Interreg
EUROPEAN UNION
2 Seas Mers Zeeën
MOBI-MIX
European Regional Development Fund

# Did shared mobility pilots reduce $CO_2$ emissions and car usage in the five MOBI-MIX cities?

*D3.4.1 Monitoring of demonstrators*

| | |
|---|---|
| **Status** | **Final** |
| **Authors** | **Albert Gragera (Bax & Company)**<br>**Samuel Rouquette (Bax & Company)**<br>**Joan Estrada (Bax & Company)**<br>**Lorena Axinte (Bax & Company)**<br>**Ignacio Magallón (Bax & Company)** |
| **Work package** | **WP3 – Implementation of demonstrators** |
| **Activity** | **A3.4 Performance monitoring (reduction of $CO_2$ and congestion) of the demonstrators** |
| **Dissemination level** | **PU** |
| **Issue date** | **21 December 2022** |

# Table of Contents

## List of figures



## List of tables

# Executive summary

The Interreg 2Seas project, MOBI-MIX, has been showing in the past three and a half years that shared mobility can bring numerous advantages, if cities nurture the collaboration with private mobility providers and together seek to continuously improve services. Partner cities have experimented with various solutions, such as Mobility as a Service (Antwerp), mobility hubs (Norfolk, Valenciennes), shared cars (Rotterdam), shared e-scooters (Norfolk), shared e-cargo bikes and universal transport schemes (Mechelen).

As the project ends in December 2022, we analyse the results of all pilots. Although we recognise that shared mobility might have impacts on various domains (e.g., health, accessibility, road safety, public space, etc.), we focus on $CO_2$ emissions and private car usage, in particular.

To understand the MOBI-MIX pilots' effects, we use the MObility DEcisions framework (MODE), specifically designed to estimate impact at different project stages. The following pages demonstrate the methods' flexibility in different cases, depending on data availability and intrinsic characteristics of the solutions implemented. Still, since data collection was based on surveys, the number of complete responses has been in some cases a limiting factor, preventing us from completing all three stages (exploratory, ex-ante and ex-post analyses) in all five cities.

Nonetheless, our results show that the total $CO_2$ reduction achieved by MOBI-MIX in the mid-term is between 225,51 – 399,91 tons/year. For a similar timeframe, the project should be able to reduce 2.456.416 car veh-km/year. This is a rather conservative estimate since it does not include some of the smaller pilots where data was insufficient for a comparative analysis (e.g., Rotterdam's station-based carsharing pilot, Mechelen's Sharing Neighbourhoods pilot). Still, our results show that the MOBI-MIX project is in line with its initial goals.

To achieve the full potential of shared mobility solutions and reach beyond early adopters, we recommend longer implementation time frames. The cities continuing implementation past the MOBI-MIX project's lifetime should seek to repeat the impact analysis regularly, to understand behaviour changes and tweak mobility solutions accordingly. While cities should continue to monitor $CO_2$ emissions savings, they should also analyse a broader set of impacts related to shared mobility solutions, such as time savings, accessibility, or health. Due to the project's limited scope, we have only lightly considered them, yet cities could expand the MODE analysis to get further insights.

# 1 Introduction

The MOBI-MIX project has supported five European cities – Antwerp, Mechelen, Norfolk, Rotterdam, and Valenciennes – to implement shared mobility solutions and progress towards decarbonising the transport sector. Thanks to this project, cities have developed the expertise and tools to facilitate the implementation in collaboration with private actors, ensuring that new mobility solutions fulfil their potential to improve transport in cities.

Since impact assessment has been embedded in the project from the beginning, MOBI-MIX strived to produce an accurate assessment of the impact of shared mobility, Mobility as a Service (MaaS) and mobility hubs on $CO_2$ emissions and private car use. Filling a knowledge gap, we defined a novel MObility DEcisions framework (MODE) to offer transport decision-makers strategic support in the planning, implementation and assessment of mobility pilots, projects, and policies.

With MODE, we aimed to overcome some of the limitations of the current available evidence, which might be slightly over-optimistic about the potential behavioural changes induced by shared mobility services. Most studies included in our impact repository[1] provided naïve before/after descriptive measures, failing to account for confounding factors (such as age, educational levels, income, etc.). Most studies disregarded factors simultaneously affecting users and non-users, and the systematic differences between those who enrol and those who do not. Thus, these studies might be offering upward biased figures for the different impacts considered.

Accurate impact assessment requires data collection and analysis pre- and post-pilot. For this reason, we designed two surveys to gather users' stated preferences and apply the MODE framework. The methodology allowed understanding who intends to join a given shared mobility solution, as well as their subjective perception regarding their potential travel behaviour adaptations.

Since the MOBI-MIX project focused on carbon emissions and private car km reduction, the current report only investigates these aspects. Nonetheless, the impact assessment method can easily be extended beyond carbon emission to account for impacts on congestion, air pollution, noise, health benefits, traffic safety, and the use of public space. This way, it can provide a much broader impact assessment framework that can help determine the contribution of a shared mobility solution to specific SUMP target goals. The sum of these impacts, as well as the comparison of implementation costs and users' private benefits can be assessed through a simplified cost-benefit analysis. In fact, two of the MOBI-MIX cities (Rotterdam and Norfolk) chose to expand their impact assessment and can now evaluate the welfare benefits of their shared mobility pilots.

[1] The impact repository is a collection of academic and non-academic studies which analyse the impact of shared mobility on aspects such as environmental pollution, travel behaviour, quality of public space, accessibility, health, etc. We developed and used the repository to perform the exploratory analysis, when no real data from pilots was available.

Although all five cities have strived to implement pilots on time and collect the data necessary for the ex-ante and ex-post evaluations, the COVID-19 pandemic has had significant negative impacts. Because of it, pilots have been postponed multiple times, affecting the survey launch, too. In most cases, this has resulted in an insufficient number of answers which prevented us from completing the assessment. Rotterdam and Norfolk are the only two cities where surveys had sufficient answers for the two evaluations, although the high attrition rate in the second survey led to statistically insignificant results in the ex-post analysis. Mechelen and Valenciennes only gathered enough responses in the first survey, allowing us to perform only the ex-ante analysis. In the case of Antwerp, the small number of responses and the different survey structure (simplified to fit the MaaS pilots) prevented us from applying the same methodology altogether. In this case, we have provided a descriptive analysis and a summary of the information available for the three MaaS pilots.

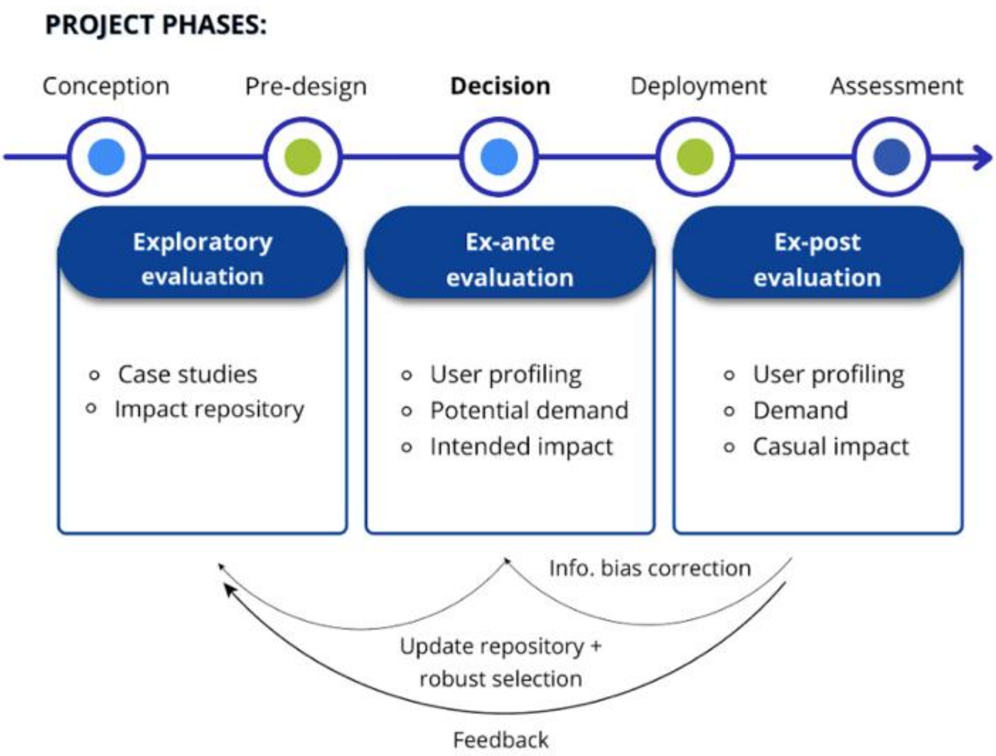
The report continues by introducing the MODE framework and explaining the methodological approach used to evaluate the impact of different shared mobility solutions in MOBI-MIX. Then, section three introduces the five cities, describing their pilots, the potential complications for data collection, and the results of the analysis. The fourth and last section provides a summary of the results and policy recommendations based on the lessons learned in MOBI-MIX.

# 2 Methodological approach

The MOBI-MIX evaluation has used a sequential method to assess the impact of the different shared mobility solutions deployed by cities, tailored to the evidence available at each moment or project phase.

An exploratory analysis was performed in A1.3 (available here) when no pilot-specific evidence was yet available. In this case, the impact assessment was preliminarily conducted based on evidence provided by the review of available similar case studies (gathered in an impact repository) and adapted to some of the characteristics and attributes of both pilots and cities.

***Figure 1. Impact assessment process***




## 2.1 Exploratory analysis

In the exploratory analysis report, we describe partner cities' local contexts and mobility ecosystems, including the mobility goals pursued by each of them. We also provide the details and timelines of the pilots reflecting the situation in June 2021. Wherever situations have changed, we detailed the adjustments in this report. Based on the exploratory impact evaluation described, we assess that all pilots combined are expected to yield a 495 $CO_2$ equivalent tonnes/year reduction around their implementation date (short-run) with a reduction of 3,3M vehicle-km travelled by car. Such figures are higher than the initial target of the project. Additionally, once expected car ownership reductions arise, such impact could increase up to 6.695 $CO_2$ equivalent tonnes/year (long run) with a reduction of 39,5M vehicle-km travelled by car, exclusively driven by pilots involving carsharing solutions (being the only ones with available evidence on car ownership reductions). The sensitivity of results to change depending on values used in the analysis is also reported. This shows that they are relatively robust, but heavily dependent on the transferability of impact assessed in other case studies and the non-negligible limitations of such studies, as explained in the introduction.

Within the current report, we further refine the results of the exploratory analysis. Expanding on the evidence directly linked to the piloted solutions implemented in the different cities, we develop the ex-ante and ex-post evaluations depicted in Figure 1. We collected evidence through two rounds of surveys (pre- and post-pilot, for ex-ante and ex-post analyses, respectively). Using surveys to gather users' stated preferences allows inspecting who intends to join a given shared mobility solution, as well as their subjective perception regarding their potential travel behaviour adaptations.

The surveys included a **travel diary**, where respondents had the option to report the trips they would do on a typical week. The characteristics of the trip included the purpose, the transport mode, the distance, and the frequency (times per week). In the pre-pilot survey (used for the ex-ante analysis), they were also asked which percentage of each trip they were willing to substitute by the shared mobility option being studied in each city. In addition, the survey also asked for socio-economic data, attitudes towards cars, vehicle ownership, and preference towards shared mobility services. The socio-economic profile of the respondents is summarised for each of the five cities in their respective chapters.

## 2.2 Ex-ante evaluation

The **ex-ante evaluation** comes into play before the implementation of a specific shared mobility solution, and assesses the **intended behavioural adaptation subjectively reported by potential users** (including modal shift and car ownership). This offers pilot- and city-specific evidence about the prospective impact with the proposed solution. In this case, we undertake two differentiated approaches: (1) potential demand and within-sample average behavioural change; and (2) preliminary causal impact through matching.

### 2.2.1 Potential demand and within-sample change

Using the first approach we assess the potential demand (and user profiles) a given shared mobility solution will attract through discrete choice models, evaluating how consumers' characteristics, mobility patterns and attitudes affect the respondents' likelihood to enrol in each piloted solution. To do so, using first round survey responses, we first estimate the following **logit model**:

$$logit\ (p) = \alpha + \beta \cdot S + \gamma \cdot MO + \delta \cdot TP + \theta \cdot PC$$

Where,

> $\boldsymbol{p}$ is the probability to join a specific shared mobility service (piloted solutions)
>
> $\boldsymbol{S}$ is a vector of sociodemographic characteristics, including age, gender, household income, and whether there are kids in the household (distinguishing per age groups)
>
> $\boldsymbol{MO}$ is a vector of mobility options at hand, including if respondents hold a public transport subscription, and the number of cars and bikes in their household
>
> $\boldsymbol{TP}$ is a vector of travel pattern variables, including the number of vehicle-km (veh-km) travelled per week by walking, bike, public transport, and private car
>
> $\boldsymbol{PC}$ is included as postcodes fixed effects, to control for potential unobserved heterogeneity in the likelihood to join a shared mobility solution due to unobservable characteristics of the build environment in each neighbourhood

Based on the estimates for this model we compute the marginal effect of each variable included, which yields a measure of how much each of these characteristics can change the probability to join that specific shared mobility solution. This alone can help define the set of potential users' profiles with the highest likelihood to join.

Next, going a step further, we use those figures to predict the probability to join for each of the respondents, measuring the potential demand for a given shared mobility solution. We provide different estimates of potential demand using different probability cut-offs to consider that a given user would enrol in the pilot program, ranging from the 0,5 (standard) up to 0,7 (conservative estimate). These estimates are computed from the aforementioned logit model.

Moreover, by combining this potential demand with intended travel shift to the new mobility solution (included as a question in the respondents' travel diary), we assess the within-sample intended shift in veh-km per mode of those joining the pilot and the associated change in carbon emissions. Such change is estimated based on the carbon emission differentials computed per transport mode making use of standard emission factors[2] (as reported in Table 1). Additionally, in a similar way, we can also assess the intended change in car ownership levels through their intention to purchase or get rid of their car in the following year.



[2] The standard emission factors used come from a Parisian case study for e-scooters, from Fraselle et. al, (2021) for e-cargobikes and from the Handbook of external costs of transports for all other modes.

