Who is more likely to support or oppose pedestrianization projects?

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SHORT SUMMARY

One of the approaches to reduce car dependency is implementing car-free projects. Although pedestrianization provides many benefits, there is sometimes public resistance against these projects. Based on a database of 95 variables collected through an online survey with over 1300 respondents, this study aims to detect the supporters and opponents of pedestrianization and investigate the roots of such opinions. A cluster analysis is implemented to detect the supporters and opponents. Then, an interpretable ensemble learning approach is applied to understand people's position on pedestrianization better. The key differences between supporters and opponents of pedestrianization are attitudes toward the cohabitation of pedestrians and two-wheeler users and the opinion on the impact of pedestrianization on individuals' mobility and travel patterns. Further, having experience in cycling, a higher frequency of cycling, and a better perception of safety on car-free streets increase the level of satisfaction with the cohabitation of cyclists and pedestrians.
Keywords: Active transit; clustering; ensemble learning; pedestrianization; public support.

1. INTRODUCTION

Although motorized personal vehicles have dominated urban mobility for decades, the current approach is to shift toward sustainable transportation modes to compensate for environmental damage and the problems related to health that such practice causes (Marcheschi et al., 2022). One practical approach to reducing car predominance is implementing shared street and car-free programs (Friedman, 2021). These car-free transformation programs (called "pedestrianization") convert streets to car-free zones by banning all motorized vehicles, and as a result, active transportation is promoted. Pedestrianization reduces car dependency, traffic, needs for parking, and noise pollution, improves the liveability of the city, safety, and accessibility for sustainable mode users, and increases social interactions, public transit use, and economic growth (Soni and Soni, 2016).

Although pedestrianization provides many benefits, there has often been a public response to these projects. The advocates of car use find pedestrianization a barrier to their mobility. Further, public transit users fear rerouting public transport and the possible negative impact of pedestrianization on their current travel patterns (Semple and Fountas, 2023). Hence, it is crucial to investigate the attitudes toward pedestrianization and detect the advocates and opponents of car-free programs. Accordingly, researchers have begun to examine the impact of various parameters on public support for car-free programs. For example, Boveldt et al. (2022) investigated the level of support for pedestrianization of Brussels' residents (Belgium). A survey was conducted, and the outcome showed that car drivers, residents of suburbs, and elderly groups were more likely to resist pedestrianization projects.

Melia and Shergold (2018) investigated the influence of various parameters on supporting car-free projects in Brighton, United Kingdom. The outcomes of a regression model revealed that males, non-full-time employees, and those who do not own a car are more interested in visiting car-free streets. Similarly, these groups are more likely to prefer pedestrianized streets as a location to shop, eat, and drink. On the other hand, those with access to cars and full-time employees think there is much traffic in areas close to car-free streets. Semple and Fountas (2023) analyzed the importance of socio-demographic variables on the perceived advantages of car-free streets. A survey was carried out, and a machine learning technique was employed for modeling. The results suggested that trip purpose was the most influential variable in the perceived personal benefits of pedestrianization. The following top variables were preferred transportation mode to visit the pedestrianized street, employment status, age, home region, yearly salary, and gender.

Beyond this short literature review, studies on variables associated with opposition or support for pedestrianization are scarce. Further, a few variables were generally applied to distinguishing supporters and opponents of car-free programs. This study implements a large-scale survey to better understand supporters and opponents of pedestrianization in Montreal, Canada. The first objective of this study is to determine the significant differences between people with different levels of support for pedestrianization using a clustering analysis. The other aim of this study is to investigate the roots of these differences using an interpretable machine learning approach.

2. METHODOLOGY

The methodology of the current study is briefly illustrated in Figure 1. The data preparation is first presented. Then, the methods applied for the modeling are briefly described.

Data and survey

A survey was conducted in Montreal, Canada, to collect data. The survey was distributed online during the fall of 2022. In Montreal, 12 streets were converted to car-free zones from early June to late September 2022. The survey participants visited those zones at least once. The respondents needed to respond to 93 questions. Those questions collected information about socio-demographics, the experience in visiting car-free zones, perceived influence of car-free streets on their mobility and travel pattern, trip satisfaction when visiting car-free zones, current travel pattern, frequency of transportation mode usage in a particular summer week, and opinion on the behavior of cyclists in car-free zones.

