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Changes in students' inner-city traveling habits caused by protective measures against COVID-19 disease – example of the medium-sized university city in the Balkans

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ABSTRACT

Imposed measures for the protection of public health and prevention of the uncontrolled spread of COVID-19 disease affected before established community traveling patterns. One of the questions scientific community consequently wonders consider the potentials of the occurred circumstances to leave permanent change to community traveling behavior. With that regard, this study examines changes in students' traveling habits in a medium-sized university city in the Balkans. The research was based on 486 students' responses amassed by Google questionnaires, before and during the COVID-19 pandemic. The study includes data interpretation and data analysis. Among six introduced classification models, random forest proved as the most suitable to accurately fit the students' demographic details to students' attitude towards future traveling habits (as changed or not changed permanently). Additionally, the model was optimized and further analyzed on variable influence and variable partial dependence. Data interpretation indicates higher reliance on personal automobiles as a cause for a 15% increase of the families owning two of the vehicles. Because of that, the share of the students who walked to the University during the pandemic declined by approximately 20%, while those using public transportation stayed relatively unchanged (decrease by around 3%). On the other side, the best of six classification models was used to determine the factors causing a permanent change in students' attitudes towards inner-city transportation. Derived classification models deduce where to expect potentially permanent changes in traveling patterns – distances between 2 and 4 km from the University, and among which students – those who are visiting lectures less frequently than others.

1. Introduction

Transportation has an important role in everyday life and overall economic and social development. It is estimated that around 5.2% of countries' gross domestic product is attributable to the existence of transportation services (Rodrigue et al., 2016). Besides, the transportation sector contributes to cultural cooperation among countries; improves business and education opportunities and enhances overall life quality. In addition, constant development of internal and external road and route networks influenced a decrease in both, travel costs and travel duration. Besides the obvious benefits for modern communities, high social reliance on well-arranged and widespread traffic networks retains downsides that can be particularly visible in the events of social crises. In the

light of the events, such are slowdowns of global or national economies, disruption of international relations, natural disasters, and pandemics, effects that transportation sector has on society and the environment can be noticed more clearly. During the global crisis caused by the Coronavirus disease (COVID-19), governments of countries and regions imposed various measures that limited travel behaviors (i.e. travel frequency, peak hour departure, trip destination, travel mode), and activities (i.e. trip pattern diversity, trip purpose, and time spent at home) (Huang et al., 2023). The public transportation sector was subjected to these measures due to the anticipated rapid spread of contagious viral diseases to which it can contribute (Ali et al., 2020). Besides that, public commuting became unpopular due to fear of contagion (Tori et al., 2023).

Thus, limited and rearranged mobility affected the previous state of the environment and society. Regarding the environment, the effects were positive: less carbon emission and better urban air quality (Chen et al., 2021). Specifically, since the beginning of the pandemic, global carbon emission was reduced by 7%, while the decrease in road transport emission was 10%. A significant decrease in pollutant concentrations related to traffic reduction contributed to apparent air quality improvement in some of the the big cities (Kim, 2021) and medium-sized municipalities (Metryka-Telka & Kowalik, 2022).

For example, since the pandemic outbreak, urban air quality[1] in Istanbul (Turkey) has been improved by 47% (Sahraei, 2021) similar to the air quality improvement measured in Delhi (India) (40 – 50%) (Mahato et al., 2020). Regarding society, private-public arrangements in the transportation sector became disrupted by the fragile supply-demand equilibrium, affecting human activities and causing disorder in the social functioning mechanisms (Nikolaidou et al., 2023). Adopted measures regarding the type of social distancing reduced the capacity of public transportation from 47% up to 84% of predicted (Ali et al., 2020). As a result of the imposed measures and the precaution of citizens, the number of passengers relying on public transportation has significantly dropped (Nundy et al., 2021). For example, the number of passengers in almost all big cities across the east and west coast of the USA dropped in between 40% and 80% depending on the city, in Italy and Australia the decline amounted to over 80% ("Coronavirus & Your Commute: How COVID-19 is Affecting Public Transportation Around the World: Moovit," 2021). In the city of Bogota (Colombia), the number of passengers has been reduced by 87% while in Santander (Spain) by 93% (Aloi et al., 2020). Most of the Moovit users who said that they abandoned public transport were found in Italy and Greece (Nikolaidou et al., 2023).

In Norway, citizens who relied more on walking reported improved mood and work performance (Fyhri et al., 2023).

This way, results of the research dealing with the quantification of the effects preventive measures left on the environment and society, raise additional questions:

1) How do citizens perceive and contribute to the change of before-established transportation and social functioning patterns?
2) How will the imposed measures, related to the prevention and management of COVID-19 disease, influence future social behavior related to public mobility?

The goal of the present study is to answer these questions following the changes in students' traveling behavior in the university city in southern Balkans. The study aims to define demographic factors influencing the permanent change of students' inner-city traveling habits. Definition of these factors could contribute to a better understanding of the perception causes, while their organized exploitation could influence further changes towards more sustainable societies (Rikalović et al., 2021).

