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Two-Step Cluster Analysis of Passenger Mobility Segmentation during the COVID-19 Pandemic

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Abstract: In this paper, we analyse the specific behaviour of passengers in personal transport commuting to work or school during the COVID-19 pandemic, based on a sample of respondents from two countries. We classified the commuters based on a two-step cluster analysis into groups showing the same characteristics. Data were obtained from an online survey, and the total sample size consists of 2000 respondents. We used five input variables, dividing the total sample into five clusters using a two-step cluster analysis. We observed significant differences between gender, status, and car ownership when using public transport, cars, and other alternative means of transportation for commuting to work and school. We also examined differences between individual groups with the same socioeconomic and socio-demographic factors. In total, the respondents were classified into five clusters, and the results indicate that there are differences between gender and status. We found that ownership of a prepaid card for public transport and social status are the most important factors, as they reach a significance level of 100%, unlike compared to other factors with importance ranging from 60 to 80%. Moreover, the results demonstrate that prepaid cards are preferred mainly by female students. Understanding these factors can help in planning transport policy by knowing the habits of users.

Keywords: cluster analysis; mobility; COVID-19; travel behaviour

MSC: 91C20; 62H30

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1. Introduction

The basic measure in the sustainability of transport is based on attracting a larger number of inhabitants to the public transport sector or active modes of transport [1]. One of the key factors in public transport is safety, and it is of great importance for the number of passengers [2,3]. This factor has been greatly disrupted by the COVID-19 pandemic in 2020 [4]. The outbreak of COVID-19 has affected the whole world and raised safety concerns [5] and feelings of anxiety in public transport [6], because people are usually close to each other in such environments, which facilitates the spread of infectious diseases [7]. In other words, most people preferred cars to public transport.

Public transport is of the sources that spread the virus [8]; therefore, its use has been restricted worldwide through various measures and lockdowns [9]. Despite these measures, many people use public transport as their primary or only mode of transport, which results in an increased risk of infection [10,11].

To combat sprawl and related inequalities, it is essential to focus on those people who continue to use public transport or other alternative options. Research on COVID-19 quickly focused mainly on the following areas:

(1) Detection of the decrease in traveling and mobility [12–14];
(2) Virus spread [15–17].

Several studies have examined changes in travel behaviour related to income, ethnicity, psychological traits, and political views [18–20]. In this research, authors collected data using surveys (especially online) or data obtained from a mobile phone about movement, or the means of transport used. Recently, several studies have dealt with a comprehensive view of the relationships between socioeconomic factors and citizens' changes in public transport use during the pandemic [21–23].

To slow the spread of COVID-19, many countries have imposed mobility restrictions, the temporary closure of businesses, and encouraged social distancing. A substantial majority of passengers abandoned public transport out of fear for their health and changed their usual mode of transport, according to research from around the world [24–27]. In his survey, Shibayama reports that 70–80% of respondents from Austria, Bulgaria, Germany, Hungary, and Japan changed their mode of commuting from public transport to another mode in order to eliminate risk [28]. This behaviour led to the abandonment of shared space and encouraged the use of individual transport vehicles.

Collecting users' opinions and analysing people's traffic patterns [29] are some of the ways to identify gaps and deficiencies in public transport services and the necessary infrastructure [30–33]. The choice of the mode of transport is motivated by a whole range of locational, socio-demographic, psychological, and cultural factors, but lately mainly safety determinants [34,35].

The main problem is the heterogeneous subjective opinion of travellers and users in the analysis of service quality [36,37]. Dividing travellers into specific segments that have similar opinions or habits can bring a better view of differences in heterogeneity [38]. Segmentation is applied either based on demographic and social characteristics or other techniques such as cluster analysis [39]. Cluster analysis is used to obtain segments of the initial user sample; these segments represent passenger profiles [40]. The main goal of cluster analysis (CA) is to classify data with similar characteristics based on the similarity between elements within a cluster and the dissimilarity between elements between clusters [41]. Anable, in the study [42], demonstrates the utility of cluster analysis in extracting naturally occurring, relatively homogeneous, and meaningful clusters to be used for proposing transport policies.

The application of cluster analysis of latent classes [43] in public transport during COVID-19 was used in Toronto. The results suggest that a subset of individuals used public transportation for non-essential travel during the pandemic, likely due to a lack of access to a private vehicle [44]. To predict the spread of COVID-19 in Mexico, they used cluster analysis based on mobility trends to commute to work in neighbourhoods separately instead of all neighbourhoods at once.

In Sicily, Basbas and others analysed three clusters of public transport users with specific socio-demographic characteristics and acceptance rates of national recommendations for public transport using descriptive and cluster analysis techniques [45]. In further research, they divided the respondents into five different groups according to socioeconomic data, thus emphasizing how the pandemic affected people with different social backgrounds. The results show that those with poor financial backgrounds continue to travel by public transport, establishing a link between wealth and the risk of exposure to a potentially fatal disease [46].