The postal code of respondents' home location was also collected in the survey. It allowed for enriching the database with the Walk Score and Bike Score of the home location of survey participants. The Walk Score and Bike Score measure the accessibility to services by walking and bike using a range of 0 (no accessibility) and 100 (maximum accessibility) (Walk Score, 2021). The final data set included 1376 observations (complete responses) and 95 variables (93 questions, Walk Score and Bike Score). The selected socio-demographics of respondents are shown in Table 1.

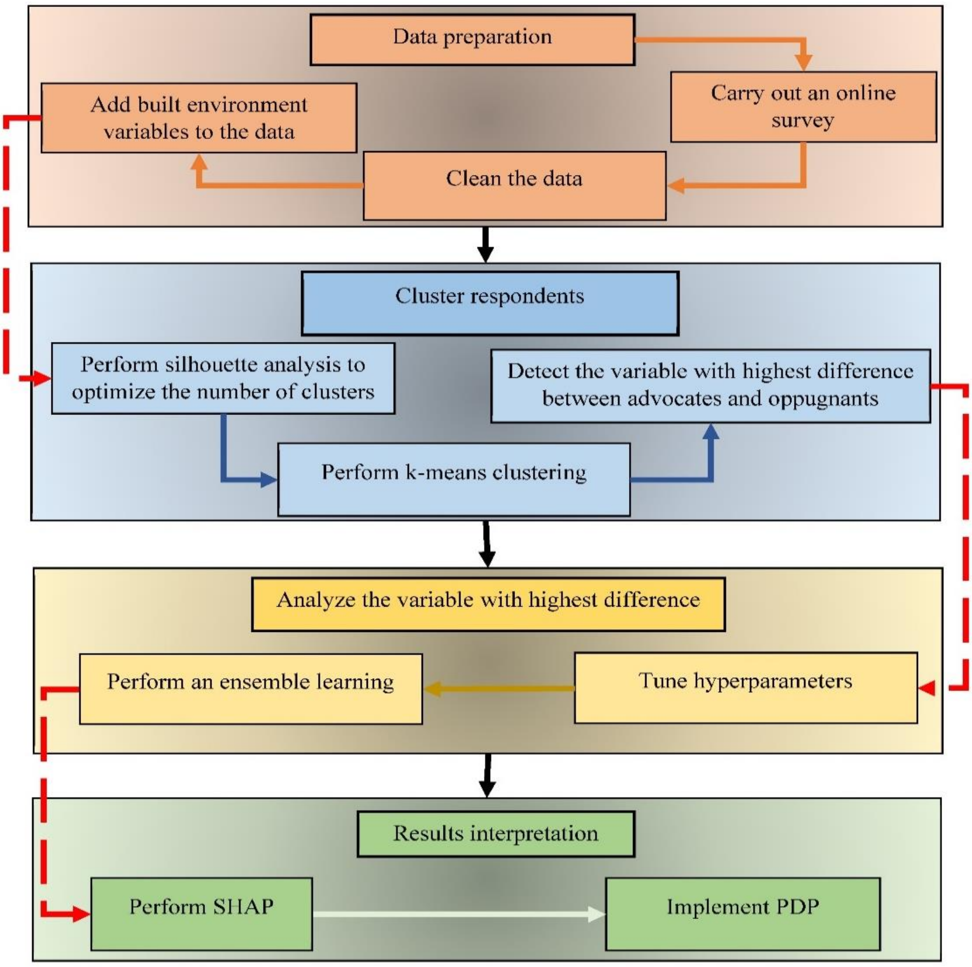


Figure 1: The flowchart of the methodology

Table 1: Socio-demographic of survey participants

Variable	Frequency (%)	Variable	Frequency (%)
Age		Limitation in walking	
<30	10.03	Yes	2.91
30-40	37.80	No	97.09
40-50	24.72	Number of cars in the household	
50-60	14.93	0	45.57
>60	12.52	1	48.33
Gender		2 and more	6.10
Female	64.03	Household income	
Male	34.67	<50 000$	18.60
I identify myself differently	0.65	50,001$-100,000$	35.25
Prefer not to answer	0.65	100,001$-150,000$	19.40
Driving license		150,001$-215,000$	11.63
Yes	83.14	>215,000$	6.54
No	16.86	Prefer not to answer	8.58

