



Holistic Approach for Providing Spatial & Transport Planning Tools and Evidence to Metropolitan and Regional Authorities to Lead a Sustainable Transition to a New Mobility Era

D5.3 Applications of the passenger tactical and operational simulators and forecasting

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SUMMARY SHEET

PROJECT

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
ABM	Activity-based model
TPS	Tactical Passenger Simulator
PA	Primary Activity
HBW	Home-based work (Home – Work – Home tour)
HBO	Home-based other (Home – Other – Home tour)
NHB	Non-home based tour
WBO	Work-based tour
RW	Remote work
MC	Mode choice



MTO	Mobility tool ownership
DDS	Dynamic Demand shift
OXS	Oxfordshire
TUR	Turin
RP	Revealed Preference
SP	Stated Preference

EXECUTIVE SUMMARY

Deliverable D5.3 is the final deliverable of WP5 and presents the final architecture of the implemented Tactical Passenger Simulator, results from the application in OXS (including some final results for TUR – models which were not ready when D5.2 was submitted) and an overall discussion of the application of the TPS.

The Tactical Passenger Simulator, developed as the main outcome of WP5, utilizes data from the Moby app data collection process and after thorough data cleaning and heuristics, produces the detailed, synthetic agent (household and person) schedules of activities and travel on a daily basis. The temporal capacity of the models is very detailed; all activities are modelled in a minute basis for the whole day. The model application presented in D5.3 includes main and secondary activities. The final specification of the TPS includes the following modular components: activity participation and duration for main and secondary activities, activity start time, activity and travel scheduling based on specific rules described on Chapter 2, destination choice and mode choice models. All modules/models are modular, as described in the overall architecture of the TPS and retain their autonomy hence for the dependencies downstream (e.g., the destination choice model requires the scheduling to be already in place to be *applied* to the synthetic schedules but can be *estimated* independently).

In OXS we utilize MSOA zones, based on availability of census data, skim matrices and other useful data. The TPS can be easily adjusted to be applied to more detailed zoning system (e.g. LSOA or OA) but as we “zoom-in” into the spatial dimension more detailed data collection is needed in order to account for the spatial heterogeneity of travel and activity preferences. In essence, what this means is that to apply the model to a finer spatial dimension more sample is required.

Overall, D5.3 presents a complete, integrated picture of the final architecture, data flow, methodological framework, model estimations and guideline towards the decisions and logic of the TPS and the BAU application for OXS. The structure of D5.3 is designed to be user-friendly, acting as a detailed manual of the TPS, with methodological details and jargon utilized only when unavoidable.

1. Introduction

Project Summary

HARMONY's vision is to assist metropolitan areas with evidence-based decision making, by providing a state-of-the-art model suite that quantifies the multidimensional impact of various policies, investments and mobility concept applications, while simultaneously identifying the most appropriate solutions and recommending ways to exploit the disruptive mobility innovations. HARMONY proposes an integrated approach through the development of the HARMONY MS, which integrates new and existing sub-models. This integrated approach is necessary to understand if, how and to what extent new policies, investments and mobility concepts can produce results that are in line with the objectives set by authorities.

The HARMONY MS is envisioned as a **multi-scale, software-agnostic, integrated activity-based** system that combines various models, which enables end-users such as planners, decision-makers, researchers and transport operators/providers to couple/link independent models and analyse a portfolio of regional and urban interventions for both passenger and freight mobility, including policies and capital investments, land-use configurations, economic and sociodemographic assumptions, travel demand management strategies and new mobility service concepts. The main objective behind the model system's architecture is to enable the evaluation of such interventions with regard to their impact on land use, economic growth, transportation networks, energy, vehicular noise and emissions. While, at the same time, providing recommendations for Sustainable Urban Mobility Plans (SUMP) of the new mobility era.

WP5 is concerned with passenger demand in the context of HARMONY MS. It develops a series of sub-models which predict activities and travel for passengers in the two pilot areas of OXS and TUR. The Tactical Passenger Simulator (TPS) is the component responsible for predicting and simulating passenger demand in HARMONY MS and communicates directly with the Strategic Simulator and the Passenger Operational Simulator. TPS hosts all the different sub-models which predict the components of activities and trips. TPS features a software component which is responsible for fitting the different model results and applying them to the synthetic population following specific, location-based rules and sequencing: the Adaptive Scheduler (AS). The adaptive scheduler is discussed in detail in Chapter 5, while initial architecture is presented in D5.1

Deliverable Objectives

Deliverable 5.3 is the third version of the deliverables in WP5 and presents the results from the OXS models, the final integration of the TPS in the HARMONY MS and the final scheduler specifications in the form of templates of the HARMONY MS.

Deliverable Structure

Deliverable 5.2 is divided into the following chapters:

1. Chapter 1: Introduction
2. Chapter 2: Final TPS architecture and integration to the HARMONY MS
3. Chapter 3: Presentation of OXS data
4. Chapter 4: Model estimation for OXS application of the TPS
5. Chapter 5: Long-term model estimation for OXS

6. Chapter 6: Conclusions and future steps for TPS
7. Appendix A-B: Model estimations and integration code

Chapter 2: Final TPS architecture and integration to the HARMONY MS

Chapter 2 presents the final tactical passenger simulator architecture and the steps of integrating it into the HARMONY MS. The process of finalizing the TPS architecture necessitated the creation of the pipeline, the adaptive scheduler, but also required extensive testing and adaptation to available data and identification of data gaps. For these reasons, the final TPS architecture is presented in D5.3, accounting for the particularities and gaps identified in data collection both in TUR and OXS.

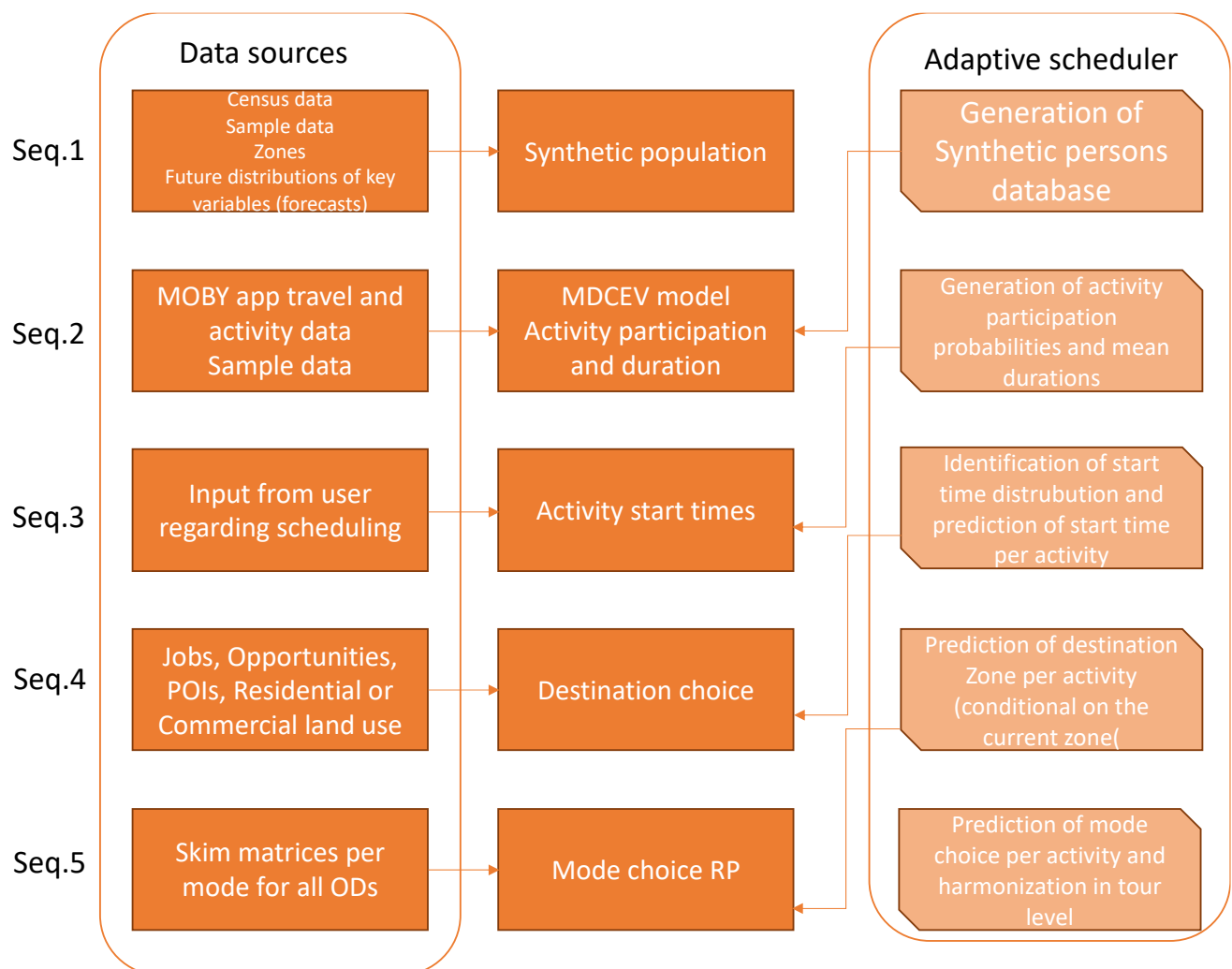


Figure 1 Final architecture of the TPS

Figure 1 presents the architecture of the TPS . The key core modelling components are presented in the middle of the Figure. The high-level sequence of the models include the modelling of activity participation and duration (MDCEV model – predicting simultaneously activity participation and duration see Bhat (2008) and D5.2), the modelling of activity start times, the destination choice models and the mode choice models using the RP data. For every modelling group, we identify

necessary data inputs, both from external and internal sources. Additionally, for each step in the TPS architecture the adaptive scheduler (right of the model components in the figure) performs necessary data transformations and schedules the activity sequence.