2. Materials

In order to examine the participation of students in overall city transportation pattern (frequency of the travel, most frequently used modes of transport, causes influencing to/not-to choose particular means of transportation, etc.) online survey was conducted on second-year students at the Faculty of Engineering, University of Kragujevac[2], Serbia. A voluntary survey had been conducted throughout the Google Form platform in 4 year period (2018 – 2021) (Jurišević et al., 2022). Last years' survey was extended with additional questions referring to students' perception of the effects caused by the COVID-19 changes in traffic organization.

According to the survey (486 participants) around half of the total share of the respondents (49.25%) was permanently residing in the university city (UC). The other half came from other cities and was temporarily residing in dormitories or private accommodations near the University. Share of distances from the main Faculty building (FB) to the students permanent or temporary residences in the UC, as well as representation of permanent places of residences in the Republic of Serbia for all the respondents, is presented in figure 1.

[1] Pollutants that in general determine air quality are: particulate matter (PM), sulfur dioxide (SO_2), oxides of nitrogen (NO_x), and carbon monoxide (CO).

[2] University of Kragujevac with 14000 enrolled students is 4th largest university in the Republic of Serbia.

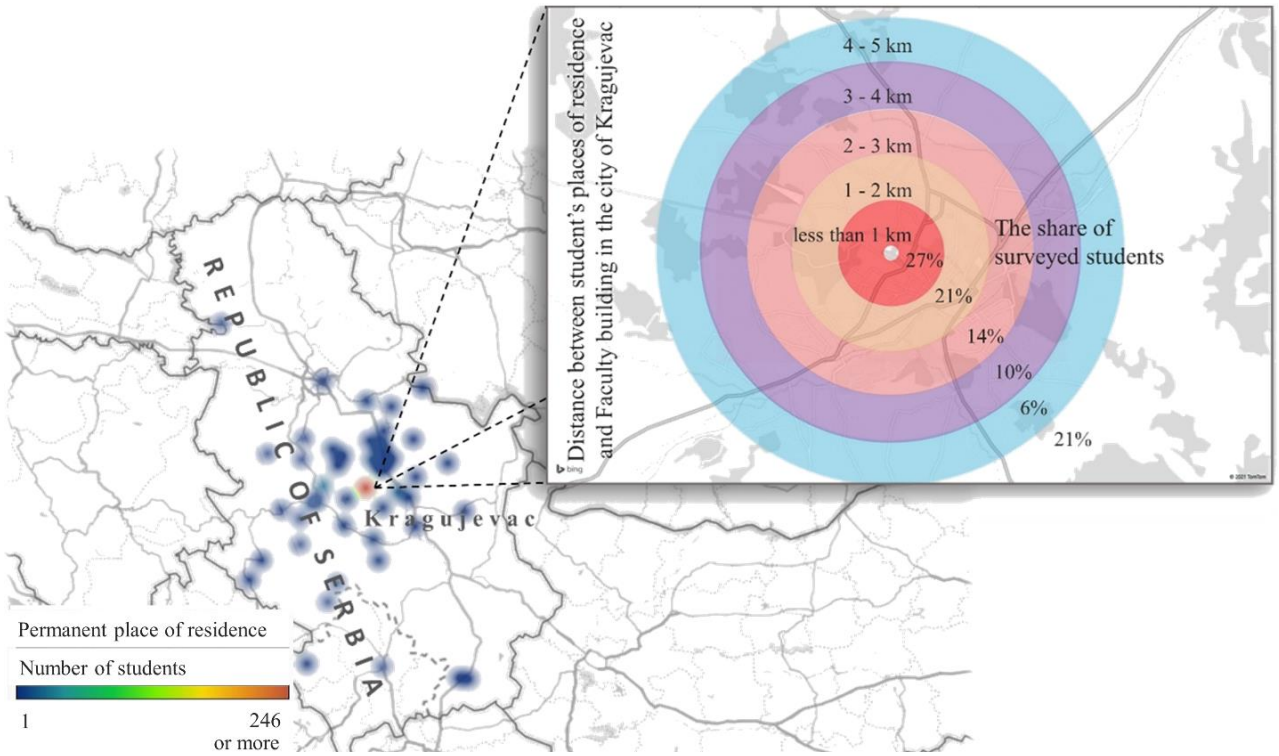

Figure 1. The representation of permanent places of residences for all the students, and share of distances from the main FB to the students permanent or temporary places of residences in the UC

As it can be seen from the figure 1, the highest share of students (more than a fourth) have their places of residence less than a kilometer away from the main FB. Up to 5 km of distance, the share of students residences decreases around 5% per kilometer. Approximately a fifth of all the respondents (21%) is situated more than 5 km away from the main FB.