Problem formulation

First, all the variables are normalized using Equation (1):

$$N = \frac{V - A}{S}$$

Where N is the normalized value, V implies the initial value, A signifies the average value of the variable over the whole data samples, and S is the standard deviation of the variable.

Then, a silhouette analysis is performed to identify the optimal number of clusters. To this end, K-means clustering is performed for clusters between 2 and 8. The silhouette coefficients of these clustering models are compared, and the optimal number of clusters is determined (maximum silhouette coefficient). Subsequently, the difference between the average normalized value of variables for supporter and opposing groups is calculated, called the center distance. Afterward, the variables are sorted based on the distance. That is, variables are prioritized based on the difference between supporters and opponents of car-free programs.

Then, the top-rank variable (highest distance between supporters and opponents) is further analyzed using eXtreme Gradient Boosting (XGB). In this regard, the top-rank variable is considered the dependent variable in XGB, and other variables are considered independent variables. The correlated variables with the top-rank variable (the variables with a correlation coefficient of over 0.5) are excluded from the independent variables. To evaluate the performance of XGB, 20% of data is randomly considered testing data. Further, K-fold cross-validation and Grid search were applied to tune hyperparameters of XGB. XGB is an ensemble learning technique that can solve complex prediction problems with high prediction accuracy. This technique simultaneously implements many weak learners to construct a powerful classification method (Naseri et al., 2023). After running XGB, SHAP is applied to determine the relative influence of independent variables on the top-rank variable. SHAP is a game theory model that syncs with machine learning techniques and evaluates the relative influence of independent variables on dependent variables based on local explanations (Lundberg and Lee, 2017). Finally, PDP is employed to illustrate the influence direction of the variables with the highest relative influence on the top-rank variable. PDP depicts the non-linear relationship between independent variables and the dependent variable in machine learning models (Alnahit et al., 2022).

3. RESULTS AND DISCUSSION

Clustering analysis

The silhouette coefficient of the clustering model for different numbers of clusters is indicated in Figure 2. The optimal number of clusters is two for this dataset.

