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STARS

Shared mobility opporTunities And challenges foR European citieS

Research and Innovation action

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Overall assessment of the drivers for behavioural change

Deliverable D4.3

Version n° 1

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Table of content

List of Tables

List of Figures

Acronyms

CS	Car Sharing	**TAM**	Technology Acceptance Model
FFOA	Free floating with operational area	**PBC**	Perceived Behaviour Control
FFPS	Free floating with pool stations	**EU**	Ease of Use
P2P	Peer-to-peer	**PN**	Personal Norms
RTSB	Roundtrip station based	**TRA**	Theory of Reasoned Action
RTHB	Roundtrip homezone based	**SDGs**	Sustainable Developmental Goals
TPB	Theory of Planned Behaviour	**UN**	United Nations
PU	Perceived Usefulness	**MultiOC**	Multiple Operational Characteristics
SN	Subjective Norms	**SEM**	Structural equation model
EA	Environmental Awareness		

SUMMARY

The final task of work package 4 is to draw on the empirical evidence collected in the previous tasks of this current WP as well as the results of WPs 2 and 3. The aim is to give an overall picture of the underlying mechanisms behind observed behavioural changes towards an increased use of shared mobility services. The objective is furthermore to assess the relative importance of sociodemographic, individual and contextual factors as well as advance the analyses of how the characteristics of the different services and the business models (classified into car sharing operator profiles) interact with users profiles (of sociodemographic and attitudinal characteristics) and mobility styles (including user attitudes, travel modes and frequencies). Finally, the WP includes a workshop with the aim to discuss and validate the results with experts on car sharing both from the inside as well as the outside of academia. The workshop took place on the 24th of January in Bremen, Germany.

The report consists of four main sections; Introduction, Method, Results and Conclusions. Furthermore, the Method and Result sections have three subsections; one on the work carried out by UGOT i.e. the SEM analyses, another section describing the work by POLITO on car sharing user trends according to different user profiles, and a final subsection describing the work-shop hosted by the city of Bremen.

The main findings of this deliverable are:

- ★ Users of free floating car sharing (Italian sample) and free floating with pool stations (Sweden) were the users with the lowest percentage of car-free household.
- ★ In Italy, users of free floating services are more likely to subscribe to more than one service (1.5 on average) of the same typology of service.
- ★ The frequent users of private cars are, at the same time those that envisage greater use of car sharing in the future than today, while among those who own and use private cars less frequently (MultiOC users, who are registered to more than one car sharing variant in parallel, and FFPS), there is a lower propensity for an increase compared to the current level of car sharing use.
- ★ Even though all MultiOC users are registered to a free floating service in combination with another car sharing typology (FFPS in Italy, RTSB in Sweden and Germany), they are more frequently users of PT and active modes (walk and bike) and they have a higher degree of car-free households than the free floating users. Therefore, services integration and a higher degree of MultiOC users may be one important key to reduce the use of private cars and consequently its impacts.
- ★ The FFOA service is more likely to grow in terms of number of subscribers in Italy; while in Sweden, round trip station based service have the highest number of potential users. Clearly these predictions may be affected by the actual provision of such services in the cities if there is a lack today.

- The strongest direct predictors of behavioural intention (BI) to use (or increase using) car sharing services in a near future (6 months) were perceived behaviour control (PBC), currently being registered on a car sharing service, a lower degree of past car based travels and trust in the quality of the service delivered**.**
- The number of current car sharing operators in the city was not a predictor of behaviour intention, which indicates that by only increasing the number of operators within cities or fleet sizes, is not enough to induce behaviour change. It is instead more important to increase the perceived usefulness of car sharing services for people's travels necessities. Women could be a target niche in the market, since being a woman has a positive direct effect on BI to use car sharing in the future. In addition, increasing trust in the service availability and quality is also a possible strategy to foster use of car sharing.
- Past travels by car based modes leads to driving habit formation and when this habit becomes stronger, one is less likely to express a strong intention to use car sharing
- The expert work shop in Bremen contained presentations of the STARS project in general and results from WP 4 summarized above in particular. Experts from car sharing organisations, cities and other research projects attended. Overall the work shop proved that the knowledge is welcome and can be useful when developing the services, as well as implement those services in a city.

1 Introduction

The current work package 4 (WP4) has several aims and challenges. The general aim is to contribute to the overall objectives of the STARS project and investigate the factors and trends both societal as well as individual that would be influential, when cities in Europe face the introduction of car sharing as a mobility option among its citizens. The implications of the results can therefore point out a direction for how we should regard these factors in relation to different kind of actors (decision makers, car sharing operators, users and non-users of car sharing services, etc.) as well as in terms of the United Nations Sustainable Development Goals (SDGs)[1] which entails a range of economic, ecological and social aspects.

In the current task previous results from task 4.1 and 4.2 are highlighted and put in the wider context of WP2 and WP3. The analyses made in this task are building on previous findings and data collected within STARS up until now.

The structure of the report is as follows. The rest of the introduction is giving an overview of the knowledge assembled in WP4 so far. The starting point and base of this current task is described. This is followed by a method section and a results section each describing the three main research activities within the task that is; 1) Analysing the trends and profiles in relation to mobility styles. 2) Assessing the factors associated with behaviour change in a structural equation model (SEM). 3) The description and report of the expert work-shop. In the final section we provide the main conclusions.

1.1 Empirical findings and conclusions this far

One of the aims of this task is to provide an overview and conclusion of what has been found in the STARS project so far, that is in the previous work packages in STARS (WP2 and WP3), as well as in the previous tasks within WP4 (D4.1 & D4.2).

WP 2 and 3 relied on multiple sources and methods: first on previous research findings and available data bases, second on data gathered from a survey to car sharing services and finally on information available on the websites of the car sharing operators. WP 4 contains survey data from car sharing users and non-users, case studies, interviews and focus group discussions. Altogether there is a rich and extensive material that has been collected and analysed this far. We can conclude that car sharing operators in European cities show a lot of variability regarding operational characteristics. Related to that, car sharing users also show a variability of profiles in terms of sociodemographic backgrounds and motivational factors. The work this far has therefore put a lot of effort into describing and understanding how these factors relate to each other in a number of

[1] https://www.un.org/sustainabledevelopment/sustainable-development-goals/

profiles and styles. The current deliverable is building on the conclusions and data found up until now.

1.1.1 The role of sociodemographic- and underlying variables

The theoretical framework used to understand the relationships between sociodemographic variables and underlying variables, such as attitudes and behaviour intention, is based on two models from social psychology: the Theory of Planned Behaviour (TPB) (Ajzen, 1991; Ajzen, 2015) and the technology acceptance model (TAM)(Yousafzai, Foxall, & Pallister, 2007a, 2007b). This framework was presented in WP2 (D2.2) and used when developing the survey to users and non-users of car sharing presented in D4.1.

The linear model described in D4.1 investigated the degree of effect of each behavioural, psychological and sociodemographic variables for predicting car sharing use within a near future. A multiple regression model where the variables were added to the model in separated steps (in order to control for differences in the sociodemographic variables) found that the psychological variables were stronger predictors compared to the sociodemographic variables. The results showed that the main predictors of behaviour intention to use car sharing were:

- Perceived usefulness (PU), which is related to how practical car sharing is perceived in relation to travel needs (reaching destinations and activities).
- Perceived behaviour control (PBC), which is the degree of control an individual believes one has in order to carry out certain behaviours. A high perceived behaviour control is associated with having the relevant knowledge, resources and skills.
- Social norms (SN), the individuals´ normative beliefs regarding what is morally right and/or the expected behaviour according to others (family and friends) and/or the society.

The predictors with the strongest negative effect within this model were:

- Age. Older individuals have a weaker intention to use it.
- Income. Individuals with higher incomes share the same tendencies as those in the older groups, meaning weaker intention to use car sharing within a near future.

The conclusions thus far show that the intention to use car sharing depends to a large extent on two aspects: whether the service is perceived as useful (PU) and whether people feel in control to use it (PBC). PU is related to people's perception that the car sharing services meet their mobility needs while the PBC is related to people's general knowledge of how the service works, how to book and pay, and where to find vehicles. Social norm (SN) was the final psychological variable with influence on the planned behaviour (behaviour intention, BI). Individuals who have a social network which supports car sharing are more inclined to use it themselves. In addition, we can conclude that individuals belonging to the higher income groups as well as the groups with a higher mean age have a weaker intention to use car sharing in the future.

1.1.2 Car sharing operators' characteristics, user profiles and mobility styles

In WP2, car sharing operators were studied with regard to a number of operational characteristics business models, fleet size etc. This work which was a result of both desktop research as well as responses to an online survey directed to 20 selected cities and a subsequent statistical analyses resulted in six profiles (or typologies) of car sharing operators (see D2.1).

- Profile 1 – Free floating car sharing systems
- Profile 2 – Free floating car sharing systems with pool stations
- Profile 3 – Peer-to-peer car sharing systems
- Profile 4 – Privately owned roundtrip station based car sharing systems
- Profile 5 – Publicly owned car sharing systems
- Profile 6 - Association-based car sharing systems

About 40% of the operators included in D2.1 (page 83) did not fall into any of the above profiles. However, in the user/non-user survey 90% of the operators of the current users belonged to profile 1-6 above, with the majority belonging to profile 1, 2 and 4.

The attempt of a validation of the profiles by a number of experts (see D2.1 page 93) failed to fully comply with the profiles found, even though the same expert concluded that the profiles do have certain advantages in terms of taking a range of factors into account as well as statistical robustness. A similar but perhaps more comprehensive and straightforward classification of car sharing variants was therefore identified and suggested to be used (for a full description see D4.1 page 21). These variants will be used in the analyses in the current deliverable.

- Free-floating with operational area: The vehicles stand within a defined operational area distributed freely. Within the business area clients can undertake one-way journeys.
- Free-floating with pool stations: The variant functions exactly like the free-floating car sharing with operational area. But the vehicles do not stand freely distributed in the street, but are parked by clients at special pool stations.
- Roundtrip station-based: The vehicles stand in reserved parking spaces. There clients pick them up and return them after the drive.
- Roundtrip homezone-based: This variant operates exactly like the roundtrip station-based car sharing, however the vehicles are not made available in select parking places. Instead, the vehicles stand anywhere within a narrow geographical area – usually a neighbourhood or a parking space management zone.
- Combined car sharing: With this option a car sharing enterprise offers clients roundtrip and free-floating vehicles from a single source.
- Peer-to-peer: The vehicles are offered by private vehicle owners via an online platform made available by the service provider. The location of the vehicles is most commonly regulated according to the home zone model.

The next step for the STARS project has been to explore car sharing user profiles regarding socioeconomic circumstances and attitudinal aspects and relate these to memberships of operators and the operational characteristics (variants/typologies) above. First, previous research was investigated by POLITO and presented in D4.1. Secondly the user, non-user survey in D.4.1 provided descriptives of the profiles. It was also concluded that some users had multiple memberships and/or had access to a car sharing service via their work place/company (see Table 8, page 61 in D4.1.). These users, as well as some users who fell into an "other" category comprised about 10 % of the users in the survey (they were referred to as profile 7, 8 & 9).

In the same deliverable (D4.1), the variables described earlier, that is the same behavioural, psychological and sociodemographic aspects investigated with the full sample of the user/non-user survey were addressed in a case study in Germany. An investigation of the profiles of users of these different kinds of car sharing services (station bases, free-floating, combined and peer-to-peer) revealed some particularities for each of them. **Above all, the users of free-floating car sharing have a profile that differs from the others: they have the least percentage of households with children, they are in general well paid employees or students, they have the lowest percentage of car-free households, they make shorter, frequent and non-planned trips within the inner city compared to the other profiles. Regarding their attitudes, they see car sharing as complement for the private car instead of a substitute and they are not satisfied with the availability of vehicles provided by their car sharing operator.**

Once the main psychological, behavioural and sociodemographic factors to predict intention to use car sharing were identified, the focus of the deliverable 4.2 was to establish a number of mobility styles from the sample mainly based on the Italian and Swedish datasets. In order to do so, a cluster analysis was performed to differentiate and group the users and non-users of car sharing regarding their attitudes, personal norms, environmental awareness, political views and travel patterns. The five mobility styles identified were:

- Mobility style 1 – Multi-mode Ambivalent (Multi-m Amb)
- Mobility style 2 – Car-focused Green (Car-f Green)
- Mobility style 3 – Active P-T transit Green (A P-t Green)
- Mobility style 4 - Car-focused Ambivalent (Car-f Amb)
- Mobility style 5 - Car-flexible Green (Car-flex Green)

Mobility styles 1-3 were found among current car sharing users, and 4 and 5 among non-users (see D4.2 for detailed descriptions and results). These mobility styles (clusters) will be further investigated in chapter 3 of the current report, especially regarding the last two related to non- users. Such mobility styles will be named for simplicity "cluster 4" and "cluster 5" in the following.

2 Method

2.1 Sample description

The participants were residents of European cities, current users (n = 1519) and non-users (n = 5303) of car sharing services, corresponding to a total of 6822 respondents. For more details of the sample, see deliverable 4.1., and the results section of this report.

2.2 Procedures

2.2.1 Dataset and cluster profiling

The data used in this study come from the online survey administered to car sharing users and non-users, which were carried out by the STARS consortium in many countries around Europe. For more detailed information on data collection process the reader is kindly referred to the D4.1 STARS report.

The resulting dataset was first elaborated by adding the car sharing operational scheme to which each user is registered (as defined in D2.1 STARS report) as well as the mobility style cluster to which it belongs (as defined in D4.2 STARS report). It was then possible to group car sharing users by operational scheme they belonged to, similarly to what was done for the German sample in the D4.1 STARS report.

The six different car sharing variants listed in section 1.1.2 above, which varies regarding their operational characteristics, were considered in the user survey that was administered (see D 4.1 for details, where they are called "variants" or "typologies"). The variances of the operational characteristics of the services are in fact rather intuitive to understand, and therefore they have been used in the survey. On the other hand, the operational characteristic is one of the elements that denote the seven car sharing profiles that were introduced in section 1.1.2. These latter are the result of a more complex classification exercise done at the beginning of the project, which encompasses several different characteristics beyond the operational scheme (e.g. pricing policies, rental conditions etc.). Therefore, considering the STARS car sharing profiles beyond the mere differences in operational characteristics can lead to a richer interpretation of the results when putting them in relation with the differences of individuals using different services. The correspondence between car sharing variants and profiles is as follows:

- Free floating with operational area (FFOA), which is the operational characteristic that is associated to Profile 1 of D2.1 STARS report;
- Free floating with pool stations (FFPS), which is the operational characteristic that is associated to Profile 2 of D2.1 STARS report;

- Peer-to-peer (P2P), which is the operational characteristic that is associated to Profile 3 of D2.1 STARS report;
- Roundtrip station based (RTSB), which is the operational characteristic that is associated to Profile 4 and 5 of D2.1 STARS report;
- Roundtrip homezone based (RTHB), which is the operational characteristic that is associated to Profile 6 of D2.1 STARS report;
- Combined or Multiple operational characteristics (MultiOC), which are the operational characteristics associated to Profile 7 added in D2.1 STARS report.

It can be seen that different schemes fall in different profiles, with the exception of RTSB that is shared between profiles 4 and 5.

The following step involved the derivation of average user profiles for different car sharing operational schemes on the basis of the socioeconomic and travel-related characteristics which are listed in the table below.

Car sharing user profiles
Household information
Household size
Children
Car ownership
Individual information
Gender
Age
Education
Employment
Income
Travel behaviour
Public transport season ticket and car sharing subscriptions ownership
Public transport, car opinion and use frequency
Travel attitudes towards car sharing
Influence on other modes
Car sharing trip purposes

Table 1: Variables considered in the definition of car sharing user profile

Differences between mean values of different groups have been analysed with the Kruskal-Wallis test to check for statistical significance. Kruskal-Wallis is a nonparametric (distribution free) test, and is used when the assumptions of the ANOVA are not met. The test determines if differences between groups are simply due to the case or the groups belong to different population. If a significant statistical difference is individuated, a Kruskal-Dunn post-hoc test was performed in order to understand among which groups the statistical difference exists. The results of all Kruskal tests are reported in Appendix 1.

The above procedure was developed in R, which is an open source software environment for statistical computing and graphics.

A second stream of analyses involved profiling the two clusters of non-users as they are defined into the D4.2 STARS report (there labelled as “cluster 4” and “cluster 5”), i.e. finding the mean values of the features listed in the above table in these two clusters. By comparing the profiles of these two clusters with the above profiles pertaining to users of different car sharing services, one can get a preliminary indication of which car sharing operational schemes can have a stronger appeal for non-users. This qualitative approach has been further refined with a machine learning technique that is described in the following subsection, namely decision trees.

2.2.2 Identification of cluster trends: decision trees classifiers

In order to identify different trends for the different clusters of services, a decision tree model has been used.

The main idea is to try to predict which typology of car sharing is more likely to be adopted by non-users using the prediction algorithm of a decision tree model trained on the characteristics of users in a dual approach: on one hand considering the socioeconomic characteristics of the non-user and on the other hand considering their attitudes, personal norms, environmental awareness, political views and travel patterns. The output results of both models should converge to the same prediction.

The use of a dual approach is supported by previous STARS results, where the socioeconomic variables did not turn out to be as good as the behavioural ones in the car sharing adoption prediction (STARS, Deliverable 4.1: The influence of socioeconomic factors in the diffusion of car sharing, 2018).

Since only the Italian and Swedish subset mobility style clusters are available, this information has been used as input to the decision tree model (excluding the German dataset because it was not included in the D4.2 clusters).

Concerning the methodology, classification is the task of the learning target function ***f*** that maps each attribute set ***x*** to one of the predefined class labels ***y***. The target function is also known as a classification model. Contrarily to regression models (with the exception of logistic regression) where ***y*** is a continue attribute, in classification the class label must be a discrete attribute.

A classification model is useful for both descriptive modelling (it is used as explanatory tool to distinguish between objects of different classes) and predictive modelling (it is used to predict class label of unknown records) (Tan, Steinbach, & Kumar, 2005).

Thus, a classification model seems to be a good solution for the pursued objective: the class label is represented by the typology of car sharing previously defined; this information is already known for car sharing users and it might be known for non-users as a result of predictive modelling application.

The decision tree is one of the most widely used classifiers among other classification techniques. It employs a learning algorithm to identify a model that best fits the relationship between the attribute set and class label of the input data. The model generated by a learning algorithm should both fit the input data well and correctly predict the class labels of records it has never seen before (Tan, Steinbach, & Kumar, 2005).

The above procedure was developed in KNIME, which is an open source platform useful for data analysis (Berthold, et al., 2009). It is based on a modular data pipelining approach that allows the connection of different components representing machine learning and data mining techniques.

The main workflow here adopted is showed in the below Figure 1.