2.1. Survey

In order to determine factors influencing the pattern of students' traveling habits, the conducted survey consisted of questions that refer to:

- Type and number of vehicles owned by the respondent household members[3], and
- Aspects influencing the choice of transportation type

In order to observe possible changes in student responses caused by the imposed measures for traffic reorganization[4], all the answers were divided into two groups: 1) **pre**-COVID-19, and 2) **during**-COVID-19 pandemic. In addition, last year's survey consisted of questions aimed at investigating potentially permanent changes in students' traveling habits for which they believe will affect the traveling patterns in the **post**-COVID-19 period.

2.1.1. Vehicle ownership

Share of the type and number of the three most common transportation modes – namely: automobiles, motorcycles, and bicycles per students' households in the **pre**-COVID-19 period are presented in figure 2.

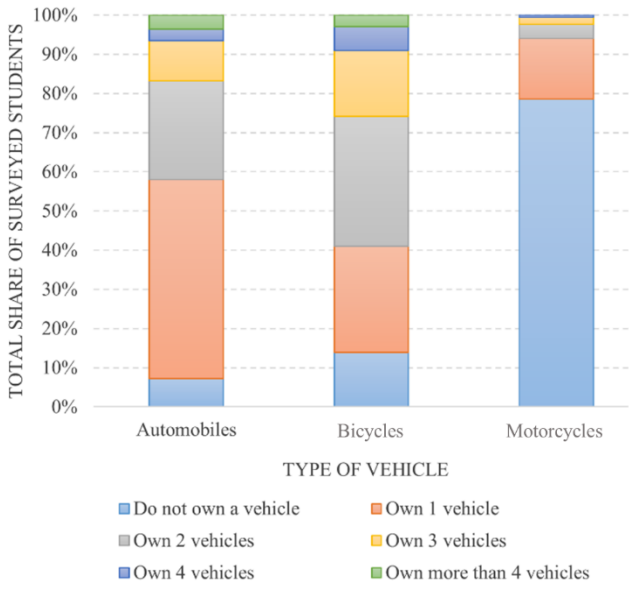

Figure 2. Share of type and number of owned vehicles per students' households in **pre**-COVID-19 period

[3] The study considers a household vehicle as a property shared among housold members.

[4] Decreased number of passengers in public transport, reorganization of public transport timetable, etc.

In approximately half of the responses (51%), student's household members own one automobile in total, while 79% of the respondents neither they household members own a motorcycle. It is relatively interesting that among those households where a bicycle is owned, there are more of those who own two of the vehicles (33%) than those who own just one (27%). During the COVID-19 pandemic, the shares of categories of owned vehicles (Table 1) changed significantly compared to the **pre**-COVID-19 period; in particular, the share of categories referring to the number of owned automobiles and bicycles (Jurišević et al., 2022).

Table 1. Changes in the shares of owned vehicles by category, during-COVID-19 comparison to the pre-COVID-19 period

Category of answer	Automobiles	Motorcycles	Bicycles
Do not own a vehicle	-4%	-2%	-4%
Own 1 vehicle	-13%	2%	-2%
Own 2 vehicles	15%	0%	7%
Own 3 vehicles	1%	-1%	-2%
Own 4 vehicles	2%	-1%	0%
Own more than 4 vehicles	-1%	1%	1%

Results presented in table 1 indicate that a decrease in the share of the first two categories of answers (*Household members do not own a vehicle*; *Household members own 1 vehicle*) was caused by the increase in the share of third category answers (*Household members own 2 vehicles*). Specifically, the reorganization of public transportation **during-**COVID-19 period, as well as increased caution for personal health, influenced those who did not own an automobile or own just one, to rely on an additional vehicle of this type in their households. The same trend was present in the share of bicycle ownership categories, although for more than a half smaller share compared to the change in automobiles ownership categories (7% and 15%, respectively). Although non-negligible, this increase could be considered as not relatively significant compared to 76% in the increase of riders per hour recorded in 16 embedded countries (Monfort et al., 2021). The category of students whose household members *own one motorcycle* increased by 2% compared to the **pre**-COVID-19 period, as much as the category of those who *do not own a motorcycle* decreased. In 2020 the trend of an annual increase in the number of owned automobiles was noted on the republic and regional level, 4% and 8%, respectively (Statistical Office of the Republic of Serbia, 2021). In addition to official statistical reports, studies such as this could contribute to further analysis of the increase of the number of vehicles in households.

2.1.2. Aspects influencing the choice of transportation

Different aspects influence students' choice of inner-city transportation mode. They can refer to travel time, travel costs, comfort, safety, climate conditions, the possibility to travel with friends, and many others. The frequencies of the survey responses referring to positive and negative traveling aspects influencing the choice of transportation mode in the **pre**- and **during the** COVID-19 period, are presented in figure 3 (Jurišević et al., 2022).