***Table 1. Emission factors used to compute carbon emissions in the analysis***

| | | Carsharing | | Transit | | | | |
|---|---|---|---|---|---|---|---|---|
| | Car | ICE | EV | Bus | Train | Bike | e-Scooter | Walking |
| gr $CO_2$/pkm | 230 | 200 | 57 | 43 | 20 | 0 | 0 | 0 |
| s.d.: | 60 | 40 | 15 | 15 | 5 | 0 | 0 | 0 |

This way, we obtain the average change in carbon emissions for the subset of respondents reporting their willingness to join the piloted solution. Yet, this means that within those willing to join the piloted solution we might have a high proportion of early-adopters or extremely favourable-types of users reporting a willingness to change their behaviour that is not in line with the general pool of potential users. This is usually the case whenever joining a shared mobility service is voluntary, meaning that we deal with self-selection of users into treatment (assignment to shared mobility is not random, as it would be in a controlled experiment). This means that those users would likely change their behaviour in the absence of the piloted solution too, interfering with the aim of this study, which is measuring the extent to which the piloted solution is causing the change in behaviour. The next section explains how we overcome this issue.

### 2.2.2 Preliminary causal impact through matching

Knowing that the previous method can cause bias in the impact assessment estimates, we devise a second approach that mitigates self-selection. We apply matching techniques to ensure that the sample of users we rely on to assess the behavioural change is similar enough to their non-user counterparts. In a perfect setting, the users in the treatment group (those willing to join the pilot) and their counterparts (those not joining the pilot), would have identical characteristics apart from the willingness to join the pilot. This requires a very large sample of respondents, which was not available in most cases in MOBI-MIX (mostly due to time constraints and reduced pilot scales).

Nonetheless, we use two different matching methods to produce a first tentative causal estimation of the intended impact of a shared mobility solution on travel behaviour and car ownership levels. Both are widely used within the impact assessment literature and are complementary. The first one is **Propensity Score Matching (PSM)**, that takes advantage of the previously estimated logit model to assign each respondent with a propensity score equal to the probability to join given their observable characteristics. This reduces the dimensionality problem of trying to match respondents on several relevant characteristics, summarizing their similarity in a single scoring measure. Once scores are computed, respondents in treatment and control groups are matched using a nearest neighbour algorithm. However, given potential ties derived from completely different combination of characteristics, we can think of PSM as matching users almost at random within the common support area (the space over propensity score where both treated and controls are available for matching), where bias can arise.

The second matching approach implemented is **Coarsened Exact Matching (CEM)**, where treated and controls are matched based on a relevant set of their characteristics if the values lay within specified bins (groups of variables with specific brackets). In our case, this fits perfectly with the already defined bins for the categorical variables set up in the survey and used in the logit model (i.e.: age groups, income brackets, etc.). This technique ensures that respondents matched (treated and controls) have identical observable characteristics for all relevant dimensions, and the only difference between them is their willingness to join the pilot. Additionally, to compensate for matches across combinations of bins with different number of respondents, we apply weights to the regression analysis to obtain a relevant average impact assessment on the treated respondents (for the matched subsample).

Although this method is the most robust option at this project stage, it still faces some **caveats**. First, matching implies pruning the dataset (selecting only some of the data for optimisation purposes). This can be important whenever there is high heterogeneity between treated and controls, meaning there are few comparable respondents from one group to another (small common support). Through this approach, we lose statistical power by reducing the sample size, which might impose some limitation in the method's ability to retrieve statistically significant impact estimates even when there is an impact. This might happen especially when its effect is relatively small compared to the noise in the data. Second, whenever users' selection into treatment depends on unobservable characteristics, matching will still yield biased estimates. To partially overcome this, an ex-post evaluation can take advantage of the before/after comparison of outcomes for both groups. As mentioned in the introduction though, due to reduced number of answers for the second survey, we were only able to perform an ex-post evaluation for Rotterdam and Norfolk.

## 2.3 Ex-post evaluation

This observational study aims to assess the causal impact of each the piloted shared mobility solutions. To do so, the **ex-post evaluation** compares the pre- and post-pilot surveys which reflect the users' behaviour and attitudes at two different moments in time. This way, we can assess the realized change and assign causality. We first provide a couple of simple comparisons that are most commonly found in the reported evidence for other case studies[3], and then move towards the set of estimators that provide causal effect estimates with different levels of robustness. Below we describe their computation, interpretation, and limitations, summarizing them in Figure 2.

The first comparison is a simple **difference across groups (DAG)**, where post-treatment mean values of the outcome variables (travelled distance per mode, car ownership,

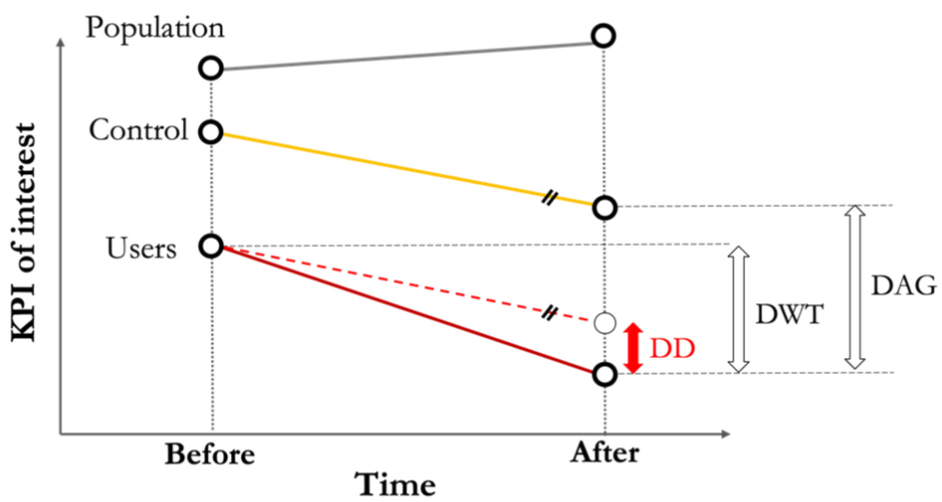


[3] This evidence has been gathered for the exploratory analysis.

intention to sell cars, etc.) of the users joining the pilot is compared to the one of the general population or the control groupFigure 2. While this provides valuable information about the difference in outcomes across groups, it should never be considered a measure of the effect of the piloted solution. The result is a simple reflection of the intrinsic differences across such groups, most likely driven by self-selection of users into treatment (i.e., not joining the new shared mobility solution at random).

The second comparison is a simple **difference within treated (DWT)**, measured as the mean difference in the outcome variable between pre- and post-intervention (before/after), only for users joining the piloted solution, as depicted in Figure 2. This offers valuable insights regarding the extent to which the adopters of a shared solution have changed any given outcome variables post-intervention, as compared to pre-intervention. This is usually the type of evidence reported in studies coming from shared mobility operators, as they tend to rely only on data coming from the users joining their service. This estimator should not be considered as the causal effect of a shared mobility solution on any given outcome variable, as it attributes all changes across time for that group of users to the piloted solution. The estimator disregards ongoing trends and other factors that could have affected the outcomes alongside the implementation of the pilot.

***Figure 2. Visual description and interpretation of the different estimators reported***




The causal impact of the pilots will be determined by the difference in behavioural change among users enrolled in a specific pilot with respect to the changes that occurred in a control group, as suggested in the CIVITAS process and impact evaluation framework. This derives into the **differences-in-differences (DD) estimator**, that is computed as the change in outcomes for the treated group and the change in outcomes for the control group. The first difference controls for factors affecting the treated group that can be assumed constant over time. The second one captures the time-varying factors potentially affecting both groups (assuming they are exposed to the same environment and conditions besides treatment). The DD estimator is then computed by subtracting the second difference from the first one, cleaning all time-varying factors from the change in outcomes for the treated group.

The key identifying assumption for the DD is the parallel trend assumption. This means that the measured impact assumes that treated users would have behaved the same way as control users in absence of the pilot (as parallel yellow and red dashed lines show in Figure 2. In our specific setting we cannot test the validity of such an assumption, as no tracking of both treated and controls is conducted prior to the decision to implement a new shared mobility service. Different control group specifications are designed to test for potential biases on our estimation due to substantial dissimilarities across treated and control groups arising from users' self-selection into the program. We do so by enhancing the DD estimator through a matching procedure that allows for building a subset of data where treatment and control groups are sufficiently similar based on observable characteristics. This is expected to increase the likelihood of the non-existence of time-varying differences across treated and controls.

Specifically, we produce two different estimates based on the matching approaches already introduced in the ex-ante analysis:

(1) **Differences-in-differences with Propensity Score Matching (DD-PSM)**, where treated and controls are matched based on a propensity score estimated on a logit model (probability to join the program)

(2) **Differences-in-differences with Coarsened Exact Matching (DD-CEM)**, where treated and controls are matched within bins of the exact same characteristics (e.g., age, income brackets)

As for the ex-ante analysis, we estimate these different models to assess the impact on travel behaviour (measuring the change in veh-km shifted from each mode) and car ownership levels (measuring the change in the number of registered cars and the intention to purchase/get rid of their car). These are then transformed into carbon emissions using equivalent assumptions as the ones described in the previous subsection.

## 2.4 Further methodological considerations

As with any impact assessment based on survey methods, our approach is liable to certain caveats. Respondents were asked to describe a representative week in their travel diary, to overcome the major risk for recall biases found in retrospective studies (i.e., differences in the accuracy or completeness of the recollections retrieved by study participants regarding events or experiences from the past). The travel diary designed for this study can also lead to biases, depending on how respondents aggregate their travel patterns or simplify them due to survey fatigue. Our hypothesis is that this issue is less important than the problems faced by the studies surveyed for the exploratory analysis. The latter are often based on hypothetical questions that force respondents to reflect on scenarios without the mobility service under study existing at the time of taking the trip. In those scenarios, respondents could have undertaken other behavioural adaptations rather than just mode substitution, without the trip substitution being necessarily long-term. Thus, other studies can be overstating the impact of the mobility service.

It is also worth noting that for some of the pilots, this methodology imposes significant limitations if it is not easy to define the users joining the pilot. This is particularly relevant for mobihubs, as the use of a physical facility would require on-site interviews, which were not feasible to undertake due to the COVID-19 pandemic. Alternatively, data could be obtained through a complex model of collaboration involving all mobility providers of a mobihub. As most pilots have faced delays in implementation, making significant changes to the data collection technique was not possible. To overcome these issues, the surveys were modified to include a few questions that allowed computing the potential modal shift derived from the trips where respondents used mobihubs. Then, we computed carbon emission reductions considering the transport modes that respondents stated they were shifting away from.

# 3 Results

The following sections are structured per city, presenting the results of the impact analysis. For Rotterdam and Norfolk, we provide both ex-ante and ex-post analyses, thanks to the larger number of complete survey responses gathered. Nonetheless, the hight attrition rate in the second survey led to statistically insignificant results in the ex-post analysis. For Mechelen and Valenciennes, only the ex-ante results can be reported due to the limited number of responses for the second survey. In the case of Antwerp, the MaaS pilots' intrinsic characteristics (novelty, start of implementation during the pandemic, etc.) led to a significantly lower number of responses. Since the MODE methodology is not applicable here, we provide insights based on the information shared by MaaS providers, as well as the few survey respondents.

Each section includes a socio-demographic visual which reflects the sample of respondents. While this information might be limited, it still offers an insight into those who might be interested or curious to join and learn about shared mobility options.

## 3.1 Rotterdam

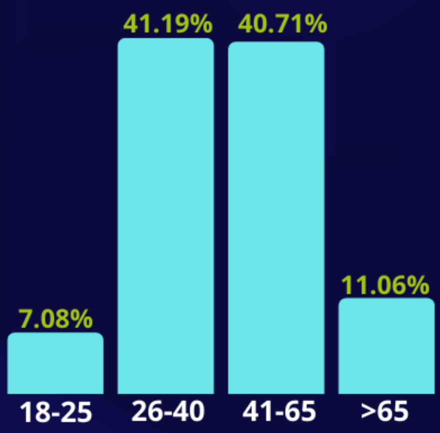
In MOBI-MIX, Rotterdam aimed to test three models of carsharing to understand which (combination of) model(s) is most likely to reduce private car use and $CO_2$ emissions. Since 2021, the city has switched from a completely free market system to a permit-based one, requiring carsharing operators to develop an exploitation plan and deploy only electric vehicles.

The three carsharing models planned were free-floating, station-based, and cooperative-based. The **free-floating** model allows up to 600 electric vehicles not bound to a location, intended to be deployed by three different companies. The location of the **station-based** carsharing model is in Kruispleingarage, where a maximum of 20 cars could operate for one year. The **cooperative-based** model did not materialise during MOBI-MIX due to limited interest. Nonetheless, the city aims to learn from the positive results of other use cases, in cities such as the Hague.

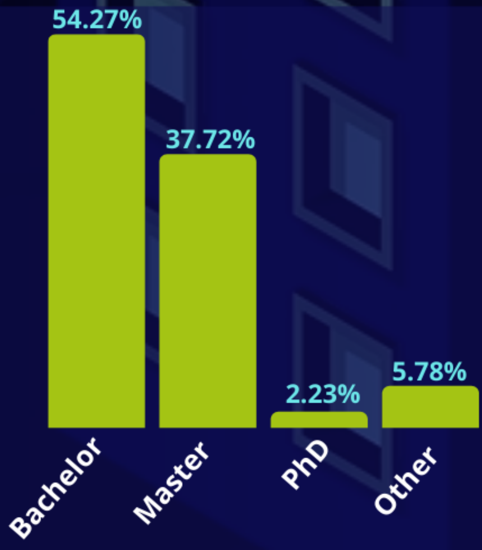
When we conducted the impact assessment, the free-floating model had only 120 active vehicles, and the station based 10. Our analysis is based solely on the free-floating pilot, due to the lack of responses from the station-based survey.

Nonetheless, both pilots are expected to continue developing beyond the MOBI-MIX project lifetime, and we foresee significant benefits resulting from longer implementation time frames.

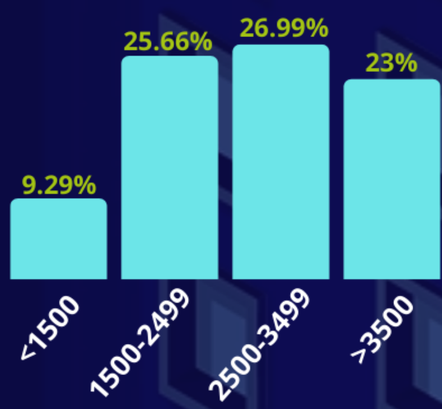
# Who answered the MOBI-MIX survey in Rotterdam?




