desk and go straight to their room (Dehler, 2024; Feng et al., 2022; Vitezić et al., 2015). The in-room experience has also been enhanced by the integration of modern technology, thanks to smart room technologies that allow guests to customise different parts of their environment with voice commands or smartphone apps (Gao & Yang, 2022). The hotel industry is also starting to introduce personalised recommendation systems based on behavioural research and customer preferences. Hotels can offer individualised experiences to their guests by using AI and data to curate unique leisure activities or recommend personalised facilities (D'souza et al., 2023).

The main objective of this paper was to determine the attitudes and behaviour of users in relation to the adoption of modern technologies, privacy and security issues, and the perceived benefits of their use in the hospitality industry. In addition to the main objective, the following objectives were formulated:

a) to analyse the influence of gender on survey responses and to identify significant differences between male and female respondents,
b) to analyse the influence of education level on survey responses and determine whether there are significant differences between the lower and higher education levels of respondents, and
c) investigate the possibility of forming groups of respondents based on their answers in order to identify clusters with satisfactory homogeneity.

Therefore, three different hypotheses are proposed: H1, H2 and H3:

$H1_0$: There are no significant differences between the responses in terms of educational level.

$H1_1$: There are significant differences between the responses in terms of educational level.

$H2_0$: There are no significant differences between the responses in terms of gender.

$H2_1$: There are significant differences between the responses in terms of gender.

$H3_0$: There is no significant difference in the quality or structure of the clusters between the cluster numbers k, k>=2.

$H3_1$: There is significant difference in the quality or structure of the clusters between the cluster numbers k, k>=2.

2. Related work

This section provides an overview of the research topic, the research motivation and the research gaps that still need to be explored. In addition, a bibliometric analysis of the field of interest was carried out to show the current trend. The current state of the art in the hospitality industry is centred on improving the guest experience by migrating to the cloud, replacing frequently touched items and introducing new technologies (Shiji Group, 2021).

The impact of the integration of cutting-edge technologies and smart tourism on the guest experience was analysed in Lima et al. (2024). Similarly, İştin et al. (2022) emphasise the transformation of the guest experience in hotels offering tailored and wearable technologies (elimination of waiting lists, location-based services, personalised services etc.). Choe & Tou, (2024) conducted a segmentation and identified three groups ('Neutral,' 'Coexist,' and 'Committed') based on familiarity with smart technologies, perception of smart city features, safety concerns, willingness to use smart technologies, and various demographic and travel-related characteristics. Gonzáles-Santiago et al. (2024) performed a systematic review of scientific publications on the introduction of smart technologies such as robots, AI, virtual reality, and automation on cruises. Peruchini et al. (2024) provide an overview of the existing research on the impact of AI on the customer experience and the areas of the customer experience in tourism that are more affected by AI. Han et al. (2021) investigated tourists' acceptance of and willingness to use smart technologies to improve the hotel experience.

In their study, Zhang et al., (2022) examined the impact of smart technologies on enriching tourists' experiences, while Pai et al., (2020) examined tourists' satisfaction with their experiences with smart technologies and the impact of modern technologies on customer satisfaction and revisit intention. Similar themes in terms of acceptance, value perception, behavioural intentions and overall satisfaction were also found in (Shen et al., 2020; Huang et al., 2017; Gretzel et al., 2015). The research by Kim et al. (2021) aimed to determine the expected benefits of smart hotels for customers, the role that these benefits play in loyalty and purchase intention, and in particular to observe the differences between gender and age.

Han et al., (2021) differentiated smart technologies that influence experience enhancement from those that only provide operational functionalities. Some of the constructs that have been used to explore the application of smart technologies in hotels are similar to those used in this study, such as: technology acceptance, perceived usefulness, and privacy concerns. Various studies have shown different results in terms of customers' attitudes, perceptions and behaviour towards modern technologies depending on demographic characteristics such as age and gender (Ivanov et al., 2018; Lu & Kandampully, 2016; Hudson et al., 2017; Kim et al., 2021; Dinet & Vivian, 2014; Hwang et al., 2019). Therefore, it is necessary to further investigate the differences between the key demographic characteristics of respondents in the above context, and that is the motivation of this research.

In view of the popularity of the topic of "modern technologies" in connection with tourism, an analysis of the Scopus database is presented. The search string S of the publication fields is a combination of title, abstract and keywords in the last five years: S= (TITLE-ABS-KEY (("modern technolog*" OR "mobile technolog*" OR "smart technolog*" OR "AI")) AND TITLE-ABS-KEY

("touris*")) AND PUBYEAR > 2018) showed a total number of 1060 publications (131 in 2024, not included in Table 1) with a significant increase from year to year (Table 1).