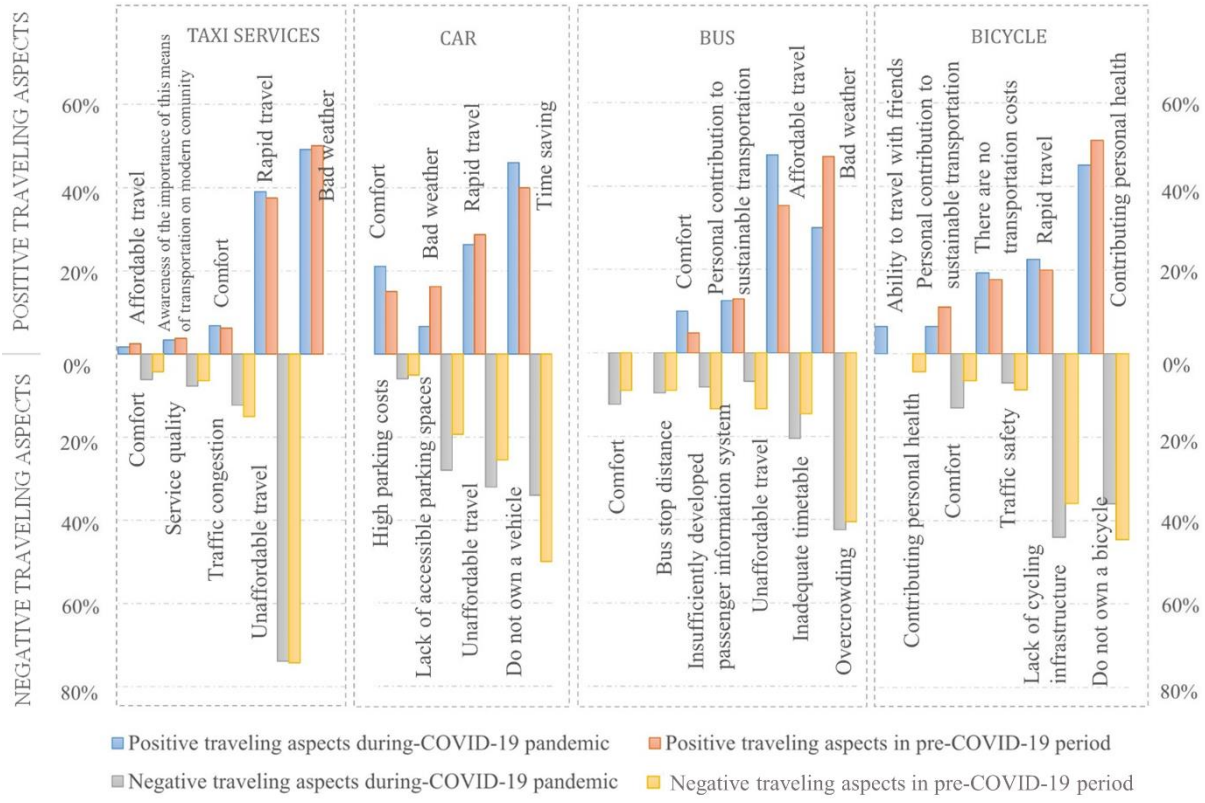

Figure 3. Positive and negative traveling aspects influencing the students' choice of inner-city transportation mode

From the figure can be seen that car travel became more desirable during pandemics referring to *time-saving* and *comfort* aspects (6% more frequent answer compared to **pre-**COVID-19 period). On the other side, *the lack of accessible parking spaces* and *travel costs* made this type of transportation less favorable than before (9% and 6% more frequent responses, respectively). Referring to busses in the **pre-**pandemic period, *bad weather* conditions were the strongest cause for the ride. Contrary to that, the main aspect in the following period becomes *affordability of travel* (13% more frequent responses than before). As the main downside of the bus travel students noted *overcrowding*, while *inadequate timetable* was recognized as a bigger problem during the pandemic than before. Longer waiting for delivery was described as an increased problem for citizens when describing delivery services as well (Ivanisevic & Simović, 2021).

There are no significant changes in the responses referring to positive aspects related to bicycles for both of the periods. It is relatively interesting that the weakest aspect for a ride during a pandemic – *the ability to travel with friends*, before the pandemic, was not considered as an aspect at all. Referring to downsides, although there are fewer of those who do not own a bicycle than before (9% less frequent responses during the pandemic) the aspect of bicycle ownership (*students nor household members own a bicycle*) stayed the strongest negative considering higher reliance on cycling. Among other negatives, more than before were recognized *lack of cycling infrastructure* as well as the *absence of comfort* (8% and 6% more frequent answers compared to **pre-**COVID-19 period, respectively).

Referring to taxi services, there were no significant changes in aspects influencing the choice of transportation in both of the periods. Unchanged students' attitude towards this mode of transport does not correspond the belief of the taxi drivers who perceive themselves to be at occupationally related risk of COVID-19 (James et al., 2021).

2.1.3. Assessment of future travel behavior

In order to assess permanent changes in students' inner-city traveling habits, last year's survey included questions answers to which could quantify the strength of potential change compared to the **pre**-COVID-19 period. Concerning the questions, students were able to describe the strength of their beliefs towards the change on a scale from minus 5 to plus 5, for all the modes of transport. Zero on the scale represents *no change* in the future traveling behavior, while negative and positive values represent smaller and higher reliance on particular modes of transportation, respectively.