AGE

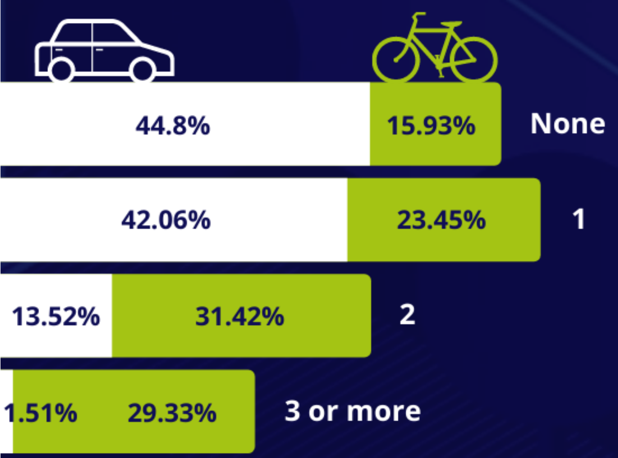



EDUCATION LEVEL

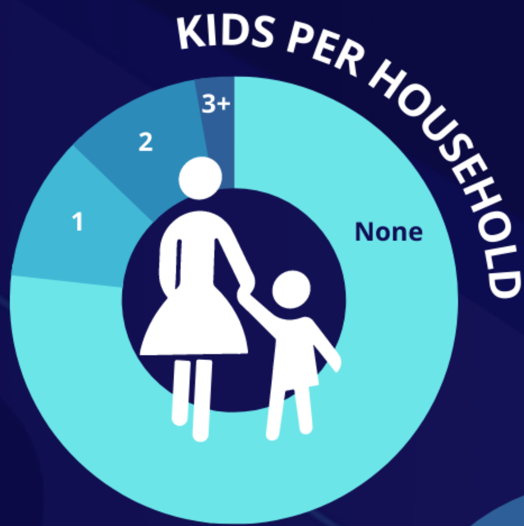


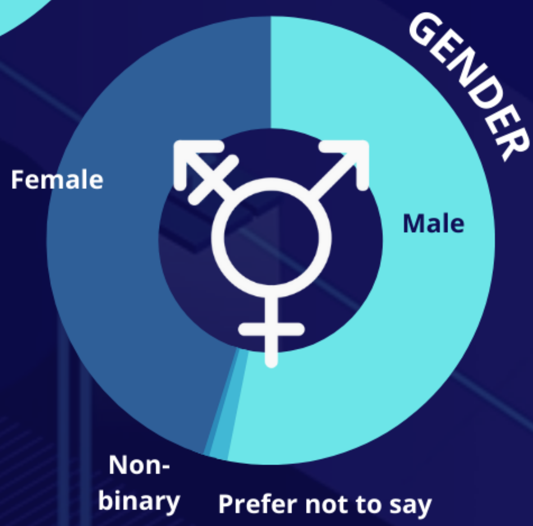

INCOME

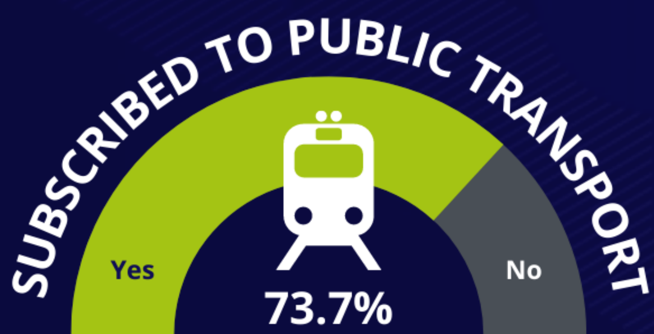
## CARS AND (E-)BIKES PER HOUSEHOLD




N = 811



### 3.1.1 Ex-ante impact assessment

The magnitude of the modal shift and its statistical significance is reduced as we move towards more robust estimates of the intended impact. In this case, preferred estimates at this stage are the ones shown by CEM, where the shift from public transport and private cars towards carsharing is estimated at an average of 1,31 and 9,18 veh-km/week per user, respectively. Table 2below summarises the results of the ex-ante analysis using the three estimators previously described (difference across groups – DAG, propensity score matching – PSM, and Coarsened Exact Matching – CEM).

In a best-case scenario, 32.1% of users would be swapping their private cars in favour of shared cars, whereas only 5.8% would shift away from public transport. These results would require various factors to materialise, such as respondents behaving the same way they reported they would, no barriers like car availability or price occurring, etc. Therefore, the results should be interpreted as an upper bound to the impact of the carsharing program on users' travel behaviour, akin to a best-case scenario for respondents stating their intentions before joining the program and experiencing the service.

The results can be transformed into **total reduction of veh-km travelled by private car** by simply multiplying the weekly effect per user by the number of relevant weeks per year (48, discarding approx. 4 weeks to account for holidays which might show unusual patterns) and the number of users registered so far in the carsharing program (3080 users). This computation results in an intended **reduction of 1,36M veh-km of private car travel per year**, substituted by 1,55M veh-km travelled by carsharing due to the shift away from public transport. We can translate these impacts to **carbon emissions** obtaining a **reduction of 188 Tn of $CO_2$ per year**.

These results are in line in terms of magnitude with the ones obtained in the exploratory analysis: 1,88M veh-km shifting away from private cars and 158 Tn $CO_2$ avoided in the short run, even though the exploratory analysis was based on a larger number of carsharing vehicles deployed (i.e., 460 free-floating vehicles). The ex-ante analysis computations are based on the users enrolled to a free-floating carsharing service with 120 vehicles. Still, the estimation of carbon emissions reduction is higher here due to the shift away from public transport being far lower (5,8%) than the average coming from the case studies in the impact repository (33%), while the shift away from private cars (32,1%) is larger in other similar studies than the one assumed there (24%).

***Table 2. Rotterdam - Results for the ex-ante impact assessment estimates***

| | Ex-ante analysis | | |
|---|---|---|---|
| **OUTCOMES** | **DAG** | **PSM** | **CEM** |
| Walking veh-km travelled per week | 0,418 | 0,106** | 0,00907 |

| | Ex-ante analysis | | |
|---|---|---|---|
| **OUTCOMES** | **DAG** | **PSM** | **CEM** |
| s.e. | (0,315) | (0,046) | (0,0082) |
| Observations | 372 | 233 | 208 |
| R-squared | 0,306 | 0,008 | 0,006 |
| Bicycle veh-km travelled per week | 5,046*** | 4,884*** | 0,548 |
| s.e. | (1,857) | (1,155) | (0,437) |
| Observations | 369 | 230 | 203 |
| R-squared | 0,627 | 0,028 | 0,008 |
| Public transport veh-km travelled per week | 10,29*** | 13,91*** | 1,311*** |
| s.e. | (2,949) | -2,025 | (0,483) |
| Observations | 371 | 233 | 207 |
| R-squared | 0,655 | 0,069 | 0,035 |
| Private car veh-km travelled per week | 26,79*** | 17,23*** | 9,182*** |
| s.e. | (4,804) | (2,432) | (1,876) |
| Observations | 365 | 231 | 203 |
| R-squared | 0,524 | 0,074 | 0,106 |
| Number of cars intended to own by household | -0,175* | -0,035 | 0,00161 |
| s.e. | (0,0990) | (0,239) | (0,0122) |
| Observations | 374 | 234 | 208 |
| R-squared | 0,681 | 0,101 | 0,302 |
| Number of cars intent to purchase in the next year | -0,103 | 0,215 | 0,535 |
| s.e. | (0,217) | (0,462) | (0,573) |
| Observations | 315 | 180 | 203 |
| R-squared | 0,426 | 0,006 | 0,500 |

| | Ex-ante analysis | | |
|---|---|---|---|
| **OUTCOMES** | **DAG** | **PSM** | **CEM** |
| Number of cars intent to sell/scrap in the next year | -0,0790 | 0 | 1,070 |
| s.e. | (0,0683) | 0,145 | (0,749) |
| Observations | 347 | 210 | 207 |
| R-squared | 0,502 | 0,001 | 0,270 |

All models include covariates and postcode fixed effects. Robust standard errors in parentheses. ***p<0,01, **p<0,05, *p<0,1

Covariates are user characteristics of participants, used as "controls" to enhance the preciseness of the analysis. They include age, gender, number of household member, level of education, level of income, detention of driving license and/or transit subscription.

P-values are statistical measures indicating whether the result is statistically significant or not. As an example, a p-value minor than 0,05 (**) means that the result is within 95% confidence interval (in other words, we are 95% sure about it). It quantifies the likelihood of the results to occur by chance alone. A low p-value (5%,**) is the widely accepted threshold in the statistical literature. It indicates that there is at most a 5% chance that the results would have occurred by chance alone.

Focusing on the effects on car ownership levels, we see that there is no statistically significant difference across groups (DAG) on the number of registered cars in the household and their intent to purchase or sell/scrap a car in the next year[4]. After controlling for potential self-selection into treatment based on observable characteristics, this remains the same and no difference arises between those reporting to be willing to join the program and those who do not.

Thus, from an ex-ante analysis perspective, we cannot reject the null hypothesis that there is no differential car ownership or willingness to modify it due to carsharing program enrolment at this stage. This does not come as a surprise knowing that car ownership decisions are taken in a mid- to long-term time frame. When joining a carsharing program, users probably have a hard time foreseeing how much the registration can change the utility they get from ownership. These results suggests that no additional car travel or carbon reductions should be added to previous figures, as no change in car ownerships is likely to materialize in the short run. This means that the exploratory analysis figures would hardly be attained in the upcoming years.[5]

[4] Only a 0,17 lower number of registered cars per household is found at a 10% significance level

[5] Updated figures for the exploratory analysis (based on 120 carsharing vehicles) estimated a potential saving of 8,8M veh-km travel by private car and 1.498 Tn of carbon emissions per year, with an average car ownership reduction of 3 cars / 100 users. Please note these figures assume a complete reduction of the average milage each household does with their private cars (13.700 km/car-year) which households can potentially substitute by other travel modes for occasional travel reducing previous figures. This should be considered a very optimistic potential impact in any case.

### 3.1.2 Ex-post impact assessment

The results show no statistically significant difference between treated and controls in terms of travel behaviour, as also visible in the descriptive estimates DAG (difference across groups) and DWT (difference within treated). The same is evident for DD (differences in differences) and its matching extensions, differences-in differences with Propensity Score Matching (DD-PSM) and differences-in differences with Coarsened Exact Matching (DD-CEM). Table 3 below summarises the results of the ex-post analysis using the different estimators.

The results indicate that we cannot reject the null hypothesis that there is no difference in the travel behaviour of those that joined the carsharing program compared to those who did not. Due to the limited sample we end up with, due to high attrition in response rates across the first and second rounds of the survey, we cannot provide conclusive inference for whether the pilot had no effect (different from zero), or the effect is too small for us to capture it (lack of precision masking the true result).

When focusing on car ownership, we see that the post-treatment difference across groups (DAG) in terms of the number of registered cars is significant, where those joining the carsharing program have on average 0,37 registered cars less than their counterparts. As explained in section 2.3, this figure should not be attributed as a carsharing program effect, as it contains both the difference due to self-selection and the effect of the program. The difference within treated across pre- and post-treatment (DWT) is not significant for the number of registered cars, showing that users kept a similar car ownership level. We observe a statistically significant before/after difference on purchase and selling intent within treated users. However, no significant difference for any of the DD estimates arises, showing that although there is a difference in ownership across groups, it remained constant over the treatment period. Similarly, purchase/selling intent evolved in the same way for both treated and controls (see Table 3).

These results suggest that the program so far has not modified car ownership levels or users' intention to change; that is, not to a degree that we can detect in the short run.

***Table 3. Rotterdam - Results for the ex-post impact assessment estimates***

| | Ex-post analysis | | | | |
|---|---|---|---|---|---|
| **OUTCOMES** | **DAG** | **DWT** | **DD** | **DD-PSM** | **DD-CEM** |
| Walking veh-km travelled /week | 0,501 | -1,791 | -0,175 | 0,664 | 0,174 |
| s.e. | (1,945) | (2,020) | (1,215) | (0,861) | (1,491) |
| Observations | 176 | 135 | 355 | 332 | 135 |

| | Ex-post analysis | | | | |
|---|---|---|---|---|---|
| **OUTCOMES** | **DAG** | **DWT** | **DD** | **DD-PSM** | **DD-CEM** |
| R-squared | 0,322 | 0,395 | 0,206 | 0,009 | 0,328 |
| Bicycle veh-km travelled /week | -2,511 | 2,761 | 2,756 | 2,236 | -14,88* |
| s.e. | (9,486) | (14,05) | (8,458) | (7,762) | (8,322) |
| Observations | 170 | 122 | 332 | 293 | 118 |
| R-squared | 0,515 | 0,442 | 0,357 | 0,001 | 0,497 |
| Public transport veh-km travelled /week | 7,210 | 2,886 | 7,361 | -2,895 | -9,550 |
| s.e. | (12,01) | (21,96) | (10,88) | (10,92) | (18,08) |
| Observations | 175 | 131 | 346 | 311 | 126 |
| R-squared | 0,576 | 0,269 | 0,403 | 0,002 | 0,396 |
| Private car veh-km travelled /week | -17,01 | 59,01 | 9,513 | 0,762 | -16,16 |
| s.e. | (21,12) | (36,55) | (16,27) | (19,88) | (16,13) |
| Observations | 171 | 123 | 337 | 263 | 124 |
| R-squared | 0,545 | 0,723 | 0,531 | 0,016 | 0,465 |
| Number of cars owned by household | -0,369** | 0,261 | 0,145 | 0,177 | 0,198 |
| s.e. | (0,179) | (0,221) | (0,140) | (0,153) | (0,169) |
| Observations | 192 | 142 | 384 | 366 | 144 |
| R-squared | 0,612 | 0,650 | 0,527 | 0,080 | 0,656 |
| Number of cars intent to purchase | 0,105 | -0,511** | -0,107 | -0,118 | -0,133 |
| s.e. | (0,136) | (0,240) | (0,103) | (0,109) | (0,176) |
| Observations | 141 | 107 | 296 | 262 | 106 |
| R-squared | 0,715 | 0,599 | 0,484 | 0,027 | 0,534 |

| | Ex-post analysis | | | | |
|---|---|---|---|---|---|
| **OUTCOMES** | **DAG** | **DWT** | **DD** | **DD-PSM** | **DD-CEM** |
| Number of cars intent to sell/scrap | -0,0302 | -0,0610 | -0,0290 | 0,00313 | -0,0281 |
| s.e. | (0,142) | (0,187) | (0,0907) | (0,0861) | (0,144) |
| Observations | 158 | 123 | 334 | 297 | 122 |
| R-squared | 0,550 | 0,466 | 0,327 | 0,003 | 0,474 |
| Preference for cars vs public transport | -0,785** | -0,491** | -0,571* | -0,583** | -1,099*** |
| s.e. | (0,368) | (0,239) | (0,292) | (0,295) | (0,407) |
| Observations | 162 | 129 | 338 | 296 | 130 |
| R-squared | 0,009 | 0,032 | 0,445 | 0,036 | 0,505 |

All models include covariates and postcode fixed effects. Robust standard errors in parentheses. ***p<0,01, **p<0,05, *p<0,1

Covariates are user characteristics of participants, used as "controls" to enhance the preciseness of the analysis. They include age, gender, number of household member, level of education, level of income, detention of driving license and/or transit subscription.