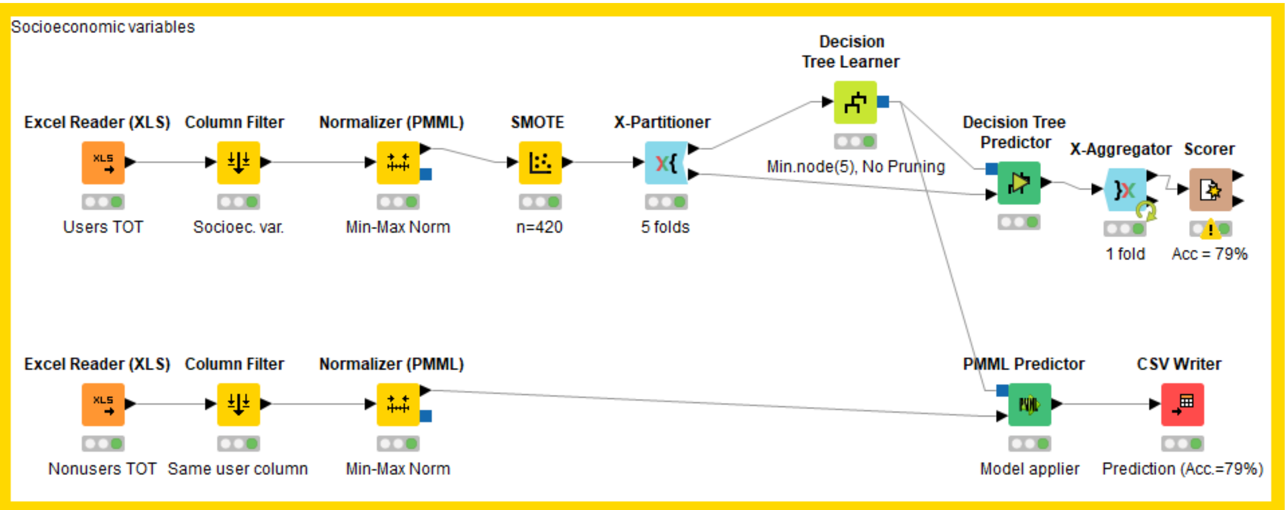


Figure 1: Decision tree workflow

It is worth stressing that this workflow was run many times in order to make the different cluster predictions based on socioeconomic variables, behavioural variables, Italian sample, Swedish sample and aggregated sample. Variants in the experimental design include the input dataset, the cross-validation folds and the set-up of the decision tree learner.

Observing Figure 1 from the left to the right, it is possible to see all the stages of the applied method, which are commented in details in Appendix 2: Decision tree workflow.

2.2.3 SEM method description

Structural Equation Modelling (SEM) is a confirmatory analysis. One works with this statistic method to evaluate the degree of fit that a theoretical model has to the observed model. One may estimate causal paths among latent variables and estimate the degree of influence that they have on each other. If compared to the linear regression model described in the deliverable 4.1, SEM is a more powerful analysis. With a linear regression model, one may estimate the degree in which a variable is influencing the outcome. The coefficients are the slopes of the regression lines and when standardized, they are more easily interpreted, indicating the effect size of the variable on the given model. With SEM, one may identify the regression paths, and also the chain of causality among the variables.

The objective with the SEM analysis is to test the following theoretical model in which the arrows indicate the direction of effects among variables (latent and observed variables) on the predicted variable (in some context referred to as the dependent variable) Behaviour Intention to use car sharing (BI) (Figure 2). The paths represent linear regressions among the variables connected and the paths with coefficients are those that were modelled to have indirect effect from the observed variables age, gender, income and use of car sharing. The model is determined by latent variables (represented by circles) and observed variables (represented by squares). The confirmatory and the SEM analysis were conducted with package lavaan in the software R (Rosseel, 2012).

- Latent variables:

  BI = Behaviour Intention to use car sharing

  Habits = Subjective habit for car driving and past frequency of car use

  EA = Environmental Awareness

  PN = Personal Norms

  SN = Social Norms

  PBC = Perceived Behaviour Control

  Attitudes = Attitudes towards car sharing

  Trust = Trust on the car sharing service

  EU = Ease of use

  PU = Perceived Usefulness

★ Observed variables:

Age

Income

Gender (0= male, 1= female)

User group (0= non-user, 1= user of car sharing)

Number of car sharing services in the city (0 to 5)

Car based = mean frequency of past travels by car and car sharing

Active = mean frequency of past travels by bicycle and walking

Public transport = mean frequency of past travels by tram, bus and train

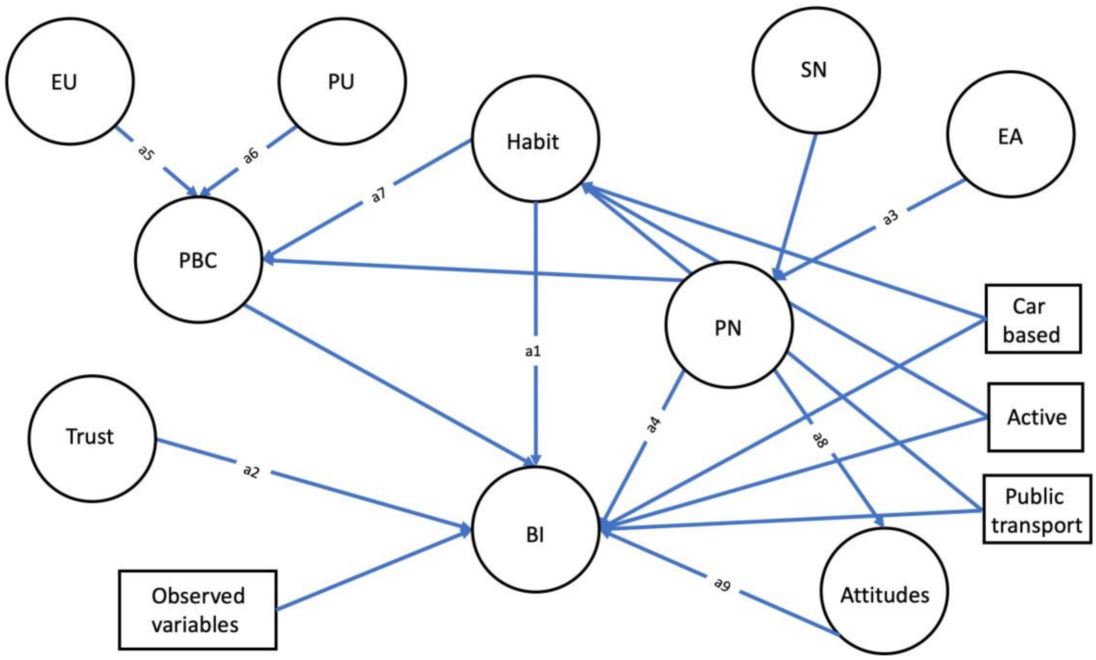


Figure 2: Conceptual Model.

2.2.4 Workshop description

An expert workshop to validate the results of WP 4 was organised on the 24th January 2019. The one-day workshop was hosted by the city of Bremen in Germany. Target groups of the workshop were scientists in the field of mobility, city authority representatives and representatives from car sharing operators. The invitation to the workshop was sent out via the consortium members' mailing lists and via social media channels. The invitation was also presented on the websites of bcs and Autodelen. Several consortium members also sent out personal invitations to members of its' network and to relevant third party mailing-lists in Germany.

A total of 29 participants attended the workshop – 10 from the science-community, 8 from the public authority side, 7 from the operator side and 4 from NGOs that work on related topics (Car policy, Bike policy). Participants came from the following countries: Germany, Great Britain, and Sweden.

The workshop consisted of three presentations:

1. bcs: Mobility behaviour and attitudes in different car sharing variants
2. UGOT: Underlying factors of the behaviour change towards car sharing
3. POLITO: How car sharing variants have different impacts on different traveller groups

After the presentations, experts were asked to give their feedback along the following questions:

1. Do you see similarities or contradictions with other existing research or your experience in the field?
2. What is new/interesting about the presented results?
3. Do you have recommendations for further analysis or further research in the STARS project?
4. What should cities do to promote car sharing according to their policy goals?
5. How can operators enhance the demand for car sharing by optimizing their service/their marketing communication?

See section 3.3 for a description of the results and conclusions made from this discussion.

3 Results

3.1 Car sharing trends according to different user profiles

3.1.1 Identification of the user profiles

Concerning the analysis of car sharing user groups, users registered to a single typology of service (roundtrip station based or free floating with operational area etc.) and users registered to more services with different operational characteristics, then named Multi-Operational Characteristic users (MultiOC) were distinguished. On the contrary, users registered to more than one service with the same operational characteristic fall in the same group of those who have just one subscription to that typology of service.

A breakdown of the number of subscribers in each of the six car sharing operational schemes, already introduced in subsection 2.2.1, is reported in Table 2. Each group of subscribers of a particular form of car sharing, and nationality is making up a distinct user profile, and will be analysed separately.

Car sharing operational schemes	CS users in Italy (n=653)	CS users in Sweden (n=565)
Only free-floating with operational area (FFOA)	386 (59.1%)	34 (6.0%)
Only free-floating with pool stations (FFPS)	93 (14.2%)	13 (2.3%)
Only peer-to-peer (P2P)	Not available	Not available
Only roundtrip station based (RTSB)	19 (2.9%)	398 (70.4%)
Only roundtrip homezone based (RTHB)	Not available	10 (1.8%)
Multiple operational characteristics (MultiOC)	96 (14.9%)	25 (4.4%)
Not identified	59 (8.9%)	85 (15.0%)

Table 2: Number of subscribers by car sharing typologies in Italy and Sweden

As seen in the table a total of nine user profiles have been studied. Four found in Italy and five found in Sweden.

As already detected in D4.1 STARS report, most of surveyed users are registered to a free floating car sharing service in Italy, while round trip station based subscribers are most commonplace in the Swedish dataset[2].

[2] Due to an error in coding the information in the database from the desktop research (D2.1), the Swedish Sunfleet car sharing service was misclassified as free floating with pool stations instead of roundtrip station-based scheme. Therefore, the results presented on page 61-62 of STARS D4.1 showed an overestimation of FFPS customers for the Swedish sample.

The last row of Table 2 reports the number of individuals that declared the subscription to a service that could not be classified into any of the previous six operational schemes in both the Italian and the Swedish sample. Three different kinds of services fall in this category:

1. Services indicated by people that consider themselves car sharing users but then indicated carpooling, ride-hailing services or car rental services instead of a proper car sharing service (e.g. Uber, Blablacar);
2. Services that were not inventoried in the previous desktop research (STARS, Deliverable 2.1 - Car sharing in Europe: a multidimensional classification and inventory, 2018);
3. Car sharing services that opened after January 2018 (end of the data collection activity of D2.1).

These cases, together with the related additional car sharing profiles (namely profile 8 and profile 9 defined in paragraph 2.3.3 of the STARS D 4.1 report) have been excluded from further analysis.

Once identified the car sharing operational schemes in use both in Italy and Sweden, the above introduced user profiles can be quantitatively described by computing the average values of some key socioeconomic and travel-related characteristics of the individuals falling in each profile. The resulting car sharing user profiles for each car sharing operational scheme in those two countries are showed in Figure 3 below, along with the German user profiles which are derived from D4.1 STARS report and not computed here. For simplicity, user profiles are named with the acronyms identifying the corresponding car sharing operational scheme that are introduced in the first column of Table 2.

It can be noted that an additional "Combined service" user group is shown for Germany, next to the MultiOC group that is in common with the other countries. The latter group is in line with the definition done for Italian and Swedish samples however, since many combinations of services were individuated in Germany in D4.1 STARS report, only the biggest group, which represent users registered to FFOA and RTSB services, is here reported. On the other hand, users of combined services are customers of one car sharing operator offering different schemes (e.g. FFOA + RTSB). At the time in which this research was completed, this scheme was available in cities in Germany, Belgium and France. Only one combined system in Frankfurt took part in the survey. In the top right side of the plot, the box "CS user profile" is reported, showing a definition of all the considered variables. Since the German survey slightly differs from the Swedish-Italian version, some variables might not be available in all countries.

CS service profile
Operational characteristic
Fleet dimension
Business model
Organisational form
Deposit
Subscription fee
Contract
Mode of reservation
Max. reservation in advance
Max. duration of booking
Pricing
Fuel
Opening technology

CS Profile 1: Free floating with operational area

CS Profile 2: Free floating with pool stations

CS Profile 3: Peer to peer

CS Profile 4: Privately owned RTSB

CS Profile 5: Publicly owned RTSB

CS Profile 6: Association-based CS

CS Profile 7: Combined service/ Multiple OC

CS users profiles		
Household info	Household size	1
	Children	2
	Car ownership at HH level	3
Individual info	Gender	4
	Age	5
	Education	6
	Employment	7
	Income	8
Travel behaviour	PT season ticket (for Germany), CS subscriptions ownership (for Italy and Sweden)	9
	Transport modes which are daily used by at least 15% of the sample	10
	PT, car opinion (for Germany only), Travel attitudes towards car sharing (for Italy and Sweden)	11
	Influence on other modes (for Germany)	12
	Car sharing trip purposes	13

User profile: FFOA [◊]

	Germany (n = 190/1122 = 16.9%)	Italy (n = 386/594 = 65%)	Sweden (n = 34/480 = 7.1%)
1	2 persons	2.7 persons	2.5 persons
2	No children (86.3%), with children (13.7%)	No children (51.5%), 1 child (29.3%) [*, †]	No children (45.8%), 1 child (41.7%)
3	No car (31.6%)	No car (6.2%),1 car (58%), 2 cars (29.8%) [+, †, ‡]	No car (52.9%), 1 car (32.4%), 2 cars (14.7%)
4	Man (54.5%)	Man (57.4%) [†]	Man (70.6%) [+]
5	39 years old	40 years old [*]	35 years old
6	Degree (71%), Diploma (23%)	Degree (61.9%), Diploma (37.2%)	Degree (85.2%), Diploma (14.6%)
7	Employed (69%), Self-employed (16.1%), Student (12.3%), NW and NS (0.6%)	-	-
8	3,584 €	2,350 €	3,875 € [‡]
9	PT season ticket (47.4%)	1.5 CS subscriptions (65% to 1 operator) [*, †, ‡]	1 CS subscription (100%) [†]
10	Daily use of PT (26.3%), car (18.5%) and bike (17.4%)	Daily use of car (25.1%) [*, †] and walk (37.6%)	Daily use of PT (26.5%) and walk (61.8%)
11	Like PT (2.9/5), car rather than PT (3.4/5)	I will continue to travelling like today (81.1%) [†], I will continue to use CS (87.9%), I plan to use the car sharing more than today (80.1%) [*, †]	I will continue to travelling like today (85.3%), I will continue to use CS (76.4%), I plan to use the car sharing more than today (26.4%)
12	PT -22.8%, bike +0% , car -19.7%	-	-
13	Dinner at restaurant (19.5%), Bulk shopping (14.8%), Shopping in city centre (13.8%)	Running an errand in the city centre (16.6%), going out for dinner (16.6%), weekend activities (8%)	Excursion in nice weather (9.1%), visit relatives/friends (8.8%), weekend activities (6%)

User profile: FFPS [*]

	Italy (n = 93/594 = 15.7%)	Sweden (n = 13/480 = 2.7%)
1	2.9 persons	2.3 persons
2	No children (72%), 1 child (26.9%) [◊, ‡]	No children (72.7%), 1 child (18.2%)
3	No car (17.2%), One car (37.6%), 2 cars (33.3%) [+, †, ‡]	No car (38.5%), 1 car (38.5%), 2 cars (15.4%)
4	Man (55.1%) [†]	Man (76.9%) [+]
5	35 years old [◊, †, ‡]	45 years old
6	Degree (71%), Diploma (29.1%)	Degree (92.3%), Diploma (7.7%)
7	-	-
8	1,650 €	2,675 €
9	1 CS subscription (100%) [◊, †]	1 CS subscription (100%) [†]
10	Daily use of PT (28%) and walk (53.8%) [◊, ‡]	Daily use of PT (25%), walk (53.8%) and bike (23.1%)
11	I will continue to travelling like today (81.4%), I will continue to use CS (83.4%), I plan to use the car sharing more than today (34.4%) [◊, ‡]	I will continue to travelling like today (92.3%), I will continue to use CS (84.6%), I plan to use the car sharing more than today (30.8%)
12	-	-
13	Running an errand in the city centre (23.9%), going out for dinner (26.1%), weekend activities (12.1%)	Visit a shopping center (7.7%), weekend activities (7.7%)

User profile: P2P

	Germany, national level (n = 131/1122 = 11.7%)
1	2.3 persons
2	No children (71%), with children (29%)
3	No car (63.1%)
4	Man (53.2%)
5	45 years old
6	Degree (43%), diploma (25%)
7	Employed (60.4%), Self-employed (21.6%), Student (6.3%), NW and NS (9%)
8	2,559 €
9	PT season ticket (46.9%)
10	Daily use of bike (31.5%), PT (27.7%) and car (18.5%)
11	Like PT (2.9/5), car rather than PT (3.3/5)
12	PT (-8.7%), bike (-1.8%), car (-15.6%)
13	Visiting relatives/friends (20.9%), bulk shopping (17.8%), recreational (14%), excusion in nice weather (12.4%)

Combined / **User profile: MultiOC [†]**

	Combined: Germany (n = 157/1122 = 14%)	MultiOC: Germany (n= 311/1122 = 27.7%)	MultiOC: Italy (n = 96/594 = 16.2%)	MultiOC: Sweden (n = 25/480 = 5.2%)
1	2.1 persons	2.2 persons	2.4 persons	1.9 persons [+]
2	No children (70.7%), with children (29.3%)	No children (71.3%), with children (28.7%)	No children (74.2%), 1 child (20.6%) [◊, ‡]	No children (82.4%), 1 child (11.8%)
3	No car (78.3%)	No car (75%)	No car (20.8%), One car (38.5%), 2 cars (28.1%) [◊, *]	No car (83.3%), 1 car (16.7%)
4	Man (42.8%)	Man (67.9%)	Man (73.6%) [◊, *]	Man (80%) [+]
5	49 years old	44 years old	39 years old [*]	45 years old
6	Degree (76%), Diploma (14%)	Degree (77%)	Degree (79.4%), Diploma (20.6%)	Degree (84%), Diploma (16%)
7	Employed (72.1%), Self-employed (11.6%), Student (4.1%), NW and NS (12.2%)	Employed (73.3%), Self-employed (18.4%), Student (3%), NW and NS (5%)	-	-
8	3,460 €	3,802 €	2,000 €	3,875 €
9	PT season ticket (55.4%)	PT season ticket (62.5%)	2.8 CS subscriptions (62% has a subscription with 3 operators) [◊, *, ‡]	2.2 CS subscriptions (84% to 2 operators) [◊, *, +, ‡]
10	Daily use of bike (47.1%) and PT (25.5%)	-	Daily use of PT (25%) and walk (50.5%) [◊, ‡]	Daily use of walk (76%), PT (48%) and bike (20%)
11	Like PT (3.6/5), car rather than PT (2.2/5)	Like PT (3.6/5), car rather than PT (2.4/5)	I will continue to travelling like today (83.4%) [◊], I will continue to use CS (88.3%), I plan to use the car sharing more than today (39.7%) [◊, ‡]	I will continue to travelling like today (92%), I will continue to use CS (96%), I plan to use the car sharing more than today (32%)
12	PT (+7.1%), bike (+9.8%), car (-38.3%)	PT (+4%), bike (+9.8%), car (-38.3%)	-	-
13	Bulk shopping (40.8%), visiting relatives/friends (34.4%), recreational (21%), excursion in nice weather (17.8%)	Excursion in nice weather (43.6%), bulk shopping (41.6%), visiting relatives/friends (26.8%), recreational (24%)	Running an errand in the city centre (18.8%), going out for dinner (24%), weekend activities (13.7%)	Weekend activities (24%), excursion in nice weather (20%), visit relatives/friends (20%)

User profile: RTHB [+]

	Sweden (n = 10/480 = 2.1%)
1	3 persons [†]
2	No children (40%), 1 child (40%)
3	No car (90%), 1 car (10%) [◊, *]
4	Woman (60%) [◊, *, †, ‡]
5	45 years old
6	Degree (100%)
7	-
8	3,875 €
9	1 CS subscription (100%) [†]
10	Daily use of bike (60%), walk (50%) and PT (20%)
11	I will continue to travelling like today (80%), I will continue to use CS (80%). Not plan to use car sharing more than today
12	-
13	Excursion in nice weather (40%), visit relatives/friends (30%), visit a shopping center (20%)

User profile: RTSB [‡]

	Germany (n = 269/1122 = 24%)	Italy (n = 19/594 = 3.2%)	Sweden (n = 398/480 =82.9%)
1	2.1 persons	2.8 persons	2.4 persons
2	No children (73.6%), with children (26.4%)	No children (31.2%), 1 child (56.2%) [*, †]	No children (53%), 1 child (32.1%)
3	No car (80.7%)	No car (26.3%), One car (26.3%), 2 cars (47.4%)	No car (80.5%), 1 car (15.4%), 2 cars (3%) [◊, *]
4	Man (51.9%)	Man (57.9%)	Man (62.3%) [+]
5	50 years old	43 years old [*]	45 years old
6	Degree (77%), Diploma (14%)	Degree (63.1%), Diploma (36.9%)	Degree (90.2%), Diploma (9.8%)
7	Employed (73.9%), Self-employed (13.9%), Student (2.4%), NW and NS (9.8%)	-	-
8	3,500 €	2,350 €	3175 € [◊]
9	PT season ticket (68%)	1 CS subscription (100%) [◊, †]	1 CS subscription (100%) [†]
10	Daily use of PT (35.3%) and bike (29.7%)	Daily use of car (47.4%) and walk (31.6%) [*, †]	Daily use of walk (59.1%), PT (31.7%) and bike (24.5%)
11	Like PT (3.6/5), car rather than PT (2/5)	I will continue to travelling like today (73.8%), I plan to use the car sharing more than today (73.7%) [*, †]	I will continue to travelling like today (91.3%), I will continue to use CS (88.5%), I plan to use the car sharing more than today (19.1%)
12	PT (+13%), bike (+6.8%), car (-38.8%)	-	-
13	Bulk shopping (41.2%), visiting relatives/friends (28.9%), excursion in nice weather (25.8%), recreational (20.2%)	Going out for dinner (15.8%), shopping for groceries (15.8%), visit shopping center (15.8%), excursion in nice weather (15.8%)	Excursion in nice weather (18.1%), visit relatives/friends (18.1%), visit a shopping center (16.6%), weekend activities (16.6%)

Figure 3: Car sharing user profiles divided by car sharing typologies and countries

We already recalled in section 2 the importance of considering the seven car sharing profiles defined in STARS D2.1 to have a richer interpretation of the results. Therefore, Figure 3 also portrays the relationship between the seven car sharing service profiles and the user profiles through some arrows. It is worth recalling that the car sharing profiles differ regarding at least one characteristic among those listed in the "CS service profile" box reported at the top left corner of the plot.