Share of the frequency of the answers is presented in Figure 4. From the figure can be seen that *no change* answers were the most common for all the modes of transportation. Nonetheless, the share of the answers indicating a change in behavior was significant as well, in particular those referring to *walking*, *driving*, and *cycling*. Concerning *walking* and *(car) driving*, almost half of the responses indicated higher reliance in the **post**-COVID-19 period, where 17% and 21% of the answers were rated with the highest grade on the scale, respectively. In respect to bicycles, more than a third of the responses (36%) indicated higher reliance in the future, contrary to a tenth of those who do not. These expectations are relatively similar to car and public commuters in the UK, where some 20.5% of those who commuted by public transport and 10.1% of those who commuted by car in **pre-**pandemic may switch to walking or cycling once restrictions lift, while predisposition towards the car will remain (Harrington and Hadjiconstantinou, 2021).

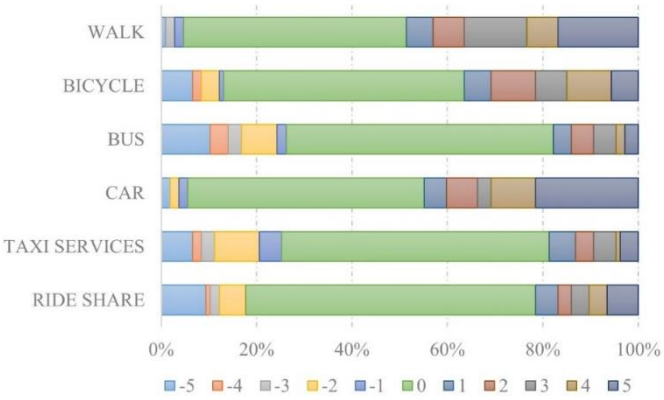

Figure 4. Share of the grades describing assessment of students' post-COVID-19 travel behavior: (0) – no change in travel behavior, (1) to (5) – the intensity of higher reliance on transportation mode, (-5) to (- 1) – the intensity of lower reliance on transportation mode

Share of the survey answers referring to the assessment of future travel behavior in respect to *rideshare* consisted of almost the same number of positive and negative grades on the scale, while reliance on *busses* and *taxi services* is expected to drop in the upcoming period.

3. Factors influencing students' inner-city travel behavior

To describe the changes in traveling patterns caused by COVID-19 traffic reorganization, this study is defining and quantifying factors affecting students' attitudes towards inner-city traveling habits as changed or not changed permanently. Consequently, the study will provide the findings: *where to expect the changes* and *what will cause them*, all in order for the community to be aware, try to preserve, and seek the way to exploit the effects forced traffic reorganization has brought to societies. With that regard, the study pursues to define the relation between students' demographics – namely: *Gender*, *From UC/From out UC*, *Distances between students UCR and FB*, *Weekly lectures attendance*, *Commonly used mode of transportation in the UC*, and

students' responses – concretely: *Attitude towards future traveling habits* (*changed* or *not changed* permanently). With that aim, the study tends to find a classification model able to describe the relationship with the best of accuracy, and afterward analyze the influence of the variables in the model.

4. Methods

The data used for the analysis (inputs and outputs) consisted of classes of students' answers amassed by the google questionnaire (Table 2). To cure the problem of output binary classification in the presence of imbalanced data[5], balancing the data was performed by simple oversampling with replacement from the minority class. The study sample, after resampling, was randomly split into training (70%) and testing (30%) sets. Characteristcs of the data sets and data sets' classes are presented in table 2. Distances between students UCR and FB consist of 5 classes, whereby every class represent 1 km of distance, except the last class that represents 5 km or more of distance. Weekly lectures attendance consists of 5 classes, whereby every class represent the number of weekly lectures attendances. Commonly used mode of transportation in the UC consist of 5 classes, whereby every class represent a different transport mode (walking, (car) driving, bus, taxi, cycling)

Table 2. Characteristics of the training and testing set

Characteristics	Training set (n=228)	Testing set (n=96)	*P*-value
Gender [M/F - 0/1] n (%)	153 (67.1)	62 (64.2)	0.700
From UC/From out UC [0/1] n (%)	113 (49.6)	56 (58.3)	0.180
Distances between students UCR and FB [1-5] n (%)	40/43/34/37/74 (17.5/18.9/14.9/16.2/32.5)	19/17/12/17/31 (19.8/17.7/12.5/17.7/32.3)	0.963
Weekly lectures attendance [1-5] n (%)	31/21/42/41/12/81 (13.6/9.2/18.4/18/5.3/35.5)	10/8/15/22/8/33 (10.4/8.3/15.6/22.9/8.3/34.4)	0.731
Commonly used mode of transportation in the UC [0-4] n (%)	126/63/23/15/1 (55.3/276.6/10.1/6.6/0.4)	49/33/9/4/1 (51/34.4/9.4/4.2/1)	0.669
Attitude towards future traveling habits *(changed / not changed permanently)* [0/1] n (%)	114/114 (50/50)	48/48 (50/50)	1.000