P-values are statistical measures indicating whether the result is statistically significant or not. As an example, a p-value minor than 0,05 (**) means that the result is within 95% confidence interval (in other words, we are 95% sure about it). It quantifies the likelihood of the results to occur by chance alone. A low p-value (5%,**) is the widely accepted threshold in the statistical literature. It indicates that there is at most a 5% chance that the results would have occurred by chance alone.

We additionally reviewed the impact on the respondents' attitudes towards cars. We assume that changes in perception can lead to potential changes in ownership in the future. As described in Table 3, we find a negative and significant effect on respondents' preference for cars over public transport (i.e., an increase in the preference for public transport over cars). This is explained by the fact that users of the carsharing service reduce their preference for cars (a full category) by 1.1 points within a 0 to 4 Likert scale, equivalent to a 50% reduction from the mean value in our sample.

We believe this can be indicative of potential future changes of behaviour, as the users' exposure to the advantages of carsharing programme could trigger behavioural adaptations over time, especially in terms of car ownership levels.

### 3.1.3 Summary

With respect to the project's target goals, we can see that the impact of carsharing within the pilot time framework is relatively limited and more time is needed for the potential impacts to materialize. This is illustrated in Table 4, which summarizes results for different time frames taking into account the different findings obtained throughout the project.

Mid-term results are extracted from the ex-ante analysis under the assumption that intended behavioural change reported by survey respondents can take some more time to materialize.

Long-term results offer a best-case scenario approach by updating exploratory analysis calculations, adopting the figures of the ex-ante analysis and still assuming an average car ownership reduction of 0,03 cars/user (6% reduction in the motorization rate)[6]. These long-term results would only be attainable if a car ownership reduction of this magnitude is materialized, which might prove to be difficult in light of our impact assessment results.

***Table 4. Rotterdam – Summary of carsharing pilot results***

| | | **Long-term (exploratory)** | **Mid-term (ex-ante)** |
|---|---|---|---|
| **FF** | $\Delta CO_2$ (tn/year) | 1.498 | 188 |
| | $\Delta CAR$ (veh-km/year) | 8.800.000 | 1.360.000 |
| **SB** | $\Delta CO_2$ (tn/year) | 581 | n/a |
| | $\Delta CAR$ (veh-km/year) | 3.368.049 | n/a |

Note: Long-term figures are an adaptation of the exploratory analysis ones as described in footnote 5. Those should be considered as a best-case scenario for the impact of the carsharing program, as assume car ownership reduction and the elimination of all car travel done with the forgone cars.

[6] The car ownership reduction figure is the result of the ex-post DD. The reduction in motorisation is taken from the survey data [(total number of people owning a car at period 0 / total number of people at period 0) / (total number of people owning a car at period 1/ total number of people at period 1)].

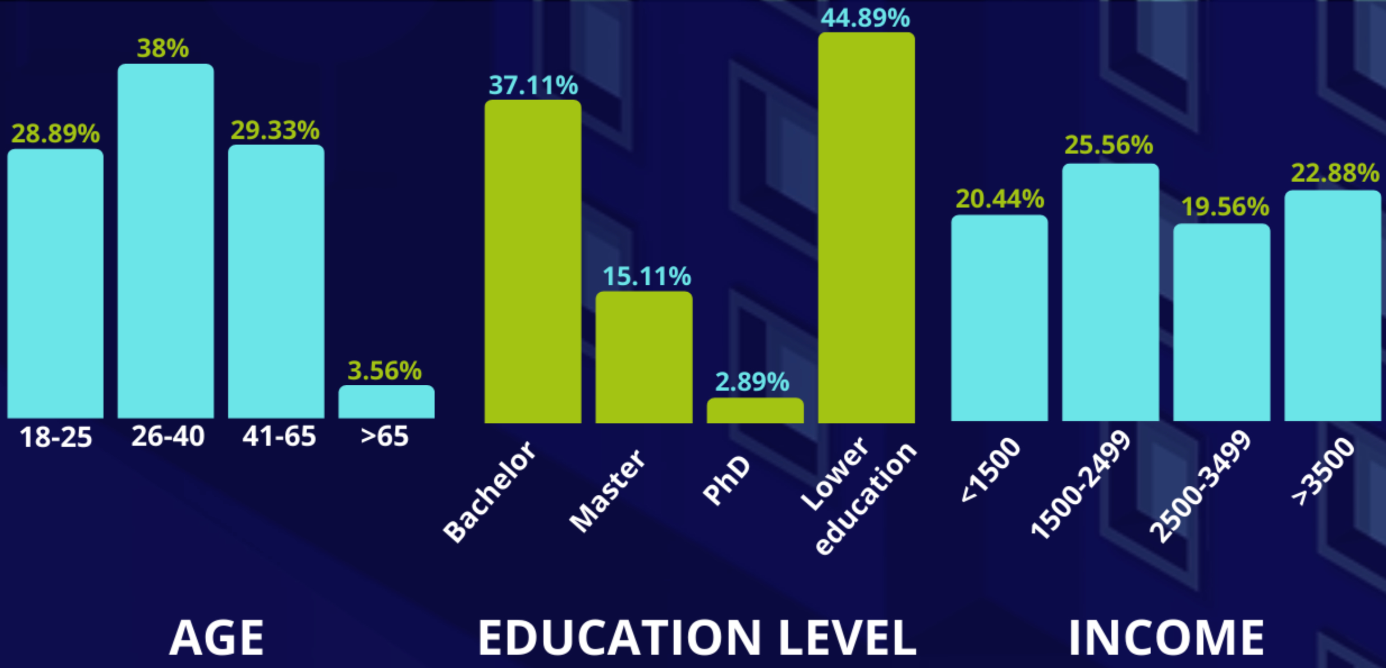
## 3.2 Norfolk

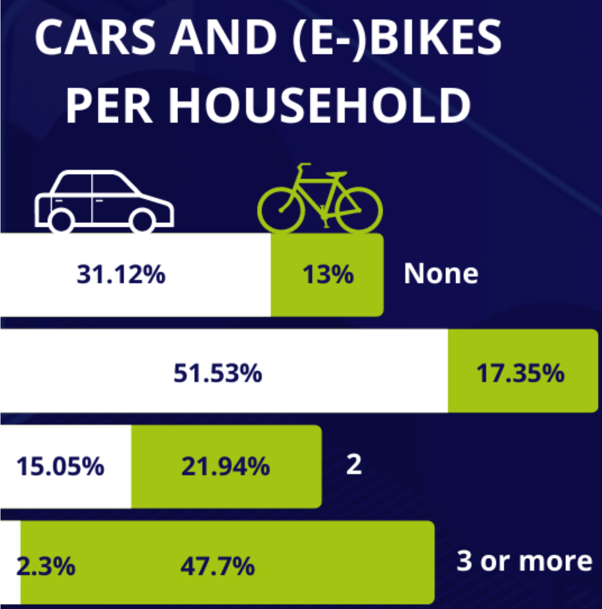
As part of MOBI-MIX, Norfolk County Council started running an e-scooter pilot, as an extension of an existing fleet providing shared bikes and e-bikes. With the onset of pandemic, the UK introduced trials of shared e-scooters to aid socially distanced travel. Before this time, e-scooters were illegal on public roads, and Norfolk has been one of the forerunner cities to find safe and legal options for deployment.

The pilot included around 300 vehicles and around 6300 active users at the time when the impact assessment was conducted.

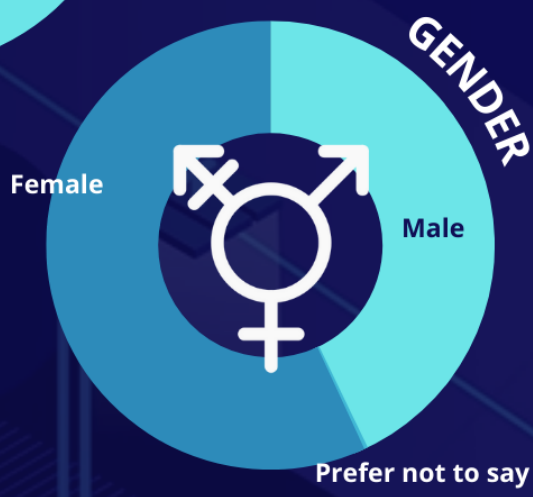
Additionally, Norfolk County Council started implementing mobihubs, with the first two being located at its bus and train stations, and a third being considered for the university campus.

# Who answered the MOBI-MIX survey in Norfolk?

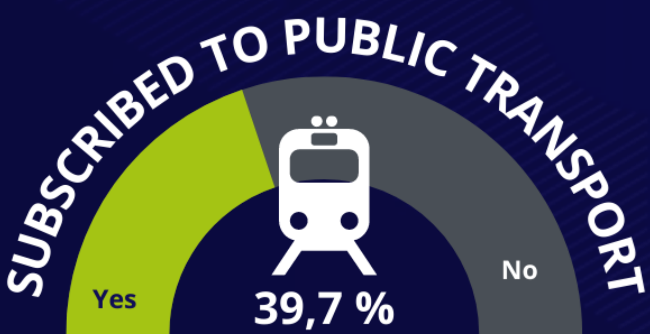







N = 450



### 3.2.1 Ex-ante impact assessment

The results indicate a statistically significant impact of respondents joining the e-scooter pilot in terms of their intended modal share, as they intend to substitute up to 0,7 km per week of walking with e-scooter trips. This implies a 21,5% substitution effect with respect to the mean weekly walking distance reported in our sample (3,3 veh-km), driven by the 19% of users willing to join that intend to substitute on average around 3,6 km per week. In any case, it is important to note that this intended effect estimate is half of the effect reported in other studies that were used for the exploratory analysis (41%). This can be beneficial from a carbon emission perspective, but detrimental for travel time savings. The ex-ante impact assessment results are shown in Table 5

Similarly, we also find a positive and significant intent to substitute private car travel for e-scooters on average of around 1,6 veh-km per week for those willing to join the pilot. This implies a 7% substitution effect from private cars to e-scooters, which is considerably lower than the average estimates reported in the literature (24%) and used in the exploratory analysis. However, this is compensated by a much larger magnitude of travel distance that is subject to potential switch (12,1 veh-km), as compared to the distance reported by other studies.

These results can be transformed into **total veh-km travel reduction by private car** by simply multiplying the weekly effect per user by the number of relevant weeks per year (48, discarding approx. 4 weeks to account for holidays which might show unusual patterns) and the number of average active users at the kick-off of the pilot (around 2000 users). This computation equates to an intended **reduction of 0,16M veh-km of private car travel per year** and **4 to 36 Tn of $CO_2$ per year**, depending on the assumption about e-scooter carbon emission contribution. This ranges from 141 gr $CO_2$/km to virtually 0, depending on the source, operational set-up and most importantly, the lifespan of e-scooters. As mentioned before, these figures are smaller in magnitude than the ones described in the exploratory analysis (i.e., shift of 0,3M veh-km away from private cars and a reduction of 77 Tn $CO_2$ per year).

***Table 5. Norfolk - Results for the ex-ante impact assessment estimates***

| | | Ex-ante analysis | | |
|---|---|---|---|---|
| **INTENDED OUTCOMES** | | **DAG** | **PSM** | **CEM** |
| Walking veh-km travelled per week | | 0,613*** | 0,682*** | 0,717** |
| | s.e. | (0,197) | 0,189 | (0,300) |
| | Observations | 313 | 298 | 153 |
| | R-squared | 0,161 | 0,030 | 0,329 |

| | | Ex-ante analysis | | |
|---|---|---|---|---|
| **INTENDED OUTCOMES** | | **DAG** | **PSM** | **CEM** |
| Bicycle veh-km travelled per week | | 0,117 | -0,139 | 0,155 |
| | s.e. | (0,229) | 0,455 | (0,277) |
| | Observations | 312 | 297 | 153 |
| | R-squared | 0,247 | 0,002 | 0,143 |
| Public transport veh-km travelled per week | | -0,190 | -0,432 | 1,300 |
| | s.e. | (0,691) | 0,815 | (0,861) |
| | Observations | 312 | 297 | 152 |
| | R-squared | 0,445 | 0,000 | 0,157 |
| Private car veh-km travelled per week | | 0,925 | 1,570 | 1,645** |
| | s.e. | (1,868) | 1,699 | (0,649) |
| | Observations | 312 | 297 | 152 |
| | R-squared | 0,428 | 0,000 | 0,290 |
| Number of cars intended to own by household | | -0,0885 | -0,144 | -0,0445 |
| | s.e. | (0,0861) | 0,152 | (0,119) |
| | Observations | 313 | 298 | 153 |
| | R-squared | 0,455 | 0,013 | 0,315 |
| Number of cars intent to purchase in the next year | | 0,0585 | 0,097 | 0,144* |
| | s.e. | (0,0553) | 0,084 | (0,0743) |
| | Observations | 246 | 232 | 118 |
| | R-squared | 0,309 | 0,002 | 0,269 |
| Number of cars intent to sell/scrap in the next year | | -0,00912 | 0,018 | -0,0247 |
| | s.e. | (0,0480) | 0,064 | (0,0498) |
| | Observations | 292 | 277 | 144 |

| | Ex-ante analysis | | |
|---|---|---|---|
| **INTENDED OUTCOMES** | **DAG** | **PSM** | **CEM** |
| R-squared | 0,192 | 0,000 | 0,287 |

All models include covariates and postcode fixed effects. Robust standard errors in parentheses. ***p<0,01, **p<0,05, *p<0,1

Covariates are user characteristics of participants, used as "controls" to enhance the preciseness of the analysis. They include age, gender, number of household member, level of education, level of income, detention of driving license and/or transit subscription.