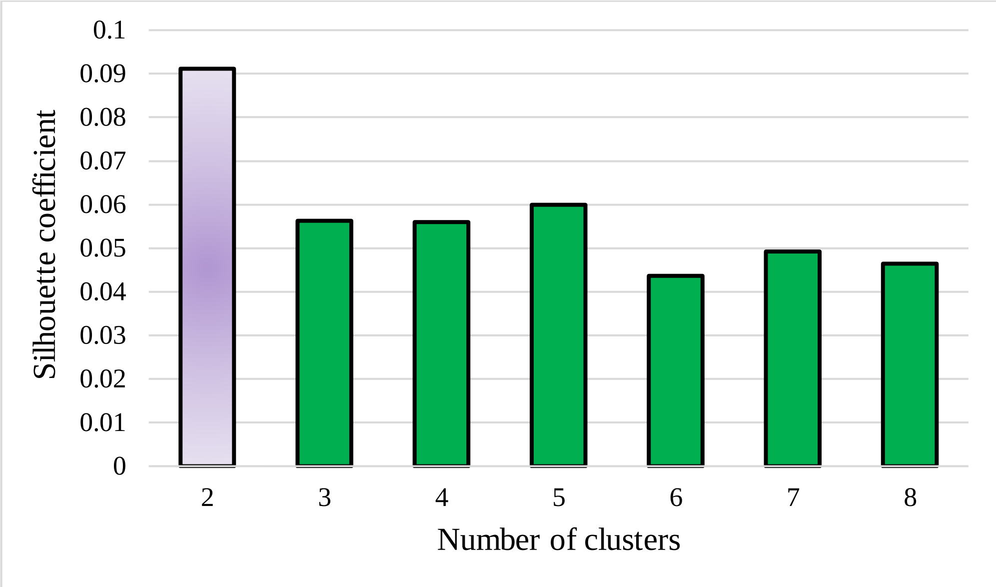


Figure 2: The silhouette coefficient for different number of clusters

Accordingly, the K-means clustering model is run considering K equals two. The model was also run considering K equals five (the second highest silhouette coefficient). Given the word count limitations for this manuscript, we decided to show only results for K=2 here. However, we suspect that K=5 can give fascinating additional insight while still being mathematically sound. Further analyses are ongoing, and if the paper will be accepted, they will be presented at the conference. Subsequently, the distance between the coordinates of cluster centers for all variables is calculated. Then, the variables are ranked based on the mentioned distances. Since the variables are normalized, a higher cluster centers' distance implies a higher difference in the clusters. The variables with the highest cluster centers' distance and the most frequent responses of each group (i.e., cluster) to these questions are presented in Table 2. As can be seen, the respondents can be classified into two groups: supporters (67%) and opponents (33%) of pedestrianization projects. The level of satisfaction with the cohabitation of pedestrians and cyclists is the variable with the highest center difference between these two groups. Further, all the top variables are related to the cohabitation of pedestrians and two-wheeler users (e.g., cyclists) and the influence of pedestrianization on individuals' mobility and travel patterns.

A more detailed look at the results reveals that supporters of car-free projects are quite satisfied with the cohabitation of two-wheeler users and pedestrians. Nevertheless, the opponents are not at all satisfied with this cohabitation. The supporters are more likely to agree slightly with the travel speed of cyclists and their respect for pedestrian priority, while the opposing group strongly disagrees with the current speed of cyclists on car-free streets and their respect for pedestrian priority. The other difference between supporters and opponents of car-free streets is relevant to the influence of pedestrianization projects on their mobility. In other words, the supporters of car-free streets strongly agree that pedestrianization of a location encourages them to go there more often, stay there longer, spend more time in the street shops, and change their route to get there. Nonetheless, pedestrianization cannot encourage the mobility pattern of opponents.

Table 2: The results of the clustering analysis

Top variables	Center distance	Most frequent response	
		Supporters	Opponents
Members		922 (67%)	454 (33%)
What is your satisfaction with the cohabitation of pedestrians and “traditional” cyclists?	1.31	Quite satisfied	Not at all satisfied
As a pedestrian, to what extent do you agree that the cyclists travel at the speed acceptable for the cohabitation with the pedestrians?	1.30	Slightly agree	Strongly disagree
Do the pedestrianization and developments carried out on a location encourage you to go there more often?	1.30	Strongly agree	Neither agree/nor disagree
Do the pedestrianization and developments carried out on a location encourage you to stay there for longer time?	1.29	Strongly agree	Neither agree/nor disagree
What is your satisfaction with the cohabitation of pedestrians and other two-wheels users (e.g., skateboard and scooter)?	1.27	Quite satisfied	Not at all satisfied
As a pedestrian, to what extent do you agree that the cyclists are respectful of pedestrian priority during their passage?	1.25	Slightly agree	Strongly disagree
Do the pedestrianization and developments carried out on a location encourage you to spend more in the street shops there?	1.25	Strongly agree	Neither agree/nor disagree
Do the pedestrianization and developments carried out on a location encourage you to change your route to get there?	1.21	Strongly agree	Agree

The socio-demographics and availability of different transportation modes for the clusters are compared in Figure 3. As shown, the supporters of pedestrianization projects are more likely to own a bike, a monthly transit pass, a monthly car-sharing subscription, and a monthly bike-sharing subscription than the opponents. Moreover, the car ownership of supporters is less than that of the opponents. Therefore, shared mode users and cyclists are more likely to support car-free projects, while car drivers are less likely to support these projects. Additionally, the supporter's cluster includes more females and younger respondents than the opponents. Finally, the opponents include more individuals with limitations in walking, cycling, and using buses.