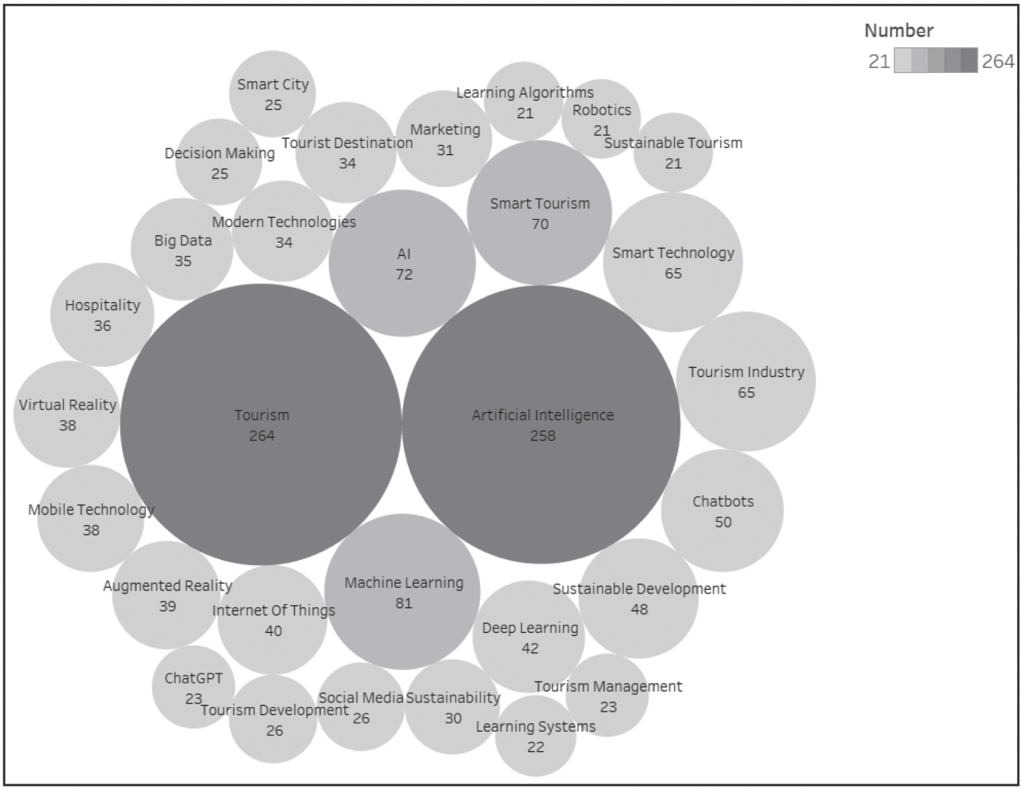
Table 1: Publications in Scopus database regarding search string S

Year	Publications
2023	336
2022	225
2021	154
2020	131
2019	83

Source: author

The keywords from these publications with a frequency of >20 are visualised in the word cloud (Figure 1).

Figure 1: Keywords frequency of publications in Scopus from search string S



Source: author

It is obvious that this field of research is constantly evolving as it follows the development of modern technologies, especially in the field of AI. This research focuses on the acceptance of modern technologies, the willingness to share private data, the perception of the benefits of personalised content, and the intention to purchase hotel offers with personalised content. It also aims to determine differences between genders and education levels and to identify the main characteristics of customer profiles in this area.

3. Methodology

This paper presents the analysis of the survey in which some parameters of descriptive statistics, the two-sample t-test (after analysing the variance between groups with the F-test) and the k-means clustering method were used to obtain different user profiles. The research methodology was based on a quantitative research design to analyse customer perceptions of the integration of modern technology in the hospitality industry. The questionnaire included some demographic questions such as gender and education level as well as 15 key statements.

For data collection, the author provided questionnaires in the form of online questionnaires (Lime Survey). The data collection was carried out between January and February 2024. A total of 289 participants answered and returned the questionnaires. However, only 217 questionnaires were completed correctly, on the basis of which further analyses were carried out. The survey instrument contained a five-point scale to measure 15 variables. Variables V1-V4 (use of modern technologies) were adopted from Agarwal & Karahanna, (2000), V5-V8 (willingness to disclose private data) from Kozyreva et al, (2021), V9-V11 (perception of benefits of personalised content) from Fang, (2019) and V10-V15 (intention to purchase hotel offers with personalised content) from Dou et al, (2020). The main part of the questionnaire (15 statements) was given on a 5-point Likert scale, where 1 – strongly disagree, 2 – disagree, 3 – neutral, 4 – agree and 5 – strongly agree.