5. Results and discussion

Following the data stratification, the study derived 6 ML models by the use of R software, namely: a logistic regression model, artificial neural network, decision tree, and 3 ensembled tree-based ML algorithms, i.e., random forest (RF), gradient boosted trees, and extreme gradient boosted model. Due to the relatively limited data, training performances of the models were calculated using tenfold cross-validation. Subsequently, derived algorithms show different levels of performances, whereby accuracies and error rates for predicting *Attitude towards future traveling habits* for all the models are presented in fig 5. As can be seen from the figure, the best-performing model was RF. Following the model selection, default model parameters[6] were optimized[7] for the RF to *fit* the data as best as possible. Model optimization was conducted by the use of the H2O scalable and fast open-source platform ("Distributed Random Forest (DRF) — H2O 3.34.0.7 documentation," 2021).

[5] Imbalanced data characterize the classification with unequal distribution of classes in the training dataset.

[6] Default parameters of the RF model were: number of the tree [ntree=50], maximum depth of each tree [max_depth=20].

[7] In order to optimize the model, a "cartesian" grid search was applied. The parameters specific to the RF algorithm were tuned as following: the ntree 50 – 200 in increments of 50, the number of variables to be sampled as split criteria at each node (mtry) 2 – 5 in increments of 1, the max_depth 20 – 60 in increments of 20, the minimum number of observations for a leaf (min_rows) 1 – 2 in increments of 1, and the row sampling rate (sample_rate) 0.55, 0.632, 0.75 (that is a total of 288 model combinations).

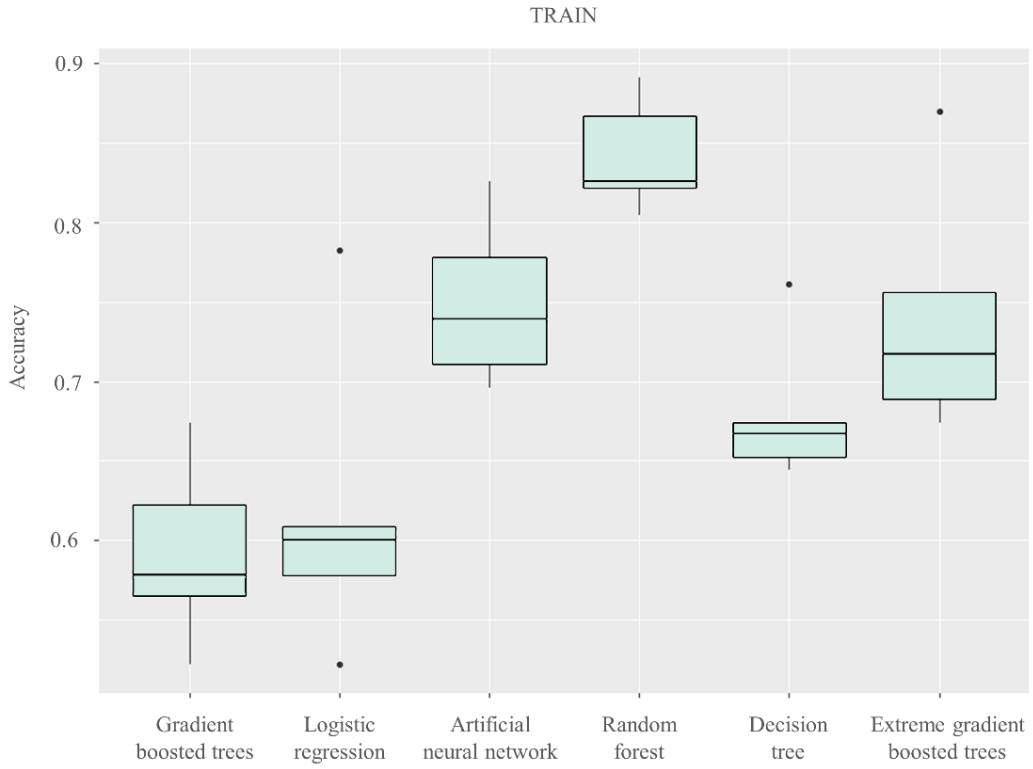

Figure 5. Comparison of classification accuracies

The summary of cross-validation metrics of the default and final [8] RF model on training and test sets is presented in Table 3. From the table can be seen that the final model slightly outperformed the model with default parameters in the training set. Furthermore, Cohen's Kappa coefficient for the optimized model (0.90) indicates an almost perfect agreement between real output classes and the classes predicted as the outputs by the RF algorithm. Following the end of the optimization process, the study considers that an optimal model to fit the analyzed data has been found. In the next step, the comparative importance of the variables was quantified. That way, the study expects to range by significance all of the factors influencing students' perception towards future traveling habits to become permanently changed.