As discussed in the above methodological section, observed differences in mean values of all variables across different user profiles have been checked for statistical significance according to Kruskal-Wallis and Kruskal post-hoc tests for both Italian and Swedish profiles (as above mentioned, the German ones are directly derived from D 4.1 and therefore such tests were not carried out). Whenever the threshold value p=.05 was met, a typographical symbol is added in the relevant cell of the figure to help the reader understanding whether the mean in that cell is significantly different from the corresponding mean in any other user profile for the same country. The association between symbol and user profile is presented in the Table 3 below.

Typographical symbol	User profiles
◊	Free-floating with operational area (FFOA)
*	Free-floating with pool stations (FFPS)
‡	Roundtrip station based (RTSB)
+	Roundtrip homezone based (RTHB)
†	Multiple operational characteristics (MultiOC)
Not available[3]	Peer-to-peer (P2P)

Table 3: Legend of symbols used to flag statistically significant differences in mean values of characteristics of different profiles

As already noted in subsection 2.2.1 when mapping car sharing operational schemes and corresponding profiles, the two roundtrip station based service profiles 4 and 5 fall in the same user profile (RTSB). Therefore a total of six car sharing user profiles have been identified jointly considering German, Italian and Swedish users. Of those, only four are available in all three countries, clearly with a different market penetration.

In the following two subheads, the main differences among car sharing user profiles within each country are first described, followed by a complementary description of how each car sharing user profile is changing across different countries.

[3] P2P users were detected in Germany only; German user profiles were built in D4.1 considering statistical significance of different groups but information concerning the variables analysed here is not available.

3.1.1.1 Car sharing user profiles within each country

Since a very detailed description of the German car sharing users was already carried out in D4.1 STARS report, it will be not covered again in the car sharing user groups per country description; however, a summary table is reported for completeness in the below Table 4, where numbers in the first column are identifiers of the variables under consideration according to the legend that is reported in the top right corner of Figure 3. German users' profiles will be therefore reported along with in the following comparison of users' groups among countries.

Germany					
	User profile: FFOA [n = 190/1122 = 16.9%]	User profile: MultiOC [n= 311/1122 = 27.7%]	User profile: Combined [n = 157/1122 = 14%]	User profile: P2P [n = 131/1122 = 11.7%]	User profile: RTSB [n = 269/1122 = 24%]
1	2 persons	2.2 persons	2.1 persons	2.3 persons	2.1 persons
2	No children (86.3%), with children (13.7%)	No children (71.3%), with children (28.7%)	No children (70.7%), with children (29.3%)	No children (71%), with children (29%)	No children (73.6%), with children (26.4%)
3	No car (31.6%)	No car (75%)	No car (78.3%)	No car (63.1%)	No car (80.7%)
4	Man (54.5%)	Man (67.9%)	Man (42.8%)	Man (53.2%)	Man (51.9%)
5	39 years old	44 years old	49 years old	45 years old	50 years old
6	Degree (71%), Diploma (23%)	Degree (77%)	Degree (76%), Diploma (14%)	Degree (43%), diploma (25%)	Degree (77%), Diploma (14%)
7	Employed (69%), Self-employed (16.1%), Student (12.3%), NW and NS (0.6%)	Employed (73.3%), Self-employed (18.4%), Student (3%), NW and NS (5%)	Employed (72.1%), Self-employed (11.6%), Student (4.1%), NW and NS (12.2%)	Employed (60.4%), Self-employed (21.6%), Student (6.3%), NW and NS (9%)	Employed (73.9%), Self-employed (13.9%), Student (2.4%), NW and NS(9.8%)
8	3,584 €	3,802 €	3,460 €	2,559 €	3,500 €
9	PT season ticket (47.4%)	PT season ticket (62.5%)	PT season ticket (55.4%)	PT season ticket (46.9%)	PT season ticket (68%)
10	Daily use of PT (26.3%), car (18.5%) and bike (17.4%)	-	Daily use of bike (47.1%) and PT (25.5%)	Daily use of bike (31.5%), PT (27.7%) and car (18.5%)	Daily use of PT (35.3%) and bike (29.7%)
11	Like PT (2.9/5), car rather than PT (3.4/5)	Like PT (3.6/5), car rather than PT (2.4/5)	Like PT (3.6/5), car rather than PT (2.2/5).	Like PT (2.9/5), car rather than PT (3.3/5)	Like PT (3.6/5), car rather than PT (2/5)
12	PT -22.8%, bike +0% , car - 19.7%	PT (+4%), bike (+9.8%), car (-38.3%)	PT (+7.1%), bike (+9.8%), car (-38.3%)	PT (-8.7%), bike (-1.8%), car (-15.6%)	PT (+13%), bike (+6.8%), car (-38.8%)
13	Dinner at restaurant (19.5%), Bulk shopping (14.8%), Shopping in city centre (13.8%)	Excursion in nice weather (43.6%), bulk shopping (41.6%), visiting relatives/friends (26.8%), recreational (24%)	Bulk shopping (40.8%), visiting relatives/friends (34.4%), recreational (21%), excursion in nice weather (17.8%)	Visiting relatives/friends (20.9%), bulk shopping (17.8%), recreational (14%), excusion in nice weather (12.4%)	Bulk shopping (41.2%), visiting relatives/friends (28.9%), excursion in nice weather (25.8%), recreational (20.2%)

Table 4: Car sharing user profiles in Germany

Italian car sharing user profiles are summarized in the below Table 5. It is worth stressing that the Italian sample refers to a representative[4] sample of the population living in a city where at least one car sharing service is available. Therefore, the sample of users itself can be considered as representative of the whole population of the country but not of the population of car sharing users.

As mentioned in previous STARS deliverables (STARS, Deliverable 2.1 - Car sharing in Europe: a multidimensional classification and inventory, 2018) (STARS, Deliverable 4.1: The influence of

[4] The representativeness is defined on gender and age.

socioeconomic factors in the diffusion of car sharing, 2018), most of the Italian car sharing users interviewed are associated with the free floating with operational area scheme. This is probably due to the fact that at the time that the present research was carried out (December 2018), the offer of other schemes is very weak. Roundtrip users in the sample are very few (19) even considering those having a subscription to another car sharing typology that has been classified as "multiOC" users (just 7 over the 96 reported in the table).

It is important to keep this in mind in the analysis of results, because the sample dimension can affect the significance of the observed patterns in average characteristics.

Italy				
	User profile: FFOA ◊ [n = 386/594 = 65%]	User profile: FFPS * [n = 93/594 = 15.7%]	User profile: MultiOC † [n = 96/594 = 16.2%]	User profile: RTSB ‡ [n = 19/594 = 3.2%]
1	2.7 persons	2.9 persons	2.4 persons	2.8 persons
2	No children (51.5%), 1 child (29.3%) [*, †]	No children (72%), 1 child (26.9%) [◊, ‡]	No children (74.2%), 1 child (20.6%) [◊, ‡]	No children (31.2%), 1 child (56.2%) [*, †]
3	No car (6.2%),1 car (58%), 2 cars (29.8%)	No car (17.2%), One car (37.6%), 2 cars (33.3%)	No car (20.8%), One car (38.5%), 2 cars (28.1%)	No car (26.3%), One car (26.3%), 2 cars (47.4%)
4	Man (57.4%) [†]	Man (55.1%) [†]	Man (73.6%) [◊, *]	Man (57.9%)
5	40 years old [*]	35 years old [◊, †, ‡]	39 years old [*]	43 years old [*]
6	Degree (61.9%), Diploma (37.2%)	Degree (71%), Diploma (29.1%)	Degree (79.4%), Diploma (20.6%)	Degree (63.1%), Diploma (36.9%)
7	-	-	-	-
8	2,350 €	1,650 €	2,000 €	2,350 €
9	1.5 CS subscriptions (65% to 1 operator) [*, †, ‡]	1 CS subscription (100%) [◊, †]	2.8 CS subscriptions (62% has a subscription with 3 operators) [◊, *, ‡]	1 CS subscription (100%) [◊, †]
10	Daily use of car (25.1%) [*, †] and walk (37.6%)	Daily use of PT (28%) and walk (53.8%) [◊, ‡]	Daily use of PT (25%) and walk (50.5%) [◊, ‡]	Daily use of car (47.4%) and walk (31.6%) [*, †]
11	I will continue to travelling like today (81.1%) [†], I will continue to use CS (87.9%), I plan to use the car sharing more than today (80.1%) [*, †]	I will continue to travelling like today (81.4%), I will continue to use CS (83.4%), I plan to use the car sharing more than today (34.4%) [◊, ‡]	I will continue to travelling like today (83.4%) [◊], I will continue to use CS (88.3%), I plan to use the car sharing more than today (39.7%) [◊, ‡]	I will continue to travelling like today (73.8%), I plan to use the car sharing more than today (73.7%) [*, †]
12	-	-	-	-
13	Running an errand in the city centre (16.6%), going out for dinner (16.6%), weekend activities (8%)	Running an errand in the city centre (23.9%), going out for dinner (26.1%), weekend activities (12.1%)	Running an errand in the city centre (18.8%), going out for dinner (24%), weekend activities (13.7%)	Going out for dinner (15.8%), shopping for groceries (15.8%), visit shopping center (15.8%), excursion in nice weather (15.8%)

Table 5: Car sharing user profiles in Italy

Household dimension and children

Concerning the average household dimension, no big differences have emerged between free floating (2.7) and roundtrip (2.8) users, while MultiOC users belong to smaller households (2.4) with the lowest percentage of children (26.8%). Regarding the number of children, which is a variable that differs with a statistical significance among many car sharing user groups, in Italy few RTSB users have no children in their household (31.2%) while almost one over two FFOA user have a child.

Looking at both average household dimensions and presence of children, it is interesting to note that FFPS users live in bigger household (2.9 persons on average) but mainly without children (28% has one or more children). It is likely that in this case the interviewees are living with their parents or with mates / friends without having family ties (typically students). These interpretations are supported by the lowest average age of the group (35 years) as well as the lowest average income (1650€).

Car ownership within households

Car sharing users' car availability differs among user groups: RTSB and MultiOC users share the highest percentage of car free household, 26.3% and 20.8% respectively, while only the 6.2% of FFOA users do not own a car. This is something similar to what already observed in the German case. Quite surprisingly RTSB users, which have the highest percentage of no car households, have also the highest percentage of households with two cars. It is also interesting to observe that MultiOC, which are representative of FFOA+FFPS users for more than 90%, have a good number of households without cars: the registration to many car sharing services seems to be a condition to get better results in term of car ownership reduction, even from FFOA users.

Users' individual information: gender, age, education and income

The proportion of men lies between 55 and 60% in all profiles with the exception of MultiOC users where the percentage of men raises to 73.6%.

Car sharing users are, on average, younger than non-user. Among the individual operational schemes, the FFPS users are the youngest (35 years) with a significant difference from other groups. RTSB users are on the contrary the oldest ones.

The level of education is high in all groups, over 60% of users get a degree; particularly high is the percentage of individuals having a university degree among MultiOC users (79.4%).

Concerning the monthly net individual income, a range of incomes was proposed to interviewees; the value reported in Table 5 is the mean value of the most selected category. RTSB and FFOA users have the highest income (2350€) while FFPS the lowest (1650€), but for FFPS users just two answers relative to the income were collected.

Travel behaviour

Travel behaviour information, such as the number of car sharing subscriptions to different services, the usage frequency of different travel modes, the expected changing in travel habits and the main activities carried out using car sharing are summarized in the lower part of Table 5.

One of the most significant variables (at least statistically speaking) is the number of car sharing subscriptions: the average value of the MultiOC users group is clearly the highest since the group represents those users that are registered to more than one service typology. As already mentioned, in this group users registered to a combination of services among the other three detected in Italy (FFOA, FFPS, RTSB) can be found, but most of the group is represented by FFOA + FFPS users.

Not only MultiOC users have many subscriptions: to a lesser extent FFOA users are likely to own more than one subscription (1.5 on average), which are clearly to the same typology of car sharing, while RTSB and FFPS users are generally registered to one service. On one hand this is due to the service availability, since in all considered Italian cities where a FFPS or a RTSB car sharing service is available, it is generally the only one in its typology. Contrarily, the number of FFOA services is very high and it is quite common to find two or three services operating in the same city and almost in the same operational area.

On the other hand, FFOA users might be registered to many operators (such as Car2Go, Enjoy and DriveNow) for increasing vehicles availability in their areas of interest. It is in fact well known that availability of shared cars near to the user position is one of the most critical aspect for FFOA users (D4.2 STARS report, par. 2.4.3).

Anyway, it is impossible to know through the survey if multiple subscriptions belong to active users or those numbers are inflated by users registered during promotional offers or just because the subscription is free of charge.

Concerning the daily usage of different transport modes, walking is the most common means with a fraction of car sharing users that walks everyday ranging from 53.8% (FFPS users) to 31.6% (RTSB users).

The second daily used mode for both FFPS and MultiOC is public transport (28% of the FFPS users and 25% of the MultiOC ones), while it is the car for FFOA and RTSB (25.1% of the FFOA users and 47.4% of the RTSB ones). Frequent car use among FFOA users was expected, in line to the previous STARS consortium findings, while the relatively high percentage (47.4%) related to RTSB car sharing users is surprising.

The situation does not change even when lower use frequencies are considered, according to the data reported in Table 6 below.

Car sharing user group	daily	4-6 days/week	1-3 days/week	once/a few times a month	more seldom	never
FFOA (n=386)	97 (25.1%)	39 (10.1%)	76 (19.7%)	60 (15.5%)	33 (8.5%)	81 (21%)
FFPS (n=93)	15 (16.1%)	7 (7.5%)	21 (22.6%)	16 (17.2%)	12 (12.9%)	22 (23.7%)
MultiOC (n=96)	15 (15.6%)	7 (7.3%)	22 (22.9%)	12 (12.5%)	18 (18.8%)	22 (22.9%)
RTSB (n=19)	9 (47.4%)	0 (0%)	2 (10.5%)	2 (10.5%)	4 (21.1%)	2 (10.5%)

Table 6: Frequency of driving a private car per user group (row percentages in brackets)

Regarding the travel habits, all car sharing users think that they will not change the way of travelling and they will continue to use a car sharing service, without relevant difference among groups; slightly lower percentages are registered in the RTSB users' group.

Different opinions concerning an increase of use of car sharing between user groups have emerged: a higher percentage of FFOA and RTSB users plan to use car sharing more than today (80.1% and 73.7% respectively); that percentage falls for MultiOC users' group (39.7%) and it falls even more for FFPS users' group (34.4%).

The case of MultiOC users might be explained by the fact that they are currently quite frequent users of the service; in fact more than one third of the users rent a shared car 1-3 days a week as showed in Table 7, which reports the car sharing use frequency by user groups.

FFPS users might be less attracted by cars instead. As already reported, they use public transport and soft modes (cycling and walking) rather than cars, and so car sharing.

Car sharing user group	daily	4-6 days/week	1-3 days/week	once/a few times a month	more seldom	never
FFOA (n=386)	8 (2.1%)	40 (10.4%)	59 (15.3%)	168 (43.5%)	102 (26.4%)	9 (2.3%)
FFPS (n=93)	4 (4.3%)	7 (7.6%)	19 (20.7%)	41 (44.6%)	18 (19.6%)	3 (3.3%)
MultiOC (n=96)	1 (1%)	6 (6.2%)	33 (34%)	41 (42.3%)	15 (15.5%)	1 (1%)
RTSB (n=19)	1 (5.3%)	3 (15.8%)	4 (21.1%)	6 (31.6%)	4 (21.1%)	1 (5.3%)

Table 7: Car sharing use frequency per user groups (row percentages in brackets)

Concerning car sharing trip purposes, the three most frequently reported activities are reported here. Free floating users and MultiOC users use car sharing for running an errand in city centre, for going out for dinner and to perform weekend activities; on the other hand, RTSB users use car sharing for going out for dinner but prefer to use car sharing to do shopping in groceries and in shopping centre instead of running an errand in the city centre and they prefer have excursions in nice weather. This last activity is the one that most benefits from the advantages of this scheme of car sharing, since it enables longer rental periods.

Differently from the Italian case, five different car sharing user groups have been identified through the interviewees in Sweden; these groups are summarized in Table 8 below.

As mentioned in previous STARS deliverables (STARS, Deliverable 2.1 - Car sharing in Europe: a multidimensional classification and inventory, 2018) (STARS, Deliverable 4.1: The influence of socioeconomic factors in the diffusion of car sharing, 2018), most of the Swedish car sharing users are associated with the roundtrip station based scheme. This is probably due to the fact that at the time that the present research was carried out (December 2018), number of interviewees for the other groups is very small.

Once again, it is important to keep this in mind in the analysis of results, because the sample dimension can affect the significance of the observed patterns in average characteristics.