By empirically testing a combination of objective and subjective characteristics such as spatial, socio-economic, and political structures and mobility-related preferences and practices, the authors of another study analysed 44 German cities with more than 100,000 inhabitants. By performing factor and cluster analysis, they obtained six clusters that differ in regime orientation as well as socio-economic and spatial characteristics [47]. Kopsidas et al.

determined the factors influencing the behaviour of public transport travellers in Athens, Greece, after the pandemic using a clustering algorithm and the discrete duration model. The cluster model showed that students and regular travellers would like to use public transport for a long time after the COVID-19 pandemic [48].

In the available literature, we did not find an evaluation of passenger behaviour based on the criteria we mentioned. Attention was focused on the habits of travellers in two states that once formed a single state. The task is to know the habits of passengers well to be able to plan public transport or integrated transport not only at the national level but also at the international level. This understanding of behaviour is important to us, and we consider the sample to be specific.

This paper aims to divide travellers based on common socio-demographic and other factors into the same groups during the COVID-19 pandemic in two countries with similar travel habits. In other words, we identify key differences in travel behaviour between the selected groups. Attention was focused on five variables: status, gender, vehicle availability, commuting to school or work, and prepaid ticket. These findings help to focus on a potential group with specific characteristics. The purpose of this paper is to help transport companies reach these passengers not using public transport with appropriate marketing tools in targeted addressing. The originality of this paper represents knowledge in the area of commuting to work and school in this region, unlike other studies.

The following research questions were formulated:

- How many clusters of commuters to work or school with specifically different socio-demographic and travel behaviour exist during the COVID-19 pandemic?
- Which factor has the highest degree of significance in passenger segmentation during the COVID-19 pandemic?
- Does owning a prepaid public transport card support public transport and trains during the COVID-19 pandemic?
- Do employees mainly use the car as their usual means of transport for commuting to work?

Our research applies a two-step cluster analysis algorithm in IBM SPSS 26 [49]. This procedure automatically selects the optimal number of clusters in the data set by detecting the increase in the distance between the two nearest clusters across all stages of hierarchical clustering. Clustering as a method is mostly used in the field of marketing as a technique to understand customer behaviour, but it is also used in other areas such as automation and transportation [50].

2. Methodology

The total sample consists of almost 2000 respondents. Table 1 reveals that these respondents are divided into three criteria: country, status, and gender.

As can be seen, respondents from the Czech Republic represent the majority (more than 70%). The largest group consists of female students (899 respondents, more than 45%). On the other hand, less than 12% of respondents are male employees. Czech female students are the largest subgroup in the Czech Republic sub-sample, in contrast to the Slovak Republic sub-sample. This sub-sample consists mainly of male students. These data were obtained from an online questionnaire given from 27 April 2022 to 6 June 2022.

We use five independent variables: gender, social status, car ownership in the household, ownership of a prepaid card for public transport, and the most frequently used means of transport. We segmented passengers using two-step cluster analysis in the statistical-analytical program IBM SPSS 26. This program calculated the relative importance of the predictor based on the formula below.

$$\mathrm{VI_i} = \frac{-\log_{10}(\mathrm{sig_i})}{\max_{j\in\Omega}\left(-\log_{10}\left(\mathrm{sig_j}\right)\right)} \tag{1}$$

where the components are as follows:

Ω Set of predictor and evaluation fields;
sig_i The *p*-value computed from applying a certain test; if sig_i equals 0, set sig_i= MinDouble, where MinDouble is a minimal double value [51].

Table 1. Sample.

Country			Gender		Total
			Male	Female	
Czech Republic	Status	Employee	145	167	312
		Student	332	754	1086
	Total		477	921	1398
Slovak Republic	Status	Employee	93	108	201
		Student	248	145	393
	Total		341	253	594
Total	Status	Employee	238	275	513
		Student	580	899	1479
	Total		818	1174	1992

The two-step cluster analysis segmented respondents to describe passenger behaviour and mobility during the COVID-19 pandemic period. The two-step cluster method analyses continuous and categorical variables. Quantitative variables with different scale units and nominal scaled may be simultaneously analysed. The process assumes that all variables are independent, continuous variables have a normal distribution, and behaviour-categorical variables have multinominal distribution. Moreover, the extra benefit includes the automatic determination of the optimal number of clusters. This method is applied to larger samples with more than 500 respondents [52,53].

This methodology includes several steps, such as cluster quality, optimal cluster number, and distance measure [54,55].

Cluster quality. Silhouette's value measures the similarity of an object to its cluster (cohesion) compared to other clusters (separation). Cluster cohesion demonstrates the average distance between a sample and all other data points within the same cluster. In contrast, cluster separation explains the average distance between a sample and all other data points in the nearest cluster [56,57]. This metric ranges from 1 to −1. Silhouette's value identifies the following:

- Poor classification from −1.0 to 0.2;
- Fair classification from 0.2 to 0.5;
- Good classification from 0.5 to 1.0 [58].