The process of applying the TPS can be summarized in the below steps:

1. Defining the zone system for the study area. This is important to happen at the beginning of the process, because all the spatial representations of the datasets and the models should follow the zoning system identified in this step. If there is an available zoning system from an existing transport or land-use model in the study area it is advised to use this zoning system in order to gain access to key datasets (such as skim matrices) without additional effort.
2. **Sequence 1:** Generating the synthetic population datasets. As described in previous deliverables of WP5, the synthetic population module generates two main datasets, a synthetic household dataset with number of rows equal to the total number of households in the study area and a synthetic person dataset with number of rows equal to the total number of individuals in the study area. The step is mandatory in order to derive the synthetic datasets on which the model results will be applied to. Special consideration should be given to performing data checks on the totals and ensuring the correct distribution of key variables in the spatial levels pre-defined (zoning system). It is possible that some aggregation can happen, especially if the collected sample is not as spatially diverse as would be required. In the case of the current version of the TPS, which uses PogGen (Pendyala, 2012) it is possible to temporarily aggregate neighbouring zones with low frequency of households/individuals in the sample.
3. The output of the synthetic population module is the synthetic dataset, which contains all agents and their characteristics, as well their home zones and habitual travel behaviour. This is the database on which all model results will be sequentially applied to. Note that this is a large dataset (ranging from 400MB to 1GB in our deployments of the TPS) which can create some delays in data processing, version control and data exchange.
4. **Sequence 2:** Initiating the model sequence. The first model which is developed is the activity participation and duration model. As mentioned in previous WP5 deliverables this uses an MDCEV model (Bhat, 2008) which predicts the activity participation probability and the activity duration for each activity. This model is developed using the activity and travel diary data derived from MOBY app for each of the cities in HARMONY. The format of the database is presented in Appendix A. The model is then applied to the synthetic dataset, deriving predictions of activity participation and duration for each agent in the synthetic dataset. The output of this step of the TPS (model and prediction) is an updated synthetic dataset which includes the probability of each agent to participate to an activity during their daily schedules and the mean activity duration for all activities, including the necessary travel time to move between locations.
5. **Sequence 3:** The next step in the modelling and sequencing pipeline is the identification of start times for all activities. For each different activity the TPS reviews the distribution of start times and allocates a necessary model type to model their start. As an example, the “Eating out at a restaurant” activity was discovered to be bimodal, so the decision was to split the activity into Breakfast/Lunch and Dinner and fit two different regression models to model the activity start time.



6. After modelling and predicting the activity start times, the synthetic dataset is populated by the participation, duration and activity start times for all agents. This allows the TPS to calculate also the end times of activities, at the moment without taking into account travel times and spatial fragmentation of activities. The adaptive scheduler initiates a process to form tours from the activities in the following steps:
 - a. Scheduling the work tour: if a working activity is predicted for an agent for the specific simulation day the adaptive scheduler schedules the Work tour
 - b. If joint travel is predicted before or after the Work tour the scheduler makes the tour complex by adding a stop before or after the work activity
 - c. If a secondary activity is predicted to happen (by its start time) during the work activity the scheduler schedules a work-based tour (work → secondary → work)
 - d. If a secondary activity is predicted to happen in a time window of <60 minutes after the work end time, the trip to home is scheduled to be complex and to include this secondary activity
 - e. If another activity is also in this time window the scheduler will also fit this activity in the work tour. Maximum number of stops in the return to home trip is 2 at the moment.
 - f. If no work tour is scheduled for this day, the scheduler schedules the out-of-home tour with the first activity of the day (temporally-wises). Again, if another activity falls into the time window of the first activity the tour becomes complex and other stops are added.
 - g. If the time window between the end of a secondary activity and the beginning of another secondary activity is >60 minutes the agent is directed to their home.
 - h. *It should be noted that the above rules are based on rules observed in existing activity-based models and their specific adaptations in each study area. We are developing a front-end interface to allow the final user to specify such parameters. Calibration of the set of rules is pending at the moment.*
7. After this rather complex chain of scheduling, the synthetic database now contains the tour and trips for each agent based on their predicted activities for each day. We should note that the 60-minute window we refer to is customizable by the TPS user and can be adjusted to match travel times from and to home for each agent, in subsequent runs of the simulation
8. **Sequence 4:** The next step in the modelling sequence is the destination choice modelling. The destination choice models developed in TUR and OXS are split by activity type: a work/edu destination model and a secondary activity destination model. Based on data availability and quality, the TPS can be adjusted to develop destination choice model for each specific secondary activity type. This version of the TPS models destination using only accessibility indicators, land-use characteristics and distance-based metric between zones and not individual characteristics. Future version of the TPS may integrate also individual characteristics in the destination choice process. After the models for main and secondary activity purposes are estimated, the predictions are applied to the synthetic database for each tour and trip. It should be noted that the process of applying the model and predicting destination is quasi-dynamic, meaning that for each new trip the origin zone changes.
 - a. Example: if the first trip for an agent is a trip to work, the destination choice model predicts the effect of distance from home zone to all potential work destinations, number of jobs in the destination zone, etc. Then the model is applied with origin zone the home location of each individual and predicts the work destination. However if a secondary activity is predicted to follow the work activity, the origin of the trip is the



work zone, which changes the origin zone of the prediction of the model and updates the distances from this origin for each step of the process.

9. The above, and other particularities of the destination choice models sequence make this module one of the most computationally intensive modules of the TPS. Based on some code optimization and the use of sampled choice set in the destination choice set results in an average of ~12-15 minutes of run time for each trip/stop in the schedule, which can result into some hours if the tour structure of the individual is complex or if many trips are scheduled. Of course this is proportional to the number of agents each time (rows in the dataset).
10. The destination choice models and sequencing utilize external data: distance matrix between zones, number of jobs, schools and other zone-specific variables (derived via the REM model of the HARMONY MS), points of interest and land-use mixture in the zone (derived via OSM) and finally any activity-specific predictor.
11. **Sequence 5:** After the destinations of each trip/tour, the model sequence continues with the prediction of the mode for each trip. At this point, given that the origin and destination of each trip are known, we can derive the skim matrices of cost and travel for each OD. The mode choice produces the final piece of the puzzle and applies the predictions to the synthetic database.
12. A series of feedback loops can be generated at this point. We mention a few in the form of examples / use-cases below:
 - a. Reinitiating of the simulation process to account for more realistic representation of travel times and to make the coupling of activities more tight or more relaxed based on travel time to home
 - b. Further detailed analysis of joint trips
 - c. Reinitiating of the simulation process after receiving feedback from the assignment (external) and updated travel and cost skims
 - d. Application of the TPS to a future scenario where some or all of the below can be updated:
 - i. Synthetic population marginal distributions → New synthetic database for year 20XX
 - ii. New distribution of land-use, points of interest, jobs, schools etc. in a future year
 - iii. New skim matrices based on infrastructure interventions
 - iv. New modes to be included

After step 12 is concluded, the synthetic database contains detailed representation of the simulated agent schedules, filled with activities and trips for the day.

Chapter 3: Presentation of OXS data

Table 1 presents the summary statistics of the Oxfordshire sample. The sample was collected using MOBY app, with the process, sampling strategy, and details of the data collection described in D3.4. The sample consisted of 1146 respondents with an average age of 34.2 years old. The respondents were almost equally divided into males and females, with 50.9% of them being females. As for their marital status, the majority of the respondents (55.3%) are single, while most of them (61.1%) hold at least an undergraduate degree. The sample mainly consists of employees (82.7% are employed) who have various work schedule flexibilities. It is interesting to note that a large majority of them (59.1%) have flexible work schedule, with flexibility in both start and finish times.

Table 1. Individuals' socio-economic characteristics

Variable	Variable categories/description	Sample	Census
Age [in years]	Age (mean)	34.2	41.9
	Age (min)	18	
	Age (max)	78	
Gender [in %]	Male	44.3%	45.3%
	Female	50.9%	51.2%
	Other	3.8%	3.5%
	Prefer not to answer	1.0%	
Marital status [% of respondents]	Single	55.3%	28.2%
	Married/Civil partnered	32.7%	51.8%
	Divorced	7.7%	9.8%
	Widowed	4.3%	
Education level [% of respondents]	No formal qualifications	1.7%	13%
	High school or less than high school	8.6%	8.5%
	Vocational school	25.2%	32.2%
	Undergraduate	30.6%	41%
	Master's degree	19.6%	
	Doctorate degree	10.9%	



	Other	3.3%	2%
Employment status [% of respondents]	Full time paid employment	37.6%	54%
	Full time self-employment	4.6%	
	Part-time paid employment	12.4%	19.5%
	Part time self-employment	28.1%	
	Student	5.3%	17.3%
	Unemployed and looking for work	2.0%	4.4%
	Unemployed and not looking for work	1.6%	
	Retired	5.8%	17.7%
	Homekeeper	2.0%	-
Working schedule [% of respondents]	Fixed work schedule	22.9%	-
	Flexible work schedule - with flexibility in finish times only	6.8%	-
	Flexible work schedule - with flexibility in start times only	7.3%	-
	Flexible work schedule - with flexibility in both start and finish times	59.1%	-
	Rotating shift work schedule	3.9%	-
Work location [in days]	Number of days working from home	2.12	-
	Number of days travelling to work	2.96	-
Driving license [% of respondents]	Car license	25.2%	
	Motorcycle license	3.9%	3%
Dwelling type [% of respondents]	Terrace house	16.8%	27.7%
	Semi-detached house	22.9%	27.3%
	Detached house	13.4%	28.1%
	Bungalow	8.2%	1.4%
	Converted flat	7.5%	15.7%



	Purpose built flat (less than 6 storeys high)	30.7%	
	Purpose built flat (at least 6 storeys high)	0.6%	

In addition, as indicated in Figure 2, an important percentage of the respondents live very close (within 0.5 miles) to a bus/tram stop (38.4%), a grocery store (23.4%) and a park/green space (35.5%). Moreover, 32.5% of them live within 1 to 2 miles from a train station.

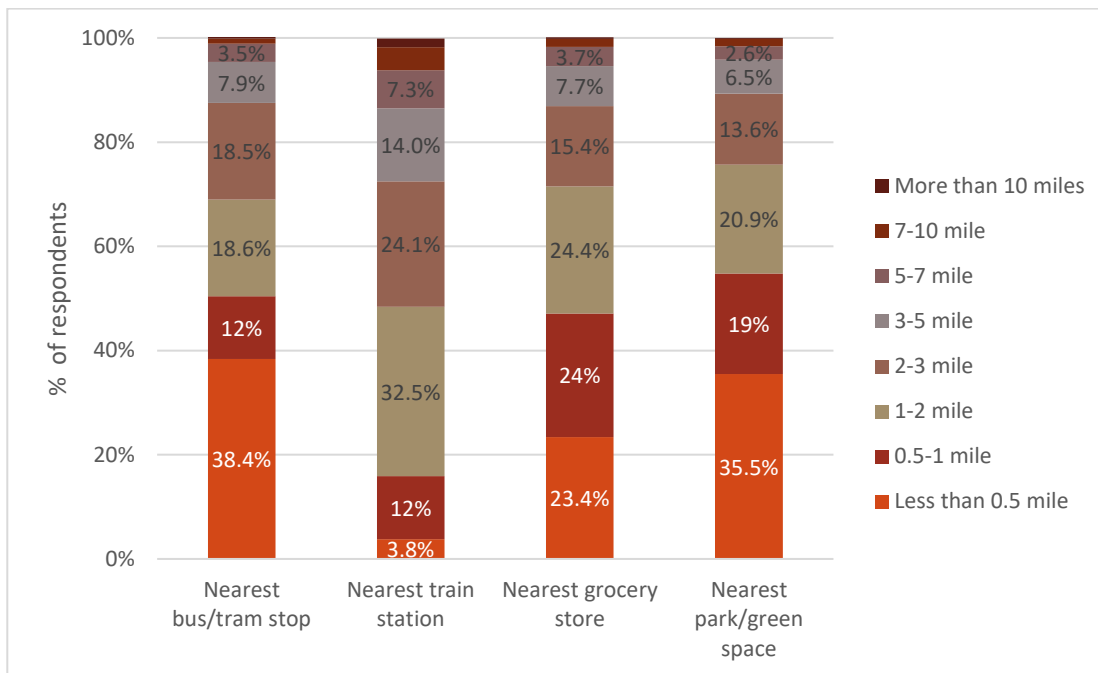


Figure 2. Distance of different places from the respondents' home

Table 2 presents the respondents' mobility patterns, indicating the sample's usage of the different transport modes. Based on this, walking is used for a substantial number of trips in an average week (11.48 trips on average), followed by the use of private cars (5.18 trips as a driver) and cycling (2.04 trips). In addition, 45.6% of the respondents use public transport, while scooters are frequently used by the sample (38.3% use them 3-4 times a week, while 22.4% of the sample use scooters a couple of times per week).