P-values are statistical measures indicating whether the result is statistically significant or not. As an example, a p-value minor than 0,05 (**) means that the result is within 95% confidence interval (in other words, we are 95% sure about it). It quantifies the likelihood of the results to occur by chance alone. A low p-value (5%,**) is the widely accepted threshold in the statistical literature. It indicates that there is at most a 5% chance that the results would have occurred by chance alone.

As mentioned in the methodology section, we introduced specific questions in the survey to analyse the potential use of mobihubs and the associated modal shift. Based on previous figures on the number of active users and knowing that 51% of respondents make use of the designated location for Norfolk's mobihubs, we compute the potential shift. We multiply the travelled distance per specific mode by the respondents' self-reported visit frequency and likelihood of shift to shared mobility. This approximate estimate, based on around 300 responses, suggests that the potential weekly veh-km shift away from each main transport mode associated to mobihubs would be on average the ones reported in Table 6. As an example, we can say that on average, users intend to substitute 2,5 veh-km driven by private cars for any solutions available in the mobihubs.

Again, these figures can be transformed into **total veh-km travel reduction by private car associated to mobihubs** by simply multiplying the weekly effect per the number of active users reporting to visit the hub by the number of relevant weeks per year (48 weeks). In our calculations, we assume that the entire shift towards shared mobility transfers to shared e-scooters or another mobility mode with a similar carbon emission factor. This computation equates to an intended potential **reduction of 120.000 veh-km of private car travel per year** and **5,6 to 31,1 Tn of $CO_2$ per year.**

***Table 6. Norfolk – Ex-ante estimated mobihub potential veh-km shifting away per mode***

| Variable | Mean | Std. Dev. |
|---|---|---|
| Walking | 0,6022909 | 2,235293 |
| Bike | 0,5368691 | 3,670103 |

| Variable | Mean | Std. Dev. |
|---|---|---|
| Transit | 1,572597 | 8,808917 |
| Car | 2,52498 | 12,40472 |

### 3.2.2 Ex-post impact assessment

The relatively limited sample in the first survey and the high attrition rate in the second hindered a proper application of the different models specified in the ex-post methodology. Paired with the respondents' heterogeneity, these aspects did not allow for detecting any statistically significant effect. This does not necessarily mean that the effect is not present, but that the detection capacity of these models is limited for small sample sizes.

***Table 7. Norfolk - Results for the ex-post impact assessment estimates.***

| | Ex-post analysis | | | | |
|---|---|---|---|---|---|
| **OUTCOMES** | **DAG** | **DWT** | **DD** | **DD-PSM** | **DD-CEM** |
| Walking veh-km travelled per week | 2,923 | -0,714 | 0,874 | 1,300 | -2,546 |
| s.e. | (2,157) | (1,689) | (2,206) | (3,039) | (4,042) |
| Observations | 21 | 78 | 120 | 202 | 85 |
| R-squared | 0,967 | 0,263 | 0,140 | 0,005 | 0,210 |
| Bicycle veh-km travelled per week | 5,700 | -84,85 | -56,94 | -43,75 | -111,1 |
| s.e. | (7,729) | (80,68) | (70,07) | (42,89) | (141,4) |
| Observations | 21 | 78 | 122 | 206 | 88 |
| R-squared | 0,872 | 0,182 | 0,138 | 0,015 | 0,281 |
| Public transport veh-km travelled per week | 23,06 | 14,41* | 21,95* | 1,790 | 29,33 |
| s.e. | (38,04) | (8,467) | (12,88) | (6,899) | (20,49) |
| Observations | 21 | 78 | 122 | 206 | 88 |

| | Ex-post analysis | | | | |
|---|---|---|---|---|---|
| **OUTCOMES** | **DAG** | **DWT** | **DD** | **DD-PSM** | **DD-CEM** |
| R-squared | 0,641 | 0,175 | 0,177 | 0,029 | 0,160 |
| Private car veh-km travelled per week | -95,82 | -10,89 | -6,035 | 1,228 | -36,94 |
| s.e. | (84,96) | (16,03) | (67,71) | (20,69) | (38,81) |
| Observations | 21 | 78 | 122 | 206 | 88 |
| R-squared | 0,728 | 0,329 | 0,300 | 0,009 | 0,424 |
| Number of cars owned by household | 0,710 | 0,00384 | 0,674* | 0,137 | 0,233 |
| s.e. | (0,506) | (0,195) | (0,344) | (0,207) | (0,376) |
| Observations | 21 | 78 | 122 | 206 | 88 |
| R-squared | 0,840 | 0,508 | 0,480 | 0,006 | 0,408 |
| Number of cars intent to purchase | -0 | 0,0165 | 0,135 | 0,0655 | 0,220 |
| s.e. | (0) | (0,142) | (0,205) | (0,117) | (0,405) |
| Observations | 15 | 64 | 100 | 159 | 63 |
| R-squared | 1,000 | 0,347 | 0,224 | 0,013 | 0,283 |
| Number of cars intent to sell/scrap | 0,0494 | -0,0296 | 0,0170 | -0,0517 | 0,114 |
| s.e. | (0,138) | (0,0997) | (0,136) | (0,102) | (0,223) |
| Observations | 19 | 74 | 112 | 182 | 79 |
| R-squared | 0,920 | 0,188 | 0,138 | 0,009 | 0,230 |

All models include covariates and postcode fixed effects. Robust standard errors in parentheses. ***p<0,01, **p<0,05, *p<0,1

Covariates are user characteristics of participants, used as “controls” to enhance the preciseness of the analysis. They include age, gender, number of household member, level of education, level of income, detention of driving license and/or transit subscription.

P-values are statistical measures indicating whether the result is statistically significant or not. As an example, a p-value minor than 0,05 (**) means that the result is within 95% confidence interval (in other words, we are 95% sure about it). It quantifies the likelihood of the results to occur by chance alone. A low

| | Ex-post analysis | | | | |
|---|---|---|---|---|---|
| **OUTCOMES** | **DAG** | **DWT** | **DD** | **DD-PSM** | **DD-CEM** |

p-value (5%,**) is the widely accepted threshold in the statistical literature. It indicates that there is at most a 5% chance that the results would have occurred by chance alone.

Still, we used the ex-ante impact estimates and updated the total veh-km travel reduction by private car and change in carbon emissions with the newly estimated average number of active users (around 6300). We obtained an approximate estimate for a potential **reduction of 0,49M veh-km of private car travel per year** and **13,6 to 114 Tn of $CO_2$ per year.**

Repeating the descriptive approach undertaken for mobihubs during ex-ante assessment, we see that the previously stated shift associated to use is in line with previous results. However, a limited sample does not allow for drawing strong conclusions. Extrapolating ex-ante results to the new estimated number of active users indicates that the shift away from private cars would be approximately **0,36M veh-km per year and a 16 to 90 Tn $CO_2$ reduction**.

### 3.2.3 Summary

The analysis shows that the impact of the e-scooter pilot is relatively limited within the project's timeframe. A longer implementation period could allow the potential impacts to materialize. This is illustrated in Table 8, summarizing applicable results for the different time frames, taking into account the different results obtained throughout the project.

***Table 8. Norfolk – Summary of e-scooter and mobihub pilot results***

| | | **Long-term (exploratory)** | **Mid-term (ex-ante)** | **Short-term (updated ex-ante)** |
|---|---|---|---|---|
| **E-scooter** | $\Delta CO_2$ (tn/year) | n/a | 4 - 36 | 13,6 - 114 |
| | $\Delta CAR$ (veh-km/year) | n/a | 160.000 | 490.000 |
| **Mobihub** | $\Delta CO_2$ (tn/year) | 58 | 5,6 - 31,1 | 16 - 90 |
| | $\Delta CAR$ (veh-km/year) | 359.544 | 120.000 | 360.000 |

Note: We found no evidence for car ownership change. Carbon emission reduction estimates are reported as a range, based on assumptions for e-scooter emission factors (ranging from 0 to 141gr $CO_2$/veh-km). Ex-post estimates are an update of ex-ante methodology instead of the causal inference approach.

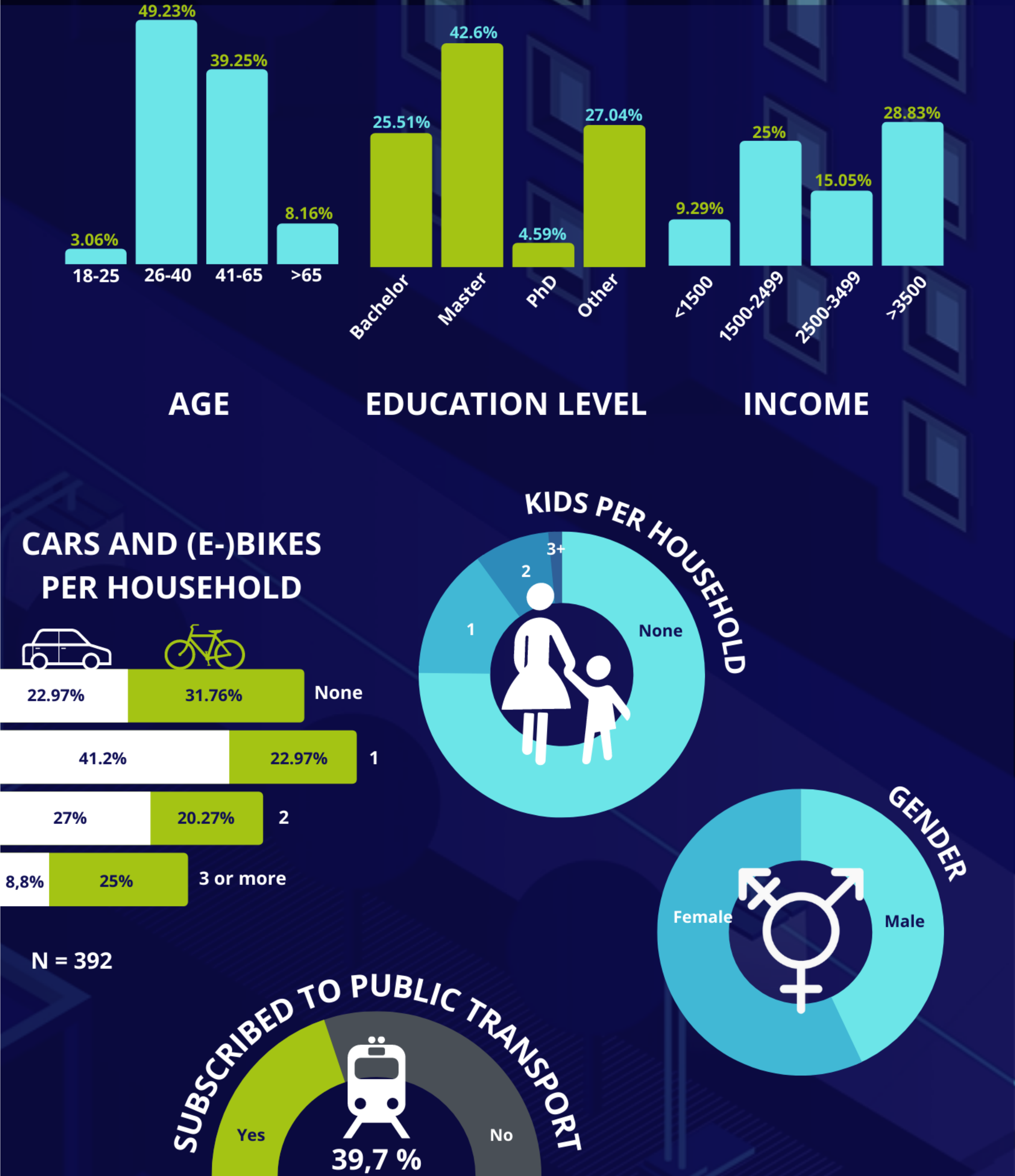
## 3.3 Mechelen

Within MOBI-MIX, Mechelen implemented two different pilots: shared electric cargo bikes and a universal travel allowance scheme, called Sharing Neighbourhoods.

Mechelen has already experimented with shared e-cargo bikes through a previous European project. In MOBI-MIX, the city expanded its fleet from 2 to 9 e-cargo bikes, for an initial agreement of two years with Cargoroo, the e-cargo bike provider, continuing beyond the scope of MOBI-MIX.

The Sharing Neighbourhoods pilot is the second iteration of a universal travel allowance scheme implemented for one month in 2019. During MOBI-MIX, Mechelen expanded the pilot to 2 months, to increase the chances of changing travel behaviour. The initial plan was to offer 30 households from a specific neighbourhood free access to public and shared mobility, to understand the impact on private car use and ownership. However, the pilot ended up engaging 27 persons.

# Who answered the MOBI-MIX survey in Mechelen?



### 3.3.1 Ex-ante impact assessment

Electric cargo bikes

The results indicate a statistically significant impact for respondents joining the e-cargo bike pilot regarding their intended modal share, as they intend to substitute up to 0,32 km per week of walking trips with e-cargo bikes. This translates into an 8,3% substitution effect with respect to the mean weekly walking distance reported in our sample (4,4 veh-km), driven by the 32% of users willing to join that intend to substitute on average around 0,12 km per week. It is worth to note that this intended effect estimate is almost three times bigger than the one reported in the exploratory analysis (3%), suggesting substantial benefits in terms of time saving. The results of the ex-ante analysis for the Cargoroo e-cargo bike pilot in Mechelen are summarised in Table 9.