Sweden					
	User profile: FFOA ◊ [n = 34/480 = 7.1%]	User profile: FFPS * [n = 13/480 = 2.7%]	User profile: MultiOC † [n = 25/480 = 5.2%]	User profile: RTSB ‡ [n = 398/480 =82.9%]	User profile: RTHB + [n = 10/480 = 2.1%]
1	2.5 persons	2.3 persons	1.9 persons [+]	2.4 persons	3 persons [†]
2	No children (45.8%), 1 child (41.7%)	No children (72.7%), 1 child (18.2%)	No children (82.4%), 1 child (11.8%)	No children (53%), 1 child (32.1%)	No children (40%), 1 child (40%)
3	No car (52.9%), 1 car (32.4%), 2 cars (14.7%) [+, †, ‡]	No car (38.5%), 1 car (38.5%), 2 cars (15.4%) [+, †, ‡]	No car (83.3%), 1 car (16.7%) [◊, *]	No car (80.5%), 1 car (15.4%), 2 cars (3%) [◊, *]	No car (90%), 1 car (10%) [◊, *]
4	Man (70.6%) [+]	Man (76.9%) [+]	Man (80%) [+]	Man (62.3%) [+]	Woman (60%) [◊, *, †, ‡]
5	35 years old	45 years old	45 years old	45 years old	45 years old
6	Degree (85.2%), Diploma (14.6%)	Degree (92.3%), Diploma (7.7%)	Degree (84%), Diploma (16%)	Degree (90.2%), Diploma (9.8%)	Degree (100%)
7	-	-	-	-	-
8	3,875 € [‡]	2,675 €	3,875 €	3175 € [◊]	3,875 €
9	1 CS subscription (100%) [†]	1 CS subscription (100%) [†]	2.2 CS subscriptions (84% to 2 operators) [◊, *, +, ‡]	1 CS subscription (100%) [†]	1 CS subscription (100%) [†]
10	Daily use of PT (26.5%) and walk (61.8%)	Daily use of PT (25%), walk (53.8%) and bike (23.1%)	Daily use of walk (76%), PT (48%) and bike (20%)	Daily use of walk (59.1%), PT (31.7%) and bike (24.5%)	Daily use of bike (60%), walk (50%) and PT (20%)
11	I will continue to travelling like today (85.3%), I will continue to use CS (76.4%), I plan to use the car sharing more than today (26.4%)	I will continue to travelling like today (92.3%), I will continue to use CS (84.6%), I plan to use the car sharing more than today (30.8%)	I will continue to travelling like today (92%), I will continue to use CS (96%), I plan to use the car sharing more than today (32%)	I will continue to travelling like today (91.3%), I will continue to use CS (88.5%), I plan to use the car sharing more than today (19.1%)	I will continue to travelling like today (80%), I will continue to use CS (80%). Not plan to use car sharing more than today
12	-	-	-	-	-
13	Excursion in nice weather (9.1%), visit relatives/friends (8.8%), weekend activities (6%)	Visit a shopping center (7.7%), weekend activities (7.7%)	Weekend activities (24%), excursion in nice weather (20%), visit relatives/friends (20%)	Excursion in nice weather (18.1%), visit relatives/friends (18.1%), visit a shopping center (16.6%), weekend activities (16.6%)	Excursion in nice weather (40%), visit relatives/friends (30%), visit a shopping center (20%)

Table 8: Car sharing user profiles in Sweden

Household dimension and children

Concerning the household dimensions, no big differences have emerged between free floating (2.5 and 2.3 persons per household) and RTSB users (2.4 persons). Roundtrip homezone based (RTHB) users belongs to bigger households (3 persons on average) that also have the highest percentage of children (60%). At the opposite, MultiOC users belong to smaller households (1.9 persons) with the lowest percentage of children (17.6%). The variable "number of children" has shown statistical significance between MultiOC and RTHB indeed. Among the others users' groups, FFPS follow the MultiOC group with a high percentage of households without children (72.7%), while FFOA and RTSB users with children in their household represent almost the 50% of the respective group.

Car ownership within households

Car sharing users' car availability differs among user groups: RTHB users' group have the highest percentage of car free household (90%), followed by RTSB and MultiOC users' groups with very high percentages (80.5% and 83.3% respectively). The percentage of car free household within FFOA users' is relatively low (52.9%), but it falls to a very low value in case of FFPS users (38.5%).

It is interesting to observe that MultiOC in Sweden is mainly composed by FFOA + RTSB users (84%): the integration of the two service typologies gets the best results in term of car ownership reduction.

Users' individual information: gender, age, education and income

Gender is a significant variable for RTHB users; in this group most of users are women (60%), while in all the others the most of users are men. Considering the proportion of men in individual user groups, MultiOC users have the highest percentage (80%) followed by FFPS (76.9%), FFOA (70.6%) and RTSB (62.3%).

Regarding age, among the individual variants, the FFOA users are the youngest average at 35 years, while for all the others groups the average age is 45. In this case the average ages of different groups are exactly the same since in the questionnaire range of ages were proposed to interviewees (40-49 years was the most selected in all groups).

The level of education is very high in all groups, over 84% of users get a degree; particularly high is the percentage of degree among RTSB users (90.2%) and FFPS users (92.3%), while all RTHB users have a degree.

Concerning the monthly net individual income, range of incomes were proposed to interviewees; the value reported in Table 8 is the mean value of the most selected category. FFOA, MultiOC and RTHB users have the highest income (3875€) while FFPS the lowest (2675€).

Travel behaviour

Travel behaviour information, such as the number of car sharing subscriptions to different services, the frequency of different travel modes, the expected change in travel habits and the main activities carried out using car sharing are summarized in the lower part of Table 8.

Another significant variable for user group identified in Sweden is the number of car sharing subscriptions: the average value of the MultiOC users group is clearly the highest since the group represents those users that are registered to more than one service typology. Except from them, all the users belonging to other groups are registered to a single operator.

Concerning the frequency of the use of different transport modes, Swedish car sharing users walk, ride a bicycle and use public transport in their daily routine (Table 10). Among different car sharing operational schemes, the MultiOC group has the highest percentage of users that use PT every day (48%), followed by RTSB users (31.7%), FFOA (26.5%), FFPS (25%) and RTHB (20%). Moreover, the MultiOC group has the highest percentage of users that walk in combination with other modes on a daily base (76%). The RTHB group has the highest percentage of users that ride a bike everyday (60%), while FFOA users do not use a bike.

Regarding travel habits, all car sharing users think that they will not change their way of travelling and they will continue to use a car sharing service. There are no relevant differences among the groups.

Among RTHB users, nobody is thinking of using car sharing more in the future. Few car sharing users are planning to use car sharing more than today in the other users' groups: the percentages between groups has a very low variance. The RTSB users have the lowest percentage (19.1%), while MultiOC has the highest one (32%).

Concerning car sharing trip purposes, the three most frequent activities are reported in the last line of Table 10. The low percentages for free floating users (both FFOA and FFPS) suggest an even distribution of trip purposes for those groups. Excursions in nice weather, visiting friends and weekend activities are the top three purposes of car sharing for FFOA users; visiting a shopping center and weekend activities are the top two for the FFPS users.

RTHB and RTSB user choose car sharing mainly when it comes to excursion in nice weather, while MultiOC perform weekend activities. Excursions in nice weather is the second main purpose for MultiOC, while visiting relatives/friends in another city is the second most rated purpose for RTSB and RTHB.

3.1.1.2 Car sharing user profiles within each operational scheme

In the previous section, many differences between car sharing user groups living in the same country were observed. Those differences were not only among different car sharing types but also among the same user groups according to the country it belongs to. Under this subheading, user profiles of Germany, Italy and Sweden are compared on the basis of the operational characteristics of the car sharing service. User profiles encountered just in one country are therefore not considered here.

Therefore, four out of six user profiles have been compared:

- FFOA, the user profile constituted by people uniquely registered to free floating with operational area car sharing services (Table 9).
- FFPS, the user profile constituted by people uniquely registered to free floating with pool stations car sharing services (Table 10).
- MultiOC, the user profile constituted by people registered to multiple car sharing services with different operational characteristics in parallel (Table 11).
- RTSB, the user profile constituted by people uniquely registered to round trip station based car sharing services (Table 12).

The share of the different car sharing typologies varies between countries and since the survey respondents are not a strictly representative sample this picture may not be entirely representative of the market penetration: However, in Italy most of the users belong to FFOA group (65%) while in Germany and Sweden the highest percentage of users belong to the RTSB profile.

Furthermore, when focusing on differences among users of the same car sharing variant, living in the different countries, it is hard to define common trends in user profiles.

User profile: FFOA [◊]			
	Germany [n = 190/1122 = 16.9%]	Italy [n = 386/594 = 65%]	Sweden [n = 34/480 = 7.1%]
1	2 persons	2.7 persons	2.5 persons
2	No children (86.3%), with children (13.7%)	No children (51.5%), 1 child (29.3%) [*, †]	No children (45.8%), 1 child (41.7%)
3	No car (31.6%)	No car (6.2%),1 car (58%), 2 cars (29.8%) [+, †, ‡]	No car (52.9%), 1 car (32.4%), 2 cars (14.7%)
4	Man (54.5%)	Man (57.4%) [†]	Man (70.6%) [+]
5	39 years old	40 years old [*]	35 years old
6	Degree (71%), Diploma (23%)	Degree (61.9%), Diploma (37.2%)	Degree (85.2%), Diploma (14.6%)
7	Employed (69%), Self-employed (16.1%), Student (12.3%), NW and NS (0.6%)	-	-
8	3,584 €	2,350 €	3,875 € [‡]
9	PT season ticket (47.4%)	1.5 CS subscriptions (65% to 1 operator) [*, †, ‡]	1 CS subscription (100%) [†]
10	Daily use of PT (26.3%), car (18.5%) and bike (17.4%)	Daily use of car (25.1%) [*, †] and walk (37.6%)	Daily use of PT (26.5%) and walk (61.8%)
11	Like PT (2.9/5), car rather than PT (3.4/5)	I will continue to travelling like today (81.1%) [†], I will continue to use CS (87.9%), I plan to use the car sharing more than today (80.1%) [*, †]	I will continue to travelling like today (85.3%), I will continue to use CS (76.4%), I plan to use the car sharing more than today (26.4%)
12	PT -22.8%, bike +0% , car -19.7%	-	-
13	Dinner at restaurant (19.5%), Bulk shopping (14.8%), Shopping in city centre (13.8%)	Running an errand in the city centre (16.6%), going out for dinner (16.6%), weekend activities (8%)	Excursion in nice weather (9.1%), visit relatives/friends (8.8%), weekend activities (6%)

Table 9: Free floating with operational area users in different countries

FFOA users characteristics of German, Italian and Swedish samples are reported in Table 9.

Regarding the number of cars, FFOA users in Germany and Italy have the lowest percentage of car free households. The lowest percentage of car free households in Sweden, is among FFPS users.

The higher number of households with a car is also reflected in the higher percentage of private car use on a daily base in Germany (18.5%) and Italy (25.1%).

The users belonging to this group are quite young: German and Swedish FFOA users are the youngest ones, with 39 years and 35 respectively. In Italy the average age of this group is 40 years, slightly higher than MultiOC (39 years) and FFPS (35 years) Italian users.

User profile: FFPS [*]		
	Italy [n = 93/594 = 15.7%]	Sweden [n = 13/480 = 2.7%]
1	2.9 persons	2.3 persons
2	No children (72%), 1 child (26.9%) [◊, ‡]	No children (72.7%), 1 child (18.2%)
3	No car (17.2%), One car (37.6%), 2 cars (33.3%) [+, †, ‡]	No car (38.5%), 1 car (38.5%), 2 cars (15.4%)
4	Man (55.1%) [†]	Man (76.9%) [+]
5	35 years old [◊, †, ‡]	45 years old
6	Degree (71%), Diploma (29.1%)	Degree (92.3%), Diploma (7.7%)
7	-	-
8	1,650 €	2,675 €
9	1 CS subscription (100%) [◊, †]	1 CS subscription (100%) [†]
10	Daily use of PT (28%) and walk (53.8%) [◊, ‡]	Daily use of PT (25%), walk (53.8%) and bike (23.1%)
11	I will continue to travelling like today (81.4%), I will continue to use CS (83.4%), I plan to use the car sharing more than today (34.4%) [◊, ‡]	I will continue to travelling like today (92.3%), I will continue to use CS (84.6%), I plan to use the car sharing more than today (30.8%)
12	-	-
13	Running an errand in the city centre (23.9%), going out for dinner (26.1%), weekend activities (12.1%)	Visit a shopping center (7.7%), weekend activities (7.7%)

Table 10: Free floating with pool stations users in different countries

FFPS user characteristics of Italian and Swedish are reported in Table 10.

A common characteristic of this profile in the different countries is the net monthly income: the users of FFPS have the lowest average income compared to the other users' groups. On the other hand, the FFPS user group hold the highest number of users with a degree: 71.2% of users in Italy and 92.3% of users in Sweden.

MultiOC user profiles are reported in Table 11 below. As already mentioned, for the German sample both users registered to multiple services as well as users registered to combined services are reported. Also, MultiOC users in Sweden are registered to FFOA and RTSB services as the German, while in Italy MultiOC users are mainly registered to FFOA and FFPS services (93%).

	Combined	User profile: MultiOC [†]		
	Germany [n = 157/1122 = 14%]	Germany [n= 311/1122 = 27.7%]	Italy [n = 96/594 = 16.2%]	Sweden [n = 25/480 = 5.2%]
1	2.1 persons	2.2 persons	2.4 persons	1.9 persons [+]
2	No children (70.7%), with children (29.3%)	No children (71.3%), with children (28.7%)	No children (74.2%), 1 child (20.6%) [◊, ‡]	No children (82.4%), 1 child (11.8%)
3	No car (78.3%)	No car (75%)	No car (20.8%), One car (38.5%), 2 cars (28.1%) [◊, *]	No car (83.3%), 1 car (16.7%)
4	Man (42.8%)	Man (67.9%)	Man (73.6%) [◊, *]	Man (80%) [+]
5	49 years old	44 years old	39 years old [*]	45 years old
6	Degree (76%), Diploma (14%)	Degree (77%)	Degree (79.4%), Diploma (20.6%)	Degree (86%), Diploma (14%)
7	Employed (72.1%), Self-employed (11.6%), Student (4.1%), NW and NS (12.2%)	Employed (73.3%), Self-employed (18.4%), Student (3%), NW and NS (5%)	-	-
8	3,460 €	3,802 €	2,000 €	3,875 €
9	PT season ticket (55.4%)	PT season ticket (62.5%)	2.8 CS subscriptions (62% has a subscription with 3 operators) [◊, *, ‡]	2.2 CS subscriptions (84% to 2 operators) [◊, *, +, ‡]
10	Daily use of bike (47.1%) and PT (25.5%)	-	Daily use of PT (25%) and walk (50.5%) [◊, ‡]	Daily use of walk (76%), PT (48%) and bike (20%)
11	Like PT (3.6/5), car rather than PT (2.2/5)	Like PT (3.6/5), car rather than PT (2.4/5)	I will continue to travelling like today (83.4%) [◊], I will continue to use CS (88.3%), I plan to use the car sharing more than today (39.7%) [◊, ‡]	I will continue to travelling like today (92%), I will continue to use CS (96%), I plan to use the car sharing more than today (32%)
12	PT (+7.1%), bike (+9.8%), car (-38.3%)	PT (+4%), bike (+9.8%), car (-38.3%)	-	-
13	Bulk shopping (40.8%), visiting relatives/friends (34.4%), recreational (21%), excursion in nice weather (17.8%)	Excursion in nice weather (43.6%), bulk shopping (41.6%), visiting relatives/friends (26.8%), recreational (24%)	Running an errand in the city centre (18.8%), going out for dinner (24%), weekend activities (13.7%)	Weekend activities (24%), excursion in nice weather (20%), visit relatives/friends (20%)

Table 11: Multi operational characteristic of users in different countries

The percentage of men in this user profile is very high compared to all the other groups in different countries.

The lowest percentage of children is registered among the Italian (74.2%) and the Swedish (82.4%) MultiOC users. German users have a very low percentage of children (71.3%) but the lowest value is reached by the FFOA user group (86.3%).

A peculiarity of this users' group is the level of education: it shows the highest percentage of users with a degree compared to the other service typologies' users in Germany (77%), Italy (79.4%) and Sweden (86%).

It is interesting to observe that despite MultiOC users are in every case FFOA users, the registration to another car sharing typology reduces car ownership, since users from all three countries have a higher percentage of car free households than FFOA unique users. Another positive effect of service integration in Germany is related to the fact that MultiOC users like more PT (3.6/5) and less the car (2.4/5) compared to FFOA unique users (2.9/5 like PT and 3.4 like car rather than PT). In Sweden, MultiOC users count a higher percentage of use of PT (48%) on a daily base respect to the compatriots FFOA users (26.5%). Similarly, in Italy the 25% of MultiOC users use PT on daily base, while in the other groups only FFPS users stated the daily use of PT.

RTSB user profiles of the three countries are summarized in Table 12 below.

User profile: RTSB [‡]			
	Germany [n = 269/1122 = 24%]	Italy [n = 19/594 = 3.2%]	Sweden [n = 398/480 =82.9%]
1	2.1 persons	2.8 persons	2.4 persons
2	No children (73.6%), with children (26.4%)	No children (31.2%), 1 child (56.2%) [*, †]	No children (53%), 1 child (32.1%)
3	No car (80.7%)	No car (26.3%), One car (26.3%), 2 cars (47.4%)	No car (80.5%), 1 car (15.4%), 2 cars (3%) [◊, *]
4	Man (51.9%)	Man (57.9%)	Man (62.3%) [+]
5	50 years old	43 years old [*]	45 years old
6	Degree (77%), Diploma (14%)	Degree (63.1%), Diploma	Degree (90.2%), Diploma (9.8%)
7	Employed (73.9%), Self-employed (13.9%), Student (2.4%), NW and NS(9.8%)	-	-
8	3,500 €	2,350 €	3175 € [◊]
9	PT season ticket (68%)	1 CS subscription (100%) [◊, †]	1 CS subscription (100%) [†]
10	Daily use of PT (35.3%) and bike (29.7%)	Daily use of car (47.4%) and walk (31.6%) [*, †]	Daily use of walk (59.1%), PT (31.7%) and bike (24.5%)
11	Like PT (3.6/5), car rather than PT (2/5)	I will continue to travelling like today (73.8%), I plan to use the car sharing more than today (73.7%) [*, †]	I will continue to travelling like today (91.3%), I will continue to use CS (88.5%), I plan to use the car sharing more than today
12	PT (+13%), bike (+6.8%), car (-38.8%)	-	-
13	Bulk shopping (41.2%), visiting relatives/friends (28.9%), excursion in nice weather (25.8%), recreational (20.2%)	Going out for dinner (15.8%), shopping for groceries (15.8%), visit shopping center (15.8%), excursion in nice weather	Excursion in nice weather (18.1%), visit relatives/friends (18.1%), visit a shopping center (16.6%), weekend activities

Table 12: Roundtrip station based users in different countries

A characteristic feature of this group is represented by age: users belonging to RTSB group have the highest average age (it is equal in the case of Swedish sample where age ranges were asked).

The users belonging to this group have the highest percentages of car free household in all three countries. However, it is interesting to observe the strong difference among countries: while in Germany and Sweden the number of households without a car lies at almost 80%, in Italy this value falls to 26.3%. This together with the low degree of car-free households among the other user profiles makes the Italian households emerge as the most car oriented. Comparison of non-user profiles with user profiles characteristics

In order to get a preliminary indication of which car sharing operational schemes can have a stronger appeal for non-users, a comparison between the above car sharing user profiles and non-users characteristics was carried out. Two different non-user profiles, corresponding to the two mobility style clusters defined in D4.2 STARS report and here labelled as "cluster 4" and "cluster 5", were considered. Since many differences emerged between Italian and Swedish car sharing users, non-users of the two countries were also separately considered. Therefore, four different non-user profiles were evaluated. For all of these, the average values of the same variables considered to characterise the user profiles were computed.

Non user profile: Cluster 4				
	Italy (n = 813/1797= 45.2%)	User Italy	Sweden (n = 742/1694 = 43.8%)	User Sweden
1	2.8 persons	→ RTSB	2.4 persons	→ RTSB
2	No children (44.5%), 1 child (43.9%)	→ FFOA	No children (64.2%), 1 child (23.1%)	→ FFPS
3	No car (1.8%), One car (48.2%), 2 cars (41.3%)	→ FFOA	No car (10.3%), 1 car (57.7%), 2 cars (25.4%)	→ FFPS
4	Man (53.4%)	→ FFPS	Man (71.6%)	→ FFOA
5	49 years old	→ RTSB	55 years old	→ RTHB
6	Degree (48.9%), Diploma (40.5%)	→ FFOA	Degree (73%), Diploma (19%)	→ MultiOC
7	-	-	-	-
8	2,218 €	→ FFOA	3,175 €	→ FFPS
9	-	-	-	-
10	Daily use of car as a driver (41.2%) and walk (30.9%)	→ RTSB	Daily use of car as a driver (31.3%), of PT (10.4%) and walk (38.8%)	-
11	-	-	-	-
12	I will continue to travelling like today (76%), I plan to use a car sharing service (75%)	-	I will continue to travelling like today (95.3%), I plan to use a car sharing service (<15%)	-
13	PT use is more used than others in running an errand in the city centre (39.6%), all the other activities are performed with car (avg 75%)	→ RTSB	PT use is more used than others in running an errand in the city centre (45.9%), in going out for dinner (47.1%), all the other activities are performed with car (avg 70%)	-

Table 13: Non users cluster 4 profile

In Table 13, non-user profiles of Italy and Sweden belonging to cluster 4 (Labelled as Car-focused Ambivalent in STARS D 4.2) are reported. Each non-users characteristic has been compared with the respective one among users of different services in the same country. Therefore, the users' profile that best matches in term of average characteristic is reported on the third and last column of the table.