Table 2. Individuals' travel habits

Variable	Variable categories/description	Value
Percentage of individuals using public transport [% of respondents]		45.6%
Frequency of using their car [% of respondents]	Never	1.6%
	Once in a fortnight	26.8%
	Couple of times per week	28.5%
	3-4 times a week	19.9%



	Once per day	8.9%
	Several times per day	14.3%
Frequency of using their scooter [% of respondents]	Never	6.2%
	Once in a fortnight	11.7%
	Couple of times per week	22.4%
	3-4 times a week	38.3%
	Once per day	7.8%
	Several times per day	13.6%
Average number of motorcycles or scooters owned by the household [in motorcycles]		0.38
Average number of bicycles owned by the household [in bicycles]		1.33
Number of days that people travel by bus in a typical week [% of respondents]	0	40.5%
	1	14.1%
	2	31.4%
	3	6.0%
	4	3.4%
	5	2.7%
	>6	1.9%
Average hours per week that the people use carsharing services in a typical month [in hours]		10.74
Average number of trips that people conduct in an average week by mode [in trips]	Bus	1.69
	Tram / metro	0.59
	Train	1.06
	Private car as a driver	5.18
	Private car as a passenger	1.90
	Taxi	0.99
	Ride-sharing (e.g. Uber)	0.51



	Cycling	2.04
	Walking	11.48
	Motorcycle	0.82
	Scooter	0.61
	Car sharing	0.49

As for the individuals' satisfaction with the different transport modes, the majority of the respondents appear to be satisfied with most of them. Specifically, more than 50% of the respondents are satisfied with public transport (bus, tram/metro, train), taxis, ride-sharing and private cars. However, their satisfaction is lower when considering scooters and car sharing.

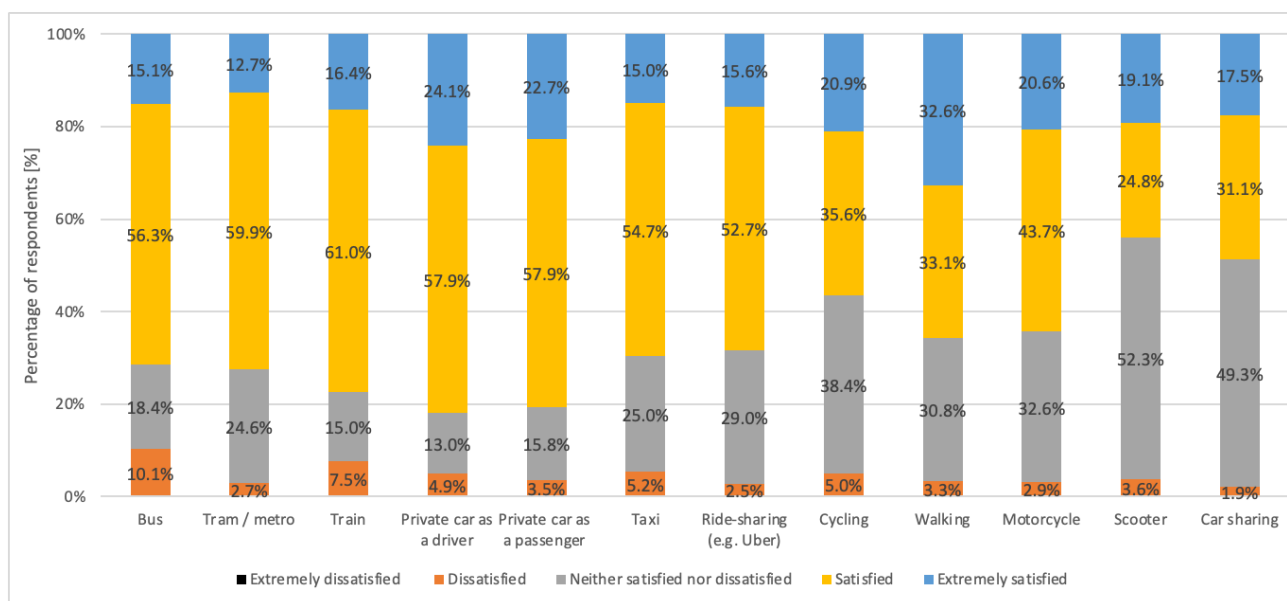


Figure 3. Individuals' satisfaction with travelling by different transport modes

Concerning the respondents' household characteristics, the summary statistics indicate that almost half of the respondents belong to a household of up to 2 persons owing only 1 car (per household). In most of the households (72.9% of total households) there are 2 employed people, while in the vast majority of them, up to 2 people hold a valid driving licence.

Table 3. Household's socio-economic characteristics

Variable	Variable categories/description	Value
Household size of respondents [% of the respondents]	One person in the household	27.2%
	Two persons in the household	23.4%
	Three persons in the household	18.2%

	Four persons in the household	24.3%
	Five persons in the household	5.7%
	More than six persons in the household	1.2%
Household income [% of respondents]	less than £5,000	1.0%
	£5,000 - £9,999	1.0%
	£10,000 - £14,999	4.5%
	£15,000 - £19,999	13.8%
	£20,000 - £24,999	17.7%
	£25,000 - £34,999	11.3%
	£35,000 - £49,999	15.4%
	£50,000 - £74,999	18.2%
	£75,000 - £99,999	8.6%
	£100,000 or more	5.2%
	Prefer not to answer/Don't Know	3.4%
Number of cars in the household [% of respondents]	0	31.5%
	1	49.1%
	2	15.7%
	3	3.3%
	4	0.5%
Percentage of households having access to a leased car or company car		7.2%
Employed people in the household (apart from the respondent) [% of respondents]	0	2.9%
	1	11.9%
	2	72.9%
	3	9.0%
	4	2.6%
	5	0.7%

Number of people in the household holding valid driving licences (including the respondent) [% of respondents]	0	5.8%
	1	36.0%
	2	53.0%
	3	3.9%
	>4	1.3%

This part presents some summary statistics of the main and secondary activities conducted by the sample. As presented in Figure 4, for a substantial percentage of the respondents the main activity includes home (20.9%) and work/education (14.0%). We should also note that 81.9% of the participants did not conduct secondary activities. From those participants that conducted secondary activities in their trips, 14.1% were related to home.

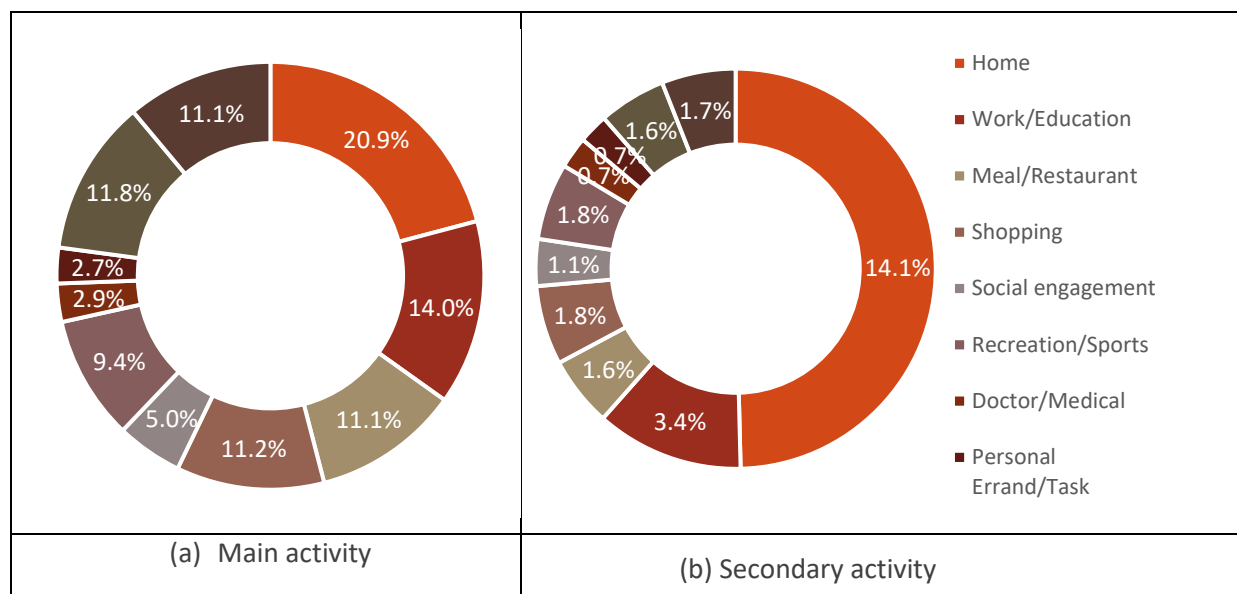


Figure 4. Type of (a) main and (b) secondary activities conducted by the participants