In other words, first, Silhouette's value of 1 indicates that the object is far away from other clusters. Second, Silhouette's value of 0 indicates that the object is between two neighbouring clusters. Finally, Silhouette's value less than 0 indicates that those objects have been assigned to the wrong cluster. In other words, the higher value identifies that the object is better fitted to its cluster than to other clusters. Silhouette's value is calculated as

$$s(i) = \frac{b(i) - a(i)}{\max(b(i),\ a(i))} \tag{2}$$

$$\overline{S} = \frac{1}{N}\sum_{i=1}^{N} S_i \tag{3}$$

where

$S(i)$ Silhouette coefficients for i-th object;

$b(i)$ Average of the minimum distance between i-th object in a different cluster (average inter-cluster distance);
$a(i)$ Average of the minimum distance between i-th object in the same cluster (average intra-cluster distance);
$\overline{S}$ The average value for the Silhouette coefficients;
N Total number of observations [57].

Optimal cluster number. The optimal cluster is determined based on the lowest BIC score. Schwarz's Bayesian Criterion (BIC) is calculated for each number of clusters within a specific range as

$$BIC_R = -2\sum_{r=1}^{R} \xi_R + m_R \log(N) \tag{4}$$

With

$$m_R = R\left\{2K^A + \sum_{k=1}^{K^B}(L_k - 1)\right\} \tag{5}$$

where the components are as follows:

BIC_R Total number of clusters;
R Number of clusters;
ξ_R The r^{th} cluster variance;
K^A Number of continuous variables;
K^B Number of categorical variables;
m_R Ratio in r cluster developed during the hierarchical clustering stage;
L_k The number of groups in k categorical variables [58].

BIC with a lower value indicates the optimal number of clusters, and the optimal number of clusters has the lowest BIC value. In addition, we also monitored the large ratio of BIC changes and the large ratio of distance measures. However, the statistical-analytical program automatically determines the optimal number of clusters without the author's decision [59] in the statistical-analytical program IBM SPSS 26.

Distance measure. Log-likelihood measures object similarity using mixed categorical and numerical variables compared to the Euclidian algorithm [56]. This algorithm is chosen only for continuous variables. The formula of log-likelihood distance can be seen as follows:

$$d_{(R)(S)} = \xi_R + \xi_S - \xi_{(R,S)} \tag{6}$$

$$\xi_v = -N_v\left(\left(\sum_{k=1}^{K^A}\frac{1}{2}\log\left(\hat{\sigma}_k^2 + \hat{\sigma}_{v.k}^2\right)\right) + \left(\sum_{k=1}^{K^B}\hat{E}_{v.\,k}\right)\right) \tag{7}$$

$$\hat{E}_{v.\,k} = -\sum_{l=1}^{L_k}\left(\frac{N_{v.k.1}}{N_v} * \log\left(\frac{N_{v.k.1}}{N_v}\right)\right) \tag{8}$$

where the components are as follows:

K^A Total number of continuous variables;
K^B Total number of categorical variables;
R_k The interval of the k continuous variable;
N Number of observations;
N_k Number of objects in the k cluster;
$\hat{\sigma}_k^2$ Estimated variance of the k continuous variable for all data;
$\hat{\sigma}_{Rk}^2$ The estimated variance of the k continuous variables in the R cluster;
N_{Rkl} Number of objects in the R cluster, and k categorical variables take the l category;
$d_{(R)(S)}$ Distance between the R and the S;
(R, S) An index representing clusters by joining the clusters R and S [60,61].

3. Results

3.1. Model Summary

Table 2 shows that the sample consists of almost 2000 respondents from the Czech and Slovak Republics. As can be seen, only 29 respondents (less than 2% of all) are excluded from the sample due to missing data. Unfortunately, these respondents did not answer all the questions focusing on passengers' behaviour and mobility in the questionnaire during the COVID-19 pandemic. The cluster analysis divides the total sample into five clusters, and each cluster has more than 300 respondents. The fourth cluster has the most respondents (almost 500), while on the other hand, the third cluster has the fewest respondents (less than 330).

Table 2. Cluster distribution.

		N	% of Total (with Excluded Respondents)	% of Total
Cluster	1	333	17.00	16.70
	2	445	22.70	22.30
	3	323	16.50	16.20
	4	478	24.40	24.00
	5	384	19.60	19.30
	Combined	1963	100.00	98.50
Excluded respondents		29		1.50

We applied the two-step cluster analysis to segment respondents to describe passenger behaviour and mobility during the COVID-19 pandemic. We used five independent variables: gender, social status, car ownership in the household, ownership of a prepaid card for public transport, and the most frequently used means of transport. All these input variables are important factors to describe passenger behaviour, and because the predictor importance is higher than 60%, independent variables such as social status and ownership of a prepaid card for public transport have the greatest impact on the classification of passengers commuting to work or school. Figure 1 shows all categorical variables used in a two-step cluster analysis with predictor importance.