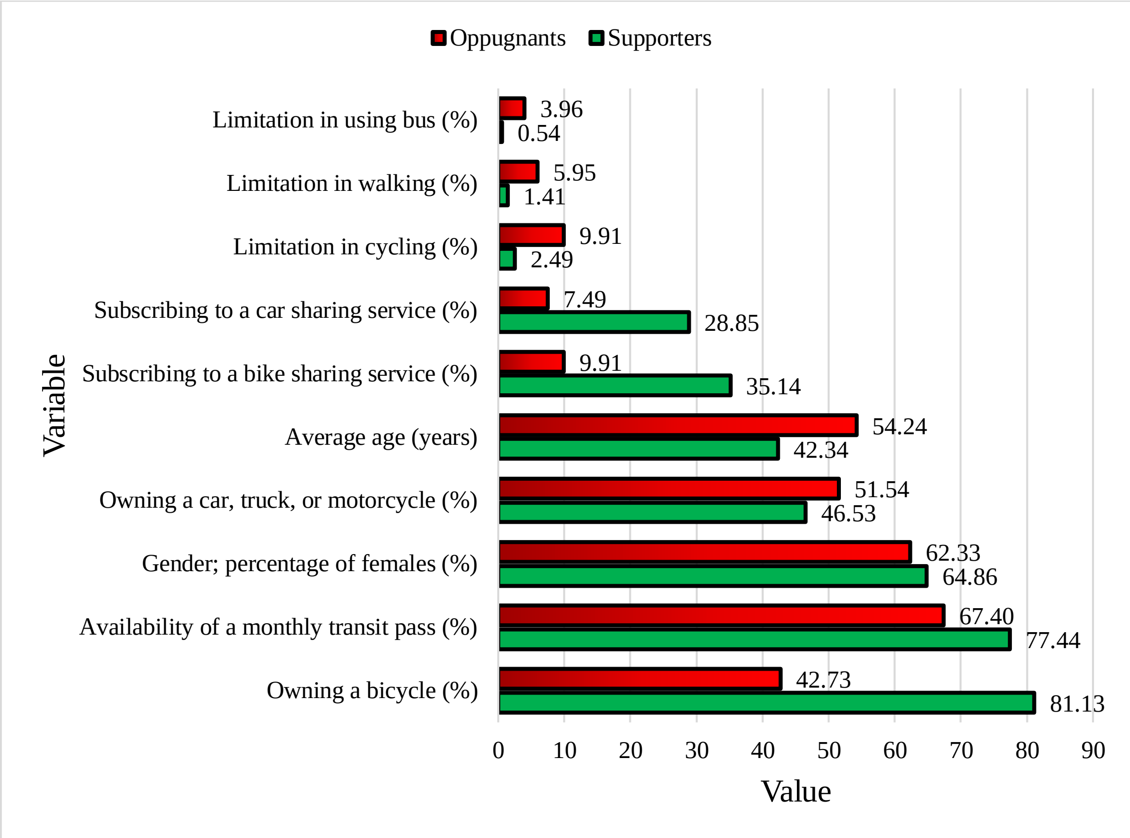
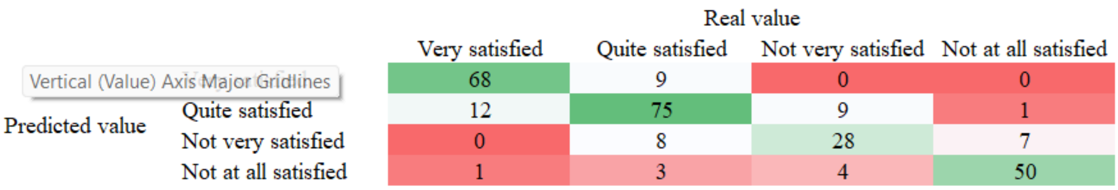


Figure 3: The socio-demographic-based comparison of supporters and opponents of car-free projects.