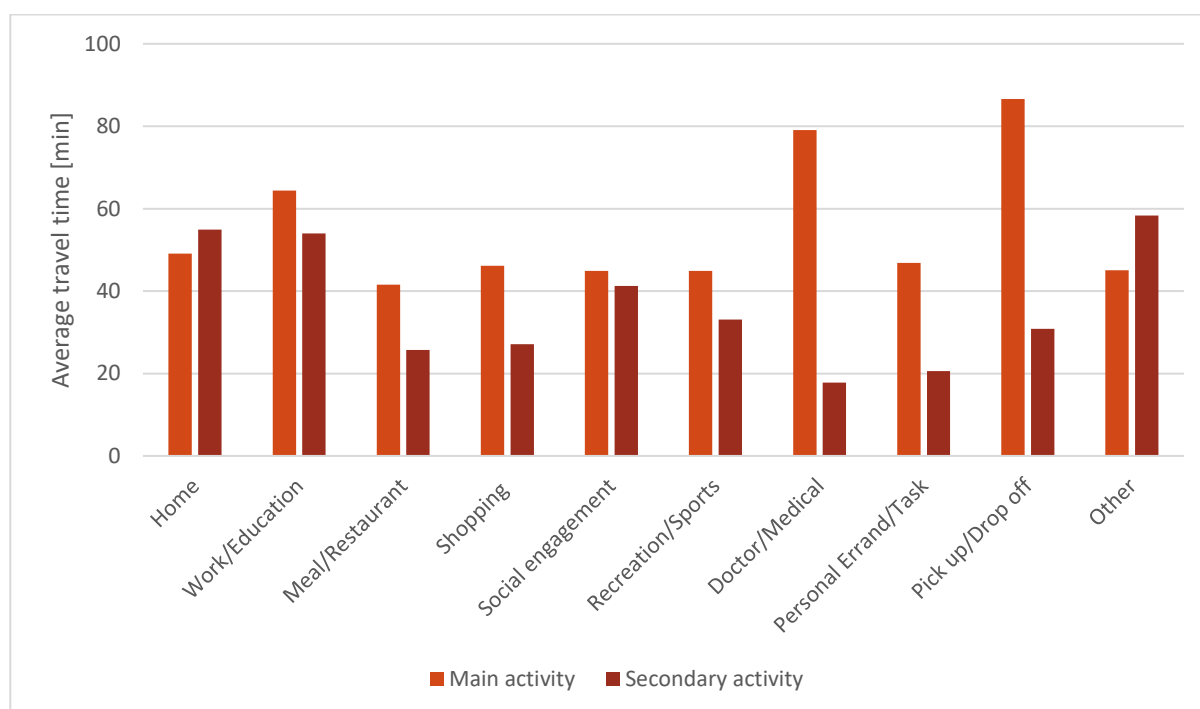


Figure 5. Average travel times per activity purpose

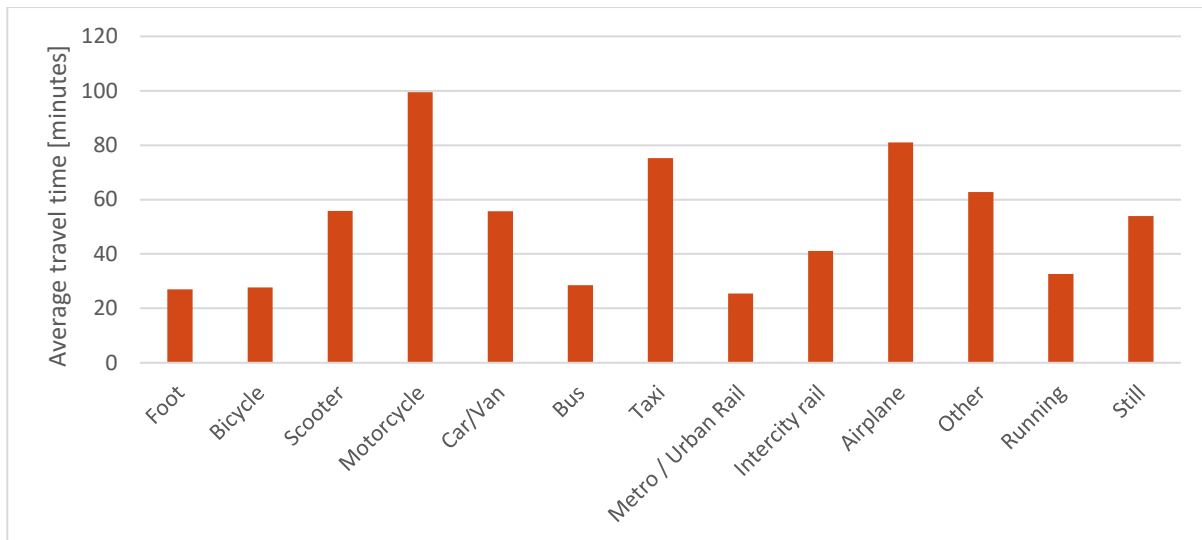


Figure 6. Average travel times per mode

Table 4. Types of modes used by trip purpose

Trip mode	Trip type	Home	Work/ Education	Meal/ Restaurant	Shopping	Social engagement	Recreation/ Sports	Doctor/ Medical	Personal Errand/Task	Pick up/ Drop off	Other
Not asked	-	44.6%	45.1%	63.3%	40.5%	39.8%	46.7%	60.1%	44.8%	36.9%	48.2%
Car/Van	Unimodal	17.2%	14.3%	6.9%	14.4%	11.3%	10.7%	12.2%	13.6%	24.0%	8.9%
Foot	Unimodal	17.0%	14.4%	12.1%	18.3%	17.5%	18.6%	2.6%	13.2%	6.5%	17.6%
Bicycle	Unimodal	6.6%	4.2%	1.2%	3.3%	4.3%	4.3%	0.7%	1.6%	3.7%	1.8%
Car/Van, Foot	Multimodal	3.4%	2.5%	1.2%	2.9%	1.9%	2.3%	0.0%	3.2%	1.8%	3.8%
Still	Unimodal	2.8%	2.0%	1.1%	0.5%	6.1%	1.0%	1.1%	1.2%	0.4%	2.7%
Foot,Car/Van	Multimodal	1.8%	1.9%	1.5%	3.8%	2.6%	3.0%	0.4%	0.4%	0.5%	2.7%
Motorcycle	Unimodal	0.1%	7.0%	6.8%	9.8%	6.5%	4.6%	14.4%	9.2%	19.4%	3.0%
Taxi	Unimodal	0.1%	1.0%	1.3%	0.7%	1.3%	0.7%	3.7%	2.4%	1.3%	1.2%
Running	Unimodal	0.5%	1.2%	1.2%	1.3%	1.7%	1.6%	1.5%	3.2%	0.5%	1.0%
Scooter	Unimodal	0.3%	1.5%	1.4%	1.0%	2.6%	1.7%	2.6%	4.8%	0.5%	3.6%
Bicycle, Foot	Multimodal	1.2%	0.6%	0.2%	0.3%	0.2%	0.5%	0.0%	0.8%	0.5%	0.3%
Bus	Unimodal	0.7%	0.6%	0.3%	0.4%	0.4%	0.6%	0.0%	0.0%	0.7%	0.4%



Foot,Bus	Multimodal	0.6%	0.5%	0.2%	0.8%	0.6%	1.0%	0.0%	0.4%	0.0%	0.1%
Foot,Bicycle	Multimodal	0.2%	0.6%	0.6%	0.6%	0.9%	0.6%	0.0%	0.8%	0.1%	0.9%
Other	-	2.9%	2.6%	0.7%	1.4%	2.3%	2.1%	0.7%	0.4%	3.2%	3.8%

Chapter 4: Model estimation for OXS application of the TPS

Chapter 4 presents the results of the estimation of the core models of the TPS for the purposes of activity and travel scheduling and predictions. To avoid duplication, when the model approach is the same as the one presented in D5.2 the model name and its methodology is mentioned but no more information is included regarding methods.

Activity participation and duration

The first model of the modelling sequence and pipeline is the activity participation and duration model. Using an MDCEV (Bhat, 2003) model approach, we utilize the activity data from the MOBY app organized in daily activities by individual. It should be noted that we have data for multiple days for each individual. Table 5 includes the results of the activity participation and duration model.

Table 5 MDCEV model results

	Estimate	Rob.std.err.	Rob.t-ratio(0)
alpha_base	-15.07	0.16	-93.98
gamma_work	3.43	0.49	6.96
gamma_MealRestaurant	1.17	0.07	16.33
gamma_shopping	0.71	0.06	12.68
gamma_leisure	1.48	0.10	14.65
gamma_personal	0.99	0.08	12.55
delta_work	-3.84	0.12	-30.87
delta_MealRestaurant	-3.95	0.11	-36.53
delta_Shopping	-3.81	0.11	-35.91
delta_personal	-3.45	0.12	-29.06
delta_leisure	-3.63	0.09	-41.80
delta_shopping_highincome	0.45	0.36	1.26
delta_restaurant_highincome	-0.03	0.39	-0.08
delta_work_Employ_1	0.44	0.26	1.69
delta_work_Employ_2	-0.23	0.23	-0.99
delta_work_Employ_6	-0.06	0.19	-0.30
delta_personal_size_hh	-0.04	0.05	-0.94



delta_shopping_distancegrocery	-0.14	0.14	-1.00
delta_leisure_distancegreen	0.10	0.21	0.49
sig	1	NA	NA

After the successful estimation of the model, the model parameters are applied to the synthetic population database in order to create the activity participation and duration variables. For each activity a discrete and continuous variable prediction is generated: the discrete is the probability of an agent participating to each activity [0,1] and the continuous is the predicted duration of each activity in minutes. For both the export a mean and an SD value are generated.

Activity start times

The second core module of the TPS is a set of regression models which model the start time of each activity. The model specification includes a test of whether the dependent variable (start time of activity in minutes from midnight) has a normal or a different distribution. In the OXS case it is observed that the dining-out activity has a bimodal distribution. We proceeded by splitting the activity (using the antimode) to lunch and dinner activities and we model the two activities separately by regression.

Table 6 presents the results from the regression models used to model the start time of each main and secondary activities.

Table 6 Activity start times models

Activity	Work/Edu		Lunch		Dinner		Shopping		Social		Recreation/Sports		Medical		Personal	
Coefficients	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	3.400e+04	21.75	514.1588	13.02	1059.4518	13.97	717.8802	14.64	827.2982	6.49	713.5415	13.04	543.8952	5.79	605.1448	4
Activity duration	-3.369e-01	-13.87	-0.0066	-4.72	-0.0029	-1.34	0.0133	7.69	-0.0097	-5.52	-0.002	-1.76	0.0067	-2.6	-0.0071	-2.24
Number of children			22.6164	0.81	-17.2845	-0.56	2.0776	0.1	-166.0315	-2.95	-38.4079	-1.37	161.6799	3.7	72.4909	1.22
Age	1.184e+02	3.538	1.2403	1.63	-0.5578	-0.46	1.632	1.94	0.8511	0.36	-0.3553	-0.35	-0.156	-0.07	2.9762	0.84
Number of employed persons in household			-15.7947	-1.54	26.3238	1.55	-33.1165	-2.71	-19.4539	-0.88	-24.2415	-1.71	-23.6411	-0.92	1.9212	0.04