These input variables divide the total sample into five clusters. This paper aims to identify the specific passenger behaviours in personal transport commuting to work or school during the COVID-19 pandemic. Figure 2 demonstrates that the cluster analysis with five independent variables is good/fair because Silhouette's measure of cohesion and separation indicates 0.5 (between the fair and good band) [52]. If Silhouette's measure is higher than 0.2, this metric demonstrates the fair zone. These results demonstrate that the behaviours are significantly different from each other, but respondents in individual groups have similar behaviours in passenger mobility.

3.2. Clusters

Table 3 reveals that five clusters are the optimal number based on the highest ratio of distance measures. In addition to this metric, we demonstrate BIC, BIC change, and the ratio of BIC changes. Table 3 demonstrates the BIC values calculated for 15 clusters. In general, a high number of clusters leads to a difficult model. The statistical-analytical program adopts an automatic solution based on a compromise between a large ratio of BIC changes and a large ratio of distance measures. The optimal number of clusters is five (ratio of BIC changes = 0.538, ratio of distance measures = 1.638).

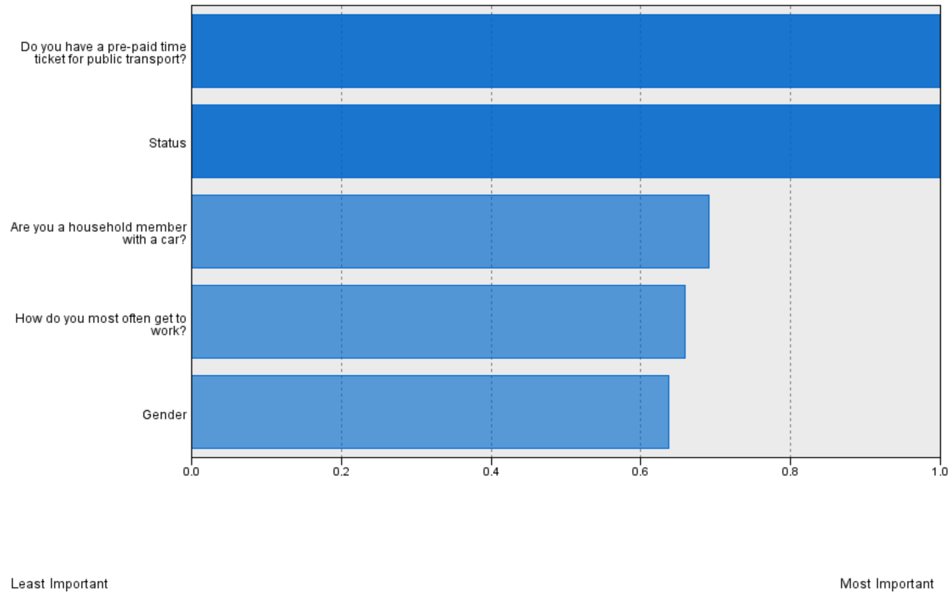

Figure 1. Five important predictors in segmentation in everyday travel behaviour.

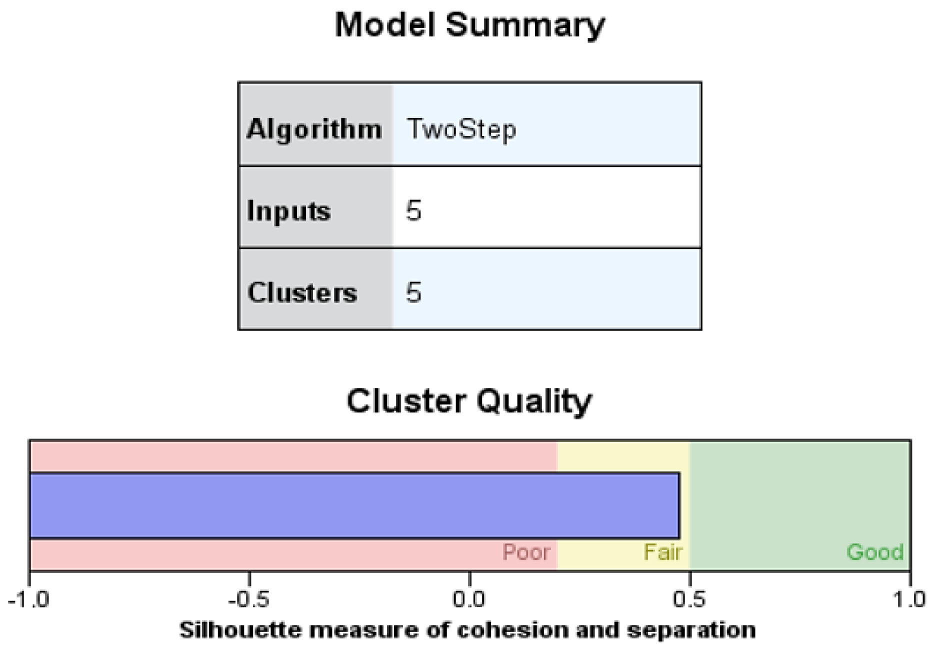

Figure 2. Model summary and cluster quality based on Silhouette's measure of cohesion and separation.