Analyzing the variable with the highest center difference (cohabitation)

This study also aims to better understand how the variable leads to a significant difference between supporters and opponents. As shown in Table 2, the level of satisfaction with the cohabitation of pedestrians and traditional cyclists is the variable with the highest center distance between the clusters (i.e., top-rank). Hence, this variable is considered the dependent variable, and other variables are considered independent variables in an ensemble learning model (i.e., XGB). The possible responses to the dependent variable are “Very satisfied”, “Quite satisfied”, “Not very satisfied”, and “Not at all satisfied”. XGB can predict the dependent variable with a testing data accuracy of 80% and a testing data F1-score of 79.3%. The confusion matrix of the developed model for testing data is shown in Figure 4. As it can be perceived, the model performs well to predict responses in different categories.



		Real value			
		Very satisfied	Quite satisfied	Not very satisfied	Not at all satisfied
Predicted value	Vertical (Value) Axis Major Gridlines	68	9	0	0
	Quite satisfied	12	75	9	1
	Not very satisfied	0	8	28	7
	Not at all satisfied	1	3	4	50

Figure 4: The testing data confusion matrix

Then, SHAP is applied to determine which variables have the highest relative influence on the level of satisfaction with the cohabitation of pedestrians and cyclists. The top 15 variables on this variable are illustrated in Figure 5. As shown, using a bike to visit car-free streets, the level of agreement that pedestrians share the car-free streets with cyclists, frequency of bicycle use, and the level of satisfaction with safety and personal safety are the most influential variables on the level of satisfaction with the cohabitation of pedestrians and cyclists.