As already highlighted in D4.2 STARS report, the comparisons between the two mobility styles of non-users shows that the non-user Car-focused Ambivalent mobility style (Cluster 4) has the highest level of private car use and the smallest level of public transportation use across all mobility styles.

The percentage of car free households is very low in both Italy (1.8%) and Sweden (10.3%); moreover, this profile shows the highest percentage of car usage on a daily base, namely 41.2% for the Italian sample and 31.3% for the Swedish one.

Considering the average household dimension, both Italian and Swedish non-users belonging to cluster 4 have the closest values to those evaluated in RTSB users' group. For all the other variables, the differences between the users' profiles of the two countries are aligned with the differences that can be observed between the Swedish and the Italian cluster 4 profiles.

In Italy the presence of children in households is more similar to what was observed for FFOA users' group, where 51.5% of the households have no children while the 29.3% has one. Among the other users' groups, FFOA have the lowest percentage of car free household (6.2%): it is the closest to the very low value registered among non-users belonging to both, cluster 4 (1.8%) and cluster 5 (6.6%).

The proportion of men among non-users cluster 4 lies at 53.4 %, which is more similar to the average age evaluated from FFPS users.

The average age of all non-users (49-50) in Italy is higher than the average age evaluated in every user profiles of the country: it reflects that car sharing services are still more appealing for younger people. Among individual user groups RTSB is the one with the highest average age (43 years), so it has been associated to both non-users clusters.

Contrarily, level of education and average net monthly income of non-users clusters are closer to those evaluated for FFOA user profiles.

Concerning travel attitudes and travel behaviour, the comparison between users and non-users' profiles was more difficult, since different questions were asked to users and non-users about future car sharing use intentions, while questions related to car sharing trip purposes were not addressed to non-users. Finally, the same combination of daily usage of different transport modes was hard to find.

Consequently, no matches with users travel behaviours were found in the cluster 4 of the Swedish non-users' group. On the contrary, the quite high use on a daily base of the private car together with the walking of the Italian cluster 4 was detected in the RTSB users' profile.

In the last row of Table 13, private car trip purposes were considered rather than car sharing travel purposes, which clearly are not available for non-users. So, if all the typical travel purposes of a car sharing profile were performed by private car from non-users, the two profiles have been matched. In the Italian case, non-users belonging to cluster 4 drive a car to complete all the trips that a RTSB users would usually do with car sharing. Differently from other car sharing users' profiles, car sharing is not used by RTSB users for running an errand in the city centre.

In conclusion, Italian non-users belonging to cluster 4 have average characteristics that are similar to RTSB users as well as FFOA, therefore both typologies of car sharing can be attractive to this non-users group. The non-user cluster 4 profile has average characteristics that are more aligned with FFPS users in Sweden; here no similarities have been found concerning behavioural features.

However, it is worth stressing that the above cluster is composed by non-users with the lowest attitudes towards car sharing services.

Non-users profiles of Italy and Sweden belonging to cluster 5 (labelled as Car-flexible Green in D 4.2) are reported in Table 14.

Non user profile: Cluster 5				
	Italy (n = 984/1797 = 54.8%)	User Italy	Sweden (n = 952/1694 = 56.2%)	User Sweden
1	2.7 persons	→ FFOA	2.3 persons	→ FFPS
2	No children (53%), 1 child (39.8%)	→ FFOA	No children (61.3.7%), 1 child (25.2%)	→ FFPS
3	No car (6.6%), One car (47.8%), 2 cars (39.8%)	→ FFOA	No car (36.7%), 1 car (53.3%), 2 cars (9.3%)	→ FFPS
4	Man (48%)	→ FFPS	Man (49%)	→ RTHB
5	50 years old	→ RTSB	45 years old	→ RTHB
6	Degree (54.3%), Diploma (44.6%)	→ FFOA	Degree (85.4%), Diploma (13.9%)	→ FFOA
7	-	-	-	-
8	2,109 €	→ FFOA	2,675 €	→ FFPS
9	-	-	-	-
10	Daily use of PT (9.8%), car as a driver (19.3%) and walk (52.5%)	→ MultiOC	Daily use of PT (31.8%), walk (59.6%) and bike (17.2%)	→ RTSB
11	-	-	-	-
12	I will continue to travelling like today (76%), I plan to use a car sharing service (99%)	-	I will continue to travelling like today (93%), I plan to use a car sharing service (<15%)	-
13	PT use is more used than others in running an errand in the city centre (51.9%), all the other activities are performed with car (avg 60%)	→ RTSB	PT use is more used than others in running an errand in the city centre (55.1%), in going out for dinner (56.3%), while shopping for groceries by bike (54.9%). All the other activities are performed with car (avg 42.4%)	-

Table 14: Non users cluster 5 profiles

The average age of non-users cluster 5 profile is slightly lower than cluster 4, in both Italy and Sweden. Therefore, it exactly corresponds to the average age of FFOA users in Italy (2.7) and to the average age of FFPS users in Sweden (2.3).

The non-users sample belonging to the cluster 5 in Sweden is mainly composed by women (51%) like the RTHB users group, in which women represent the 60%.

However, the average age (45 years) is similar to the one of many users' profiles: RTHB was indicated since it has higher percentages of people with ages ranging from 40-49, 50-59 and more than 60.

Swedish cluster 5 has a higher level of education than cluster 4 and it better matches with the educational level of FFOA users.

Daily usage of many modes indicated by the majority of cluster 5 non-users in both countries indicates a more multimodal group. In Italy only FFPS and MultiOC users' groups indicated a daily use of PT together with walking; the latter has the closest percentages. A match was identified even in the Swedish cluster 5, where the daily use of PT (31.7%), walk (59.1%) and bike (24.5%) of non-users is closer to the RTSB users daily use of the same transport means.

In conclusion, average characteristics of non-users cluster 5 in Italy best match those of free floating with operational area car sharing users while, once again, in Sweden the non-user profile has average characteristics that are more in line with FFPS users.

3.1.2 Car sharing usage trends for different user profiles through decision trees

Similarly to the previous analysis, decision tree models were applied to the Italian and Swedish datasets where non-users' clusters have been identified according to D4.2 STARS report.

In order to use a decision tree for making predictions, it is necessary to have two main datasets: one with the labelled class that is going to be predicted and one without it. The first dataset is used for training the classifier (like the calibration process in a model) and the other to apply the rules (the model) learned through the training dataset and to determine the unknown class. Both datasets need to have the same features, or at least those that will be considered as dependent variables in the model, and the same range of variation.

In the survey conducted by the STARS consortium (D4.1 activity) users and non-users were discriminated through the following screening question:

"Do you have any experience with car sharing services?"

1="Yes, I am currently using car sharing services";

2="Yes, I have previous experience with car sharing but I am not using it anymore";

3="No, I have no experience with car sharing but I know what it is";

4="I am not familiar with the concept of car sharing"

Clearly, the first answer identifies users and the last three non-users. However, the same group of questions among those listed in Table 24 and Table 25 (see Appendix 2) were later posed only to those that indicated one the first three answers in the above screening question. The obvious exception is the car sharing users' profile, since it is clearly unknown for non-users and it is exactly the variable that will be predicted by the decision tree.

Accordingly, records with code 4 in the screening question are excluded a priori. Then those records who did not answer to one of the questions listed in Table 24 and Table 25 were removed (listwise deletion). Moreover, not all users were considered: only the ones belonging to one of the previously identified users' profiles have been taken into account.

A breakdown of users and non-users data with the respective answers to the screening question is reported in Table 15 (Italian sample) and in Table 16 (Swedish sample). The last row reports the total number of users and non-users used in the model.

Experience with car sharing services					
	Current user	**Previous experience**	**No experience**	**Not aware**	**Tot**
Users	594	0	0	0	594
Non-users	0	515	1797	439	2751
Tot	594	515	1797	439	3345
Retained observations	**589 (99%)**	**514 (99%)**	**1797 (100%)**	**0 (0%)**	**2900 (87%)**

Table 15: Data considered in decision trees from the Italian sample

All Italian non users considered in this analysis (which are 514+1797 = 2311 according to the second and third cell of the last row of Table 15) can then be split in the two above mentioned non-users profiles as follows:

- 813 (35.2%) non-users belong to the cluster Car-focused Ambivalent (4);
- 984 (42.6%) non-users belong to the cluster Car-flexible Green (5);
- 514 (22.2%) do not fall in any cluster.

The same information is reported in Table 16 below for the Swedish sample.

Experience with car sharing services						
	Current user	**Previous experience**	**No experience**	**Not aware**	**Not Answered**	**Tot**
User	480	0	0	0	0	480
Non-user	0	481	1686	27	41	2235
Tot	480	481	1686	27	41	2710
Retained observations	**475 (99%)**	**481 (100%)**	**1686 (100%)**	**0 (0%)**	**0 (0%)**	**2642 (97%)**

Table 16: Data considered in decision trees from the Swedish sample

All Swedish non users considered in this analysis (which are 481+1686 = 2167 according to the second and third cell of the last row of Table 15) can then be split in the two above mentioned non-users profiles as follows:

- 734 (33.8%) non-users belong to the cluster Car-focused Ambivalent (4);
- 948 (43.7%) non-users belong to the cluster Car-flexible Green (5);
- 485 (22.3%) do not fall in any cluster.

Once the country dataset of users and non-users was defined, many combinations of decision tree were analysed. In the following subheadings, the following decision trees that gave the most accurate results are showed:

1. Decision tree trained on socioeconomic characteristics of Italian users, then applied to Italian non-users;
2. Decision tree trained on behavioural characteristics of Italian users, then applied to Italian non-users;
3. Decision tree trained on socioeconomic characteristics of Swedish users, then applied to Swedish non-users;
4. Decision tree trained on behavioural characteristics of Swedish users, then applied to Swedish non-users;

In addition, decision tree trained on socioeconomic characteristics and on behavioural characteristics of the total users' sample (Italy + Sweden) were studied. Since their prediction was less accurate than the others, they are not presented here. Confusion matrices, accuracy statistics and predictions together with all the simplified tree schemes are reported in Appendix 3: Additional Decision tree trained on sociodemographic and behavioural variables of Italian and Swedish users jointly.

3.1.3.1 Prediction on Italian non-users sample

The confusion matrix resulting from the *Scorer* defined in methodology is reported in the Figure 4 below.

The real classes are listed in the rows of the matrix, while the classes predicted by the trained decision tree are in the columns. Synthetic indicators of the quality of the decision tree predictor are the accuracy, the error (complement of the accuracy) and the Cohen's kappa, which varies between zero and one.

The accuracy represents the number of correctly classified elements over the total number of cases, while the Cohen's kappa is a statistical measure of the degree of agreement or concordance between two independent raters, that takes into account the possibility that agreement could occur by chance alone (Salkind, 2010). A range of kappa between 0.61 and 0.80 indicates substantial agreement, while larger values indicate near perfect agreement.

It is worth stressing that the total number of users is bigger than the real one, because of the SMOTE technique in which lower classes are oversampled in order to obtain a balanced dataset (see the above methodological section and technical Appendix 2: Decision tree workflow for details). After

SMOTE, all car sharing users' profile have the same number of elements of the larger class (FFOA in the Italian case).

q31_user_...	FFPS	FFOA	MultiOC	RTSB
FFPS	304	9	70	2
FFOA	22	310	24	18
MultiOC	64	33	284	5
RTSB	3	20	5	357

Correct classified: 1.255 Wrong classified: 275

Accuracy: 82,026 % Error: 17,974 %

Cohen's kappa (κ) 0,76

Figure 4: Confusion matrix of the decision tree trained on Italian socioeconomic variables

Additionally, accuracy statistics such as True-Positives (e.g. real number of FFOA users that are correctly predicted), False-Positives, True-Negatives, False-Negatives are reported in Figure 5 below.

Row ID	TruePo...	FalsePo...	TrueNe...	FalseN...	Recall	Precision	Sensitivity	Specifity	F-meas...
FFPS	304	89	1056	81	0.79	0.774	0.79	0.922	0.781
FFOA	310	62	1094	64	0.829	0.833	0.829	0.946	0.831
MultiOC	284	99	1045	102	0.736	0.742	0.736	0.913	0.739
RTSB	357	25	1120	28	0.927	0.935	0.927	0.978	0.931

Figure 5: Accuracy statistics of the decision tree trained on Italian socioeconomic variables

In Figure 6 the decision matrix evaluated using behavioural variables in the decision tree instead of using socioeconomic variables is reported. The respective accuracy statistics are instead reported in Figure 7: Accuracy statistics of the decision tree trained on Italian behavioural variablesFigure 7.

q31_user_...	FFPS	FFOA	MultiOC	RTSB
FFPS	288	19	79	0
FFOA	17	295	41	27
MultiOC	79	37	262	8
RTSB	0	16	1	369

Correct classified: 1.214 Wrong classified: 324

Accuracy: 78,934 % Error: 21,066 %

Cohen's kappa (κ) 0,719

Figure 6: Confusion matrix of the decision tree trained on Italian behavioural variables

Row ID	TruePo...	FalsePo...	TrueNe...	FalseN...	Recall	Precision	Sensitivity	Specifity	F-meas...
FFPS	288	96	1056	98	0.746	0.75	0.746	0.917	0.748
FFOA	295	72	1086	85	0.776	0.804	0.776	0.938	0.79
MultiOC	262	121	1031	124	0.679	0.684	0.679	0.895	0.681
RTSB	369	35	1117	17	0.956	0.913	0.956	0.97	0.934

Figure 7: Accuracy statistics of the decision tree trained on Italian behavioural variables

Comparing the two previous confusion matrices, the decision tree model has a higher accuracy when socioeconomic variables are considered (82%) instead of behavioural ones (78.9%). In both cases the Cohen's kappa indicates a substantial agreement.

Decision tree predictors (PMML predictor reported in Figure 1 in methodology) were then applied to the Italian non-users sample by separately considering the two models (one with socioeconomic and the other with behavioural variables) with the above described characteristics. The results are showed in Table 17 and Table 18 below.

User profiles	Non-users not in clusters	Non-users clusters		Total
	0	4	5	
FFOA	353 (68.7%)	611 (75.2%)	666 (67.7%)	1630 (70.5%)
FFPS	34 (6.6%)	31 (3.8%)	38 (3.9%)	103 (4.5%)
MultiOC	44 (8.6%)	42 (5.2%)	117 (11.9%)	203 (8.8%)
RTSB	53 (10.3%)	59 (7.3%)	70 (7.1%)	182 (7.9%)
NP	30 (5.8%)	70 (8.6%)	93 (9.5%)	193 (8.4%)
Column Total	514 (100%)	813 (100%)	984 (100%)	2311 (100%)

Table 17: Prediction for Italian non-users sample based on socioeconomic characteristics – absolute values (column percentages)

User profiles	Non-users no cluster	Non-users clusters		Total
	0	4	5	
FFOA	366 (71.2%)	575 (70.7%)	706 (71.7%)	1647 (71.3%)
FFPS	27 (5.3%)	45 (5.5%)	45 (4.6%)	117 (5.1%)
MultiOC	32 (6.2%)	63 (7.7%)	47 (4.8%)	142 (6.1%)
RTSB	81 (15.8%)	113 (13.9%)	168 (17.1%)	362 (15.7%)
NP	8 (1.6%)	17 (2.1%)	18 (1.8%)	43 (1.9%)
Column Total	514 (100%)	813 (100%)	984 (100%)	2311 (100%)

Table 18: Prediction for Italian non-users sample based on behavioural characteristics – absolute values (column percentages)

The two tables are structured as follow:

- In the first column, car sharing users' profiles based on the availability of the specific operational scheme in the country are reported. The "NP" row represents those non-users that have not been classified by the decision tree.

- In the last column, the total number of non-users that could fall within each users' profile is reported.
- In the three central columns the number of non-user either not belonging to any cluster (cluster 0) or belonging to clusters 4 and 5 are reported.

Considering the last column of both tables, the two decision trees give almost the same output: free floating systems with operational area service have the highest number of potential users, i.e. around 70% of non-users. FFPS and MultiOC services almost keep the same number of potential users. The prediction of potential RTSB users is however more complicated: when using behavioural variables, the number of potential users is doubled compared to the number predicted by the decision tree (DT) calibrated on socioeconomic variables. It is not possible to define which one is the most correct, but the accuracy of the behavioural DT might be an explanation of the lowest number of "Not Prediction" that can inflate the other classes (comparing Figure 5 and Figure 7, false positives are higher in the behavioural DT than in socioeconomic one).

When individual clusters are considered, FFOA keeps the highest percentage of potential users and FFPS the lowest one. It is interesting to note the difference in the MultiOC prediction based on socioeconomic characteristics between cluster 4 and cluster 5: within the non-users' cluster 5 there are relatively more potential MultiOC users (11.9% for cluster 5 versus 5.2% for cluster 4 – see Table 19) mainly at the expense of FFOA group, which is in line with the more positive attitude towards car sharing of the cluster 5. However, the same difference between the two clusters is not observed when considering predictions based behavioural characteristics, where MultiOC attracts more non users from cluster 4.

On the contrary, when observing the prediction based on behavioural variables, MultiOC profile loose many potential users in favour of RTSB ones. Once again, the more positive attitude toward car sharing of cluster 5 emerges in FFOA and RTSB potential users compared to cluster 4.

3.1.3.2 Prediction on Swedish non-users sample

Tests carried out on the Italian sample where replicated on the dataset collected in Sweden. In the following Figure 8, Figure 9, Figure 10 and Figure 11 confusion matrices together with the accuracy statistics are reported.

q31_user_...	MultiOC	RTSB	FFOA	FFPS	RTHB
MultiOC	352	29	11	1	0
RTSB	38	269	52	21	13
FFOA	26	31	329	0	7
FFPS	5	13	2	373	0
RTHB	0	9	0	4	380

Correct classified: 1.703 Wrong classified: 262

Accuracy: 86,667 % Error: 13,333 %

Cohen's kappa (κ) 0,833

Figure 8: Confusion matrix of the decision tree trained on Swedish socioeconomic variables

Row ID	TruePo...	FalsePo...	TrueNe...	FalseN...	Recall	Precision	Sensitivity	Specifity	F-meas...
MultiOC	352	69	1503	41	0.896	0.836	0.896	0.956	0.865
RTSB	269	82	1490	124	0.684	0.766	0.684	0.948	0.723
FFOA	329	65	1507	64	0.837	0.835	0.837	0.959	0.836
FFPS	373	26	1546	20	0.949	0.935	0.949	0.983	0.942
RTHB	380	20	1552	13	0.967	0.95	0.967	0.987	0.958

Figure 9: Accuracy statistics of the decision tree trained on Swedish socioeconomic variables

q31_user_...	MultiOC	RTSB	FFOA	FFPS	RTHB
MultiOC	327	42	12	0	12
RTSB	44	280	36	23	10
FFOA	18	32	337	5	1
FFPS	1	14	2	368	8
RTHB	1	18	0	1	373

Correct classified: 1.685 Wrong classified: 280

Accuracy: 85,751 % Error: 14,249 %

Cohen's kappa (κ) 0,822

Figure 10: Confusion matrix of the decision tree trained on Swedish behavioural variables

Row ID	TruePo...	FalsePo...	TrueNe...	FalseN...	Recall	Precision	Sensitivity	Specifity	F-meas...
MultiOC	327	64	1508	66	0.832	0.836	0.832	0.959	0.834
RTSB	280	106	1466	113	0.712	0.725	0.712	0.933	0.719
FFOA	337	50	1522	56	0.858	0.871	0.858	0.968	0.864
FFPS	368	29	1543	25	0.936	0.927	0.936	0.982	0.932
RTHB	373	31	1541	20	0.949	0.923	0.949	0.98	0.936

Figure 11: Accuracy statistics of the decision tree trained on Swedish behavioural variables

Comparing the confusion matrices of the Swedish dataset, once again decision tree model has a higher accuracy when socioeconomic variables are considered (86.7%) instead of behavioural ones (85.6%). In both cases the accuracy is very high and the Cohen's kappa indicates a near perfect agreement.