Table 2: Relevant variables (statements) for the analysis

V1. If I heard about a new information technology, I would look for opportunities to experiment with it.
V2. Among my colleagues, I am usually the first to try out new information technologies.
V3. I like to experiment with new information technologies when I have the opportunity.
V4. Generally, I hesitate to try out new information technologies.
V5. I am concerned about my private data when using the internet.
V6. I have no problem with social media and other websites collecting and using data about my previous online activities to personalise various internet services, e.g., search results or offers.
V7. I consent to internet platforms and applications using any of the following information to create personalised advertising, e.g. gender, age, political views, sexual orientation.
V8. I consent to web services and applications recording and using the following types of information they collect on their platform, e.g. browsing and search history, location history, email content and online messages.
V9. If a mobile application could deliver personalised content during my stay at the hotel, I would be satisfied.
V10. Being informed about current offers and information at the hotel would improve my overall stay at the hotel.
V11. Providing personalised content during the stay would increase loyalty and interest in the hotel company.
V12.Receiving timely personalised notifications about hotel offers in the mobile application would encourage me to make a purchase.
V13.Receiving location-based notifications about hotel offers in the mobile application would tempt me to make a purchase.
V14.Receiving personalised notifications about hotel offers in the mobile application would reduce my effort when searching for specific products.
V15.Receiving personalised notifications about hotel offers in the mobile application would help me save time when selecting products.

Source: author based on (Kozyreva et al., 2021; Dou et al., 2020; Fang, 2019; Agarwal & Karahanna, 2000)

The two-sample t-test was used to investigate whether there were significant differences between the answers to all fifteen statements of a questionnaire in relation to gender and educational level. Several steps were carried out for this purpose:

1. Four nominal values for educational level (high school, undergraduate, graduate and postgraduate) were combined into two main values: lower degree (the first two levels) and higher level (the last two levels). For gender, two groups were formed, comprising 106 males and 111 females. For educational level, the following groups were formed: 121 with lower degrees and 96 with higher degrees.
2. For each of the 15 variables (questions), the normal distribution was checked by drawing histograms and calculating the mean and median. All variables were found to be at least approximately normally distributed.
3. T-test and F-test in XLSTAT and Excel Data Analysis Pack, F-test for analysing the data variability of groups (when the data are distributed differently) were used. In Excel it is performed for exactly two groups. The null hypothesis is that the variances of the two groups are equal. If the p-value is less than 0.05 (significance level), the null hypothesis is rejected and it is concluded that the variance differs between the groups.

For the second part of this study, RapidMiner Studio 10.3 was used to perform k-means. The aim is to investigate whether the dataset of 217 responses to 15 statements can be divided into homogeneous groups that show similarities. Clustering is an unsupervised machine learning approach that can be used for unlabelled data as it does not require a label attribute, as is the case in this 15-variables dataset. Each record (observation or example from a dataset) is assigned to exactly one cluster using the k-means method, resulting in a set of *k* clusters (RapidMiner, 2024). To check whether the obtained clusters are well separated and homogeneous, the Davies-Bouldin Index (DBI) is used (a commonly used performance measure in methods such as k-means, where a value closer to zero is better). To additionally check for the significance means' differences between groups for three clusters, one-way ANOVA with post-hoc t-tests were performed.

4. Results and discussion

The Results after the F-test for each of the 15 variables for both cases – taking into account two groups for educational level and two gender groups – are shown in Table 3.The two-sample t-test is performed assuming either equal variances (for the F-test p-value >=0.05) or unequal variances (for the F-test p-value <0.05, marked as bold underlined in Table 3).

The results are shown in tables 4 and 5. In the t-test, the null hypothesis is that the mean values of the two observed groups are equal. If p<0.05, the hypothesis is rejected and the alternative hypothesis that significant differences exist is accepted.

Table 3: F-test for two rounds of observations – gender and educational level groups' variances

Variables	p-value (gender)	Variances	p-value (Educational level)	Variances
V1	0.114	equal	0.088	equal
V2	0.210	equal	0.369	equal
V3	**0.034**	**non equal**	0.156	equal
V4	0.147	equal	0.369	equal
V5	0.102	equal	0.335	equal
V6	0.124	equal	0.153	equal
V7	0.234	equal	0.423	equal
V8	0.129	equal	0.377	equal
V9	0.202	equal	0.409	equal
V10	**0.007**	**non equal**	**0.016**	**non equal**
V11	0.269	equal	0.305	equal
V12	0.299	equal	0.199	equal
V13	0.108	equal	0.422	equal
V14	**0.039**	**non equal**	0.351	equal
V15	0.059	equal	0.443	equal

Source: author

Table 4 shows the results of the two-sample t-test for the educational level groups (two-sample t-tests assuming unequal variances were used for V10 and two-sample t-tests assuming equal variances were used for the other variables.

It could be concluded for the higher educated group (graduates and postgraduates) that they are more willing to use modern technologies, less concerned about sharing private data, see more benefits in personalised content and are more willing to be loyal and buy products when using them in the context of the hotel industry. The significant differences between the two groups according to the two-sample t-test were found for V1, V3, V10, V13 and V15 ($p<0.05$).