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High income			107.6616	3.16	-7.7082	-0.2	92.3985	2.94	24.4749	0.33	3.7569	0.1	218.7226	2.81	62.6538	0.39
Mid income	4.229e+03	4.026	68.945	3	15.1977	0.68	15.2835	0.78	-22.5619	-0.5	54.9308	2.35	62.1317	1.54	-23.1091	-0.4
Low income			-0.7126	-0.06	-69.3425	-1.17	-48.9556	-2.03	-71.0631	-0.88	-45.4674	-1.37	-28.1022	-0.99	-235.4314	-1.25
Lowest education	-1.830e+03	-0.740	-147.4291	-1.05			-21.3192	-0.81	-289.6418	-0.99	-461.3972	-2.01			-379.982	-1.36
Lower education			127.459	3.18	-80.3862	-1.82	-136.8242	-5.27	7.6779	0.12	-39.8235	-0.96	69.3921	0.73	22.007	0.17
Mid education	1.457e+03	2.202	57.1612	3.55	13.5602	0.24	77.6393	3.32	-16.9376	-0.21	-64.5295	-1.73	30.6408	0.87	288.3628	1.81
Fully employed			32.8813	1.66	-18.5789	-0.51	-24.9177	-0.74	160.6429	2.59	133.8512	4.51	35.1381	0.81	93.7774	0.89
Partially employed	-3.307e+03	-3.679	-7.4869	-0.3	-53.0034	-0.86	-63.0697	-1.48	-58.8422	-0.81	39.3021	1.12	-42.9415	-0.81	-104.4014	-0.85

Fully employed - Self	- 3.965e+02	- 2.326	- 20.1808	- 0.78	- 40.3167	- 0.54	- 58.8731	- 0.48	142.6224	1.2	95.6973	1.68	- 40.2406	- 0.48	- 148.7608	- 0.96
Partially employed - Self	- 1.881e+03	- 1.601														
Pensioner									61.2468	0.21	176.8694	0.76	- 80.3553	- 0.92		
Weekend			13.4031	0.94	13.708	0.55	5.2923	0.3	- 11.9296	- 0.33	- 49.8734	- 2.32	- 6.0406	- 0.16	- 35.5739	- 0.59
Adj. R2	0.41		0.10		0.20		0.32		0.298		0.14		0.23		0.21	

After the successful estimation of the start times models, we use a predictive module to generate the activity start times for all the synthetic persons, given that they are predicted to participate in such an activity for the respective day. It should be noted that the regression models take into account the day of the week, for example for some activities it is statistically significant if the day of the week is a weekend (e.g. during the weekend the recreation/sports activity generally takes place 50 minutes earlier than a weekday).

Sequencing of activities

The next step of the pipeline includes the sequencing of activities and the generation of tours and trips. Based on the so far predictions and applied variables, we have a synthetic population database which includes the probability of an activity to happen for each agent and activity, the duration of this activity and the start time of the activity. We then proceed with the scheduling and dynamic rescheduling of the activities based on the following rules.

1. The work or education activity and tour are scheduled first. If an agent is predicted to participate in a work or education activity (out-of-home) a work tour is created. The work tour may be simple or complex
 - a. The work tour is originally created as simple (HWH).
 - b. If there is a joint activity predicted, a flexible discrete choice model is run in order to determine whether the joint activity happens before, after or both before and after work tour. This is the first way that the work tour can become complex
 - c. If a secondary activity is scheduled to start and end while the work duration is running a work-based tour is scheduled. This is the second way that the work tour can become complex
 - d. If a secondary activity is predicted to start in the time window after the work activity ends but very close to it, we add a stop to the return home trip. In this specification of the model, we used a time window of twice the travel time to home from work. For example, if the work of an agent ends at 17:00 and the model predicts a medical appointment at 17:15, the return to home trip is adjusted to account for a secondary stop. This is the third way that the work tour can become complex
 - e. We allow for a tertiary stop in the return to home trip, if the model predicts it for an agent
 - f. At the moment we do not allow for a stop before work other than joint activities, mainly because there are very few observations in the data and because it pushes the work start time which is considered a strong constraint in the time-prism of the daily schedules.
2. The secondary activity tour is scheduled then, it is the primary tour if the agent is predicted not to participate to a work activity and the secondary tour if the agent has a work tour
 - a. Rules b to e apply for the secondary tour also
 - b. We allow up to 3 stops in a tour, with the same temporal window used in the work tour
3. Other secondary activity tours are scheduled then – at the moment the maximum number of tours in a day is 5.
4. We perform a series of time corrections, attempting to respect the start times and the duration of activities predicted by the models
5. We create a time-bank to account and check for temporal inconsistencies. Any majorly delayed activities or very shortened durations are indicated in the time-bank and may be rescheduled.
6. The notation of the tours and the trips, along with their purpose and start time are exported.
7. We generate placeholders for future updating of time when calibrating the model

The above rules are based on the existing state-of-practice in ABMs, mostly influenced by the SIMAGENT framework (Goulias et al., 2011). However they are not validated step-by-step by any secondary data and the calibration happens on the output of the sequencer rather than in each step.

Destination choice

The next step in the pipeline is the estimation and application of the destination choice model. Overall, this is an MNL model, which uses a random sampling of the destination zones for each individual, both for model performance and for computational time optimization. For example, out of the 269 zones in TUR we sample 150, while in OXS out of the 86 zones we sample 50. The sampling is currently done randomly but other techniques (e.g. distance-based) are under development.

Table 7 Destination choice models

City	TUR			OXS		
Trip purpose	Work	Education	Secondary	Work	Education	Secondary
Distance from origin zone	-3.6053e-04 (-32.30)	-4.4532e-04 (-12.67)	-2.3433e-04 (-21.45)	-1.322-04 (-12.30)	-1.2452e-04 (-3.67)	-1.1134e-04 (-25.41)
Number of jobs in destination zone	1.5024e-04 (27.35)			2.4024e-03 (7.12)		
Commercial density in destination zone			1.72e-02 (2.45)			9.72e-02 (22.01)
Number of schools/universities in the destination zone		7.99e-01 (23.22)			2.02e-01 (2.23)	
Points of interest in destination zone			8.23e-02 (21.45)			2.345e-02 (1.45)
Adj. rho square	0.23	0.20	0.42	0.19	0.2	0.29

The destination choice model module is a rather complex module which takes input from many sources, namely:

- A distance matrix for the OD matrices in the simulation
- Jobs, schools, population and other variables (not all are used in the models) from the DFM and REM models
- Points of interest and densities of land-use from OpenStreetMap

After the successful estimation of the destination choice models, we proceed with the application of the model. The first origin zone is set to the home of each individual, and then dynamically, the model applies the respective parameters for each tour and trip. For example, if the first trip for agent x is a trip to work the model applies the parameters of the work purpose destination choice model, if the first trip for agent y is a trip for dinner, it applies the parameters of the secondary destination choice models. The origin zones change dynamically depending on the current zone of the agent. Computationally wise this part of the TPS takes 2+ hours to run on a 8-core server.

Mode choice RP

The final step in the sequence includes the mode choice models using RP data. This is essentially the data from the MOBY app, which includes detailed representation of origins and destinations for each trip. Based on a) the need for aggregation to the model zones and b) the need for diffusion to allow for spatial anonymity we proceed with the aggregation of the origin and destination coordinates of each trip to the model zones. Subsequently we pull from the existing skim matrices the time and cost skims for each modelled travel mode. We developed a series of MNL models including various specifications and travel modes, but in terms of applicability, performance and harmonization with the TUR models, we decided to run models for private car, bus and rail for OXS too.

Table 8 presents the results of the mode choice model

	Estimate	Std.err.	t-ratio(0)
asc_car	1.16	0.52	2.25
asc_bus	0.31	0.50	0.62
asc_rail	0.00	NA	NA
b_tt_car	-0.02	0.01	-2.26
b_tt_bus	-0.02	0.01	-2.57
b_tt_rail	-0.06	0.02	-3.95
b_tc_rail	-0.68	0.22	-3.07
b_tc_bus	-0.11	0.03	-3.58
b_tc_car	-0.10	0.09	-1.1
b_car_young	-0.76	0.13	-5.69
b_pt_students	1.18	0.19	6.15
b_pt_lowinc	1.10	0.19	5.78
b_car_ownership	1.16	0.09	13.66
b_distance_to_station	0.81	0.31	2.60

After the models are successfully estimated, the adaptive scheduler applied the models to each trip predicted by the pipeline so far. Cases where the mode is conformed due to the tour-based nature of the TPS include:

1. The return from work trip has to be conducted with the same mode as the home to work trip if a private car is used as a mode. Additionally, all secondary stops are conformed to this rule. Exception: the case of a work-based tour, where the mode is predicted freely by the mode choice model

2. The return to home trip for a secondary tour is again conformed to private car if the home to first stop of the tour is private car. Subsequent stops can be freely predicted by the model but the last stop to home is again conformed to be a car
3. Joint tours cannot happen by public mode for this version of the TPS
4. For the purposes of the LEV use-cases (see D2.5 for more information), we include a private car LEV mode in the mode choice model, using the vehicle stock model prediction as basis for the estimation.

After the application of the mode choice model, the agent schedules are complete. There is a post-processing module which transforms the agent schedules to OD matrices if this type of output is needed.

Chapter 5: Long-term model estimation for OXS

This chapter presents the results of the long-term models (based on the SP data) for OXS and for some missing cases in TUR. As in Chapter 4, this section does not get into much detail regarding the methodology of the developed models to avoid duplication. However if there are changes and updates to the methodology from the reported ones in D5.2 the methodology is presented again. The long-term (SP) models are important for the prediction of the future scenarios which are the basis for the use-cases. Where applicable, the prediction process is also commented on.

Remote work SP

The remote work model is an MNL model which estimates the willingness-to-participate to remote work. The SP experiment (presented in D5.2) includes 5 options ranging from fully remote to fully office work. Table 8 presents the results from the model estimation in OXS.

Table 8 Remote work model results for OXS

	Estimate	Rob.std.err.	Rob.t-ratio(0)
asc_FullyRemote	-0.94	0.26	-3.65
asc_PartiallyRemote	0.16	0.23	0.71
asc_Balanced	0.00	NA	NA
asc_PartiallyOffice	-0.21	0.14	-1.51
asc_FullyOffice	-0.23	0.14	-1.72
wage_FullyRemote	0.36	0.13	2.73
wagePR	0.23	0.08	2.80
wageBalanced	0.41	0.11	3.58
wage_PartiallyOffice	0.52	0.13	4.03
wage_FullyOffice	0.11	0.13	0.85
hours_FullyRemote	-0.19	0.13	-1.52
hours_PartiallyRemote	0.07	0.09	0.77
hoursBalanced	-0.22	0.13	-1.72
hours_PartiallyOffice	-0.14	0.13	-1.09
hours_FullyOffice	-0.20	0.14	-1.46
b_age_remote	0.29	0.21	1.87
b_high_edu_FR	-0.45	0.17	-2.65
b_RP_RemoteWorkDays	0.73	0.13	5.74
full_office_child	0.13	0.26	1.52

The results show a general preference of mostly remote work (as compared to balanced office and remote setting) and positive influence of wage increase (as expected) for all work settings. In the case of fully office work, the wage increase is not significant. For the increase of working hours, the parameters did not reach significance across all work settings. Additionally, from the socio-demographic characteristics explored, only younger age (marginally) in the fully remote setting and higher education (negative) for the fully remote setting were significant. As opposed to TUR results having children does not affect the fully office setting in a statistically significant way. Finally, the reported days of remote work has a positive influence in the choices of fully or partially remote work in the model. The above parameter is tricky to extrapolate in the future while being the most significant in the model. At the moment we utilize the number of remote workdays present in the sample and extrapolated in the process of the synthetic population to apply the model to future temporal settings. This is not the ideal application, and we are currently investigating the use of random draws or simulation to model this in the future.