Figure 3 summarizes the results of the two-step cluster analysis as the cluster size, the importance of the input variables (see the scale), and the most numerous groups of respondents depending on the selected independent variable. Figure 3 reveals the ranking of the input predictors according to within-group importance in each cluster. We find that gender is the most significant factor in the fourth and fifth clusters, unlike the others. Moreover, the results show that status is the most significant predictor in the second cluster, which is almost exclusively made up of employees. On the other hand, the first and third clusters differ from the others because socio-demographic characteristics such as gender and status do not play such a significant role compared to ownership of a car in the household in the first cluster or the ownership of a prepaid time ticket in the third cluster.

Table 3. Auto-Clustering.

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change [a]	Ratio of BIC Changes [b]	Ratio of Distance Measures [c]
1	14,281.882			
2	12,153.995	−2127.887	1.000	1.164
3	10,334.258	−1819.737	0.855	1.366
4	9018.404	−1315.855	0.618	1.141
5	7873.041	−1145.362	0.538	1.638
6	7197.318	−675.723	0.318	1.016
7	6532.913	−664.405	0.312	1.365
8	6062.276	−470.637	0.221	1.039
9	5611.429	−450.847	0.212	1.295
10	5277.087	−334.342	0.157	1.041
11	4958.395	−318.692	0.150	1.138
12	4685.766	−272.629	0.128	1.058
13	4431.516	−254.250	0.119	1.057
14	4194.208	−237.309	0.112	1.069
15	3976.103	−218.105	0.102	1.095

[a] The changes are from the previous number of clusters in the table. [b] The ratios of changes are relative to the change for the two-cluster solution. [c] The ratios of distance measures are based on the current number of clusters against the previous number of clusters.

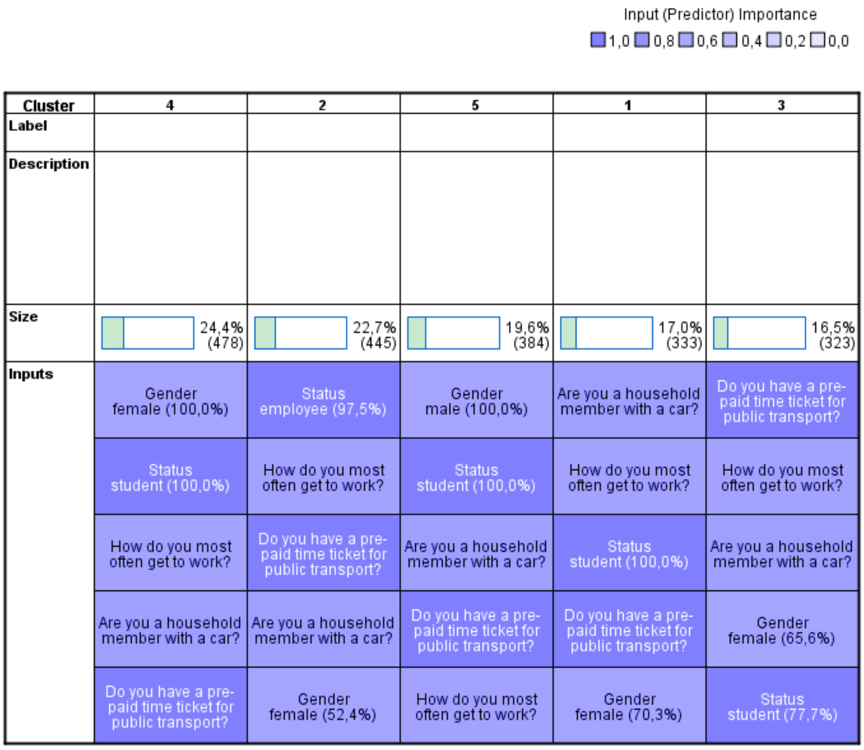

Figure 3. Clusters.

Table 4 reveals that three of the five clusters are made up of only students. The second and third clusters are composed of students and employees. The second cluster, unlike the other clusters, consists mainly of employees (almost 86% of all employees in the sample). Finally, the sample consists mainly of students (almost 75% of all).

Table 4. Status.

		Employee		Student	
		Frequency	**%**	**Frequency**	**%**
Cluster	1	0	0.00	333	22.90
	2	434	85.80	11	0.80
	3	72	14.20	251	17.20
	4	0	0.00	478	32.80
	5	0	0.00	384	26.40
	Combined	506	100.00	1457	100.00

Table 5 shows that the fourth cluster consists only of women, unlike the fifth cluster. The other clusters are made up of both men and women, but women dominate in all these clusters. The second cluster has approximately equal representation of men and women, and approximately twice as many women are in the first and third clusters. The sample consists mainly of women (almost 60%).

Table 5. Gender.