Therefore, hypothesis **H1$_0$** can be rejected since differences were identified for variables V1,V3,V10, V13, and V15 ($p<0.05$) regarding educational level and **H1$_1$** is accepted.

Table 4: Two-sample t-test results for educational level, **bold underlined** significant differences

Educational level groups				**Lower degree**	**relation**	**Higher degree**
Variables	t-Stat	**df**	**p**	M_1		M_2
V1	**-2.163**	**215**	**0.032**	3.397	<	3.698
V2	0.100	215	0.921	2.496	>	2.479
V3	**-1.976**	**215**	**0.048**	2.719	<	3.031
V4	-1.248	215	0.213	3.545	<	3.740
V5	0.906	215	0.366	3.372	>	3.219
V6	-1.056	215	0.292	2.388	<	2.552
V7	-0.922	215	0.357	2.587	<	2.740
V8	0.469	215	0.640	2.281	>	2.208
V9	-1.805	215	0.072	3.355	<	3.604
V10	**-2.188**	**215**	**0.030**	3.669	<	3.958
V11	-1.498	215	0.136	3.430	<	3.646
V12	-1.787	215	0.075	3.025	<	3.292
V13	**-1.951**	**215**	**0.049**	2.967	<	3.260
V14	-1.474	215	0.142	3.380	>	3.594
V15	**-2.304**	**215**	**0.022**	3.488	<	3.813

Source: author

Table 5 shows the results of the two-sample t-test for the gender groups (two-sample t-tests assuming unequal variances were used for V3, V10 and V14 and two-sample t-tests assuming equal variances were used for the other variables).

Table 5: Two-sample t-test results for gender, **bold underlined** significant differences

Gender groups				**male**	**relation**	**female**
Variables	t-Stat	**df**	**p**	M_1		M_2
V1	-0.419	215	0.676	3.500	<	3.559
V2	1.807	215	0.072	2.642	>	2.342
V3	1.415	215	0.159	2.972	>	2.748
V4	-0.229	215	0.819	3.613	<	3.649
<u>V5</u>	**-2.702**	**215**	**<u>0.007</u>**	3.075	<	3.523
V6	1.217	215	0.225	2.557	>	2.369
V7	-0.713	215	0.477	2.594	<	2.712
V8	-0.405	215	0.686	2.217	<	2.279
<u>V9</u>	**-2.208**	**215**	**<u>0.028</u>**	3.311	<	3.613
<u>V10</u>	**-3.253**	**215**	**<u>0.001</u>**	3.575	<	4.009
<u>V11</u>	**-2.424**	**215**	**<u>0.016</u>**	3.349	<	3.694
V12	-0.883	215	0.378	3.075	<	3.207
<u>V13</u>	**-2.514**	**215**	**<u>0.013</u>**	2.906	<	3.279
V14	-1.702	215	0.090	3.349	<	3.595
<u>V15</u>	**-3.463**	**215**	**<u>0.001</u>**	3.387	<	3.865

Source: author

From the semantics of the variables, which can be seen in table 2, the following statements should be emphasised:

- for V2, a lower mean score indicates greater openness to new technologies,
- for V5, a higher mean score indicates greater concern about data security and data protection,
- for V6, V7 and V8, higher mean values indicate that respondents are more willing to disclose their private data in order to benefit from personalised content
- The semantics of the mean values of the other questions indicate that the higher the value, the greater the acceptance and awareness of the perceived benefits of modern technologies.

Looking at the results for the gender groups, the differences between males and females are not significant for V1-V4, while for V5 the difference in responses is significant (p=0.007), i.e. females are more concerned about privacy and security online than men. For questions V9-V11, which deal with the impact of personalised content on customer satisfaction, there is also a significant difference between the responses of males and females, with females indicating higher satisfaction and faster loyalty. V13 and V15 showed that females are more willing to buy hotel offers with personalised content.

Therefore, hypothesis $\mathbf{H2_0}$ can be rejected since differences were identified for variables V5,V9-V11, V13, and V15 ($p<0.05$) regarding gender and $\mathbf{H2_1}$ is accepted.

To gain additional insight into the profile of respondents, k-means clustering was performed for the number of clusters (groups or segments), k=2 and k=3 (cluster performance for k>3 was lower and was not considered).

The quality of clustering comprises the criteria homogeneity of observations within a cluster and separability of observations between two different clusters (Everitt & Hothorn, 2006). The quality/homogeneity of the clusters was measured with the Davies-Bouldin index (D-B index), which indicates the ratio of the distances within the clusters to the distances between the clusters. Clusters that are further apart and less dispersed lead to a better result and are reflected in a lower D-B index – the closer this parameter is to zero, the better the quality of the clusters.