Decision tree predictions based on socioeconomic variables and on behavioural variables of the Swedish sample are presented in Table 19 and Table 20 below.

Considering prediction results without non-users' subdivision in clusters, the two decision tree give the same output: round trip station based service have the highest number of potential users (60%), followed by FFOA, FFPS, MultiOC and RTHB users' groups, clearly with slight different percentages.

When individual non-users' clusters are considered, non-users with a more positive attitude towards car sharing (cluster 5) are mainly predicted as RTSB potential users.

User profiles	Non-users not in clusters	Non-users clusters		Total
	0	4	5	
FFOA	86 (17.7%)	147 (20%)	174 (18.4%)	407 (18.8%)
FFPS	57 (11.8%)	110 (15%)	83 (8.8%)	250 (11.5%)
MultiOC	40 (8.2%)	57 (7.8%)	82 (8.6%)	179 (8.3%)
RTHB	13 (2.7%)	14 (1.9%)	14 (1.5%)	41 (1.9%)
RTSB	288 (59.4%)	406 (55.3%)	595 (62.8%)	1289 (59.5%)
NP	1 (0.2%)	(0%)	(0%)	1 (0%)
Column Total	485 (100%)	734 (100%)	948 (100%)	2167 (100%)

Table 19: Prediction for Swedish non-users sample based on socioeconomic characteristics – absolute values (column percentages)

User profiles	Non-users not in clusters	Non-users clusters		Total
	0	4	5	
FFOA	89 (18.4%)	180 (24.5%)	168 (17.7%)	437 (20.2%)
FFPS	45 (9.3%)	61 (8.3%)	132 (13.9%)	238 (11%)
MultiOC	23 (4.7%)	42 (5.7%)	44 (4.6%)	109 (5%)
RTHB	20 (4.1%)	18 (2.5%)	30 (3.2%)	68 (3.1%)
RTSB	307 (63.3%)	433 (59%)	574 (60.5%)	1314 (60.6%)
NP	1 (0.2%)	(0%)	(0%)	1 (0%)
Column Total	485 (100%)	734 (100%)	948 (100%)	2167 (100%)

Table 20: Prediction for Swedish non-users sample based on behavioural characteristics – absolute values (column percentages)

The number of potential users of a FFOA car sharing service in cluster 4 is higher than in cluster 5, in both decision trees; FFPS users' prediction differs among the two DT set up: using socioeconomic characteristics cluster 4 is larger than cluster 5 while when it comes to behavioural variables cluster 5 is bigger than cluster 4. In both predictions RTHB potential users are rarely individuated.

3.2 Structural Equation Modelling (SEM)

3.1.2 Confirmatory Factor Analysis

There are many fit indexes reported in the literature of SEM analysis. Quite often, this diversity of tests is reported relying basically on thresholds with no attention for a careful interpretation. In this report, the values of global fit and fit indexes are reported on the Table 21, following the specific interpretations. The parameter estimates are showed on the Appendix 4: Standardized parameter estimates for the measurement model. For each parameter, the first measurement had its coefficient fixed, while the other was set for free variance.

The first index reported is the model chi-square, $\chi 2(d.f. = 482) = 4088.259$, $p < 0.001$. The chi-square statistics test the exact-fit hypothesis that there is no difference between the covariance in the tested model and the population covariance matrix. By rejecting this hypothesis, one may conclude that there is evidence against the given model explanation and that the discrepancies between the given model and the data should be further interpreted. **The binary decision of rejecting or not the hypothesis does not imply that the model should be retained or reject (Kline, 2016).** This argument is based on the fact that the chi-squared test is sensitive to non-normality distribution, correlation size among variables, unique variance of some variables and sample size. For instance, the sample size in this study is considered large for this kind of analysis and it is possible that small discrepancies between the model and the data have led to this p-value.

Although the chi-square test had a significant p-value, the other fit indexes show good fit. **The value of RMSEA is .062 and the 90% confidence interval has a good narrow range (CI = [.060, .063]), giving a strong confidence of good fit.** This index is an indicator of badness-of-fit statistic in which values closer to zero indicates better results. **The fit of the analysed path model is about 91% better than that of the independence model (the null model) (CFI=.919). Moreover, the standardized square root of the average squared covariance residual has an indication of good fit (SRMR = .046).**

Estimator	ML
Model Fit Test Statistic	4088.259
Degrees of freedom	482
P-value (Chi-square)	0.000
Comparative Fit Index (CFI)	0.919
Tucker-Lewis Index (TLI)	0.906
RMSEA	0.062
90 Percent Confidence Interval	[0.060, 0.063]
P-value RMSEA <= 0.05	0.000
SRMR	0.046

Table 21: Confirmatory Factor Analysis - model fit.

3.1.3 SEM interpretation

As showed in Figure 12, the variables in the circles represent latent variables, while those in the squares represent directed measures. Basically they represent the scores from the items in the online questionnaire described in the previous deliverable 4.1.

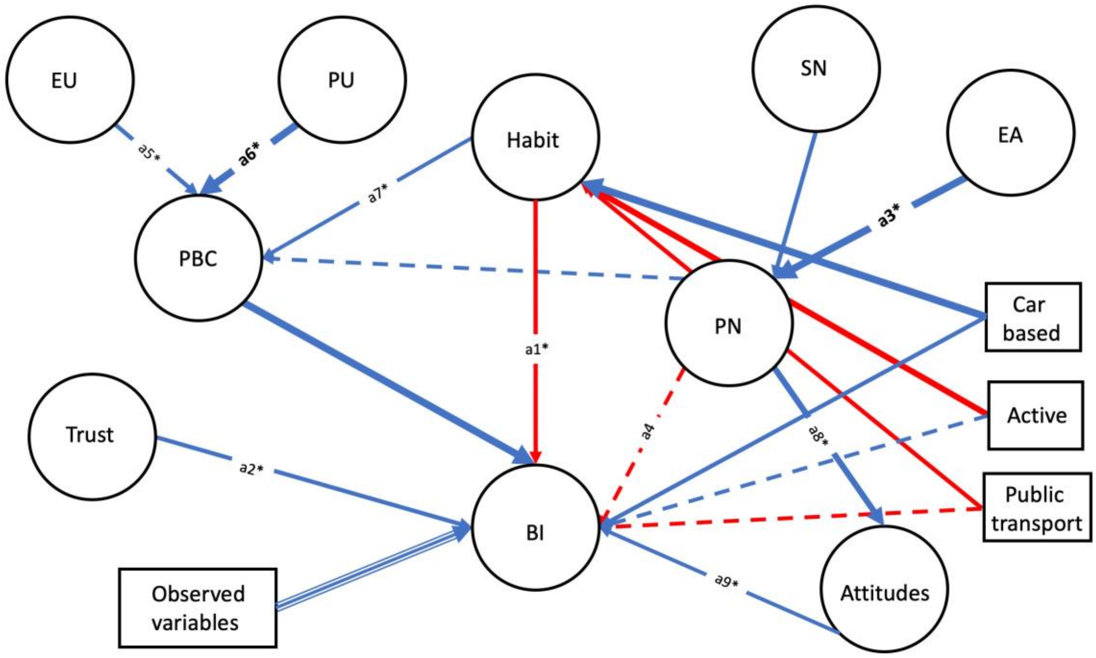
Behavioural Intention is the target variable of investigation and therefore it is an endogenous variable in the model. Based on previous research and theories, it was predicted that BI would have a complex set of relationships among the variables. Those variables specified in the model have direct and indirect effects on BI. The direct effects tested were the effects from attitudes, perceived behaviour control, personal norms, habit, trust, car sharing use, gender, income and age. However, personal norms, income and frequency of past travel by public transport and actively did not show direct effects on the BI.

Personal norms have a double function, as both exogenous and endogenous variable. It was tested as an exogenous variable to affect BI, perceived behaviour control and attitudes. As mentioned before, it did not have a direct effect on BI or on perceived behaviour control, but it had an effect on attitudes. As an endogenous variable, personal norms had social norms and environmental awareness as exogenous variables, both with significant paths.

Perceived behaviour control is also a variable with a double function. It is an exogenous variable for BI, but it is also endogenous for ease of use, perceived usefulness, habit and personal norms. The regression path between ease of use and perceived behaviour control needs further explanation. As it is shown on the Table 22, this path had a negative coefficient (path a5). This is a case of a so called suppression, in which the direction of the coefficient changes in the regression even when the variables are positively correlated (Friedman & Wall, 2005).

A possible explanation for this suppression could be that the variance in perceived behaviour control is already explained by perceived usefulness and habit, leaving no room for further variance explained by the variable ease of use. This explanation is also consistent with the theory. Ease of use and perceived usefulness are variables from the Technology Acceptance Model (TAM) which was built in light of the Theory of Reasoned Action (TRA) that is the basis for the Theory of Planned Behaviour (TPB). One of the factors that all these theories have in common is the importance of individual perception of self-efficacy, in other words, how much people perceive that they have the capability and resources to perform certain behaviours. Given that explanation, ease of use can be seen as a redundant parameter for this specific model once perceived usefulness and perceived behaviour control are already explaining this aspect of prediction of behaviour intention.

A careful approach is needed to interpret the relationships between past car based travels, driving habit and their effect on behavioural intention. The coefficients for the paths from past car based travels to driving habits and to behavioural intention are high and positive, indicating that those that have reported being frequent travellers of car based modes tend to form stronger driving habits and are more likely to use car sharing in the near future. However, the path from habits to behaviour intention is negative, indicating that as the habit for driving a car becomes stronger it is less likely that the driver would choose car sharing for travelling. **In other words, past travels by car based modes leads to driving habit formation, but if this habit becomes stronger, one is less likely to rely on car sharing for their travels.**



Red paths = negative effect; Blue paths = positive effect; Straight line = p-values < .05; Dashed lines = p-values >.05. The thickness of lines represents the effect sizes, thicker lines indicate bigger coefficients.

Observed variables: car sharing use (users or non-users), gender, income, age and number of car sharing services available in the city.

*** Significant indirect effects (a*). Bold indirect effects (a*) indicates stronger relationships.**

Figure 12: Empirical model to predict behavioural intention to use car sharing.

Regression paths:		Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PBC =~							
EU	**(a5)**	-0.235	0.113	-2.075	0.038	-0.160	-0.160
PU	**(a6)**	1.251	0.112	11.119	0.000	0.850	0.850
habit	**(a7)**	-0.073	0.022	-3.258	0.001	-0.079	-0.079
PN		-0.028	0.029	-0.952	0.341	-0.029	-0.029
habit =~							
carbased		1.189	0.038	31.218	0.000	0.741	0.605
active		-0.339	0.023	-14.930	0.000	-0.211	-0.257
public transport		-0.248	0.019	-13.305	0.000	-0.155	-0.232
PN =~							
SN		0.245	0.038	6.352	0.000	0.159	0.159
EA	**(a3)**	1.058	0.044	24.142	0.000	0.688	0.688
attitudes =~							
PN	**(a8)**	0.388	0.022	17.481	0.000	0.512	0.512
BI =~							

attitudes (a9)	0.095	0.033	2.904	0.004	0.078	0.078
PBC	0.470	0.029	16.217	0.000	0.488	0.488
PN (a4)	-0.001	0.026	-0.042	0.967	-0.001	-0.001
habit (a1)	-0.275	0.032	-8.584	0.000	-0.312	-0.312
trust (a2)	0.259	0.036	7.271	0.000	0.182	0.182
(CS)use (b1)	0.312	0.040	7.784	0.000	0.220	0.165
gender (b2)	0.195	0.062	3.133	0.002	0.138	0.065
income (b3)	-0.010	0.011	-0.965	0.335	-0.007	-0.020
age (b4)	-0.141	0.021	-6.701	0.000	-0.100	-0.145
number of services	0.070	0.023	3.033	0.002	0.049	0.065
carbased	0.261	0.053	4.939	0.000	0.184	0.150
active	0.035	0.027	1.336	0.181	0.025	0.030
public transport	-0.029	0.022	-1.346	0.178	-0.021	-0.031

Table 22: Regression paths for the structural model.

The variables included on the square entitled “observed variables” were variables that describe sociodemographic factors without relying on people’s perceptions. The variables were *car sharing use, gender, income, age and number of services on the city of residence*. Within the observed variables, being a user of car sharing service is the strongest predictor of intention to use it in the future. *Gender* and *age* are the following important predictors in this category; while women are more likely to use car sharing in the future, older ages are associated with less intention to use car sharing. The number of services in the city had a small effect size, showing low impact on people’s intention.

It was also defined in this model that the objective measures of age, income, gender and use of car sharing would have direct effect on BI and indirect effects on the paths in which the coefficient are represented by a1, a2, a3, a4, a5, a6., a7, a8 and a9. The coefficients for the objective measures are represented by b1, b2, b3 and b4. The equations are followed described:

PBC ~ a5*EU + a6*PU + a7*habit + PN

habit ~ carbased + active + public_transport

PN ~ SN + a3*EA

attitudes ~ a8*PN

BI ~ a9*attitudes + PBC + a4*PN + a1*habit + a2*trust + b1*(cs)use + b2*gender + b3*income + b4*age + nservices + carbased + active + public_transport

Perceived usefulness (PU) and Environmental awareness (EA) were the variables with stronger indirect effects of use of car sharing, gender and age. Overall, income did not have any indirect effect, neither direct effect on behavioural intention. Moreover, none of the interactions on paths a4 and a5 had significant p-values, indicating that personal norms and ease of use had no interaction effects with use of car sharing, gender, age, and income (see Table 23).

Defined Parameters:						
	Estimate	Std.Err	z-value	P(>| z |)	Std.lv	Std.all
(a1)						
Habit*use	-0.086	0.015	-5.649	0.000	-0.069	-0.052
Habit*sex	-0.054	0.018	-2.927	0.003	-0.043	-0.020
Habit*inc	0.003	0.003	0.958	0.338	0.002	0.006
Habit*age	0.039	0.007	5.192	0.000	0.031	0.045
(a2)						
Trust*use	0.081	0.015	5.239	0.000	0.040	0.030
Trust*sex	0.050	0.018	2.865	0.004	0.025	0.012
Trust*inc	-0.003	0.003	-0.956	0.339	-0.001	-0.004
Trust*age	-0.036	0.007	-4.868	0.000	-0.018	-0.027
(a3)						
EA*use	0.330	0.045	7.408	0.000	0.152	0.114
EA*sex	0.206	0.066	3.107	0.002	0.095	0.044

EA*inc	0.011	- .011	0 0.964	- .335	0 0.005	· 0.014	-
EA*age	0.149	- .023	0 6.457	- .000	0 0.069	· 0.100	-
(a4)							
PN*use	0.000	- .008	0 0.042	- .967	0 0.000	· 0.000	-
PN*sex	0.000	- .005	0 0.042	- .967	0 0.000	· 0.000	-
PN*inc	000	0. .000	0 .042	0 .967	0 .000	(.000	0
PN*age	000	0. .004	0 .042	0 .967	0 .000	(.000	0
(a5)							
EU*use	0.073	- .037	0 2.005	- .045	0 0.035	· 0.026	-
EU*sex	0.046	- .027	0 1.730	- .084	0 0.022	· 0.010	-
EU*inc	002	0. .003	0 .875	0 .382	0 .001	(.003	0
EU*age	033	0. .017	0 .983	1 .047	0 .016	(.023	0
(a6)							
PU*use	390	0. .061	0 .378	6 .000	0 .187	(.141	0
PU*sex	244	0. .081	0 .016	3 .003	0 .117	(.055	0
PU*inc	0.013	- .013	0 0.961	- .336	0 0.006	· 0.017	-
PU*age	0.177	- .031	0 5.740	- .000	0 0.085	· 0.124	-

(a7)							
Habit*use	121	0. .017	0 .111	7 .000	0 .113	(.085	0
Habit*sex	076	0. .025	0 .084	3 .002	0 .070	(.033	0
Habit*inc	0.004	- .004	0 0.964	- .335	0 0.004	· 0.010	-
Habit*age	0.055	- .009	0 6.257	- .000	0 0.051	· 0.075	-
(a8)							
PN*use	0.023	- .008	0 3.005	- .003	0 0.017	· 0.013	-
PN*sex	0.014	- .006	0 2.258	- .024	0 0.011	· 0.005	-
PN*inc	001	0. .001	0 .925	0 .355	0 .001	(.002	0
PN*age	010	0. .004	0 .930	2 .003	0 .008	(.012	0
(a9)							
Attit ude*use	030	0. .011	0 .707	2 .007	0 .017	(.013	0
Attit ude*sex	018	0. .009	0 .123	2 .034	0 .011	(.005	0
Attit ude*inc	0.001	- .001	0 0.915	- .360	0 0.001	· 0.002	-
Attit ude*age	0.013	- .005	0 2.652	- .008	0 0.008	· 0.011	-

Table 23: Estimates of indirect effects on the structural model.

3.3 Workshop

In general the participants of the workshop view the presented STARS results as interesting and relevant. Two questions were pointed out to be especially relevant:

1. Do the use of car sharing and the impact of car sharing on travel behaviour differ with different car sharing variants?
2. Which attitudes, circumstances and service-features are relevant for the conversion of non-users to car sharing?

Participants of the workshop see the STARS results as evidence, that question (1.) can be answered with “yes”. They also see evidence in the STARS results that the use and impacts of car sharing varies in different countries. Participants suspect that these differences are connected to the car sharing schemes available there and to differences in attitude towards the private car.

Some participants would like to have more information about the places where respondents in the Italian and Swedish sample live. They suspect that the different access to car sharing offers and to different variants may have influenced the results of the surveys. Participants point out that the effect of low-availability and/or low availability of an accompanying public transport offers becomes even more relevant, if the whole sample is divided into different user-groups or potential target groups.

City representatives point out, that their goal is to reduce car ownership and car use. From this point of view the fact that free-floating-only users generally also own private cars in parallel is disappointing. They conclude that free-floating car sharing has to be connected or combined with roundtrip car sharing to bring car sharing in line with city goals. Some representatives think, that roundtrip car sharing has to be promoted in the first place and free-floating car sharing should be just an addition to that.

In respect to question (2.) participants of the workshop view the UGOT results - namely that perceived usefulness of the car sharing offer influences conversion to car sharing - as very interesting. They discuss “perceived usefulness” with some intensity. Main topics are:

- What is / what leads to perceived usefulness of a shared car from the point of view of a car owner?
- How can operators practically improve perceived usefulness of their service?

Participants recommend that the STARS consortium should elaborate on these questions to strengthen the practical relevance of the STARS findings. As an example the relevance of role models is discussed: there are hints in the STARS research that the availability and convenience of existing car sharing services is underestimated by many non-users. If this is the case, role models of existing, satisfied users might be a good marketing tool to encourage non-users to test the service.

Workshop participants once again recommend to better describe the geographical origin of the respondents of the Swedish sample. They suspect that perceived usefulness of car sharing is connected to the places in town where people live, the length of ways they have to travel daily and the available mobility options they have.