		Male		Female	
		Frequency	**%**	**Frequency**	**%**
Cluster	1	99	12.30	234	20.20
	2	212	26.30	233	20.10
	3	111	13.80	212	18.30
	4	0	0.00	478	41.30
	5	384	47.60	0	0.00
	Combined	806	100.00	1157	100.00

Table 6 reveals that the car and the train are the most frequently used means of transport for commuting to work or school. On the other hand, alternative means of transport such as shared bicycles and scooters, but also public transport, are less preferred means of transport compared to others. Alternative means of transport are used as the most frequent means of transport for commuting to work or school by only 41 respondents. The results show that the first cluster prefers walking and the train as a means of commuting to work or school. On the other hand, the second, fourth, and fifth clusters prefer a car. The third cluster prefers public transport. We find that the train is a popular means of transport in all clusters except the second cluster, because the train is the second most frequently used means of transport for commuting to work or school. Respondents in the second cluster prefer walking as a second way to commute to work or school. However, walking is not a popular mode of transportation to work or school for the fourth cluster. Moreover, the fourth and fifth clusters do not contain any respondents using an alternative means of transport.

Table 7 shows that the fourth and fifth clusters consisted of respondents living in a household with a car. The other groups are composed of respondents without access or with access to a car in the household. The first cluster, unlike the second and third clusters, consists mainly of respondents without access to a car. Most respondents have access to a car (less than 77% of all).

Table 6. How do you most often get to work?

		Walking		Public Transport		Car		Train		Alternative Transport Modes	
		Frequency	%	Frequency	%	Frequency	%	Frequency	%	Frequency	%
Cluster	1	160	46.00	40	14.10	10	1.20	117	24.00	6	14.60
	2	83	23.90	20	7.10	279	34.70	34	7.00	29	70.70
	3	36	10.30	143	50.50	18	2.20	120	24.60	6	14.60
	4	0	0.00	40	14.10	314	39.10	124	25.40	0	0.00
	5	69	19.80	40	14.10	182	22.70	93	19.10	0	0.00
Combined		348	100.0	283	100.0	803	100.0	488	100.0	41	100.0

Table 7. Are you a household member with a car?

		Never		Always/Sometimes	
		Frequency	%	Frequency	%
Cluster	1	271	59.20	62	4.10
	2	50	10.90	395	26.20
	3	137	29.90	186	12.40
	4	0	0.00	478	31.80
	5	0	0.00	384	25.50
	Combined	458	100.00	1505	100.00

Table 8 reveals that the majority of respondents do not have a prepaid card for public transport (more than 83% of all). Three of the five clusters consist only of respondents without a prepaid card. On the other hand, the third cluster consists of more than 300 respondents with a prepaid card for public transport (almost 98% of all respondents with a prepaid card). Other respondents with a prepaid card for public transport are part of the fourth cluster.

Table 8. Do you own a prepaid time ticket for public transport?

		No		Yes	
		Frequency	%	Frequency	%
Cluster	1	333	20.40	0	0.00
	2	445	27.30	0	0.00
	3	0	0.00	323	97.90
	4	471	28.80	7	2.10
	5	384	23.50	0	0.00
	Combined	1.633	100.00	330	100.00

3.3. Cluster Comparison

Figure 4 shows that the fifth (dark blue) cluster consists exclusively of male students living in a household with a car, preferring a car or train as one of the most frequently used means of transport for commuting to school. Moreover, none of them have a prepaid card for public transport. On the other hand, the third (yellow) cluster consists of 251 students and 72 employees. The results show that the majority of respondents live in a household with access to a car, and there are almost twice as many women as men in this cluster. Nevertheless, these respondents mostly prefer public transport or the train compared to walking, driving, and alternative means of transport such as shared bicycles or scooters for commuting to work or study. We find that all these respondents have prepaid cards for public transport. This cluster is one of the two groups in which there are respondents with a prepaid ticket for public transport. However, the fourth cluster has only seven respondents with this ticket, and most respondents do not have such a ticket. These results demonstrate that the third cluster prefers combined and sustainable transport for lower transport costs than the comfort of a private car.