For k=3, 10 runs, with a maximum of 100 optimisation iterations and Euclidean distance measure, three clusters were obtained, labelled Cluster 0 (53 members), Cluster 1 (85 members) and Cluster 2 (79 members), D-B index 0.14. In addition, a new attribute labelled Cluster was created, which has three different values. A demographic overview by cluster can be found in Table 6.

Table 6: Demographic data of three clusters

Gender	**Cluster 0**	%	**Cluster 1**	%	**Cluster 2**	%
Male	28	52.83%	48	56.47%	30	**37.97%**
Female	25	47.17%	37	43.53%	49	**62.03%**
Total	53		85		79	
Age	**Cluster 0**	%	**Cluster 1**	%	**Cluster 2**	%
18-25	20	37.74%	38	44.71%	30	37.97%
26-35	19	35.85%	23	27.06%	25	31.65%
36-45	8	15.09%	11	12.94%	17	21.52%
46-55	3	5.66%	8	9.41%	6	7.59%
56-65	3	5.66%	3	3.53%	0	0.00%
>65	0	0.00%	2	2.35%	1	1.27%
Total	53		85		79	
Educational degree	**Cluster 0**	%	**Cluster 1**	%	**Cluster 2**	%
Higher degree	22	41.51%	39	45.88%	56	**70.89%**
Lower degree	31	58.49%	46	54.12%	23	**29.11%**
Total	**53**		**85**		**79**	

Source: author

The members of Cluster 2 differ from the others in that they have a higher proportion of females (62%) and a higher level of education (71%).

Looking at the centroid values for each variable (V1-V15), three clusters correspond to three user profiles: Cluster 0 members could be described as moderately interested in modern technology, but are very concerned about sharing data and against receiving or using personalised content.

Cluster 1 members are the users who are less interested in modern technology, moderately concerned about online security and privacy, and moderately open to the benefits of using personalised content and speed, which makes them moderately willing to buy hotel deals. Cluster 2 members are most interested in modern technology, least concerned about security and data sharing, and open to the benefits of personalised content and speed, making them highly likely to buy hotel deals. It is interesting to note that cluster 2 also has a higher proportion of females and a higher level of education.

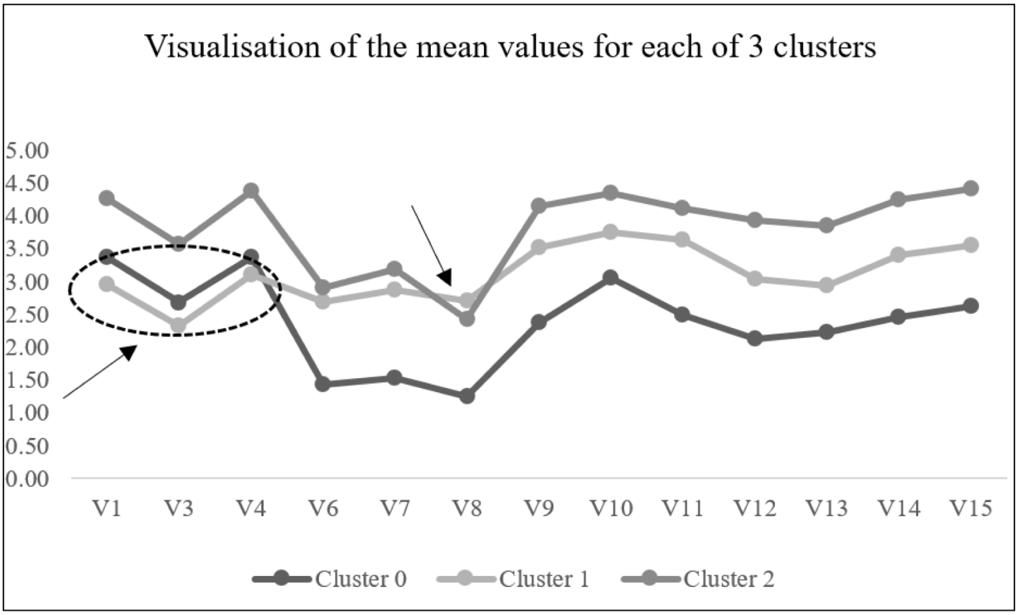
Table 7: Clustering with k-means (k=3) and three clusters' centroids for each question

Cluster ID	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
Cluster 0	3.36	2.45	2.68	3.36	3.94	1.43	1.53	1.25	2.38	3.06	2.49	2.13	2.23	2.45	2.62
Cluster 1	2.95	2.91	2.32	3.11	3.01	2.69	2.87	2.71	3.52	3.75	3.62	3.04	2.94	3.40	3.54
Cluster 2	4.27	2.06	3.56	4.38	3.19	2.90	3.18	2.43	4.14	4.34	4.11	3.94	3.85	4.24	4.41

Source: author

To better visualise the differences between the centroids of the three clusters, V2 and V5 were excluded (due to the opposite semantics of the other variable values) – Graph 1.