After the model estimation, the results are applied to the synthetic population database to generate the percentage of people working remotely. The percentage of people predicted to work fully remote are excluded from further scheduling of work trips, the percentage of people working partially remote, balanced or mostly office is predicted to have work tours in a probabilistic way, given that for the current applications of the TPS the model simulates a single day.

Mode choice SP

The mode choice model is a mixed logit model, where travel time and travel cost parameters for private vehicle and public transport are modelled to be randomly distributed. From the initial overview of the ASCs it seems as the private vehicle is the most popular travel mode. The model predicts significant parameters for travel time and cost across all modes, with the travel cost and time for private vehicle and travel cost for public transport showing significant heterogeneity in their distribution among respondents. In terms of waiting or parking time, only waiting time for shared vehicle is significant and negative. Interestingly enough the number of co-travellers is not significant, and the options of flying shared taxi, uber-like ride hailing service and any level of autonomy in the case of private vehicle are not statistically significant.

Table 9 Mode choice SP results for OXS

	Estimate	Rob.std.err.	Rob.t-ratio(0)
asc_shared	-1.59	0.48	-3.33
asc_prt	0.00	NA	NA
asc_bike	-0.68	0.45	-1.51
asc_walk	-1.28	0.45	-2.81
asc_PT	-0.47	0.60	-0.78
asc_RH	-2.09	0.49	-4.22
b_tt_shared	-0.01	0.00	-2.55
sigma_log_b_tc_prt	0.26	0.11	2.30
mu_log_b_tc_prt	-15.03	0.17	-88.27
sigma_log_b_tt_prt	-1.80	0.15	-11.71
mu_log_b_tt_prt	-3.61	0.27	-13.21
sigma_log_b_tc_put	0.90	0.16	5.61
mu_log_b_tc_put	-0.90	0.29	-3.06
sigma_log_b_tt_put	1.03	0.85	1.20
mu_log_b_tt_put	-4.83	1.02	-4.75
b_tt_RH	-0.01	0.00	-3.37
b_wt_shared	-0.04	0.01	-3.13
b_wt_private	0.00	0.01	0.43
b_wt_PT	-0.01	0.01	-0.44
b_wt_RH	0.02	0.01	1.65
b_tc_shared	-0.09	0.04	-2.12
b_tc_RH	-0.09	0.04	-2.02
b_tt_bike	-0.96	0.14	-6.72
b_tt_walk	-0.38	0.07	-5.24
b_shared_cotravellers	0.01	0.20	0.07
b_PT_full	0.02	0.15	0.15
b_uber	-0.11	0.21	-0.52
b_flying	0.13	0.20	0.63
b_prt_av	-0.14	0.14	-1.05
b_RH_cotravellers	-0.02	0.19	-0.10

Applying the results of the model to the synthetic population when using a mixed logit specification can be challenging. For this reason we revert to a simple MNL when applying the model results to make predictions. This way we generate the future scenario plans, where we can observe the new predicted modal split when all new modes are available in the market.

Mobility tool ownership SP

To enable an efficient switch away from the ICE (Internal combustion engine) vehicle, it is important to assess how prospective owners can be attracted to more sustainable modes of vehicle ownership. Furthermore, it is important to assess how their personal circumstances, such as household income, socio-economic status, vehicle ownership status and so on impact on future vehicle purchase choices. Given the many challenges in the transportation industry, such as decarbonisation, it is of great importance to accurately predict how vehicle ownership will develop. For this reason, more and more literature is targeted at these issues (e.g., Wenjian and Chen, 2021). Existing findings suggest that being male and having higher educational attainment are associated with positive effects on EV adoption. Further, the availability of fast charging stations are important.

To add to this body of literature, we investigate how people respond to alternative vehicles when deciding on purchasing a new car. To aid this investigation, a Stated Preference (SP) survey was employed to assess how people would react to these alternative vehicle offerings. The alternatives presented were based on the method of propulsion (e.g., petrol, diesel, hybrid or electric). In the SP, factors such as vehicle size, vehicle price, fuel price, CO₂ emission, VED tax, MPG (miles per gallon) and electricity price are considered as can be seen in D5.2

Results

The model specification resulted from including the attributes from the SP design, whilst for the socio-demographics, a systematic process of selecting suitable candidate variables from the travel behaviour and socio-demographic survey was performed. For the choice variables, attributes were only included if the t statistic was around 1 and were otherwise discarded.

The model results are presented in 10 and Table 11, included model statistics such as log likelihood, AIC, BIC and the rho squared. The models have satisfactory performance and yields stable results, with parameters having the expected signs. To contrast the Turin and Oxfordshire region, two models have been developed with the same parameters, whereby Turin serves as the benchmark. Regarding the SP attributes included in the model, many attributes are not statistically significant, or only at the 70% level at least. For this reason, only variables significant at the 70% level were included for the Turin model. To contrast differences between the regions, the very same model was estimated for Oxfordshire.

For the Turin model, only vehicle price and fuel price contributed to the model, with fuel price variables only significant at the 70% level and vehicle price components performing better and showing statistically significant results at the 95% level. For Oxfordshire, only the vehicle price components, apart from Diesel and Hybrid, contribute to the model, whilst the fuel price variables are insignificant at the 70% level. It thus seems that fuel price does not impact on vehicle choice for Oxfordshire, whilst for Turin it does. This could be explained by the survey period in Oxfordshire, which coincided with record high fuel prices.

For Turin, the price parameters all have negative signs, indicating that an increase in price leads to a lower probability of respondent i preferring vehicle alternative j . There are however differences in magnitudes of the parameters. For the diesel vehicle price, it is notable that respondents are much more price sensitive relative to other alternatives, whilst hybrid and electric have lower price sensitivities. An explanation could be that if people have a large budget for a vehicle, they would rather spend this on vehicles with newer propulsion technologies, such a hybrid or an EV (which could explain why these two vehicle types have lower price sensitivities), whilst respondents on a lower budget likely cannot afford these vehicles, choose between petrol and diesel and have high price sensitivities, thus only considering hybrids when the price is reasonably low. It may also be the case that respondents are more price sensitive regarding diesel vehicles, perhaps due to recent controversies surrounding

diesel vehicles, e.g., the VW scandal, and perhaps incoming environmental regulations more likely to target diesel vehicles. This may indicate that diesel vehicles are perceived as a more 'risky' purchase. Regarding the fuel price, it is notable that there is some evidence to suggest that higher fuel prices impact on the probability for choosing the current vehicle and the hybrid vehicle. It could be that respondents are preferring to purchase another vehicle if their current vehicle has higher fuel costs. For the hybrid vehicle, it could be that respondents are sensitive to the fuel price, since part of the reason for purchasing a hybrid could be that they wish to decrease their fuel costs with this investment.

For Oxfordshire, only the price parameters for the Petrol, Hybrid and Electric have negative signs. Interestingly, the price for the current vehicle has a positive impact, which indicates that the more expensive the current vehicle is, the more likely the respondent is to prefer his/her current vehicle. This effect is not observed for Turin, however in Turin, most of the respondents did not own overly expensive vehicles, whilst there are participants owning vehicles in the high-end range in Oxfordshire. Interestingly, fuel prices don't impact on vehicle choice, but as mentioned, the survey took place during unprecedented fuel prices in Oxfordshire. Finally, it should be noted that in Oxfordshire, 32% of the respondents does not currently own a vehicle, whilst this is only 12% for Turin. This explains why the alternative specific constants are positive in Oxfordshire and not in Turin.

Regarding the socio-demographics several variables have been included. Several interesting results can be derived. For participants in Turin that do not own a vehicle currently, there seems to be a higher probability for preferring a petrol car relative to the other alternatives. Perhaps non-car users are hesitant to adopt an EV or a hybrid, perhaps because they are not too familiar with vehicles to begin with and thus 'play it safe'. Interestingly, in Oxfordshire, participants without a vehicle are much less likely to prefer the petrol car relative to other alternatives. This could be due to more attractive subsidy regimes, perhaps better provision of charging infrastructure in this region. Respondents that do own a vehicle, a vehicle less than 2 years old, are much less likely to prefer for the diesel or petrol vehicle relative to the other alternatives. Interestingly, for the hybrid and EV, no significant result is visible. This indicates that there might be scope to target them for a hybrid or EV purchase, even if they purchased a vehicle recently. Another factor that could lead to preferring a new vehicle is the household size, with larger households being less likely to prefer their current vehicle. Finally, age has been added and kept constant across the four new vehicle alternatives. The parameter sign indicates that increasing with age, the probability of preferring a new vehicle decreases, with this effect being stronger in Oxfordshire than Turin.

Finally, to create correlation across choices for the same respondent, error components have been added to the model for the 'current vehicle', 'diesel', 'petrol' and 'EV' alternatives. These are statistically significant and confirms the presence of correlation across choice scenarios.