Nonetheless, for those willing to join the pilot, we also find a negative and significant intention to substitute public transport travel with e-cargo bikes on average of around 4,5 veh-km per week. This implies a 9% increase effect due to e-cargo bikes, contrary to the figure reported in the exploratory analysis (-10%). This effect implicitly suggests that users do not intend to substitute their distance travelled by public transit but rather increase it, as opposed to their distance travelled by cars, which is clearly beneficial in terms of carbon emissions and environmental externalities. In the same line, we observe a significant and negative effect on the number of cars owned by households. Additionally, we see a significant substitution effect from standard bicycles to e-cargo bikes of around 3 veh-km travelled per week. This may suggest that bicycle users need a higher loading capacity for carrying objects or passengers while driving their vehicles.

These figures can be transformed into **total veh-km travel reduction by private car** by simply multiplying the weekly effect per user by the number of relevant weeks per year (48 weeks) and the number of average active users at the kick-off of the pilot (around 60 users). This computation equates to an intended **reduction of 12.373 veh-km of private car travel per year** and **3,1 Tn of $CO_2$ per year.** These figures are in line with the ones estimated in the exploratory analysis (shift of **12.719 veh-km** away from private cars and a reduction of **3 Tn $CO_2$** per year).

***Table 9. Mechelen (cargo-bikes) - Results for the ex-ante impact assessment estimates.***

| | | Ex-ante analysis | |
|---|---|---|---|
| **INTENDED OUTCOMES** | **DAG** | **PSM** | **CEM** |
| Walking veh-km travelled per week | 0,0575 | 0,104 | 0,329** |
| s.e. | (0,102) | (0,0892) | (0,160) |
| Observations | 264 | 253 | 131 |

| | Ex-ante analysis | | |
|---|---|---|---|
| **INTENDED OUTCOMES** | **DAG** | **PSM** | **CEM** |
| R-squared | 0,194 | 0,005 | 0,185 |
| Bicycle veh-km travelled per week | 1,583 | 3,029** | -1,925 |
| s.e. | (1,702) | (1,188) | (1,737) |
| Observations | 262 | 251 | 130 |
| R-squared | 0,284 | 0,025 | 0,160 |
| Public transport veh-km travelled per week | -0,727 | 1,178 | -4,485* |
| s.e. | (2,064) | (2,949) | (2,278) |
| Observations | 265 | 254 | 133 |
| R-squared | 0,279 | 0,001 | 0,155 |
| Private car veh-km travelled per week | 6,033 | 3,242 | -1,925 |
| s.e. | (3,819) | (2,632) | (1,737) |
| Observations | 263 | 252 | 130 |
| R-squared | 0,236 | 0,006 | 0,160 |
| Number of cars intended to own by household | -0,0300 | -0,170* | -0,00117 |
| s.e. | (0,0802) | (0,0905) | (0,0941) |
| Observations | 265 | 254 | 133 |
| R-squared | 0,510 | 0,014 | 0,355 |
| Number of cars intent to purchase in the next year | 0,112 | 0,0418 | 0,0141 |
| s.e. | (0,171) | (0,136) | (0,214) |
| Observations | 203 | 192 | 101 |
| R-squared | 0,247 | 0,000 | 0,185 |
| Number of cars intent to sell/scrap in the next year | 0,0248 | 0,0748 | -0,00172 |
| s.e. | (0,0580) | (0,0562) | (0,0556) |

| | Ex-ante analysis | | |
|---|---|---|---|
| **INTENDED OUTCOMES** | **DAG** | **PSM** | **CEM** |
| Observations | 248 | 238 | 129 |
| R-squared | 0,193 | 0,007 | 0,077 |

All models include covariates and postcode fixed effects. Robust standard errors in parentheses. ***p<0,01, **p<0,05, *p<0,1

Covariates are user characteristics of participants, used as “controls” to enhance the preciseness of the analysis. They include age, gender, number of household member, level of education, level of income, detention of driving license and/or transit subscription.

P-values are statistical measures indicating whether the result is statistically significant or not. As an example, a p-value minor than 0,05 (**) means that the result is within 95% confidence interval (in other words, we are 95% sure about it). It quantifies the likelihood of the results to occur by chance alone. A low p-value (5%,**) is the widely accepted threshold in the statistical literature. It indicates that there is at most a 5% chance that the results would have occurred by chance alone.

Hereafter, we replicate former approaches on potential usage, retrieving survey data for the intended modal shift to e-cargo bikes. Based on previous figures on the number of active users and knowing that 32% of respondents intended to make use of the e-cargo bikes, we compute the potential shift by the travelled distance per specific mode multiplied by their self-reported visit frequency and likelihood of shifting to shared mobility. This approximation based on around 400 responses suggests that the potential weekly veh-km shift away from each main mode of transport towards e-cargo bikes would be on average the ones reported in Table 9. Considering the example of cars, there is a potential substitution to e-cargo bikes of 4,2 veh-km of weekly distance, and a shift of 2,1 veh-km weekly travelled distance from public transit.

***Table 10. Mechelen (cargo-bikes) – Ex-ante estimated e-cargo bike potential veh-km shifting away per mode per week and per person***

| **Variable** | **Mean** | **Std. Dev.** |
|---|---|---|
| Walking | 0,0607143 | 0,5650323 |
| Bike | 2,103018 | 8,29506 |
| Transit | 2,486220 | 18,85696 |
| Car | 4,296296 | 18,18748 |

Sharing Neighbourhoods

Due to the small number of participants (and the even smaller number of survey respondents), this pilot does not allow us to apply the full set of statistical methods, since the results are not statistically significant with such a small number of responses (n = 27). However, we will evaluate the reported trips and the respondents' willingness to shift to shared mobility modes. The results of the ex-ante analysis of the Sharing Neighbourhoods pilot are summarised in Table 11.

In the analysis carried out, we observed the trips reported by the users as well as users' willingness to substitute them by the transport options made available by the pilot. We see that users are willing to shift around 9,96 veh-km from private car trips, followed by a 2,7 veh-km from public transport. Although the results are not statistically significant, the positive direction of these results should encourage the city in keep promoting shared mobility options.

Additionally, the results suggest a modest users' intentions to sell or scrap their own personal car, with an average of 0,26 cars per person.

***Table 11. Mechelen (Sharing Neighbourhoods) - Results for the ex-ante impact assessment estimates***

| INTENDED OUTCOMES | | Ex-ante analysis |
|---|---|---|
| Walking veh-km shifted per week | | 0,0938 |
| | s.d. | (0,1875) |
| Bicycle veh-km shifted per week | | 0,9828 |
| | s.d. | (1,7902) |
| Public transport veh-km shifted per week | | 2,7812 |
| | s.d. | (4,5651) |
| Private car veh-km shifted per week | | 9,963 |
| | s.d. | (10,01) |
| Number of cars intent to purchase in the next year | | 0 |
| Number of cars intent to sell/scrap in the next year | | 0,2632 |

### 3.3.2 Summary

In terms of project target goals, a limited number of survey answers did not allow a causal analysis to be conducted. To do so, our estimators should have been enhanced by matching procedures (PSM, CEM) which require a substantial number of complete survey answers.

However, the accuracy of the ex-ante estimations is in line with both literature and mid-term exploratory analysis, emphasizing the goodness-of-fit of the models for similar future impact analyses. Moreover, the mid-term intended impact for such pilot is aligned to some of the most relevant outcomes targeted by the project: substantial reductions in distance travelled by private cars, a shift towards both e-cargo bikes and public transport, and albeit small, reductions in the intentions to own private cars.

***Table 12. Mechelen – Summary of e-cargobike pilot results***

| | | **Mid-term (ex-ante)** |
|---|---|---|
| **E-Cargobike** | $\Delta CO_2$ (tn/year) | 3,1 |
| | $\Delta CAR$ (veh-km/year) | 12.400 |

Note: Carbon emission reduction estimates are based on life-cycle assessment assumptions for e-cargo bikes emission factors, retrieved from Fraselle et. al, (2021).

We replicate below our former approaches on potential usage, retrieving survey data from the intended modal shift to e-cargo bikes. Based on previous figures on the number of active users and knowing that 32% of respondents intended to make use of the e-cargo bikes, we compute the potential shift by the travelled distance per specific mode multiplied by their self-reported visit frequency and likelihood of shift to shared mobility. This approximation over around 400 respondents suggests that the potential weekly veh-km shift away from each main transport modes associated e-cargo bikes would be on average the ones reported in Table 10.

Again, these figures can be transformed into total private car veh-km travel reduction associated to e-cargo bikes. We do this by simply multiplying the weekly effect per the number of active users reporting to join the pilot by the number of relevant weeks per year (48 weeks). To compute the emission related to the pilot, we assume that the entire shift towards shared mobility transfers to shared e-cargobikes or another mobility mode with similar carbon emission factor. This computation equates to an intended potential **reduction of 12.400 veh-km of private car travel per year** and **3,1 Tn of $CO_2$ per year**.

For the Sharing Neighbourhoods pilot, due to its smaller scale, it is not possible to derive any robust impact on $CO_2$ and private car veh-km reduced, due to the limited sample and the consequent lack of statistical significance. Nevertheless, we presented here several results to show the trends of the users that took part in it, to understand if these kinds of pilots are beneficial or not. In general, we see a positive trend to shift veh-km from cars to more sustainable modes, whether it is public transport or shared mobility. In addition, there is also a relatively small willingness to get rid of the car, although further materialisation of this impact would require time and long exposure to the mobility options included in the pilot.

Also, for the second survey carried out in the Sharing Neighbourhoods pilot, although it only reached a small number of respondents (n = 11), we can show some encouraging results:

- 1 person reported he/she wants to get rid of 1 car next year.
- 1 person reported he/she will buy an e-bike next year, and 1 said the same for an e-scooter.
- Although no major difference exists in the trips reported and their distance, we can see a mild increase in cycling and using the train. We couldn't observe a significant change for car use.
- A minor improvement in their attitudes towards cars, especially regarding their impact on air pollution.

## 3.4 Valenciennes

As part of the MOBI-MIX project, Valenciennes Métropole implemented two mobility hubs to improve access to sustainable and shared mobility, in the Nungesser/Pompidou P&R, and in the Mont Houy/Transalley Campus.

The Nungesser/Pompidou P&R was created together with the opening of the tram line nº 1. Located in a dense urban area near the city centre and close to a shopping centre, this mobihub could expand the mobility solutions and encourage active modes for citizens to reach the downtown.

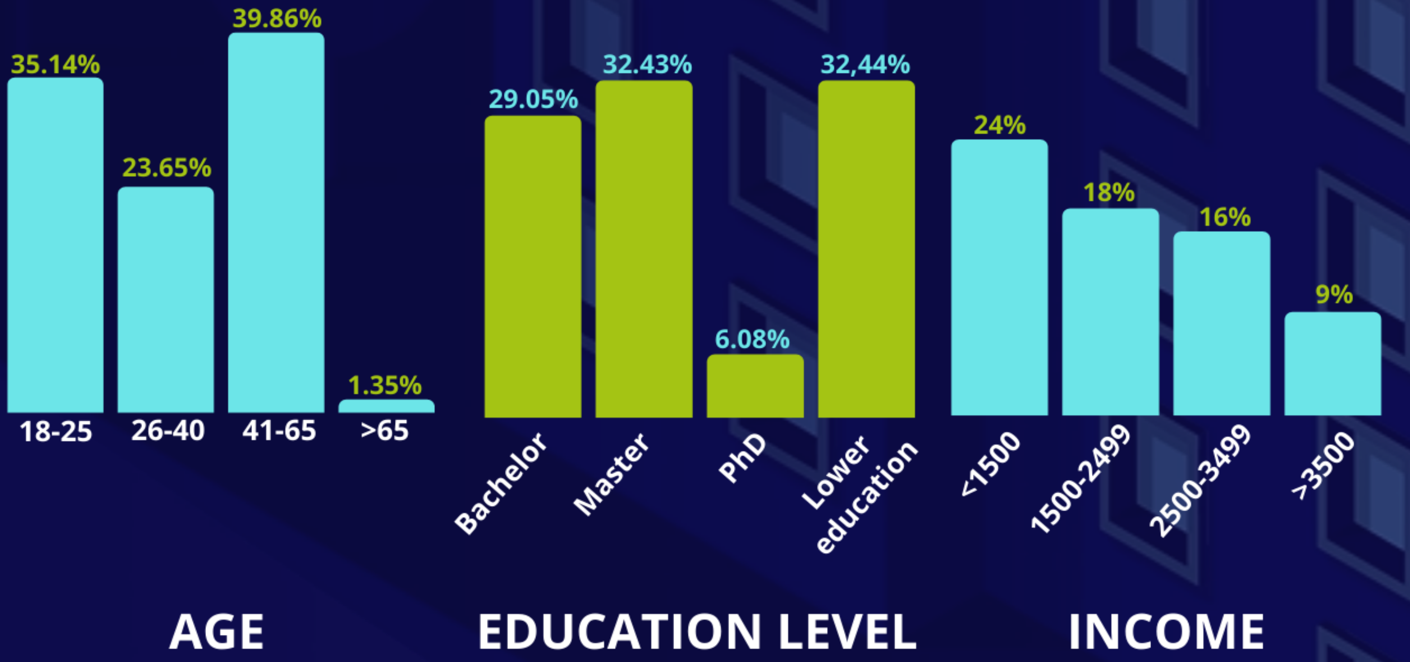
The Mont Houy/Transalley Campus is part of three municipalities (Aulnoy-lez-Valenciennes, Famars, and Trith-Saint-Léger), covering 79 ha. The site is mixed-use, hosting an innovation park dedicated to sustainable mobility, teaching and research institutions, two university housing units and two restaurants. Pre-pandemic, the site hosted nearly 8500 users (7000 students and 1500 employees). The mobihub would facilitate multimodal trips within and outside of the campus, increasing access to training, education and employment.