Graph 1: Centroids of three clusters



Source: author

In the Graph 1 centroids of V1, V3 and V4 for cluster 0 and cluster 2 are very similar, as are the centroids of V8 between clusters 1 and 2 (black arrows). To investigate whether there were significant differences between the three clusters, a one-way ANOVA was performed between the three clusters for each variable. To analyse the differences between the individual pairs of the three groups, three different T-tests with adjusted p-values after

Bonferroni correction were also performed. This is one of the methods used to reduce the possibility of a type I error – obtaining false positives (false statistically significant differences) – by adjusting a p-value using the Bonferroni correction (by dividing the alpha value by the number of tests). In this particular case, the corrected p-value =0.017 (alpha of 0.05 divided by three). The results of the one-way ANOVA (F-value and P-value) and the t-test between two of three clusters are shown in Table 8 (C0 cluster 0, C1 cluster 1 and C2 cluster 2).

The one-way ANOVA results show significant differences between the clusters (high F-values and low P-values – so at least for one pair of clusters the difference in means was statistically significant). Additionally, three t-tests were performed to analyse which mean values of the clusters were significantly different. Although alpha was 0.05, the dark grey cells mark the p-values > 0.0167 (not significantly different), which was determined after Bonferroni correction.

Table 8: One-way ANOVA between three clusters with T-tests between each pair of clusters

Variables	ANOVA between clusters		t-test (C0,C1), df=136		t-test (C0,C2), df=130		t-test (C1,C2), df=162	
	F Value	P value	t-Stat	p	t-Stat	p	t-Stat	p
V1	50.01	1.51E-18	2.60	0.0103	10.33	1.60E-19	-5.72	1.22E-07
V2	10.57	4.18E-05	2.33	0.0215	-1.83	0.070	-4.49	1.37E-05
V3	30.03	3.34E-12	1.92	0.0573	-4.78	4.67E-06	-8.03	1.87E-13
V4	36.72	1.95E-14	1.29	0.1992	-5.55	4.27E-07	-9.07	7.28E-16
V5	10.69	3.77E-05	4.82	3.77E-06	3.45	7.63E-04	-0.94	0.348
V6	40.03	1.71E-15	9.44	1.43E-16	9.46	2.56E-16	1.22	0.223
V7	44.26	8.21E-17	-8.88	4.28E-15	-9.85	1.98E-17	1.79	0.076
V8	38.90	3.89E-15	-11.69	3.33E-22	-7.75	4.26E-12	1.62	0.108
V9	85.89	4.14E-28	-8.21	1.53E-13	-12.23	4.58E-21	5.57	1.05E-07
V10	34.70	8.89E-14	-3.79	2.84E-04	-7.12	5.15E-10	5.07	1.09E-06
V11	57.82	8.37E-21	-6.50	4.28E-09	-9.64	4.42E-15	4.08	7.11E-05
V12	72.12	1.14E-24	-5.99	1.78E-08	-11.66	6.00E-22	-6.95	8.46E-11
V13	52.13	3.60E-19	4.28	3.54E-05	-9.43	3.00E-15	-6.72	2.97E-10
V14	76.99	6.47E-26	6.09	1.11E-08	-11.51	7.20E-19	-7.24	1.84E-11
V15	82.24	3.19E-27	6.07	1.18E-08	-12.05	6.52E-20	-7.65	1.91E-12

Source: author

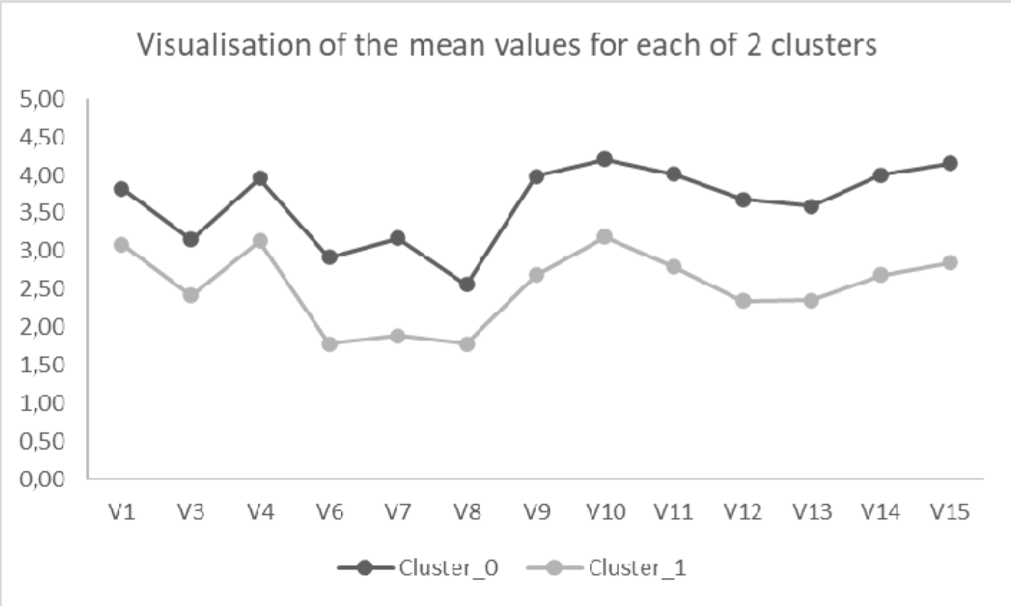
To try to obtain more homogeneous groups, k-means was performed with exactly two clusters (k=2, 10 runs, 100 optimisation iterations, Euclidean distance measure). The performance was indeed better (D-B index from 0.14 to 0.12). Cluster 0 had 130 and cluster 1 87 members (the centroids are given in Table 9). For better visualisation, V2 and V5 were again excluded.