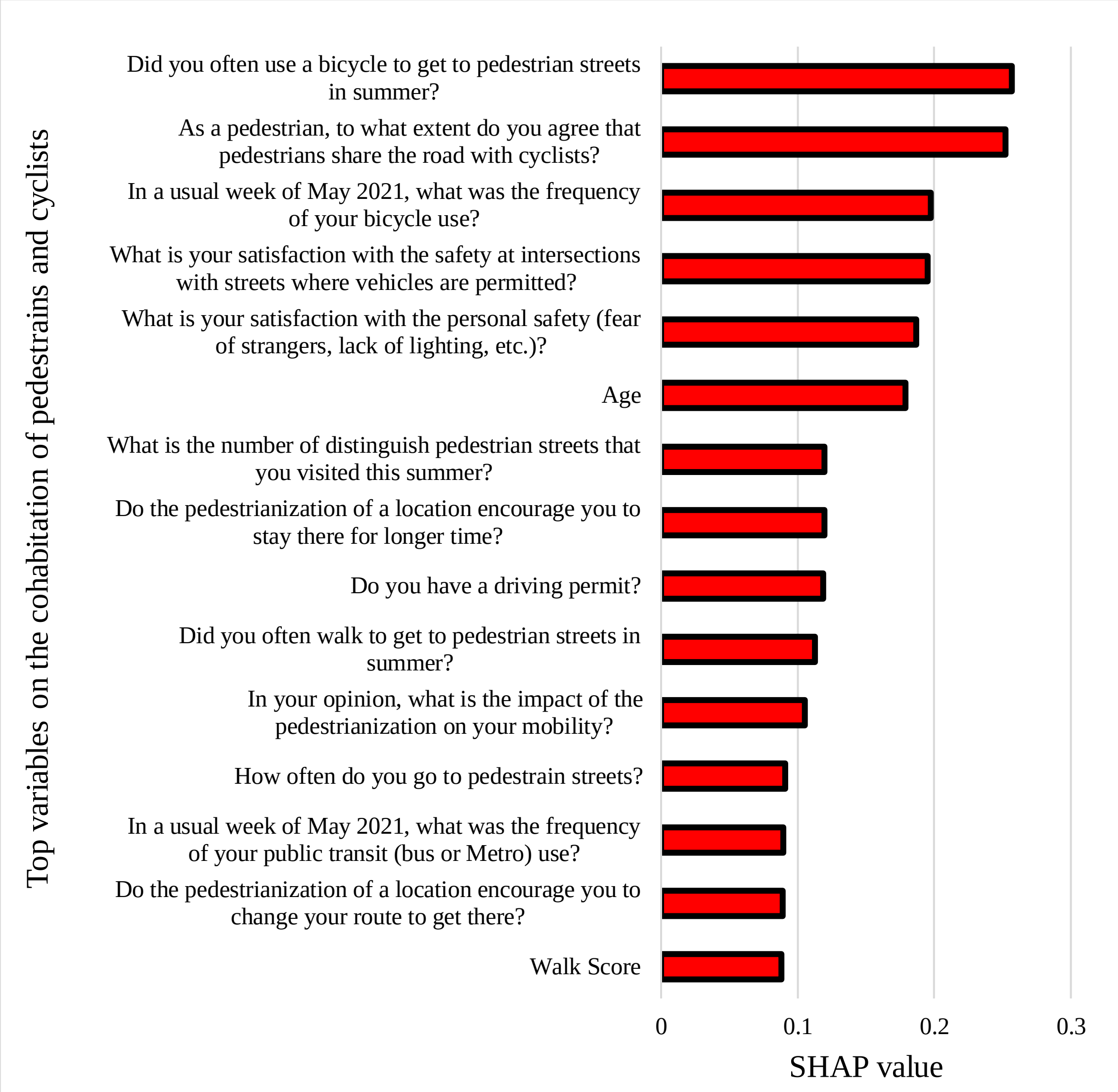


Figure 5: Top variables on the level of satisfaction with cohabitation of pedestrians and cyclists

Subsequently, PDP is applied to demonstrate the direction influence (e.g., linearly, positively, and quadratically) of the variable with the highest SHAP value on the level of satisfaction with the cohabitation of pedestrians and cyclists. The results of PDP are indicated in Figure 6. Those who did not use bicycles to get to the car-free streets are more likely to be not at all satisfied with the cohabitation. However, those who cycle on pedestrian streets are more likely to be very satisfied with the cohabitation. The individuals who strongly agree or agree that pedestrians share the road with cyclists are more probable to be very satisfied with the cohabitation. The people who cycle every day are most likely to be very satisfied with the cohabitation. Occasional cyclists (sometimes per week) are most likely to be quite satisfied with the cohabitation.

On the other hand, those who never cycle are expected to be not very satisfied or not at all satisfied with the cohabitation. There is a direct correlation between safety and personal safety on pedestrian streets and the level of satisfaction with the cohabitation. In other words, the level of satisfaction with safety is more likely to be the same as the level of satisfaction with the cohabitation of pedestrians and cyclists.