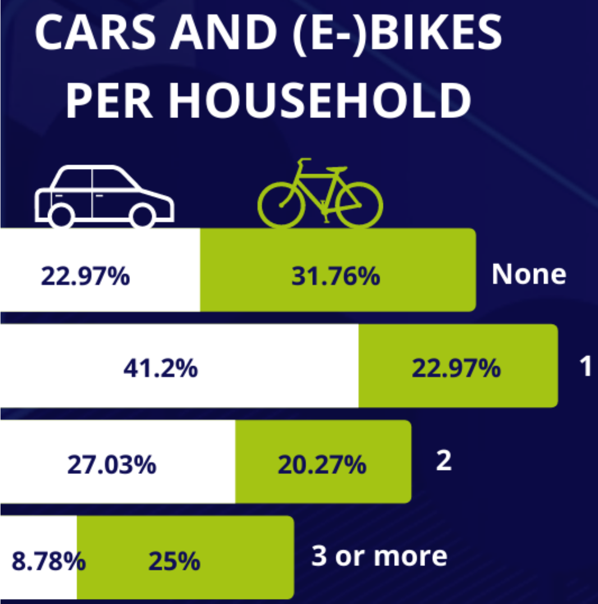
Each mobihub is expected to provide:

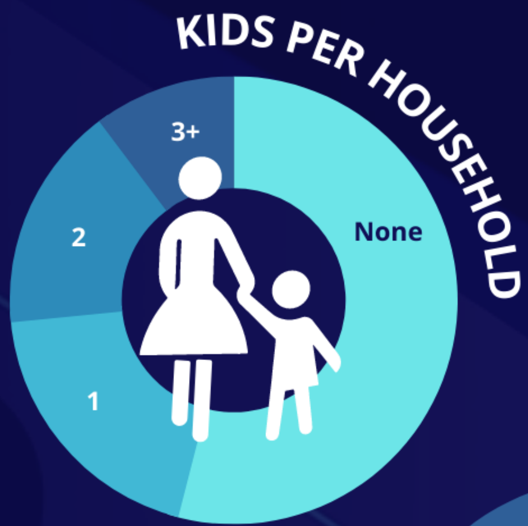
- easy access to public transport
- shared mobility options: shared bikes, shared e-scooters, shared cars, and carpooling
- a range of services to improve the mobility offer and user experience (e.g., passenger information totem, signage, waiting area, electric charging station, bicycle parking, etc.)
- a range of other extra services (e.g., restaurant/café/snack options, lockers, delivery services, etc.)

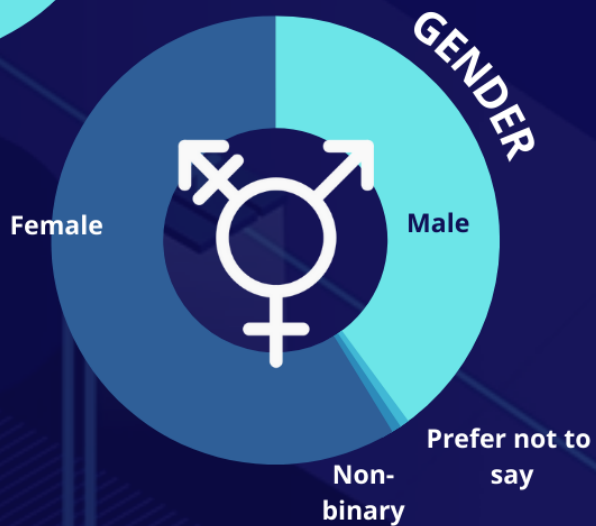
At the time the impact assessment was conducted, the mobihubs had three mobility services: shared bikes, shared cars and public transport. Given the delayed implementation of mobihubs caused by the pandemic and the short time available to run surveys, the ex-post analysis could not be carried out. However, significant results from ex-ante impact assessment allow us to provide meaningful insights on potential carbon emission reductions and car modal shift.

# Who answered the MOBI-MIX survey in Valenciennes?

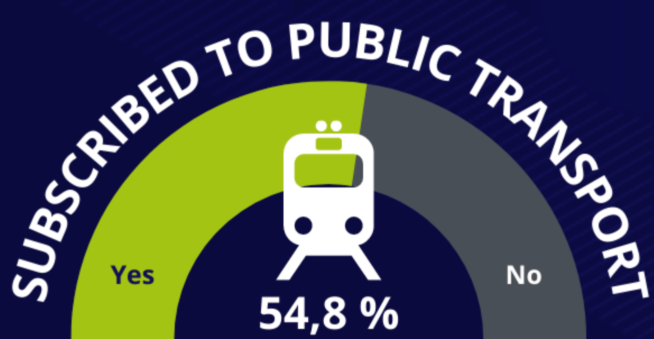



N = 148



### 3.4.1 Ex-ante impact assessment

The ex-ante impact assessment results suggest that there is a slight, yet positive intention of respondents joining the mobihub pilots in terms of their modal share, as they intend to substitute up to 0,06 km per week of walking trips to any mode available in the mobihubs. This implies a 20% substitution effect with respect to the mean weekly walking distance reported in our sample (0,3 veh-km), driven by the 10,34% of users willing to join the pilot and who intend to substitute on average around 0,2 km per week. It should be noted that this intended effect estimate is substantially below the one estimated in the exploratory analysis. Nevertheless, the effect suggests benefits in health aspects as walking distance is intended to increase. The ex-ante impact assessment results are shown in Table 13.

Along the same lines, we find a positive and significant effect on private car substitution for modes of transport available in mobihubs, on average of around 1,6 veh-km per week for those willing to joining the pilot. This implies a 16% substitution effect from private cars to mobihub solutions, just below the average mentioned in the literature and used in the exploratory analysis.

These figures can be translated into total veh-km travel reduction by private car by multiplying the weekly effect per user by the number of relevant weeks per year (48 weeks) and the number of average active users at the kick-off of the pilot (around 100 users captured by the ex-ante survey). This calculation equates to an **intended reduction of 215.000 veh-km of private car travel per year** and **0,9 Tn of $CO_2$ per year**.

*Table 13. Valenciennes – Summary of mobihubs pilot results*

| OUTCOMES | | DAG |
|---|---|---|
| Walking veh-km travelled per week | | 0,0687 |
| | s.e. | (0,0934) |
| | Observations | 132 |
| | R-squared | 0,315 |
| Bicycle veh-km travelled per week | | n/a |
| | s.e. | n/a |
| | Observations | n/a |
| | R-squared | n/a |
| Public transport veh-km travelled per week | | -1,020 |
| | s.e. | (1,017) |

| OUTCOMES | | DAG |
|---|---|---|
| | Observations | 143 |
| | R-squared | 0,014 |
| Private car veh-km travelled per week | | 1,612** |
| | s.e. | (0,0484) |
| | Observations | 132 |
| | R-squared | 0,255 |
| Number of cars intended to own by household | | -0,0300 |
| | s.e. | (0,157) |
| | Observations | 137 |
| | R-squared | 0,678 |
| Number of cars intent to purchase in the next year | | -0,408*** |
| | s.e. | (0,130) |
| | Observations | 60 |
| | R-squared | 0,661 |
| Number of cars intent to sell/scrap in the next year | | -0,000239 |
| | s.e. | (0,0730) |
| | Observations | 131 |
| | R-squared | 0,349 |

All models include covariates and postcode fixed effects. Robust standard errors in parentheses. ***p<0,01, **p<0,05, *p<0,1

Covariates are user characteristics of participants, used as "controls" to enhance the preciseness of the analysis. They include age, gender, number of household member, level of education, level of income, detention of driving license and/or transit subscription.

P-values are statistical measures indicating whether the result is statistically significant or not. As an example, a p-value minor than 0,05 (**) means that the result is within 95% confidence interval (in other words, we are 95% sure about it). It quantifies the likelihood of the results to occur by chance alone. A low p-value (5%,**) is the widely accepted threshold in the statistical literature. It indicates that there is at most a 5% chance that the results would have occurred by chance alone.

The survey data allowed us to analyse the potential mobihub usage and the modal shift linked to it. Based on previous figures on the number of active users and knowing that 64% of respondents make use of the designated locations for Valenciennes' mobihubs, we compute the potential shift by the travelled distance per specific mode multiplied by their self-reported visit frequency and likelihood of shifting to shared mobility. This raw estimate is presented in Table 14. As an example, potential car weekly travelled distance could be reduced up to 1,05 veh-km on average.

***Table 14. Valenciennes – Ex-ante estimated mobihubs potential veh-km shifting away per mode***

| **Variable** | **Mean** | **Std. Dev.** |
|---|---|---|
| Walking | 0,291667 | 0,2079899 |
| Bike | 0,6728336 | 2,009223 |
| Transit | 3,907767 | 2,683161 |
| Car | 1,052469 | 4,596656 |

### 3.4.2 Summary

Overall, our computations reveal the following potential impacts:

- A 215.000 veh-km annual reduction in travelled distance by private car
- A 0,9 Tn annual reduction of $CO_2$ emissions
- A significant decrease in the intention to purchase a car

However, it is important to note the short time span of the ex-ante survey, as well as its launch at a time when mobihubs were not present in the city, and therefore not popular among the potential users. We can assume that on the long term, the number of users will be far higher than 100 people, thus enlarging the impact of the pilot on both car use and $CO_2$ emissions reduction.

*Table 15. Valenciennes – Summary of mobihub pilot results*

| | | Long-term (exploratory) | Mid-term (ex-ante) |
|---|---|---|---|
| **Mobihubs** | $\Delta CO_2$ (tn/year) | n/a | 0,9 |
| | $\Delta CAR$ (veh-km/year) | n/a | 215.000 |

## 3.5 Antwerp

As part of MOBI-MIX, the city of Antwerp has trialled business-to-business (B2B) Mobility as a Service (MaaS) solutions through three different schemes: Olympus4Antwerp, Skipr Trial Offer, and CAR(r)educe Antwerp. The city aimed to find smart solutions mainly for work-related travel (commuting, business trips, etc.), tailor-made for companies in search of a sustainable corporate mobility model. However, Antwerp's case has been strongly affected by the COVID-19 travel restrictions, resulting in reductions of commuting trips.

Despite these challenges, the MOBI-MIX project helped to enable 2 out of 3 MaaS providers to expand their activities and sign long-term contracts. While home office has been an initial barrier to the rollout of the pilots, MaaS is increasingly seen as an asset for flexible working schedules. These two providers – Olympus4Antwerp and Skipr Trial Offer, will remain active in Antwerp after the end of MOBI-MIX, too, which is a great achievement.

The complex nature of the pilots made data collection in Antwerp difficult. Although the survey was shortened and adapted to the B2B MaaS context, the number of responses received was too small (n = 82) to allow for meaningful impact assessment. Similarly, the data that MaaS operators collected could not be disaggregated to separate between B2B and B2C users, as it only contained information regarding transactions. Therefore, we were unable perform the ex-ante and ex-post analyses for Antwerp.

Nevertheless, using the number of employees from the companies registered for all 3 MaaS schemes (see Table 16 below), we update the exploratory analysis in the next section, to estimate a future scenario for $CO_2$ and private car km reduction. To explore the full potential of MaaS, we furthermore include the companies that planned to join some schemes in 2023 (e.g., in Skipr Trial Offer), as well as the participants from the interrupted scheme, since the company remaining from the initial consortium (Commuty) has expressed intentions to restart in 2023.

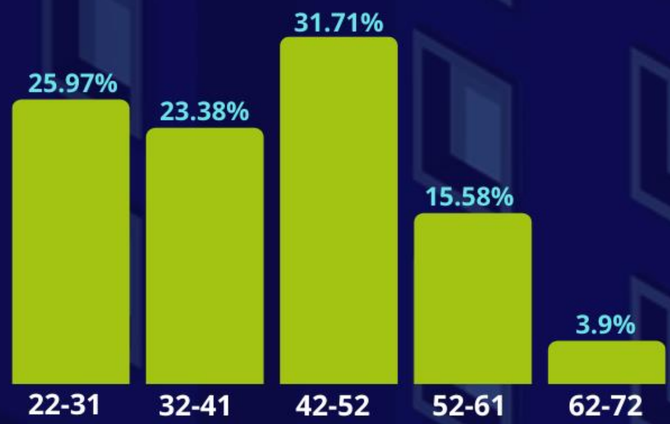
***Table 16. Antwerp – Number of engaged employees and companies per MaaS provider***

| MaaS scheme | Olympus4Antwerp | Skipr Trial Offer | CAR(r)educe Antwerp (interrupted) |
|---|---|---|---|
| Number of companies | 28 | >5: Lantis, Deloitte, Port of Antwerp-Bruges, BDO Belgium, other small companies | 3 large employers |
| Number of employees/ participants | 348 participants | 50 employees<br>+1700 employees (from 2023 on) | 1000 participants |

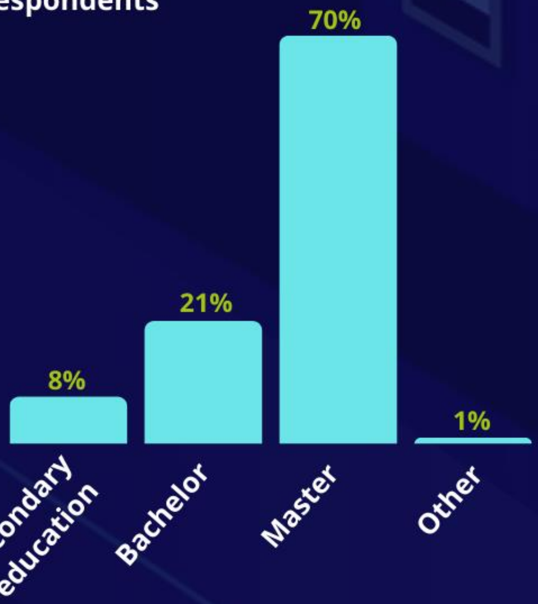
# Who answered the MOBI-MIX survey in Antwerp?

N = 82

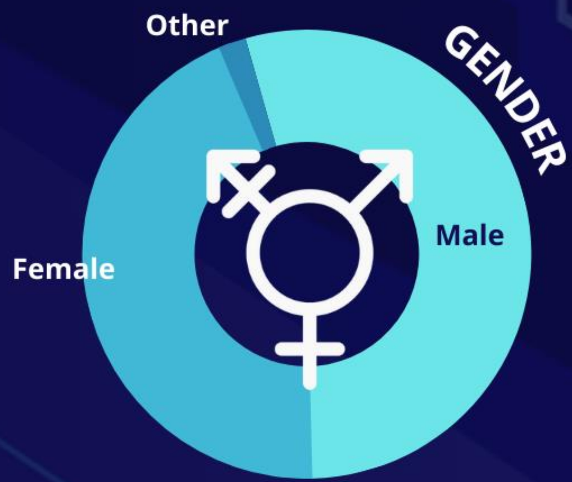
Respondents




## AGE




## EDUCATION LEVEL




## VEHICLES PER HOUSEHOLD

ON AVERAGE

### 3.5.1 Updated exploratory analysis

As mentioned above, the city of Antwerp carried out a survey aimed at the employees that took part in the pilot. However, the low sample and the high number of empty responses did not allow for deriving a credible quantitative analysis applying the full set of statistical methods that has been applied in the other cities.