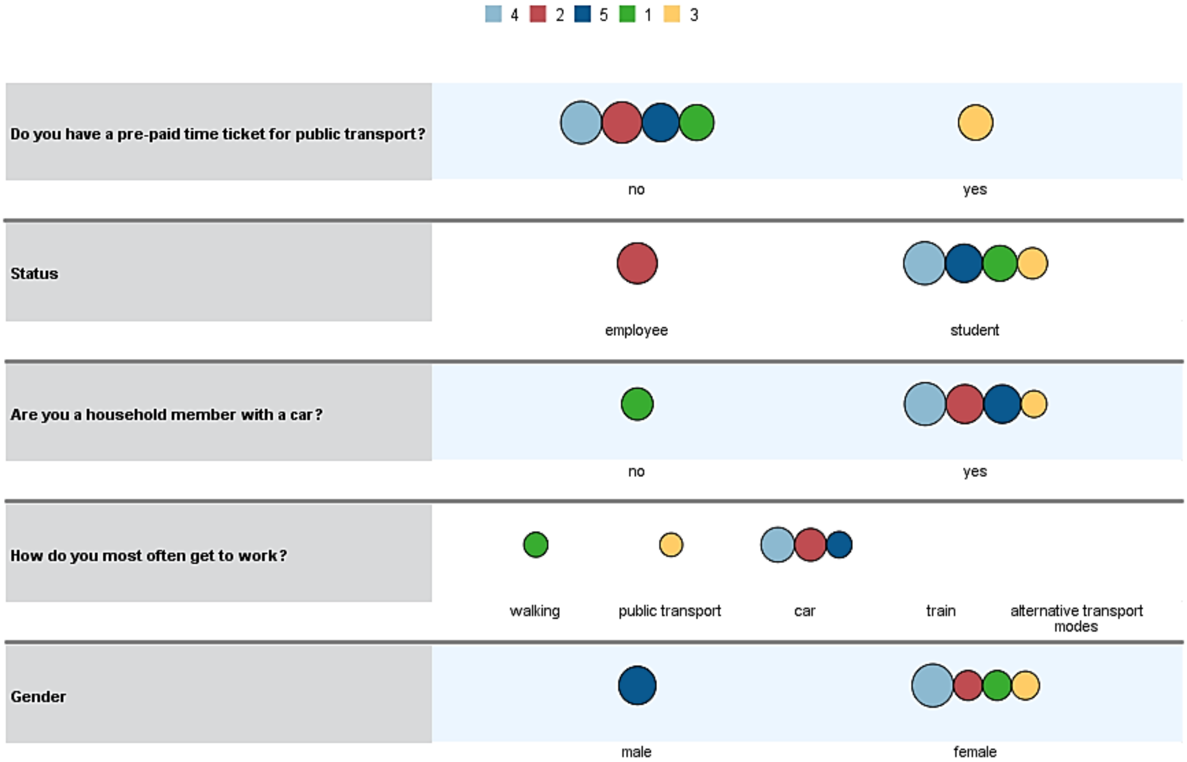

Figure 4. Cluster comparison.

The second (red) and third (yellow) clusters are composed of students and employees. Other groups are made up of students only. The second cluster contains almost 86% employees. On the other hand, this cluster consists of only 11 students (less than 1% of all students). This cluster comprises mainly women; nevertheless, the cluster has an equal representation of men and women. The results show that employees dominantly prefer the car as one of the means of transportation for commuting to work. However, some of them, specifically 83 respondents, most often walk to work or school.

The first (green), fourth (light blue), and fifth (dark blue) clusters consist only of students. The fourth cluster consists only of women and the fifth cluster consists only of men. The first cluster is a combination of both sexes, but women make up more than 70% of all respondents. Many students from the first cluster do not live in a household with access to a car, so these respondents walk or take the train to school. Moreover, the results show that the fourth and fifth clusters most often prefer the same means of transport, namely the car and the train for commuting to school. We find that the majority of women in the fourth cluster choose the car, train, and public transport: other transport options such as walking and alternative means of transport are not interesting for this group. The cluster analysis demonstrates that these two groups differ in that male students are willing to walk to school, unlike females, as the fourth cluster does not prefer walking at all.

Alternative means of transport are generally not among the commonly used means of transport for commuting to work or school, as only 41 respondents prefer shared bicycles and scooters. Twenty-nine of all respondents preferring alternative means of transport make up the second cluster. This cluster is mainly made up of employees, and women and men have approximately the same representation.

4. Discussion

The onset of the COVID-19 pandemic caused a global transformation of economic, political, and social aspects, including changes in the behaviour and direction of the entire population. The safety of the transport system is defined as one of the decisive requirements when choosing a mode of travel. Due to the onset of the COVID-19 pandemic, this term acquired two meanings. In addition to the level of safety due to the nature of road traffic or the security system in the railway sector, the need to ensure the safety of passengers against the spread of infection inside the means of transport was highlighted.

Patterns of citizen behaviour within society as well as activities in businesses in the context of the COVID-19 pandemic were recognized and defined in many studies through cluster analysis. The hierarchical clustering method outlined the economic and behavioural patterns of e-commerce activity while comparing the value of e-commerce sales and customer relationship management to meet the demands of online customers [62]. Cluster analysis also evaluated individual mobility considering the mode of transport in Mexico [63]. Due to the temporary stoppage of economic and social aspects, businesses were forced to change their mindset and accelerate the onset of digitization. The active introduction of online applications allowed businesses to continue their economic activity continuously during the pandemic situation [64–66]. A study in Turkey investigated the impact of the pandemic on mobility and confirmed the importance of some types of mobility, such as regarding grocery stores or workplaces [67]

Prediction of COVID-19 severity was evaluated in another study using longwise cluster analysis, which was evaluated as an effective way of redistributing patients based on different clinics [68]. The high accuracy of the cluster analysis was also shown in a contribution focused on the allocation of vaccines in the fight against pandemics, where individual clusters were based on the level of spread of infection [69]. Mobility during the COVID-19 pandemic depended on the degree of fear of contagion and various psychosocial factors, which were addressed by several studies [70–72].