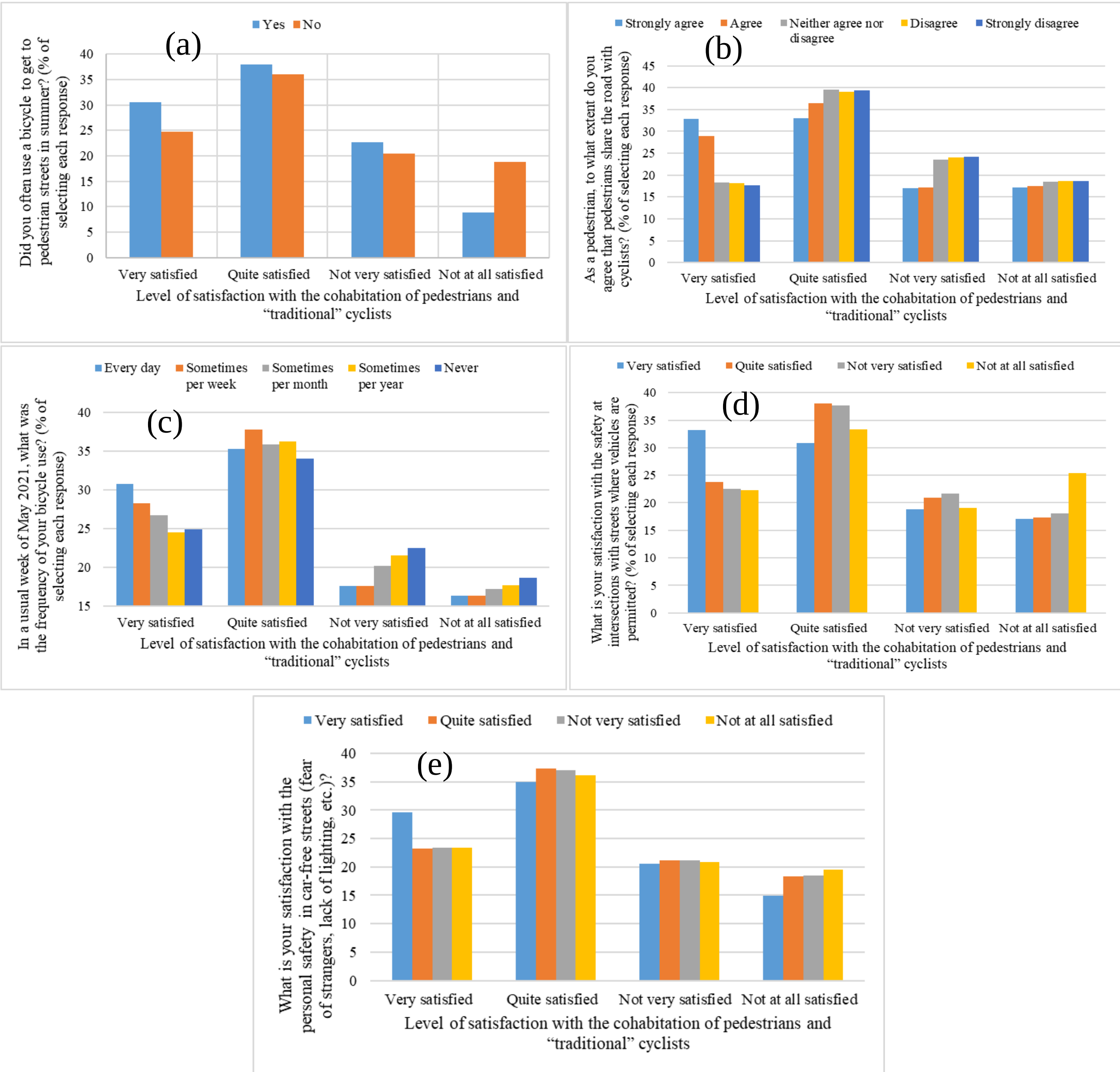


Figure 6: Influence direction of variables with the highest SHAP value on the level of satisfaction with the cohabitation

4. CONCLUSIONS

This study investigates the variables associated with opposition or support for pedestrianization projects. A survey is implemented to collect large-scale data containing many variables. A clustering analysis is first performed to determine the supporters and opponents of pedestrianization. The results suggest that the significant differences between supporters and opponents are related to the cohabitation of pedestrians and two-wheeler users and the influence of pedestrianization on individuals' mobility and travel patterns. Further, the supporters of car-free streets are younger and include a higher percentage of females and a lower percentage of people with limitations in walking, cycling, and using buses. This group uses more shared and public transit and is less likely to own a car than opponents.

The other aim of this study is to investigate the cohabitation between pedestrians and cyclists since that variable is the significant difference between supporters and opponents. An interpretable machine learning approach is applied. The outcomes reveal that experience in cycling can significantly increase the level of satisfaction with the cohabitation of pedestrians and cyclists. Similarly, increasing the frequency of cycling leads to a higher level of satisfaction with this cohabitation. The opinion on sharing the road significantly influences the level of satisfaction with the cohabitation. Interestingly, there is a direct and positive correlation between the perception of safety on pedestrian streets and their intersections and the level of satisfaction with cohabitation.

It should be stressed that our goal was to get insight into who are supporters and opponents of pedestrianizations and what motivates their stance, but we did not decide ex-ante that we would have two groups. This is rather a result of this work; we could have found that more than two groups, corresponding to different degrees of support/opposition and, in any case, to more nuanced opinions, was the best way to group the respondents. The fact that the maximum distance among groups is found with two means that opinions are quite polarized, which is clearly an element that policy-makers should pay attention to. By the time of an eventual presentation at hEART, a thorough discussion of the policy implications of this and the other findings of the paper will be presented.

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