Table 9: Clustering with k-means two clusters' centroids
(higher values marked in grey shading)

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
Cluster 0	3.82	2.38	3.15	3.96	3.09	2.92	3.17	2.56	3.98	4.21	4.02	3.68	3.59	4.00	4.15
Cluster 1	3.09	2.64	2.41	3.14	3.62	1.78	1.89	1.78	2.69	3.18	2.79	2.34	2.36	2.69	2.85

Source: author

Graph 2: Centroids of two clusters



Source: author

A demographic overview by cluster can be found in Table 10.

Table 10: Demographic data of two clusters

Gender	Cluster 0	%	Cluster 1	%
Male	58	**44.62%**	48	55.17%
Female	72	**55.38%**	39	44.83%
Total	130		87	
Age	**Cluster 0**	**%**	**Cluster 1**	**%**
18-25	52	40.00%	36	41.38%
26-35	42	32.31%	25	28.74%
36-45	20	15.38%	16	18.39%

46-55	12	9.23%	5	5.75%
56-65	3	2.31%	3	3.45%
>65	1	0.77%	2	2.30%
Total	130		87	
Educational degree	**Cluster 0**	%	**Cluster 1**	%
Higher degree	82	**63.08%**	35	40.23%
Lower degree	48	**36.92%**	52	59.77%
Total	130		87	

Source: author

The members of Cluster 0 differ from Cluster 1 in that they have a higher proportion of females (55%) and a higher level of education (63%).

T-tests were performed for two clusters to analyse significant mean differences between the clusters (Table 11).

Table 11: T-tests for V1-V15 (df=215)

Variables	**t-Stat**	**p**
V1	5.47	1.25E-07
V2	-1.53	0.127
V3	4.82	2.70E-06
V4	5.39	2.47E-07
V5	-3.26	1.30E-03
V6	8.67	1.14E-15
V7	9.31	1.92E-17
V8	5.52	1.02E-07
V9	11.44	1.17E-22
V10	7.95	6.15E-13
V11	9.57	3.22E-17
V12	10.88	3.08E-22
V13	9.29	1.01E-16
V14	10.63	3.82E-20
V15	10.91	6.25E-21

Source: author

All variables for two cluster values presents significant differences based on their p values, except V2 (hesitation to use technology).

The two customer profiles (Table 9 and Graph 2) show that cluster 0 with 130 respondents is the group that has a solid, more positive attitude towards modern technologies, data sharing, receiving and using personalised content and shopping in connection with hotel offers.

The grey shading for V2 and V5 in Table 9 corresponds to this profile, as the semantics of V2 are more hesitant (i.e. lower scores correspond to cluster 0 attitudes) and V5 (concerns about security and privacy – lower scores correspond to profile characteristics). The profile of Cluster 0 members is labelled as *technology users and beneficiaries*. In this cluster, there was also a larger proportion of female respondents and a higher level of education.

Cluster 1, in which 87 respondents were classified, shows their reservations about using modern technologies, massive concerns about privacy and security on the internet, a strong rejection of sharing their data and a lack of satisfaction with receiving personalised content (for customer loyalty or purchasing in the hotel industry). The profile of Cluster 1 members is described as *technology sceptics*.

After the post-hoc clustering analyses with one-way ANOVA and t-tests (for k=3 and k=2), the D-B index value for k=3 and k=2 (0.14 for k=3 vs 0.12 for k=2), as well as the visualisations (good separation of centroid values for two clusters, Graph 2), it is concluded that two clusters (k=2) represent best segmentation. D-B index for k>3 was considerably worse indicating lower cluster structure quality.

Therefore, hypothesis **H3**$_0$ is rejected because the structural quality of two clusters is better than other cluster numbers and **H3**$_1$ is accepted.