The cluster analysis in our study focused on delineating independent variables to determine the severity of their influence on the classification of commuters during COVID-19. Our research showed that passengers can be divided into five different clusters based on specific characteristics. Input variables consisted of gender, status, ownership of a car in the household, ownership of a prepaid card for public transport, and the usual means of transport used for commuting to work and school. The limitation of our study can be considered the availability of population mobility data within the consideration of two EU states, while future studies could be devoted to analyses within the scope of the expansion and diversification of the territory. Another important limitation of this study was that the sample of travellers was under-represented in all demographic groups, especially age. This is due to the inherent weaknesses of online surveys, which do not attract the attention of older people but are the only viable survey tool under the COVID-19 containment measures.

The travel survey of the German population brought insight into individual changes in behaviour in using not only public transport but also bicycles and individual car transport. The study evaluated individual car transport as a convenient and safe mode of transport during the pandemic and singled out public transport as negative due to the higher risk of infection [73].

A study in Greece, with a similar approach to our study, assessed the influence of personal identity on the choice of transport mode. The respondents were divided into three clusters according to specific characteristics. The importance of individual identities was emphasized in understanding different travel behaviours to design targeted strategies for achieving sustainable urban mobility [74].

A global study including 124 countries evaluated and confirmed the change in mobility based on the stringency level of anti-COVID-19 government policy and human mobility changes using cluster analysis for four country groups [75]. The following study confirmed the impact of the pandemic on public transport and also dealt with the issue of the gender gap in travel behaviour during the development of the pandemic. This contribution, as well as the results of our research, highlighted the increased risk of infection in women [76]. A study in Belgium about mobility indicated a high proportion of infected women out of the total number of people infected with the COVID-19 virus. Women were predominantly frontline workers using mainly public transport during the lockdown [77]. Our study also confirmed the higher risk of infection for women, as they prefer public transport over individual car transport. A two-tier hierarchical mobility model was also proposed in Brazil based on mobile network data. Identified clusters according to the intensity of traffic made it possible to apply targeted blocking measures and restrictions [78]. Our study was based on the online questionnaire survey reflecting travel habits due to the COVID-19 pandemic. The spatiotemporal pattern of human mobility was modelled based on a spatiotemporal cluster analysis of COVID-19 cases, which confirmed the link between lockdown and traveling [79].

Burke et al. [80] used cluster analysis in the evaluation of an alternative mode of transport, namely cycling transport. Their research shows that even if the pandemic had an impact on the popularity of cycling, only its subsequent promotion and investment in cycling infrastructure will result in a more permanent benefit to its preference in the future.

This study dealt with the daily mobility of people affected by the pandemic. Patterns of behaviour and factors influencing decision making were analysed, while also focusing on differences between different social groups. The research confirmed the change in mobility due to the fear of infection by the pandemic [81].

5. Conclusions

During the COVID-19 pandemic situation, anti-epidemiological measures and traffic restrictions affecting the movement of people were approved. In general, mobility rates are closely related to travel behaviour. This paper focused on assessing the impact of the COVID-19 pandemic on passenger mobility segmentation using a two-step cluster analysis.

A broad-spectrum cluster analysis was chosen to evaluate the impact of the pandemic on mobility within individual groups. From the analysis of a large number of sources of the application of cluster analysis, it can be concluded that its use is frequent in various areas and provides a high accuracy of outputs.

The paper aimed to segment travellers based on common socio-demographic and other factors into the same groups during the COVID-19 pandemic. In other words, we identified key differences in travel behaviour between selected groups. These findings helped target a potential group with specific characteristics. This research focused on a two-step cluster analysis in which the analysed sample of respondents was naturally redistributed into five clusters. Each of the clusters consisted of at least 300 respondents. These five independent variables included gender, ownership of a car in the household, and the most frequently used means of transport. However, variables such as social status and ownership of a prepaid public transport card had the greatest influence on passenger classification.

Individual clusters were analysed in more detail and compared with each other. We found that gender is the most significant factor in the fourth and fifth clusters, unlike the others. Moreover, the results showed that status is the most significant predictor in the second cluster, which is almost exclusively made up of employees. On the other hand, the first and third clusters differed from the others because socio-demographic characteristics such as gender and status did not play such a significant role compared to ownership of a car in the household in the first cluster or the ownership of a prepaid time ticket in the third cluster.

The research task focused on segmenting passengers into individual clusters according to specific characteristics. We identified significant differences in passenger behaviour across individual clusters. They were also evaluated based on the comparison of students and employees, as well as the difference in the travel habits of men and women. Individual car transport and the train took the leading places when comparing the use of means of transport, while alternative modes of transport represented only a small percentage. We found that ownership of a prepaid card for public transport and social status are the most important factors. The research showed that 80% of the analysed sample of respondents did not have a public transport card. There is therefore an opportunity for public transport to offer competitive services in the future and to attract passengers to public transport or convince them to use alternative modes of transport.

In this paper, this segmentation analysis provided a clear overview of population behaviour on mobility affected by COVID-19. In our opinion, this study opens the possibility of applying a cluster analysis as a suitable tool for the redistribution of the analysed variables in future studies as well.

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