Table 3. Predictive performance of default and final model based on training and test datasets

Performance metrics mean ± SD or (95% CI)	Default RF	Final RF	Final RF
	Training set	Training set	Testing set
Accuracy	0.937 ± 0.053	0.942 ± 0.052	0.948 (0.883 – 0.983)
Precision	0.922 ± 0.090	0.928 ± 0.089	0.978 (0.882 – 0.999)

The comparative intensity of the variable importance presented in figure 6 ranges from 0 to 1, i.e. from the least to the most influential model input, respectively. From the figure can be concluded that *Distances between students UCR*, similarly to findings presented in (Hu et al., 2021), *and FB* and *Weekly lectures attendance* have the highest importance on the model performance i.e. student traveling habits. On the other hand, variables such are *From UC/From out UC* and *Gender* demonstrated relatively low impact on the change of students' inner-city traveling behaviour.

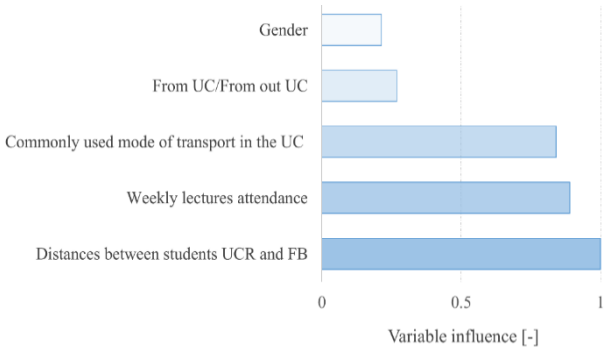

Figure 6. Variable importance for the optimized RF model

[8] Parameters of the best optimized RF model: ntree = 100, mtries = 2, max_depth = 20, min_rows =1, and sample rate 0.75. The best optimized RF model achieved a root mean square error (RMSE) of 0.263 on 10-fold cross-validation using the training data.

Along with variable importance, this study aims to define the direction of variable influences i.e. functional relationship between the classes of students' answers and the output classes of the model response. With that regard, a partial dependence plot[9] (PDP) of the adopted RF model was performed (Figure 7). Figure 7 consists of 6 independent plots (charts), whereby each of the plots represents the direction of individual variable influence.

Classes of students' answers per variable are presented on the *x*–axis, while the mean response of the model per unmarginalized class[10] is given on the *y*–axis. The change of partial dependence per variable class is presented with the line in the center of green field representing 95% of the output confidence interval. From figure 7. a) can be noticed that functional relationship between the classes of students' answers – referring to the most influential variable – *Distances between students UCR and FB*, and the output results

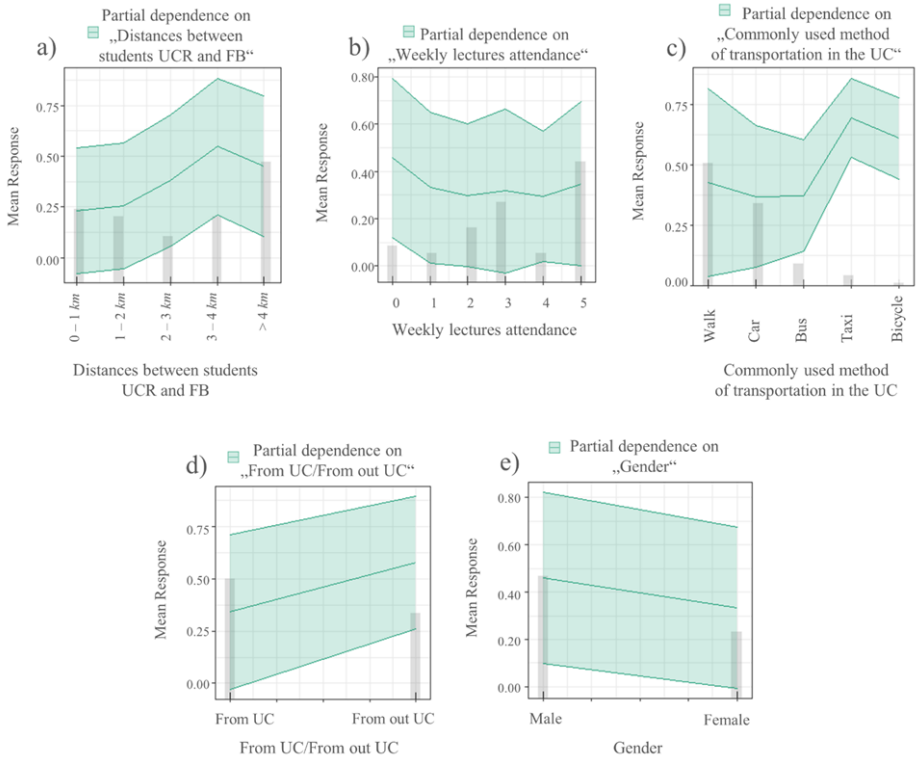

Figure 7. PDP for the optimized RF model

– referring to *permanently changed attitude towards future trawling habits*, generally arise with the increase of the answer class. Therefore, the analysis concludes that students who are seated further from the university are predisposed to permanently change the choice of transportation mode in inner-city travel more than the

students seated elsewhere. This particularly considers students seated 2 – 4 km from the main FB, as the most liable to assume a permanent change of their future traveling habits. According to the questionnaire, **during**-COVID-19 pandemics 30% less of them walked to the university, as much more preferred a car as their choice of transport. Further on, the possibility for the students to permanently change their traveling habits decreases with the increase of *Weekly lectures attendance* (figure 7, b)).