Table 10 Turin modelling results

	Current vehicle	Diesel	Petrol	Hybrid	Electric
Alternative specific constant		-2.617 (-1.987)	-1.640 (-1.2507)	0.194 (0.1486)	-1.936 (-1.4977)
<i>SP attributes</i>					
Vehicle price	-0.698 (-1.748)	-0.252 (-2.287)	-0.413 (-4.415)	-0.32 (-5.816)	-0.204 (-3.560)
Fuel price	-0.563 (-0.996)			-0.453 (-1.1712)	
<i>Socio-demographics</i>					
Vehicle ownership: No current vehicle			0.719 (1.9913)		

Current vehicle age: Less than 2 years old	-1.496 (-2.1138)	-1.065 (-1.9904)		
Household size	-0.361 (-1.7271)			
Age (fixed across alternatives with 'current' as reference)*	-0.024 (-1.3286)			
Pseudo-Panel effect	3.558 (10.519)	2.277 (9.484)	1.795 (10.034)	1.944 (10.131)
<i>Model statistics</i>				
Observations	1962			
Number of decision makers	327			
LL(start)	-2624.11			
LL(final)	-2257.13			
Rho-squared	0.2688			
AIC	4554.26			
BIC	4665.89			
Number of inter-individual draws	2000 (mlhs)			

Table 11 Oxfordshire modelling results

	Current vehicle	Diesel	Petrol	Hybrid	Electric
Alternative specific constant		7.557 (2.5359)	11.967 (4.2199)	8.993 (3.1847)	8.832 (3.0461)
<i>SP attributes</i>					
Vehicle price	0.765 (1.055)	0.090 (0.664)	-0.100 (-1.140)	-0.050 (-0.650)	-0.199 (-2.362)
Fuel price	0.772 (0.838)			0.162 (0.309)	
<i>Socio-demographics</i>					
Vehicle ownership: No current vehicle			-3.001 (-6.952)		
Current vehicle age: Less than 2 years old		-1.097	-1.096		
Household size	-0.81782 (-1.906)				
Age (fixed across alternatives with 'current' as reference)*	-0.223 (-3.468)				
Pseudo-Panel effect	4.160	1.545	3.373		1.896

	(6.210)	(5.923)	(12.377)	(8.425)
<i>Model statistics</i>				
Observations	2316			
Number of decision makers	386			
LL(start)	-2648.78			
LL(final)	-2047.31			
Rho-squared	0.4251			
AIC	4128.62			
BIC	4226.33			
Number of inter-individual draws	2000			
	(mlhs)			

Within-day Re-evaluation SP

The study of travel behaviour dynamics is a significant but complex issue in transportation demand modelling. Recently, it has become increasingly relevant with the rise of new transportation services and advanced traveller information systems. These systems provide travellers with real-time information and alternative travel options, making their decision-making process more flexible and less dependent on their established patterns. However, unexpected events, both exogenous (e.g., weather conditions, car malfunction) or endogenous (e.g., congestion), can impact their plans. When faced with frequent travel disruptions, individuals may adjust their behaviour in both the short-term and the long-term. For example, they may alter their trip facets in response to a road closure, but they may also change their habitual daily schedule, such as working from home on days of anticipated delays. Ultimately, individuals are found to progress towards a stable state and (re)develop a set of day-to-day travel habits through the reinforcement of specific strategies.

In D5.2, we presented the dynamic demand shift module which aims to capture the inherent dynamics of within-day choices at the operational level in presence of live information, as a result of travel time fluctuation. In this deliverable, we present the research on the factors and sociodemographic characteristics that affect this re-evaluation behaviour, by defining the notion of Adaptive Travellers. We explore this latent variable using Structural Equation Modelling (SEM), enabling us to identify the factors that contribute towards different levels of sluggishness and resistance to change.

Data Collection

The re-evaluation of daily scheduling choices is a complex phenomenon influenced by various unobserved variables and characterized by strong interpersonal heterogeneity. Within the HARMONY project, these travel behaviour dynamics were studied by collecting data through the application of a stated adaptation experiment (D5.2), but also through a series of attitudinal Likert statements, as part of the wider travel survey applied through the MOBY smartphone application. In the design phase of these statements, factors that were found of interest include, but are not limited to, travel time punctuality, social norms, flexibility, traveller information seeking, comfort and convenience. Nevertheless, those attitudinal statements typically found in literature were adapted towards the new mobility standards set by the COVID-19 pandemic (e.g., remote work options), which also provided interesting findings regarding its effect on the travellers' perceptions going forward. In addition, we explored two important attitudinal factors related to travel demand dynamicity, i) *resistance to change*, the inertia observed in the adaptation of individuals' habitual travel patterns and ii) *tendency maximization*, the concept of selecting good enough (satisficing) alternatives versus utility optimizing ones. Within the concept of re-evaluation, these factors are prominent and often observed through the *similarity* in the habitual alternative choices and are key in the subsequent selection of the appropriate dynamic model.

The selected attitudinal statements were used to measure the level of agreement of 1070 recruited individuals in the Oxfordshire region. Exploratory factor analysis was then applied on the

complete set of attitudinal statements of the experiment, to identify latent factors that could be linked with the behavioural process of travel re-evaluation. Table 12 presents the grouped 16 statements, along with the mean and standard deviation of the recorded responses. Examining those tendencies,

Indicators of Adaptive Travellers		Mean	SD	we
IADP1	It is very important for me to have short travel time to my main activities	5.17	1.23	
IADP2	I am willing to depart earlier or later if it can reduce my travel time	5.28	1.16	
IADP3	I would like to have flexible working hours to avoid rush hour commute	5.28	1.30	
IADP4	I would like to have remote work options to avoid rush hour commute	5.24	1.34	
IADP5	I would prefer working from home instead of commuting	4.80	1.51	
IADP6	I acquire travel information from my phone, as I am sure of their reliability	5.23	1.22	
IADP7	I acquire travel information from my phone when I go somewhere I have never been before	5.41	1.28	
IADP8	I would acquire travel information from my phone if I came across congestion on my route	5.23	1.27	
IADP9	I am willing to acquire travel information while en-route to my destination	5.25	1.24	
IADP10	I acquire travel information from mobile devices prior to my trip	5.34	1.26	
IADP11	I would feel lost if I run out of battery while travelling	5.04	1.42	
IADP12	When I encounter delays in my travel plans, it stresses me out	4.89	1.28	
IADP13	I always try to maximize the efficiency of my trips	5.28	1.12	
IADP14	Whenever I need to adapt my trip schedule, I try to imagine all potential options	5.13	1.14	
IADP15	I always try to choose what I consider the best mode for my trips	5.32	1.10	
IADP16	I always try to optimize the route I choose for my trips	5.31	1.11	

hypothesize that a latent variable affecting within-day travel decisions relates to the sensitivity to travel time, the dependence and reliability to travel information applications, and the level of optimizing or satisficing nature of the individual. We broadly name this latent variable as 'Adaptive Travellers'. It describes individuals that place a high priority on minimizing travel time and reducing stress associated with delays. In order to maximize the efficiency of their daily travelling choices, they are willing to proactively seek out advanced travel information prior to departure or en-route to their destination. We would like to identify the sociodemographic factors that can explain those tendencies but also test whether higher value of this latent variable is associated with higher probabilities of modifications and lower resistance to change at the within-day level.

Table 12 Attitudinal statements on within-day re-evaluation

Methods

Within the scope of the project, the Structural Equation Modelling method selected is based on the ordered probit model, in order to address the discrete and ordered nature of the collected Likert statements. Having defined the notion of Adaptive Travellers, it can be treated as a Latent Variable, which is evaluated using a structural equation,

$$\mathcal{X}^* = \lambda_0 + \sum_{k=1} \lambda_k X_k + \omega, \text{ where } \omega \sim N(0, \Sigma_\omega)$$

where \mathcal{X}^* is the latent variable based on the decision maker's attitudes or perceptions, X_k are explanatory observed variables, λ_k is a set of parameters, and ω is a normally distributed error term, in addition to a measurement equation,

$$I_s^* = \theta_{0s} + \theta_s \mathcal{X}^* + v_s^*, \text{ where } v_s^* \sim N(0, \Sigma_v)$$

where I_s^* is the latent continuous level of agreement to the indicators, θ_s is a set of parameters, and v_s^* is a normally distributed error term. As the indicators collected are discrete Likert-scale, we define the symmetrical thresholds τ_s -to be estimated from data- such that the probability of observing the responses j_s is,

$$\begin{aligned} Pr(I_s = j_s) &= Pr(\tau_{s-1} \leq I_s^* \leq \tau_s) = Pr(\tau_{s-1} \leq \theta_{0s} + \theta_s \mathcal{X}^* + \sigma_s^* u_s^* \leq \tau_s) \\ &= Pr\left(\frac{\tau_{s-1} - \theta_{0s} - \theta_s \mathcal{X}^*}{\sigma_s^*} < u_s^* \leq \frac{\tau_s - \theta_{0s} - \theta_s \mathcal{X}^*}{\sigma_s^*}\right) = \Phi\left(\frac{\tau_s - \theta_{0s} - \theta_s \mathcal{X}^*}{\sigma_s^*}\right) - \Phi\left(\frac{\tau_{s-1} - \theta_{0s} - \theta_s \mathcal{X}^*}{\sigma_s^*}\right) \end{aligned}$$

which is the CDF of the standardized normal distribution (Daly et al., 2012). Table 13 presents the estimation results for the measurement and structural equation models respectively.

Results

The output of the SEM provides some useful insights on the Adaptive Travellers latent variable. The piecewise linear specification of age indicates that individuals under 30 years old are more prone to adapting their schedule, which might be related to their higher usage and familiarity with smartphone travel applications. Interestingly, the effect is reversed for individuals over 45 years old, who gradually show less reliability to travel information and higher resistance to scheduling changes (Figure 7). This could be linked with factors such as established travel patterns and preferences, but also reduced mobility, especially for third age individuals, which could contribute towards a lower level of adaptiveness in daily travelling. In addition, the positive signs of driving licence and transit card ownership imply that those individuals have more flexibility and opportunities to adjust their schedule when in need, at a lower cost. Specifically, the driver licence provides a sense of independence and greater control over choices such as departure times and routes for a given trip. Higher education attainment is also found positively related to Adaptive Travellers.

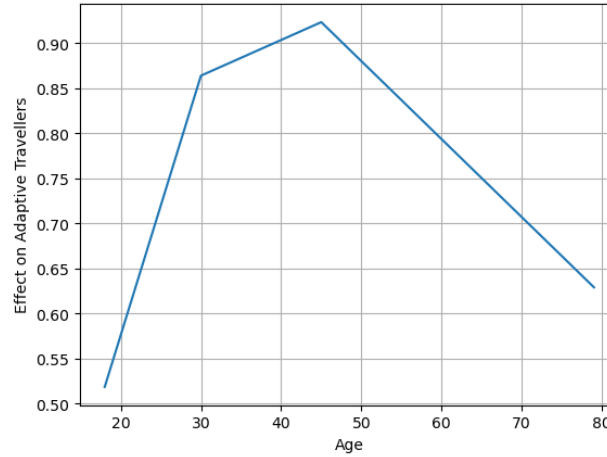


Figure 7 Piecewise linear specification of Age for Adaptive Travellers

These findings can be useful for answering various policy-related questions, such as the personalization of travel information provision based on the user's sociodemographic characteristics, and identification of high-probability travel alternatives when creating menu sets for recommendation systems. In addition, these heterogeneity measures will be utilized at the HARMONY Operational level to capture demand shift phenomena, which will be behaviourally grounded and more informed than typical numerical approaches of simulation environments. Specifically, the Adaptive Travellers latent variable could be integrated in the dynamic demand shift models of D5.2 as a hybrid (ICLV) modelling extension, further enhancing the realism and heterogeneity of the simulated daily schedules.