5. Conclusion

This article deals with the integration of various modern technologies in the hotel and tourism industry. Thus, the main objective was to investigate the attitudes and behaviour of users in relation to the adoption of modern technologies, privacy and security issues and the perceived benefits of their use in the hospitality industry. In particular, the influence of gender and level of education on the differences in survey responses was analysed, as well as the possibility of creating sufficiently homogeneous groups of respondents to define their profiles.

After a summary of the current state of the art and development trends, including the impact of AI on this industry, the survey results were analysed using K-Means clustering (including one-way ANOVA with post-hoc t-tests for three clusters and t-tests for two clusters), F-test and two-sample t-test. The two-sample t-test was used to analyse whether there were significant differences in respondents' answers in terms of gender (males, females) and educational level (lower and higher degree). From the proposed hypotheses, it can be concluded that: **H1**$_1$ can be accepted as there are significant differences for V1, V3, V10, V13 and V15 (two-sample t-test, $p<0.05$) with respect to two different levels of education (lower and higher). Confirmed with Table 4.

The results regarding the level of education suggest that respondents with a higher level of education are more willing to adopt new technologies, see more benefits in them and are more inclined to make purchases with them. **H2**$_1$ can be accepted as significant differences were found for V5, V9-V11, V13 and V15 (two-sample t-test, $p<0.05$) in relation to gender (males and females). Confirmed with Table 5.

The results related to gender suggest that females are more concerned about privacy and online safety than males, that females are more satisfied and loyal faster, and that they are more willing to buy hotel offers with personalised content than males. **H3**$_1$ can be accepted for the detailed quality analysis of the structure of two, three and more than three clusters, where two clusters resulted in the best quality structure. Confirmed with tables 7-9 and 11, diagrams 1,2 and D-B index values.

Two clusters correspond to two user profiles: *technology users and beneficiaries* (Cluster 0, higher proportion of females and higher level of education than in Cluster 1) and *technology sceptics* (Cluster 1).

The research results indicate that the acceptance of modern technologies and the benefits for users and also for service providers is a sensitive area. There is still a strong scepticism regarding security and privacy protection as well as a lack of understanding of how modern technologies fulfil their functions (the collection of personal data is necessary for personalised content and smart suggestions). The intention for the future research plan is therefore to continue to monitor the development of the integration of new technologies in hospitality and tourism from the perspective of customers and service providers.

The limitations of the research are the relatively small number of respondents (especially in some age groups, which is why it was not possible to explore significant differences) and a more detailed insight into various specific modern technologies used in the hospitality industry.

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Sažetak

KORISNIČKA PERCEPCIJA MODERNIH TEHNOLOGIJA INTEGRIRANIH U HOTELSKOJ INDUSTRIJI

Ugostiteljstvo i industrija turizma značajno su se promijenili korištenjem modernih tehnologija, kako za putnike tako i za pružatelje usluga. Digitalizacija, AI mogućnosti, IoT i mobilne tehnologije omogućile su personalizirano iskustvo rezervacije, putovanja i smještaja, pružajući putnicima pravovremene i korisne sugestije, informacije i pomoć. Također su se otvorile nove mogućnosti za marketing i interakciju s korisnicima, kao i naprednu analitiku koja omogućuje ugostiteljskoj industriji da dosegne širu publiku i pruži personalizirane ponude i usluge. Cilj ovog rada je istražiti stavove korisnika prema korištenju modernih tehnologija, njihovu spremnost da dijele svoje privatne podatke kako bi primili personalizirani sadržaj putem digitalne komunikacije, njihove percepcije o koristi personaliziranog sadržaja i utjecaju koji ima na namjere kupnje. Detaljnije je analiziran utjecaj spola i stupnja obrazovanja na odgovore u anketnom upitniku te mogućnost formiranja grupa u odnosu na profile ispitanika. Metode korištene u ovom istraživanju bile su anketa, k-means klaster, jednofaktorska ANOVA i t-test (dva uzorka). Korišten je prethodno kreiran upitnik s 15 ciljanih pitanja sa dobivenih ukupno 217 odgovora. Segmentiranje korisničkog ponašanja k-means klaster metodom rezultiralo je dobivanjem dva dovoljno homogena klastera indicirajući dva dominantna korisnička stava prema modernoj tehnologiji. t-test (dva uzorka) je proveden kako bi se analizirale značajne razlike između odgovora dvije grupe vezane za spol i dvije grupe različitog obrazovnih statusa. Rezultati su pokazali značajne razlike u oba slučaja za više pitanja, kako je detaljno prikazano u poglavlju rezultati i diskusija.

Ključne riječi: *ugostiteljstvo i turizam; moderne tehnologije; korisničko iskustvo; t-test (dva uzorka), k-means klasteri.*