Accordingly, students that travel less frequently will, in general, be more suitable for permanent change of inner-city traveling habits as well as those who usually travel by bus and taxi services (figure 7, c)). For example, among the students attending lectures less than three times a week share of those walking to the university decreased by 30% **during** the COVID-19 period, while the share of those traveling by car and bus increased by 17% and 10% respectively. Besides that, PDP indicates that students from out UC will be more compliant to a permanent change of inner-city traveling habits (figure 7, d)) as males will be compared to females (figure 7, e)). The first indication can be justified by the fact that 23% more of the students from other cities decided to travel to the UC by car **during**-COVID-19 period. Thus, their mobility in the UC became more reliant on personal vehicles. Factors referring to gender confirmed the earlier findings of similar research (Lee et al., 2021)**.**

[9] A PDP plots the average model response across one feature marginalized over the other features and thus gives a global view of the feature effect on the model output (response) (Inouye et al., 2020).

[10] Mean response per input class refers to mean value of the predicted output classes for the prediction performed for the unmarginalised variable having the value of just one of its classes. Mean response is succesivly determined for all the classes of all the variables. Model responses (ouputs) could have the values of 0 and 1.
0 – Attitude towards future inner-city traveling habits is permanently changed; 1 – Attitude towards future inner-city traveling habits is not permanently changed

However, findings in this study could be influenced by the fact that the share of male students seated up to 2 km of distance from the university (according to PDP, the distance with the smallest expectation for permanent change of inner-city traveling habits) decreased by 10% referring to the **pre**-COVID-19 period, while the share of females in the same distance did not change. To sum up, the RF model, in general, indicates that attitude towards future traveling habits among the studying population is mainly influenced by the distance between the university building and students' residences as well as the frequency of students' lecture attendance.

6. Conclusion

This study analyzed the change of students' inner-city traveling behavior in a medium-sized university city in the Balkans, in **pre-** and **during**-COVID-19 period. The research was based on relatively simple data interpretation and relatively advanced data analysis.

Referring to data interpretation: It was found that a significant share of student households increased the number of family vehicles to two, 15% more compared to the **pre**-COVID-19 period. Increased reliability to automobiles was followed by high concerns towards personal health i.e. high sense of comfort related to this mode of transport. Consequently, lack of available parking spaces and travel costs contributed public transportation mode to become affordable for students' community more than it was before the pandemic. It was unexpected to observe that share of students walking to lectures decreased by around 20% compared to the **pre**-COVID-19 period. Besides that, students' attitude towards future traveling habits indicates reduced reliance on public transport, and increased reliance on personal automobiles and walking.
Referring to data analysis: Investigation was conducted to determine the importance of demographic factors affecting students' traveling habits, as well to determine partial dependence among the two. The best performing algorithm (RF) among the six introduced, contradicted the students' expectations considering walking. The model indicates that, among those who consider personal traveling habits as permanently affected by the pandemic, the change will cause less of the walk and increased reliance on automobiles.

Besides that, according to model analysis, the study concludes that *Distances between students UCR and FB* and *Weekly lectures attendance* are the factors with the highest influence on students' attitude towards traveling habits to become permanently changed. According to PDP, the study was able to deduce where to expect the change in the future traveling pattern – distances between 2 and 4 *km* far from the university, and among which students – those who are visiting university less frequently than others.

In this context, the study's findings can be used to advise local public utilities on how to react and support positive change in the study location society, i.e. to recommend where the number of bus lines and bus stops should be increased, and where the use of personal motor vehicles should be discouraged by increasing parking fees, reducing number of parking spaces, etc.

Directions of further research

Because the present study does not cover all factors influencing changes in inner-city travel behavior, further research will consider the influence of non-demographic factors. This primarily refers to citizen perceptions of air quality as a trigger for sustaining positive changes in society.

Study limitations

A limitation of this work is that it was based on students' self-report. Respondents were asked to provide the details of their demographics as well as to describe traveling habits. Relying on self-reported data may raise questions about the validity of the methodology. Nonetheless, in order for the data to be accurate, the online questioner was voluntary so just the students who were willing to respond applied to contribute to the research. That way, the respondents had no reason to mask their preferences.

Aside from that, the study looked into changes in student travel behavior, which could be argued to be a narrow age group. However, the study aimed to compare the data university staff collected before the pandemic to the data collected during the COVID-19 pandemic. That way, the study provided valuable details related to the change in travel habits of the most mobile community members – students, who are considered as an individual group in other similar types of research.

Abbreviations

ML Machine learning
PDP Partial Dependence Plot
RF Random Forest

FB Faculty building
UC University city
UCR University city residence

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