Table 13 Structural Equation Model results (Adaptive Travellers)

SEM			Measurement Model			Structural Model		
Param	Value	t-test	Param	Value	t-test	Param	Value	t-test
Θ_{ADP2}	-0.0515	-0.142	θ_{ADP12}	0.871	2.52	$\lambda_{AGE_UNDER30}$	0.0288	3.58
Θ_{ADP3}	-0.674	-1.26	θ_{ADP13}	0.899	2.71	λ_{AGE_30-45}	0.00396	2.05
Θ_{ADP4}	-0.823	-1.45	θ_{ADP14}	0.83	2.6	λ_{AGE_OVER45}	-0.00866	-2.96
Θ_{ADP5}	0.0171	0.506	θ_{ADP15}	1.46	3.2	$\lambda_{HIGHEREDU}$	0.115	3.63
Θ_{ADP6}	-0.0951	-0.257	θ_{ADP16}	1.55	3.26	$\lambda_{LICENCE}$	0.0658	2.98
Θ_{ADP7}	-0.0451	-0.878	σ_{ADP2}	0.934	28.4	$\lambda_{PUBTRAN}$	0.0987	3.1
Θ_{ADP8}	-0.454	-0.978	σ_{ADP3}	1.1	27.7	$\lambda_{INTERCEPT}$	0.0483	0.198
Θ_{ADP9}	-0.343	-0.781	σ_{ADP4}	1.14	27.7			
Θ_{ADP10}	-0.668	-1.24	σ_{ADP5}	1.27	28.2	Sample size	1070	
Θ_{ADP11}	0.0334	0.0918	σ_{ADP6}	0.985	28.4	Null Likelihood	-32164.15	
Θ_{ADP12}	-0.118	-0.364	σ_{ADP7}	1.1	27.5	Final Likelihood	-27061.32	
Θ_{ADP13}	0.168	0.54	σ_{ADP8}	1.05	28.2	AIC	54234.64	
Θ_{ADP14}	0.115	0.383	σ_{ADP9}	1.02	28.2			
Θ_{ADP15}	-0.351	-0.733	σ_{ADP10}	1.05	27.9			
Θ_{ADP16}	-0.409	-0.914	σ_{ADP11}	1.2	28			
θ_{ADP2}	1.14	2.97	σ_{ADP12}	1.01	28.8			
θ_{ADP3}	1.87	3.29	σ_{ADP13}	0.898	28.3			
θ_{ADP4}	1.99	3.31	σ_{ADP14}	0.901	28.5			
θ_{ADP6}	0.531	1.47	σ_{ADP15}	0.89	28.1			
θ_{ADP7}	1.15	2.93	σ_{ADP16}	0.888	28.1			
θ_{ADP8}	1.74	3.18	ζ_{T1}	0.36	33.8			
θ_{ADP9}	1.55	3.14	ζ_{T2}	0.745	37.7			
θ_{ADP10}	1.45	3.11	ζ_{T3}	0.937	37			
θ_{ADP11}	1.89	3.31						

Chapter 6: Conclusions and future steps for TPS

Deliverable D5.3 presents the final specification of the TPS, the scheduling sub-models results for OXS, the long-term (SP) model results for OXS and discusses the application of the model parameters to the synthetic population database in order to derive the final output of the TPS, which is the agent schedules.

Overall, an important outcome of this deliverable is the fully functional prototype of the TPS, which is now applied to the OXS and TUR cases, with differences in the code and the model estimations based on area particularities, data availability and quality and specification of the use-cases. The biggest difference among the two applications is the final output, which is in the form of OD matrices for TUR and in the form of detailed agent schedules for OXS. The TPS follows the overall “software agnostic” philosophy of the HARMONY MS, which is actively demonstrated in the TPS, by generating output in the form of OD matrices to connect to an existing 4-step model and its assignment module in the case of TUR and to an AIMSUN model in the case of OXS. Additionally, as in D5.2 presents the results of the long-term models (Remote work, MTO, MC) which are an in-between step across strategic and tactical simulators.

Comparing the digital activity and travel surveys (generated from MOBY app surveys) we were able to recalibrate the corrective algorithms that are a necessary step of data cleaning before the survey data is ready for modelling. During the process we were also able to notice differences in the quality of data between the two cities, which can be attributed to many factors but is out of scope of this deliverable to comment on. An important step for calibrating and adjusting the TPS includes to create flexible data transformations and adaptations of the models and code in order to create a more generic version of the TPS which can account for data variability among cities and contribute towards the transferability of the TPS.

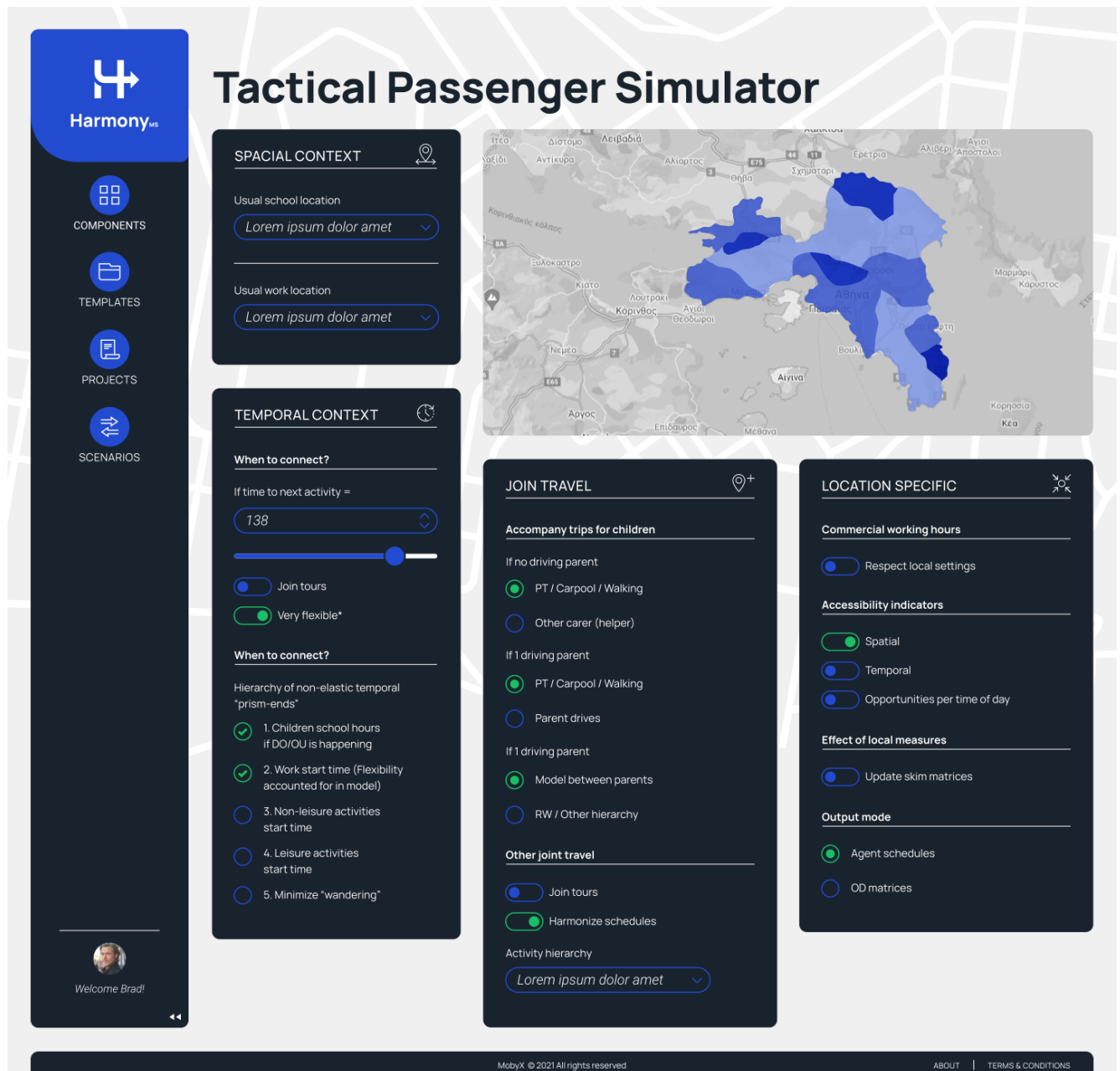
The Tactical Passenger Simulator is developed to an extent where it can essentially play the role of an integrated pipeline which gets input from a digital travel and activity survey and outputs synthetic agent schedules. Further steps in the development of the TPS include: a) more sophisticated or optimally chosen model methods, e.g. the inclusion of logsums in the communication between models or accessibility indicators when communicating to strategic models; b) the further code optimization to reduce computational time; at the moment the TPS takes ~4 hours to run for a synthetic population of 2 million agents; c) the integration of more models in the adaptive scheduler sequence, for example the creation of code which automatically checks for inconsistencies between model predictions and proactively offers solutions and re-scheduling and d) the finalization of the specification/input screen (GUI) where the user can determine specified inputs and interact with specification file in a user-friendly way. Finally, while components of the model have been calibrated for the case of TUR using outputs from previous models and secondary available data sources, a thorough end-to-end calibration process is currently running for both OXS and TUR, which focuses also on refining the set of rules of the adaptive scheduler.

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Appendix A – Screenshots of the Front-end user screen (under development)



Appendix B – final json file of integration to the HARMONY MS

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  "value": "EDU_DUR_par.csv"
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  "value": "WORK_TIME_par.csv"
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  "required": true,
  "value": "MainTourMC_par.csv"
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  "label": "Parameters from number of trips in secondary tours model",
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  "required": true,
  "value": "Trips2ndTours_par.csv"
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{
  "fieldType": "file",
  "key": "MCSecondaryActivity",
  "label": "Parameters from the mode choice to secondary activity model",
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}

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},
{
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  "key": "JointTravelLoc",
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  "description": "List of the estimated parameters from the joint activity location model. In comma separated (.csv) format.",
  "required": true,
  "value": "JointAct_Loc.csv"
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  "fieldType": "file",
  "key": "JointTravelMC",
  "label": "Parameters from joint activity mode choice model",
  "description": "List of the estimated parameters from the joint activity mode choice model. In comma separated (.csv) format.",
  "required": true,
  "value": "JointAct_MC.csv"
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  "value": "SchedulerSteps.csv"
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  "required": true,
  "value": "SchedulerRules.csv"
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  "description": "The results of the applied parameters to the synthetic population for all models, as a CSV-file.",
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  "value": "Shipments_REF.shp"
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  "value": "ODMatrices.csv"
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  "description": "The passenger demand in the study area, as a CSV-file.",
  "value": "workers_output.csv"
}
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  "label": "Output - simulation results of students decisions and activity participation",
  "description": "The passenger demand in the study area, as a CSV-file.",
  "value": "students_output.csv"
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  "key": "nonworkersOutput",
  "label": "Output - simulation results of non-workers decisions and activity participation",
  "description": "The passenger demand in the study area, as a CSV-file.",
  "value": "nonworkers_output.csv"
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  "key": "aggregatedStatistics",
  "label": "Output - Calculated main aggregate statistics",
  "description": "Modal split, pkms, flows, as a CSV-file."
}
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