Furthermore many participants stress that conversion to car sharing (or buying a car) is usually connected to a change in the circumstances of life (e.g. end of education, beginning of job, birth of a child, move to another town). They think that this should be considered in the STARS project.

The presentation from POLITO, showing the affinity of different non-user target groups to different car sharing variants is considered to be a step into the right direction by most participants. However many participants criticize the small size of the samples in the POLITO analysis. A recommendation is to look for affinity to car sharing use- and non-use in the first place and not for affinity to different car sharing variants.

City representatives and operator representatives stress, that cities can promote car sharing by installing car sharing stations in public streets, as the City of Bremen does. Many participants agreed, that this is a fundamental measure to show the availability of car sharing for everyone and thus trigger conversion.

4 Conclusion

The aim of the current deliverable was to make an overall assessment of the drivers for behavioural change. The results of this research show that profiles of car sharing users differ among different European countries, according to the existing cultural and sociodemographic differences within the population of those countries. Another explanation to those differences regards the service availability. Existing car sharing systems differ from one country to another, and even among different cities in the same country, as already seen in previous STARS deliverables (D2.1). Therefore, it is hard to define common trends and generalise such results, since the samples analysed here are not representative of any car sharing users' population.

Similarly to what was found in the German case study, in the Italian sample free floating users had the least percentage of car-free household, while in Sweden the lowest percentage of car-free households belongs to the free floating with pool stations users. In Italy low percentages of car-free households were encountered among all users, in line with more general national trends.

In Italy free floating users are likely to own more than one subscription (1.5 on average) to the same type of service. The high number of free floating services operating in the same cities with almost the same operational area might be seen as an opportunity for the users to face the critical aspect of the car availability near to the user position, which is a threat that was already detected among users of free floating services (D4.2 STARS report, par. 2.4.3).

Concerning travel habits, a high percentage of car sharing users in Italy (without distinction among car sharing variants to which they are registered) walk every day; higher use of PT is encountered among MultiOC and FFPS users, while FFOA and RTSB users use more their private car.

It is interesting to note that those who mostly use private cars are at the same time those that envisage greater use of car sharing than today, while among those who use it less frequently (MultiOC and FFPS) there is a lower propensity for a greater use in the future. This suggest a greater potential for an increase in car sharing use in the previous group.

Another important finding regards the MultiOC users group: even if all these users are registered to a free floating service in combination with another car sharing typology (FFPS in Italy, RTSB in Sweden and Germany), they use more frequently PT and active modes (walk and bike) and they have higher value of car-free households than the free floating stand-alone users. Therefore, services integration seems to be the key to get better results against the use of private cars and consequently its impacts.

In order to determine potential users among non-users group, user profiles were compared to non-users profiles derived for the two mobility styles' clusters (identified in D4.2), considering the

Italian and Swedish sample separately. Mobility style "Car-focused Ambivalent" represents non-users with strong car habits and the lowest attitudes towards car sharing, while the mobility style "Car-flexible Green" represents non-users with weaker car habits, more likely to adopt car sharing with high environmental awareness.

Considering the Italian sample, as a result of the comparison between users and non-users profiles (built on average characteristics), the Italian non-users sample belonging to the Car-focused Ambivalent cluster might be more attracted by FFOA and RTSB services, while non-users characteristics of the Car-flexible Green cluster best match with those of free floating with operational area.

In Sweden the situation is different. Both non-user clusters have average characteristics that are more aligned with FFPS users, even if the majority of the current users belonging to the Swedish sample of D4.1 have a subscription to a roundtrip service.

Through the use of decision tree with different groups of input variables, it could be concluded that the FFOA service is more likely to grow in terms of number of subscribers in Italy, so a higher potential trend is expected compared to the other services. On the contrary, round trip station based service has the highest number of potential users in Sweden.

Clearly these previsions might be affected to a certain extent by the existence of such services in the cities where the non-users lives.

The strongest direct predictors of behavioural intention (BI) to use car sharing services in a near future were perceived behaviour control (PBC), currently being registered on a car sharing service, past car based travels and trust in the quality of the service delivered. Among these variables, PBC was the most relevant to predict BI. This result indicates that among all behavioural and socioeconomic variables included in the model, this is the most predictive.

PBC has perceived usefulness as its main predictor, it means that the extent that people expect that car sharing will help them to achieve their activities and how useful the service is for them will strongly predict their intention to use it. Moreover, PU's effect on PBC is also indirectly affected by previous use, of car sharing gender and age. The effect of being a current user and female gender are positive and the effect of age is negative, which means that the relationship between PU and PBC is negatively affected by older ages.

The factor measuring the user's gender also have shown some direct and indirect effects. Being female is a positive predictor to BI to use car sharing services and it has positive indirect effects on PU, trust, environmental awareness (EA), habit and attitudes. The direct effect was stronger, but it showed indirect effects in some extent as well.

The number of car sharing operators in the city was not a predictor of behaviour, which indicates that by only increasing the number of operators within cities or fleet sizes is not enough to induce behaviour change. It is necessary to increase the perceived usefulness of car sharing services for people's travel necessities. Women could be a target niche in the market, since that this is a variable with direct effect on BI. Along with that, increasing trust in the service availability and quality is also a possible strategy to foster use of car sharing.

When it comes to travel patterns, the conclusions to be drawn should be carefully interpreted. While past travel have positive direct effects on BI and on driving habit, strong driving habits have a negative direct effect on BI. On interpretation for this result is that **past travel by car based modes leads to driving habit formation, but if this habit becomes stronger, one is less likely to rely on car sharing for their travels.**

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Appendix 1: Results from Kruskal-Wallis and Kruskal post-hoc tests

In this section the results of Kruskal-Wallis test and post-hoc test are reported.

Italian car sharing users

HH_size

```
> kruskal.test(dataset_user.an$q7,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 6.9001, df = 3, p-value = 0.07515
```

Children (Yes/No)

```
> kruskal.test(dataset_user.an$q8_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q8_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.0122, df = 3, p-value = 0.2602
```

Number of Children

```
> kruskal.test(dataset_user.an$q9,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q9 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 34.595, df = 3, p-value = 1.484e-07
```

Number of cars

```
> kruskal.test(dataset_user.an$q13,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q13 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 0.83168, df = 3, p-value = 0.8419
```

Number CS subscription

```
> kruskal.test(dataset_user.an$q28,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q28 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 230.64, df = 3, p-value < 2.2e-16
```

Age

```
> kruskal.test(dataset_user.an$q68,dataset_user.an$q31_user_STR)
```

```
        Kruskal-Wallis rank sum test

data:  dataset_user.an$q68 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 16.415, df = 3, p-value = 0.0009323
```

Education

```
> kruskal.test(dataset_user.an$q69,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q69 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.1971, df = 3, p-value = 0.241

> kruskal.test(dataset_user.an$q70,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q70 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.1971, df = 3, p-value = 0.241
```

Income

```
> kruskal.test(dataset_user.an$q71,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q71 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 1.093, df = 3, p-value = 0.7788

> kruskal.test(dataset_user.an$q71_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q71_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 0.49211, df = 3, p-value = 0.9206
```

Gender

```
> kruskal.test(dataset_user.an$q65_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q65_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 9.0045, df = 3, p-value = 0.02923
```

Car opinions

- **I feel strange travelling without a car.**

```
> kruskal.test(dataset_user.an$q14_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 33.07, df = 3, p-value = 3.114e-07
```

- **I use the car without planning ahead.**

```
> kruskal.test(dataset_user.an$q14_2,dataset_user.an$q31_user_STR)
```

```
        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_2 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 12.236, df = 3, p-value = 0.006618
```

- **It would require an effort for me not to use a car.**

```
> kruskal.test(dataset_user.an$q14_3,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 13.349, df = 3, p-value = 0.00394
```

- **Using a car is part of my daily routine.**

```
> kruskal.test(dataset_user.an$q14_4,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 21.565, df = 3, p-value = 8.035e-05
```

- **Using a car is something that I do automatically.**

```
> kruskal.test(dataset_user.an$q14_5,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_5 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 1.9446, df = 3, p-value = 0.584
```

- **I have been using a car for a long time.**

```
> kruskal.test(dataset_user.an$q14_6,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_6 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 18.252, df = 3, p-value = 0.0003903
```

- **Driving a car saves time.**

```
> kruskal.test(dataset_user.an$q14_7,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.7795, df = 3, p-value = 0.1887
```

- **Driving a car makes life easier.**

```
> kruskal.test(dataset_user.an$q14_8,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_8 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 21.839, df = 3, p-value = 7.046e-05
```

Transport modes frequency of use

- **Private car as a driver**

```
> kruskal.test(dataset_user.an$q17_1,dataset_user.an$q31_user_STR)
```

```
        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 8.8155, df = 3, p-value = 0.03185
```

- **Private car as a passenger**

```
> kruskal.test(dataset_user.an$q17_2,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_2 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 22.042, df = 3, p-value = 6.395e-05
```

- **Car sharing**

```
> kruskal.test(dataset_user.an$q17_3,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 8.6435, df = 3, p-value = 0.03443
```

- **Public Transport**

```
> kruskal.test(dataset_user.an$q17_4,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 5.1307, df = 3, p-value = 0.1625
```

- **Motorcycle/ scooter**

```
> kruskal.test(dataset_user.an$q17_5,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_5 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 58.438, df = 3, p-value = 1.268e-12
```

- **Taxi**

```
> kruskal.test(dataset_user.an$q17_6,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_6 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 58.112, df = 3, p-value = 1.488e-12
```

- **Cycling**

```
> kruskal.test(dataset_user.an$q17_7,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test
```

```
data:  dataset_user.an$q17_7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.9421, df = 3, p-value = 0.1761
```

- **Walking**

```
> kruskal.test(dataset_user.an$q17_8,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_8 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.9987, df = 3, p-value = 0.1719
```

Trip purpose/mode

- **Visiting a close relative / friend / relative / family in another town.**

```
> kruskal.test(dataset_user.an$q19_1,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 7.8785, df = 3, p-value = 0.04859
```

- **Running an errand in the city center.**

```
> kruskal.test(dataset_user.an$q19_2,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_2 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 9.3795, df = 3, p-value = 0.02465
```

- **Going out for dinner.**

```
> kruskal.test(dataset_user.an$q19_3,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 2.0924, df = 3, p-value = 0.5535
```

- **Taking an excursion in nice weather.**

```
> kruskal.test(dataset_user.an$q19_4,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 6.8455, df = 3, p-value = 0.07699
```

- **Shopping for groceries.**

```
> kruskal.test(dataset_user.an$q19_5,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_5 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 16.328, df = 3, p-value = 0.0009713
```

- **Visiting a shopping center.**

```
> kruskal.test(dataset_user.an$q19_6,dataset_user.an$q31_user_STR)
```

```
        Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_6 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 9.6302, df = 3, p-value = 0.02199
```

- **Weekend activities.**

```
> kruskal.test(dataset_user.an$q19_7,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 5.4516, df = 3, p-value = 0.1416
```

I will continue to travelling like today

```
> kruskal.test(dataset_user.an$q55_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q55_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 7.8321, df = 3, p-value = 0.04961
```

I will continue to use car sharing

```
> kruskal.test(dataset_user.an$q55_3,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q55_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 2.2642, df = 2, p-value = 0.3224
```

I plan to use the car sharing more than today

```
> kruskal.test(dataset_user.an$q55_4,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q55_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 84.836, df = 3, p-value < 2.2e-16
```

POST-HOC TESTS

Number of children

```
> posthoc.kruskal.conover.test(dataset_user.an$q9,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Conover's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q9 and dataset_user.an$q31_user_STR

        FFOA    FFPS   MultiOC
FFPS    3.4e-05 -      -
MultiOC 6.7e-05 0.9485 -
RTSB    0.4737  0.0087 0.0087

P value adjustment method: holm
Warning message:
In posthoc.kruskal.conover.test.default(dataset_user.an$q9, dataset_user.an$q31
_user_STR) :
  Ties are present. Quantiles were corrected for ties


> posthoc.kruskal.conover.test(dataset_user.an$q9,dataset_user.an$q31_user_STR,
p.adjust="bonf")
        Pairwise comparisons using Conover's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q9 and dataset_user.an$q31_user_STR

        FFOA    FFPS  MultiOC
FFPS    3.4e-05 -     -
MultiOC 8.1e-05 1.000 -
RTSB    1.000   0.013 0.015

P value adjustment method: bonferroni
Warning message:
In posthoc.kruskal.conover.test.default(dataset_user.an$q9, dataset_user.an$q31
_user_STR,  :
  Ties are present. Quantiles were corrected for ties.


>posthoc.kruskal.dunn.test(dataset_user.an$q9,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q9 and dataset_user.an$q31_user_STR

        FFOA    FFPS   MultiOC
FFPS    5.2e-05 -      -
MultiOC 0.0001  0.9501 -
RTSB    0.5014  0.0113 0.0113

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q9, dataset_user.an$q31_us
er_STR) :
  Ties are present. z-quantiles were corrected for ties


>posthoc.kruskal.dunn.test(dataset_user.an$q9,dataset_user.an$q31_user_STR,p.ad
just="bonf")
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q9 and dataset_user.an$q31_user_STR
```

```
        FFOA    FFPS    MultiOC
FFPS    5.2e-05 -       -
MultiOC 0.00012 1.00000 -
RTSB    1.00000 0.01695 0.01975

P value adjustment method: bonferroni
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q9, dataset_user.an$q31_us
er_STR,  :
  Ties are present. z-quantiles were corrected for ties.
```

Number CS subscription

```
> posthoc.kruskal.dunn.test(dataset_user.an$q28,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q28 and dataset_user.an$q31_user_STR

        FFOA    FFPS    MultiOC
FFPS    7.1e-07 -       -
MultiOC < 2e-16 < 2e-16 -
RTSB    0.0092  0.7469  < 2e-16

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q28, dataset_user.an$q31_u
ser_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Gender

```
> posthoc.kruskal.dunn.test(dataset_user.an$q65_1,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q65_1 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC
FFPS    1.000 -     -
MultiOC 0.028 0.048 -
RTSB    1.000 1.000 0.817

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q65_1, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties
```

Age

```
> posthoc.kruskal.dunn.test(dataset_user.an$q68,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q68 and dataset_user.an$q31_user_STR

        FFOA    FFPS    MultiOC
FFPS    0.00065 -       -
MultiOC 0.72989 0.09410 -
```

```
RTSB    0.72989 0.06464 0.72989

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q68, dataset_user.an$q31_u
ser_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Car opinions

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_1,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q14_1 and dataset_user.an$q31_user_STR

        FFOA    FFPS   MultiOC
FFPS    0.0012  -      -
MultiOC 1.1e-05 0.7006 -
RTSB    0.7006  0.0374 0.0099

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_1, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.


> posthoc.kruskal.dunn.test(dataset_user.an$q14_2,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q14_2 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC
FFPS    0.0044 -      -
MultiOC 1.0000 0.0886 -
RTSB    1.0000 1.0000 1.0000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_2, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.


> posthoc.kruskal.dunn.test(dataset_user.an$q14_3,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q14_3 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC
FFPS    0.066 -     -
MultiOC 0.021 1.000 -
RTSB    1.000 0.288 0.238

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_3, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_4,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q14_4 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC
FFPS    0.0023 -      -
MultiOC 0.0016 1.0000 -
RTSB    1.0000 0.4114 0.4114

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_4, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_6,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q14_6 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC
FFPS    0.0029 -      -
MultiOC 0.0149 1.0000 -
RTSB    1.0000 0.2482 0.2980

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_6, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_8,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q14_8 and dataset_user.an$q31_user_STR

        FFOA    FFPS    MultiOC
FFPS    0.00051 -       -
MultiOC 0.00594 1.00000 -
RTSB    1.00000 0.48593 0.61983

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_8, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Transport modes frequency of use

```
> posthoc.kruskal.dunn.test(dataset_user.an$q17_1,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q17_1 and dataset_user.an$q31_user_STR

        FFOA FFPS MultiOC
FFPS    0.31 -    -
MultiOC 0.12 0.56 -
RTSB    0.54 0.31 0.18
```

```
P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_1, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.

> posthoc.kruskal.dunn.test(dataset_user.an$q17_2,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q17_2 and dataset_user.an$q31_user_STR

        FFOA  FFPS MultiOC
FFPS    0.12  -    -
MultiOC 5e-05 0.21 -
RTSB    0.91  0.72 0.20

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_2, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.

> posthoc.kruskal.dunn.test(dataset_user.an$q17_3,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q17_3 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC
FFPS    1.000 -     -
MultiOC 0.026 0.401 -
RTSB    1.000 1.000 1.000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_3, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.

> posthoc.kruskal.dunn.test(dataset_user.an$q17_5,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q17_5 and dataset_user.an$q31_user_STR

        FFOA    FFPS    MultiOC
FFPS    1.8e-07 -       -
MultiOC 1.7e-05 0.5014  -
RTSB    0.0041  3.5e-07 2.7e-06

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_5, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.

> posthoc.kruskal.dunn.test(dataset_user.an$q17_6,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q17_6 and dataset_user.an$q31_user_STR

        FFOA    FFPS    MultiOC
FFPS    1.4e-08 -       -
```

```
MultiOC 5.0e-06 0.44639 -
RTSB    0.10344 2.4e-05 0.00014

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_6, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

I will continue to travelling like today

```
> posthoc.kruskal.dunn.test(dataset_user.an$q55_1,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q55_1 and dataset_user.an$q31_user_STR

        FFOA FFPS MultiOC
FFPS    0.38 -    -
MultiOC 0.14 1.00 -
RTSB    1.00 0.50 0.45

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q55_1, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

I plan to use the car sharing more than today

```
> posthoc.kruskal.dunn.test(dataset_user.an$q55_4,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q55_4 and dataset_user.an$q31_user_STR

        FFOA    FFPS   MultiOC
FFPS    1.2e-13 -      -
MultiOC 5.0e-10 0.6289 -
RTSB    0.7338  0.0056 0.0264

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q55_4, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Swedish car sharing users

HH_size

```
> kruskal.test(dataset_user.an$q7,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q7 and dataset_user.an$q31_user_STR
```

```
Kruskal-Wallis chi-squared = 9.5551, df = 4, p-value = 0.04863
```

Children (Yes/No)

```
> kruskal.test(dataset_user.an$q8_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q8_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 6.5408, df = 4, p-value = 0.1622
```

Number of Children

```
> kruskal.test(dataset_user.an$q9,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q9 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 7.6585, df = 4, p-value = 0.1049
```

Number of cars

```
> kruskal.test(dataset_user.an$q13,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q13 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 28.697, df = 4, p-value = 9.007e-06
```

Number CS subscription

```
> kruskal.test(dataset_user.an$q28,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q28 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 478.81, df = 4, p-value < 2.2e-16
```

Age

```
> kruskal.test(dataset_user.an$q68_t,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q68_t and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 1.1755, df = 4, p-value = 0.8821
```

Education

```
> kruskal.test(dataset_user.an$q71,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q71 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 7.367, df = 4, p-value = 0.1177
```

Income

```
> kruskal.test(dataset_user.an$q72,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q72 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 15.471, df = 4, p-value = 0.003818
```

Gender

```
> kruskal.test(dataset_user.an$q65_1,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q65_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 7.066, df = 4, p-value = 0.1324
```

Car opinions

- **I feel strange travelling without a car.**

```
> kruskal.test(dataset_user.an$q14_1,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 34.628, df = 4, p-value = 5.54e-07
```

- **I use the car without planning ahead.**

```
> kruskal.test(dataset_user.an$q14_2,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_2 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 30.195, df = 4, p-value = 4.468e-06
```

- **It would require an effort for me not to use a car.**

```
> kruskal.test(dataset_user.an$q14_3,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 16.695, df = 4, p-value = 0.002215
```

- **Using a car is part of my daily routine.**

```
> kruskal.test(dataset_user.an$q14_4,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 24.116, df = 4, p-value = 7.57e-05
```

- **Using a car is something that I do automatically.**