Additionally, several questions in the survey were presented in a qualitative way, which would require significant assumptions *a posteriori* to derive quantitative results. For example, we obtained data on respondents' intention to use certain modes more or less frequently after exposure to the MaaS pilot (see Figure 3). However, we are unable to identify which mode they are shifting to exactly, neither the number of km they would replace.

Alternatively, we attempted to derive results based on the data that the MaaS providers had made available, but when doing so, we encountered several issues. For example, we could see the number of transactions (items sold) from the MaaS providers; however, these numbers hold for Belgium instead of only for Antwerp. This was due to privacy issues and the risk of exposing commercially sensitive information. Additionally, when aiming to examine characteristics of the trips done with the options included in the MaaS app, we would need to consider the operator level. However, the operators often have data for both B2C and B2B MaaS users, without the possibility to disaggregate them and thus avoid exposing personal data.

Therefore, we provide an estimated $CO_2$ reduction, using the methodology applied in the exploratory analysis and updating it with the current figures obtained after the pilot. Some parameters will remain the same as before: modal shift, number of shared vehicles[7], number of users per shared vehicle, number of trips per user, and average distance per trip.

***Table 17. Antwerp – Information on shared mobility characteristics***

| | ANTWERP | |
|---|---|---|
| | MaaS | |
| | Hypothesis | s.d. |
| **Number of shared-bikes deployed =** | **4812** | |
| Number of users/veh = | 28,93 | 47,88 |
| Trips per user (per year) = | 34,45 | 45,52 |
| Average distance (km)/trip = | 2,03 | 0,73 |
| **Number of shared e-scooters deployed =** | **1400** | |
| Number of users/veh = | 130,65 | 26,13 |
| Trips per user (per year) = | 21,51 | 4,3 |



[7] Using figures of 2020 based on https://mobilitytrends.slimnaarantwerpen.be/maglr-en/use

| | ANTWERP | |
|---|---|---|
| | MaaS | |
| | Hypothesis | s.d. |
| Average distance (km)/trip = | 3,8 | 0,76 |
| **Number of shared cars deployed =** | **631** | |
| Number of users/veh = | 121,46 | 53,035 |
| Trips per user (per year) = | 9,54 | 5,39 |
| Average distance (km)/trip = | 12,58 | 9,37 |
| Type of car = | EV | |
| Type of service = | FF | |

***Table 18: Antwerp - Travel behaviour change factors for each shared mobility solution. Proportion of travellers that use each mobility solution and previously used another mobility mode***

| | **Shared bikes** | | **e-Scooters** | | **Carsharing** | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Station-based | | Free-floating | |
| | Change | s.d. | Change | s.d. | Change | s.d. | Change | s.d. |
| **Replaced CAR** | -12% | 7% | -24% | 15% | -33% | 21% | -24% | 21% |
| **Replaced TRANSIT** | -40% | 18% | -21% | 12% | -33% | 12% | -33% | 12% |
| **Replaced BIKE** | -8% | 3% | -19% | 17% | -8% | 8% | -8% | 8% |
| **Replaced WALKING** | -30% | 13% | -41% | 11% | -15% | 0% | -15% | 0% |
| **Car ownership** | 0% | 0% | 0% | 0% | -22% | 18% | -6% | 2% |

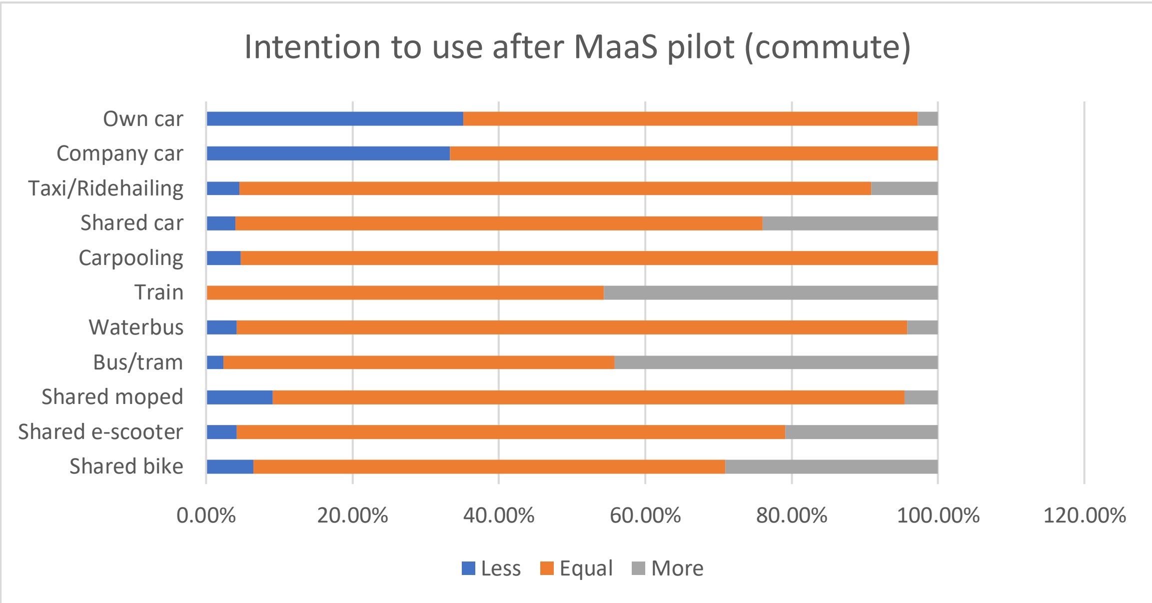
In the exploratory analysis we assumed that 9,4% of the workforce in the metropolitan area would enrol in the pilot, which is the equivalent of around 55.000 employees. As stated in the exploratory report however, this would be unlikely to happen during the pilot lifetime. This is due to the assumptions that only some of the companies active in Antwerp would decide to join a specific MaaS provider, not all the vehicles would be available through it, and not all employees would adopt it as a viable mobility option. After the pilot implementation, we see that the companies involved were able to engage 1398 employees, which represents a 0,2% of the workforce in the metropolitan area.

Altogether, the updated exploratory analysis computation equates to an intended **reduction of 19.016,44 veh-km of private car travel per year** and **3,91 Tn of $CO_2$ per year.**

In addition to those numbers and given the unique situation for the pilot in Antwerp, some additional insights can be obtained from the survey.

Looking at the intended modal shift after the B2B MaaS pilot for commuting trips in Figure 3, more than 30% of respondents reported a reduction in car use, either privately or company owned. Almost 50% of respondents report the intention to use more public transport modes such as trains or busses/trams. Between 20-30% of respondents state that they would use more shared mobility options after the pilot, referring to bikes, e-scooters or cars.

*Figure 3. Antwerp - Intention to use different modes after the MaaS pilot for commuting trips*




Dividing a trip in 3 legs – the access, the main trip, and the egress – we asked the respondents for their preferred transport mode. The modal split reported is presented in Table 19. In general, we observe that 20% of respondents use the same mode of transport for all trip legs, while 80% use a combination of transport modes.

For the access leg of the trip, the most used modes are walking (34%) and (e-)bike use (33%), followed by car use (27%). Regarding the main leg of the trip, the most used mode is public transport (57%), referring to trains (35%) and busses/trams (22%). (E-)bike usage for the main trip is around 20% and car use around 16%. The trip egress is mostly done by walking (47%), followed by using (e-)bikes (19%)

*Table 19. Antwerp – Modal split reported*

| Mode | Pre-trip | Main trip | Post-trip |
|---|---|---|---|
| On foot | 34% | 2% | 47% |
| Shared scooter | 1% | 0% | 4% |
| Bike | 21% | 13% | 11% |

| Mode | Pre-trip | Main trip | Post-trip |
|---|---|---|---|
| (E-)bike | 12% | 7% | 8% |
| Pedelec | 1% | 2% | 1% |
| Shared bike | 1% | 1% | 8% |
| Bus or tram | 3% | 22% | 13% |
| Train | 0% | 34% | 0% |
| Waterbus | 0% | 2% | 0% |
| Company car | 12% | 9% | 3% |
| Own car | 15% | 7% | 5% |

### 3.5.2 Summary

In summary, the analysis carried out in Antwerp yields a potential to reduce **19.061,44 car km**, meaning a **$CO_2$ reduction of 3,91 tonnes per year**. In the long-term, assuming that MaaS will affect car ownership, the potential of $CO_2$ emissions' reduction could count up to **14,94 tonnes per year**.

The qualitative insights from the survey suggest that MaaS offers great potential for employees to shift to more sustainable modes and reduce their use of cars. Additionally, we found that:

- The MaaS app is primarily used to buy public transport tickets. The purchase of shared mobility trips within the app is more limited, especially for shared bikes and shared cars.
- While MaaS seems to increase the use of shared mobility only slightly, it does seem to lead to less car use and more use of public transport modes.
- The finding that most people combine different transport modes for their entire journey suggests the need to improve the MaaS offer and integration of public transport and shared mobility, to improve the smoothness of trip transfers.

***Table 20. Antwerp – Summary of B2B MaaS pilot results***

| | | Long-term (updated exploratory) | Mid-term (updated exploratory) |
|---|---|---|---|
| **B2B MaaS** | $\Delta CO_2$ (tn/year) | 14,94 | 3,91 |
| | $\Delta CAR$ (veh-km/year) | 69.800,24 | 19.016,44 |

# 4 Conclusions and policy recommendations

The MOBI-MIX project brought together public authorities and mobility providers to ensure that the implementation of shared mobility brings clear benefits to cities and their inhabitants. As the project reached its end, we have analysed the impact of new mobility solutions on reducing $CO_2$ emissions and private car usage. For this, we developed an impact assessment framework (MODE) which has a double purpose: to overcome data scarcity and be applicable in different stages of project implementation, and to offer insights into the causal impacts of a proposed solution.

*Methodology*

The five cities' varying local contexts in terms of pilot stage and data availability have helped to test MODE. In Rotterdam and Norfolk, we conducted both the ex-ante and the ex-post analyses. While the first survey gathered enough responses for the ex-ante analysis, the high attrition rate in the second survey reduced the method's capacity of detecting any statistically significant effects during the ex-post analysis. In Mechelen and Valenciennes, due to significantly smaller number of respondents, we have only relied on the ex-ante analysis. In Antwerp, given the various barriers for data collection (implementation during COVID when travel restrictions led to teleworking, complex governance system within the MaaS ecosystem, etc.) we have updated the initial exploratory analysis and tried to extract some insights from the limited number of survey responses. While MODE worked well for individual shared mobility pilots, the surveys required some adaptation for mobility hubs and MaaS, where various services are bundled. Nonetheless, MODE showed enough flexibility to understand the impact on $CO_2$ emissions and car travel reduction, albeit with different robustness levels.

Data collection through surveys had both advantages and disadvantages. On the one hand, the surveys yielded valuable information which did not exist before. In addition, the data could be obtained independently from mobility providers, circumventing the need for a data reporting framework between the city and the provider. On the other hand, the survey set-up, adaptation to local context and mobility pilot, dissemination and analysis were time consuming. Survey dissemination and data collection seemed easier when a dedicated team took care of the public campaign, or when the mobility provider also contributed to sharing the survey.

*Summary of results*

The table 21 below summarises the $CO_2$ and car veh-km reduction obtained in the MOBI-MIX pilots. Using the lower and upper figures from Norfolk (dependent on the e-scooter carbon emission contribution), the total reduction in the mid-term is between 225,51 – 399,91 $CO_2$ tons/year and 2.456.416 car veh-km/year. This does not account for some of the smaller pilots where we have not collected sufficient data (e.g., Rotterdam station-based carsharing pilot, Mechelen Sharing Neighbourhoods pilot). Nonetheless, these figures are in line with the initial project objectives (reduction of 365 tons of $CO_2$-emissions by avoiding/replacing 2.6M fossil-fuelled car-kilometres).

***Table 21. Summary of CO2 emissions and car veh-km reduction***

| | Rotterdam | Norfolk e-scooters | Norfolk mobihubs | Mechelen | Valencie-nnes | Antwerp | Total |
|---|---|---|---|---|---|---|---|
| **$CO_2$ tons/ year** | 188 | 13,6 - 114 | 16 - 90 | 3,1 | 0,9 | 3,91 | 225,51 – 399,91 |
| **Car veh-km/year** | 1.360.000 | 490.000 | 360.000 | 12.400 | 215.000 | 19.016 | 2.456.416 |

*Policy recommendations*

1. Mobility pilots need longer implementation time frames to yield meaningful results. Behaviour change is lengthy and requires sustained availability of new solutions to reach beyond the first adopters.
2. Cities where pilots are continuing past MOBI-MIX should seek to repeat the impact analysis regularly, to understand behaviour changes and tweak mobility solutions accordingly.
3. While surveys can provide important information, mobility data sharing between providers, cities and impact evaluators is essential for efficient impact assessment purposes. There is a need for a framework regulating these exchanges of data, as highlighted in the 4th MOBI-MIX Insight Report.
4. The vehicles' lifespan is a strong determinant of $CO_2$ emissions. Cities should seek agreements with operators to ensure that vehicles are kept in operation for as long as possible (e.g., e-scooters minimum 5 years).
5. Combining shared mobility and public transport ticketing can be a cost-effective way to achieve long-term private car substitution, as in some cases – such as e-cargo bikes, we see that individuals do not intend to reduce their use of public transport when new shared mobility modes become available. Since the opposite seems to occur when individuals have access to carsharing solutions, cities should consider mitigating policies that incentivise certain types of trips (e.g., minimum trip length) or specific locations for carsharing to complement the public transport offer.
6. In the long term, larger implementation of shared mobility modes requires infrastructure adaptation for safety, cost, and practical purposes. This is particularly relevant for slower modes (e.g., bikes and e-scooters) to reduce road

vulnerability, but also for services such as carsharing to improve findability and user experience.

7. $CO_2$ emissions are an important aspect and the MOBI-MIX pilots have demonstrated the benefits achieved in this regard. Nonetheless, shared mobility solutions bring other types of benefits, too (e.g., a more diverse transport offer, time savings, more physical activity in some cases, etc.). Due to the project's limited scope, we have only lightly considered them, yet cities should seek to expand the MODE analysis to get further insights.