```
> kruskal.test(dataset_user.an$q14_5,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test
```

```
data:  dataset_user.an$q14_5 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 22.644, df = 4, p-value = 0.0001491
```

- **I have been using a car for a long time.**

```
> kruskal.test(dataset_user.an$q14_6,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_6 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 17.377, df = 4, p-value = 0.001633
```

- **Driving a car saves time.**

```
> kruskal.test(dataset_user.an$q14_7,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 12.369, df = 4, p-value = 0.01481
```

- **Driving a car makes life easier.**

```
> kruskal.test(dataset_user.an$q14_8,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q14_8 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 18.525, df = 4, p-value = 0.0009739
```

Transport modes frequency of use

- **Private car as a driver**

```
> kruskal.test(dataset_user.an$q17_1,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 19.443, df = 4, p-value = 0.0006432
```

- **Private car as a passenger**

```
> kruskal.test(dataset_user.an$q17_2,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_2 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 11.44, df = 4, p-value = 0.02204
```

- **Car sharing**

```
> kruskal.test(dataset_user.an$q17_3,dataset_user.an$q31_user_STR)

        Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 3.9815, df = 4, p-value = 0.4085
```

- **Public Transport**

```
> kruskal.test(dataset_user.an$q17_4,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 5.2038, df = 4, p-value = 0.267
```

- **Motorcycle/ scooter**

```
> kruskal.test(dataset_user.an$q17_5,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_5 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 12.905, df = 4, p-value = 0.01175
```

- **Taxi**

```
> kruskal.test(dataset_user.an$q17_6,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_6 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 17.088, df = 4, p-value = 0.001858
```

- **Cycling**

```
> kruskal.test(dataset_user.an$q17_7,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 4.0893, df = 4, p-value = 0.3941
```

- **Walking**

```
> kruskal.test(dataset_user.an$q17_8,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q17_8 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 3.4172, df = 4, p-value = 0.4906
```

Trip purpose/mode

- **Visiting a close relative / friend / relative / family in another town.**

```
> kruskal.test(dataset_user.an$q19_1,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_1 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 19.231, df = 4, p-value = 0.0007081
```

- **Running an errand in the city center.**

```
> kruskal.test(dataset_user.an$q19_2,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_2 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 10.303, df = 4, p-value = 0.03562
```

- **Going out for dinner.**

```
> kruskal.test(dataset_user.an$q19_3,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_3 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 2.7728, df = 4, p-value = 0.5965
```

- **Taking an excursion in nice weather.**

```
> kruskal.test(dataset_user.an$q19_4,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_4 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 3.4915, df = 4, p-value = 0.4792
```

- **Shopping for groceries.**

```
> kruskal.test(dataset_user.an$q19_5,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_5 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 6.0511, df = 4, p-value = 0.1954
```

- **Visiting a shopping center.**

```
> kruskal.test(dataset_user.an$q19_6,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_6 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 10.503, df = 4, p-value = 0.03275
```

- **Weekend activities.**

```
> kruskal.test(dataset_user.an$q19_7,dataset_user.an$q31_user_STR)

	Kruskal-Wallis rank sum test

data:  dataset_user.an$q19_7 and dataset_user.an$q31_user_STR
Kruskal-Wallis chi-squared = 15.503, df = 4, p-value = 0.003764
```

POST-HOC TESTS

HHsize

```
> posthoc.kruskal.dunn.test(dataset_user.an$q7,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                          comparisons of independent samples
data: dataset_user.an$q7 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC RTHB
FFPS    1.000 -     -       -
MultiOC 0.264 0.960 -       -
RTHB    0.960 0.960 0.049   -
RTSB    1.000 1.000 0.104   0.672

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q7, dataset_user.an$q31_us
er_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

HHcars

```
> posthoc.kruskal.dunn.test(dataset_user.an$q13,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                          comparisons of independent samples
data: dataset_user.an$q13 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    0.9758 -      -       -
MultiOC 0.0251 0.0072 -       -
RTHB    0.0450 0.0146 1.0000  -
RTSB    0.0015 0.0016 1.0000  1.0000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q13, dataset_user.an$q31_u
ser_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Number CS subscription

```
> posthoc.kruskal.dunn.test(dataset_user.an$q28,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                          comparisons of independent samples
data: dataset_user.an$q28 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    1      -      -       -
MultiOC <2e-16 <2e-16 -       -
RTHB    1      1      <2e-16  -
RTSB    1      1      <2e-16  1

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q28, dataset_user.an$q31_u
ser_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Income

```
> posthoc.kruskal.dunn.test(dataset_user.an$q72,dataset_user.an$q31_user_STR)
        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples
data: dataset_user.an$q72 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC RTHB
FFPS    0.470 -     -       -
MultiOC 1.000 0.753 -       -
RTHB    1.000 1.000 1.000   -
RTSB    0.014 1.000 0.122   1.000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q72, dataset_user.an$q31_u
ser_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Car opinions

- **I feel strange travelling without a car.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_1,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_1 and dataset_user.an$q31_user_STR

        FFOA    FFPS    MultiOC RTHB
FFPS    0.19641 -       -       -
MultiOC 0.01227 1.00000 -       -
RTHB    0.00035 0.34232 0.34534 -
RTSB    3.5e-07 1.00000 1.00000 0.40238

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_1, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **I use the car without planning ahead.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_2,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_2 and dataset_user.an$q31_user_STR

        FFOA    FFPS   MultiOC RTHB
FFPS    1.0000  -      -       -
MultiOC 0.0197  0.4182 -       -
RTHB    0.0024  0.0525 0.5215  -
RTSB    1.8e-05 0.1282 1.0000  0.5215

P value adjustment method: holm
Warning message:
```

```
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_2, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **It would require an effort for me not to use a car.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_3,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_3 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    1.0000 -      -       -
MultiOC 0.0896 0.4808 -       -
RTHB    0.1048 0.4105 1.0000  -
RTSB    0.0041 0.4105 1.0000  1.0000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_3, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Using a car is part of my daily routine.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_4,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_4 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    1.0000 -      -       -
MultiOC 0.2423 0.3432 -       -
RTHB    0.0560 0.0817 0.9030  -
RTSB    0.0007 0.0437 1.0000  1.0000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_4, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Using a car is something that I do automatically.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_5,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_5 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    1.0000 -      -       -
MultiOC 0.1226 0.3976 -       -
RTHB    0.0440 0.1226 1.0000  -
RTSB    0.0006 0.1226 1.0000  1.0000
```

```
P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_5, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **I have been using a car for a long time.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_6,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_6 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    1.0000 -      -       -
MultiOC 0.0997 1.0000 -       -
RTHB    0.0043 0.2049 0.4429  -
RTSB    0.0060 1.0000 1.0000  0.2105

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_6, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Driving a car saves time.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_7,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_7 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC RTHB
FFPS    0.723 -     -       -
MultiOC 1.000 0.387 -       -
RTHB    0.681 0.123 1.000   -
RTSB    0.415 0.039 1.000   1.000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_7, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Driving a car makes life easier.**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q14_8,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                         comparisons of independent samples

data: dataset_user.an$q14_8 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC RTHB
FFPS    0.795 -     -       -
MultiOC 0.481 0.220 -       -
RTHB    0.048 0.029 0.554   -
```

```
RTSB    0.031 0.037 0.795   0.554

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q14_8, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Transport modes frequency of use

- **Private car as a driver**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q17_1,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                                 comparisons of independent samples

data: dataset_user.an$q17_1 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    0.3775 -      -       -
MultiOC 0.2819 0.0768 -       -
RTHB    0.0094 0.0013 0.1948  -
RTSB    0.1710 0.0336 0.7606  0.0768

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_1, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Private car as a passenger**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q17_2,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                                 comparisons of independent samples

data: dataset_user.an$q17_2 and dataset_user.an$q31_user_STR

        FFOA  FFPS  MultiOC RTHB
FFPS    1.000 -     -       -
MultiOC 1.000 1.000 -       -
RTHB    0.037 0.014 0.117   -
RTSB    1.000 1.000 1.000   0.020

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_2, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Motorcycle/ scooter**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q17_5,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
```

```
                    comparisons of independent samples

data: dataset_user.an$q17_5 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    0.7025 -      -       -
MultiOC 0.4402 1.0000 -       -
RTHB    0.2099 1.0000 1.0000  -
RTSB    0.0049 1.0000 1.0000  1.0000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_5, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

- **Taxi**

```
> posthoc.kruskal.dunn.test(dataset_user.an$q17_6,dataset_user.an$q31_user_STR)

        Pairwise comparisons using Dunn's-test for multiple
                    comparisons of independent samples

data: dataset_user.an$q17_6 and dataset_user.an$q31_user_STR

        FFOA   FFPS   MultiOC RTHB
FFPS    0.0086 -      -       -
MultiOC 1.0000 0.1396 -       -
RTHB    1.0000 0.6142 1.0000  -
RTSB    0.0085 0.6142 0.6142  1.0000

P value adjustment method: holm
Warning message:
In posthoc.kruskal.dunn.test.default(dataset_user.an$q17_6, dataset_user.an$q31
_user_STR) :
  Ties are present. z-quantiles were corrected for ties.
```

Appendix 2: Decision tree workflow

All stages of the KNIME's workflow used to build the Decision tree, its calibration and its prediction are described in the following bullet points:

1. **Excel reader:** this function allows toimport the dataset in the KNIME environment. User and non-user Italian, Swedish and joint dataset were imported.
2. **Column filter:** it allows tofilter dataset information by column. Thus, specific input variable for the decision tree were selected among the extensive number of variables collected through the users/non-users survey. The socioeconomic variables considered in the decision tree model as well as the behavioural ones are presented in the below Table 24 and Table 25 respectively.

Question ID[5]	Information
Response ID	Unique respondent's code
Q5	City
Q7	Household size
Q8_1	Presence of children (Y/N)
Q9	Number of children
Q13	Number of cars within the household
Q17_1 ->Q17_8	Use frequency of different transport modes
Q27	Experience with car sharing
Q31_user_STR	Car sharing typology according to D2.1 STARS report
Q65	Gender
Q69	Education
Q71	Income
Cluster	Contains both users (namely 1,2 and 3) and non-users (4 and 5) mobility styles' clusters according to D4.3 STARS report

Table 24: Socioeconomic variables considered in the decision tree

[5] Variable labels from the survey presented in D 4.1

Question ID[6]	Information
Response ID	Unique respondent's code
Q5	City
Q19_1 -> q19_7	Habits on car use and other modes
Q27	Experience with car sharing
Q31_user_STR	Car sharing typology according to D2.1 STARS report
Q46, Q47, Q49, Q50	Attitudes towards car sharing
Q57_1, Q57_2	Environmental awareness
Q59_1, Q59_2, Q59_3	Personal norms
Q61	Green political scale
Q63	Political opinion
Cluster	Contains both users (namely 1,2 and 3) and non-users (4 and 5) mobility styles' clusters according to D4.3 STARS report

Table 25: Behavioural variables considered in the decision tree

3. **Normalizer:** it allows to normalize the data. Features are normalized through a min–max normalization so that each variable stands in a [0,1] range, to provide a value homogeneity with the binary features (Pirra & Diana, 2018).
4. **SMOTE:** The SMOTE (Synthetic Minority Oversampling Technique) method is an advanced method of over-sampling that aims to solve problem of unbalanced sample (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). The principle of this method is to generate new observations in the minority class by interpolating the existing ones: for each observation "i" of the minority class, its k-nearest neighbour is identified; then random neighbours are selected (the number depends on the rate of over-sampling) and artificial observations are spread along the line joining the original observation "i" to its nearest neighbour (Bekkar & Dr. Alitouche, 2013).
5. **X-Partitioner and X-Aggregator:** these two nodes define a cross-validation loop: the partitioner splits the user dataset in five equal-sized partitions, sampled randomly but maintaining the class distributions of the whole dataset, and one of these partitions is used for testing (20% of data) while the others are used for training the classifier (80% of data). The procedure is run five times, so that each partition is used once for testing (Tan, Steinbach, & Kumar, 2005). At the end of the loop the aggregator node collects the results from each iteration.

[6] Variable labels from the survey presented in D 4.1

6. **Decision Tree Learner:** this algorithm builds a function that best fits the relationship between the attribute set and class label (class column) of the input training dataset. One of the main problems of decision tree is the training data overfitting, which means that the training data are fitted too well by the tree (and the tree is too large). Pruning should reduce the size of a learning tree without reducing predictive accuracy. There are many techniques for tree pruning that differ in the measurement that is used to optimize performance.
   In Figure 13 below a screenshot of one iteration is reported for illustrative purposes, where an early stopping or pre-pruning is adopted instead of pruning. Pre-pruning is an alternative method to prevent overfitting that stop the tree-building process early, before it produces leaves with very small samples. In all tests carried out a minimum number of records per leaf was set up (5).

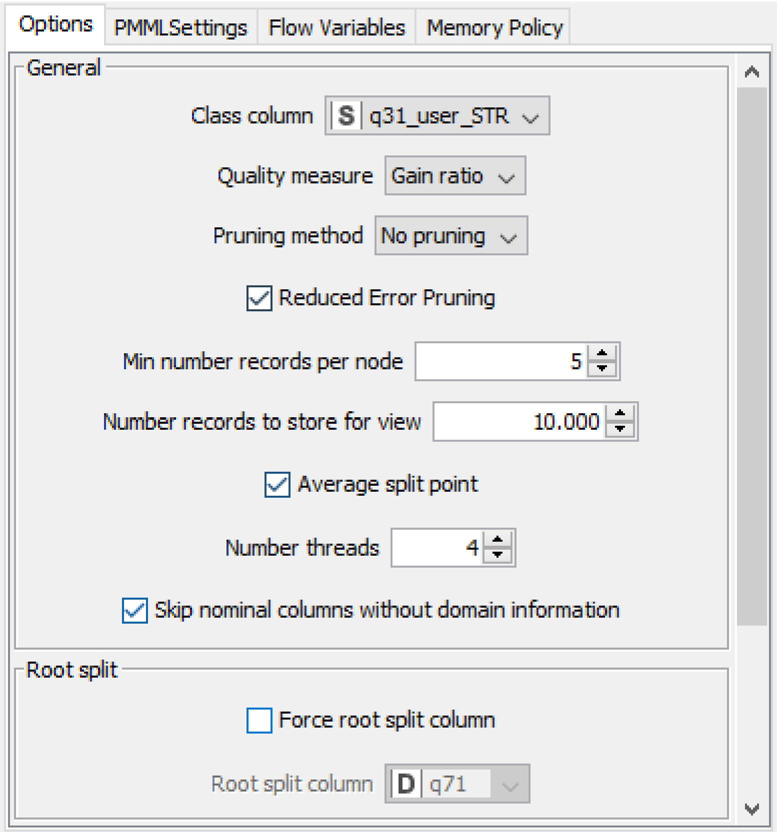

Figure 13: Decision Tree learner set-up

7. **Decision Tree Predictor:** once the learner ends the training with the respective dataset, it provides a function as output. This function is then applied with the test dataset as input of the predictor algorithm. The output of the predictor is the class feature we previously set-up.
8. **Scorer:** the scorer takes in input the Decision Tree Predictor outcomes and compare the predicted class of each record with the real belonging class. The outputs are the global accuracy [the percentage of right classified items], the error [percentage of wrong classified

items] and the confusion matrix. The confusion matrix shows the distribution of the predicted classes amongst the real classes.
The accuracy statistics table allows to understand where the errors in the model prediction are.

9. **PMML predictor :** once concluded calibration (learning) and validation (testing) processes, the parameters settings of the model chosen as well as the target function available in the decision tree learner node are applied to the non-users dataset. The output is the prediction of the typology of car sharing for each unknown record.

Appendix 3: Additional Decision tree trained on sociodemographic and behavioural variables of Italian and Swedish users jointly

Confusion matrices, accuracy statistics of the most accurate decision tree trained on jointed characteristics of Italian and Swedish users are reported in this section.

q31_user_...	FFPS	FFOA	MultiOC	RTSB	RTHB
FFPS	303	23	68	25	0
FFOA	21	346	24	25	0
MultiOC	80	28	271	39	2
RTSB	21	30	30	327	9
RTHB	2	0	2	9	407

Correct classified: 1.654 Wrong classified: 438

Accuracy: 79,063 % Error: 20,937 %

Cohen's kappa (κ) 0,738

Figure 14: Confusion matrix of the decision tree trained on socioeconomic variables of Italy and Sweden sample

Row ID	TruePo...	FalsePo...	TrueNe...	FalseN...	Recall	Precision	Sensitivity	Specifity	F-meas...
FFPS	303	124	1549	116	0.723	0.71	0.723	0.926	0.716
FFOA	346	81	1595	70	0.832	0.81	0.832	0.952	0.821
MultiOC	271	124	1548	149	0.645	0.686	0.645	0.926	0.665
RTSB	327	98	1577	90	0.784	0.769	0.784	0.941	0.777
RTHB	407	11	1661	13	0.969	0.974	0.969	0.993	0.971

Figure 15: Accuracy statistics of the decision tree trained on socioeconomic variables of Italy and Sweden sample

q31_user_...	FFPS	FFOA	MultiOC	RTSB	RTHB
FFPS	300	21	75	22	1
FFOA	29	310	45	25	0
MultiOC	79	39	256	45	0
RTSB	14	25	33	336	10
RTHB	0	0	0	8	412

Correct classified: 1.614 Wrong classified: 471

Accuracy: 77,41 % Error: 22,59 %

Cohen's kappa (κ) 0,718

Figure 16: Confusion matrix of the decision tree trained on behavioural variables of Italy and Sweden sample

Row ID	TruePo...	FalsePo...	TrueNe...	FalseN...	Recall	Precision	Sensitivity	Specifity	F-meas...
FFPS	300	122	1544	119	0.716	0.711	0.716	0.927	0.713
FFOA	310	85	1591	99	0.758	0.785	0.758	0.949	0.771
MultiOC	256	153	1513	163	0.611	0.626	0.611	0.908	0.618
RTSB	336	100	1567	82	0.804	0.771	0.804	0.94	0.787
RTHB	412	11	1654	8	0.981	0.974	0.981	0.993	0.977

Figure 17: Accuracy statistics of the decision tree trained on behavioural variables of Italy and Sweden sample

Appendix 4: Standardized parameter estimates for the measurement model

Latent Variables:	Estimate	Std.Err	z-value	P(>|z|)
BI =~				
BI1N	1.000			
BI2T	1.176	0.023	51.080	0.000
BI3T	0.562	0.018	30.616	0.000
habit =~				
H1	1.000			
H2	1.090	0.037	29.838	0.000
H3	1.337	0.037	36.335	0.000
H4	1.431	0.038	38.056	0.000
H5	1.192	0.036	33.213	0.000
H6	0.975	0.037	26.176	0.000
H7	0.958	0.030	31.452	0.000
H8	0.984	0.032	30.277	0.000
H9	0.962	0.028	34.861	0.000
EA =~				
EA1	1.000			
EA2	0.916	0.016	57.370	0.000
PN =~				
PN1	1.000			
PN2	0.908	0.019	48.374	0.000
SN =~				
SN1T	1.000			
SN2T	1.337	0.039	33.991	0.000
SN3T	1.160	0.036	31.857	0.000
PBC =~				
PBC1T	1.000			

PBC2T	1.151	0.036	32.406	0.000
attitudes =~				
A1	1.000			
A2	0.929	0.026	35.986	0.000
A3T	1.009	0.031	32.829	0.000
A4T	0.577	0.029	20.141	0.000
A5T	0.172	0.028	6.141	0.000
trust =~				
T1T	1.000			
T2T	0.949	0.020	47.314	0.000
T3T	1.016	0.019	52.298	0.000
EU =~				
EE1T	1.000			
EE2T	1.283	0.029	43.992	0.000
EE3T	0.319	0.025	12.900	0.000
PU =~				
PE1T	1.000			
PE2T	1.039	0.025	40.958	0.000

Appendix 5: Diagram with standardized paths for the Structural Model